POLITECNICO DI TORINO

Master's Degree
in Data Science and Engineering

Master's Degree Thesis

Tales of Work in the Age of The Blind Watchmakers(AI)

An anthological & mixed-methods study of the clashes of schools of thought and public perceptions.

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To my father,

who instilled in me as a child the love for knowledge and righteousness & who always supported me, even when he did not understand.

Summary

It would not be an overstatement to demarcate this decade as the Age of AI, considered a hype or monomania by some and the path towards singularity by others. Whichever may be the case, the purpose of this work is to set aside these mythical, tale-like futures and to focus on others, also tale-like, but definitely less bound to sci-fi tropes. This study aims to explore in an anthological manner the perceptions of young people (18-35) regarding work, AI, and the impact of AI on the world of work. It seeks to provide a broad and multifaceted view of work, highlighting differing perspectives among various schools of thought and analytical models, with a focus on the quality of work. AI, which is now becoming (if it hasn't already) a general purpose technology (Lipsey et al., 2005) ought to be viewed as a socio-technical system and is analyzed as such, following up on work from Chen and Metcalf (2024). This ought to be done in such a way that the social matters are not thought of as some add-ons to the technical ones but rather to fully embrace the anti-technological determinism view that *"technology is society"* (Castells, 1996). It is only due to clarity and necessity that words like "impact" are used and they have to be read with reservation whilst thinking of the overall framework. In fact, the case is made, mainly based on arguments from Pasquinelli (2023) that AI is a labor-centered socio-technical system that has its very *raison d'être* ; it is constructed by and in turn constructs new forms of work and work-arrangements.

Various theoretical analytical models from some of the most prominent economists and social scientists in the field are confronted with the perceptions of young people, primarily from Italy, Albania, and Kosova, with some additional data from other countries. Perception analyses are of imperative importance because, irrespective of which theory best describes phenomena and prescribes solutions in "objective" terms, what materializes in the convictions of society, and consequently in policies and political realities, is largely dependent on what people perceive. This research uses a mixed-methods approach, combining qualitative interviews with quantitative survey analysis through data science techniques such as assessing statistical significance, exploring correlations, and performing classification and regression tasks. While established European datasets of population surveys are used where relevant, particularly the European Social Survey (ESS) dataset, the majority of the analysis relies on an original dataset collected specifically for this study between September 2023 and December 2024. The need for original data collection rose due to the disparity of well-known open datasets have with respect to the information regarding the perceptions on AI in particular and its expected impact in the multiple facets of work.

The data-collection process went as follows: 76 initial interviews (1.5 hrs on average) were made to co-design with the young people the questions for the online survey. This element is particularly important because in the cases where a known analytical model from an expert on the field was not used, the questions and specifically the dimensions of the questions were refined together with the interviewees. This exhibits the importance of a participatory research approach that prioritizes the lived experiences and conceptual frameworks of the research subjects themselves rather than imposing purely theoretical categories from above. The first online survey had 72 questions and resulted in 104 data points and took about 1 hour on average. The respondents had access to the author in real-time and throughout the entire process. In order to increase the cardinality of the dataset, a subset of these questions was chosen and a second survey was disseminated, which resulted in 112 data points. This second survey did not have real-time monitoring, however, some respondents said it lasted about 25 minutes on average. Finally, a last set of 36 interviews was made for questions that required elaboration and were not fit for the online surveys format and lasted about 1 hour on average. This resulted in a total of 254 hours of monitored/active data collection processes. While snowball sampling techniques were employed, maximal effort was made to ensure diverse demographics.

Storytelling is integrated to map the conceptual landscape and allow for proper science communication towards the wider public. The outline is set as a storyline, situated in the mythical-real city of Berat, Albania, and notions from novelas, tales, etc., for example from the Albanian author Kadare and his work "The Palace of Dreams" are employed. The end goal is very simple: In the cacophony that surrounds the impact AI will have on work, *anyone* reading this lengthy thesis can draw some insights on the key discussions that are being made among economists, technologists and social scientists in general. Each chapter follows a consistent structure: a fictional tale associated with neighborhood sketches serves as a visual outline, followed by theoretical, analytical and data science analysis, concluding with a "Tale in Brief" summary.

The first three chapters are situated in the *Mangalem* neighborhood of the mythical-real city: Chapters 2 and 3, Tales of Work and Tales of Artificial Intelligence, serve as a foundational exploration before examining the impact of AI on work in Chapter 4.

Chapter 2 investigates definitions of work through Word Cloud visualizations of open-ended survey responses, revealing that most people associate work with an "activity" to "get" "money." The chapter explores underemployment, and what makes work good & meaningful or in a contrapositive sense, a drudgery. The results show that the most defining dimensions of a good job is "work-life" balance with a score of 456 out of a ceiling of 520. A work-life balance index is constructed using Principal Component Analysis (PCA) to address multicollinearity among determinants measured through Variance Inflation Factor (VIF). Multiple linear regression shows demographic variables explain only limited variance in work-life balance ($R^2 = 0.007$). Moreover, work-life balance index is used to predict job satisfaction and using techniques to address severe class imbalance.

Chapter 3 examines AI histories, definitions, and public perceptions. Word-clouds of AI definitions from Online Survey 2 show the public associates AI with human-like thinking, despite current AI development being predominantly connectionist, highlighting urgent needs for better science communication. Statistical tests compare optimism about AI's societal impact, trust in institutions, and usage patterns across demographic groups. Spearman correlation reveals a moderate relationship between AI interest and optimism ($\rho = 0.323$, $p < 0.001$). Multiple linear regression predicting AI optimism from interest, age, gender, and political orientation explains 28.2% of variance ($R^2 = 0.282$, adjusted $R^2 = 0.221$), with all OLS assumptions verified, a relatively decent result for social science studies, where multiple factors influence outcomes and such a small sample.

Chapter 4 analyzes AI's impact on labor by first laying out the way economists have historically studied the impact of technology on work and how currently AI advancements and task encroachment are measured. Matters such as RBTC vs SBTC, the impact of AI in wages, job-loss, work-life balance, job satisfaction etc., were discussed. A special attention was given to the modern productivity paradox. An important result is the existence of a weak but statistically significant positive relationship (Spearman's $\rho = 0.219$, $p = 0.026$), suggesting that individuals who are more optimistic about AI's societal impact tend to anticipate a greater shift away from work-centricity. Also, Friedman test was conducted to examine how the respondents perceived different levels of underemployment across three dimensions (time, skills, and wage) changing after 10 years of AI development, revealing no statistically significant difference ($\chi^2 = 0.67$, $p = 0.717$).

Throughout these chapters, Mann-Whitney U tests were used for statistical comparisons particularly between Millennials versus Gen Z and between males and females. The results yielded statistically significant differences in very few instances, implying that attitudes toward work and AI are remarkably homogeneous across these demographic categories in their central tendencies, but more data are needed to have generalization.

Then a theoretical and conceptual bridge is crossed, leading to the *Gorica* neighborhood, where arguments are laid for the existence of a new form of unpaid work and the fabrication of desires in Chapter 5, which leads to a new business power in Chapter 6. Chapter 5 argues that AI has brought the rise of a new form of unpaid AI labor and the fabrication of desires, challenging the current theory of value as a cornerstone of modern economics. A Friedman test examining value creation perceptions reveals statistically significant differences among beneficiaries, $\chi^2(3) = 45.09$, $p < .001$, indicating participants perceived varying levels of value creation for themselves, friends/family, platform owners, and society through their social media participation. Chapter 6 introduces instrumentarian power as a distinct category beyond classical business powers (instrumental, structural, discursive), arguing it is particularly relevant in platform social-media AI-driven companies. Interviewees were exposed to existing power categories and asked whether this new power merits its own classification, with 21 out of 36 agreeing this is a new power and the opponents considering it as either "structural"(40%) or "discursive" (60%).

This study should be considered exploratory, laying the groundwork for future research with representative sampling and larger datasets to increase statistical power.

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Last but not least, I want to thank whatever the collective imagination of my country of origin had to offer. In the words of Mary Oliver: *"Someone I loved once gave me a box full of darkness.It took me years to understand that this too was a gift."* Among the many offerings contained in the culture of that place, I searched for the tales, and they formed a structure within me almost just as much as I imposed my imagination upon them, even in a world increasingly focused on deconstruction.

Contents

List of Tables

List of Figures

"So there you sit. And how much blood was shed
That you might sit there. **Do such stories bore you?**
Well, don't forget that others sat before you
who later sat on people. Keep your head!
Your science will be valueless, you'll find
And learning will be sterile, if inviting
Unless you pledge your intellect to fighting
Against all enemies of all mankind.
Never forget that men like you got hurt
That you might sit here, not the other lot.
And now don't shut your eyes, and don't desert
But learn to learn, and try to learn for what."

[Bertolt Brecht, To the Students of the Workers' and Peasants' Faculty]

"...and want during times that beg questions,
where something is up,
to be among those in the know,
(*unter den Wissenden sein*)
or else be alone."

[Rainer Maria Rilke, I Am Much Too Alone in This World, Yet Not Alone]

"Na të birtë e shekullit të ri,
...
duem ngadhnim!
ngadhnim, ndërgjegje dhe mendim të lirë!"

[Millosh Gjergj Nikolla, Të birtë e shekullit të ri]

Chapter 1

Introduction

Figure 1.1. The Outline situated in the mythical-real city of Berat

1.1 The research design, methodology and outline

For eons, thinkers have attempted to name phenomena, mainly after themselves, not only hoping to go down in history but most importantly to understand the very nature of reality. It was not always the case that some life-changing discovery was made, but when politicians and technologists alike name the upcoming future "The Age of AI" (Kissinger et al., 2021) and economists name the time we leave behind "The Age of Labor" (Susskind, 2020) and the one we face "The Second Machine Age" (Brynjolfsson and McAfee, 2014), when numerous people are attempting to name the age we face and the one we leave behind, something indeed metamorphic is occurring. Consequently, it is imperative to thoroughly explore the impact of these technologies on society and unravel the complex amalgam of consequences that come along with it. The emergence of groundbreaking technologies triggers extensive repercussions onto a multitude of societal domains. This is in fact the core argument of science and technology studies (STS), and that to obtain alignment with societal values, a certain degree of work in a variety of interdisciplinary fields needs to be conducted (Macnaghten et al., 2019).

This study aims to explore, from an anthological perspective, **the impact of AI on the world of work**. It seeks to provide a broad and multifaceted view, highlighting differing perspectives among various schools of thought regarding AI's effects. These theoretical insights are further enriched by the analysis of the perceptions of young people(18-35), primarily from Italy, Albania, and Kosovo, with some additional data from neighboring countries. The research employs a mixed-methods approach, combining qualitative methods such as interviews with quantitative analyses of survey data using data science techniques, and integrates storytelling, where relevant, to contextualize and deepen the findings.

In McLuhan's book "The Medium is the Message"(1967), which essentially predicted the rise of the mass media, it is noted: *"In his amusement born of rational detachment of his own citation, Poe's mariner in "The Descent into the Maelstrom" staved off disaster by understanding the action of the whirlpool. His insight offers a possible stratagem for understanding our predicament, our electrically configured whirl."* The argument in this work goes likewise. We are most certainly facing a maelstrom both in terms of complexity and in the diverging perspectives regarding the changes in work due to AI and the ways in which these are communicated. However, there is no other way to deal with it but right through it. That in turn explains the nature of this work, both in its lengthy and anthological components. There is a need for an anthological work that gathers multiple perspectives on how AI will impact the world of work, by examining the various determinants of work not only in quantitative but also in qualitative terms, and by considering not just wage-labor but also emerging forms of unpaid labor and the shifting power dynamics within these evolving work structures.

There are indeed large disagreements among researchers, not only regarding the impact that AI is expected to have in the future in the world of work but also on what is happening at this very moment due to IT technologies and automation, in general. For example, one of the main disagreements is the RBTC (Routine Biased Technological Change) versus the SBTC (Skill Biased Technological Change). The former proclaims that it is the occupations that are the most routine that are prone to be automated whereas the later states that the more skilled you are the less likely you are to be impacted by technological change. One of the proponents of RBTC, Autor (2015) contends that the interaction between machines and humans allows computers to take over routine, rule-based tasks, while increasing the relative advantage of workers in areas requiring problem-solving, flexibility, and creativity. This leads for many a hollowing out of the "middle class" or what is commonly known as "job polarization" (Autor, 2015), though there are notable discussions in weather technological factors are the ones leading to it (Fernández-Macías and Hurley, 2017). The proponents of SBTC dispel what they call "the myth of polarization" (Oesch and Piccitto, 2019) by stating that the polarization thesis does not hold empirically and it goes counter to the well-established SBTC. Instead, Oesch and Piccitto (2019) state that *"Job growth was by far strongest in occupations with high job quality and weakest in occupations with low job quality, regardless of the indicator used"*. This matter will be discussed at length in Chapter 4.

Who is right? This work aims to bring forth these different perspectives which give rise to different narratives, or better, to different *tales*, as we call them. They are most certainly not based only on narratives but also different data and different analytical models and operationalizations of the object of their study. The aim here is not for the author to determine which is better than which by some list of criteria but rather to discuss in a comparative fashion a subset of prominent theories about the impact that recent technologies like AI (and slightly its predecessors of IT) have and will have on labor. However, the goal here is not to be merely descriptive, even if in comparative terms, but rather to understand and **confront these concepts, ideas, theories, tales with the perceptions of young people in Europe.** The relevance of understanding the perceptions of young people regarding the development of AI and their understanding of work cannot possibly be understated. As Macnaghten et al. (2019) state: *"It is now widely recognized that understanding the processes through which publics make sense of emerging technologies and develop responses to them is critical for the design and coordination of reflexive mechanisms for public engagement and participation"*. **Regardless of which theory describes phenomena and prescribes solutions in the best way in "objective terms" (presuming that such a thing can be established), often what materializes in convictions of society at large and consequently in policies and political realities, is largely depended on what people perceive to be true.** After all, if there is anything to be learned from the myth of the Giant Antaeus [1] is the importance of keeping one's feet on the ground. Hence, this work confronts definitions, determinants and analytical models about work, AI and the impact of AI in work with the perceptions of a sample of young people, aged 18-35. In the first part, the author does not make an evaluation or argue for specific theories but rather simply present them

[1] Giant Antaeus was said to gain strength from contact with the earth. For more information, see `https://en.wikipedia.org/wiki/Antaeus`.

through online surveys and interviews and illustrate either through descriptive statistics, models or qualitative texts from interviews the results. In the second part, two theories are presented and argued for and then again confronted with the perceptions of samples of young people in Europe.

For the scope of this work, the perceptions of young people (aged 18-35) in Europe were chosen. There are many open-source datasets, like the award-winning European Social Survey (ESS) [2], the datasets of the International Labor Organization [3], World Value Survey [4], etc., that have collected perceptions, sentiments and opinions of people in Europe for many decades using different sampling techniques. Where possible, these datasets or statistics coming from these datasets will be used for analysis. However, these datasets have very little information regarding the perceptions on AI in particular and its expected impact in the multiple facets of work. As a result of this disparity, **there rose a necessity for data collection to fulfill the objectives of this work**. The pipeline and the multiple stages of the data-collection process are illustrated in Figure 1.2.

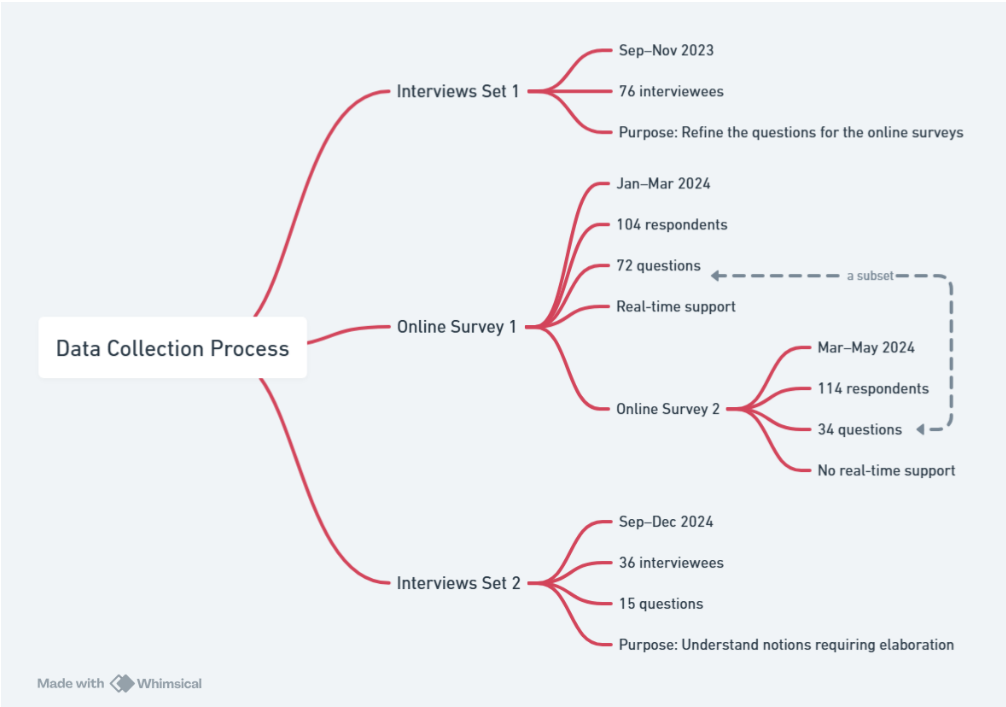

Figure 1.2. The research design and the data collection process.

[2]European Social Survey Data Portal
[3]International Labor Organization
[4]World Value Survey Database

The methodological approach adopted in this research follows a mixed-methods design, combining qualitative and quantitative techniques in a sequential and complementary way. Initially, a first set of 76 semi-structured interviews was conducted, which will be denoted from now and onward as **Interview Set 1**, to co-design and refine the survey instrument, ensuring that the questions reflected the perspectives and language of the young participants. Subsequently, an online survey was defined from that initial set of interviews, composed of 72 questions and was administered (**Online Survey 1**). It resulted in 104 data points. Later on, due to the lengthy nature of Online Survey 1, the 72 questions set was distilled and a subset of 34 questions was selected to enhance the number of data points(**Online Survey 2**). Finally, a second set of in-depth interviews with 36 participants was carried out to explore themes that were too complex or context-dependent to be adequately captured in the online survey (**Interview Set 2**). This integration of methods allowed for both the breadth of understanding through quantitative data and the depth of interpretation through qualitative insights, ensuring a more holistic understanding of how young people perceive the impact of AI on the world of work. Given that this is a non-funded research project, participants were recruited using **snowball sampling**.[5] However, maximal effort was made to ensure as much as possible balanced participation in terms of sex, occupations, and age groups (see the in-depth analysis of the demographics in 1.2.3). This research is exploratory and initial in nature; future studies should be conducted using representative sampling methods to ensure broader generalization of the findings. To ensure data quality in the two online surveys, an **attention-check question** [6] was included in the survey to verify that respondents were reading and engaging attentively with the items. Attention check questions are important in surveys because they help ensure that respondents are reading and understanding the questions carefully, thereby improving data quality and reducing the impact of inattentive or random responses (Berinsky et al., 2014).

In fact, alongside the seemingly hyper-technological imagery that have filled the popular imagination, with futuristic-looking robots and abstract neon-colored brains, something more archaic has received renewed attention: **the art of storytelling**. This work uses storytelling techniques, or in fact *tale-telling*, in order to become more accessible to the generic reader and integrate in a smooth and continuous manner the amalgam of concepts involved here. A more detailed view on why storytelling is relevant will be discussed in 1.2.1.

The entirety of this work, its outline, is superimposed on an arch-tale, that of the residents of the mythical-real city of Berat, as it can be observed in Figure 1.1. While we go through the different concepts, theories and components that make up the world of

[5]Snowball sampling is a non-probability sampling technique in which existing study participants recruit future participants from among their acquaintances. See `https://en.wikipedia.org/wiki/Snowball_sampling` for more details.

[6]An attention check question is a survey item designed to verify that respondents are paying careful attention, for example by instructing them to select a specific answer.

work *as is* and *as it will change* due to AI, the entire thing will be built as a journey in this mythical-real city. The primary reason the city of Berat was chosen is due to the fact that it is a cultural, political and social artifact which has been conquered by multiple empires at different moments in time and it is now a constellation and superimposition of the remnants that elsewhere would contradict one another. In fact, if we are to depict the impact AI is to have on society, particularly on work, I could not think of a more adept metaphor. As previously mentioned, there exists a constellation of contradictory theories, models and narratives *(or our favorite word: tales)*, that engulf this domain. Furthermore, the choice of a cultural artifact as opposed to a natural one, which is so common when it comes to what has inspired artificial intelligence scientists and businesses, is purposely chosen to highlight the fact that AI is a socio-technical system, subject to powers, political choices, cultures and narratives extended it time. Thus, it should be studied and understood as such. Placing the archaic and the futuristic in juxtaposition is done deliberately, particularly in this case to transmit the message that *the future is neither deterministic nor pre-ordained*, unlike some like to proclaim.

The outline of this work proceeds as follows: the first three chapters are situated in the *Mangalem* neighborhood of Berat encompassing the following topics: Tales of work in Chapter 2, Tales of Artificial Intelligence otherwise considered *The Blind Watchmakers* in Chapter 3 and Tales of AI's impact[7] on Work in Chapter 4, see Figure 1.1. In the first three chapters, the author of this work (or the chronicler as it is depicted in the tales), transmits the varieties of models and theories from state of the art research and then analyzes the opinions of young people that are confronted with those, without attempting to convince the reader of the superiority of a model or theory over another. However, Chapters 5 and 6 are depicted in the tales as situated in the neighborhood of *Gorica* (otherwise known as the neighborhood in which the sun doesn't shine in winter-time). This shift is ignited by crossing the theoretical and physical Bridge of Gorica through the usage of social media companies as the most exemplifying case study. In Chapters 5 and 6, the author of this work then tries to make the case for two theoretical points and then tests their convincing power in the residents of the mythical-real city *(read: the interviewees or respondents of the online surveys)*.

Chapters 2 and 3, Tales of Work and Tales of Artificial Intelligence, serve as a foundational exploration before examining the impact of AI on labor in Chapter 4.

Chapter 2 investigates the definitions of work, including arguments for unpaid labor being considered as work (Himmelweit (1995) , Miranda (2011)) which will then serve as a foundational basis to argue the rise of a new form of unpaid labor due to AI in Chapter 5. The definitions of work were an open ended question in the surveys and they are analyzed by constructing Word-Clouds with the frequency of the words having the largest fragments in the visualizations, in order to unravel the key terms associated with work. The

[7]One must understand conservatively the notion of "impact" as a non-deterministic approach in terms of technology is being taken here.

results show that most people associate work with an "activity" to "get" "money". Furthermore, underemployment and the qualities that make work good, meaningful or a drudgery, emphasizing qualitative aspects such as work-life balance and personal fulfillment are explored. When discussing work, a design decision is made to focus disproportionately on the quality of work as opposed to quantitative metrics. In terms of underemployment, its three types are studied in 2.3 in order to understand if the sample is aware of the concept, which kind they have experienced personally and to rank the types of underemployment based on the relevance for young people in Europe. This analysis is done through visualizations based on Interview Set 2. Moreover, what makes work *good* is studied in 2.4, by analyzing first the naive baseline of how much people like their jobs from Online Survey 1 and from ESS data in rounds 5 and 10. Differences among the two sexes and age-groups (18-26 and 27-35) are studied using statistical tests and two logistic regressions are used to try and classify job satisfaction levels into low (0-5) and high (6-10), based on sex, age and country for the first and only sex and age for the second. The dataset is highly imbalanced with respect to the job satisfaction category and thus under-sampling and oversampling techniques are employed. However, the analysis shows that demographic factors alone, namely sex, age, and country, have very limited predictive power for job satisfaction. What makes a job *good* is studied more in-depth beyond the intuitive job satisfaction and in Online Survey 1 a question was present where various dimensions were ranked as to what would make a job on an ad, a good job, with the work-life balance coming up as the predominant one, even when the analysis is made based on sex and age-groups. Hence, the work-life balance as a notion is studied in 2.4.2, by constructing an index for it using the Principal Component Analysis (PCA)'s first PC based on the data coming from ESS round 10. The PCA is used due to the presence of multicollinearity among the determinants of the work-life balance measured through the Variance Inflation Factor (VIF). Visualizations of the distributions of the work-life balance index are made to compare the two sexes and age-groups and then a multiple linear regression is made to try and predict the work-life balance through demographic variables. The model explains only a small proportion of variance in work-life balance ($R^2 = 0.007$), suggesting that other factors beyond age and gender contribute to differences in work-life balance. In addition, a logistic regression is built to try and understand if the work-life balance is a good categorizer of job satisfaction, again considering techniques to handle the severe class imbalance, exhibiting a 64.5% accuracy. Using the data and rationales provided during Interview Set 2, we go beyond *good* work towards *meaningful work* in 2.4.3 and the negative definition of what makes work a *drudgery* in 2.4.4. The interviewees were asked to rank the dimensions of what makes work meaningful (based onBankins and Formosa (2023)) and the dimensions of what makes it a drudgery (based on Bootle (2019)) and visualizations of the heatmaps for the rankings also based on the occupational groups and their respective rationales are provided. Last but not least, the respondents of Online Survey 1 were asked to rank the reasons they have for working in their current jobs as well as what they fear more in terms of risks on losing their current jobs in 2.5 and Spearman's rank correlation is measured among the two categories and all their determinants. People appear to fear *bad management* the most and mostly work *in order to make money.*

Chapter 3 presents AI histories, definitions, socio-technical perspectives, and public perceptions, thus, providing context for understanding how this technology is being currently developed and how it is understood by the young people that were sampled. Initially, a brif history of AI is presented in 3.2.1 and then the case is made in 3.2.2 that *AI is a labor-centered socio-technical system*, following arguments from Pasquinelli (2023), Chen and Metcalf (2024) and the deconstruction of the labeling *The Blind Watchmakers* is provided. The chapter then examines contemporary perceptions, levels of trust in various institutions, and usage patterns of AI, paying particular attention to young people's attitudes as revealed through survey results in 3.3. First, Word-Clouds of the AI definitions are shown based on data from Online Survey 2, illustrating how the popular imagination tends to associate AI with what is considered in the field a *symbolist* approach. However, currently AI is mostly developed in the *connectionist* one, highlighting the urgent need for better science communication with the public. Respondents of Online Survey 1 are queried on multiple matters such as: how optimistic they are about AI's impact in society; how interested they are in AI; how much they trust the abilities of various institutions to handle matters of AI; expectations on how AI may change inequality in society, etc. For each of these matters, descriptive statistics are provided together with visualizations such as histograms, plots that show the differences in percentage points among various demographic groups and statistical tests to measure if there are statistically significant differences among the sexes and age-groups. In 3.3.3, the relationship between *interest in AI* and *the optimism regarding AI's impact in society* is explored. First, the Spearman rank correlation is measured showing a minor ($rho = 0.323$) but statistically significant relationship, given that the $p - value < 0.001$. Furthermore, regressive analysis is made to predict optimism about AI's impact in society through AI interest by first using a simple linear regression. Then, a second model, a multiple linear regression model is build predicting AI optimism from AI interest, age, gender, and political orientation explains approximately 28.2% of the variance in optimism ($R^2 = 0.282$, adjusted $R^2 = 0.221$), indicating a moderate fit for social science data. In addition, all key OLS assumptions have been verified and met. Overall, the results suggest that attitudes toward AI's impact in society among young people are shaped by both individual interest in AI and demographic characteristics, though the best model leaves a substantial portion of variance unexplained, pointing to other factors that may influence optimism.

Chapter 4, Tales of AI's Impact in Labor, examines the concrete and theoretical effects of AI and automation on work. First, as all the other chapters, it begins with a fictional narrative that mirrors real concerns about the future of work and then moves toward a systematic discussion of how tasks, occupations, and skills can be analyzed to understand the mechanisms of automation and augmentation. The two forces: the substitution effect and the complement effect are explored and then perspectives are analyzed in their trajectory with AI development with arguments from economists like Susskind (2020), Autor (2015), Acemoglu and Restrepo (2019), Brynjolfsson (2022) etc. These forces are then explained to the people in Online Survey 2 and their responses are analyzed. Furthermore, in Interview Set 2 the matter of *"Is this time different?"* was present insinuating the potential of technological unemployment. Their answers both in terms of percentages w.r.t sex and occupational groups as well as their rationales are provided. This was one of the few matters that truly split the sample in half. The, a comparative analysis of different analytical models in measuring task automation due to AI is made in 4.2.2 using the works of Felten et al. (2018), Brynjolfsson et al. (2018) and Tolan et al. (2021) in order to allow the generic reader or even the technologist without a background in economics to understand how the advancements of AI and the automation of tasks by AI are operationalized. Further, the matter of SBTC vs. RBTC is discussed in 4.3 and comparisons are made between those that believe one or the other theory based also on occupational groups and sex from Interview Set 2. The expected changes with respect to wage-labor are analyzed in 4.4.1, considering matters like wages, the expected % of job losses, job satisfaction and working hours, all with data coming from Online Survey 2, disintegrating based on sex and age-groups. The three types of underemployment are revisited and their amelioration or deterioration after 10 years of AI development is analyzed based on responses from Interview Set 2. Qualitative aspects of work such as the work-life balance, work as a drudgery and overall work quality are also analyzed in 4.4.2 based on the expectations of participants in Online Survey 2 and Interview Set 2 after 10 years of AI development. Furthermore, the matter of the changes that AI is expected to cause in the amount of time spent in unpaid (household) work are also analyzed in 4.4.3. Finally, the matter of the Modern Productivity Paradox is given some special attention in 4.5, stemming from arguments made since 1987 by Solow on the mismatch of the omnipresence of computers but that not being reflected in productivity statistics. This is reiterated by Brynjolfsson et al. (2019) and others with the recent developments in AI and four potential explanations are provided: false hopes, implementation and restructuring lags, concentrated distribution and mismeasurement. The analysis of these four lines of thought is provided to the participants of Interview Set 2 and illustrations are made based on which theory seems more believable to them. As it was observed, the majority of the respondents "buy" the implementation lags argument, followed by concentrated distribution in the second place. Moreover, the respondents of Online Survey 2 were asked how productive AI makes them *now* and their expectations after 10 years of AI development on a scale from 0 to 10. The Sankey diagrams are used to show the movements on the expected scores on productivity.

The two theoretical points that are trying to be made in this work in Chapter 5 and Chapter 6 are the following:

1. The rise of AI has brought the rise of a **new form of (free) AI labor** and the **fabrication of desires**, thus breaking down the current theory of value that we use as a cornerstone of modern economics. This argument will be made in Chapter 5. This Chapter is mostly designed as a digression and it is only a very small fragment in this work. The two theories are then confronted with the perceptions of young people in Interview Set 2, complemented by questions in Online Survey 1.

2. This setting has brought **a new form of business power**: the *instrumentarian* one, if we use the demarcation of Zuboff (2019) but argue it in comparison to more "classical" forms of business power such as: instrumental, structural and discursive (Fuchs and Lederer, 2007). The argument made here is that his new power **is distinct** from those and it is particularly relevant in platform social-media AI-driven

companies. This argument will be made in Chapter 6. As in the previous case, the interviewees in Interview Set 2 are exposed to the current categories of business power and then are introduced to the new one and are asked to state if they believe this is truly a new power that merits its own category or if it belongs to one of the existing ones and if so, which. Descriptive statistics and visualizations on the matter as well as the rationales of the interviewees are provided.

Each chapter is organized as follows: first a tale is told about what we are expected to find in the chapter and it is associated with a sketch of a particular neighborhood of our mythical-real city to serve as a visual illustrator of the outline. Then, the theoretical and/or analytical analysis is made, depending on the chapter. At the end of each chapter, a summary is provided which is denoted as *Tale in Brief*.

From a data science perspective, this work primarily involves assessing statistical significance, exploring correlations, and performing classification tasks using "classical"[8] machine learning techniques, which are particularly suitable given the low cardinality of the datasets. In an age where the focus is often exclusively on big data, these methods remain highly effective for extracting meaningful patterns from small datasets, which can often be inevitable. Some subchapters focus primarily on theoretical considerations and descriptive statistics, particularly those where the qualitative responses from Interview Set 2 are considered. The overall goal of this work is to compare a subset of the main theories on the impact of technologies such as AI on labor and to confront them with the perceptions of young people in Europe, using an interdisciplinary set of tools ranging from data science techniques to narrative approaches. Given the fact that the analysis is predominantly a demographic one, in addition to visualizations and tables with frequency counts to understand the overall trends, statistical tests are used. The most used statistical tests are non-parametric ones such as Mann-Whitney U Test and Kruskal-Wallis-Test, given the fact that for the variables of interest, data did not follow a normal distribution. With respect to Online Survey 1 and 2, as well as data coming from external datasets, the two most studied demographic categories are the age-groups, specifically Gen Z (18-26) vs. Millennials (27-35) and males vs. females. The goal was to understand if there were statistically significant differences (at a 5% significance level) among these groups in the entirety of this work. Whereas in terms of data coming from Interview Set 2, the analysis is mostly based on descriptive statistics due to the lower number of data points and where relevant the demographics compared with statistical tests of significance are sex and the three occupational groups. Moreover, in many occasions the respondents and interviewees were asked to rank dimensions of certain notions, for example: to rank the dimensions of what makes work a drudgery. In these cases, heatmaps with the rankings are provided and where relevant, the Spearman Rank correlation is used to compare if, for example, the rankings provided to the motivations of doing their current job correlate with those of the risks on losing their current job. Furthermore, where relevant, regression and classification models are used to understand if demographic data are good predictors

[8]If we can actually consider as *classical* methods developed in the last 50-70 years.

of our variables of interest, for example: the satisfaction at work. Last but not least, using external data from The European Social Survey dataset, an index on work-life balance is built using The Principal Component Analysis, given the fact that the dimensions that were used to build the index showed high values of multicollinearity, measured through the VIF (Variance Inflation Factor) and Tolerance. This index is then used to classify satisfaction at work using Logistic Regression.

Most importantly, this work is designed to be accessible to a wide variety of readers, both technical and non-technical, and this is embedded in its very choice of words, structure and overall approach.

1.2 A descent into the maelstrom: a detailed view of the methodology, the data collection process and demographics

1.2.1 The rationale behind using storytelling or rather tale-telling techniques: Conte De Fées

"Creole began to tell us what the blues were all about. They were not about anything very new... For, while the tale of how we suffer, and how we are delighted, and how we may triumph is never new, it always must be heard. There isn't any other tale to tell, it's the only light we've got in all this darkness." Sonny's Blues, James Baldwin

We have been telling stories in a variety of ways since the beginning of time. From the earliest oral traditions passed down through generations to the intricate narratives woven into literature, art, and music, storytelling has been an essential part of human culture and identity — thus, something deeply ingrained. Slightly less than a hundred years ago, the German philosopher Walter Benjamin (1936) lamented the death of storytelling and, in his own words: *"It is as if something that seemed inalienable to us, the securest among our possessions, were taken from us: the ability to exchange experiences."* For him, the triad of the rise of the novel, the information age, and the trauma of the First World War rendered experience, the very core component of storytelling, completely valueless. However, paradoxically, telling the story of lived experience was never more valuable, given that *"for never has experience been contradicted more thoroughly than strategic experience by tactical warfare, economic experience by inflation, bodily experience by mechanical warfare, moral experience by those in power."* (Benjamin, 1936). However, we see a new trend on the rise and the revival of storytelling but with a twist: it is not the story that the individual tells. Given that *"people think narratively rather than argumentatively or paradigmatically"* (Weick, 1995), the potential of storytelling techniques and more recently storytelling with data has been currently exploited by technology companies, advertising agencies, politicians etc. It might sound contradictory that storytelling techniques have relevance in the seemingly "neutral, analytical and mathematical Age of AI", but its significance has gained an ever-increasing traction since the late 1990s. As noted by the management guru Stephen Denning about two decades ago in Harvard Business Review, (2004): *"Although good business arguments are developed through the use of numbers, they are typically approved based on a story—that is, a narrative that links a set of events in some kind of causal sequence. Storytelling can translate those dry and abstract numbers into compelling pictures of a leader's goals."* The usage of storytelling, combined with advances in machine learning (ML) and artificial intelligence (AI) has been successful in a variety of business domains.

Furthermore, differences are drawn between narratives and storytelling as techniques, in which a story is what someone tells and a narrative is a researcher's account of what someone tells (Rooney et al., 2016). In addition, the narrative as a term has been utilized in a loose manner, to signify a variety of qualitative texts, even interviews. Whereas stories, told by individuals about their life experiences, utilize universal "plots" assimilated from the world around them. Individuals then embed these plots into their own retelling of life events and happenings. It can be argued that because of this, stories are not creations of the individual alone but are constructed based on an understanding of the elements that guide a good narrative tale (Rooney et al., 2016). Thus, stories embed in themselves historical, societal and arguably political elements, without which their understanding would be rendered impossible.

However, the diversity of the lived experience expressed through storytelling is being rendered ever more uniform when it comes to the present and the future of Artificial Intelligence. Furthermore, despite its success, predominantly in business and political domains, and its constant and inundating usage by the technological sector, strangely storytelling has had limited usage and analysis from the perspective of academia, in terms of understanding the development of AI. However, it must be noted there are some efforts in this direction. For example, Tafani (2022) in analyzing the narratives when it comes to AI, particularly to ethics, drawing similarities with magical thinking and determining what's wrong with them:
"Artificial intelligence is the subject of a constellation of narratives – i.e. of ideas that are spread in the form of stories – which bear three features typical of magical thinking: the tendency to conceive of certain objects of technology in anthropomorphic terms; the magicians' move of showing a result, or an effect, at the same time concealing its concrete causes and costs and, thirdly, the belief that the future behavior of each individual person can be predicted (belief which is grounded, like astrology, on refined mathematics and on a hybrid mixture of superstition and science)."

In fact, the domain of AI has, since its very conception, been highly linked to bold claims and closely tied to critiques of magical thinking, exemplified perhaps best by the resistance of John McCarthy, one of the founding fathers of AI, to consider distinctions between mind and machine, claiming them illusory in the 1961 centennial celebration of the M.I.T(Greenberger, 1962), accompanied by the notable critique of Hubert Dreyfus in his work with the clearly indicative title "Alchemy and Artificial Intelligence." (Dreyfus, 1965)

More concerning and perhaps even more important is the widespread acceptance of "neutrality" and the perception of AI's future as deterministically inevitable, accompanied by a general reluctance to critically examine the narratives constructed around it, aside from a few notable exceptions like those mentioned above. Furthermore, not only are these discourses deterministic but also "enchanted", clearly utilizing the terminology of magical elements (Campolo and Crawford, 2020).

Contrary to popular rhetoric, there is no singular trajectory of development of Artificial Intelligence, no single story. Thus, no single way AI can shape the future of work. In fact, one of the main strategies employed by some technological companies, particularly the platform ones, to legitimize the immense power they have accumulated is a discursive one, naming themselves as inevitable vectors of progress (Yates, 2020). They draw upon the strategic importance of our collective imagination about the future, combining disruption, insurgency, and innovation to legitimize themselves as the one and only inevitable future through the usage of narration and storytelling. **One of the main goals of this work is to emphasize the existence of multiple lines of storytelling when it comes to the impact AI is having and will have on society, with a particular focus on work, viewed from the clashing perspectives of researchers and the perceptions of young people in Europe**. Stories hold a pivotal role in this work because they render complex, technical subjects accessible to a broader audience, ensuring that intricate analyses of AI and its societal impacts are understood beyond academic circles. By embedding scientific findings within narrative frameworks, this work enhances science communication, turning abstract data and analytical models into tangible, relatable experiences. This approach not only enriches the discussion by offering alternative perspectives, challenging the deterministic narratives often promoted by dominant viewpoints, but also revives the art of storytelling as a bridge between empirical research and the human experience. In doing so, it situates the research within a diverse landscape of voices and experiences, ultimately empowering the public to engage critically with the evolving story of technology and society.

Furthermore, for the purposes of this work, we will be moving semantically beyond stories, and onto its more archaic version, **tales**.

"Once upon a time" serves as an enchanting portal, opening the imagination to infinite possibilities. *"A tale is a narrative that is typically shorter than a story and often involves elements of folklore, mythology, or legend"* '(Manaher, 2023). When encountering what is seemingly a new age, referencing back to the old and familiar may be a useful tool to aid understanding, to challenge possible utopias and dystopias. Throughout this work, an overarching tale will unfold, drawing on tale-like motifs and the "arche" stories that shape both Albanian and wider European cultures. As noted by Heller (2006):
"A master narrative can be termed an 'arche' of a culture in both interpretations of the Greek word. The 'arche' stories are stories to which we always return, they are the final, or ultimate foundations of a type of imagination. Yet as the guides of imagination they also rule, control, and are vested with power. Direct or indirect references to master narratives provide strengths and power to new stories or new images, they lend them double legitimacy: legitimacy by tradition and by charisma, for in case of master narratives tradition itself is charismatic. References to a shared tradition are not just cognitively understood but also emotionally felt, without footnotes, without explanation or interpretation. It is not even necessary for single men and women to be familiar with the master narrative itself, for they are living in a world where a host of memories and interpretations are imbued by their spirit."

In fact, in yet another striking parallel between the archaic and the hyper-technological modern world, the very birth of the fairytale genre can be understood as an act of humanizing the singularized identity imposed on women by the society of the time. Through the use of fairies embodying a multitude of personality traits, these stories countered reductive portrayals, offering a wide view of personality traits, approaches and ways of being. This dynamic finds a necessary contemporary parallel in the way people, work, and technology must likewise be represented today, not through a singularized rhetoric, but through the acknowledgment of their multiple and diverse dimensions.

While tales have been told for eons, built by, and building, the imagination of peoples, and have been shaped by the interaction of orality, print, and other technological innovations, the fairy-tale genre is difficult to define and study. As studied by Zipes (2011), this is particularly challenging given the fact that none of the writers had used that term until 1697 when Marie-Catherine d'Aulnoy published her collection contes de fées, or fairy tales as it became commonly used in English. When, unexplainably, d'Aulony decided to baptize her collection as fairy tales, she was unaware of the epidemic and the explosion of imagination that was about to ensue. Fairies became the central figures of stories in tales, embodying fantastic characteristics and woven into stories that were told by women in French, Italian, Spanish and English saloons. The noun "fairies" came to largely determine the noun "tales" personifying and enacting traits that *"with their kind and nasty personalities, stood in opposition to the court of Louis XIV and the Catholic Church, and they were the antithesis of the pietistic Madame de Maintenon, Louis's morganatic wife, who insisted on introducing a reign of strict piety at the court and preached against secularism and worldliness"* (Zipes, 2011). Women writers, which at the time, were not afforded much space, if any, to determine the dialectic relation of a peoples with an entire literary genre, an embodiment of culture, history and the polis, suddenly were the ones to do so for the fairy tales. These literary salons served as safe havens, encouraging these women to read and perform their stories before being published. Afterall, in a socio-political world confined by other groups, *"it was only in a fairy-tale realm, not supervised by the Church or the dictates of King Louis XIV, that they could project alternatives that stemmed from their desires and need"* (Zipes, 2011).

If it was fairies and women writers in literary saloons that defined the nature of tales so much so that the two are almost always seen together in their blend word version "fairytale" and their semantics have become practically indistinguishable, which will be the noun that will serve as the defining feature of work and what is commonly denoted nowadays as artificial intelligence? Will it be a blend word, formed by a process which unsurprisingly is called blending, in which a word is formed from parts of two or more other words? Or will it be a portmanteau word, a literary device which encourages imagination by combining two distinct words into one and the new word takes on a whole new meaning? And, equally important, who will be the entities, social groups that determine it?

What will captivate the imaginations and shape the minds of the forthcoming generations transitioning from the world of yesteryear to the realm of tomorrow? Will labor stand in juxtaposition with its other word, having a contrasting effect and being in conflict with one another or will they be in alignment, placed close together precisely to highlight their commonalities? It could perhaps be that this defining word will in fact change the meaning of labor itself. It is not only the case that epochs and phenomena have their defining features embedded in words and narratives, but also that the very nature of certain phenomena gets altered due to political processes, so much so that the old meaning of labor and the new meaning of labor and the stories we told about it seem nothing alike.

The reader might be disappointed to discover that these questions will remain unanswered throughout this work. The goal here is to raise questions, tell and compare tales composed of narratives, analytical models, empirical models, and use critically whatever tools are at our disposal. The answers are for the collective to determine. However, it must be noted that the purpose here is not only to compare, but hopefully to understand. Equally important, the goal is to awaken the imagination and to impose on the world the reality that we would like to see ourselves.

The utility of the prevalence of the term "tales" in this work is three-fold:

1. First and foremost, it serves to aid understanding and awaken the imagination. Given the anthological nature of this study, which seeks to explore how AI will impact the nature of work, many different aspects and schools of thought are considered. To avoid confusion and to render conceptual connections more accessible, this work is framed through an overarching tale, that of the residents of a mythical-real city, Berat. At the beginning of each chapter, a tale introduces the themes we are expected to encounter, accompanied by a sketch of a particular neighborhood of this mythical-real city, serving as a visual illustration of the outline. The choice of Berat as the central metaphor is deliberate: it is a cultural, political, and social artifact that has been conquered by multiple empires at different moments in time and now stands as a constellation of remnants that, elsewhere, might contradict one another. If we are to depict the impact of AI on society, and particularly on work, few metaphors could be more apt. As will be observed throughout this work, there exists a constellation of contradictory theories, models, and narratives (or, in our preferred term, *tales*) that shape this domain. Moreover, the choice of a cultural artifact, rather than a natural one, which has so often inspired artificial intelligence scientists and businesses, is intentional. It underscores that AI is a socio-technical system, subject to powers, political choices, and narratives extended over time, and that it must be studied and designed as such. As the reader moves through this text, she will journey across the different parts of our mythical-real city, encountering its neighborhoods as she engages with the concepts under study. To understand the reliability of these concepts, given that perception analysis lies at the core of this work—the question will continually be posed: who are the people living in these houses? For instance, work–life balance is often considered a key indicator of the quality of work. Which inhabitants of our city regard it as the most important element? Who believes that AI will undermine work–life balance, and who believes that it will improve it? Some of these questions will be answered through statistical analysis, providing insight into how different perspectives inhabit and shape the shared landscape of work in the age of AI.

2. It is already the case that AI is presented with magical and tale-like characteristics, but the myths told are very much one sided. As clearly noted by Matteo Pasquinelli

in "The eye of the master: A Social History of Artificial Intelligence" (2023): *"propaganda about the almighty power of AI is the norm and sometimes even repeats the folklore of machines achieving 'superhuman intelligence'"* and that *"mythologies of technological autonomy and machine intelligence are nothing new: since the industrial age, they have existed to mystify the role of workers and subaltern classes."* The usage of tales in this work challenges the wide-spread deterministic rhetoric that often, ridiculously raises the predictions to astrological levels.

3. It serves as a constant reminder to think critically about new technologies by pushing to the seemingly extreme notion of tales, that here we have varieties of stories, often based on data, analytical and empirical models but nevertheless varieties of storylines based on the choices we make on their operationalization, consequently empowering the public.

However, let us not dwell any longer on the semantic distinctions between narratives, stories, and tales. It may be the case that the three notions are also used interchangeably at some point in this work, but the more prevalent use of the term "tales" is also an arbitrary choice made to achieve the above-mentioned goals. As it will be observed by the attentive reader, the matter of demarcation is constantly recurring in this work, whether it is forms of narration, forms of artificial intelligence, forms of work and labor or entire economic systems that are being discussed. After all, isn't it always the case that in times of disruptions we go back to classical questions, such as "What's in a word?"

1.2.2 The rationale behind choosing "Work" as the key social dimension to be studied

When reflecting about Artificial Intelligence's impact on society the focus is usually on what is commonly framed as GELSI (governance, ethical, legal, and social implications) [9]. For the purposes of this work, the focus will be on the anticipated impact that AI is to have in the world of work. In particular, the analysis concentrates on the social dimension of these implications, exploring how AI is expected to transform the structures, relations, and meanings surrounding work. The discussion highlights the clashing perspectives that emerge from economists and technologists regarding these transformations, including debates over the quality of work, shifting power dynamics, and the rise of new forms of unpaid or invisible labor, and how such changes are perceived and experienced by young people in particular.

The matter has indeed garnered significant attention from the wider public, but almost always under the imagination-captivating, fear-generating and ever obscure notion of "automation". The general public has been bamboozled by flashy articles that predict significant job losses with widely varying statistics and, at times, even the end of work as we know it. Others claim the ultimate economic paradise. However, this domain is

[9] The acronym GELSI expands another acronym, ELSI (Ethical,Legal and Social Implications), which originated in the fields of biotechnology and genetics.

subject to a variety of clashing perspectives from researchers and thinkers in the field, from neo-slavery to the rise of techno-feudalism (Varoufakis, 2023), to others claiming the end of scarcity and fully automated luxury communism. Understanding these divergent thoughts and predicted outcomes is no easy task. In an era dominated by thirty-second reels [10] and fragmented attention spans, it becomes increasingly important to disintegrate prevailing narratives and highlight their variety and the models they rest upon.

Analyzing and comprehending the impact that AI is having and will have on the world of work, including how it shapes work and is, in turn, shaped by it, is arguably one of the most, if not the most important discussion to be had when considering the broader impact of AI in society. There are three reasons why, among the other domains of socio-economic implication, work was chosen for this analysis:

1. The first reason can be seen as somehow arbitrary. From the perspective of the author of this work, labor is still the most important determinant of the shapes that the material basis of societies and social relations take. However, as it was observed by the lengthy analysis of Manuel Castells on The Rise of the Network Society (1996), it is acknowledged that dramatic changes have taken place and social movements have been primarily focused in matters of identities of all sorts: individual or collective, ascribed or constructed. Indeed, as noted by Castells (1996), shifts have been made from the *"considerable empowering of capital vis a vis labor, with the concomitant decline of the labor movement; increasing diversification of working relationships"*, etc and the fact that when change and chaos ensue *"people tend to regroup around primary identities: religious, ethnic, territorial, national"*. All these developments have profoundly affected societies and individual lives; yet, *ceteris paribus*, **it is the conviction of this author that work is *still* the central determinant of one's life**. It would require an entire other work to argue this centrality of labor in comparison to the other determinants or notions of societal organization that are impacted by technologies and that determine technologies, but it is not the scope of this work. However, this bias, or rather conviction, ought to be brought forward as the primary force that drives this work.

2. The second reason follows the rationale of Matteo Pasquinelli in his recent work from 2023 "The Eye of the Master: A social history of Artificial Intelligence" but also in his other works. As Pasquinelli (2023) analyzes, following the developments in the novel field of critical AI studies there are multiple (he denotes 3) positions on AI: mechanist, modelist and workerist. The first two positions presume respectively that: AI is either developed in order to imitate the biological intelligence and brain, what inspired the dreams of Turing and others, commonly known as symbolic AI or AI holds a different kind of intelligence and is used to create models of the world, exemplified by the current successful achievements in machine learning

[10] Referring to the dominance of short-form digital content (e.g., TikTok, Instagram Reels, YouTube Shorts), which has been shown to shape public discourse and attention patterns by favoring immediacy over depth.

and deep learning. The position that he is a proponent of is what he labeled as a "workerist" one, which presumes that **AI's very *raison d'être* is to automate labor.** In Pasquinelli (2023)'s own words: *"the inner code of AI is constituted not by the imitation of biological intelligence but by the intelligence of labour and social relations."* The fact that the current way we are developing AI is labor-centered in its very core will be explicitly argued in Chapter 3.2.2. Likewise, some historians of economics argue that the impact of technology on labor since the debates of the early Industrial Revolution have been paramount to the very birth and definition of the field of economics (Berg (1984), Card and DiNardo (2002)). Thus, it seems like the most natural duo to be studied.

3. Last but not least, **AI as a socio-technical system** has managed to surpass its "winter years" due to the developments in processors but also the availability of large "free" datasets to be exploited. The very existence of these datasets is due to our "free labor", as it will be discussed in Chapter 5. Without it, any benchmark successes of AI algorithms would be rendered impossible. In this work the approach of studying AI as a socio-technical system is employed, following the clear approach of Chen and Metcalf (2024): *"Although it may seem like an academic difference, this approach is distinct from the truism that technology influences, impacts, or affects society (and vice versa), as if the two are distinct entities that occasionally interact under specific circumstances. Rather, a sociotechnical approach asserts that technology and society are inextricable."* Thus, even when the terminology "impacts" is used, as in Chaper 4 for example, the reader is pleaded to not take the semantics at face value. Rather, the reader is invited to see beyond that and understand that for the purposes of this work, the theory of technological determinism[11] is set aside or even the whole matter considered a false question as in the case of Castells (1996): *"...the dilemma of technological determinism is probably a false problem, since **technology is society**, and society cannot be understood or represented without its technological tools."*

1.2.3 The data collection process and the demographics of the samples

As previously noted the data collection part included 4 stages: Interview Set 1, Online Survey 1, Online Survey 2 and Interview Set 2. In this section a detailed look will be given to the samples from each stage, given the fact that snowball sampling and not representative sampling was used and such a step is paramount to understanding and properly contextualising the finidings.

Interview Set 1 was composed of 76 interviews conducted between September and November 2023. This first set of interviews served three purposes:

[11]Technological determinism is a reductionist theory in assuming that a society's technology progresses by following its own internal logic of efficiency, while determining the development of the social structure and cultural values. See Technological Determinism in Wikipedia.

1. To test different questions and refine their phrasing and ensure their understandability for preparing the question-set for the online surveys.

2. To collect some qualitative meta-data, where some ambiguity arose on some specific questions, not due to the nature of the questions themselves but rather to the preconceptions of the interviewees. For example, when asked about their willingness to pay for access to social media, a common response was the fact that there was an inexistent need to pay given that it is currently available for free. These "meta-data" are of paramount importance in understanding the choices and perceptions of the participants in this study.

3. To co-design the survey instruments as much as possible within the analytical framework defined by the author, involving the young people under study in shaping the questions and categories. For example, when participants were asked *"What makes a job a good job when seen in an ad?"* the intention was not to impose predefined, static categories derived solely from the researcher's perspective, but rather to compile and refine these categories collaboratively with the young participants themselves. Such participatory and reflexive design is crucial for ensuring contextual relevance and interpretive validity as well as enhancing effectiveness, as highlighted in participatory research approaches (Cornwall and Jewkes, 1995).

Most participants of Interview Set 1 came from Tirana (Albania), Prishtina (Kosova), and Torino and Firenze (Italy), with smaller numbers from Budapest (Hungary), Vienna (Austria), and other cities (see Appendix .1.1). In terms of sex, the sample was evenly balanced, with 38 males and 38 females. Regarding age, the mean is 26.59 years, which aligns closely with the expected midpoint of a group ranging from 18 to 35 years (see the age distribution in Appendix .1.2). With respect to the political orientation, the distribution shows that most interview respondents were centered (21) or slightly leaning left (17), with fewer leaning right (CR = 13, R = 7), a smaller number firmly left (12) or far left (3), and only two with no clear position (2)(see Appendix .1.3). The interview respondents represented a diverse range of occupations, spanning technical and analytical roles such as software engineers, data scientists, and IT specialists, to creative and communication-focused professions like designers, illustrators, and content creators. Many were also students or early-career professionals combining work with studies in fields such as data science, law, arts, and social sciences, reflecting a highly educated and multidisciplinary sample.

The first set of interviews produced the 72 questions that created the **Online Survey 1**, which can be seen in Appendixes .1.5, .1.6,.1.7 and .1.8. The first online survey can be thought of also as a very structured interview because the participants had the chance while filling the survey to ask for help. Hence, this first set of quantitative data collection was conducted in a very controlled setting to ensure quality. Only about 40% of the participants from Interview Set 1 were also invited to complete Online Survey 1, chosen randomly, in order to ensure a certain degree of generalization beyond the sample that helped define and clarify the questions. The average time Interview Set 1 was 1 hour and a half and Online Survey 1 was 1 hour, as it can be observed in Figure 1.3.

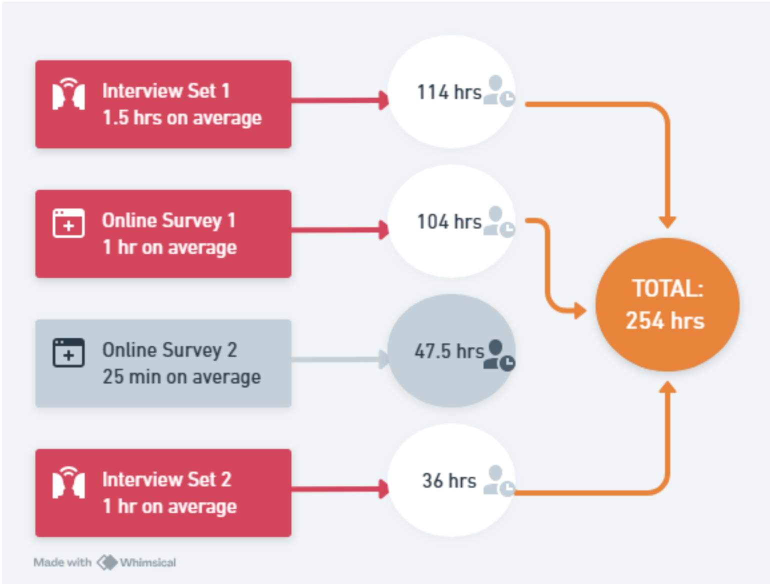

Figure 1.3. The data collection time consumption.

In terms of demographics of Online Survey 1, this also had balanced sex parity with 104 total respondents and 52 being male and 52 being female. The age distribution can be observed in Table 1.1 and the average age is 27.16. In terms of the city/country where the respondents were residing, 21% of the respondents reside in Tirana (Albania), 15% in Torino(Italy), 12.5% in Prishtina(Kosova), 7% in Firenze(Italy) and the rest distributed in various cities as it can be observed in Appendix .1.4. When asked if they were born in the country they currently live in, the respondents answered: "No" (56) and "Yes" (48). Thus, the sample encompasses both perspectives of people who have migrated and those who have not, allowing for a richer understanding of how diverse experiences shape perceptions of work and technology.

Age	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
Frequency	5	1	7	7	12	5	8	11	7	11	9	6	7	1	2	5

Table 1.1. Respondents' age distribution - Online Survey 1

Investigating further the sample composition, the sample is predominantly composed of employed individuals, either exclusively or in combination with other roles, reflecting a strong representation of active participants in the labor market. At the same time, there is diversity with students, self-employed, and unemployed respondents, ensuring that multiple perspectives on work and labor conditions are captured. The employment status was a multiple choice question in Online Survey 1 and the distribution of the responses can be observed in Table 1.2.

Current Employment Status	Frequency
Employed	58
Student	15
Student & Employed	11
Employed & Self-employed	6
Student & Unemployed	5
Unemployed	4
Self-employed	3
Student & Self-employed	2

Table 1.2. Respondents' current employment status (multiple-choice) - Online Survey 1

In terms of the education level, at the time of the survey, the majority of respondents of Online Survey 1 held a Master's degree (54) or a Bachelor's degree (38), with a smaller proportion having completed high school (9) and very few holding a PhD, some college, or vocational training (1 each). When the respondents were further asked in terms of the field of their study, omitting 13 that did not provide a response to this optional question, the results show that the respondents come from a highly diverse educational background. The largest groups are from Computer Engineering (5), Computer Science (3), Economics (3), and Software Engineering (3), while the remaining participants hold a wide variety of degrees spanning law, arts, sciences, health, and social sciences. This diversity allows the sample to capture multiple perspectives on work, technology, and societal impacts across different fields of expertise (see Appendix .1.9 for more details). In terms of the political orientation of the respondents, as it can be observed in Table 1.3, it is clear that the largest group of the respondents, 25%, self-declare as centrists and if we consider also those from center-left and center-right, the wider centrist groups accounts for 65% of the sample with the remainder in other categories but clearly more left-leaning.

Political Position	Frequency
Center	26
Center-Right	24
Left	20
Center-Left	18
Far Left	9
Right	7

Table 1.3. Frequency of respondents by political orientation - Online Survey 1

Average Respondent Description - Online Survey 1

Thus, the average respondent of Online Survey 1 is a 27-year-old male or female living predominantly in Tirana, Torino, Prishtina, or Firenze, reflecting a balance between locals and those born abroad. Most respondents are employed, with a substantial proportion of students or self-employed individuals, capturing a range of labor market experiences. In terms of education and political orientation, they mostly hold Bachelor's or Master's degrees across diverse fields, and identify primarily as centrist, with a wider range spanning left- and right-leaning positions.

Due to the high time-consumption that the initial survey required on average, see Figure 1.3, a subset of 34 questions were selected, and a second survey was created to increase the number of the data-points, namely what will be referred to as **Online Survey 2**. The selection of these 34 questions was done on the basis that they tackled an essential part of this study, namely the anticipated impact of AI in the work of these young people, which is part of Chapter 4. The question-set of Online Survey 2 made from the full-set of Online Survey 1 comprises the following:

- The entirety of the demographic questions, found in Appendix .1.5.
- Questions 23 and 24 from Section 2, see Appendix .1.6.
- The entirety of the Section 3, see Appendix .1.7, with the exception of questions 15 and 16.

The second online survey, unlike the first one, did not have "guidance" or online presence of the author of this work but was filled independently and took 25 minutes on average. It received 129 responses, out of which 15 responses *failed* the attention-catcher question and were discarded (see the question in Appendix .1.7). The remaining 112 valid responses were combined with the 104 responses from Online Survey 1, given that as mentioned the questions of Online Survey 2 were a subset of Online Survey 1. Further filtering for invalid responses[12] and concatenating the two sets, we form **the dataset with 215 data points of Online Survey 2.**

Thus, in terms of the demographics of the 215 Online Survey 2 respondents, there are 109 females and 106 males, reflecting an almost perfect sex balance within the sample. The age distribution, as shown in Table 1.4, indicates that the average respondent is in their mid-twenties, with the largest groups being 24 years old (26 respondents), 26 (19 respondents), 28 (18 respondents) and the average age being 26.63, very close to that of Online Survey 1. Overall, the sample is composed primarily of young adults, which aligns with the target population of early-career and university-level individuals, ensuring that the perspectives captured are those of a generation most directly engaged with the ongoing transformations in the world of work and technology.

[12] 1 invalid response of age being "neither", thus out-of-scope in the age-group set in this study.

Age	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
Frequency	2	3	10	5	16	17	26	12	19	17	18	17	13	11	8	4	3	14

Table 1.4. Respondents' age distribution - Online Survey 2

In terms of the cities they reside in, the largest groups of the respondents of Online Survey 2 reside in Tirana (Albania) 22%, Torino(Italy) 8.8%, Vienna(Austria) and Prishtina(Kosova) both 7.9% respecively, Budapest(Hungary) 6.5% and Firenze(Italy) 5.5%. The full distribution can be observed in Appendix .1.10. Out of the 215 total, 106 were born in the country they currently live in and 109 were not. The distribution of employment status (again, as a multiple choice question) can be observed in Table 1.5, where it can be clearly seen that the wide majority of respondents are currently employed.

Current Employment Status	**Frequency**
Employed	115
Student	28
Student & Employed	25
Self-employed	13
Student & Unemployed	13
Employed & Self-employed	12
Student & Self-employed	5
Unemployed	4

Table 1.5. Respondents' current employment status (multiple-choice) - Online Survey 2

With respect to the distribution of respondents in Online Survey 2 by educational level, as it can be observed in Table 1.6, the majority hold a Master's or Bachelor's degree, with a smaller proportion having completed high school or other educational paths, reflecting a generally highly educated sample. When the specific fields of study are asked (*optional question*), the respondents seem to come from a highly diverse range of educational backgrounds, with the largest groups in Computer Engineering (9), Political Science (9), and Software Engineering (8). Other notable fields include ICT (7), Economics (7), Architecture (6), and Computer Science (6), Medical Studies (5) while the remainder spans education, arts, social sciences, and professional disciplines. This diversity ensures that multiple perspectives on work, technology, and societal issues are captured across 80+ distinct fields of study (see Appendix .1.11). The sample of Online Survey 2 is predominantly centrist (see Table 1.7) with a slight left tendency, with 55 respondents identifying as Center, 44 as Center-Left, and 40 as Center-Right, meaning 69% of respondents fall within the broader centrist spectrum, while the remaining respondents lean toward left or right.

In addition, the demographics and the average respondent descriptions stated here are of paramount importance when interpreting the results of this analysis, particularly because snowball sampling was used, which may influence representativeness and generalization.

Education Level	Frequency
Master's degree	93
Bachelor's degree	84
High school	33
PhD	2
Some college	1
Vocational training/education	1
Primary school	1

Table 1.6. Respondents' highest education level obtained - Online Survey 2

Political Orientation	Frequency
Center	55
Center-Left	44
Left	43
Center-Right	40
Right	19
Far Left	14

Table 1.7. Respondents' political orientation - Online Survey 2

Average Respondent Description - Online Survey 2

The typical respondent of Online Survey 2 is a young adult in their mid-twenties (average age 26.63), with a nearly equal gender balance (109 females, 106 males). In terms of location, the largest groups reside in Tirana (22%), Torino (8.8%), Vienna (7.9%), and Prishtina (7.9%), while 106 respondents were born in the country where they currently live and 109 were not, reflecting a mix of native and migrant perspectives. They are primarily employed and highly educated, with most holding a Master's (93) or Bachelor's (84) degree and coming from a wide range of disciplines. Politically, the sample is predominantly centrist, with 69% of respondents identifying as either Center, Center-Left, or Center-Right.

As previously mentioned, a final set of interviews was conducted and named **Interview Set 2**, with 36 interviewees (see Figure 1.2) and with a duration of about 1 hour on average (see Figure 1.3). Its purpose was to address the concepts that required further elaboration and that were not appropriate for the online surveys format. For example, the matter of RBTC (routine biased technical change) vs. SBTC (skill biased technical change), the concept of the existence of unpaid work etc, which cannot reasonably be summarized in a short paragraph in an online survey version. The full question set for Interview Set 2 can be found in Appendix .1.12. This set of interviews targeted three particular occupational groups: artists, scientists and technicians, and those coming from political science. The nature of the majority of questions posed to the young people in the last set of interviews were predominantly to determine which theory or analytical model they "buy", particularly in matters that tend to be divisive. Thus, in a way these young people were required to establish some sort of *"truthfulness"*. Inspired by the work of the French philosopher Alain Badiou and his four domains of "truth procedures" (Badiou, 2005) (i.e., they produce truths as they are pursued), that is: scientific, artistic, political and love, the first three were chosen. This is due to the fact that these young people in these respective groups, due to their training or work, might be subconsciously used to determine truth in different fashions. In Badiou (2005)'s view, each truth procedure constitutes a distinct way of engaging with reality: science through proof, art through creation, and politics through collective action. By selecting respondents whose practices align with these domains, the research aims to capture the diversity of epistemic orientations that shape how truth is constructed and recognized. Consequently, the comparative analysis of these groups may reveal how different truth logics coexist or clash in the broader understanding of technology, society, and meaning. Thus, it should be noted that comparisons concerning the questions addressed in Interview Set 2 will be made among the three groups; however, epistemological questions are set aside and serve merely as an inspiration rather than as an object of inquiry in their own right, a pursuit that would require a separate, dedicated study.

Interview Set 2 comprises a total of 36 respondents, with 12 participants from each occupational group. The sample maintains a perfect gender balance, both overall and within each group. Furthermore, particular attention was given to ensuring diversity within the groups themselves, for example in the group of artists, avoiding representation from a single artistic domain and instead including participants from a range of artistic disciplines. The datasets present the demographics of the individuals interviewed across three distinct domains: the arts, political sector, and sciences. In the arts sector (see Appendix .1.13), the 12 participants had ages ranging from 20 to 33, including professions such as violinists, painters, and multimedia artists, and representing countries primarily from Albania, Kosova, Turkey, Spain, and Norway. In the political sector (see Appendix .1.15) the 12 participants were aged 21 to 33, covering roles such as political analysts, student assistants, activists, and advisors, born in Albania, Kosova, Hungary, Romania, Italy, and Norway, and currently located in a variety of European countries. Finally, the sciences sector (see Appendix .1.14) comprises 12 participants aged 20 to 33, working in fields including data science, bioengineering, medicine, astrophysics, and statistics, with origins and current residencies spanning Albania, Turkey, Italy, Spain, Kosova, Germany, and Switzerland.

Part I

Mangalem

Chapter 2

Tales of Work

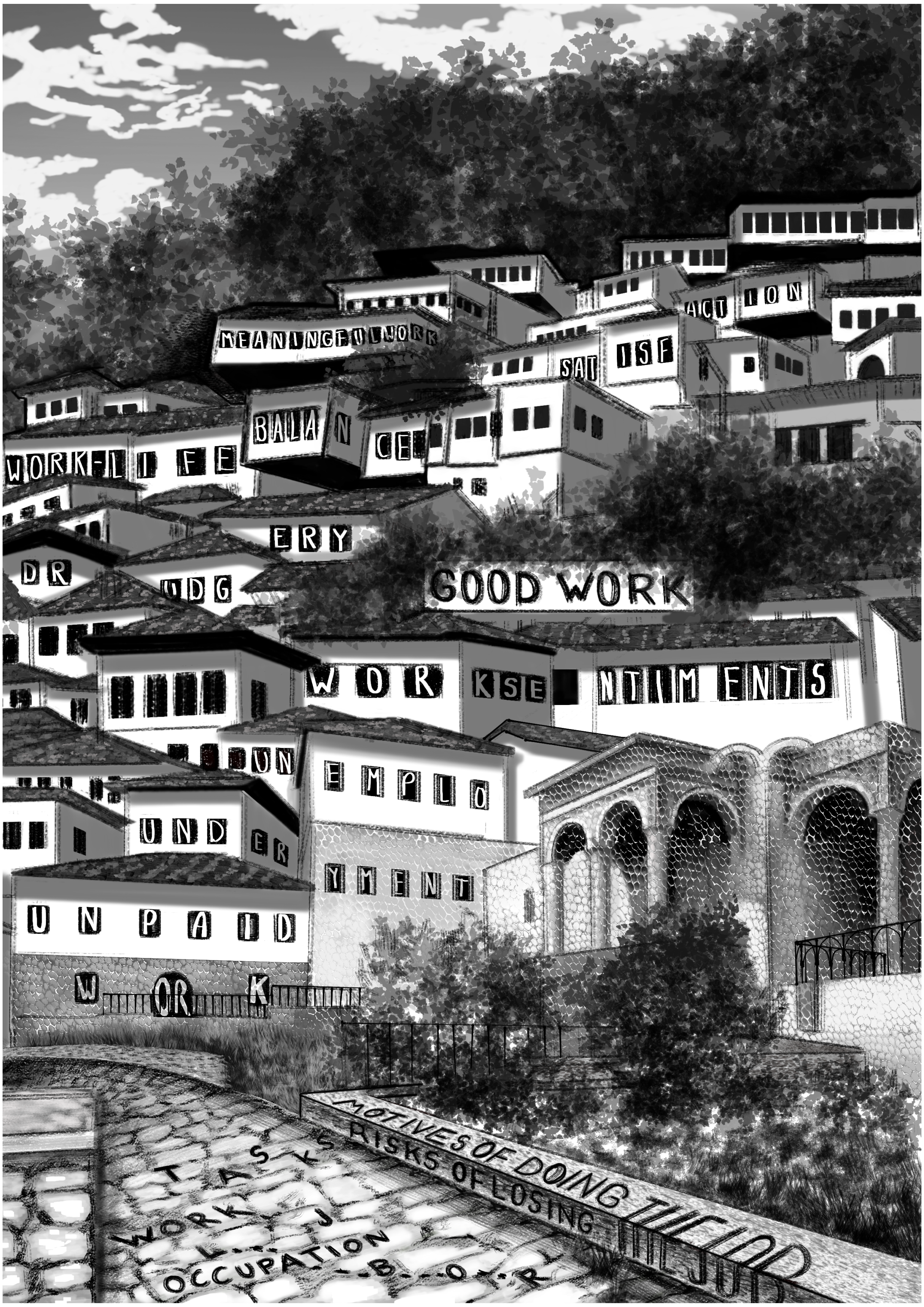

Figure 2.1. Tale 1: Mangalem - tales of work.

2.1 Tale 1: Mangalem - tales of work.

FINDING ourselves in the Mangalem neighborhood, situated on the north-east of the Gorica bridge, it will be our embarking port and entry point onto the story of labor in the age of the Blind Watchmakers. We will remain here for the first three chapters. Right after crossing the 18th century Pasha's Gate, a short cobbled road builds the path high up to the hill which culminates in Berat's castle, a 13th century construction, appropriated by both the Byzantine and Ottoman empires, home of multiple churches and mosques. However, we are still at the foot of the hill, in the cobbled road, in which we will lay the groundwork of definitions of labor, work, jobs, tasks, and occupations, without whom it would be impossible to navigate this particular facet of the hill. Standing in front of us, the first house invites us to look in its windows and understand the concept of "unpaid work", brought forward predominantly by feminists in the 60s in the west and then popularized all over the world. As we will see once we cross the Gorica bridge in Chapter 5, this concept will gain a renewed meaning for us. Work sentiments will be explored from the antiquity roots upon which this entire city is built onto the present. Who lives beyond the windows that perceive work as "good", "bad" or "neutral"? What makes work good and what makes it drudgery? Is it simply how much work is liked or how satisfied one is? The concept of "work-life balance" came to be predominant among the citizens of our city and it will be explored more in depth. However, for our citizens "good" is just not good enough and "meaningful work" will be explored. What are its determinants and which are the most important ones? Going back to the foot of the hill, the concepts of employment, unemployment and underemployment will be construed. And last but not least, lingering on the sidewalk which hosts multiple conversations among our residents while they go about their lives, movies of why they work in their concrete jobs and what they find risky in terms of losing their jobs will be explored.

2.2 The brief matter of demarcation: work and unpaid work

There are endless quotes that can be used to define and approach the concept of "work", or give a certain flavor to the notion in order to serve as an opening for this chapter. The choice was made to refrain from a particular quote precisely to highlight the fact of how diverse the definitions of such an abstraction are, and choosing only one being an impossible task. Historically, the nature of work has created a lot of ambiguity among people. This is a matter that has preoccupied not only economists but also philosophers, theologians and other thinkers. Some think of work as by its very nature as "good", one which could spare us of the three evils: vice, boredom and need, in Voltaire (1950)'s words. Others think of it otherwise and suppose that its disappearance is the utopian world we all dream of. Negative notions on work go back to the ancient Romans and Greeks, for whom, according to the analysis Spencer (2022) presents in his book "Making Light Work", work was mainly a toil. The ancients preached for a life where work was absent as the necessary condition to permit for the virtuous fulfillment of creative potential, like Plato and Aristotle. Early Christians thought alike, given that due to Adam's indiscretion, humans were condemned to a lifetime of labor. This journey into the meanings of work is done also by Roger Bootle, in his book "The AI Economy" (2019). Going back to early Christianity, he observes how there wasn't much work in the Garden of Eden. However, as Spencer (2022) also denotes, we observe major shifts with the rise of protestant ethics and how Martin Luther made work sacred. This transformation occurred while what was insofar understood simply as "work" was transitioning into wage-labor due to the Great Transformation (also mentioned in Varoufakis (2017)). With the rise of industrialization and now post-industrialization societies, the notion has taken yet again multiple shapes and we come across multiple concepts such as but not limited to: job, occupation, profession, work, career, labor, employment, etc. It would require an entire different study to distinguish between these terms. For the purposes of this study, the following will be considered:

- The colloquial word "work" will be mainly used as an umbrella term, given the fact that we are trying to analyze the perceptions of young people, particularly when discussing what work is and how it is expected overall to change in the future due to AI.

- When conducting analyses, sometimes the words "job" and "occupation" are used. Colloquially and for simplicity purposes in the design of the online surveys and the interviews, only the word "job" was used, referring to the particular role that the participants of the study have in their workplaces. This particular definition is taken into account explicitly in some of the questions, when it is stated that *"a job should be considered as a bundle of tasks"*. However, to be more specific and in accordance with Autor (2013), when thinking in higher levels of granularity and particularly when the ISCO-08 [1]classification is used, the term "occupation" will be also employed as

[1]ISCO-08 refers to the International Standard Classification of Occupations, a system developed by

a collection of tasks and as a collection of jobs that share similar characteristics.

For the purposes of this work, I want to focus on present day young people's definitions of work in general. Thus, in Online Survey 2 the question was asked: *"How do you define work? What is work for you?"*, which was an open ended question. The purpose is to create a baseline idea of how young people define work and with which words they associate it the most. Therefore, a base analysis was done using Word-Clouds.[2] This helps quickly identify the most common or significant words in a dataset.

Figure 2.2. The Word-Cloud of defining work – Online Survey 2

In our particular dataset, when visualizing the world cloud, initially the words *"work"*, *"mean"* and *"something"* appear to be the most highlighted, which is intuitive given that people have used those words a lot in the definitions but given the fact that they do not add much to our analysis, they were filtered out. The six most frequent meaningful words in the definitions provided are the following:

- **activity** — 15%
- **money** — 11%
- **get** — 10%
- **mental** — 7%
- **physical** — 6%
- **paid** — 6%

the International Labour Organization (ILO) to categorize and compare occupations across countries based on the type of work performed and the level of skill required.

[2] Word-Cloud: used to generate a visual representation of text data, where the size of each word reflects its frequency or importance in the text. The more frequently a word appears in the text, the larger and bolder it will appear.

Furthermore, words like *life*, *way*, *time*, *energy* and *order* were also quite frequent, similar to "paid". However, the frequencies are quite low, the most frequent word being only in 15% of the descriptions, which can lead one to believe that the participants in the study have a wide variety of understanding of the concept of work and that furthermore establishes the need for a study like this on perceptions of young people. The respective word cloud can be observed in Figure 2.2. When observing the Word-Cloud but also the frequencies mentioned above, the notion of work seems to be mainly associated with a *paid activity*. When disintegrating in terms of sex, in Figures 2.3 and 2.4, we can observe that while work being some sort of activity is dominant for both cases, males associate it more with "money" and "paid" than females, and in the case of females words like "mental" and "life" appear to also be quite dominant in the Word-Cloud.

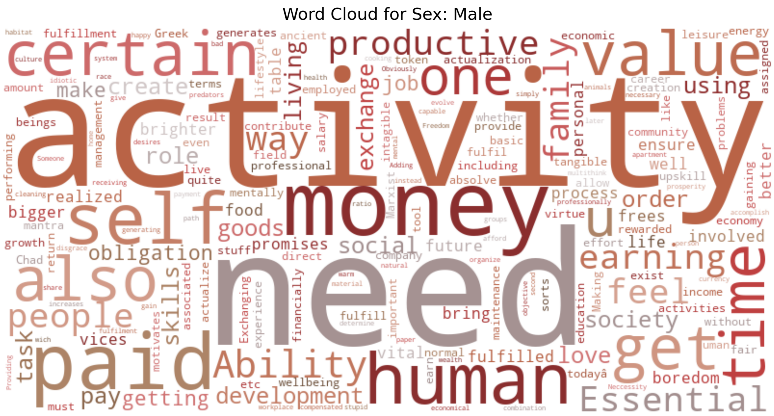

Figure 2.3. The Word-Cloud of defining work - Sex: Male – Online Survey 2

Furthermore, some attention is paid in this study to the concept of unpaid work, as it is "traditionally" (if such a word can be used), emerging in the 1960s and 1970s, largely due to feminist movements. Scholars and activists argued that domestic labor, primarily performed by women, was essential for sustaining the workforce and society, yet remained undervalued and invisible. A short excursus into these topics unfolds with a dual purpose:

- To aid the understanding of the perceptions of young people with respect to the world of work in a wider dimension.
- To understand the core arguments made to classify, mainly household tasks as work, which will later serve as an analytical basis for understanding the newer form of unpaid work due to big data and AI, or as denoted (mainly in evocative terms) "free AI labor" in Chapter 5.

Given the fact that during Interview Set 1 it was understood that the concept was not immediately clear as to what it entails, it was decided that some elaboration was

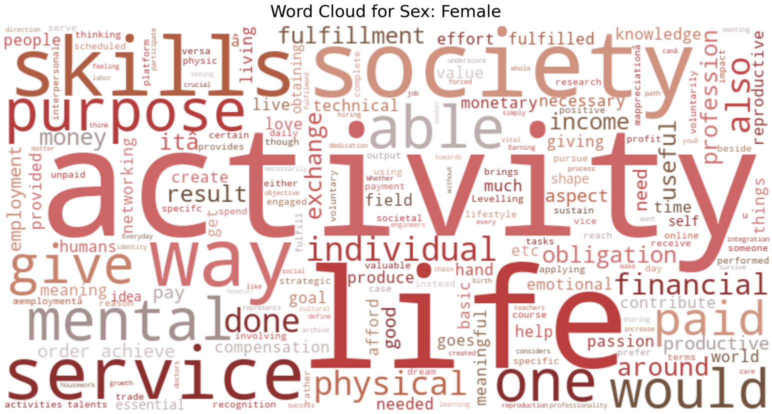

Figure 2.4. The Word-Cloud of defining work - Sex: Female – Online Survey 2

needed and thus the question was not included in the online surveys but rather as part of Interview Set 2. The second set of interviews, as discussed in the Methodology, was designed to address questions that required further elaboration or discussion for a clearer understanding. Also, this category encounters a lot of discussion as to what it covers. For the purposes of this work, the following two frameworks are used to reflect and refer to the notion of unpaid work:

- Susan Himmelweit 1995, The Discovery of "Unpaid Work": The Social Consequences of the Expansion of "Work".
- Miranda 2011, Cooking, Caring and Volunteering: Unpaid Work Around the World, published by the OECD.

Susan Himmelweit's seminal paper, The Discovery of "Unpaid Work": The Social Consequences of the Expansion of "Work" 1995, traces the historical and conceptual expansion of the category of work, particularly through the efforts of feminist scholars in the 1960s. During this period, researchers sought to establish the recognition of unpaid work, particularly housework, as a legitimate form of labor. Himmelweit identifies three main arguments that emerged in this discourse:

- First, housework, such as cleaning and cooking, was conceptualized as a *purposeful activity* rather than a personal endeavor undertaken for its own sake. These tasks were performed with specific outcomes in mind and required a significant investment of time and energy, implying an opportunity cost. As such, housework could not simply be dismissed as a leisure activity but was, instead, an integral component of daily life that merited recognition as labor.
- Second, housework was understood as *a fundamental part of the broader division of labor within society.* At the time, wage-labor was predominantly performed by men,

whereas housework was largely assigned to women, reinforcing a gendered division of labor. Scholars argued that this division positioned women not as dependents or mere consumers but as workers who contributed to the functioning of the economy through domestic labor. By re-framing housework in this way, the discourse challenged traditional notions of economic productivity and dependency.

- Finally, *the distinction between tasks and the individual performing them* reinforced the argument that housework was a form of labor. The separation between the work itself and the worker underscored that housework was not an intrinsic part of women's "nature" nor did it necessitate a so-called "woman's touch." This conceptualization rejected essentialist views that confined domestic responsibilities to women and opened the possibility of a more equitable distribution of domestic labor.

Himmelweit (1995) observed that while feminist scholars of the time did not offer a formal definition of work, these three arguments implicitly shaped an understanding of unpaid labor. This emergent definition aligned with key features of wage-labor, particularly in manufacturing, yet, like all abstractions, it did not fully encompass all types of work, including service labor, unpaid household tasks, or even all forms of product manufacturing. The expansion of this particular notion of work had far-reaching implications, extending into multiple spheres of labor beyond traditional economic metrics.

A more recent examination of unpaid labor can be found in the work of Miranda (2011), Cooking, Caring and Volunteering: Unpaid Work Around the World, published by the OECD. For the purposes of this study, Miranda's definition of unpaid work as *"the production of goods and services by household members that are not sold on the market"* (pp. 7) is particularly relevant. Furthermore, she introduces the concept of the "third-person criterion" as a key determinant in distinguishing unpaid work from leisure. According to this criterion, if a third person could hypothetically be paid to perform an activity, it qualifies as work. This definition remains valid irrespective of whether the individual performing the task derives personal satisfaction from it. For instance, activities such as cooking or playing with children may be enjoyable, but their classification as work remains unchanged, as wage labor itself often includes tasks that provide intrinsic satisfaction. This framework, as will be discussed in the very brief Chapter 5, is instrumental in making the case that the passive training of AI algorithms by social media users should be understood as labor rather than mere leisure.

The macroeconomic implications of recognizing unpaid work as labor are substantial, particularly in relation to its potential inclusion in GDP calculations. Various proxies, such as time valuation and opportunity cost, have been suggested as methods for quantifying the economic contributions of unpaid labor. The classification of unpaid work thus carries significant economic and policy-related ramifications.

In the dataset from Interview Set 2, interviewees were first presented with the definition of unpaid work and focusing on household tasks such as cleaning, cooking etc., and care work for children and the elderly. There were no attempts to convince or persuade them by using the arguments outlined by the two previously mentioned papers. Those arguments are used on the interviewees but only later on and mentioned in Chapter 5, as a means of presenting a case for unpaid work (but with specific considerations on AI). Rather, the respondents were asked to reflect on their own whether they consider these activities to constitute "work" and to estimate the number of hours per day they engaged in such tasks over the past week. This approach ensures a more nuanced exploration of how individuals conceptualize unpaid labor and its role in their daily lives.

When the interviewees were asked whether they consider unpaid household/care work as work, the vast majority, 80.6%, responded "yes". During the interviews, people were also asked to elaborate and back up their binary categorical responses with some rationale. For those that considered unpaid work as work, mainly the following arguments were provided:

- The idea of time spent that could otherwise be used on alternative activities, thus the idea of opportunity cost, was highly resounding. This was further reinforced in some cases with the idea that the time spent on the total collection of these tasks is not some sort of personal passion.
- The fact that these processes had an end result, whether that was (or could be) a product or service, alternatively. For example, one respondent noted the fact that cooking at home or eating a cooked meal in a restaurant made little difference for him, given the fact that the end "result" was the same.
- Others used the alternative term "energy", thus considering everything that requires some sort of energy as work, echoing notions from physics. On a similar tangent, others considered the fact of getting tired as an argument for it being work.
- For some, all those processes that provided value for society ought to be considered as work and the ones encompassing unpaid work, make no exception.

In this group, there were also some individuals that went further and insinuated that these activities need to be paid and made the relevant political/economic considerations, similar to those presented by the two papers mentioned above.

As for those that did not consider those tasks as work, mainly the following arguments were provided:

- Those that considered those tasks as necessary for being a functional member of society, elementary and highly personal thus, not work. However it must be noted that this very same argument was also used by a couple of the interviewees that were proponents of unpaid work being work. The very necessity and mundanity of these tasks is what made it work for them.
- Reinforcing the first argument, others went further and considered the completion of those tasks "a moral obligation" or of being "a dignified human".
- For others, the idea was that for something to be considered work, the payment dimension is mandatory.

When filtering in terms of sex, out of 18 males only 2 did not consider unpaid work as work compared to 5 females out of 18. Furthermore, as previously mentioned, Interview Set 2, considered particularly 3 groups of occupations: people coming from arts, sciences and politics. When filtering in terms of these three groups, we observe that the group with the highest number of respondents that disagree that household and care tasks are work are the artists, followed by the scientists and lastly the people from politics, with only 1 person not considering it work. The stacked bar chart can be observed in Figure 2.5.

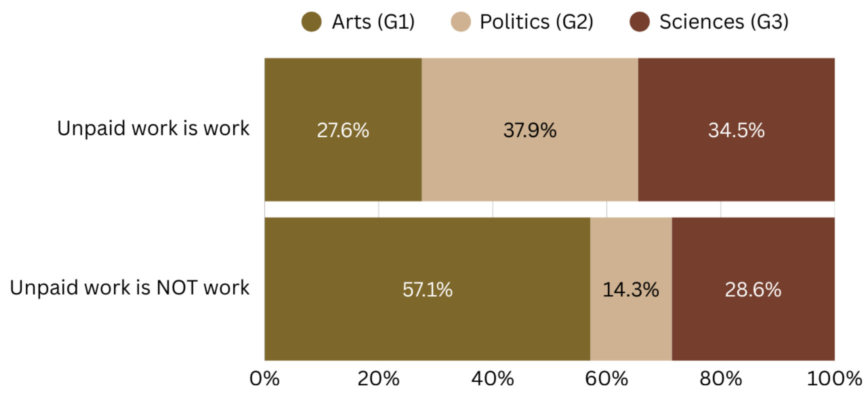

Figure 2.5. The histograms of considering unpaid household and care work as *work* by occupational group – Interview Set 2

As mentioned, I will revert to these arguments in Chapter 5 and make considerations if such arguments can be expanded to consider a new form of unpaid work: *AI work*.

2.3 Beyond Unemployment and towards underemployment

Another crucial component when one considers "tales of work", besides its definition and what it encompasses is, its very existence, or lack of, namely: unemployment. Introducing some statistics on unemployment in Europe and particularly, youth unemployment is key and will form an important baseline when we discuss in Chapter 4 the repercussions that AI will have in the world of work. However, such considerations will be brief, given the fact that as denoted in the Introduction, the focus of this work, based partially on a prior analysis of the impact of new technologies like AI in the world of work but also as a design choice, will be mainly on other aspects of work, mainly qualitative ones.

With respect to unemployment, according to data from the International Labor Organization and their SDG indicator 8.5.2 - Unemployment rate (%) – Annual [3], for the period from 2000 to 2024, as we can observe in Figure 2.6, there appear to be cyclical fluctuations in unemployment but no long-term increase is present (at least thus far). The countries taken into consideration are those most relevant for this work, in alignment with the countries represented in the online surveys and interviews. Clearly, there are peaks in the rate of unemployment post the 2008 financial crisis and higher rates in countries that were rebuilding post-war as in the case of Kosova. However, in the same period, particularly since 2010 but even more aggressively since 2016, developments in AI have been ever more present, with inventions like Generative Adversarial Networks (GANs) that enable realistic-looking AI-generated images and videos in 2016, AlphaGo beating the world's Go champion also in 2016, the birth of deepfakes around 2017 and OpenAI releases GPT-1 in 2018 (Turner, 2023). The same trend with respect to unemployment but with a longer time-trajectory is also observed by Autor (2015), who claims that: *"Clearly, the past two centuries of automation and technological progress have not made human labor obsolete: the employment-to-population ratio rose during the 20th century even as women moved from home to market; and although the unemployment rate fluctuates cyclically, there is no apparent long-run increase."*

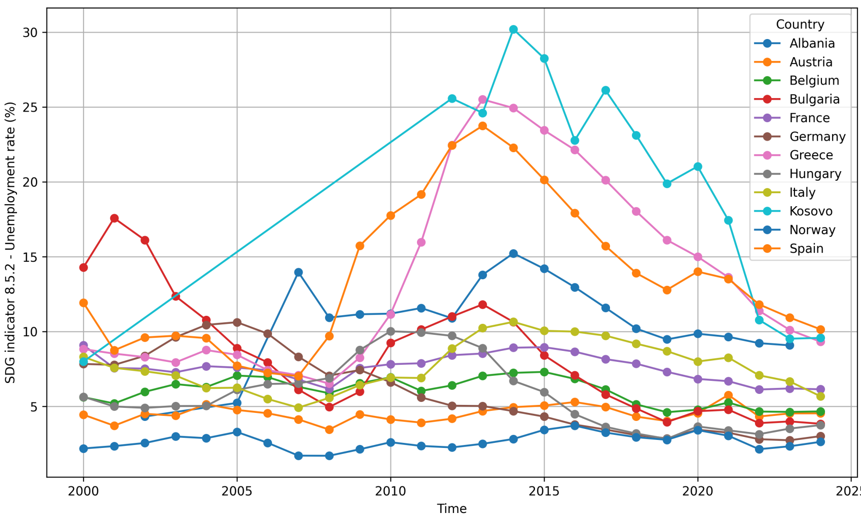

Figure 2.6. SDG indicator 8.5.2 - Unemployment rate (%) – Annual over time and various European Countries - ILO data

Another similarly-sounding notion but definitely different in terms of semantics, has gained traction, particularly during the COVID-19 pandemic (Golden and Kim, 2023), **underemployment**. There are many definitions of underemployment, the most popular

[3]See the dataset here: ILOSTAT data explorer - Unemployment

one being *"forced part-time work"*. More formally, taking into account the International Labour Organization report, unemployment and employment statistics are not enough and underemployment reflects the under-utilization of the workforce, as *"they tend to carry out an activity which is less productive than they could and would like to carry out"*(Mata Greenwood, 1999). A brief remark ought to be made about The Employment Policy Convention (No. 122) of 1964 [4] and its related Recommendations (No. 122 and No. 169) which set international labor standards to guide governments in promoting employment policies. The idea was to ensure: full employment, meaning everyone who wants to work should have access to a job; productive employment, meaning that jobs should provide fair wages, decent working conditions, and contribute to economic and social development; freely chosen employment, meaning that workers should have the freedom to choose their occupation without discrimination, coercion, or forced labor. Thus, as the ILO report argues (Mata Greenwood, 1999), the unemployment framework and consequent statistics are insufficient and therefore the concept of *underemployment* comes handy. Furthermore, underemployment appears to be particularly an issue affecting young people and it is a common yet overlooked experience affecting both disadvantaged youth with fast-track transitions and affluent youth with slow-track transition, which has been largely neglected (MacDonald, 2011). Underemployment can take many forms and to understand it further resources of "The Underemployment Project: A sociological investigation of underemployment and the lived experiences of underemployed workers"[5] are used. The underemployment project is a three-year long project started in January 2023 and addressing an important social issue: the increase in underemployed and vulnerable workers. The following are the subcategories of underemployment according to the aforementioned project (Underemployment.info, n.d.):

- Time-related: people who were willing and available to work additional hours but their hours of work in all the jobs in the given period was below their threshold. Oftentimes, it is this time-related underemployment that might cause individuals to hold multiple jobs.
- Skill-related: workers who have skills that are greater than those required in their current job.
- Wage-related: workers are underpaid for the work that they are doing. This is a complex notion, it is not typically reported in national statistics, and there is no one standard method for its estimation. The Underemployment Project measures wage-related underemployment as being underpaid in comparison to other employees in the same occupation.

For the purposes of this work, it was understood from Interview Set 1 that this was a novel notion and it was decided to be explored not in the online surveys but in Interview Set 2. The interviewees were asked the following questions:

- First, if they were familiar with the underemployment concept. Regardless of this initial response, afterwards the definition and categorizations mentioned above were provided to them.

[4]Find the link here: Employment Policy Convention 1964

[5]Find the link here: The Underemployment Project

- Which kind of underemployment they have experienced personally.
- To rank the three categories from the most relevant to the least relevant in what they think impacts young people like them in Europe today.

When the interviewees were asked regarding their familiarity with the underemployment concept, only 22.2% responded yes. When comparing in terms of sex, 6 out of 18 males said they had heard of it as opposed to only 2 out of 18 females (see Appendix .2.1). This is contradictory to the fact that, at least according to the Underemployment Project, *"there are many more women than men working part-time involuntarily"* (Underemployment.info, 2024). When comparing in terms of the three groups, so people coming from arts, politics and sciences, only 1 person said they had heard it before from arts, compared to 3 from politics and 4 from sciences (see Appendix .2.2). These findings highlight even more the need for further studies and youth education in these domains. Furthermore, it seems unlikely to organize and improve what you are not familiar with, or in simpler terms: what you lack the words for. Orwell (1946) said it better: *"But if thought corrupts language, language can also corrupt thought"* - or, in our case: a lack of language cannot construct thought and action.

In terms of the second sub-question, thus after the particularities of the underemployment concept were made clear, the interview process uncovered that most people have personally experienced skills-related underemployment, $\frac{2}{3}$ of the interviewees, followed by income, about 55.6% and then time, in which the proportions switch and more people have not experienced it, with those that have experienced it being only 22.2%. The visualization of such descriptive statistics can be observed in Figure 2.7. It appears that most of the interviewees have been engaged in jobs that require less skills than they actually have.

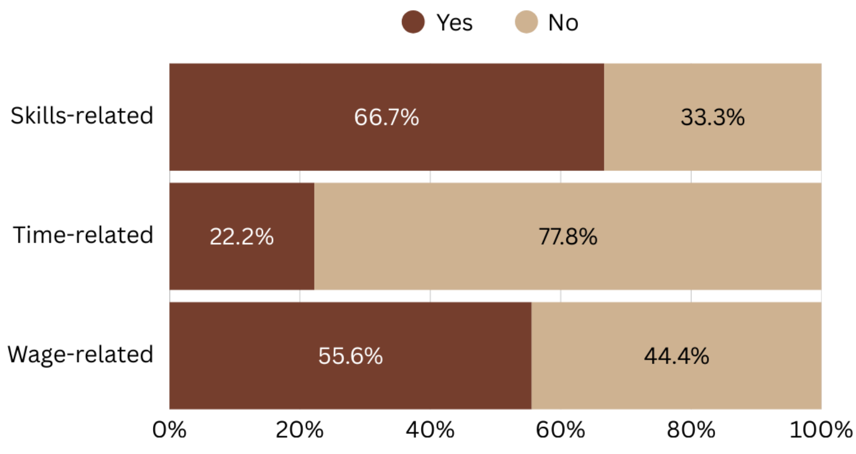

Figure 2.7. The distribution of the types of underemployment that has been personally experienced by the interviewees – Interview Set 2

When studying the matter further in terms of the three groups, artists come at the top in terms of skills-related underemployment, where 10 out of 12 state to have personally experienced it, compared to 8 out of 12 from politics and only 6 out of 12 from sciences. Artists also seem to come at the top of those that have claimed they have experienced both time-related and income-related underemployment, with the first being 5 people and the second being 8 people in the affirmative. For people coming from politics only 3 stated to have experienced time-related underemployment and 7 to have experienced the wage-related one. People coming from sciences seem to be the group with the least number of interviewees claiming to have experienced underemployment overall in comparison to other groups and in terms of wage-related only 5 have responded *yes* and no one has claimed to have experienced time-related underemployment.

Last but not least, when the grouped analysis is done in terms of sex, as we can observe in Figure 2.8 and taking into account only those people that responded "yes" with respect to experiencing the given type of underemployment some interesting trends can be observed. While both males and females appear to have the same exact amount in terms of skills-related, males claim to have experienced more income-related underemployment and females claim to have experienced more time-related underemployment.

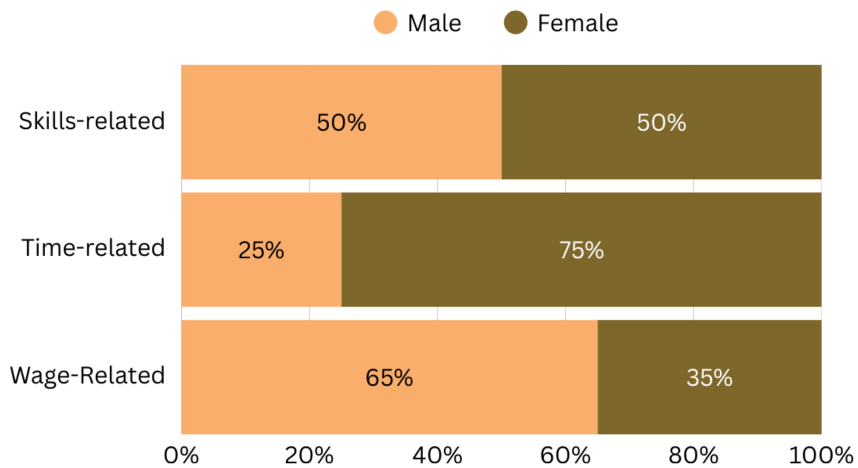

Figure 2.8. The distribution of the types of underemployment has been personally experienced by the interviewees by sex – Interview Set 2

The third sub-question and the last for this category was with respect to a ranking from 1 to 3, 1 being the most prevalent and 3 being the least, on the perceptions of the interviewees on the types of underemployment that impact the most young people *like them* in Europe today. Summing the values for each type, we observe the following: time-related: 88, skills-related: 65 and wage-related: 63. Thus, if the conclusion would be based just on these simple sums, it appears that the ranking from the most to the least prevalent would be the following: income-related, skills-related and time-related. Furthermore, a heat map is created based on the numerical frequencies for each rank 1, 2 and 3 and for each type of underemployment. The heat map can be observed in Figure 2.9.

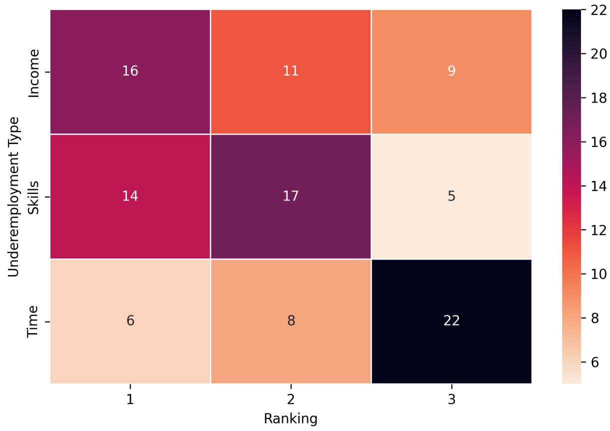

Figure 2.9. The heat map with the ranking of the types of underemployment based on which is most prevalent – Interview Set 2

Clearly and as expected, time-related comes decidedly last, and income-related and skills-related being extremely close. For those that ranked income-related first, the main arguments revolved around the fact that young people tend to be offered less money for the same job than older and more established people. Some artists also mentioned the fact that only those that are very famous get actually paid adequately for their art. The reasoning that was provided from the interviewees from those ranking skills-related first were along the following lines: that young people tend to get entry jobs (when they are lucky) in their professions of choice which usually require very basic skills that are below what they can offer; that young people tend to do jobs, particularly while studying that are not aligned with their skill set; the discrepancy between the complex skills learned at the university and the basic applications required by the industry at this moment. From those few ranking time-related first, the reasoning mentioned was that many young people were doing what they actually wanted to do as a job only part-time because they could not find full time opportunities. For example, one of the artists mentioned the fact that they needed to find another full-time job to actually serve as the financial foundation for their life and a similar argument was made by a political analyst who noted the fact that basing his monthly income only on the political analyses and debates would be an impossibility and financially not sustainable. When disintegrating the heatmaps in terms of the three groups, as it can be observed in Figure 2.10, we observe the following:

- People coming from politics are choosing skills-related underemployment as the most prevalent one, followed by wage and time related ones in the second and third positions standing tête-a-tête. However, all three seem to be very closely related in terms of numbers for the majority voting with the first being only 1 vote higher than the second and third one.

- People coming from sciences are decidedly choosing the time-related one as the least prevalent one but in equal numbers cannot decide between the skills and wage related ones for the first and second positions.
- People coming from arts have more diverging opinions, choosing in the first position wage-related but which changes only by 1 vote from the time-related and which again differs by only 1 more vote with the skills-related.

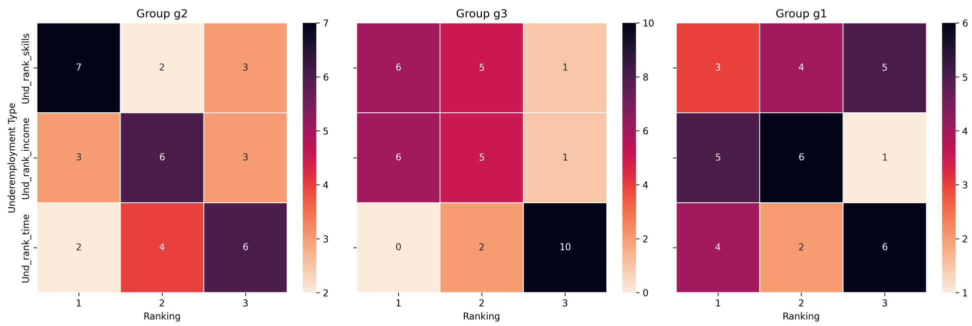

Figure 2.10. The heatmap with the ranking of the types of underemployed based on which is most prevalent by occupational group – Interview Set 2

2.4 Good and Meaningful Work

2.4.1 What makes a job - a *good* job?

As mentioned in the Introduction, the realm of work will be studied in this thesis with a particular emphasis on the quality of work and only a brief touch upon the more widely discussed topics such as employment statistics. Underemployment, mentioned in Chapter 2.3, does give a clearer picture regarding the state of work among youth than the unemployment statistic in itself. However, we need to go even further beyond these concepts to understand what comprises *good* and *meaningful* work.

When studying what makes a job a good job, a first intuitive approach would be asking people how satisfied they are with their job or how much they like it. This question was asked in Online Survey 1 and the respondents were asked to provide an estimation of how much they like their current job on a scale from 0 to 10. The histogram with the distribution of the job satisfaction can be observed in Figure 2.11. As we can observe, the graph is very left-skewed, with the majority of the people giving a vote of 8 to how much they like their job. If we consider a score of 8, 9 and 10 as a high job liking and satisfaction, then 56.73% of the respondents of Online Survey 1 appear to be highly satisfied in their current role.

In terms of sex-based distributions, as it can be observed in Table 2.1, females seem to report higher scores on liking their current job. For males, the mean job satisfaction level is 6.67 and for females that is almost 1 score higher 7.48. Given that the data are not normally distributed, the median is also measured and for the male group is 7 whereas for females, again one score higher, 8. In order to understand if there are statistically significant differences among the two sex groups of Online Survey 1 on their self-reported levels of job satisfaction, the non-parametric Mann-Whitney U test is done, given the fact that the data are not normally distributed. The test results show a $U - statistic = 1078.5$ and a $p - value = 0.0719$, and if the conventional 5% level of significance is considered, it can be reported that there is no statistically significant difference between males and females in terms of liking their current job (however, it could be marginally significant at 10%).

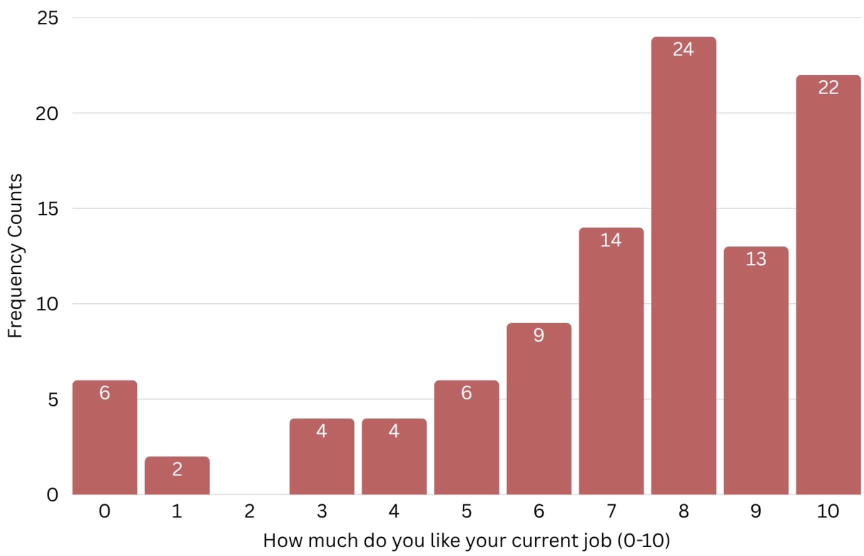

Figure 2.11. Histogram of "liking current job" – Online Survey 1

When the age groups of Gen Z (roughly 18-26) and Millennials (27-35) are taken into account, the distribution is the one observed in Table 2.2. Clearly, the younger age group accounts for all those people that gave the lowest scores, namely of 0 and 1, thus making the age-group a better discriminator than sex with respect to this question. The peak for Millennials is at the highest score 10 with a count of 14 respondents, whereas for Gen Z the peak is two scores lower at 8. Again, in order to understand if there are statistically significant differences among the two age groups, the Mann-Whitney U test was conducted. At a 5% level of significance, the results indicated a statistically significant difference in job satisfaction between Gen Z and Millennials, with a $U - statistic = 1008.5$ and a $p - value = 0.0341$. Even though the median is the same for both groups, 8, as the Mann-Whitney U test results show, Millennials generally report higher job satisfaction

Scale (0–10)	Female Count	Male Count
0	2	4
1	1	1
2	0	0
3	3	1
4	3	1
5	1	5
6	2	7
7	3	**11**
8	**17**	7
9	7	6
10	13	9

Table 2.1. Distribution of "liking current job" (0–10 scale) by sex – Online Survey 1

than Gen Z. In addition, a violin plot[6] was created to visualize the distributions as it can be seen in Figure 2.12. Clearly, Millennials tend to cluster at higher satisfaction values, whereas Gen Z appears to be more spread.

Scale (0–10)	GenZ:18-26	Millennials:27-35
0	6	0
1	2	0
2	0	0
3	3	1
4	2	2
5	2	4
6	4	5
7	3	11
8	**11**	13
9	4	9
10	8	**14**

Table 2.2. Distribution of "liking current job" (0–10 scale) by age group – Online Survey 1

The overall distribution of how much the respondents like their job is consistent with those observed when visualizing the histograms of "How satisfied you are in your main job" question, present in the European Social Survey dataset, in both rounds 5 and 10, collected in 2010 and 2020, respectively. The European Social Survey (ESS) is *"an academically driven cross-national survey that has been conducted across Europe since its establishment in 2001"* (European Social Survey, 2025). We can observe the distributions for both rounds in Figure 2.13, after filtering out the responses of Not applicable, Refusal, Don't know and No answer and selecting our age group of interest, young people aged 18-35. This dataset contains information from 20 different European Countries. The

[6] Although a violin plot is shown, the underlying data are ordinal/categorical, ranging from 0 to 10; therefore, the distribution should be interpreted with caution.

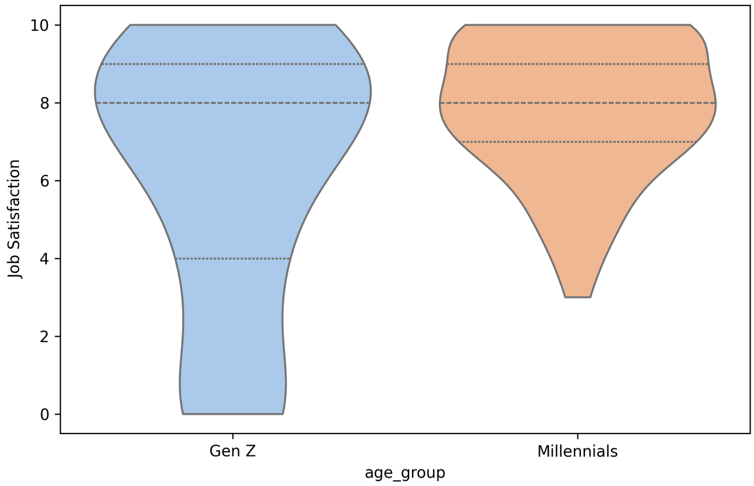

Figure 2.12. Violin plot of "liking current job" by age group - Online Survey 1

difference in the range of the values in the two images is due to the the number of respondents being different, after the filtering operations, in ESS round 5 in 2010 ($n = 3501$) and ESS round 10 in 2020 ($n = 6448$). However, the distributions appear to be highly similar, only the peak changes, with a satisfaction of 9 in 2010 and a satisfaction of 10 in 2020. It can be noted that the data distribution, particularly the fact that the majority of data points seem to be around the high scores (8,9,10) collected for the purposes of this study through Online Survey 1 and 2 are consistent with those in a representative sampling such as that of ESS, for this specific question. This supports the validity of the samples collected for the purpose of this work, given the fact that it aligns with known population patterns for that variable.

In terms of sex, if we consider data from both ESS rounds, there are in total 9949 respondents out of which there are 5067 males and 4882 females. The mean satisfaction for males is 7.22 and for females almost the same 7.21, and the median is 8 for both, clearly showing high levels of self-reported job satisfaction for young people in Europe. Given that the data do not follow a normal distribution, the Mann-Whitney U test was conducted to see if there are statistically significant differences at a 5% level of significance with respect to job satisfaction. The results show a $U - statistic = 12382383.5$ and a $p - value = 0.9217$, clearly indicating that the test does not provide enough evidence to conclude that one group tends to have higher or lower values than the other in terms of job satisfaction. When the time element is taken into consideration, meaning the potential shift in the mean job satisfaction from ESS round 5 (2010) to ESS round 10 (2020), the mean job satisfaction for young respondents increased slightly for both males (from 7.11 to 7.30) and females (from 7.10 to 7.27). The difference between genders was minimal in both rounds, suggesting that job satisfaction is roughly similar for young men and women,

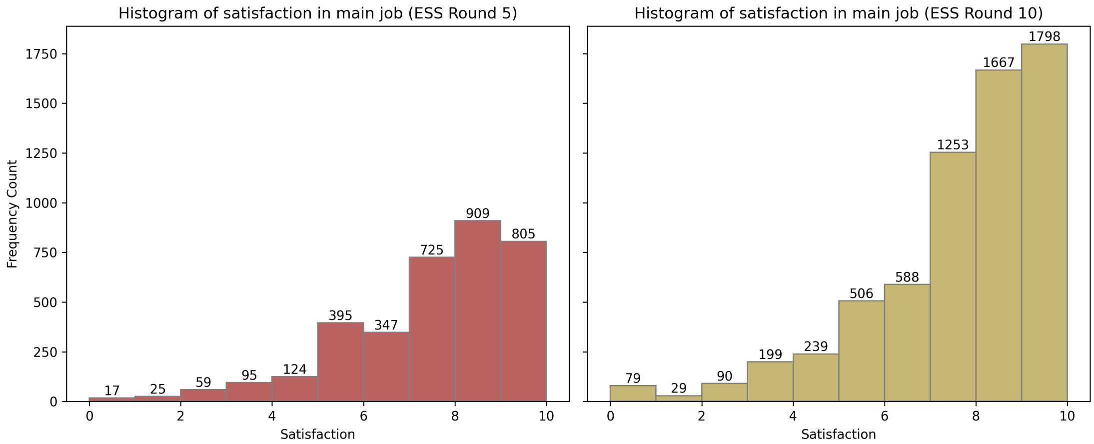

Figure 2.13. The histograms of job satisfaction levels - ESS data - rounds 5 and 10 - young people (18-35).

with a small overall upward trend over time.

In terms of age groups, considering Gen Z(18-26) and Millennials(27-35), the mean satisfaction at work scores are 7.13 and 7.26, respectively, illustrating that at least in terms of averages, Millennials report slightly higher job satisfaction scores. This illustrates a similar pattern with that of the data collected in Online Survey 1 for the purposes of this work, further increasing the validity of that sample. In terms of the median, for Gen Z was 7 and for Millennialls 8. In terms of the cardinality of each group, there are 6591 Millennials and 3358 Gen Z, thus a group is almost the double of the other. This is probably because the values where reporting job satisfaction as non-valid were filtered out, and the younger group may have not yet entered the labor market. Running again the Mann-Whitney U test, the results show a $U - statistic = 10666096.0$ and a $p - value = 0.0026$, giving the initial impression that there are statistically significant differences among Gen Z and Millennials at a 5% significance level in terms of job satisfaction. However, investigating the matter further, the rank-biserial correlation is measured and the result is $r = 0.036$, very close to 0. This indicates that although the p-value (0.0026) is statistically significant, the actual difference between the two groups is very small. Practically, the two age groups behave almost the same and the difference is likely due to the large sample size rather than a real substantive gap. When the time element is taken into account, mean job satisfaction for young respondents was similar across age groups in ESS Round 5, with 18–26-year-olds reporting 7.10 and 27–35-year-olds 7.11. By ESS Round 10, mean satisfaction had increased slightly for both groups, reaching 7.15 for 18–26 and 7.36 for 27–35, indicating a small upward trend over time, particularly among the 27–35 age group.

Moreover, a logistic regression is used to try and classify job satisfaction levels into low (0-5) and high (6-10), based on sex, age and country. It has to be noted that the majority of the respondents, 18% are from Germany and the rest distributed from various

European countries [7]. The distribution of the sample based on countries can be observed in Table 2.3.

Code	Country	Count
DE	Germany	1832
CZ	Czechia	739
GR	Greece	730
NL	Netherlands	596
IE	Ireland	570
FR	France	551
BG	Bulgaria	510
HU	Hungary	498
EE	Estonia	489
BE	Belgium	478
FI	Finland	444
HR	Croatia	401
LT	Lithuania	353
SE	Sweden	348
PL	Poland	326
NO	Norway	272
ES	Spain	255
PT	Portugal	221
SI	Slovenia	206
SK	Slovakia	130

Table 2.3. Sample distribution by country - ESS Round 10 (18-35).

The dataset is highly imbalanced with respect to the job satisfaction category, where, after grouping, there are 8092 instances of *high job satisfaction* and 1857 instances of *low job satisfaction*. Doing one-hot encoding and running Logistic Regression gives a relatively high accuracy at first, $Accuracy = 0.79$. However, as the classification report shows (see Appendix .2.3), the Precision and Recall for the low class are 0. Thus, two different methods were tested: under-sampling of the bigger class in terms of instances and oversampling of the smaller class. Using under-sampling, the Accuracy score was 0.569 (see full report in Appendix .2.4) and through oversampling (see full report in Appendix .2.5) using SMOTENC (Synthetic Minority Oversampling Technique for Nominal and Continuous features) the Accuracy was 0.44. In both cases, Precision and Recall did much better than the vanilla case. However, the Accuracy scores in both cases are clearly not very high. Given the fact that many countries are taken into consideration and doing one-hot-encoding increases the dimensionality of the dataset, another model was tested using as input only sex and age group. This resulted in an Accuracy of 0.51 and the full Logistic Regression output can be observed in Table 2.4. The results show that age group

[7] Neither Albania nor Kosova, that are the countries from which the majority of the respondents of Online Surveys and Interviews collected for this work were part of ESS Round 10 and that is why they are not taken into account

27–35 has a small but statistically significant positive effect on the likelihood of reporting high job satisfaction ($p - value = 0.032$), while sex does not have a significant effect. Overall, the model explains very little variation in job satisfaction ($Pseudo - R^2 = 0.001$), indicating that other factors likely play a much larger role.

Variable	Coef	Std. Err	z	P>|z|	[0.025]	[0.975]
const	-0.0742	0.067	-1.107	0.268	-0.206	0.057
gndr_2	-0.0436	0.069	-0.629	0.529	-0.179	0.092
age_group_27-35	0.1551	0.072	2.141	0.032	0.013	0.297

Table 2.4. Logistic regression results for predicting Job Satisfaction (high and low) (N=3342). Pseudo R-squared = 0.001064, Log-Likelihood = -2314.0, LLR p-value = 0.08499.

The analysis shows that demographic factors alone, namely sex, age, and country, have very limited predictive power for job satisfaction. The models perform poorly in identifying low satisfaction cases, particularly in the presence of class imbalance, and the overall explained variation is negligible. These results indicate that other factors beyond basic demographics are likely the primary drivers of job satisfaction.

However, this is only one limited dimension and the concept of "good work" tends to be a composition of different factors. For the purposes of this research, during the first set of interviews which, as previously mentioned, determined the final version of the questions included in the online surveys, both 1 and 2, the young people who were interviewed were asked to come up with the dimensions of this question: *"Assume you see an ad in a newspaper about a job and you think "That's a good job!". For each of the following, please give a score from 0 to 5 on how important they are for you to think of a job as a good job."* The scales from 0 to 5 were not exclusive, meaning that a respondent could mark multiple categories with the same score. In each interview, the previously added dimensions were discussed and interviewees were asked if something was lacking. At the end of the 76 interviews, there was a final list of the dimensions created as to what would make a job considered *good* (see Appendix .1.6). In this way, the young people were collaborating in the very design of this study, presenting their priorities, understanding and knowledge systems, as opposed to being provided an arbitrary list. This question was then included in Online Survey 1.

As can be observed in Figure 2.14, which visualizes the top 8 dimensions based on the total sum of votes for each category, the *good salary* dimension ranked third when it comes to how important it is for the respondents. In the second and first place came the *ability to learn new things/to self-develop* and *work-life balance* with a total score of 456, respectively. The category that ranks last (see Appendix .2.6 for the full table of rankings) is *working for a startup*, getting a summed score of 235 compared to *working for an established institution* which gets a summed score of 330. To understand this summed score better, it is worth noting that the ceiling would be 520, that is if all 104 respondents of Online Survey 1 were to give a certain category all scores of 5. Furthermore, it appears the respondents prefer the option of *working from home - sometimes*, with a summed score of 366 as compared to *working from home always* with a score of 250.

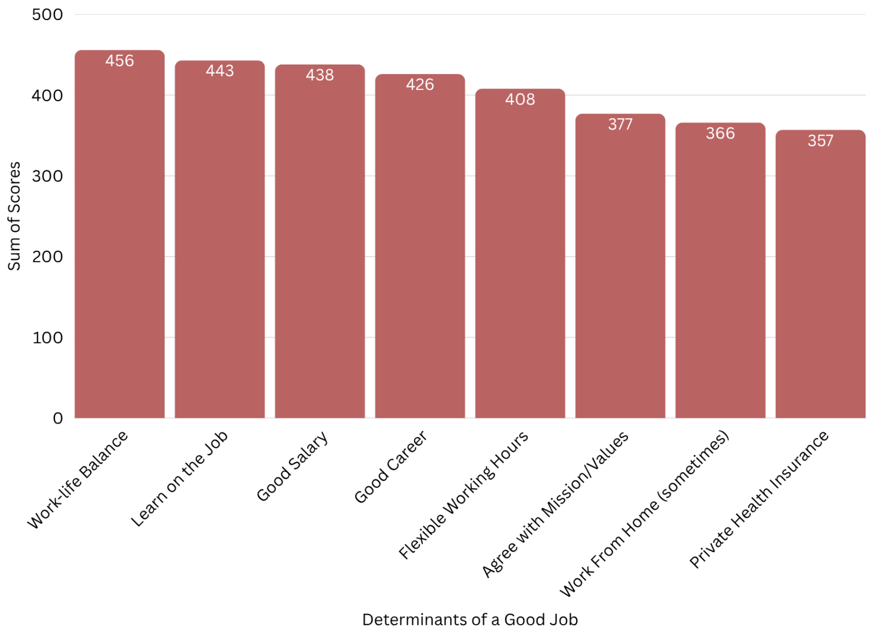

Figure 2.14. The top 8 dimensions of what makes a job - a good job - Online Survey 1

When disintegrating in terms of age-groups and sex (see Appendix .2.7), for both sexes, *work-life balance* comes in the first place with a summed score of 226 for males and 230 for females. For males, the second comes the possibility to have *a good career* with a score of 218, followed closely by *the ability to learn on the job* (217) and *a good salary* (214). For females, the second comes the *ability to learn on the job* (226), followed by *a good salary* (224) and *flexible working hours* (209).

When looking at age-groups, again considering those between 18 and 26 as Gen Z and those between 27 and 35 as Millennials (see Appendix .2.8), for both age-groups the *work-life balance* comes out to be the top dimension. This illustrates the consistency of this notion across sexes and age-groups as being the most important one. Interestingly, for Gen Z, the second most important dimension was *a good salary* (193) whereas for Millennials, even though they are the older age-group and therefore one would assume more experienced, *a good salary* (245) came in the third position, whereas the second was *the ability to learn on the job* (255). A possible explanation might be the fact that technological changes are impacting the required skills on the jobs and Millennials who have entered the job market earlier than Gen Z, see the need for re-skilling.

2.4.2 Understanding Work-Life Balance

Given that in Online Survey 1, as mentioned above, the "work-life balance" came at the first place in terms of importance on what makes a job *a good job*, this concept was decided to be further explored. It is a very ambiguous notion and there are a variety of ways to operationalize it. For the purposes of this work, the paper of Guest (2002) "Perspectives on the study of work-life balance", which is quite anthological on the topic, is taken into account. Guest (2002) notes that there are a wide variety of ways to study work-life balance, like: the compensation, spillover, conflict, instrumental, segmentation models, border theory etc. For the purposes of this work I will focus on the spillover model that posits that *"that one world can influence the other in either a positive or a negative way"*.

The main goals of this subchapter are:

- The creation of a work-life balance index in accordance with the spillover model for young people in Europe.
- Analyze the index further in terms of demographic data such as: sex and age-groups.
- Understand if the work-life balance index is correlated and/or a good predictor of the satisfaction at work.

For these purposes the ESS survey data will be used. In the ESS round 10, collected as previously mentioned in 2020, the rotating module that was present, which was named "Digital Social Contacts" is interesting for this case. The variables that will be used to create the work-life balance index (always using the "spillover effect”) are the following:

- trdawrk - Too tired after work to enjoy things like doing at home, how often (values from 1 - Never to 5 - Always)
- jbprtfp - Job prevents you from giving time to partner/family, how often (values from 1 - Never to 5 - Always)
- pfmfdjba - Partner/family fed up with pressure of your job, how often (value from 1 - Never to 5 - Always)
- wrklong - Employees expected to work overtime, how often (values from 1 - Every day to 6 - Never)
- wrkresp - Employees expected to be responsive outside working hours, how often (values from 1 - Every day to 6 - Never)

In order to build a "good index", in essence, one would have to be certain on two substantial points:

- Getting "the most" information out of your features and their individual contribution is unique - hence, no multicollinearity.
- Knowing the "weights" of the components, given that a simple average may not well represent the importance of each individual component.

The two metrics to detect multicollinearity used here were: VIF (Variance Inflation Factor) and Tolerance. VIF measures how much the variance of a regression coefficient is inflated due to multicollinearity. The formula for VIF for an independent variable X_i is:

$$\mathrm{VIF}_i = \frac{1}{1 - R_i^2} \tag{2.1}$$

Where R_i^2 is the coefficient of determination of the regression model predicting X_i using all other independent variables. Tolerance is the reciprocal of VIF and indicates the proportion of variance in an independent variable that is not explained by other variables in the model.A high VIF (typically > 10) or a low tolerance (typically < 0.1) suggests significant multicollinearity. However, this is just a rule of thumb and in more strict cases the thresholds 5 and 0.2, respectively, can also be considered. The metrics were computed and if we take into consideration the more strict thresholds, there seems to exist overall some moderate multicollinearity among the chosen variables for the index (see Appendix .2.9). The presence of multicollinearity can be problematic; thus, just doing a linear combination of the dimensions to build the index will not yield the best result. Hence, it was thought that using the PCA (Principal Component Analysis) as a way to merge the dimensions, might provide a better index.

First of all, the values which correspond to responses like “not applicable”, “refuses to respond”, etc are removed, as well as the ages that are not relevant for the age group of interest (18-35). After the data cleaning process the dataset has a cardinality of **4608 rows**. In terms of sex, the dataset is quite balanced with 2364 males and 2244 females. In terms of the two age groups, there are 3017 Millennials (27-35) and only 1591 Gen Z (18-26). This is expected as it was the case in the Sub-Chapter above, due to filtering out the not-applicable categories, which to a large extent refer to the fact that many Gen Z respondents have not yet worked. Then, the histograms of the six dimensions chosen to construct the work-life balance, as well as the "satisfaction in the main job" variable, are visualized in Figure 2.15.

It can be observed that for the two dimensions of "trdawrk" and "jbprtfp", there seems to be a bell-shaped distribution, suggesting that most employees experience a moderate impact of work on their personal lives along these two dimensions. For the cases of "wrklong" and "wrkresp", the peaks seem to be around 5 and 6, which signify “less often” or “never“, which lets us understand that the expectation to be responsive outside working hours and to work overtime are quite low. For the dimension of "pfmfdjba", which stands for "partner/family fed up with pressure of your job, how often", the distribution seems to be right skewed, peaking on 1 with 1489 respondents which stands for "never", but still taking very high values for 2 and 3 which stand for "hardly ever" and "sometimes". Whereas with respect to satisfaction in the main job, as discussed above, the distribution is left-skewed, signifying a high job satisfaction. The difference with respect to the distribution of the same variable for the same ESS round (10) seen above, after the filtering out operations with respect to the entirety of our variables of interest, changes the peak of the distribution of the satisfaction in the main job at 8 rather than 10 but the shape

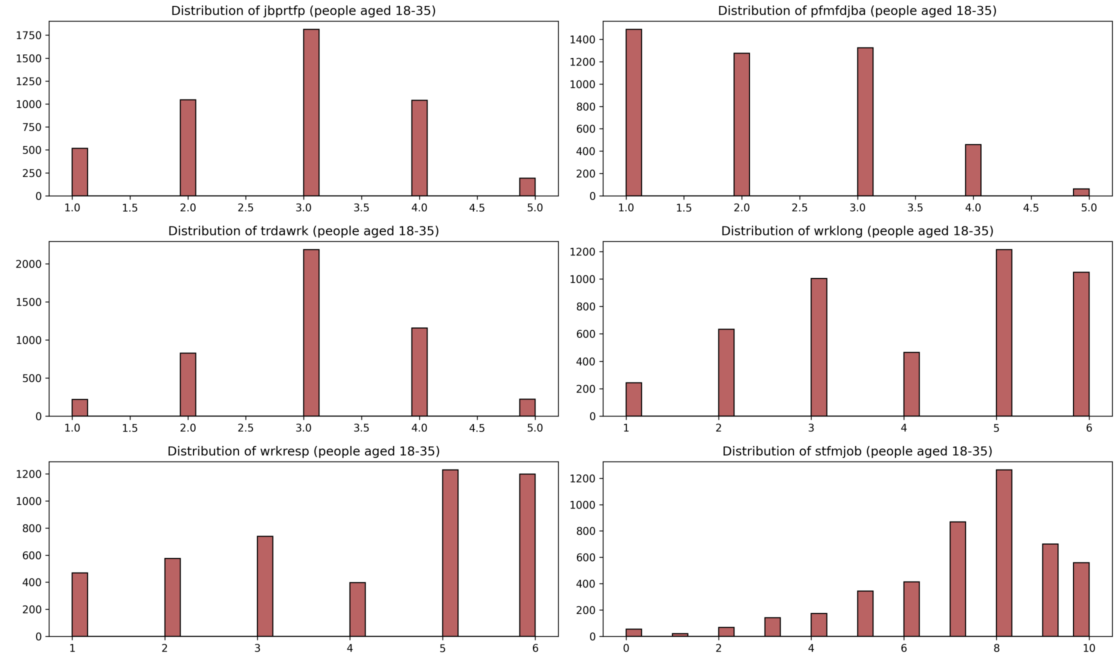

Figure 2.15. The histograms of the five variables that will make the work-life balance index + Satisfaction in main job histogram - ESS data - young people aged (18-35) - Round 10

of the distribution remains the same.

Finally, from the 5 mentioned dimensions, a work-life balance index is constructed. First the data are standardized and then the Principal Component Analysis (PCA) is applied. Plotting the Principal Components versus the Cumulative Explained Variance the following line can be observed as in Figure 2.16. Only PC1 (First Principal Component) explains around 45% of the variance and PC2 adds more variance, bringing the total explained variance to about 65%. PC3 and PC4 continue adding variance, but at a slower rate. If we want to simplify the dataset while preserving most of the information, we might keep only the first two or three principal components instead of all five. Furthermore, the first few components (especially PC1 and PC2) capture most of the variation in the data, meaning they represent the most important patterns in work-life balance factors.

Furthermore, the composition of the components is studied, trying to interpret which features (dimensions of work-life balance) contribute most to each principal component. A small epsilon,

$$\epsilon = \sqrt{\frac{1}{\text{number of features}}}$$

is chosen as a reference threshold to compare how much a feature contributes to the PCs

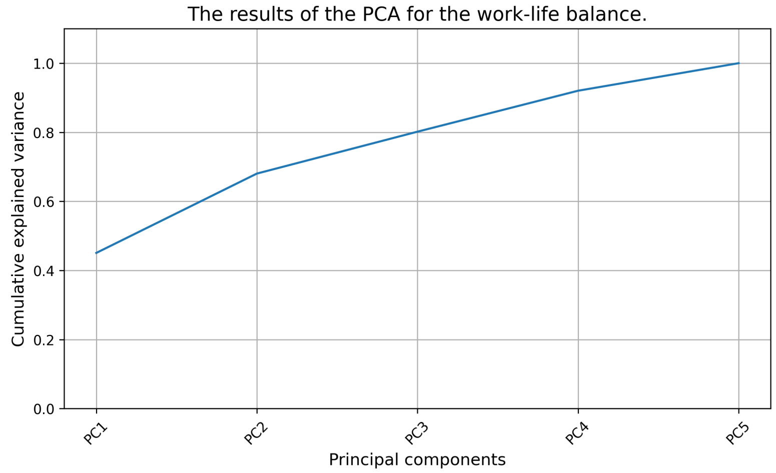

Figure 2.16. Principal Components vs. Cumulative Explained Variance for the Work-Life Balance Dimensions - ESS data - Round 10 - Young people (18-35)

and to determine which are the relevant features. With respect to the first principal component, it was observed that there are three positively highly valued dimensions, namely: *jbprtfp*, *pfmfdjba* and *trdawrk*, precisely in this order as it can also be observed in Figure 2.17. This means that if a data point has a high PC1 score then that observation has high values for these features. Given the fact that a high value on these three dimensions intuitively reflects a low work-life balance, then **a high score on PC1 would reflect a low work-life balance**. On the other hand, for PC2, as it can be observed in Figure 2.18, the relevant dimensions are *wrklong* and *wrkesp*, both of which, if they take high values, it can be considered for each row as a high work-life balance, consequently also if PC2 takes high values, it can be considered a high work-life balance. The breakdown for the other principal components can be observed in Appendix .2.10.

The work-life balance index is built only on PC1. Given the fact that we have the PC1 loadings, using the dot product, the dataset is transformed in such a way that we have a new variable that represents each observation's position along PC1 - this is our Work-Life Balance Index. The maximum value of the Index is 4.7798 and the minimum value is -3.4719. The histogram of Work-Life Balance Index 1, which can be observed in Figure 2.19. The Work–Life Balance Index 1 derived from PC1 follows an approximately normal distribution centered around zero, as expected for standardized PCA scores. This indicates that most respondents cluster near the average level of work–life balance, with fewer exhibiting extremely high or low scores.

When studying it in terms of the distributions for ISCO-08 categorizations up to 3 levels of hierarchy and considering only those that have more than 80 data points, the counts, codes and the description of the included professions is shown in Table 2.5. As it can be observed, the majority of people in the dataset are from a few key professions. The most

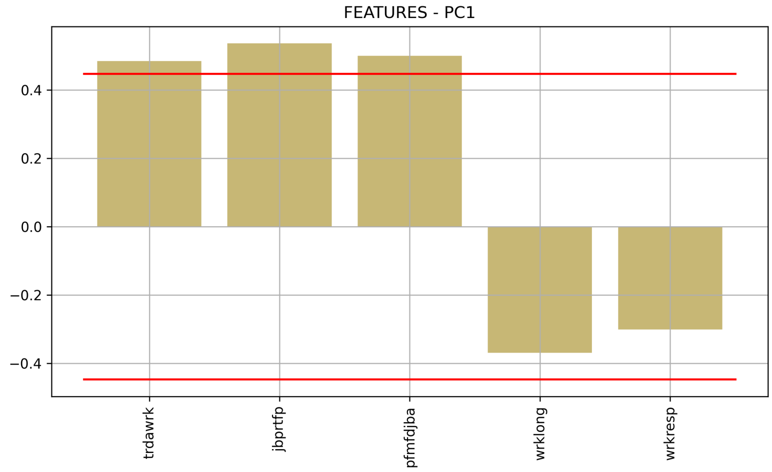

Figure 2.17. The breakdown in terms of dimensions of PC1 explaining around 45% of cumulative variance – Work-Life Balance Index Creation.

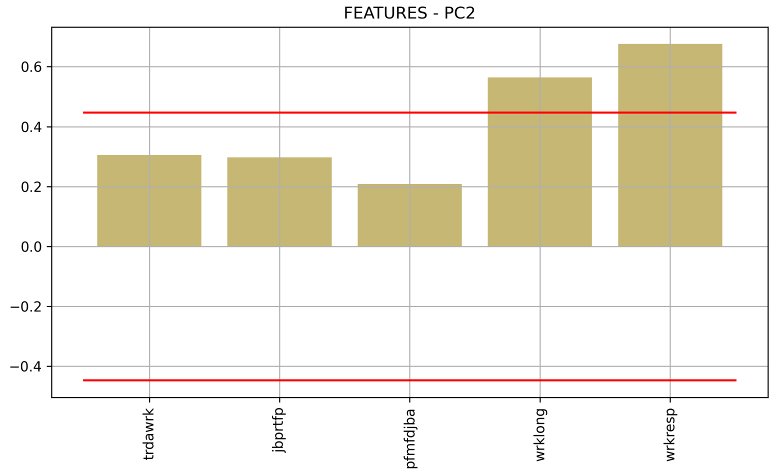

Figure 2.18. The breakdown in terms of dimensions of PC2 – Work-Life Balance Index Creation.

common are shop salespersons and software and applications developers and analysts, followed by engineering professionals (industrial, civil, environmental, mechanical, etc.), finance and administration professionals, teachers, clerks, and service workers. Considering the mean Work-Life Balance Index for each profession, it appears that the highest is the one for Engineering Professionals (214) with a $Work{-}Life{-}Balance{-}Index{-}1(mean) = 0.21583$ and the lowest for Physical and engineering science technicians(311) with a $Work - Life - Balance - Index - 1(mean) = -0.4531$, which should be interpreted as the 214 occupation code has the lowest work-life balance and the 311 occupation code

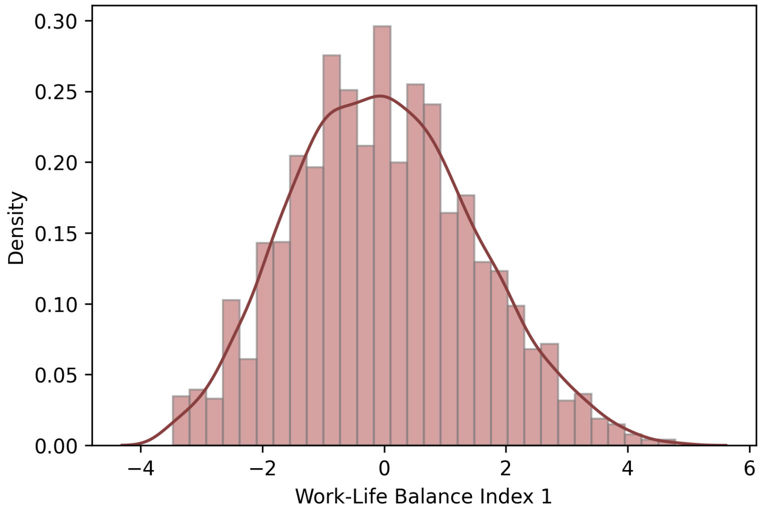

Figure 2.19. The histogram of Work-Life Balance Index made out of PC1 - ESS Round 10 data

has the highest work-life balance, considering the dimensions that contribute to PC1 as observed in Figure 2.17. Furthermore, the distribution of the Work-Life Balance Index for each sex and age-group can be observed in Figure 2.20 and Figure 2.21. With respect to the age groups, the histogram demonstrates a small but discernible generational disparity, with Millennials exhibiting a distribution slightly shifted toward higher index values (peak approximately at 0) compared to Gen Z, whose distribution centers around -1, indicating relatively lower work-life balance satisfaction among the Millennials. Conversely, Figure 2.20 reveals minimal variation between gender groups, as the density curves for males and females display near-complete overlap with both distributions centered around 0, suggesting that sex does not constitute a significant differentiating factor in work-life balance outcomes within this sample.

A multiple linear regression was conducted to examine the relationship between the Work-Life Balance Index and demographic variables. One-hot encoding was applied to the categorical variables gender and age group, with Male and Gen Z serving as the baseline categories. The results indicate that being a Millennial is associated with a significantly higher work-life balance index values and thus lower *actual* work-life balance (coefficient = 0.260, $p-value < 0.001$) compared to Gen Z, while being female is associated with a slightly higher index values than males (coefficient = 0.076), although this difference is not statistically significant ($p-value = 0.084$). The model explains only a small proportion of variance in work-life balance ($R^2 = 0.007$), suggesting that other factors beyond age and gender contribute to differences in work-life balance. This result was expected from what was observed in the distributions. The normal distribution of residuals, as it is shown in Figure 2.22 indicates that the regression model is appropriately specified and that the statistical tests (p-values, confidence intervals) are reliable and trustworthy.

ISCO-08 Code	Profession Description	Count	Mean Index
522	Shop salespersons	256	0.050
251	Software & applications developers	152	-0.366
214	Engineering professionals (industrial, civil, env.)	126	0.216
241	Finance professionals: accountants, analysts	110	-0.082
513	Waiters and bartenders	110	0.159
242	Administration professionals: management, policy, etc.	106	0.033
422	Client information workers	103	-0.020
332	Sales & purchasing agents and brokers	99	0.034
411	General office clerks	95	-0.218
234	Primary school & early childhood teachers	96	-0.215
431	Numerical clerks	80	-0.271
532	Personal care workers in health services	87	0.157
311	Physical & engineering science technicians	90	-0.453
243	Sales, marketing, public relations	87	-0.117

Table 2.5. Top professions by 3-digit ISCO-08 major code with count and mean Work-Life Balance Index (ESS Data Round 10)

Furthermore, the relatively even spread of residuals above and below zero within each categorical band, along with similar variance across bands, suggests homoscedasticity is reasonably satisfied (see Figure 2.23). Overall, the plot confirms that the model meets key regression assumptions, though the limited range of fitted values (approximately -0.20 to 0.13) reinforces the finding of low explanatory power, as the model's predictions vary minimally across different demographic groups.
Overall, the graphical representations of the distributions of demographic data w.r.t the work-life balance index corroborate the statistical findings, demonstrating consistency between exploratory visualization and inferential analysis.

Last but not least, we try to understand if the Work-Life Balance Index created here can be a good predictor of job satisfaction. In this dataset, after the filtering out operations mentioned above, there are 3806 data points with "high job satisfaction" (6-10) and 802 with "low job satisfaction" (0-5). The class imbalance was evident even previously. First of all, Work-Life Balance Index histograms are plotted with respect to the two groups which can be observed in Figure 2.24. As it can be observed in the graph, there is a clear distributional shift between job satisfaction groups, with low satisfaction

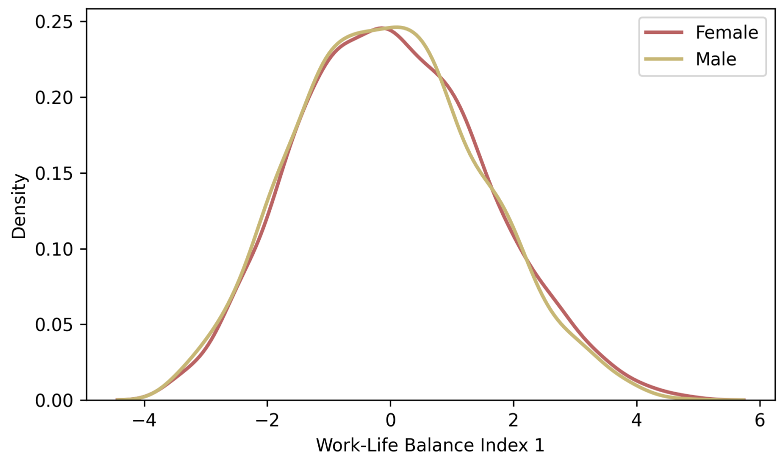

Figure 2.20. The distribution of the work-life balance index by sex - ESS data Round 10

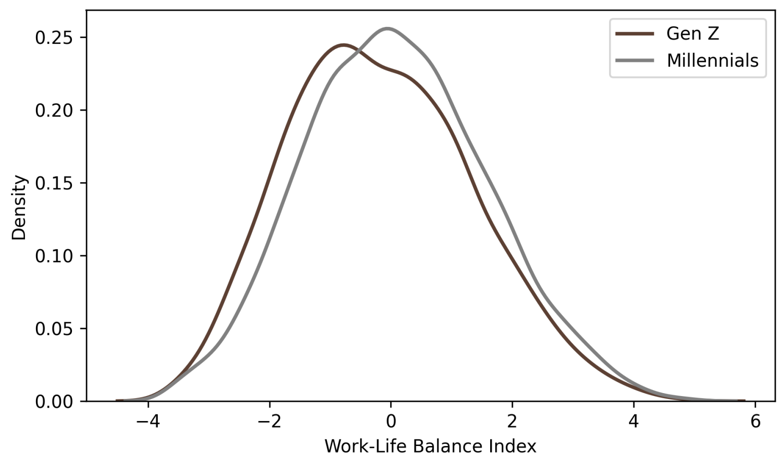

Figure 2.21. The distribution of the work-life balance index by age-group - ESS data Round 10

(0–5) centered around 0–1 on the Work-Life Balance Index, indicating poorer balance, while high satisfaction (6–10) is centered in the negative range, reflecting better balance. This visual separation confirms that work-life balance is positively associated with job satisfaction and validates its use as a predictor in logistic regression analysis.

A logistic regression was built having as input the work-life balance index to predict

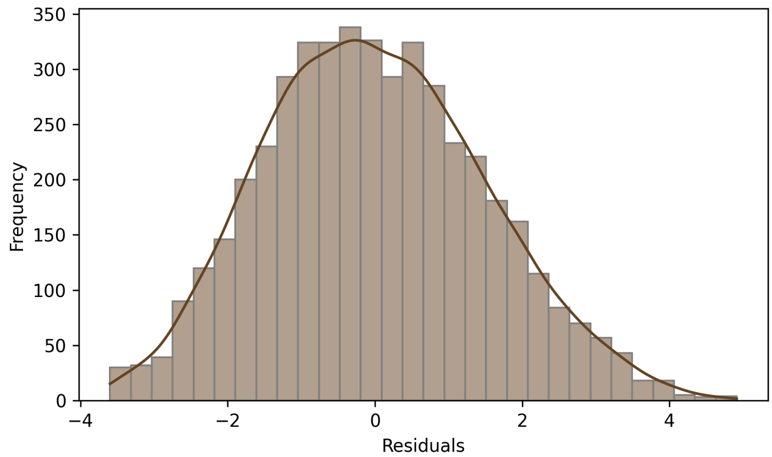

Figure 2.22. The distribution of the residuals of the multiple regression model predicting work-life balance index - ESS data round 10

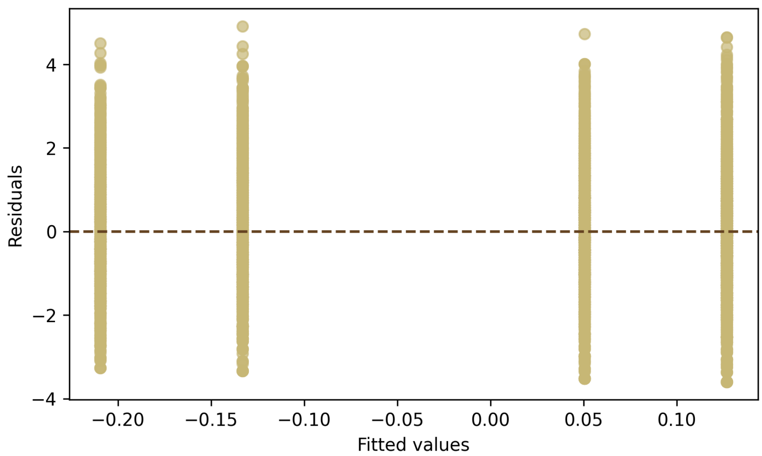

Figure 2.23. The distribution of the residuals vs. fitted of the multiple regression model predicting work-life balance index - ESS data round 10

binary job satisfaction categories, yielding an overall accuracy of 82.1%. The model coefficient for the work-life balance index is negative (-0.494, $p < 0.001$), confirming the theoretically expected inverse relationship: as the work-life balance index decreases (indicating better balance), the log-odds of belonging to the high job satisfaction category increase. However, the model exhibits substantial performance asymmetry across classes due to severe class imbalance in the dataset (757 high satisfaction vs. 165 low satisfaction cases in the test set). While the model demonstrates strong performance for the majority

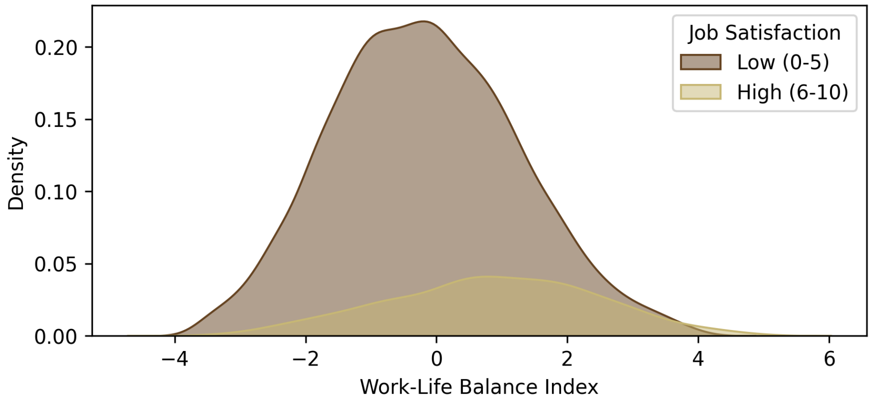

Figure 2.24. The histograms of the Work-Life Balance Index with respect to the two Job Satisfaction Groups - ESS data Round 10

class (precision = 0.83, recall = 0.99 for high satisfaction), it fails to adequately identify the minority class, achieving only 4% recall for low job satisfaction despite 50% precision.

To address the severe class imbalance in the training data (3,049 high satisfaction vs. 637 low satisfaction cases), a second logistic regression model was developed using random undersampling of the majority class. The majority class was randomly downsampled to match the minority class size, resulting in a balanced training set of 637 observations per class (1,274 total). While this model with undersampling exhibits lower overall accuracy (64.5%) compared to the original model (82.1%), it demonstrates substantially improved performance in identifying low job satisfaction cases, achieving 61% recall for the minority class compared to only 4% in Model 1. This improvement comes at the cost of reduced precision for the minority class (0.28 vs. 0.50) and decreased recall for the majority class (65% vs. 99%), resulting in 262 high-satisfaction cases being misclassified as low satisfaction. The coefficient for work-life balance index remains negative and similar in magnitude (-0.464 vs. -0.494), confirming the robustness of the predictor's direction across both models. The confusion matrix can be observed in Figure 2.25.

Overall, the results show that demographic data like sex and age-group are not strong discriminators of the Work-Life Balance Index, with the model explaining less than 1% of variance; however, age-group does emerge as a statistically significant factor, with Gen Z reporting poorer balance than Millennials. When trying to predict job satisfaction levels by the Work-Life Balance Index, the undersampled logistic regression model demonstrates that work-life balance is a meaningful predictor, particularly for identifying low satisfaction cases, though the trade-off between overall accuracy and balanced class performance highlights the challenge of working with imbalanced data.

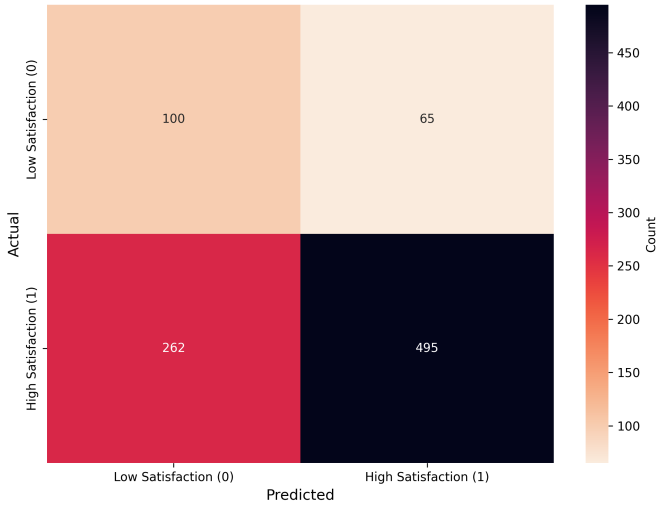

Figure 2.25. Confusion Matrix of Logistic Regression Model Predicting Job Satisfaction Categories through the Work Life Balance Index Using Undersampled Training Data - ESS data Round 10

2.4.3 Beyond good work and towards *meaningful* work

It also seemed appropriate in order to make the study of work perception and understanding more holistic, to move beyond just good work and towards *"meaningful work"*. For framing an analytical model of meaningful work this work was chosen: "The Ethical Implications of Artificial Intelligence (AI) for Meaningful Work" by Sarah Bankins and Paul Formosa 2023. There are varying frameworks on meaningful work and Bankins and Formosa (2023) take a holistic approach in this work by combining the task-based model of Hackman and Oldham (1976) which analyzes how job and task design influences experiences of meaningful work with that of Lips-Wiersma and Morris (2009) that goes beyond task focus and employs a more humanistic approach through "the development of self", "unity with others", "expressing one's full potential" etc. Thus, they come up with the following dimensions of meaningful work:

- Task integrity - the tasks an individual does and the opportunity to complete a whole piece of work, so the ability to undertake integrated rather than fragmented tasks.
- Skill cultivation and use - the ability to use and develop a range of skills at work, given that prospects for skill utilization influence opportunities for growth and development of one's potential.
- Task significance - as it connects one's work to the outer world, so how one's work contributes to the improvement of other's lives.
- Task autonomy - how freely can individuals determine their work approaches and the extent of their freedom from intrusive surveillance and monitoring.
- Belongingness - how work can make one feel connected to a wider group and evoke a sense of unity with others.

This paper is chosen as relevant for the purposes of this work, particularly because it contextualizes meaningful work in the AI era and extends ethical AI discussions to workplace dynamics. In this sub-chapter an initial analysis is conducted on what young people think makes work meaningful. In Interview Set 2, the interviewees were asked to rank the above mentioned dimensions from the most important to the least important on what they assume makes work meaningful. This matter was part of the Interview Set 2 and not the online surveys due to the need it has for elaboration on the components of meaningful work, which makes it not fitting for the online surveys format. The ranking can be observed in Figure 2.26. Clearly, the interviewees have predominantly chosen the dimension of *significance* as the top ranking one, with 50% of the interviewees ranking that first. As for the rest of the dimensions it is difficult to determine a clear, overarching ranking.

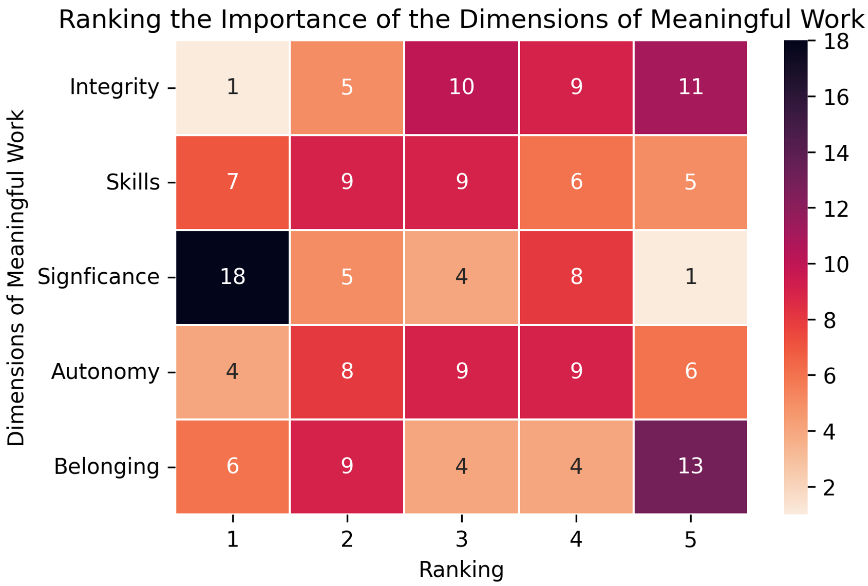

Figure 2.26. The heatmap with the rankings of the dimensions of meaningful work - Interview Set 2

When disintegrating in terms of the three groups of people coming from sciences, arts and politics, it becomes apparent that for each case the dimension that comes out to be the most important is again *task significance*, with precisely 50% of each group choosing that, as it can be observed in Figure 2.27. For people from politics a sense of *belonging to a community* comes in second place, whereas for people from arts second comes *the ability to use their skills* and for people from sciences *autonomy* ranks second. Interestingly, the sense of *belongingness* that ranked second for people from politics, ranks last for both other groups. Whereas for people from politics, *task integrity* is what ranked last.

Considering a sex-based analysis and the respective frequencies for each dimension that was ranked first, the results can be seen in Table 2.6. As it can be observed for the *task integrity* dimension, only 1 male ranked it as the most important, while no females

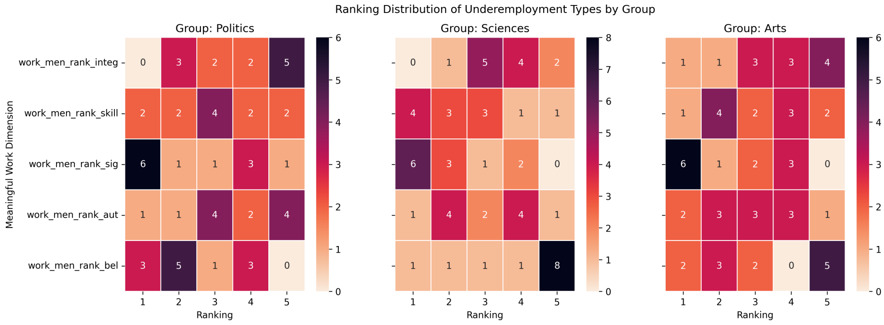

Figure 2.27. The heatmap with the rankings of the dimensions of meaningful work by occupational groups - Interview Set 2

did. Regarding *skill cultivation and use*, 4 males and 3 females ranked it as the most important, indicating a fairly balanced value placed on the ability to use and develop skills across sexes. For *task significance*, 10 males and 8 females prioritized it as the most important, showing that both sexes connect their work to improving others' lives, with a slightly higher emphasis from males. Both males and females equally ranked *task autonomy* ($Frequency$ = 2, each) as most important, highlighting the shared value of having freedom in work approaches. Lastly, 5 females ranked *belongingness* (how work fosters a sense of belonging) as most important, compared to 1 male, suggesting that females in this dataset place more importance on feeling part of a team or community at work.

Meaningful Work Dimension Ranked First	**M**	**F**
Task integrity	1	0
Skill cultivation and use	4	3
Task significance	**10**	**8**
Task autonomy	2	2
Belongingness	1	5

Table 2.6. Ranking of meaningful work dimensions as "Rank 1" by sex - Interview Set 2

During the interviews, the interviewees were asked to provide some rationale for their ranking, particularly for the dimension they ranked first. From the ones that ranked *"task significance"* as first, the rationales were along the following lines:

- People coming from arts: Artists emphasize task significance as the key factor in making work meaningful. They believe that work must have a deeper purpose beyond just earning a wage, as purpose sustains long-term engagement. They also argue that meaning comes from the impact of their work, rather than just skill development, which can happen independently. Additionally, they highlight the emotional and inspirational effect of art on others, seeing their work move and inspire people gives their art a sense of life and significance.

- People coming from sciences: Scientists rank task significance as the most meaningful aspect of work because they strive to create positive change and contribute to society. They see science as inherently driven by the desire to improve the world, whether through advancing knowledge, making a difference, or leaving a lasting impact. Many emphasize an idealistic motivation, particularly in early career stages, and professions like medicine highlight their direct role in improving lives. Ultimately, they view science as a pursuit of knowledge that serves a greater good.

- People coming from politics: Political science professionals view task significance as the most meaningful aspect of their work because it allows them to create impact and contribute to society. They emphasize that their role shapes public opinion, political discourse, and policymaking, making them feel part of something larger. For political activists, significance comes from representing people in the political sphere. Overall, they see political science as inherently public-oriented, driven by a desire to understand, influence, and improve society.

2.4.4 What makes a job - *a drudgery*?

It is essential to develop a comprehensive understanding of work that goes beyond its positive aspects, as in what constitutes meaningful, fulfilling, and high-quality work. Equally important is the exploration of its negative dimensions, examining the factors that turn work into drudgery. This means analyzing not just what makes work engaging and rewarding, but also what leads to monotony and dissatisfaction. Only understanding both sides, we can identify the conditions and factors that contribute to either experience, ultimately helping to properly and holistically understand the perceptions of young people in Europe regarding work. Making use of the framework that Bootle (2019) has made on his book "The AI Economy" we will try to understand good work by employing contrapositive reasoning and posing the negative question, so not what makes work good but rather what makes it a drudgery. For Bootle (2019), the determinants of what would make work a drudgery were the following (pp. 101):

- Repetitiveness
- Lack of connection with colleagues
- Lack of connection with the end-product and the end-user
- Lack of belief that what is being produced/ delivered is inherently worthwhile.

In Interview Set 2 (see here the full set of questions in Appendix .1.12), the interviewees were asked to rank these dimensions from the most important to the least important on what they assume makes work a drudgery. The heatmap with the 4 ranks and the 4 dimensions can be observed in Figure 2.28. We can clearly notice that out of 36 interviewees, 50% decidedly chose *the lack of belief in the inherent worthwhile-ness of the work* to be the top reason that makes work a drudgery and 39% ranked it in second place. Clearly this comes out as the most relevant dimension in this work. Ranking them in order considering the choices of the interviewees, it would go in this manner: lack of connection with the end product/ end user, repetitiveness and lack of connection with colleagues. The latter was ranked last by 41.6% of the interviewees. However, the last two rankings are entirely clearly separable.

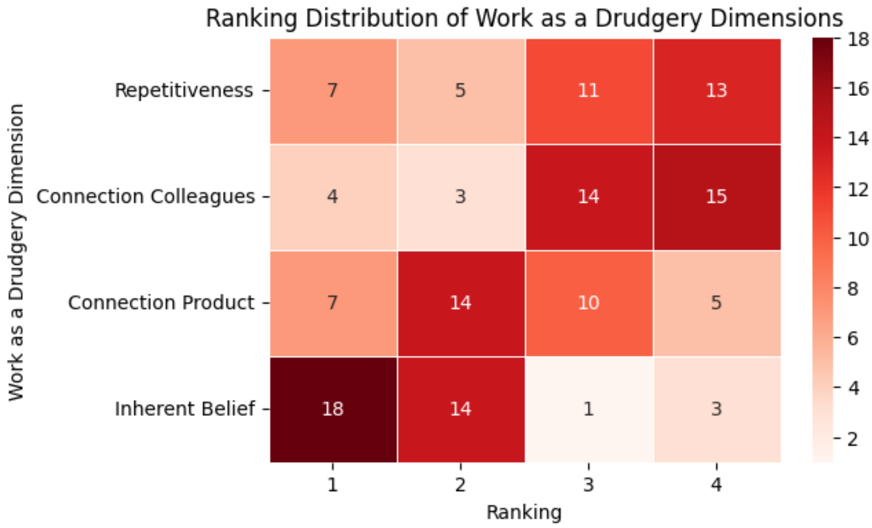

Figure 2.28. The heatmap with the rankings of the determinants what makes work a drudgery – Interview Set 2

When the interviewees were prompted to justify their choices, the primary rationales that emerged as central to making *"the inherent belief in the worthiness of the work itself"* that surfaced at the top were the following:

- A very recurrent line of reasoning: If you don't believe what you are doing doesn't have value, that can be dreadful.
- Furthermore, it appears that people seem to be complaining that they are doing a somewhat "lower" version of their profession and are required or forced to do work in which they don't believe in. For example, one of the artists mentioned the fact that the paintings that are often required to be done are very simplistic portraits that he does only because he needs to work but that they don't bring forward the actual artist in him.
- In addition, people saw it as a natural and inherent feature of the domain itself and this was true across the three domains: arts, sciences, politics. The idea was that if you are to work in that field, you must believe deeply in what you are doing, or otherwise, the work is truly drudgery.

When we observe the ranking disintegrated in terms of the three groups we are considering, as it can be seen visualized in Figure 2.29, only the politics group has decidedly chosen *the lack of belief in the inherent value of work* as the most important reason by 70%. For the other two groups, it also gets the highest number of votes for the first place, but it is less clear cut, with only about 40% choosing it as the top reason and others splitting their top vote for the other categories as well.

Furthermore, considering what is ranked first for each sex, we observe that males and females differ in their perceptions of what makes work drudgery, as the counts illustrate in Table 2.7. *Repetitiveness* is seen as a major factor by more males (5) than females (2), suggesting that men in this dataset may be more sensitive to monotonous tasks. In contrast, *lack of connection with colleagues* is ranked the most important by 4 females but no males, indicating that women might place greater emphasis on workplace relationships. *Lack of connection with the end-product and end-user* is considered as the top problematic by 5 males and 2 females ranking it first, showing that both sexes value seeing the impact of their work, though males more so. Finally, *lack of belief in the worth of what is being produced* is the most first commonly ranked factor overall, with 8 males and 10 females selecting it, suggesting that both sexes see the lack of meaning and purpose as crucial in what makes work a drudgery. For the full dimensions' ranking heatmap see Appendix .2.11. The largest majority vote for females goes for ranking as first *the lack of the inherent belief in the value of their work*, as mentioned with 10 votes and for males goes for ranking as last *connection with colleagues*, with 11 votes, so 61% of the respondents considering it as such.

Drudgery Dimension Ranked First	**M**	**F**
Repetitiveness	5	2
Lack of connection with colleagues	0	4
Lack of connection with the end-product and the end-user	5	2
Lack of belief that what is being produced/delivered is inherently worthwhile	**8**	**10**

Table 2.7. Ranking of work as drudgery dimensions as "Rank 1" by sex – Interview Set 2

2.5 Tales of Motives and Risks in the realm of Work

As a final point, to better grasp the understanding of work and the relation to it of young people in Europe today, we will try to understand why they work in the current work that they do and what are the top risks that they associate in terms of losing their job. The questions here were framed for the concrete and actual jobs that they are currently engaged in. In order to do this, the analytical model was co-designed with the young people being interviewed in Interview Set 1, where for both questions *"Why do you work in the current job you are in?"* and *"What are the risks of you losing the job you are in?"*, helped in providing possible answers and compiling the final list of dimensions for each question, as already mentioned in the methodology. The seven dimensions for each question that were agreed upon at the end of all 76 interviews from Interview Set 1 can be seen in Table 2.8.

Motives for doing the current job?	Risks of losing the current job?
Make money	Automation
Structure your days	Corruption
Give meaning to life	Bad management
Acquire skills to become self-employed	Offshoring
Socialize / Networking	Political instability in your country
Social status	A migrant takes your job
Help people / contribute to society	Clashes with colleagues' values & opinions

Table 2.8. Motivations for working and perceived job risks dimensions co-designed during Interview Set 1

Consequently, both of these questions were present in Online Survey 1, in which as mentioned previously there were 104 respondents. The respondents were asked to rank the dimensions from 1 to 7, with 1 being the most important reason and 7 being the least (see Appendix .1.6). Naturally, in this question, the ranking was mutually exclusive, meaning they were not scoring the importance of the dimensions individually, as in the case of what makes a job a good job, but rather ranking these dimensions in comparison to one-another by allocating a number only to one individual dimension. Overall, for the first question, *make money* was mostly ranked as first and *structure your days* was the one most ranked as last. For the second question, *bad management* was dominantly ranked as the top reason. Interestingly, due to the fact that this question was left as an alternative one, given the fact that not everyone filling out the survey might have been employed at the time, some people had not allocated a rank to all the dimensions. For example, in one case, in the question of *"Why do you work on your current job?"*, the respondent had forgotten to allocate a rank to one of the dimensions. This results in inconsistencies, as the number of missing values varies across dimensions. To ensure coherence and without making any assumptions that might lead to biasing the model, even in the cases that only one dimension was forgotten without rank allocation, all the rows, meaning all the individuals that had null values in any of the dimensions were dropped.

This leads to a dataset of 85 rows. Now having a coherent dataset we can study and observe the heatmaps with the rankings in Figure 2.30 and Figure 2.31. A few key observations regarding the motives on why people work in their current jobs:

- Money is the dominant motive. It has the highest number (34) in the 1st rank, meaning most people, specifically 40%, prioritize money as their main work motive in their current jobs.
- Self-employment matters because a significant number of respondents ranked it highly, particularly in the 1-4 ranks.
- Working in order to give meaning to life is highly polarized, with high values in both high and low ranks.
- Working in order to socialize, for status or structuring the days appear to be less dominant reasons.
- Contribution to society is evenly distributed. There isn't a strong consensus; it's

ranked across the board.

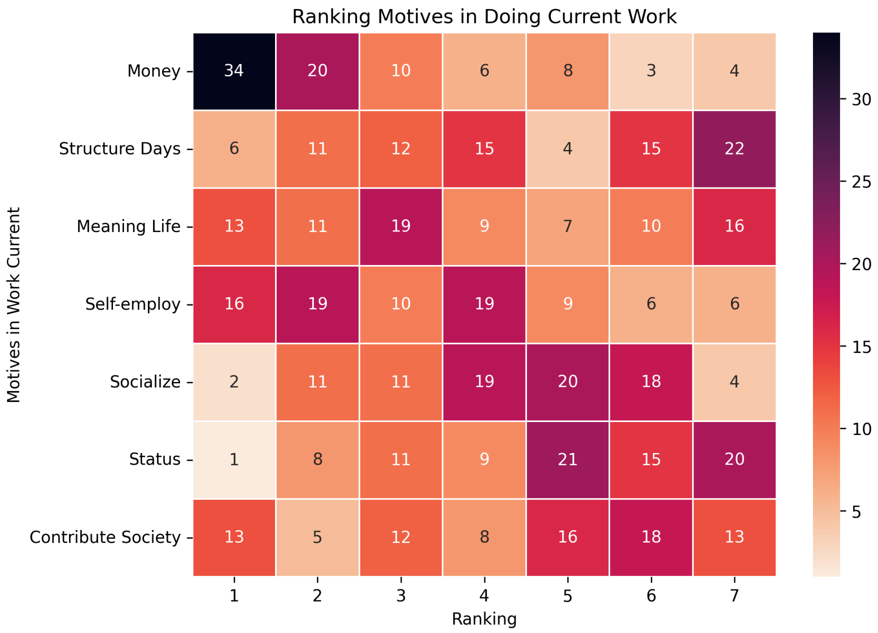

Figure 2.30. The heatmap with the rankings of the motives for doing the current job – Online Survey 1

Making some considerations in terms of sex and the frequencies of ranking as number one for the above mentioned motives, we get to the following situation as illustrated in Table 2.9. A small note has to be made that after the data cleaning process mentioned above, removing those entries which had not ranked all the dimensions, we still have a very balanced dataset of 42 females and 43 males.

Motive	**Female Count (Rank 1)**	**Male Count (Rank 1)**
Make money	**13**	**21**
Structure your days	1	5
Give meaning to life	8	5
Acquire skills to become self-employed	11	5
Socialize / Networking	1	1
Social status	0	1
Help people / contribute to society	8	5

Table 2.9. Rank 1 motives' counts on doing the current job by sex - Online Survey 1

It appears that both males and females have making money as the primary motive for working in their current jobs. However, the distributions differ widely, with 62% more males selecting making money as the primary motive compared to females. Out of the

42 females, the ones ranking making money as first are 13, 11 rank acquiring skills in order to become self-employed and 8 ranking first the motivation of helping people and/or contributing to society. On the other hand, 21 out of 43 males, so almost half, marked making money as the primary driver in their current job and the rest appear to be widely distributed.

The key observations regarding what people find the most risky in terms of losing their current job, are:

- Bad Management is the dominant factor on what the respondents of the survey estimate as the highest risk of them losing their current job. A large number of respondents, 33 or 38.8% ranked it as the most important cause.
- Automation and Clashes with colleagues' values are consistently ranked high: While not as intensely dark in the heatmap as "Bad Management" at the 1st ranking, they show a consistent presence in the higher rankings (1 - 3), indicating they are considered as significant factors across a range of importance levels.
- Corruption, Offshoring and Political Instability have similar patterns, with moderate rankings across the spectrum. They are considered factors, but their importance varies depending on the specific ranking.
- Migrant Impact is more prominent at lower importance. It's ranked relatively low in importance and shows a significant peak at the lowest importance ranking (7.0) with 31 out of 85 respondents, so 36.47% ranking it last.

The most interesting and relevant for our analysis is the fact that *fears of automation definitely are a relevant factor but not the dominant one in terms of people losing their current job.* People fear, well, *people* the most, in this case: bad management.

Conducting the same sex based analysis as in the case of the reasons behind their current jobs also for the risk estimation of people losing their current jobs, we can observe the frequencies for being ranked first for each dimension in Table 2.10. Both female and male respondents show a similar level of concern about automation, with 8 individuals from each gender ranking it as the most important risk, making it the secondary reason. In terms of corruption, males are slightly more concerned than females, with 5 males and 3 females ranking it as the highest risk. Bad management is the most commonly ranked risk for both genders, with males (18) slightly more concerned than females (15). When it comes to offshoring, political instability, and migrants taking jobs, females seem to be more worried than males. Finally, clashes with colleagues' values are slightly more concerning for males (7) than females (4), though the difference is not substantial.

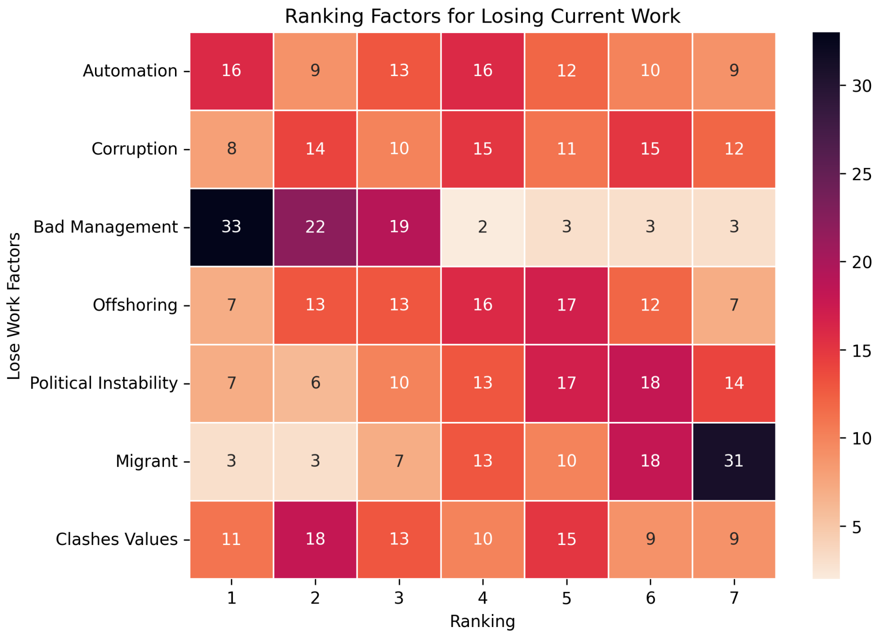

Figure 2.31. The heatmap with the rankings of the risks for losing the current job – Online Survey 1

Risk	Female Count (Rank 1)	Male Count (Rank 1)
Automation	8	8
Corruption	3	5
Bad management	**15**	**18**
Offshoring	5	2
Political instability in your country	5	2
A migrant takes your job	2	1
Clashes with colleagues' values & opinions	4	7

Table 2.10. Rank 1 risks' counts on losing the current job by sex – Online Survey 1

In order to better understand the relationship between the motives and fears the respondents of Online Survey 1 have in their current jobs, their correlation is studied. Unlike the most commonly used Pearson Correlation that measures the linear relationship between two continuous variables and is sensitive to outliers, here Spearman Rank correlation is used, which measures the monotonic relationship between two variables, particularly useful when considering ordinal data like the ones present here. The formula for Spearman Rank correlation is the following:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{2.2}$$

where d_i is the difference between the ranks of the two variables for each observation, and

n is the number of observations.

Measuring the correlation between each pair of the dimensions of why people work in their current jobs and what they consider as risks in terms of losing their current job, the heatmap is obtained that can be observed in Figure 2.32. It can be observed that most correlation values are between -0.3 and 0.3, which indicates weak associations, given the fact that Spearman Correlation has the boundaries [-1, 1]. There are no strong correlations ($rho > 0.5$ or $rho <$ -0.5), suggesting that the motivations for working and job loss fears are mostly independent or only weakly linked. However, some minor observations can be made:

- People who work for meaning in life are positively correlated with fear of corruption ($rho = 0.230$) and bad management ($rho = 0.17$) but negatively correlated with fear of migrant workers taking jobs ($rho =$ -0.219).
- People who work to contribute to society are positively correlated with fear of corruption ($rho = 0.279$) and political instability ($rho = 0.14$), but negatively correlated with fears of migrants taking jobs ($rho =$ -0.24) and clashes with colleagues' values ($rho =$ -0.22).
- In both of these cases it seems that workers focused on social contribution and meaning in life tend to worry more about corruption and bad management but fear migration less.
- People who work to structure their days show very low correlation with most fears, suggesting their reasons for working are not strongly linked to job insecurity concerns.
- Money-driven workers, which formed a wide majority of the respondents, are slightly concerned about bad management and have negative correlation ($rho =$ -0.29) with corruption as a risk of losing their job. This marks an almost diametric difference with individuals who see working too contribute to society as an important reason.
- Lastly, fears of automation are not really correlated with any of the motives, with most correlation values being less than 0.1 in magnitude.

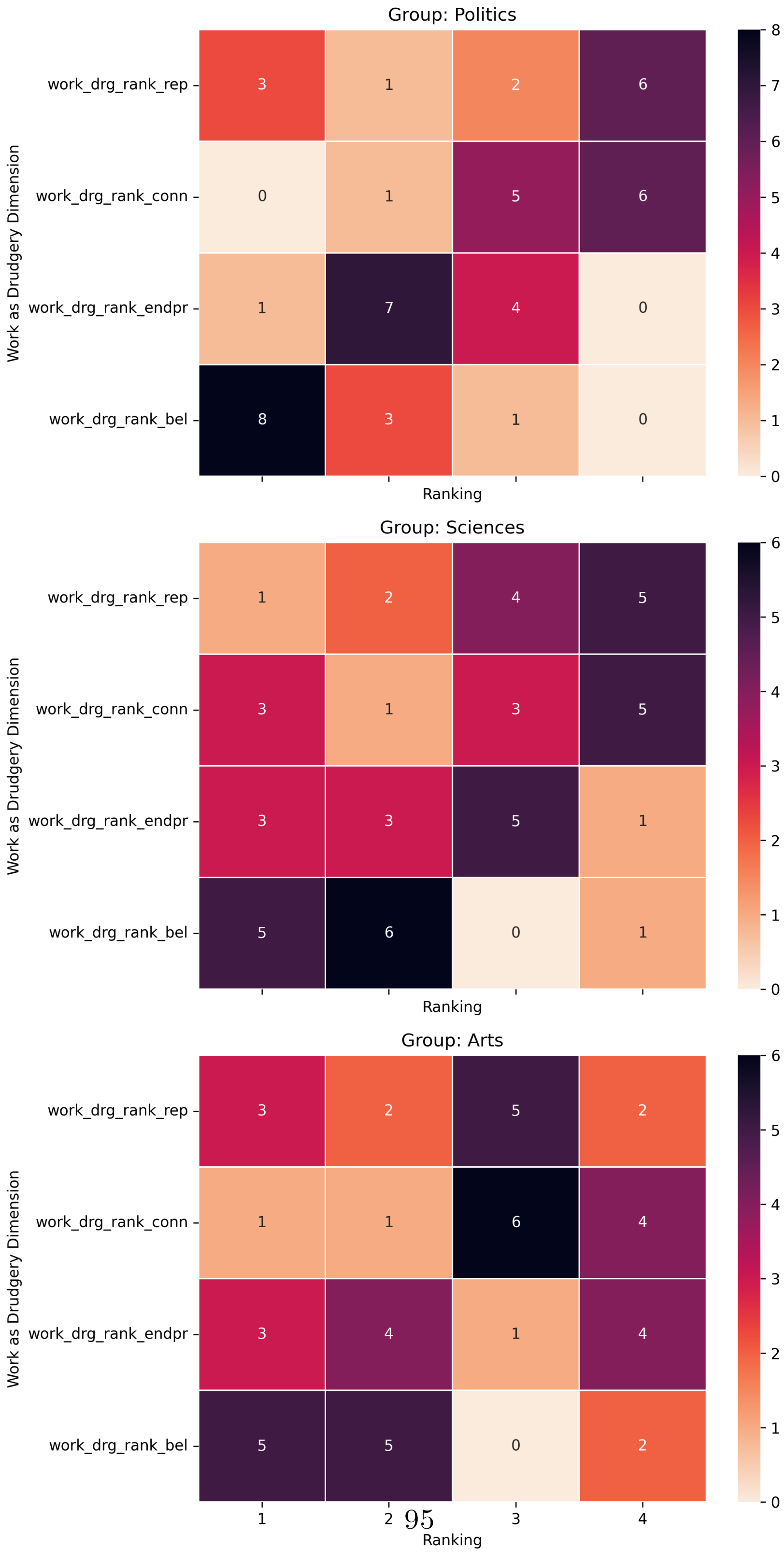

Figure 2.29. The heatmap with the rankings of the determinants what makes work a drudgery, disintegrated in terms of the 3 occupational groups - Interview Set 2

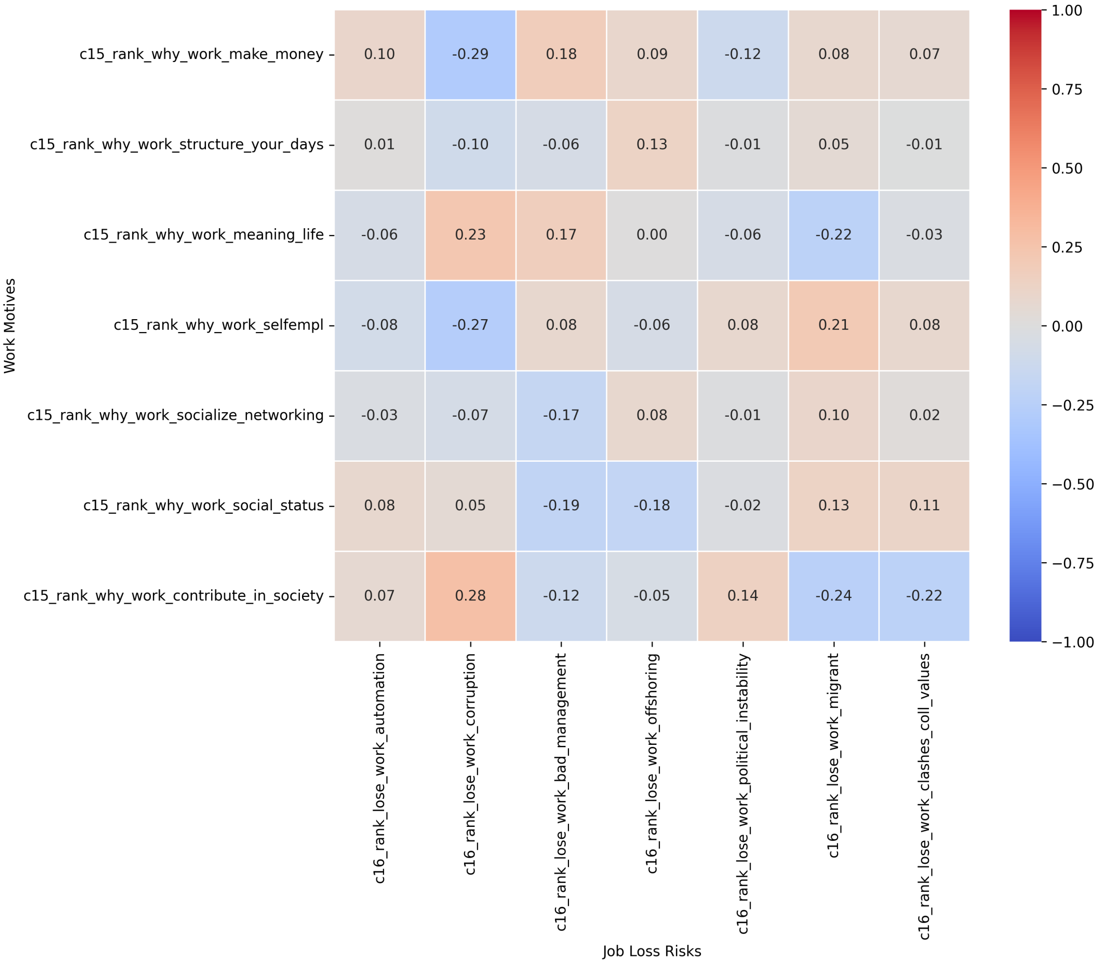

Figure 2.32. Spearman rank correlation between each motive and each risk - Online Survey 1

2.6 *Tale in Brief* - Work

In this chapter, we entered for the first time in the mythical-real city of Berat and encountered the perceptions of young people with respect to work. First we started out by defining what *work actually is*. The results showed that the respondents of Online Survey 2 associated work mostly with wage-labor and the top notions were: *activity, money, get, physical, mental*. However, the frequencies of the top mentioned words were quite low, the most frequent word being only in **15%** of the descriptions, which can lead one to believe that the participants in the study have a wide variety of understanding of the concept of work. Moreover, the notion of "unpaid work" was explored, mainly based on the work of Himmelweit (1995) and Miranda (2011), particularly with reference to household work. The results from Interview Set 2 showed that the vast majority, **80.6%**, recognized those activities as *work*. Interestingly, even in some of the few cases where such activities were not seen as work; they were seen as *a duty*, putting them to an even higher level of value recognition.

In terms of **underemployment**, the data from Interview Set 2 show that only about **22%** of the sample are familiar with the term, highlighting the need for better education in economic terms. Furthermore, it seems unlikely to organize and improve what you are not familiar with, or in simpler terms: what you lack the words for. Orwell (1946)said it better: *"But if thought corrupts language, language can also corrupt thought"* - or, in our case: lack of language cannot construct thought and action. Taking into account the three categories of underemployment (in accordance with Underemployment.info (n.d.), the ranking based on what the young people in the interviews have experienced personally would be the following: skills-related, wage-related, time-related.

However relevant metrics like unemployment and underemployment are, this work goes beyond them and gives a special focus to **the quality of work**, namely: what makes a job *good*, *meaningful* or on the negative definition, what makes it a *drudgery*.

With respect to what makes a job *good*, first a naive approach is used and the participants of Online Survey 1 were asked how much they liked their job on a scale from 0 to 10. The results showed that the distribution was more dense along the higher levels of job liking and if we consider a score of 8, 9 and 10 as a high job liking and satisfaction, then **56.73%** of the respondents of Online Survey 1 appear to be highly satisfied in their current role. A similar distribution was observed by the respondents of the well-known European Social Survey (ESS) data in both rounds 5 and 10, collected in 2010 and 2020 respectively. This affirms the validity of the dataset collected for the purposes of this work, at least on this specific point. Employing the non-parametric Mann-Whitney U test on the Online Survey 1 data, the results show that there are statistically significant differences among Millennials and Gen Z (at 5% level of significance), with Gen Z showing lower levels of liking their jobs and even make up for the entirety of the extrema scores 0 and 1. Moreover, the violin plots in Figure 2.12 show that Millennials tend to cluster around the higher scores of liking their jobs whereas Gen Z appears to be more spread. The same test was used to understand if there are statistically significant differences among males and females and if the conventional 5% level of significance is considered, it can be reported that there is no statistically significant difference between males and females in terms of liking their current job (however, it could be marginally significant at 10%). Moreover, using data from ESS, a logistic regression is used to try and classify job satisfaction levels into low (0-5) and high (6-10), based on sex, age and country. The matter of class imbalance was present given the fact that there are 8092 instances of high job satisfaction and 1857 instances of low job satisfaction, thus in addition to the vanilla case, techniques like under-sampling and oversampling were used. Furthermore, another logistic regression was built using only sex and age-group as input. In all cases the pseudo R^2 did not show very high values, indicating that classification power for job satisfaction based only on demographic data is not high.

Going beyond the simple approach of demarcating a job as *good* just based on how much people like it, another question was made where multiple dimensions were provided to be scored from 0 to 5 (not mutually exclusive, so the different dimensions can have the same score) on how important they were to consider a job seen on an ad as *good*. This list of dimensions was co-designed together with the participants of Interview Set 1, so it does not reflect only the opinions of this author but rather the worldview of the target group. It was disseminated in Online Survey 1 and the results showed that overall but also across sexes and the two age-groups considered, the most important dimension that made a job good was **work-life balance**, with a summed score of **456** where the ceiling would be 520. In terms of the secondary choices, for males comes the possibility to have *a good career* with a score of 218, followed closely by *the ability to learn on the job* (217) and *a good salary* (214). For females, the second comes *the ability to learn on the job* (226), followed by *a good salary* (224) and *flexible working hours* (209). In terms of the two age-groups, it was interesting to discover that for Gen Z, the second most important dimension was *a good salary* (193) whereas for Millennials, even though they are the older age-group and therefore one would assume more experienced, *a good salary* (245) came in the third position, whereas the second was *the ability to learn on the job* (255). A possible explanation might be the fact that technological changes are impacting the required skills on the jobs and Millennials who have entered the job market earlier than Gen Z, see the need for re-skilling.

Given the prevalence of **work-life balance** as the main indicator of a good job, this notion was studied further using the *spillover model* noted also by Guest (2002), in which the very notion is defined by *how much the work life spills to the out of work life.* An index for work-life balance was built using determinants from ESS data round 10 and due to the presence of moderate ($5 < VIF < 10$) to high multicollinearity ($VIF > 10$), the Principal Component Analysis was used to build the index. Using the first principal component as the work-life balance index, which explained about 45% of the variance in the data, the interpretation can be made (after taking a small *epsilon*) that there are three positively highly valued dimensions, namely: *jbprtfp* or Job prevents you from giving time to partner/family, how often (values from 1- Never to 5- Always); *pfmfdjba* or Partner/family fed up with pressure of your job, how often (value from 1- Never to 5- Always); *trdawrk* or Too tired after work to enjoy things like doing at home, how often

(values from 1- Never to 5- Always). Given the fact that a high value on these three dimensions intuitively reflects a low work-life balance, then a high score on PC1 would reflect a low work-life balance. **The work-life balance index** was then built by multiplying each row of the standardized data matrix by the vector of PC1 loadings to obtain each individual's index score. The data followed a normal distribution and in terms of sex the distributions were almost identical, showing minimal variation. In terms of the two age groups, the histogram demonstrates a small but discernible generational disparity, with Millennials exhibiting a distribution slightly shifted toward higher index values (peak approximately at 0) compared to Gen Z, whose distribution centers around -1, indicating relatively **lower work-life balance satisfaction among Millennials**. Then, a multiple regression is built to predict the work-life balance index through demographic data sex and age-group. The results indicate that being a Millennial is associated with a significantly higher work-life balance index values and thus lower *actual* work-life balance (coefficient $= 0.260$, $p - value < 0.001$) compared to Gen Z, while being female is associated with a slightly higher index values than males (coefficient $= 0.076$), although this difference is not statistically significant ($p - value = 0.084$). The model explains only a small proportion of variance in work-life balance ($R^2 = 0.007$), suggesting that other factors beyond age and gender contribute to differences in work-life balance. This result was expected from what was observed in the distributions and when the distribution of the residuals is visualized. It appears to be roughly bell-shaped which supports the assumptions of linear regression and makes inference reliable. Last but not least, we try to understand if the Work-Life Balance Index created here can be a good predictor of job satisfaction, again dealing with the issue of imbalanced dataset in the low and high job satisfaction cases. The model that uses under-sampling yields a lower accuracy (64.5%) compared to the original model (82.1%), but it demonstrates substantially improved performance in identifying low job satisfaction cases, achieving 61% recall for the minority class compared to only 4% in the vanilla case.

In terms of what makes work *meaningful* the analytical model of Bankins and Formosa (2023) is used, which lists five dimensions of meaningful work: Task integrity, Skill cultivation and use, Task significance, Task autonomy and Belongingness. This question was present in Interview Set 2 due to the need it has for elaboration and the participants were asked to rank these dimensions from the most to the least important. The results show that **50%** of the interviewees chose *task significance* as the top ranking one, which encompasses the connection one's work to the outer world, so how one's work contributes to the improvement of other's lives. The same dimension was chosen as the most important one across the three occupational groups and in terms of secondary dimensions, for people from *politics* a sense of *belonging to a community* comes in second place, whereas for people from *arts* second comes *the ability to use their skills* and for people from *sciences* it is *autonomy* that ranks second. In terms of sex, both groups also chose *task significance* as the primary driver of meaningful work, but for males that is followed by *skill cultivation and use* and for females that is followed by *belongingness*.

It was equally important to analyze not just what make work *good* and *meaningful* but also what made it *a drudgery* employing contrapositive reasoning and using the four dimensions highlighted by Bootle (2019): Repetitiveness; Lack of connection with colleagues; Lack of connection with the end-product and the end-user and Lack of belief that what is being produced/ delivered is inherently worthwhile. The participants of Interview Set 2 were asked to rank these dimensions from the most to the least burdensome. The results showed that **50%** of the interviewees chose *the lack of the inherent belief in the value of the work* as the primary driver of what makes work a drudgery. The dimension with the highest counts of being ranked last and thus the least reason to make work a drudgery was *the lack of connection with colleagues* with **41.6%** placing it it in the last position. In terms of the three occupational groups considered during Interview Set 2, the politics group has decidedly chosen *the lack of belief in the inherent value of work* as the most important reason by **70%**. For the other two groups, it also gets the highest number of votes for the first place, but it is less clear cut, with only about **40%** choosing it as the top reason and others splitting their top vote for the other categories as well. Both sexes chose the same reason as the most dominant one in making work a drudgery but interestingly, 4 females ranked first *lack of connection with colleagues* while 0 males did so.

Finally, the reasons why people work in their current jobs, as well as the reasons they believe they might lose those jobs, were examined. Respondents were asked to rank factors within each dimension.In this case as in the matter of what makes a job a good one, the set of dimensions layed out was co-designed with the participants of Interview Set 1 and then disseminated in Online Survey 1. The findings show that the most feared cause of job loss is *bad management*, while the primary motive for working is *to earn money*. Secondary fears regarding job loss include *automation* and *conflicts with colleagues' values*. Concerning secondary motives for working, the most prevalent was *acquiring skills in order to become self-employed*. In terms of sex, both males and females rank *making money* as the most important, but the weight they give to it differs, with **62%** more males selecting making money as the primary motive compared to females. Whereas in terms of risks, again both sexes value the same category the most, namely *bad management* with **18** males and **15** females ranking it as the most important out of 85 respondents to this question. Subsequently, Spearman's rho correlations were calculated between each pair of motives and fears. No strong correlations were identified (i.e., none exceeded 0.5 in magnitude). The strongest positive correlation was $rho = 0.28$, observed between those who work in order to contribute to society and those who fear corruption as a cause of job loss. The strongest negative correlation was $rho =$ ˘0.29, found between those who fear corruption and those who primarily work to earn money. This pattern suggests that individuals who perceive corruption as a major threat tend to differ in their work motivations, leaning either toward prosocial purposes or away.

Chapter 3

Tales of AI

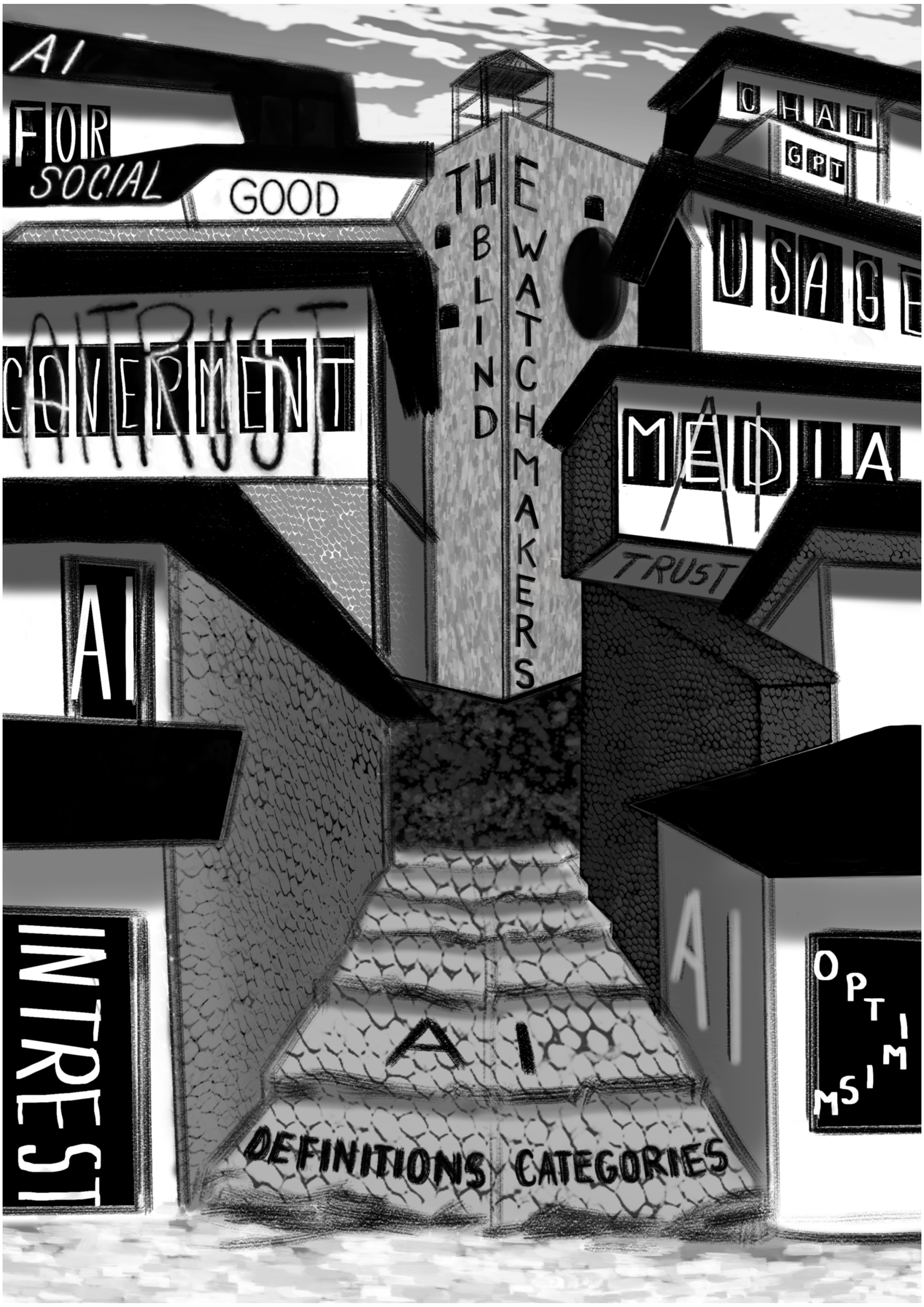

Figure 3.1. Tale 2: Mangalem - Tales of AI.

3.1 Tale 2: Mangalem - Tales of AI.

ONCE you get to the edge of Mangalemi neighborhood and at the beginning of Çelepias, but still on the northern side of Osumi river, one can observe The Clock Tower of Berati standing still firm but watchless. It is only through some whispers of the elders that one can learn that the clock that last stood there had the inscription "Torino 1880" and whose regular chimes were heard all the way to nearby villages. The watchmaker is long gone and no one has bothered to rebuild the clock. The mechanism that once stood there was transparent to all who bothered to climb the arduous steps of the tower, but now it is rendered useless by the parochial governors of our city, who have employed some modern watchmakers. The modern watchmakers argue that the time is being measured in a distributed and highly technological fashion in each home of the city of "one-above-another windows", as it is known to the local residents. However, they cannot explain the mechanism. Our watchmakers are blind to it. The time, which regulates the activities of the community, appears to be detached from its mechanism and lies as a set of incomprehensible numbers to the residents. "This is the future", the blind watchmakers proclaim. And who has the courage to be against the future? Yet, the residents still have the old Clock Tower as a common meeting point, discussing their optimism or pessimism for the seemingly irrevocable change (read: the sentiments of young people regarding AI). Some walk in disinterest and others are keenly interested. There's a lot of theories on who these blind watchmakers are exactly and we will explore that in detail (read: varying definitions young people give to the term "artificial intelligence"). Some highly trust their government and media in managing this whole ordeal and others simply cannot be convinced. Some have already gotten all hands on with these new incomprehensible clocks from the quiet of their homes and others just pass by once in a while though the corner they have ditched these number-producers (read: the usage of AI tools by young people in Europe, namely ChatGPT). Some believe these blind watchmakers will be the fairest regulators of community work, due to the obvious fact: they're blind. Others are more skeptical of these fairness cries (read: the perception of AI fairness with respect to humans will be explored). Last but not least, regardless of where they stand in this whole ordeal, the citizens of the city of "one-above another windows" want to know: Who is in charge of these blind watchmakers (read: who is creating the now dominant and widely spread AI algorithms and who develops them in Europe)? And why are they blind (read: the explanation for the "blind watchmaker" as a synonym to the current AI systems will be explored).

3.2 Artificial Intelligence: history, definitions and the Age of the Blind Watchmakers

3.2.1 A *very* brief history of AI

A brief history of artificial intelligence will be presented below with examples of the imagination going all the way back to antiquity. The dream of *automata* is indeed an ancient one. Then came the rise of the word "robot" in the 1920s from Czech, from "robota", meaning forced labour. This highlights the link of automation since its conception for the purposes of work and labor. Onward to more modern times, in the first attempts of what came to be coined as "artificial intelligence" in The Dartmouth Summer Research Project on Artificial Intelligence (see more at Dartmouth College), a 1956 summer workshop widely considered to be the founding event of artificial intelligence as a field in itself. In addition, the "Winter of AI" will be discussed and then its consequent re-vitalization due to multiple factors, including but not limited to: the commercialization of the internet, advances in computing and processing power, and the amount of data that became "freely" available and exploited. On a parallel line to the historical journey, the current definitions of "artificial intelligence" will be discussed as well as its categorization. Most importantly, a key point is understanding AI as a socio-technical system and the demarcation of *"The Blind Watchmakers"*, which will serve for the next few chapters.
The goal here is to present the wider journey of AI to the generic reader and to see it fully, beyond the sterile hyper-technical or mystical descriptions, to the socio-technical system *it actually is* and the variety of societal and economic aspects it embeds for its very existence like *the new free AI labor*, *the fabrication of desires* and *power* which will be explored at length in Chapters 5 and 6.

Long before the term artificial intelligence was coined, humans have long been fascinated with the idea of imbuing inanimate objects with life. Ancient myths across cultures, such as the Greek tale of Pygmalion[1] or the Jewish legend of the Golem [2], illustrate humanity's enduring fascination with creating life from matter. These early narratives paved the way for conceptualizing automata, devices engineered to mimic human or animal actions.

Early mechanical inventions, from the intricate automatons of ancient Greece to the sophisticated clockwork marvels of the Renaissance, reflect the persistent human impulse to mechanize repetitive or labor-intensive tasks. In the late Renaissance, Italian engineer Giovanni de la Fontana created a variety of mechanical devices, including what appeared to be a walking skeleton, an early blend of engineering and illusion aimed at simulating life (Sparavigna, 2013). In fact, this persisted beyond Renaissance. Early modern philosophers like Thomas Hobbes, believed that everything that exists, including humans, is

[1] Pygmalion was a sculptor who fell in love with a statue he had carved, see more here: Pygmalion.

[2] A golem is shaped out of an inanimate material and brought to life by magic, see more here: Golem.

made up of physical matter, what he called *"bodies in motion"*. He argued that even thoughts, emotions, and consciousness could be explained by mechanical processes in the brain, which makes his view mechanistic because it reduces all phenomena to physical, law-governed motion without invoking anything immaterial like a soul or mind (Hobbes, 2018). In Hobbes (2018)' own words in one of his greatest works "Leviathan"[3]: *"The world (I mean not the earth only... but the universe, that is, the whole mass of all things that are) is corporeal; that is to say, body; and hath the dimensions of magnitude, namely, length, breadth, and depth: also every part of body is likewise body."* Moving further into the Enlightenment period, thinkers like La Mettrie began to challenge traditional ideas about human nature. In "Machine Man and Other Writings", La Mettrie (1996)[4] observes that: *"Man is so complicated a machine that it is impossible to get a clear idea of the machine beforehand, and hence impossible to define it. For this reason, all the investigations have been in vain, which the greatest philosophers have made à priori, that is to say, in so far as they use, as it were, the wings of the spirit. Thus it is only à posteriori or by trying to disentangle the soul from the organs of the body, so to speak, that one can reach the highest probability concerning man's own nature, even though one can not discover with certainty what his nature is."* This perspective underscores the Enlightenment belief that understanding human nature must be rooted in observation and analysis of the body-soul relationship rather than abstract reasoning alone.

The modern concept of a machine performing forced labor was also encapsulated in the early 20th century with the introduction of the word "robot", derived from the Czech word robota, meaning "forced labor". This term was popularized by Karel Čapek's seminal play R.U.R. (Rossum's Universal Robots) in 1920 (Čapek, 2001). Čapek's vision not only introduced the robot to popular imagination but also highlighted the implications of a future where labor could be replaced by mechanical agents, a theme that resonates with discussions of technology's social and economic impacts today. During the first half of the 20th century, these ideas began to materialize in both fiction and technology. One important example was Westinghouse's Elektro the Robot, exhibited at the 1939–40 New York World's Fair (Norman, 2025). Developed between 1937 and 1938, Elektro could respond to voice commands, articulate up to 700 words via a record player, and perform tasks like walking, smoking, and recognizing colored lights (Norman, 2025). Even though mechanically driven, its design anticipated core themes in AI: human-machine interaction, sensory input, and automation, and played a key role in shaping public perceptions of artificial intelligence. Around that time, science fiction started exploring robots in more nuanced ways. Isaac Asimov's robot stories from the 1940s, including his prominent "Three Laws of Robotics" (Asimov, 1950), provided a foundational framework for thinking about ethical and social dimensions of artificial intelligence. In 1948, Norbert Wiener's pioneering work "Cybernetics" transformed how we view control and communication, emphasizing the role of feedback loops (Wiener, 1948). This allowed scientists to conceptualize both living systems and machines as entities capable of processing information, fundamentally

[3]Originally published in 1651.

[4]Originally published in 1748.

influencing the evolution of robotics, early computing, and the emerging field of artificial intelligence.

A significant leap toward the modern era of AI was made with the Dartmouth Summer Research Project on Artificial Intelligence in 1956 (Strickland (2021), Dartmouth College). Brought together by pioneering researchers such as John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon, a group mainly coming from computer science and engineering, though the actual group composition altered along the weeks including other people, like some coming from neuroscience (Solomonoff, 2023). The workshop represented a bold challenge, mainly coming from McCarthy, a then young professor: *"every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it."* (Strickland, 2021). This event laid the groundwork for AI as a dedicated field of research and set forth ambitious expectations for what machines might eventually be capable of achieving. The Dartmouth conference not only formalized the foundational goals and methodologies of AI research but also sparked a wave of optimism and significant investment in exploring cognitive simulation and problem-solving in computational frameworks. Furthermore, it brought forth in those weeks and the upcoming years, the various approaches towards AI, notably *the symbolists* who focus on representing knowledge through symbols and rules, and *the connectionists*, who emphasize the use of methods like neural networks to model cognitive processes through patterns of activation, though in recent years there are doubts with respect to how substantial the divergences are among them (Wang, 2017). In fact, leading symbolists like Herbert Simon, denoted how *"if a symbolic system had enough structured facts and premises, the aggregation would eventually produce broad intelligence"* (Strickland, 2021) , resounding through the centuries La Mettrie on how intricate of a machine a human is and the complexity of the collection of the totality of "facts".

Despite early enthusiasm, the decades following the Dartmouth conference were not without hardship. Overly ambitious projections, combined with limited computational resources and fundamental theoretical hurdles, led to periods known as "AI winters" (of Data Science, 2021). For example, the domain of machine translation was one that generated a lot of attention and funding from entities such as but not limited to The National Science Foundation, the Navy, the Army, the Air Force, CIA etc., in 1960, abruptly ceased all support for machine translation research by 1966 (Kuka, 2023). During these times, disillusionment set in among researchers and funding bodies alike, as the challenging realities of implementing intelligence in machines became increasingly apparent. In the case of machine translation(MT), there's a well-worn example which is cited by John Hutchins, the story of an MT system which translates the Biblical saying *"The spirit is willing, but the flesh is weak"* into Russian, onto the unintelligible *"The whisky is strong, but the meat is rotten"* (Kuka, 2023). The 1970s saw the first AI winter and this period was marked by dwindling investments and skepticism from policymakers and the public, leading to a temporary reduction in research activity and interest (Strickland (2021), Kuka (2023)). There were some minor achievements from the side of symbolic AI proponents in the 80s with the rise of expert systems but due to computational restrictions, the domain hit yet another "winter" period. AI funding declined as the high costs of development, limited storage capacity, and inadequate computing power, exacerbated by the expensive, specialized hardware required for expert systems which led companies to realize that more affordable, less-intelligent systems could still deliver comparable business results (Giacaglia, 2021).

Yet, these setbacks were not a dead end; they provided valuable lessons that refined subsequent approaches to AI, shifting the focus towards more manageable problems and realistic expectations. The eventual revitalization of AI in the 21st century was driven by several converging factors: exponential growth in computing power, massive data availability [5], and the rise of commercial internet platforms (Strickland, 2021). In terms of the schools of thought and approaches towards AI development, it seems at the moment the connectionists have "won" because of their bottom-up, data-driven approach, especially deep learning, has delivered unprecedented practical successes in areas like image recognition, language processing, and generative AI. Unlike symbolic AI,, connectionist models do not require predefined rules or representations, allowing them to scale more effectively with vast data and computing power, making them the dominant paradigm in current AI research and industry applications.

The rest is, well, *recent history*. The competitions and the click-bait articles that attract attention about the most recent AI system "defeating"[6] humans in one domain or another do not need re-telling. But to fully understand what AI is and does today, and particularly what it might do in the realm of work, a deeper perspective is needed, one that goes beyond technical achievements (which can also be discussed in a particular way as well) and enters the realm of political economy.

3.2.2 AI as a labour-centered socio-technical system and the Age of the Blind Watchmakers

"...there is no such thing as philosophy-free science; there is only science whose philosophical baggage is taken on board without examination." Dennett (1995), pp. 21

But what is AI? If we go down the path of definitions, it is certainly not a linear one. Pick a school of thought and go along with it. Actually, the whole collection of various fields and sub-fields on how they approach AI definitions can, in one perspective, be summed up to: *"... four ways can be identified when sorting through the definitions of AI—thinking humanly, thinking rationally, acting humanly, and acting rationally"* (Wang, 2017). In their influential textbook "Artificial Intelligence: A Modern Approach", Stuart Russell and Peter Norvig (2021) offered a more structured definition of AI, as *"the study of agents that receive percepts from the environment and perform actions."* Here, intelligence is not simply about mimicking human thought but about rational adaptation to

[5] *Availability* is an interesting word to use here, but more on this on Chapter 5.

[6] Though this has to be seen with care, take into account for example the work by Raji et al. (2021).

goals and environments. However, AI should not be seen solely as a machine of logic and code, but as a living intersection where technology merges with humanity, shaping and being shaped by the intricate web of social values, relationships, and ethical choices that define our world. In recent years, as AI is permeating in all possible aspects of life and society, and is becoming a general purpose technology (GPT), defining it as Lipsey et al. (2005) (pp. 98) *"...a single generic technology, recognizable as such over its whole lifetime, that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many spillover effects."* Thus, concerns and keywords are starting to appear that reflect that. One can find oneself hopping through the words - good - responsible - society - impact - manage - stakeholders - ethical - and they are all the right keywords but connected together with a tone of concern but usually without a strong analytical model, in a senseless pastiche.

However, they do point in the right direction: AI is, despite the strong technical debate of the various schools of thought: a socio-technical system. Even this term has not escaped the mass of confusion and this abused term is usually treated as a "bin" for: messy, hard to do, ethical, good etc (Chen and Metcalf, 2024). In their excellent policy brief, Brian J. Chen and Jacob Metcalf(2024, pp. 2) clearly state: *"Generally, a socio-technical perspective means viewing society and technology together as one coherent system. In other words, it is not possible to understand the "social" without the "technical", nor the "technical" without the "social."* Explaining the outcomes of any technology requires focusing on the messier "middle ground" between these two realms.

The economist Daniel Susskind also complements this view by emphasizing that AI should not be seen merely as a technical tool, but as part of a broader socio-technical system, shaped by, and in turn shaping, social institutions, labor markets, and political choices. In "A World Without Work" (2020), he argues that the most significant consequences of automation are not technological but institutional: they depend on how societies adapt to machines performing tasks once done by humans.

This view is also supported by other researchers, like those from the perspective of science and technology studies. Lucy Suchman in "Human-Machine Reconfigurations" (2006) defines AI as a *“set of sociotechnical practices—assemblages of people, machines, institutions, and discourses—that aim to make the machine appear intelligent.”* Her approach urges us to look beyond the machine and consider the broader network that produces the illusion of intelligence. This echoes Castells (1996) that considers the matter of technological determinism a false problem and infers that *technology is society* as mentioned in Chapter 1. Furthermore, despite the fact that AI systems are socio-technical systems, the field is mainly driven by computer scientists (even though that is recently changing) who must examine further whether, in constructing computational models of social concepts, if they are sufficiently engaging with conceptual models of social phenomena that originate outside of computational aims, models designed not for implementation, but to systematically illuminate the underlying structures and interconnections of these concepts, in an interdisciplinary fashion (Jones et al., 2013) .

Given the fact of it is a socio-technical system, it becomes of imperative importance for the purposes of this work to understand the trust levels in institutions that build and maintain the fabric of societies in Europe, such as governments and media. Thus, part of the perception analysis in this study, in Chapter 3.3.2, will be focused on that.

Another interesting approach is that in "The Eye of the Master"(2023) of Matteo Pasquinelli who offers a compelling reinterpretation of the history of artificial intelligence, not as a quest to replicate biological cognition, but as the automation of labor's collective intelligence. Rather than springing from pure scientific genius or abstract models of the mind, AI, he argues, must be understood as a continuation of industrial efforts to extract, formalize, and mechanize the knowledge embedded in human work and social coordination. Hence, with Pasquinelli's perspective, we move beyond a socio- technical system and more particularly to one focused on labor. Pasquinelli builds his thesis around a long arc of technological development, beginning with the industrial division of labor. In the late 18th century, Gaspard de Prony applied Adam Smith's principles to human computation, orchestrating a large-scale social algorithm of clerks to produce logarithmic tables for revolutionary France (Pasquinelli, 2023). Charles Babbage, inspired by this logic, embedded the same hierarchical structure into the Difference Engine, making computation itself an abstraction of the division of labor. For Babbage, machines were not just labor-saving devices but a way to engineer the very structure of productive knowledge (Pasquinelli, 2023). This logic advanced through Taylorism and the industrial discipline of "time and motion studies", where workers' movements were filmed and optimized in detail. The intelligence of work, once performed by skilled hands, was broken down into mechanical diagrams. AI extends this trajectory: it continues to extract patterns from collective behaviors and repackage them as algorithmic models (Pasquinelli, 2023). The rise of automation, from the loom to the self-driving car, relies not only on replacing manual strength but also on encoding tacit, social, and often unconscious knowledge. Pasquinelli (2023) points out that tasks like driving, long dismissed as manual labor, have revealed themselves to be deeply cognitive and cooperative when AI attempts to replicate them. These systems learn not only the mechanics of movement, but also cultural codes, situational judgments, and ethical decisions, all drawn from the complex social practice of driving. In this context, Pasquinelli (2023) introduces the labor theory of automation, extending classical political economy to explain technological development. Pasquinelli's history dismantles the illusion of AI as an abstract, technical phenomenon. Instead, he situates it as a deeply political project. AI, in this view, is not just a new technology. It is the eye of the master, reborn.

Today's AI systems rely on the hidden labor of millions: gig workers training algorithms, annotating images, moderating content, and verifying outputs and leading to a vast tasker underclass (Dzieza, 2023). Far from the myth of autonomous intelligence, AI is sustained by what Mary Gray and Siddharth Suri (2019) call "ghost work", often outsourced to the Global South. Similarly, Kate Crawford, in "Atlas of AI" (2021), expands the idea of AI; she writes: *"AI is made from natural resources, fuel, human labor, infrastructures, logistics, histories, and classifications."* AI systems, in her view, are deeply embedded in ecological, political, and social contexts. Furthermore, Acemoglu and Restrepo (2020), clearly state that we might even be developing the *"wrong"* kind of AI, one focused *excessively* on automation but not one to be implemented on tasks that actually raise the worker's productivity by complementing their work. In fact, they call them "so-so technologies", not as great as they are commonly depicted and *"just good enough to be adopted but not so much more productive than the labor they are replacing"* (Acemoglu and Restrepo, 2020). More on the matter of productivity will be discussed in Chapter 4.5.

So, if AI is a socio-technical system with a predominant focus on labor, what is the justification for the term **"The Blind Watchmakers"**? The eye of the master may be reborn, evoking the idea of the overseer, the authoritative gaze that surveils, disciplines, and extracts value but the tools of the master are blind. The term is borrowed from the book "The Blind Watchmaker" by Richard Dawkins (Dawkins, 1986), who in turns borrows the term "watchmaker" from William Paley in his 1802 book Natural Theology. Daniel Susskind, in his book "A world without work"(2020), goes back to these notions used in natural history, biology and theology, to help us understand the current wave of AI. In Susskind (2020, pp. 58-59)'s own words:

"The ideas of natural selection and intelligent design could not be more different. "A true watchmaker has foresight," wrote Richard Dawkins, one of the great scholars of Darwin. "He designs cogs and springs, and plans their interconnections with a future purpose in mind's eye. Natural selection, the blind unconscious, automatic process which Darwin discovered . . . has no purpose in mind. It has no mind and no mind's eye. It does not plan for the future. It has no vision, no foresight, no sight at all. If it can be said to play the role of watchmaker in nature, it is the blind watchmaker. The watchmaker of Paley's story had perfect vision and foresight, but Darwin's process of natural selection has none of that. It is oblivious to what it does, mindlessly stumbling upon complexity across eons rather than consciously creating it in an instant. The pragmatist revolution in AI requires us to make a similar reversal in how we think about where the abilities of man-made machines come from. Today, the most capable systems are not those that are designed in a top-down way by intelligent human beings. In fact, just as Darwin found a century before, remarkable capabilities can emerge gradually from blind, unthinking, bottom-up processes that do not resemble human intelligence at all."

In this connotation, "The Age of the Blind Watchmakers", is used to highlight the fact that, as mentioned in Chapter 3.2.1, the connectionist branch of thought is leading the AI revolution and methods in machine learning and deep learning have become the predominant ones. We are being led by the blind watchmakers, at this moment in time. These systems operate through statistical patterns and data correlations, rather than causal reasoning or symbolic representation of the world. However, it has to be noted that the power of causal techniques is being recognized and efforts are being made also in that direction (Matovski, 2024). This "blindness" refers to the absence of any deeper understanding or intentionality in the way these systems function. They process vast amounts of data to produce outputs without any grasp of the underlying causes or meanings behind their actions (*to the best of the current understanding*). Hence, with this "storyline" and metaphorical elements, the author hopes that it is ever clearer for the reader the deep ties linking this type artificial intelligence with work and for that not to be considered just as some exogenous impact but rather as its very *raison d'être*.

But how do young people today define AI? What do the words carefully chosen by McCarthy around 7 decades ago evoke in today's collective imagination?

Going back to the data collected for the purposes of this work, in Online Survey 2, the respondents were asked the following open ended question: *"How do you define "Artificial Intelligence(AI)"? What comes to mind when you think about AI?""* [7] Word clouds are used in order to visualize and better understand how the respondents overall but also how different demographics define AI. As a first result it was understood that "AI" and "intelligence" (see Appendix .3.1) came out to be quite dominant when descriptions were provided. Thus, they were added to the stop words custom list given their self-explanatory nature and the fact that they do not add much value to the definitions. The final word cloud, post the stop words removal, can be observed in Figure 3.2.

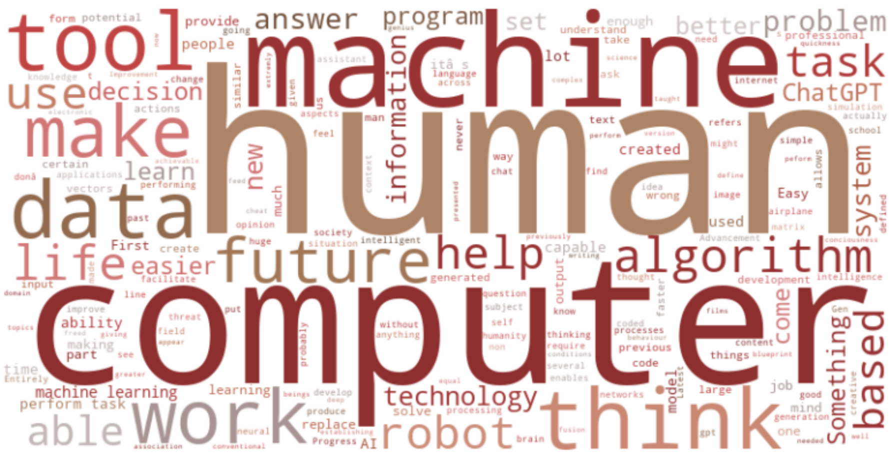

Figure 3.2. Word Cloud from AI definitions - without custom stop words - Online Survey 2.

The most frequent words, considering a frequency of above 9, came out to be the following:

- Word: human, Frequency: 19

[7] This is the only question that was present *only* in Online Survey 2 and not in Online Survey 1. Thus, the concatenation of the two that created the dataset that is denoted here as Online Survey 2 for this question, and only for this, has a lower cardinality of respondents, specifically 111 responses.

- Word: think, Frequency: 16
- Word: like, Frequency: 12
- Word: machine, Frequency: 12
- Word: tool, Frequency: 12
- Word: computer, Frequency: 11
- Word: tasks, Frequency: 11
- Word: use, Frequency: 10
- Word: data, Frequency: 9

The fact that "human" is the top term in the frequency counts, indicates that respondents commonly define AI in relation to human characteristics, behavior, or capabilities. This is further supported by notions like "think" (16) and "like" (12), suggesting a perception of AI as mimicking or approximating human thought processes. The frequent appearance of "computer" (12), "machine" (12), and "tool" (12) points to an understanding of AI as a technical or mechanical entity, something built or engineered to serve a specific function. These are not just abstract concepts; rather, they anchor AI in the realm of tangible technology. Additionally, the words "tasks" (11) and "use" (10) highlight the functional nature of AI, particularly in relation to work, as it is seen as something designed to perform tasks and be practically applied. The inclusion of "data" (9) also reflects an awareness of AI's dependency on data input for learning and decision-making. Altogether, these terms suggest that participants generally view AI as a machine-based tool that operates *like a human*, especially in its ability to think and perform tasks, all while being grounded in data-driven processes. However, it must be taken into account that the total number of respondents that have answered this question is 111. Thus, even the most frequent word here, "human" accounts for only around 17% of the respondents, indicating that the views and definitions when it comes to AI are very diverse.

Analyzing in terms of sex (the dataset is almost perfectly balanced: 57 females and 54 males), the word-clouds that come out are those in Figure 3.4 and Figure 3.3. Based on the word frequencies, distinct patterns emerge between male and female respondents. Males tend to focus more on conceptual and technical aspects of artificial intelligence, as indicated by the prominence of words such as "data", "machine", "algorithms", "learning", etc. (see Appendix .3.2 for the full frequency list). Their language suggests an emphasis on AI's capabilities, functionality, and its role in processing and generating answers. Female respondents also highlight technical elements like "computer", "machine", and "tool" but their responses show a stronger inclination toward practical applications and the human experience, with frequent use of words like "perform", "easier", "help", "things" and "work". *Both groups mention "human" and "think" prominently*, indicating a shared concern with the relationship between AI and human cognition or behavior. Interestingly, the prevalence of "think" and "human" terms, illustrate the definitions of AI seem to be closer to that of symbolic AI, regardless of the current prevalence of machine learning techniques. Hence, this would be an important point to be explored by those that guide public education and science communication for the general audience, as well as the relevant policy makers. Furthermore, this highlights the need for *"AI literacy programs"*, also in alignment with the EU Act, Article 4 (European Union, 2021). It must be mentioned that some efforts are already underway at constructing such programs and a database can be found here.

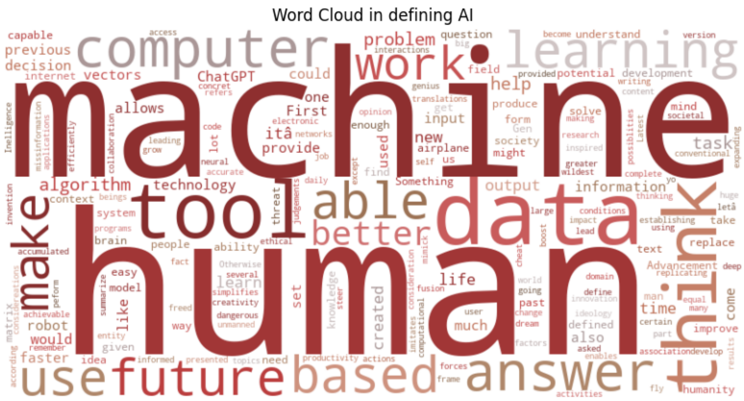

Figure 3.3. Word-Cloud of the definition of AI - Sex: Male - Online Survey 2

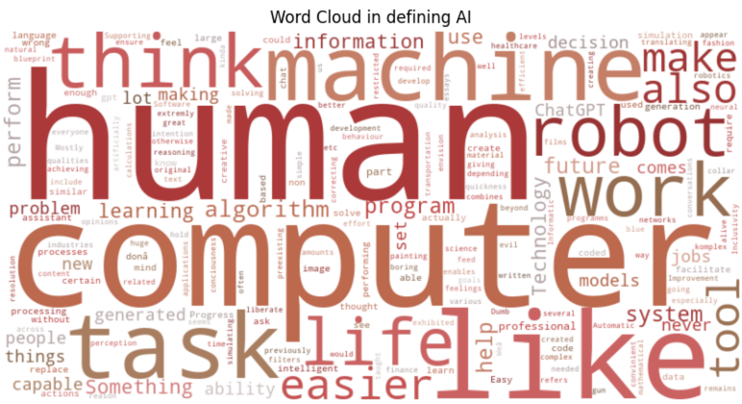

Figure 3.4. Word-Cloud of the definition of AI - Sex: Female - Online Survey 2

3.3 Perceptions, trust and usage regarding AI

In this subchapter, we will now take a closer look at the dynamic and evolving perspectives that young Europeans hold toward artificial intelligence going beyond mere definitions. Young people are not just passive observers of technological change; they are active participants whose attitudes help shape the future of AI. In the distributed questionnaire in

Online Survey 1 - Section B(see Appendix .1.6), a scale ranging from 0 to 10 was used to capture levels of personal interest and trust, optimism, etc., in AI and various societal actors engaged with AI. Before presenting the data analysis, existing studies will be explored that examine the sentiments, interests, and perceptions of this group about AI. Recent academic work shows that young people engage with AI in multi-faceted ways: while many exhibit genuine enthusiasm and curiosity, there is also a nuanced skepticism regarding its fairness and the preparedness of societal institutions to manage its impact.

Several recent studies have explored how young people engage with artificial intelligence, with findings pointing to both high levels of interest and a complex set of motivations and concerns. Nikolenko and Astapenko (2023) highlight that young people, due to their greater psychological flexibility and digital familiarity, tend to adapt more easily to technological innovations such as AI. They compare attitudes between younger (20–35) and older (40–50) respondents, showing that younger individuals are more likely to view AI positively, associating it with the simplification of everyday life (43.7%) as the dominant category, and the second being the increase in productivity (11%). Whereas the older group (40-50) saw the usage of AI systems is primarily in situations involving a risk to human life (95%) and labor automation (60%). The study also shows that there is a generally optimistic outlook from young people surveyed with respect to AI, as the majority group was a 62% reporting to have "positive" feelings and the second largest "neutral" feelings (20%) (Nikolenko and Astapenko, 2023). However, this completely contrasted the distribution of the older generation with the largest group experiencing "anxiety" (42%) and the second largest experiencing "mixed feelings" (30%) Nikolenko and Astapenko (2023). Clearly, this difference shows a generational gap in perceptions of AI, with younger respondents tending to embrace its benefits and see it as a tool for convenience and productivity, while older respondents are more cautious, focusing on potential risks and expressing higher levels of anxiety or uncertainty toward its adoption. This optimistic yet cautious attitude is in line with findings from a comprehensive study of 4,006 European citizens across eight countries (France, Germany, Italy, Netherlands, Poland, Romania, Spain, and Sweden) (Scantamburlo et al., 2025). In this study Scantamburlo et al. (2025) found that younger respondents were the most approving of AI, with 70% expressing a positive or strongly positive view, higher than both middle-aged and senior participants.

Trust in both institutions and the media plays an important role in shaping public perceptions of AI and its governance. As highlighted by Araujo et al. (2023), individuals who have greater confidence in their government's ability to manage the risks associated with AI, including concerns over privacy, ethics, and fairness, tend to hold more positive views of AI. When citizens trust that their government can regulate AI development effectively, they are more likely to see the technology as beneficial to society. Moreover, the study reveals a complex relationship between trust in the media and AI perceptions. While individuals who trust the media may hold more cautious views about AI, particularly regarding its automation in editorial tasks, this trust also plays a significant role in how informed they feel about AI technologies. In countries where the media is perceived as a credible source of information, the public may have greater confidence in understanding the implications of AI, its ethical concerns, and its potential impact on society, highlighting the importance of media not only as a source of information but also as a key player in shaping the discourse around AI regulation and its role in society. KPMG's 2023 global study(Gillespie et al., 2023) on AI trust supports the idea that trust in institutions matters. The study highlights that people tend to trust universities, research institutions, and defense forces the most to develop and govern AI responsibly. This contrasts with lower trust in government bodies and commercial organizations, where skepticism about motives and competence often prevails. When AI governance is associated with impartial institutions like research organizations, people are more likely to view the technology favorably. Araujo et al. (2023) and KPMG's 2023 global study (Gillespie et al., 2023) both underscore the importance of trust in institutions: government, media, and research organizations, in shaping public perceptions of AI. The findings suggest that when people trust the institutions responsible for AI governance, they are more likely to support the technology. When the young people in various European countries were asked in the survey by Scantamburlo et al. (2025), with respect to trusted entities ensuring a beneficial use of AI, trust in social media was the lowest for senior respondents (24%) and highest for young respondents (46%). Furthermore, a wide majority of the young respondents in the same study (71%) supported the idea of the usage of a set of policy measures to increase trust in AI (Scantamburlo et al., 2025).

As artificial intelligence increasingly integrates into public services, its potential value to citizens is becoming a significant point of discussion. Public perceptions of AI are shaped by a variety of factors, particularly the changing ideas around its advantages over traditional, human-provided services. Research by Gesk and Leyer (2022) shows that citizens may find AI appealing for certain public services, such as traffic management or administrative tasks, where efficiency and objectivity are prioritized. However, when it comes to services involving personal care, such as healthcare or social services, there remains a strong inclination towards human involvement, fueled by concerns over trust, empathy, and the nuances of human interaction.

Last but not least, a holistic evaluation of Europe's generative AI landscape reveals that while the region holds substantial promise, European organizations still lag behind their U.S. counterparts in the adoption of AI technologies by 45 to 70 percent (McKinsey &Company, 2024). In 2024, 13.5% of EU enterprises with at least 10 employees used artificial intelligence (AI) technologies, marking a significant increase from 8.0% in 2023. Adoption was highest in Denmark (27.6%), Sweden (25.1%), and Belgium (24.7%), while Romania (3.1%), Poland (5.9%), and Bulgaria (6.5%) reported the lowest usage. Every EU country saw a rise in adoption, with Sweden, Denmark, and Belgium showing the largest gains (European Commission, Eurostat, 2025). Large enterprises are far more likely to deploy AI solutions (over 41%) compared to 11.21% of small enterprises and 20.97% of medium-sized ones. Among the AI technologies in use, systems performing text mining are the most prevalent, being employed by 6.88% of enterprises, while natural language generation and speech recognition are also notable at 5.41% and 4.78%, respectively. These trends reflect the growing integration of AI in business operations across the EU (European Commission, Eurostat, 2025). This data, as reported by Eurostat (2025, "Usage of AI technologies increasing in EU enterprises"), offers key insights into the broader landscape of AI adoption in Europe and provides important context for understanding individual usage patterns.

For public administrations, large companies, policy makers, and other stakeholders, understanding the evolving nature of public opinion on AI is crucial. AI's potential value isn't solely in its ability to streamline processes or improve efficiency; it also lies in the shifting perceptions of its role in society. By acknowledging and adapting to the varied expectations and concerns of citizens, customers, and the wider public, organizations can adjust their strategies and foster a more flexible approach to AI implementation. The goal isn't necessarily to ensure AI is universally accepted, but rather to recognize the changing perceptions and evolving role of AI as societal needs and expectations continue to develop.

With respect to this study, in Online Survey 1, the questions that were used to measure the overall perception (1-3), trust (4-6) and usage (7-9) were the following (as they can be observed in Appendix .1.6):

1. How interested are you in AI (artificial intelligence) in particular on a scale from 0 to 10?
2. How optimistic are you regarding the impact that AI (artificial intelligence) will have on society on a scale from 0 to 10?
3. Overall, do you think that due to AI, inequality in society in the next 10 years will be: (5-categories scale from "much higher" to "much lower")
4. How much do you trust the government of the country that you currently live in to handle matters of AI on a scale from (0 to 10)?
5. How much do you trust the media of the country that you currently live in to handle & inform on matters of AI on a scale from (0 to 10)?
6. New technologies, like AI may be implemented for many reasons and one of them is to improve the well being of the average citizen. How committed from 0(not at all) to 5(completely committed) are the following parties to do that:
   (a) The government of your country.
   (b) The companies of your country.
   (c) The non governmental organizations in your country.
   (d) The media in your country.
7. Have you ever used AI tools like ChatGPT?
8. If yes, how often have you used them on average last week, in terms of days per week?
9. Does your company or institution use AI tools in their daily practices?

First, the histograms are built to understand the overall distributions. Then, further analysis is made in terms of sex and age. Secondly, some correlations are studied and regression analysis is made, where relevant, to further understand the perceptions of young people.

3.3.1 Overall Perceptions

As it can be observed in Figure 3.5 , the very left-skewed distribution of the interest in AI signifies that the respondents of the survey seem to be highly interested. In fact, the peak is at interest 10, with 23 people out of 104 total respondents of Online Survey 1. If we consider a regrouping such that that someone is "highly interested" if they provide an interest score of 8 or more, then 60% of the respondents seem to be highly interested.

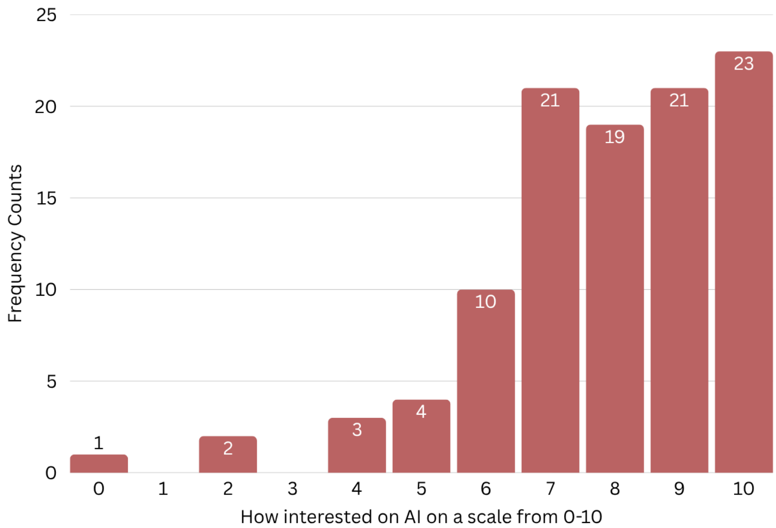

Figure 3.5. The histogram of the interest in AI on a scale (0–10) – Online Survey 1

With respect to a sense of optimism, the respondents of Online Survey 1 were asked regarding their *general optimism* levels, so without taking AI into account. The distribution roughly resembles a normal curve, slightly skewed, with a peak at 7, suggesting most respondents are moderately optimistic. In fact we can say that overall, the set of respondents is optimistic about the future also in comparative terms to their parents' generation by the majority(35) claiming that they *agree* with the statement that "*Their life will be better than their parents*" and likewise the majority(34) also *agrees* with the statement that *"Their life will be easier than their parents."* It must be noted that given the demographic data and the large number of people coming from post-communist countries may be a relevant factor in the above estimations. In contrast, *optimism about AI's impact in society* does not follow a single peak; instead, it appears to cluster into two or three groups, indicating more varied attitudes, as it can be observed in Figure 3.6. If highly optimistic people are considered those that gave a score of 8,9 and 10, then only 35.5% of the respondents of Online Survey 1 are highly optimistic about AI's impact in society.

When the analysis is considered in terms of age, the two groups are considered: Gen Z (18-26) with a count of 45 people and Millennials (27-35) with a count of 59 people. For

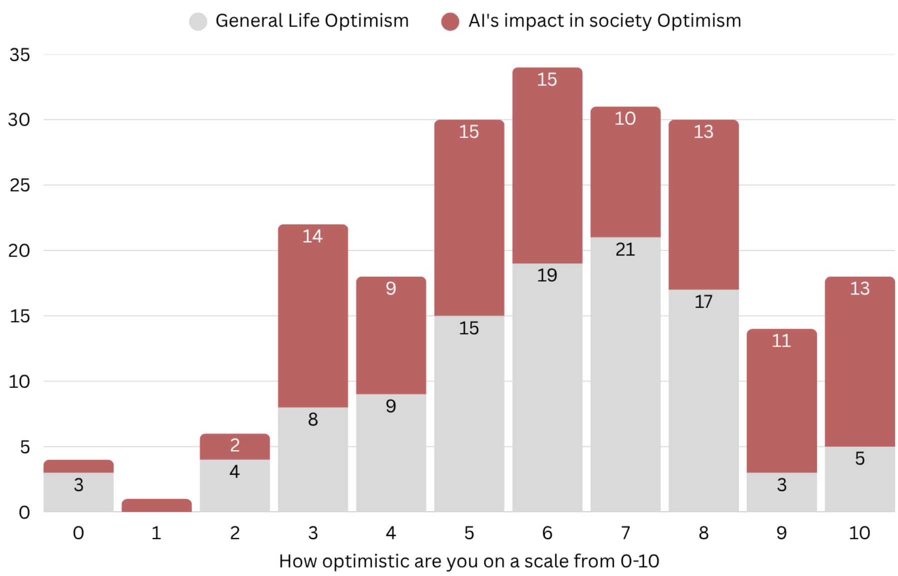

Figure 3.6. The histogram of the optimism in general and in AI - Online Survey 1

simplicity, the 18–26 age group is treated as Gen Z and the 27–35 group as Millennials, acknowledging a small overlap in birth years around 1997–1998. Table 3.1 shows that in terms of interest in AI, it appears consistently high across both age groups, especially among 18–26-year-olds, who show a strong clustering at the top end of the scale(7–10). Optimism, however, reverses this pattern as it can be seen in Table 3.1, where the older group appears to be overall more optimistic. In addition, some statistical testing is done to verify if there are statistically significant differences among the two-age groups with respect to the two variables considered here. First, the data are checked for normality and as it can be observed in the tables but also based on the Shapiro-Wilk Test [8], the data does not appear to be normal. To test whether the two age groups (18–26 vs 27–35) differ statistically in terms of interest in AI and optimism in AI, a non-parametric test, Mann–Whitney U test was chosen. In both cases, the p-value was greater than 0.05, specifically $p - value = 0.367$ for the interest in AI case and $p - value = 0.136$ for the optimism about AI's impact in society case. Thus, we fail to reject H_0, and it can be said that there is no statistically significant difference among the two age groups with respect to either of the two variables considered at a 5% significance level.

In terms of sex and the two variables of interest, optimism in AI's impact in society and interest in AI, the distribution can be observed in Table 3.2. It appears that the data does not have a normal distribution In terms of interest, both distributions are clearly

[8]Shapiro-Wilk test applied to discrete ordinal ratings; interpret with caution.

Score on AI	(18-26) - Interest	(27-35)- Interest	(18-26) - Optimism	(27-35) - Optimism
0	0	1	0	1
1	0	0	0	1
2	0	2	2	0
3	0	0	9	5
4	1	2	5	4
5	1	3	7	8
6	3	7	5	10
7	10	11	4	6
8	10	9	3	10
9	11	10	3	8
10	9	14	7	6

Table 3.1. Counts of AI Interest and Optimism in AI by age group (18–26, 27–35) – Online Survey 1

left-skewed, whereas with respect to interest the distributions appear to be more spread. The Mann–Whitney U test was conducted to examine sex differences in interest in AI. Results showed no statistically significant difference between males and females ($U = 1582.5$, $p - value = 0.128$). Although males showed slightly higher median scores, the effect was not significant at the 5% level. In terms of the optimism in AI's impact in society, again the Mann–Whitney U test is conducted to see if there are statistically significant differences among the two groups. The test shows that the difference in AI optimism between males and females is not statistically significant at the 5% level ($p - value = 0.0737$). If the distributions are observed in Table 3.2, clearly males are both slightly more interested and more optimistic in terms of AI but these are not *statistically significant* differences among males and females in the sample.

Score on AI	M - Interest	F -Interest	M - Optimism	F - Optimism
0	0	1	0	1
1	0	1	0	1
2	1	1	1	2
3	0	0	5	9
4	1	2	3	6
5	2	2	11	4
6	4	6	7	8
7	11	10	4	6
8	7	12	8	5
9	11	10	6	5
10	15	8	8	5

Table 3.2. Counts of AI Interest and Optimism in AI by sex (Male, Female) – Online Survey 1.

As a final generic question regarding the perception towards AI, the respondents of Online Survey 1 were asked regarding the expected impact of AI in overall inequality in the next 10 years, so in the short term. The distribution can be observed in Figure 3.7 and clearly shows that the vast majority expect increases in inequality, with 55% expecting it to be either much higher or higher. If the distributions based on sex and age group are considered, as they can be observed in Table 3.3, the highest frequency counts for males and for the older-group appears to the at the expectation that inequality will remain "the same". However, interestingly for females and the younger Gen Z group, the higher counts are convincingly at the category that inequality will become "higher" in the next 10 years. This leads up to questions as to how these groups which might have been more disadvantaged historically in the realm of work are more perceptive towards impending changes in inequality. However, encoding the categories of inequality on a scale from 0 (much lower) to 4 (much higher) and then running the Mann–Whitney U test, the results show that there are no statistically significant differences among the sexes in terms of the perceived changes in inequality ($U = 1313.0$, $p - value = 0.7881$) at 5% significance. Likewise, in terms of the Gen Z vs. Millennials matter, there are no statistically significant differences for the same significance level ($U = 1524.0$, $p - value = 0.1673$).

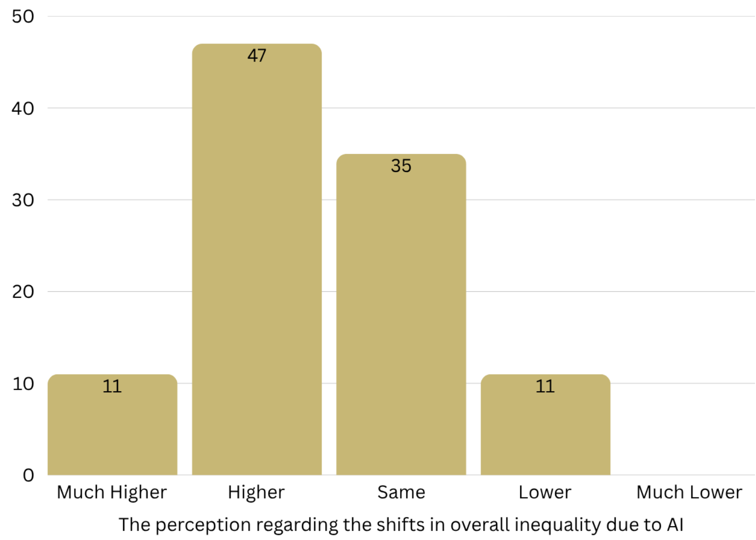

Figure 3.7. The histogram of the perception on overall inequality changes due to AI in the next 10 years – Online Survey 1

Inequality Shift	Male	Female	18–26	27–35
Much higher	8	3	4	7
Higher	18	**29**	**26**	21
The same	**21**	14	11	**24**
Lower	5	6	4	7
Much lower	0	0	0	0

Table 3.3. Expected level of inequality in the next 10 years by sex and age group – Online Survey 1

3.3.2 Trust in the abilities of governments and media to handle matters of AI

Furthermore, the matter of trust in institutions and media is considered when it comes to AI management, dissipation and public communication. Understanding public trust in institutions, particularly in governments and media, is crucial for gauging the social readiness and acceptance of AI technologies. These questions help identify which actors are perceived as responsible and credible in guiding AI's development and ensuring it serves the public good. They also shed light on potential gaps in trust that could hinder effective communication, policy implementation, and equitable deployment of AI. The histograms on the trust levels of the respondents of Online Survey 1 on a scale from 0 (not at all) to 10 (extremely) can be observed in Figure 3.8 and 3.9.

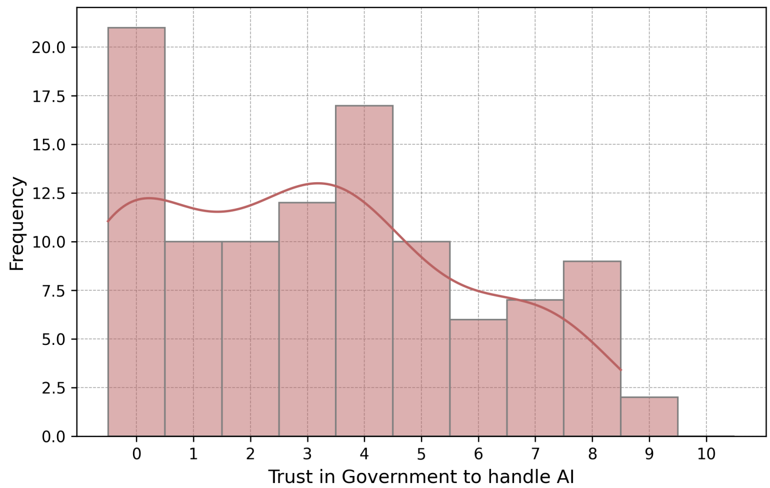

Figure 3.8. Histogram of trust in government to handle matters of AI (0-10) – Online Survey 1

The mean for trusting each actor is both 3.5, indicating low levels of trust in the sample. The median for trusting governments' ability to handle AI matters is 3.0 whereas that of trusting medias' ability to handle and inform on matters of AI is 4.0. This reveals that clearly that most people trust media more than governments in handling matters of AI.

Filtering by sex, clearly females show higher levels of trust in both the media and the government's ability to handle AI matters (see histograms in Appendix .3.4). For females, the peak of counts in trusting media is at 4 ($Frequency = 10$) whereas for males we see two peaks at 0 and at 2 (for both, $Frequency = 9$). In terms of trusting the government's ability to handle AI, for males the peak is at 0 ($Frequency = 11$) and for females there are two peaks at 0 and at 4 ($Frequency = 10$). Thus, both cases clearly show higher

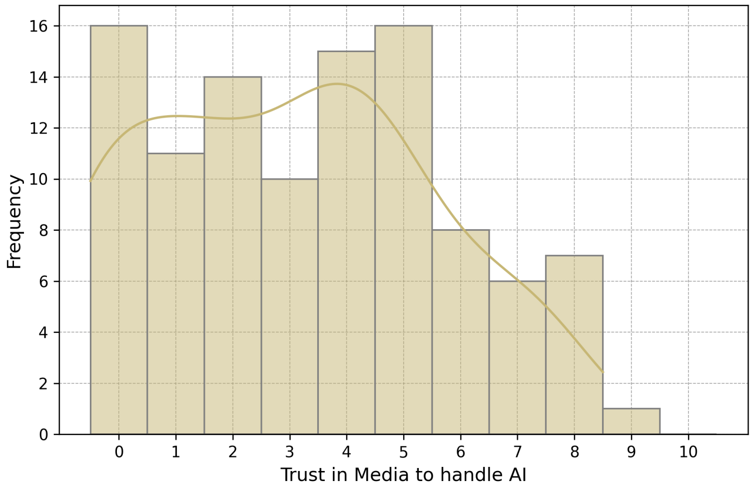

Figure 3.9. Histogram of trust in media to handle and inform on matters of AI (0-10) – Online Survey 1

trust from females in either of the two actors. Given that the data does not appear to have a normal distribution (Shapiro-Wilks Test verifies that) and it has a Likert-type ordinal scale, the Mann–Whitney U test was conducted to examine if there are statistically significant sex differences in terms of both governmental and media trust. In both cases, the trust in government's ability ($U = 1236.5$, $p - value = 0.450$) and in media's ability ($U = 1192.5$, $p - value = 0.2974$), show that for a significance level of 5%, there are no *statistically* significant differences among the trust levels of the two groups.

In terms of age and trust in media's abilities, the Millennial(27-35) age group has the peak count at trust level 4 ($Frequency = 11$) and the Gen-Z(18-26) has two peaks at 0 and 5 ($Frequency = 8$), showing the group being more split with respect to the trust levels in media's ability to manage AI. On the other hand, the trust in government's ability to handle matters of AI, the Millennial(27-35) age group has a peak at 0 ($Frequency = 12$), 4 levels down from the peak trust in media. The Gen-Z(18-26) group appears to follow again the same trend, being again split in terms of trust also in government's ability to handle AI, with the distribution having two peaks at 0 and 4 ($Frequency = 9$), slightly lower than their trust in media's ability. Furthermore, the Mann–Whitney U test was conducted to examine if there are statistically significant differences among and within each group with respect to the trust in media and government's abilites. As Table 3.5 illustrates the $U - statistic$ and $p - value$ for each test, there appear to be no *statistically* significant differences in either case.

Overall, the results show low trust levels in institutions such as government and media. This is concerning because building public trust in AI and Intelligent Systems in general

Trust Scale	18-26 Media	27-35 Media	18-26 Gov	27-35 Gov
0	8	8	9	12
1	4	7	6	4
2	6	8	4	6
3	7	3	4	8
4	4	11	9	8
5	8	8	1	9
6	2	6	5	1
7	3	3	3	4
8	3	4	4	5
9	0	1	0	2
10	0	0	0	0

Table 3.4. Counts of trust in media and government by age group and scale - Online Survey 1

Test Type	U statistic	p-value
Gen Z vs. Millennials trust in government	1383.0	0.715
Gen Z vs. Millennials trust in media	1416.0	0.561
Gen Z trust in media vs. government	1003.5	0.944
Millennials trust in media vs. government	1680.0	0.744

Table 3.5. Results of Mann-Whitney U tests for trust in media and government across age groups - Online Survey 1

is essential, given that its lack leads to the economic and social benefits of such systems not getting realized (Winfield and Jirotka, 2018).

3.3.3 Understanding the relationship between AI interest and optimism

In terms of policy making, understanding the relationship between the young people's interest in AI and the optimism they have with respect to AI's impact in society overall is is crucial because it helps policymakers anticipate public engagement, support, and potential resistance to AI initiatives. It identifies which groups are more receptive or skeptical, guiding the design of educational programs, awareness campaigns, and regulatory frameworks that align with public attitudes. As previously studied in Sub-chapter 3.3.1, both of these variables take discrete values from 0 to 10.

First, the correlation between interest in AI and optimism in AI's impact in society was measured and the results show it was positive and moderate (Spearman's rank correlation $rho = 0.323$, $p - value = 0.001$). The distribution can be observed in Figure 3.10, where the darkness of the points signifies denser areas, more points overlapping with one-another. This indicates that curiosity often aligns with optimism in a statistically relevant manner at 5% level of significance, but the association is not particularly strong.

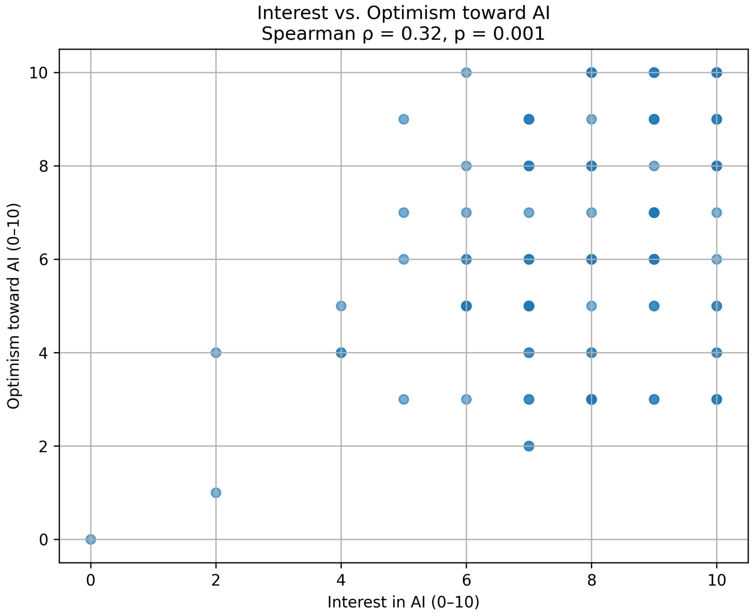

Figure 3.10. The scatter plot of interest in AI vs. optimism in AI's impact in society - Online Survey 1

Furthermore, regressive analysis is made. First a simple linear regression[9] is built with interest in AI as the independent variable and the optimism in AI's impact in society as the dependent one. The results can be observed in Figure 3.11. As indicated in the output, only 15.7% of the variation in optimism is explained by the interest alone. This is a minor but statistically significant relationship, given that the $p - value < 0.001$. The estimated coefficient for AI interest is $\beta = 0.503$ (SE = 0.116, $t = 4.35$, $p < 0.001$). The 95% confidence interval for this coefficient $[0.274, 0.732]$ does not include zero, confirming the reliability of the relationship. The intercept is estimated at 2.322 (SE = 0.932, $t = 2.49$, $p = 0.014$), indicating that respondents with zero AI interest would, on average, report a baseline optimism in AI's impact in society of approximately 2.32. Although the model explains only 15.7% of the variance in optimism ($R^2 = 0.157$), the coefficient shows that for each one-point increase in interest, optimism increases by roughly half a point, highlighting a modest but meaningful association.

[9]The limitation has to be denoted that the data have an ordinal and not continuous scale but in some cases Likert-type scales with 7+ points are treated as "quasi-interval" data, especially for such exploratory analysis.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             b6_optimai   R-squared:                       0.157
Model:                            OLS   Adj. R-squared:                  0.148
Method:                 Least Squares   F-statistic:                     18.94
Date:                Tue, 04 Nov 2025   Prob (F-statistic):           3.22e-05
Time:                        19:35:43   Log-Likelihood:                -232.55
No. Observations:                 104   AIC:                             469.1
Df Residuals:                     102   BIC:                             474.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          2.3215      0.932      2.490      0.014       0.472       4.171
b5_aiintr      0.5031      0.116      4.352      0.000       0.274       0.732
==============================================================================
Omnibus:                        9.705   Durbin-Watson:                   2.221
Prob(Omnibus):                  0.008   Jarque-Bera (JB):                3.752
Skew:                          -0.125   Prob(JB):                        0.153
Kurtosis:                       2.104   Cond. No.                         34.0
==============================================================================
```

Figure 3.11. The output of a simple linear regression - Input: Interest in AI - Output: Optimism in AI's impact in society – Online Survey 1

Although the effect size is modest, such values are common in social-attitudinal research, where perceptions and beliefs are typically shaped by a constellation of psychological and social factors. Thus, another model is built, a multiple linear regression that takes as input not only the interest in AI but also demographic factors such as age, sex and political orientation. The two categorical variables, sex and political orientation are dummy encoded before they are fed to the actual model. The output of the model can be observed in Figure 3.12. The multiple linear regression model predicting AI optimism from AI interest, age, gender, and political orientation explains approximately 28.2% of the variance in optimism ($R^2 = 0.282$, adjusted $R^2 = 0.221$), indicating a moderate fit for social science data. Among the predictors, **AI interest remains the strongest and highly significant predictor** ($\beta = 0.526$, SE $= 0.116$, $t = 4.55$, $p < 0.001$, 95% CI [0.297, 0.756]), suggesting that each one-point increase in interest is associated with an increase of roughly 0.53 points in optimism, consistent with the simple regression model where the effect was $\beta = 0.503$ (SE $= 0.116$, $t = 4.35$, $p < 0.001$). Age also has a statistically significant positive effect ($\beta = 0.190$, SE $= 0.057$, $t = 3.33$, $p = 0.001$, 95% CI [0.077, 0.304]), indicating that older participants are more optimistic about AI. In contrast, gender ($\beta = 0.453$, SE $= 0.439$, $t = 1.03$, $p = 0.306$) and political orientation (all dummy-coded coefficients non-significant) do not significantly predict optimism in this sample. The intercept of the model is estimated at -3.087 (SE $= 1.880$, $t = -1.64$, $p = 0.104$), which is not statistically different from zero, meaning the baseline optimism when all predictors are at zero is not reliably estimated. Compared to the simple regression model that included only AI interest and explained 15.7% of the variance, the inclusion of age, gender, and political orientation increases the explanatory power of the model and confirms that while interest is the primary driver, other demographic factors, particularly age, also contribute meaningfully to optimism.

OLS Regression Results

Dep. Variable:	b6_optimai	R-squared:	0.282
Model:	OLS	Adj. R-squared:	0.221
Method:	Least Squares	F-statistic:	4.654
Date:	Tue, 04 Nov 2025	Prob (F-statistic):	8.00e-05
Time:	19:33:19	Log-Likelihood:	-224.21
No. Observations:	104	AIC:	466.4
Df Residuals:	95	BIC:	490.2
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.0874	1.880	-1.642	0.104	-6.819	0.645
b5_aiintr	0.5264	0.116	4.550	0.000	0.297	0.756
age	0.1903	0.057	3.329	0.001	0.077	0.304
sex_Male	0.4526	0.439	1.030	0.306	-0.420	1.325
pos_b_Left	0.0519	0.889	0.058	0.954	-1.714	1.818
pos_c_Center Left	-0.4416	0.915	-0.483	0.630	-2.258	1.375
pos_d_Center	-0.0071	0.868	-0.008	0.994	-1.731	1.716
pos_e_Center Right	-0.6669	0.871	-0.766	0.446	-2.396	1.062
pos_f_Right	0.7827	1.117	0.701	0.485	-1.435	3.000

Omnibus:	1.191	Durbin-Watson:	2.249
Prob(Omnibus):	0.551	Jarque-Bera (JB):	1.280
Skew:	0.221	Prob(JB):	0.527
Kurtosis:	2.683	Cond. No.	266.

Figure 3.12. The output of a multiple linear regression predicting Optimism in AI – Online Survey 1

In addition, all key OLS assumptions have been verified and met: linearity (RESET test, p=0.411), homoskedasticity (Breusch-Pagan, p=0.056-0.061), normality of residuals (Shapiro-Wilk, p=0.270), and no multicollinearity (all VIF<5). The histogram of residuals and the QQ plot can be found in Figure 3.13 and Figure 3.14. The middle section of points (around -1 to +2) in the Q-Q plot follow the red line very closely, which indicates normality in the bulk of the data. This is reinforced by the Shapiro-Wilk test having a $p - value > 0.05$.

Overall, the results suggest that attitudes toward AI's impact in society among young people are shaped by both individual interest in AI and demographic characteristics, though the best model leaves a substantial portion of variance unexplained, pointing to other factors that may influence optimism.

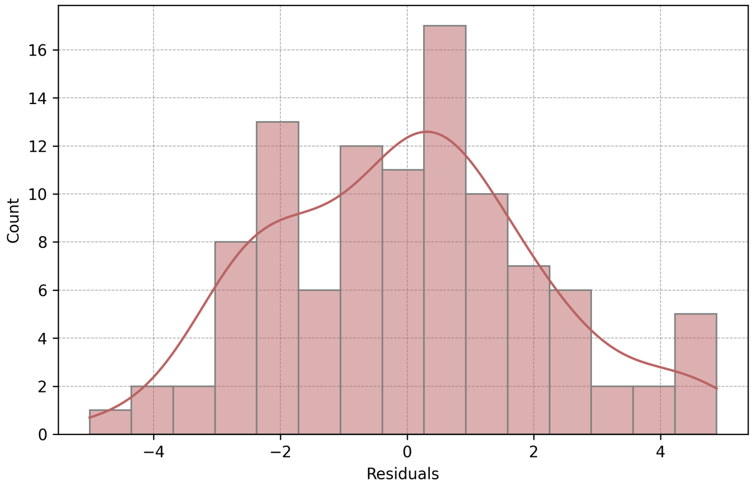

Figure 3.13. The distribution of residuals of a multiple linear regression predicting Optimism in AI – Online Survey 1

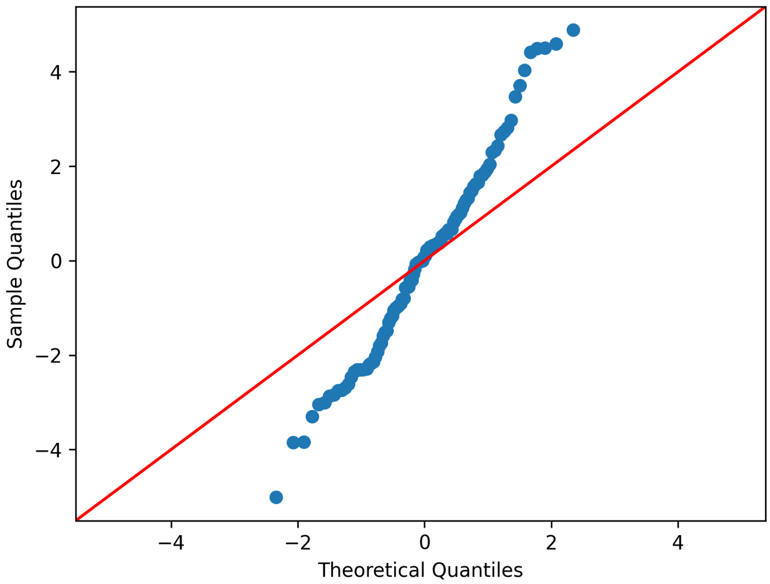

Figure 3.14. Q-Q-plot of residuals of a multiple linear regression predicting Optimism in AI – Online Survey 1

3.3.4 AI for Social Good

While applications of AI are being integrated in almost every aspect of our lives, from education, hiring to interest rates in loans, (Crawford (2021), O'Neil (2016)), initiatives like *"AI for Social Good"* have begun to spring up from multiple actors: private, public and international organizations. The more concrete idea is to develop partnerships in order to deliver positive social impact in accordance with the priorities outlined in the United Nations' 17 Sustainable Development Goals (SDGs) (Tomašev et al., 2020). Hence, multiple specific initiatives have been developed, such as the AI for Good in 2017 by the International Telecommunication Union (ITU), the United Nations (UN) leading agency for digital technologies. As their mission states they aim *"to unlock AI's potential to serve humanity through building skills, AI standards, and advancing partnerships"* (International-Telecommunication-Union-UN). However, it has to be noted that the concept in itself seems somewhat redundant, or perhaps better put: it reflects the state of affairs in our societies (as it was previously mentioned that *technology is society*). Why else would *healthy* societies develop science and technologies besides for the good of societies? The very fact that concepts as AI for social good are needed in order to develop (at least some) socially beneficial technologies in addition to the amalgam of (not socially good?) others, is a point for further work and reflection.

However, in this context, the respondents of Online Survey 1 were asked to state their *trust* in various actors to develop AI systems that *benefit society at large*. Specifically, the question was the following: *"New technologies, like AI may be implemented for many reasons and one of them is to improve the well-being of the average citizen. How committed from 0(not at all) to 5(completely committed) are the following parties to do that."* Four societal actors were taken into account: the government, the non-governmental organizations, companies (all three in their country of residence) and the European Union. The distributions can be observed in Table 3.6.

Trust Scale	**Government**	**Companies**	**NGOs**	**European Union**
0	20	6	8	7
1	18	16	19	11
2	**29**	21	22	12
3	22	24	**27**	28
4	10	**31**	21	**32**
5	5	6	7	14

Table 3.6. Trust in societal actors to implement AI for the well-being of the average citizen (scale 0–5) – Online Survey 1

Considering first a naive baseline of comparison based on the peaks of the distributions, the respondents of Online Survey 1 seem to place more trust in the companies in their countries and the European Union, both with a trust level of 4/5 in their commitment, than in the governments and NGOs in their countries with a peak at 2/5 and 3/5, respectively. If "high trust in the commitment to develop AI for the well-being of the average citizen" is considered the score of 4 and 5, then:

- 44.23% of the respondents have a high trust in the European Union's commitment to develop such AI systems.
- 35.57% of the respondents have a high trust in the companies in their countries.
- 26.92% of the respondents have a high trust in the commitment of the NGO-s in their countries.
- 14.42% of the respondents have a high trust in their government's commitment.

As it can be observed, the highest trust levels towards the commitment to develop AI that serves the well-being of the average citizen are oriented towards the European Union and the private sector. The difference in percentage points when taking as a reference the highest trusted actor, the EU, can be observed in Figure 3.15.

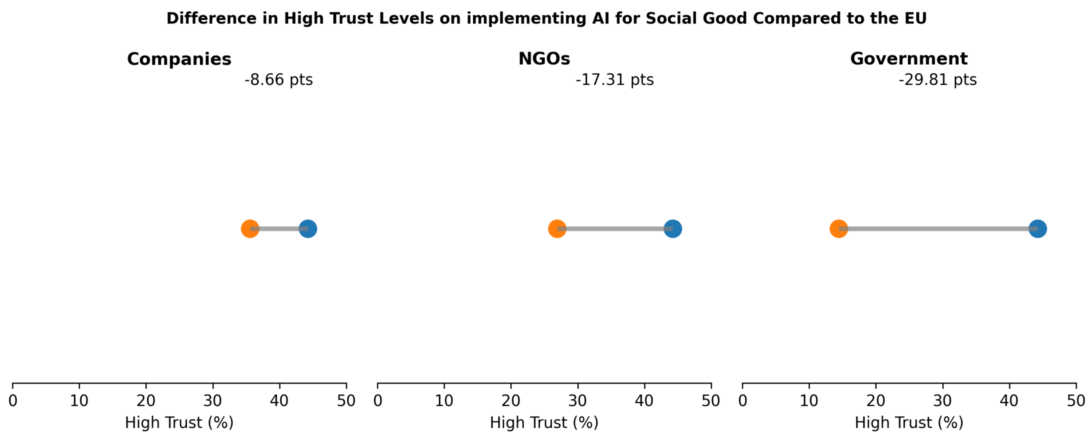

Figure 3.15. Three dumbbell (diverging) charts, each showing the difference in percentage points between the EU and another actor (Companies, NGOs, and Government) with respect to the high trust in the commitment to develop AI for social good - Online Survey 1

Studying further the two actors with the lowest overall levels of trust, we can see the distributions disaggregated based on sex in Table 3.7. For both males and females, the trust in their government's commitment to develop AI for social good peaks at (2) but males appear to have quite higher counts also for the lower levels of trust like 0 and 1. The non-parametric Mann-Whitney U Test is conducted to see if there are statistically significant differences among the groups. In terms of trusting the commitment of the NGO-s, the test results yielded a $U - statistic = 1419.0$ and a $p - value = 0.658$, thus failing to reject the null hypothesis at a 5% significance level. The situation is the same with respect to the trust in the commitment in the government of their countries and the test yielding a $U - statistic = 1251.0$ and a $p - value = 0.5039$.

Trust Scale	F (Gov)	M (Gov)	F (NGO)	M (NGO)
0	9	11	5	3
1	8	10	10	9
2	**15**	**14**	9	**13**
3	12	10	**14**	**13**
4	7	3	13	8
5	1	4	1	6

Table 3.7. Trust in government and NGOs to implement AI for the wellbeing of the average citizen, by sex (scale 0–5) - Online Survey 1

In terms of age groups, the distributions can be observed in Table 3.8. The peaks for both Gen Z and Millennials in terms of trusting the government are both at (2), with the majority, 24% of Gen Z and 30% of Millennials assigning that score. Whereas for NGO-s, Gen Z appears to assign higher trust scores than Millennials, with the majority of Gen Z, about 31% assigning a score of (3) and the majority of Millennials, 23% assigning a score of (2). The same tests were conducted as they were in terms of sex and they did not show statistically significant differences among Gen Z and Millennials at 5% significance levels. In terms of trusting the government's commitment towards AI for social good, the tests yielded a $U - statistic = 1363.5$ and a $p - value = 0.811$ and with respect to NGO-s a $U - statistic = 1522.5$ and a $p - value = 0.1923$. These results suggest that both generations exhibit comparable levels of trust toward these societal actors' commitment to develop AI for social good.

Trust Scale	18–26 (Gov)	27–35 (Gov)	18–26 (NGO)	27–35 (NGO)
0	9	11	3	5
1	8	10	6	13
2	**11**	**18**	8	**14**
3	9	13	**14**	13
4	5	5	12	9
5	3	2	2	5

Table 3.8. Trust in government and NGOs to implement AI for the wellbeing of the average citizen, by age-group (scale 0–5) - Online Survey 1

3.3.5 AI Usage

In terms of AI Usage, when the respondents of Online Survey 1 were asked if they have used AI tools like ChatGPT, the vast majority (94.23%) responded *yes*. From those 6 that responded *no*, 2 were females and 4 were males and only 1 was from Gen Z compared to 5 being Millennials. In terms of the frequency of usage (last week taken as reference), the histogram can be observed in Figure 3.16. Most people in the sample of Online Survey 1 appear to use AI tools 0-3 times per week, about 59.6%.

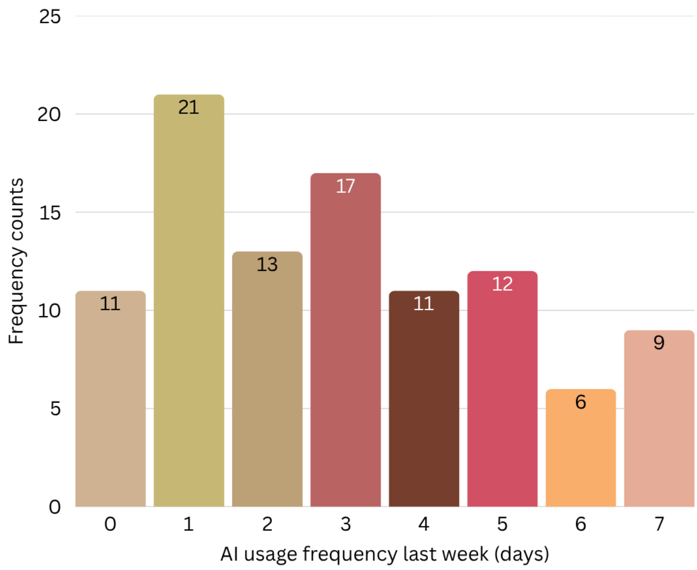

Figure 3.16. The histogram of the frequency of usage of AI tools (like ChatGPT) last week - Online Survey 1

Disintegrating in terms of the two age-groups of interest and sex, the distributions can be observed in Table 3.9 and Table 3.10. For Millennials the majority of the respondents seem to be clearly on the lower end of the frequency, whereas for Gen Z, it appears to be more evenly distributed. Dropping those four rows that had not responded this question (given the fact that this was an alternative question), there are 56 Millennials and 44 Gen Z respondents, as well as 51 females and 49 males. Likewise, for males compared to females, the distribution of the frequency of AI tools usage (last week) appears to be more well-spread. Given the fact that the data do not follow a normal distribution, the Mann-Whitney U Test is run to see if there are statistically significant differences among the demographic groups listed above in terms of their frequency of AI tools usage per week. In terms of the two age-groups, the test yielded a $U - statistic = 1276.5$ and a $p - value = 0.7574$, and in terms of sex, the test yielded a $U - statistic = 1504.0$ and a $p - value = 0.076$. This shows that there are no statistically significant differences in AI usage frequency between age groups or between males and females at the 5% significance level, although the latter result is close to the threshold and may suggest a weak trend toward higher use in one group.

Furthermore, the respondents were asked if the entity they work for uses AI in their work-related practices and filtering out the respondents that claim they have never worked, the histogram can be observed in Figure 3.17. As it can be observed, 53% of those that are currently working claim that the entities that hire them use AI in the workplace.

Frequency of AI Use (0–7)	**18–26**	**27–35**
0	5	6
1	8	13
2	6	7
3	8	9
4	5	6
5	5	7
6	2	4
7	5	4

Table 3.9. Frequency of AI use in the last week, by age group (scale 0–7) – Online Survey 1

Frequency of AI Use (0–7)	**Female**	**Male**
0	6	5
1	13	8
2	7	6
3	12	5
4	2	9
5	6	6
6	2	4
7	3	6

Table 3.10. Frequency of AI use in the last week, by sex (scale 0–7) – Online Survey 1

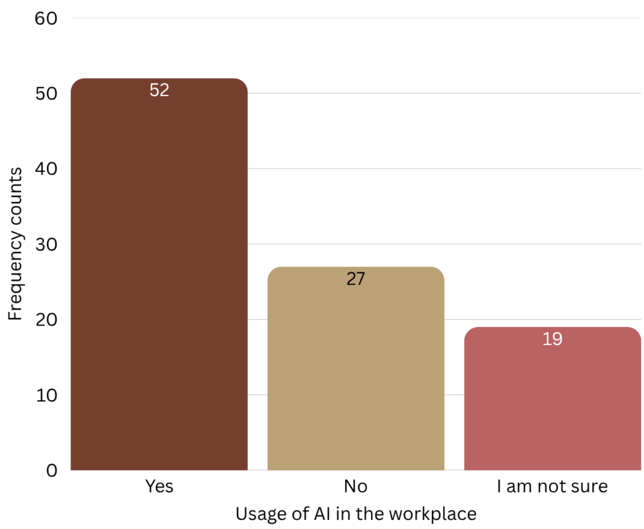

Figure 3.17. The histogram of the usage of AI tools by the entities where the respondents work – Online Survey 1

3.4 Tale in *brief* - AI

Long before AI became a formal discipline, humanity was captivated by the idea of animating matter. This was reflected in myths, mechanical inventions, and early philosophical views that framed human nature as mechanistic. The 20th century saw the rise of AI as a field, accompanied by post-war scientific enthusiasm, starting with symbolic approaches and the 1956 Dartmouth conference Dartmouth College, but it also endured setbacks like the "AI winters" due to over-promises and technical limitations. In the 21st century, breakthroughs in computing and data have propelled connectionist approaches like deep learning to dominance, yet fully understanding AI's societal impact requires moving beyond technical feats to examine its broader political and economic implications.

Recent scholarship emphasizes that AI is a socio-technical system, shaped by and shaping society, institutions, and ethical norms. Scholars argue that AI should be understood not in isolation but as embedded in social practices and institutional arrangements (Crawford (2021), Suchman (2006)). Pasquinelli (2023) specifies this view, tracing AI's roots to the industrial division of labor and arguing that modern AI continues this legacy by extracting and mechanizing collective human knowledge; thus, AI is labor-centered by its very nature. In addition, the metaphor of the "Blind Watchmaker", borrowed from Dawkins (1986) and used as a reference to AI by Susskind (2020), describes how AI systems, especially those based on machine learning, operate without foresight or understanding, driven by data patterns rather than human-like cognition.

Interestingly, from the frequency of the words and the word clouds made with the AI definitions given by the respondents of Online Survey 2, the prevalence of terms "think" and "human" illustrates that the definitions of AI seem to be closer to that of symbolic AI, regardless of the current prevalence of machine learning techniques. Hence, this would be an important point to be explored by those who guide public education and science communication for the general audience, as well as the relevant policy makers. Emphasizing the current developments using storytelling techniques or catchphrases like "The Blind Watchmakers" may be a strong solution to ignite in the popular imagination the actual current developments and thus make the reflection and decision-making of people more accurate and perhaps deeper. However, it must be noted that when the most frequent words in the definitions were analyzed, even the most frequent word "human" appears in only around **17%** of the responses of each participant. This indicates that the views and definitions when it comes to AI are very diverse.

In Online Survey 1, the young respondents were queried on multiple factors to understand their perceptions, interest, and trust regarding AI and various societal actors. The results reveal a strong engagement with the topic but mixed attitudes about its societal impact. The data show that while **60%** of respondents reported high personal interest in AI (scores 8–10), only **35.5%** felt similarly optimistic about its societal implications. In terms of the age groups (Gen Z and Millennials), the Mann-Whitney U test was employed and the results show that there is no statistically significant difference among the two age groups with respect to either of the two variables considered (interest in AI and optimism about AI's impact in society) at a 5% significance level. In terms of sex and differences in interest in AI, the same test was used. Results showed no statistically significant difference between males and females ($U = 1582.5$, $p - value = 0.128$). Although males showed slightly higher median scores, the effect was not significant at the 5% level. With respect to the optimism in AI's impact in society and sex, the test shows that the difference between males and females is not statistically significant at the 5% level ($p - value = 0.0737$). If the distributions are observed in Table 3.2, clearly males are both slightly more interested and more optimistic in terms of AI but these are not *statistically significant* differences in the sample. As a final generic question regarding the perception towards AI, the respondents of Online Survey 1 were asked regarding **the expected impact of AI in overall inequality** in the next 10 years, so in the short term. The histogram shows that the vast majority expect increases in inequality, **with 55% expecting inequality to be either much higher or higher**. The highest frequency counts for males and for the older group appears to be at the expectation that inequality will remain "the same". However, interestingly for females and the younger Gen Z group, the higher counts are convincingly in the category that inequality will become "higher" in the next 10 years. However, the Mann-Whitney U test shows there are no statistically significant differences among males and females and among Gen Z and Millennials at a 5% significance level.

The relationship between interest in AI and optimism regarding AI's impact in society was studied further in 3.3.3. The correlation between interest and optimism was moderate (Spearman's $\rho = 0.323$, $p = 0.0008$), indicating that while curiosity often aligns with optimism, the connection is not particularly strong. Moreover, a simple linear regression was built (bearing in mind the limitations of using such a technique on ordinal data, even if Likert-type scales with 7+ points can be treated as quasi-interval data) and the results show that only 15.7% of the variation in optimism regarding AI's impact in society is explained by the interest alone. Another model is built, a multiple linear regression that takes as input not only the interest in AI but also demographic factors such as age, sex and political orientation. The two categorical variables, sex and political orientation are dummy encoded before they are fed to the actual model. This model explains approximately 28.2% of the variance in optimism ($R^2 = 0.282$, $adjustedR^2 = 0.221$), indicating a moderate fit for social science data. In addition, despite ordinal predictors/outcome, the model meets OLS assumptions reasonably well. The coefficient for AI interest remains nearly identical between the simple regression ($\beta = 0.5031$) and the multiple regression model ($\beta = 0.5264$), indicating that the relationship between AI interest and optimism in AI's impact in society is stable and not confounded by demographic or political variables. This stability suggests that age, sex, and political orientation contribute independent explanatory power rather than mediating or suppressing the effect of AI interest, supporting an additive model structure where predictors make distinct contributions to explaining variance in AI optimism.

When analyzing trust in institutions related to AI, the survey uncovered widespread skepticism, particularly toward government management, where **77%** of the respondents in Online Survey 1 expressed low trust (scores 0–4), compared to **63%** for the media. The

Mann-Whitney U test was used to check if there are statistically significant differences among the sexes and the two age groups (Millennials and Gen Z) in their trust levels for both the media's and the government's ability to handle matters of AI. In terms of sex, in both cases, the trust in government's ability ($U = 1236.5$, $p - value = 0.450$) and in media's ability ($U = 1192.5$, $p - value = 0.2974$), show that for a significance level of 5%, there are no *statistically* significant differences among the trust levels of the two groups. Similarly, there appear to be no statistically significant differences in either case among Gen Z and Millennials. Overall, the results show low trust levels in institutions such as government and media.

Trust is analyzed further particularly with respect to the concept of **"AI for social good"** in accordance with International-Telecommunication-Union-UN and the willingness of various actors (the government, private sector, non-governmental organizations and the European Union) to develop AI for such purposes. The respondents of Online Survey 1 were asked to state their trust level in the commitment of the above-mentioned actors, from 0 (not at all) to 5 (completely committed) in developing and fostering the development of AI for social good. The results showed that the respondents of Online Survey 1 seem to **place more trust in the commitment to develop AI for social good in the companies in their countries and the European Union,** both with a peak trust level of 4/5 in their commitment than in the governments and NGOs in their countries with a peak at 2/5 and 3/5, respectively. If "high trust in the commitment to develop AI for the well-being of the average citizen" is considered the score of 4 and 5, then the percentage of the respondents that chose that trust level was: 44.23% for the European Union, 35.57% for the companies, 26.92% for the NGOs and 14.42% for the governments. Studying further the two actors with the lowest overall levels of trust, the Mann-Whitney U test was conducted to see if among the sexes and among the two age groups there were statistically significant differences in the central tendencies and the results showed that we fail to reject the null hypothesis at a 5% significance level.

In terms of AI usage, when the respondents of Online Survey 1 were asked if they have used AI tools like ChatGPT, **the vast majority, 94.23%, responded yes**. From those 6 that responded no, 2 were females and 4 were males and only 1 was from Gen Z compared to 5 being Millennials. In terms of the frequency of usage (last week taken as reference), most people in the sample of Online Survey 1 appear **to use AI tools 0-3 times per week**, about **59.6%**. The Mann-Whitney U Test was used on both sexes and age groups and the results show that there are no statistically significant differences in AI usage frequency between age groups or between males and females at the 5% significance level. In terms of work-place usage and implementation, **53%** of those that are currently working from the participants of Online Survey 1, claim that the entities that hire them use AI in the workplace.

As it was observed, the Mann-Whitney U test was employed in multiple cases to understand if, at a 5% significance level there were differences in the central tendencies between males and females and between Gen Z and Millennials, and their perceptions with respect to AI on various points. The results showed no such differences. With 104 respondents of Online Survey 1 divided into subgroups, the sample size may be insufficient to detect small-to-moderate differences as statistically significant, even when genuine differences exist in the population. It could also be that the lack of significant differences may reflect a real phenomenon whereby sex and generational cohort do not meaningfully predict attitudes toward AI. AI discourse may have become sufficiently widespread and homogenized through social media and popular culture that traditional demographic divides are less pronounced on these issues than might be expected, particularly among relatively similar age and highly-educated cohorts (18-35 year-olds).

Understanding how young people perceive AI is crucial, as their expectations and concerns will shape future patterns of adoption, regulation, and democratic engagement around emerging technologies. Moreover, studying these perceptions provides early insights into how societal narratives about AI are formed, negotiated, and reproduced among the generations that will soon become the primary workforce and electorate.

Chapter 4

Tales of Work in the Age of AI

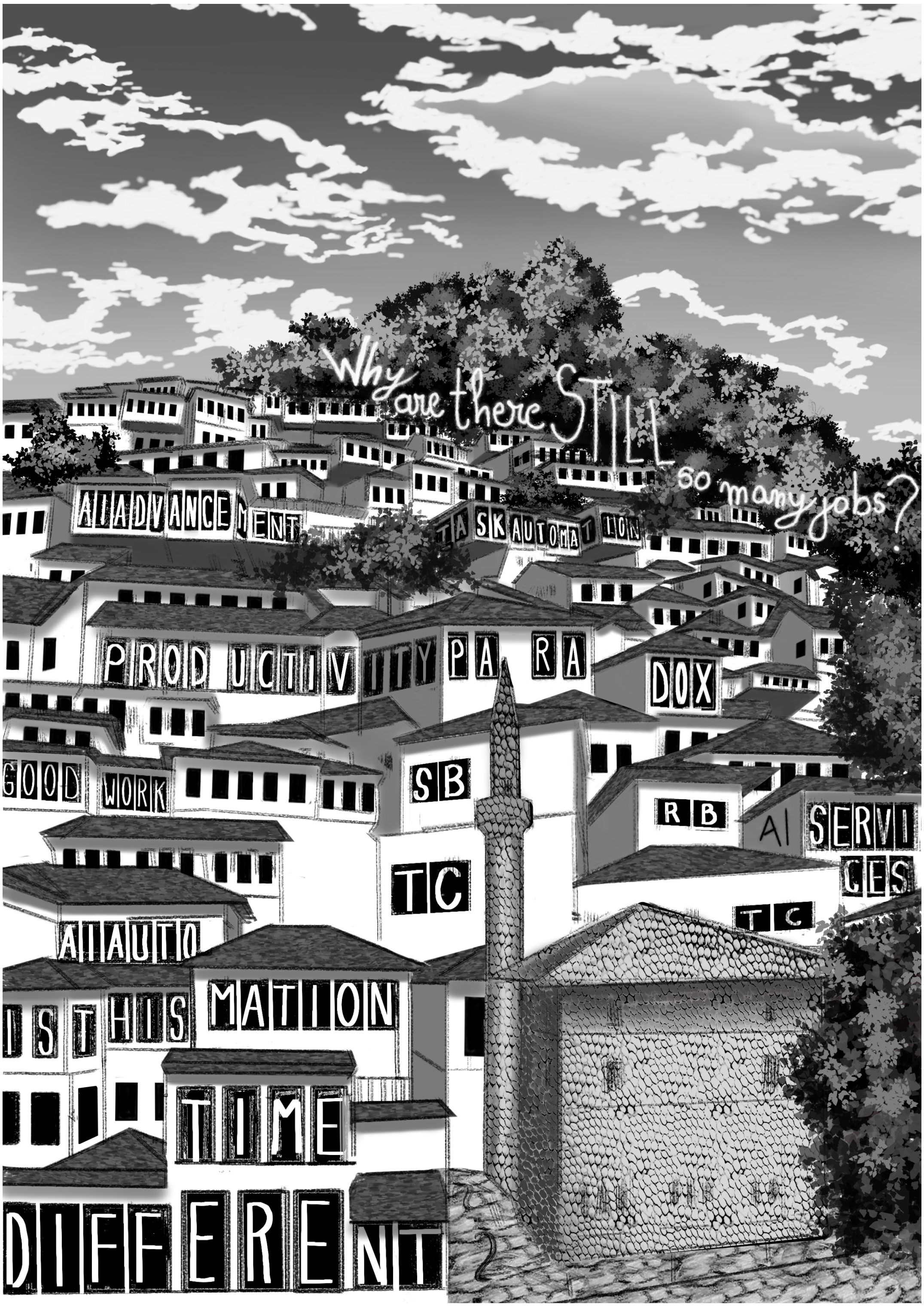

Figure 4.1. Tale 3: Mangalem - Tales of AI's impact in work.

4.1 Tale 3: Mangalem - Tales of AI's impact in work.

HISTORICAL concerns remerge on the air surrounding our little city: "Are we heading towards technological unemployment? Will all jobs disappear under the thumb of the blind watchmakers?" Out of the pine forest from the other side of the hill, the elders claim that we have been here once before and invite the residents to explore the past and why, regardless of all the developments, there are still so many jobs around. However, the elders are definitely not in unison. Not only on what will occur in the future but even on what is occurring right now. On the two sides of "The Bachelor's Mosque" or the previously known "Sylejman Pasha Mosque", pick whichever name you like but don't tell the elders, a vivid discussion is taking place: are we experiencing a skill-biased technical change (SBTC) or otherwise known as same-old same-old or a routine biased technical change (RBTC)? However, the residents that meet on a daily basis on the bars on the left-hand side of the Mosque still want to know: "Is this time different?" These people have embedded in their collective memories more than two thousand years of empires coming and going, bringing their own technologies, both kind and unkind but once they left, the locals were still there to rebuild what the wars burned down or to enjoy what they learned from the foreigners. Harsh discussions are taking place about whether things will be different with these blind watchmakers and what will happen to the jobs and the wages of the locals. Some woman, in her late 70s, is hoping that at least the unpaid work she does on all the cleaning can finally find a way to be done by them. Will that happen? The ramifications of AI automation in both wage-labor and unpaid household work will be discussed. In another bar, a few windows up, others are concerned not on whether their work will be gone but rather if their work is about to become better or worse. In the meantime, up in the hill, the elders are devising the methods of what these blind watchmakers can do. What does that imply for specific tasks? This is no easy matter because, let us not forget, the watchmakers are blind! Last but not least, looming over all these discussions and right in the center of this facet of Mangalem neighborhood, some statisticians rigorously recording what has been happening with productivity since these blind watchmakers first made their way into town are baffled and remember the quip of Solow: "We see computers everywhere, except in productivity statistics." What a paradox!

4.2 The brief matter of operationalizing work and measuring task automation

“Everyone listened to this amusing narrative with great interest, and the moment that Behemoth concluded it, they all shouted in unison: ’Lies!” — Mikhail Bulgakov, The Master and Margarita

In this very brief subchapter, a short discussion will take place presenting the understanding of "jobs as sets of tasks" and the ways in which AI advancement is measured and its current capabilities for task encroachment. This sets a foundational layer in *properly* understanding automation discourse behind bombastic click-bait articles for the generic reader. In addition, it helps contextualize present debates on AI and work within a longer and more concrete trajectory of technological change and societal adaptation.

4.2.1 Understanding jobs as sets of tasks and the forces that lead to automation and augmentation

Historical concerns regarding automation are, indeed, *a tale as old as time*. We could go back in time as far as we like and find deep concerns on how new technologies that are being developed shift societies. [1] A trip could be taken back to the Iron Age, where one could see, side by side with the optimism and thrill that new tools were bringing, such as in the case of Homer’s descriptions, also the lament of those observing how technologies were usurping societies and were inducing endless labor, as it was the case of Hesiod (Varoufakis, 2023):

"I wish I did not have to live among the people of the Fifth Age [the Iron Age], but either had died earlier or been born later.For now truly is a generation of iron who never rests from labor and sorrow by day or from perishing by night . . . But, notwithstanding the good mingled with their evils . . . [this generation] will know no favor for those who keep their oath or for the just or for the good . . . strength shall be right . . . the wicked will hurt the worthy . . . bitter sorrows will be left for us mortals, and there will be no help against evil."

When discussing the impact of historical concerns on technology and automation, such matters got so deeply ingrained in societal thinking, that a word was needed for it and *"luddite"* came into existence. Currently, it colloquially refers to those who oppose technological change[2]; however, its history and per consequence, its semantics are much more complex. The Luddites, named after "General Ned Ludd", a mythical figure, began protesting around 1811, as the cotton and wool industries were being developed

[1] Or the very fact that societies were shifting allowed the development of such technologies. The chain of causation here, as previously mentioned will always be a doubtful one.

[2] Definition taken from: https://www.merriam-webster.com/dictionary/Luddite

and mechanized, quickly spread across the UK (The National Archives, n.d.). In popular imagination, but also in factual terms, the Luddites are known for their violent uprisings: setting mills on fire, exchanging gunfire with authorities, murdering mill owner William Horsfall etc., as they were demanding higher wages and the old artisans a share in the productivity gains that the new technologies were bringing (Klein, 2019). Clearly, the Industrial Revolution *eventually* increased the well-being of the average person and brought forth much higher living standards than before, and most citizens, at least in the West, have accepted technology as the engine of their fortunes Frey (2019). More specifically, the standard narrative is that any advance that increases productivity also tends to raise the demand for employment and wages. However, such narratives are limited in their explanatory power. As noted by Acemoglu and Restrepo (2019): *"Many new technologies, those we call automation technologies, do not increase labor's productivity but are explicitly aimed at replacing it by substituting cheaper capital (machines) in a range of tasks performed by humans. As a result, automation technologies always reduce the labor's share in value added (because they increase productivity by more than wages and employment)."* Furthermore, even if long-term trajectories are observed, *eventually* can indeed be a very long time (Frey, 2019). Frey (2019) in his book "The Technology Trap", also challenges the straightforwardness of the narrative on the trajectory of technological and societal development, by noting that *"...as technology progressed in the early days of industrialization, however, living standards for many regressed."*. Hence, as we go forward understanding the perceptions of young people in Europe regarding the impact of AI in work, it has to be denoted that *change*, in whatever dimension it occurs, and particularly *advancement* is neither automatic (Acemoglu and Johnson, 2023) nor linear (Frey, 2019).

Another important element to highlight, is the fact that in economic terms jobs are usually seen as "a bundle of tasks", where a task is s a unit of work activity that produces output (Autor, 2013). Furthermore, "tasks" are different from "skills", given the fact that skills are a worker's stock of capabilities for performing various tasks, for which they get a wage. This is the overall framework under which it is usually operated.
Going into indicators, Autor (2015) succinctly observes that regardless of technological and sociological developments (like the entrance of women in the wage-labor), there are no signs of long-term increasing unemployment. In Autor (2015)'s own words: *"Clearly, the past two centuries of automation and technological progress have not made human labor obsolete: the employment-to-population ratio rose during the 20th century even as women moved from home to market; and although the unemployment rate fluctuates cyclically, there is no apparent long-run increase"*. This fact is re-established also from the statistics presented in Chapter 2.2 of this work. Moreover, Autor (2015), as Acemoglu and Restrepo (2019) and other authors mentioned above, notes the two effects of technologies:

- The substitution effect
- The complement effect

In his view, the media pay too much attention to the substitution effect without taking into account the complementary one (Autor, 2015). However, he does denote the fact that technological changes alter the jobs available and what they pay, but this is a point to be explored in the next sub-chapter. Autor (2015) then illustrates the interaction of the two effects with the example of the invention of ATMs that did not make the job of the bank teller disappear, as it would have initially been imagined but rather changed the nature of the work in itself. However, as Autor (2015) denotes, that should not be taken as paradigmatic: *"technological change is not necessarily employment-increasing or Pareto-improving."* There are three main factors to be taken into account:

- workers are more likely to benefit directly from automation if they supply tasks that are complemented by automation, but not if they primarily (or exclusively) supply tasks that are substituted,
- the elasticity of labor supply can mitigate wage gains,
- the output elasticity of demand combined with income elasticity of demand can either dampen or amplify the gains from automation.

Furthermore, Susskind (2020) in his book "A world without work" delves deeper into this complementary effect, or force as he calls it, which has been the backbone of work as we know it. He deconstructs the complementary force by laying out its dimensions: *"in the past, as we have seen, the complementary force raised the demand for displaced workers in three ways: through the productivity effect, the bigger-pie effect, and the changing pie effect."*

- The productivity effect: machines did displace workers from some tasks but also made them more productive at other activities. (Susskind (2020), pp. 113-115)
- The bigger-pie effect: workers that lost their jobs in some part of the economy could find jobs in another part, because, due to the development, increased demand for the workers could be found elsewhere. (Susskind (2020), pp. 115- 118)
- The changing-pie effect: technological development not only made the economic pie bigger but also altered it. (Susskind (2020), pp. 118 - 122)
  - Consumers: essentially wanting and willing to buy different goods and services.
  - Producers: changed the way they produce those goods and services due to technological development that allowed for old methods of production to be substituted with new, better ones.

For Susskind (2020), the "Age of Labor" is one we leave behind and in the "Age of AI", the complementary force and its determinants will not be able to withstand and technological unemployment may be a reality, hence, making us look into policies such as Conditional Basic Income. Almost 100 years ago, Keynes (1930) in his famous essay "The economic possibilities for our grandchildren", expected the unavoidable rise of *technological unemployment* but without giving much details as how that would unfold, except the fact that the pace of technological development would outrun our capabilities of finding new use for displaced labor. We are almost 100 years later from that essay and, at least at the moment, the 15 hour working week does not seem to be a possibility and in fact the discussions are going on to the opposite direction with the increase of the retirement age for example (Rihan, 2025). Thus, economists have long dismissed the potential of technological unemployment. However, according to Susskind (2020), this dismissal is a misconception because the complementing force may not be as strong as it has been in the past. The reason we cannot rely in the future to the strength of the complementary force, Susskind (2020)'s own words (pp. 113): *"...task encroachment also has a second pernicious effect: over time, it is likely not just to strengthen the substituting force, but also to wear down the complementing force as well."* Susskind expects all the three sub-forces that permit the complementary one to prevail, to weaken. Others held a more optimistic view and just a few years earlier than that, back in 2015, David Autor claimed that AI-powered automation would substitute for human labor in some domains but complement it in others, offering a more balanced view (Autor, 2015). This claim was core to a "routinization" theory which will be further explored in another sub-chapter. The World Economic Forum estimated in 2018 that technology would displace 75 million jobs but that 133 million jobs would emerge by 2022 (Forum, 2018). However, they readjusted this assessment in 2020 and lent some credibility to the more pessimistic view of Susskind (2020), by denoting how job destruction had accelerated and job creation had slowed down Zahidi et al. (2020). One thing is for sure: views on the impact of AI in the job market are definitely part of a domain of high uncertainty and diverging opinions, which is perhaps best illustrated by a report reviewing a decade of literature on the matter and coming up with the title *"The Age of Uncertainty—and Opportunity: Work in the Age of AI"* (Orrell and Veldran, 2024).

Additionally, there are other arguments that conclude that the current trend is focused towards automation and the substitution of workers in their tasks as a *choice* or rather as *a set of misaligned incentives*. Brynjolfsson (2022) states that even though technologies such as AI can be used for both automating labor as well as complementing the tasks labor does and thus augmenting its capabilities, the current layout is such that the incentives of policy makers, technologists and businesses are aligned and lean towards automation. He calls this phenomenon *"The Turing Trap"*, namely *"If machines become substitutes for human labor (rather than complements), then workers lose bargaining power, wealth concentrates with those controlling the machines, and society can get stuck in a bad equilibrium."*. The same view is also supported by Acemoglu and Restrepo (2020): *"Recent technological change has been biased towards automation, with insufficient focus on creating new tasks where labor can be productively employed. The consequences of this choice have been stagnating labor demand, declining labor share in national income, rising inequality and lower productivity growth."* Thus, they consider the current way AI is being developed to be a *"so-so technology"*, given the fact that it shifts costs from companies to consumers without generating much of a productivity boost (Acemoglu and Restrepo, 2020). Productivity will be discussed in detail in Chapter 4.5.

In the Online Survey 2, respondents were asked to identify if the entities for which they work for at that moment in time were more likely to use AI to: complement the work of people or substitute them. The option "I have never worked"[3] was also an alternative. As can be observed in Figure 4.2, the vast majority of respondents, about 75% believe in the complementary strategy. This set of responses is clearly going in the opposite direction to what was stated above by some of the economists taken into account. If only those who have chosen "substitute" are taken into account, in terms of sex, they are almost perfectly balanced with 19 males and 18 females. With respect to age groups, those aged 18-26 have a frequency count of 21 compared to those from the age group 27-35 that have a frequency count of 16, showing some difference but not substantial. In terms of political orientation, 35% identify themselves as "center-right" compared to 18% of the entire dataset of Online Survey 2. Only 43% of the respondents that chose "substitute", claim their companies are already using AI in their workplaces. In terms of their job titles, they varied widely from nurses, pastry chefs, translators, software engineers, and developers. Thus, it is difficult to detect a specific pattern.

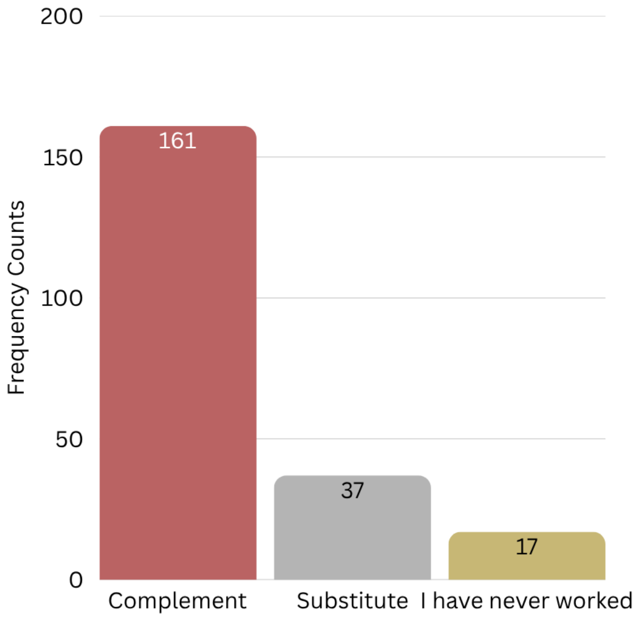

Figure 4.2. The histogram of AI complementing vs. substituting work - Online Survey 2

Moreover, in Online Survey 2, the respondents were asked an alternative question which required the percentage of tasks that AI can automate in their current job at this moment in time. They were provided with an explanation to see jobs as bundles of tasks.

[3]The option "I have never worked" was provided in the majority of the questions in Online Survey 2, which are relevant in this chapter. However, the number of people that have chosen it varies from question to question, introducing some inconsistencies.

Filtering out those that have chosen the option "I have never worked", the distribution is the one that can be observed in Figure 4.3. Clearly, the peak is at "less than 50%", with 18% of the respondents choosing that alternative. This would be a normal distribution, if it were not for a substantial group believing that 90-100% of the tasks could be automated. Studying that group more closely and considering also the question above on the matter of substitution vs. complementing, only 7 out of the 37 individuals that had chosen "substitute" have also chosen the degree of task automation between 90-100%. The job titles of people who have chosen this high level of expected automation (90-100%) category vary widely as well, from sales, to waiters, musicians, and quite a few IT professionals. In terms of sex and age, they are somewhat balanced with 13 males and 9 females as well as 14 people from the Millennial age group (27-35) and 8 people from the Gen Z age group (18-26). In terms of political orientation, the wide majority self-declare as "center-right", specifically 10 out of 22, almost 50% and the remainder are distributed in other groups. Thus, the only detectable pattern, if it can be called such, in terms of the degree of task automation and the approach of the different companies/entities with respect to automation vs. complementing, seems to be that a considerable group of people declaring to be in the center-right of the political orientation spectrum, expect the very extreme degree of automation and substitution in the workforce.

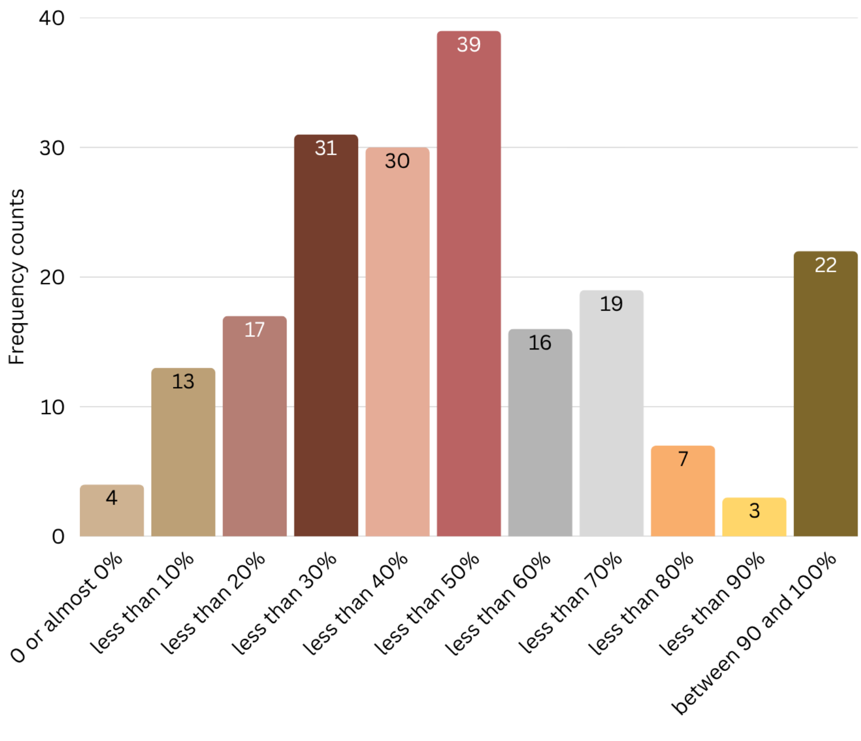

Figure 4.3. The histogram of the % of tasks AI can automate at this moment in time - Online Survey 2.

Moreover, the matter of *"Is this time different?"* was studied in Interview Set 2. The interviewees, after they were presented with the two forces of substitution and complementing, were asked if they believe that this time is different and asked if the complementing force will prove weaker than the substitution one this time, leading perhaps to technological unemployment. The results show that 17 out of 36 interviewees or 47.2% believe that this time *is* different, clearly illustrating how torn the sample was on the matter. In terms of sex the distribution can be viewed in Figure 4.4 and in terms of occupational groups the distribution can be viewed in Figure 4.5. As shown, males seem to be more skeptical than females with respect to this this time being different and people coming from sciences and politics seem to be more skeptical than those from arts.

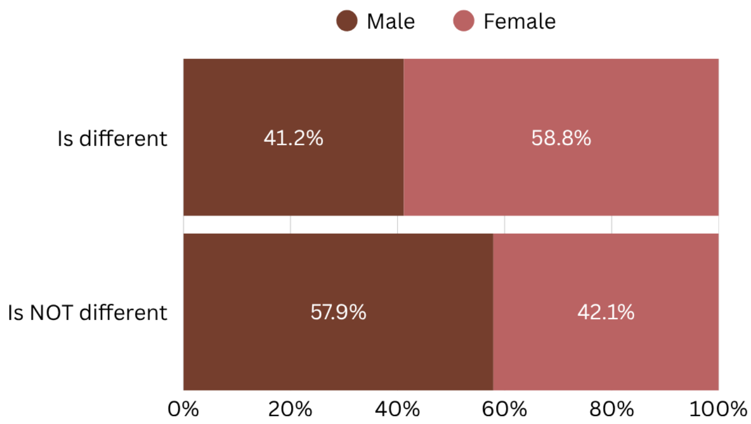

Figure 4.4. The distribution of *"Is this time different"* by sex – Interview Set 2

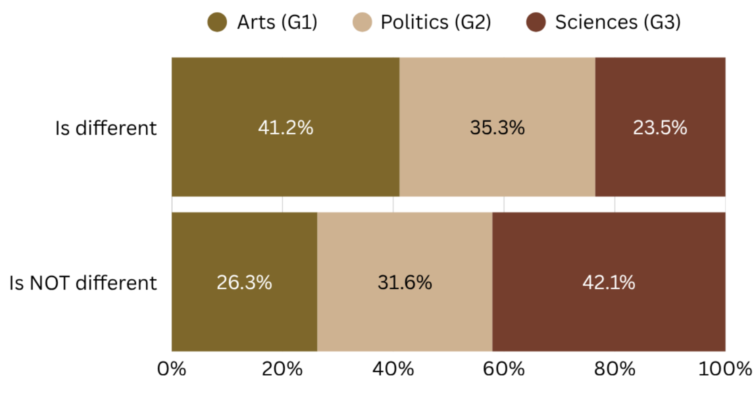

Figure 4.5. The distribution of *"Is this time different"* by occupational group – Interview Set 2

In terms of the rationales provided during the interviews, respondents were divided on whether AI represents a fundamentally different technological shift in terms of its impact on labor markets, with opponents and proponents offering distinct rationales rooted in different assumptions about economic systems, historical precedent, and technological capabilities. Among those who *argued that this time is not different*, several emphasized that the complementary force would remain stronger than the substitution effect, though their reasoning varied considerably: one respondent argued that wholesale AI replacement would not occur not due to technical limitations but because such disruption would dissolve existing economic systems and create chaos that society would not permit, while another acknowledged that this moment might approach the end of capitalism but insisted that work itself would never disappear because workers are simultaneously consumers whose purchasing power sustains the economic system. Notably, multiple respondents in this camp explicitly stated they were choosing to be optimistic rather than making what they considered realistic estimations, and even when pressed on this point, they maintained their optimistic stance, with one expressing hope that the relationship with work would alter but that the complementary force would prevail if new generations were properly prepared. A significant pattern among opponents was their reliance on historical precedent as evidence for future outcomes, with several pointing out that previous technological revolutions did not make jobs disappear but rather improved production, minimized physical labor, and created new categories of work, leading them to believe that while the physical dimension of certain jobs might vanish, people would continue working in newly created roles. In contrast, *proponents of the "this time is different"* thesis argued that AI's capabilities fundamentally exceed those of previous technologies in ways that will dramatically reduce available work: one respondent emphasized that AI could displace many more jobs than past innovations and that newly created positions might themselves be performed by AI rather than humans, while another noted that AI is already accomplishing tasks previously thought impossible for technology, citing the example of robotic conductors that enable anyone with minimal musical knowledge to direct an orchestra. The proponents generally envisioned a future where very few people would be needed for work "in the masses", pointing to examples like 3D printing eliminating jobs for sculptors as emblematic of how AI-driven automation would create an ongoing drop in work availability that qualitatively differs from historical patterns of technological displacement and job creation.

4.2.2 A comparative analysis of different analytical models in measuring task automation due to AI

Before proceeding to understand the perceptions regarding the expected impact of AI in work, it is of imperative importance to understand how the advancements of AI and the automation of tasks by AI are operationalized. For this matter, three analytical models, stemming from three papers are taken into account:

- Paper A: Felten, E. W., Raj, M., & Seamans, R. (2018, May). A method to link advances in artificial intelligence to occupational abilities. (Felten et al., 2018)
- Paper B: Brynjolfsson, E., Mitchell, T., & Rock, D. (2018, May). What can machines

learn and what does it mean for occupations and the economy? (Brynjolfsson et al., 2018)

- Paper C: Tolan, S., Pesole, A., Martínez-Plumed, F., Fernández-Macías, E., Hernández-Orallo, J., & Gómez, E. (2021). Measuring the occupational impact of ai: tasks, cognitive abilities and ai benchmarks. (Tolan et al., 2021)

The first paper, *"A Method to Link Advances in Artificial Intelligence to Occupational Abilities"* by Felten et al. (2018), aims to understand AI's impact in labor by linking the advancement in different categories of AI to different types of abilities. Two databases were used: the Occupational Information Network (O*NET) database and the Electronic Frontier Foundation (EFF) AI Progress Measurement dataset. EFF is used to track AI's advancement across 16 separate categories of metrics using known AI benchmarks, for example in Image Recognition, Reading Comprehension, etc, while O*NET is used for 52 distinct abilities which describe job requirements. The authors map 16 EFF categories to the list of 52 abilities. The O*NET occupational definitions are then used to evaluate the impact of AI advances on each occupation. This is done by weighting the effect of AI on each ability by the ability's prevalence in each occupation. In order to create an effect score for each occupation, the impact across all abilities is aggregated at an occupational level. This score is arbitrary, but allows us to compare the relative impact of AI across occupations. Then, this methodology correlates advances in AI from 2010-2015 to changes in occupational descriptions in 2018. It gives no insights on whether AI is serving as a substitute or complement to the occupations it affects. The second paper, *"What can machines learn and what does it mean for occupations and the economy?"* by Brynjolfsson et al. (2018), is an extension of their previous work (Brynjolfsson and Mitchell, 2017) in which they created a task evaluation rubric composed of multiple statements which are evaluated on a 5 point scale (strongly agree to strongly disagree). They used O*NET database and using the rubric they evaluated its 2,069 direct work activities (DWAs) based on their Suitability for Machine Learning (SML). Then, they linked SML scores also on the tasks and occupations levels. Each DWA is scored for its SML using a slightly extended version of the task evaluation rubric of Brynjolfsson and Mitchell (2017). The applied rubric has 23 distinct statements to be evaluated on a 5- point scale (strongly agree to strongly disagree). The rubric focuses on technical feasibility. This analysis suggests that ML will affect different parts of the workforce than earlier automation waves but it is still unclear how exactly. The third paper, *"Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks"* by Tolan et al. (2021), creates a multilayered framework by linking tasks to cognitive abilities, and these to indicators/ benchmarks that measure advances in different AI fields. Distinctly from the other two studies, they map 59 generic tasks from three databases: EWCS, PIAAC and O*NET to 14 cognitive abilities (from cognitive science literature) and these to a comprehensive list of 328 AI related benchmarks. Like Felten et al. (2018), they map AI's advancement impact to abilities but they go further by mapping also to tasks, thus having abilities as an intermediate layer. Another important difference between the two is the way they measure AI progress. Felten et al. (2018) measure AI progress by computing linear trends in each benchmark, while Tolan et al. (2021) measure activity levels in those benchmarks as indicators of progress, allowing comparability across benchmarks from different fields of AI. The addition of an intermediate layer of cognitive abilities and the usage of AI benchmarks are the main differences of this paper compared to Brynjolfsson et al. (2018).

Understanding the variety of methods to operationalize concepts is important, especially when from these methods policy makers draft regulations and organizations build strategies. Shifts in methods and their respective conclusions might infer shifts in entire approaches. Whatever method may be used it will naturally represent a simplified and generalized version of reality. That is inescapable. As Cohen (2013) states: *"Yet it is unassailably true that so long as we lack omniscience and do not know all of the future, all our generalizations are fallible or only probable."* This is particularly true for AI. Yet, generalizations must be made in order to be able to conceive even a caricature of reality, thus bringing us to the first criterion of evaluating the papers' methods: which is the best method to study what can AI do or current advances in AI?

As mentioned above, Brynjolfsson et al. (2018) use a custom made rubric with 23 statements answered for each DWA and generate scores using CrowdFlower. CrowdFlower considers itself a data-enrichment platform with an on-demand workforce of millions of people who complete tasks that algorithms alone cannot, at first impression seems similar to Amazon Turk. However, little or no information is provided on who these people are, their areas of expertise, working conditions, etc. On the other hand, both Felten et al. (2018) and Tolan et al. (2021) use known AI benchmarks, the first deriving 16 of them from EFF and normalizing and aggregating along different groups of metrics and the second creating their own dataset of 328 AI benchmarks but measuring not the aggregate progress along different metrics but the amount of activity around those benchmarks as a proxy to progress. However, there is a set of problems in using benchmarks (well-known datasets composed of tests and metrics) to measure advancement in AI. Researchers Raji et al. (2021), draw similarities between AI benchmarks and the children's storybook *"Grover and the Everything in the Whole Wide World Museum"* (Stiles and Wilcox, 1974), yet another example on the rare occurrence and importance of storytelling to communicate scientific concepts to the wider public, and not only. In the story, there are rooms in the museum for various categories like "things you see in the sky", "the things that can tickle you", "the carrot room" etc., but when Grover sees all of the rooms and asks where everything else is he finds a door labeled "everything else" that leads to the real world. Same goes for AI benchmarks, as having algorithms perform well in certain datasets even as large as ImageNet does not necessarily imply having the vague ability of "visual understanding", for example Raji et al. (2021). It is necessary for better metrics to be developed as well as better understandings of the limitations of currently used AI benchmarks.

The second criterion refers to the best link between AI advancements and work, namely: is it better to map AI advancements to abilities, to tasks and occupations or to some multilayered model including both? As mentioned above, Brynjolfsson et al. (2018) construct a SML score for tasks whereas both Felten et al. (2018) and Tolan et al. (2021) consider the link of AI advancements to abilities. The latter build a multilayered model linking abilities also to tasks and occupations, which could be considered as a better approach.

The advantage of this model is that it is more comprehensive and offers better comparability across AI benchmarks. Abilities can be a more fit parameter to measure progress in AI since a specific ability can be applied in a multitude of tasks. Linking AI advancement to abilities and not only tasks allows us to distinguish machines that through ML, are empowered with the abilities of performing in a range of many tasks from machines that are programmed or built to perform a specific task. This is particularly useful when one considers the potential creation of new tasks.

The reader, thus can make an analysis and make the case for each method on which would be better fitting to the task at hand. Due to the complexity of the notions involved, this was not part of the online surveys or the interviews. However, it is still presented in this work to ensure that the reader is aware, from this small sample of methods, that there exist a variety of techniques to measure the advances of AI in tasks.

4.3 Routine Biased vs. Skill Biased Technological Change

There are indeed large disagreements among researchers, not only regarding the impact that AI is expected to have in the future in the world of work, but also on what is happening at this very moment due to IT technologies and automation, in general. For example, one of the main disagreements is the RBTC (Routine Biased Technological Change) versus the SBTC (Skill Biased Technological Change). The former proclaims that it is the occupations that are the most routine that are prone to be automated whereas the later states that the more skilled you are the less likely you are to be impacted by technological change. One of the proponents of RBTC, Autor (2015) contends that the interaction between machines and humans allows computers to take over routine, rule-based tasks, while increasing the relative advantage of workers in areas requiring problem-solving, flexibility, and creativity. This leads for many to a hollowing out of the "middle class" or what is commonly known as "job polarization" (Autor, 2015), though there are notable discussions in weather technological factors are the ones leading to it (Fernández-Macías and Hurley, 2017). With respect to European countries, the hollowing out of the layer of middle paying occupations[4] has been empirically reported by Goos et al. (2014) as it can be observed in Figure 4.6. The authors have analyzed data from 16 Western European

[4]High-paying occupations are corporate managers; physical, mathematical, and engineering professionals; life science and health professionals; other professionals; managers of small enterprises; physical, mathematical, and engineering associate professionals; other associate professionals; life science and health associate professionals. Middle-paying occupations are stationary plant and related operators; metal, machinery, and related trade work; drivers and mobile plant operators; office clerks; precision, handicraft, craft printing, and related trade workers; extraction and building trades workers; customer service clerks; machine operators and assemblers; and other craft and related trade workers. Low-paying occupations are laborers in mining, construction, manufacturing, and transport; personal and protective service workers; models, salespersons, and demonstrators; and sales and service elementary occupations.

countries over the period 1993-2010, noting the job polarization phenomena and stating that the theory of routine biased technological change is a good explainer. On the other hand, the proponents of SBTC dispel what they call "the myth of polarization" (Oesch and Piccitto, 2019) by stating that the polarization thesis does not hold empirically and goes counter to the well-established SBTC. Also, these authors take into account data from European countries, using the European Labor Force Survey to analyze occupational change for Germany, Spain, Sweden, and the United Kingdom from 1992 to 2015. However, they define good and bad occupations with a more layered and complex set, of indicators. Specifically, they use four alternative indicators of job quality: earnings, education, prestige, and job satisfaction. Oesch and Piccitto (2019) state that *"Job growth was by far strongest in occupations with high job quality and weakest in occupations with low job quality, regardless of the indicator used"*. Furthermore, they analyze the problems of the job polarization model in detail, highlighting, for example, that in that theory there is the expectation that occupations dominated by routine tasks are mid-skilled, whereas occupations composed of non-routine tasks are low-skilled, which according to Oesch and Piccitto (2019) is not supported by European survey data.

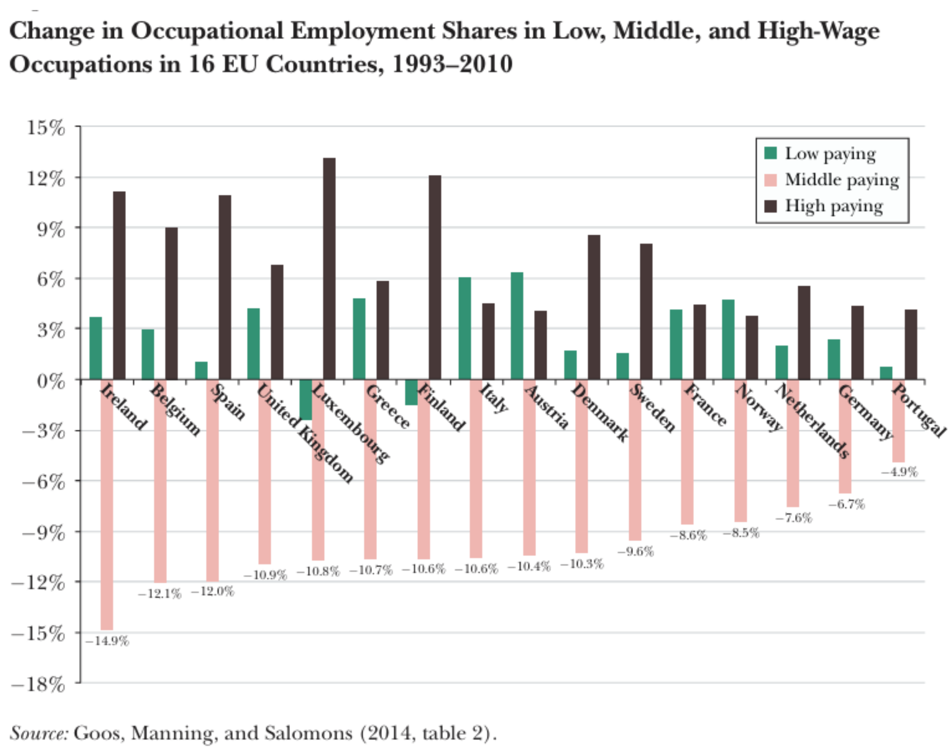

Figure 4.6. Change in Occupational Employment Shares in Low, Middle, and High-Wage Occupations in 16 EU Countries, 1993–2010 – Source: Visualization from Autor (2015) using data from Goos et al. (2014)

When the interviewees of Interview Set 2 were exposed to the two concepts of "Routine

Biased Tech Change" and "Skills Biased Tech Change" and they were asked to pick the one they found strongest in *explanatory power* in terms of what is happening right now due to AI. The results show that 30 out of 36, so 83.4% chose RBTC. In terms of sex, the situation is perfectly balanced with 3 males and 3 females choosing SBTC and the rest RBTC. In terms of the 3 occupational groups, the distribution can be observed in Figure 4.7.

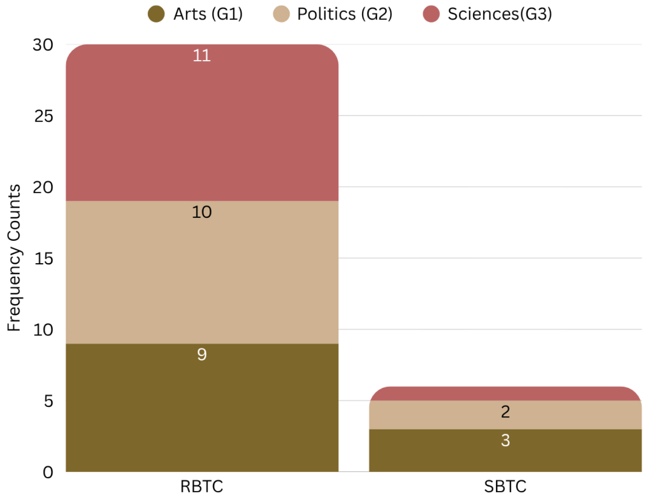

Figure 4.7. The distribution on agreeing with RBTC vs. SBTC by occupational groups – Interview Set 2

When people were asked regarding the rationale behind their choices, the following rationales were provided:

- Most people associate automatization in itself with the concept of routine-ness and repetitiveness, therefore they immediately went for the RBTC. For artists, especially those in the visual arts, they drew parallels with the mass-production through AI generated images and 3D printing, to go as far as to think that *everything has become routine* but with many concerns regarding quality.
- Furthermore, they understood the skills also in comparison to other people and for a few, in their own words they chose RBTC because: *"You don't go out of work when there are people more skilled than you but when you become redundant."*
- It seemed that many interviewees were also eager to choose RBTC because they *wanted the routine elements of their jobs to be replaced by AI* and for them to focus on other aspects of their work.
- For those that chose SBTC, they stated that regardless of the situation, skills make one irreplaceable. Furthermore, if one has the skills to incorporate whatever technologies come along in their craft, then it is only the matter of skills that differentiates and not the routine composition of the profession.

Interestingly, many people didn't find these two theories *necessarily* as mutually exclusive but rather complementary to one another, stating that while the highest skilled workers would have it easier, in any case, their routine tasks could simultaneously be substituted. The fact that respondents overwhelmingly selected Routine Biased Technological Change over Skill Biased Technological Change suggests that young people tend to interpret AI and digitization as forces that primarily automate repetitive, predictable, and routine tasks, rather than as technologies that disproportionately reward high-skill workers.

4.4 The expected impact of AI in Work in the near future (10 years time-frame)

4.4.1 The impact of AI on wage-labor: wages, unemployment, job satisfaction, underemployment

With respect to wages, the respondents of Online Survey 2 were asked if the *real wage* after 10 years of AI development would be: much more, more, the same, less, much less. The distribution can be observed in Figure 4.8. As it can be seen, the wide majority of the respondents 38.6%, do not expect some change to occur in terms of the real wage.

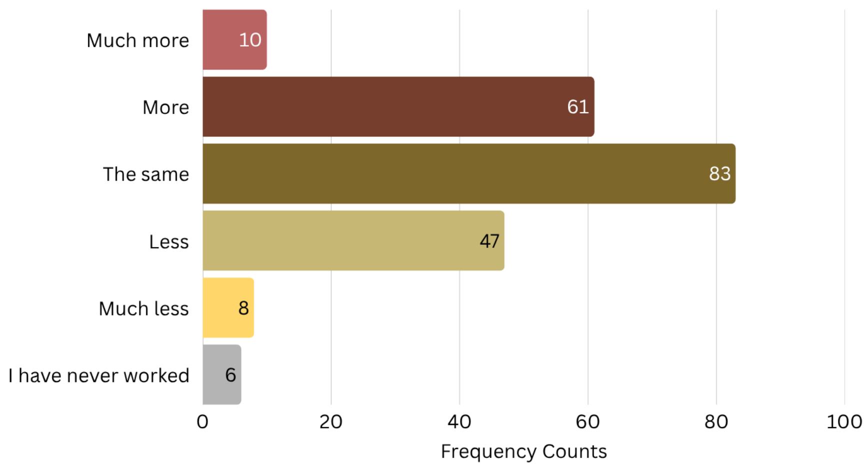

Figure 4.8. The histogram of the change in real wage after 10 years of AI development – Online Survey 2

The distribution in terms of sex and age groups, can be observed in Table 4.1. As shown, in terms of sex the peak is at "the same" and the distributions hardly differ from one-another. The same goes for Gen Z vs. Millennials, thus doing any sort of statistical tests seems in this case redundant due to the high similarity among groups.

Real wage	Female	Male	18–26	27–35
Much more	7	3	6	4
More	33	28	27	34
The same	**37**	**46**	**44**	**39**
Less	26	21	23	24
Much less	4	4	4	4
I have never worked	2	4	6	0

Table 4.1. Perceptions of real wage changes in the next 10 years due to AI, by sex and age group – Online Survey 2

In terms of expectations regarding job losses in the next 10 years due to AI, the distribution can be observed in Table 4.2. This question was also present like the one above in Online Survey 2. The distribution shows that most respondents expect limited job loss due to AI, with the majority choosing estimates below 40%. Only a small minority foresee extreme outcomes, either catastrophic job loss (90 to 100%) or an increase in jobs. This and the distribution on the expectation with respect to wages suggests generally moderate expectations about AI's impact on the wage-labor in the next 10 years. For those respondents who declared that there will be no job loss in their occupation, the following job roles were reported: Inbound Growth Consultant, Nurse, Software Engineer, KYC Officer, Waiter, Digital Forensic Examiner, Interior Architect, Marketing Manager, Terrain Surveyor, System Administrator, Operations Assistant, Project Coordinator, Analyst, Architect, Postdoctoral Fellow, Junior (Economic) Consultant, and Violinist (private orchestra). This diversity of job roles shows that the expectation of no job loss is not limited to a single sector or type of work.

In terms of sex, as shown in Table 4.3, the distribution of responses is again heavily concentrated between 10 and 40 percent for both cases, indicating that most respondents expect only moderate job loss due to AI. Notably, almost twice as many males as females expect that there will be no job loss at all. Additionally, a small number of males (3) anticipate that there will actually be more work available in their occupation, highlighting slightly more optimistic expectations among men. Those three people that expect an increase in jobs in their occupation have the three following self-declared professions: teaching assistant and young researcher, senior consultant in Data Analytics and theater artist, clearly not sharing much in common. The peak of the distribution occurs at "less than 10 percent" for males and "less than 40 percent" for females, although the difference in the number of individuals at these peaks is very small. A Mann-Whitney U test was conducted to compare perceived AI-related job loss risk between males and females, revealing no statistically significant difference ($U = 4549.5$, $p = 0.221$). This suggests that both sexes perceive similar levels of threat to their employment from AI automation.

In terms of the age groups, the distributions can be observed in Table 4.4. Removing

Expected % of job-losses	**Count**
less than 40%	33
less than 10%	32
less than 30%	30
less than 20%	29
less than 50%	23
There will be almost no job loss.	17
less than 60%	16
I have never worked.	14
less than 80%	7
less than 70%	6
between 90 and 100%	3
There will be more jobs for people doing the same work as I do.	3
less than 90%	2

Table 4.2. Perceptions of job loss (%) in their current occupation due to AI in the next 10 years – Online Survey 2

all those people that have claimed they have never worked[5], there are 96 Gen Z and 105 Millennials. The peak of Gen Z is at "less than 10 percent" with 21 respondents choosing that or 21.87% of the Gen Z respondents that are in working relations. The peak for Millennials is slightly higher at "less than 20 percent" with 19 respondents choosing that or 18% of the Millennials. Again, the Mann-Whitney U test was conducted to compare perceived AI-related job loss risk between younger (18-26) and older (27-35) age groups, revealing no statistically significant difference (U = 4523.5, p = 0.206). This suggests that both age cohorts perceive similar levels of threat to their employment from AI automation.

In terms of job satisfaction, the respondents of Online Survey 2 were asked how much they like their current job *now* on a scale from 0 to 10 and how much they expect to like it after 10 years of AI development: much less, less, the same, more, much more. The Sankey diagram shown in Figure 4.9 demonstrates varying effects on the expectations of the respondents liking their job after 10 years of AI development. In terms of those that expect to like their job "much more", 14 out of 21, come from the highest level of current satisfaction, that is 10. Even those who expect to like their job "more", out of the total of 43 respondents: 8 people already like their job at a 10-level, 9 people at a 9-level, 11 people at an 8-level and 7 people at a 7-level. So, if we consider a high level of liking their job if they give a score from 7-10, 81% of the people that expect to like their jobs "more" come from an already high level of current job satisfaction. In terms of those that expect to like their job the same, they come from various levels of current job satisfaction. Whereas for

[5] As noted, the number of people that have claimed they have never worked differs from question to question, highlighting that some people may have wanted to express their opinion on a particular matter, regardless of the fact they may have not worked up to that point.

Expected % of job-losses	**Female**	**Male**
less than 10 percent	16	**16**
less than 20 percent	16	13
less than 30 percent	15	15
less than 40 percent	**19**	14
less than 50 percent	8	15
less than 60 percent	12	4
less than 70 percent	2	4
less than 80 percent	4	3
less than 90 percent	2	0
between 90 and 100 percent	1	2
There will be almost no job loss	6	11
There will be more jobs for people doing the same work as I do	0	3
I have never worked	8	6

Table 4.3. Perceptions of job loss (%) in their current occupation due to AI in the next 10 years by sex – Online Survey 2

Expected % of job-losses	**18–26**	**27–35**
less than 10 percent	**21**	11
less than 20 percent	10	**19**
less than 30 percent	16	14
less than 40 percent	17	16
less than 50 percent	5	18
less than 60 percent	8	8
less than 70 percent	3	3
less than 80 percent	4	3
less than 90 percent	1	1
between 90 and 100 percent	1	2
There will be almost no job loss	9	8
There will be more jobs for people doing the same work as I do	1	2
I have never worked	14	0

Table 4.4. Perceptions of job loss (%) in their current occupation due to AI in the next 10 years by age group – Online Survey 2

those that expect that with the development of AI in the next 10 years they will like their job "less", the respondents come from varying levels of current job satisfaction but those that expect to like their job "much less", come from a current satisfaction of 8 and lower. The full distribution of the expected changes in job satisfaction can be observed in Table 4.5. The main conclusion is that the majority of the respondents of Online Survey 2 expect no changes in their level of liking their job. For those that do, in terms of improvements of job satisfaction levels, they already come from very high levels of job satisfaction and likewise but slightly more spread for those that expect their job satisfaction levels to lower.

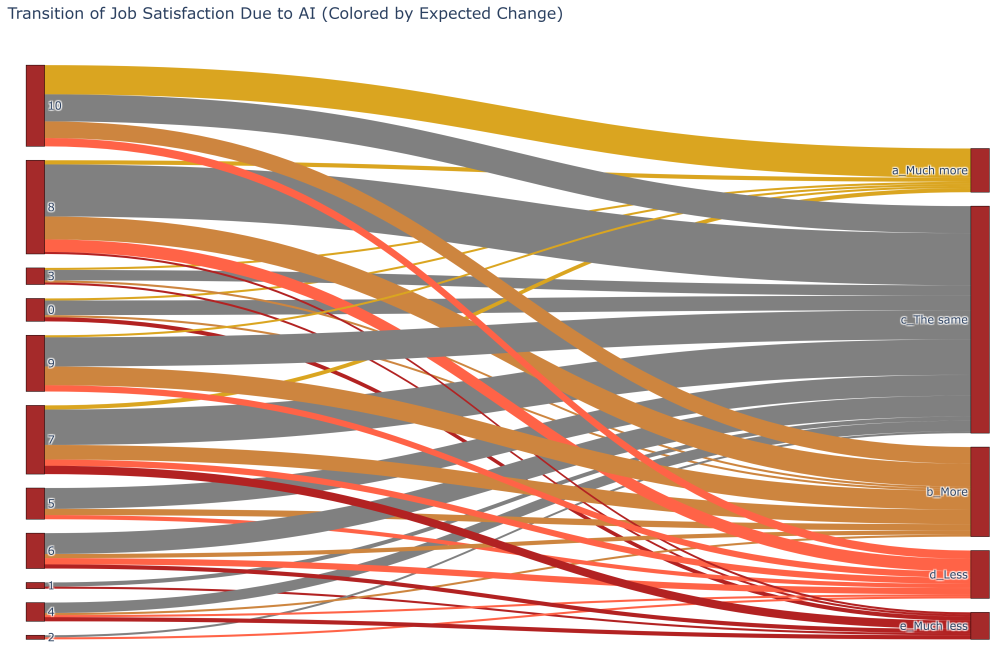

Figure 4.9. The Sankey diagram of people liking their current job and the changes they expect after 10 years of AI development – Online Survey 2

Future Job Satisfaction (10 Years)	**Count**
The same	109
More	43
Less	23
Much more	21
Much less	13
I have never worked	6

Table 4.5. Distribution of the changes in expected job satisfaction after 10 years of AI development – Online Survey 2

With respect to the changes of job liking and sex, after 10 years of AI development, the distributions can be observed in Table 4.6. Males and females appear to have similar distributions with the only exception that 9.1% of females expect to like their job "much less" after 10 years of AI development compared to only 2.8% of males. Whereas for the two age groups the distributions can be observed in Table 4.7. As it can be observed, the

Gen Z (18–26) group reports higher frequencies at the positive extreme ("much more") and a more spread distribution, showing greater uncertainty or volatility in expectations. Younger workers may anticipate more change, both positive and negative in terms of liking their jobs, as AI technologies evolve. However, when the Mann-Whitney U test was conducted to compare expected job satisfaction levels after 10 years of AI development between Millennials and Gen Z, it revealed no statistically significant difference ($U = 4769.0$, $p = 0.928$), at a 5% significance level. While Gen Z appears more polarized or uncertain (more variability), both generations have similar average expectations about job satisfaction. The Mann-Whitney U test detected that the typical (median) Gen Z respondent doesn't differ significantly from the typical Millennial respondent, even though Gen Z shows more diversity of opinion within their group.

Sex	Much more	More	The same	Less	Much less	Never worked
Female	11	22	53	11	10	2
Male	10	21	56	12	3	4

Table 4.6. Distribution of the changes in expected job satisfaction after 10 years of AI development by sex – Online Survey 2

Age group	Much more	More	Same	Less	Much less	Never worked
18–26	14	20	49	15	6	6
27–35	7	23	60	8	7	0

Table 4.7. Distribution of the changes in expected job satisfaction after 10 years of AI development by age group – Online Survey 2

In terms of the working hours, the respondents of Online Survey 2 were asked how many hours they work at their current jobs and how they expect that to change after 10 years of AI development. In Table 4.8 can be observed the distribution of the hours worked on average currently and in Table 4.9 can be observed the expected change in the working hours after 10 years of AI development. Most of the respondents work the regular 8 hours shifts and a considerable number work 10 hours on average. Clearly, most people expect to work *less* in terms of hours and if we consider only those that have been in working relations, then 41.6% of the respondents expect to work less after 10 years of AI development. In Figure 4.10, the Sankey plot shows the flows between the current working hours and expected changes. As can be observed, the respondents that work "maximum 12 hours" expect, interestingly, in their largest majority to work *the same* amount of hours after 10 years of AI development (62.5%). In terms of percentages, this comes in contrast with those who work "maximum 8 hours" that only 37.1% expect to work the same amount and with those that work "maximum 10 hours" that only 40.7% expect to work the same. Curiously, the more hours one currently works, it appears, there is a stronger tendency to expect to work the same amount even after 10 years of AI development. In any case, still the majority of the respondents that work 8 and 10 hours maximum at the moment, expect to work *less* after 10 years of AI development: 47.4% and 48.1%, respectively. The most diversified group in terms of expectations is the one working currently "maximum 6 hours".

Nr of hours worked now	**Count**
maximum 8	78
maximum 10	54
maximum 6	32
maximum 12	16
I have never worked	16
maximum 4	9
more than 12	6
maximum 2	4

Table 4.8. Counts for how many hours are on average worked per day by the respondent in their current job – Online Survey 2

Expected change in hours worked	**Count**
Less	87
The same	79
Much less	33
I have never worked.	6
More	6
Much more	4

Table 4.9. Counts for expected change in working hours after 10 years of AI development – Online Survey 2

Last but not least, in terms of *expected changes in Underemployment* after 10 years of AI development, the study got the results from Interview Set 2, which as previously mentioned had 36 interviewees. For each of the three types of underemployment, the respondents were asked if they expect it in the next 10 years of AI development to get: much better, better, the same, worse, much worse. In the sense that, for example, if skills-related underemployment gets *better* with AI development, that means that there will be less of that sort of underemployment and the young people interviewed will find it easier to find jobs that match their skill-sets. The distribution of the frequency counts can be observed in Table 4.10. The majority of the people from Interview Set 2 expect all three types of underemployment to get *worse* in more or less the same levels. A Friedman test was conducted to examine whether respondents perceived different levels of underemployment across three dimensions (time, skills, and income) after 10 years of AI development, revealing no statistically significant difference ($\chi^2 = 0.67$, $p = 0.717$). After mapping ordinal responses to numeric values (1 = much worse to 5 = much better), median ratings were consistently pessimistic across all dimensions: time underemployment ($Median = 2.0$, worse), skills underemployment ($Median = 2.5$, between worse and

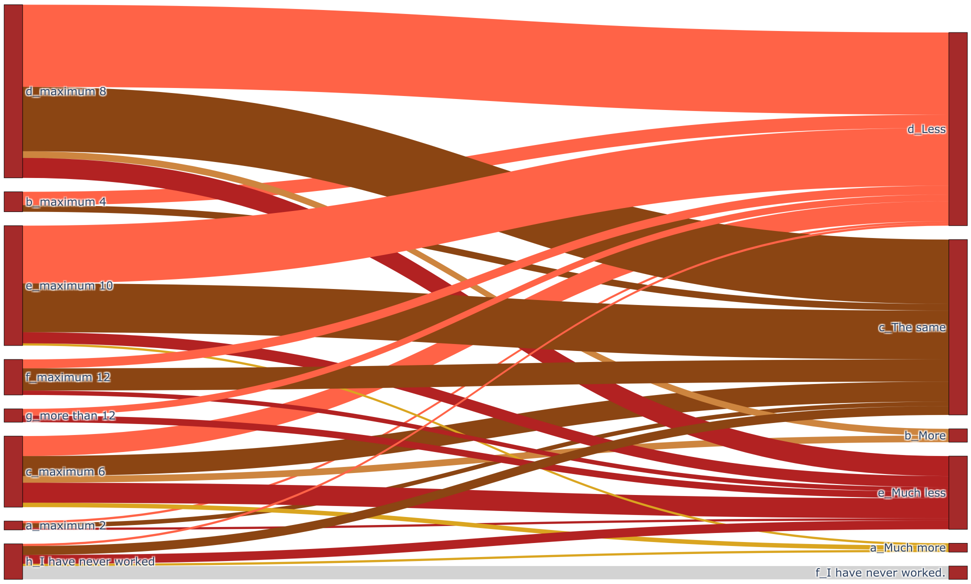

Figure 4.10. The Sankey diagram of current avg. working hours and the changes they expect after 10 years of AI development – Online Survey 2

same), and income underemployment ($Median = 2.5$, between worse and same), suggesting participants expect similar deterioration across all three underemployment aspects.

Expected change	**Time-related**	**Skills-related**	**Wage-related**
Much worse	5	5	4
Worse	**14**	**13**	**14**
Same	9	8	11
Better	4	9	7
Much better	3	1	0

Table 4.10. Perceived underemployment changes in 10 years of AI development across three domains – Interview Set 2

When asked during the interviews to provide a rationale for their choices, the following key arguments surfaced:

- For those that expected the underemployment types to *remain the same*, one of the key arguments was that 10 years appears to be a very short time-frame for substantial changes to take place. Furthermore, they did not see AI having that much of an impact. For example, an artist stated that skills-related underemployment, in the case when they play a far more simplistic music then what they are capable of, was more related to the evolving taste of society rather than tech development in itself.

- For the majority of the respondents who expect things to get *worse* in terms of underemployment with AI development in the next 10 years, the key rationales provided were:
  - People expect that the current seniors in companies or entities with the aid of AI to do more and thus have less need for the younger workers who may be forced to work either part-time (time-related underemployment) or work in jobs that are more service oriented (skills-related underemployment) even if they have more skills.
  - Many seem to be concerned with generative AI effects, particularly in writing tasks and thus linking it to their professions show concerns on different dimensions of underemployment to increase. For example, a political scientist who worked a lot with electoral campaigns showed concerns in terms of AI preparing electoral materials and thus expressing a potential increase of time-related underemployment. On the other hand, there were interviewees within the same category that did not expect AI to be such a proactive part of political organization, given how much persuasion comes in play and how much you have to work with people face to face.
- For those few who had a more optimistic view, thus expecting that underemployment gets *better*, in the sense that we will see less of it, the main argument went as follows: given the fact that AI may do many rudimentary tasks, there will be more *decent* jobs available for people.

4.4.2 The impact of AI on qualitative aspects of work: work as a drudgery, work-life balance, overall work quality.

In terms of the concept of *work as a drudgery* that was also discussed in Chapter 2.4.4, the interviewees of Interview Set 2 were asked to determine for each dimension that makes work a drudgery if after 10 years of AI development it will get: much better, better, the same, worse, much worse. The idea was that, for example, if repetitiveness gets *better*, it means that the work in itself gets less repetitive. The distribution of the expectations of the interviewees can be observed in Table 4.11. As it can be observed, while the wide majority of the interviewees expect their jobs to get less repetitive, in every other dimension the expectations are either reverted or expecting no changes. When considering the highest count for the least optimistic view, thus the dimension getting *much worse*, as show in in Table 4.11, that lies on the expectations with respect to the relationships with the colleagues. In this aspect, the main line of thought provided during the interviews was *the association of AI development with that of the remote work* and thus the expectation of lesser connections among colleagues.

Expected change	Repetitiveness	Colleagues	End Product	Inherent Value
better	17	5	9	5
much better	6	0	1	0
the same	6	12	14	15
worse	4	13	12	11
much worse	3	6	0	5

Table 4.11. Expected changes in work as a drudgery dimensions after 10 years of AI development – Interview Set 2

In terms of sex, the distributions can be observed in Table 4.12. In terms of *repetitiveness* and *the connection with the end product and the end user*, the expectations among males and females appear to be similar. However, with respect to *the connection with the colleagues*, most females expect it to get either worse or much worse at 72%, compared to 33% of males, indicating that females in the sample have a much more negative outlook on the impact AI will give to the connection with their colleagues after 10 years of development. Likewise, in terms of *the belief in the inherent value of work*, 61% of females expect it to get either worse or much worse compared to 27% of males.

Category	Repetitiveness		Colleagues		End Product		Inherent Value	
	M	F	M	F	M	F	M	F
better	9	8	3	2	5	4	3	2
much better	3	3	0	0	0	1	0	0
same	3	3	9	3	7	7	10	5
worse	1	3	4	9	6	6	4	7
much worse	2	1	2	4	0	0	1	4

Table 4.12. Expected changes in work as drudgery dimensions after 10 years of AI development by Sex – Interview Set 2

With respect to the three occupational groups and the expected changes in the work as a drudgery categories, the distributions can be observed in Table 4.13. In politics, 8 respondents expect the connection with the end product and end user to get worse, which is substantially higher than in arts (3) and sciences (1). This indicates a stronger sense of future detachment from meaningful outputs from people in politics. Moreover, while respondents in both arts and politics largely anticipate that the inherent value of their work will get worse or much worse (44% for arts and 33% for politics), those in the sciences mostly expect it to remain the same (38%). In terms of the changes to the connection with the colleagues, the three occupational groups appear to follow a similar pattern. Lastly, in terms of changes in the repetitiveness of work, most of them expect it to get better, thus work to get less repetitive but people in arts show a more spread distribution. To understand this further, violin plots were made as they can be observed in Figure 4.11. People from arts (G1) show more spread in their views about AI's impact on work repetitiveness, with responses fairly evenly distributed from "much worse" to "much better."

People from politics (G2) have a taller distribution centered around "same" to "better," suggesting more consensus that AI has a neutral to positive effect on repetitiveness. People from sciences (G3) show the most concentrated distribution skewed toward "better," indicating they more consistently feel AI has reduced repetitiveness in their work. It has to be noted that while violin plots are designed for continuous data and this visualization uses ordinal Likert-scale responses, so the smooth curves represent approximations of the distribution rather than true intermediate values between categories.

Category	**Repetitiveness**			**Colleagues**			**End Product**			**Inherent Value**		
	g1	g2	g3	g1	g2	g3	g1	g2	g3	g1	g2	g3
better	5	5	7	2	1	2	3	2	4	0	2	3
much better	0	3	3	0	0	0	1	0	0	0	0	0
same	3	3	0	3	4	5	5	2	7	4	4	7
worse	2	0	2	4	5	4	3	8	1	5	4	2
much worse	2	1	0	3	2	1	0	0	0	3	2	0

Table 4.13. Expected changes in work as drudgery dimensions after 10 years of AI development by occupational groups (G1-Arts; G2-Politics; G3-Sciences) – Interview Set 2

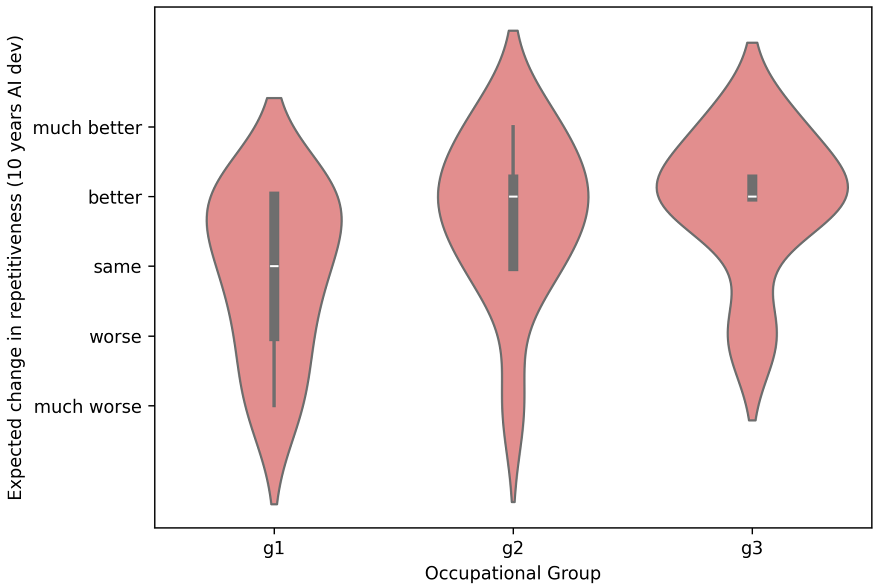

Figure 4.11. The violin plot of perceived changes on Work Repetitiveness after 10 years of AI development by occupational groups (G1-Arts; G2-Politics; G3-Sciences) – Interview Set 2

With respect to the *work-life balance*, which as observed in Chapter 2.4.2, it was the first ranking dimension that made a job - a good job, for the respondents of Online Survey 1, the concept was further explored in Interview Set 2, specifically under the *spillover model* (Guest, 2002). The goal was to understand the expected change in this dimension after 10 years of AI development, if it will become: much better, better, the same, worse, much worse. The distribution of the responses can be observed in Table 4.14. Clearly the wide majority of the respondents, that is 44.45% expect the work-life balance to get *better* due to AI development. The rationales provided during the interviews for those that expect the work-life balance to get better mainly had as a core point the fact that routine tasks would get automated and workers would have more time for either more enjoyable tasks or for themselves. For the people that expect work-life balance to remain the same even after 10 years of AI development, the key point was the fact that the whole concept of work-life balance was not tangible upon technologies in themselves but rather the culture of the workplaces and even in the cases that AI could automate some tasks, the workers and their managers would find, in an interviewee's own words: *"other stuff to stress and be anxious about"*. For the 7 interviewees that expect work-life balance to get worse they key arguments revolved around increased competition and the idea that since workers now had AI to help them, they would be expected to do much more to *justify* their work.

Expected change	**Count**
better	16
the same	12
worse	7
much better	1
much worse	0

Table 4.14. Perceived work-life balance changes in 10 years of AI development – Interview Set 2

In terms of sex and occupational groups, the distribution can be observed in Table 4.15 and 4.16. Interestingly, the majority of males, 10 out of 18, expect the work-life balance to get better compared to only 6 out of 18 females. Furthermore, out of the 7 people that expect work-life balance to get worse, 6 out of 7 are female. Across the three occupational groups, we observe a generally more positive outlook from people coming from sciences and rather more spread expectations from those coming from arts and even more spread with respect to the interviewees coming from politics. Hence, even if the majority of the participants in Interview Set 2 expect work-life balance to get *better* after 10 years of AI development, if disintegration is done based on sex and occupational groups, diverging patterns are observed. Females are more concerned than males and people from politics and arts being more concerned than those coming from sciences.

Furthermore, the respondents of Online Survey 2 were asked to take many factors into account and determine if after 10 years of AI development their *overall work quality* would be: much better, better, the same, worse, much worse. The histogram can be observed in

Expected change in work-life balance	Male	Female
better	10	6
much better	0	1
same	7	5
worse	1	6

Table 4.15. Perceived work-life balance changes in 10 years of AI development by sex – Interview Set 2

Expected change in work-life balance	Arts(G1)	Politics(G2)	Sciences(G3)
better	5	4	7
much better	0	1	0
same	5	3	4
worse	2	4	1

Table 4.16. Perceived work-life balance changes in 10 years of AI development by occupational group – Interview Set 2

Figure 4.12. Clearly, the wide majority expect the overall quality of their jobs to get *better*.

When the analysis is based on the two age groups, (18-26) Gen Z with 110 respondents and (27-35) Millennials with 105 respondents, thus a relatively balanced dataset, the distribution of the responses can be observed in Table 4.17. The 12 respondents that had selected "I have never worked" were all from the GenZ group. Thus, the new counts per each age group are 98 respondents for Gen Z and 105 respondents for Millennials. The same is done in terms of sex and after dropping those that have chosen "I have never worked", there are 101 males and 102 females, and the distribution can be observed in Table 4.18.

Age Group	Much Worse	Worse	The Same	Better	Much Better
18–26	1	14	31	46	6
27–35	2	11	24	56	12

Table 4.17. The distribution of the changes in overall job quality after 10 years of AI development by age group - Online Survey 2

Sex	Much Worse	Worse	The Same	Better	Much Better
Male	1	11	33	45	11
Female	2	14	22	57	7

Table 4.18. The distribution of the changes in overall job quality after 10 years of AI development by sex – Online Survey 2

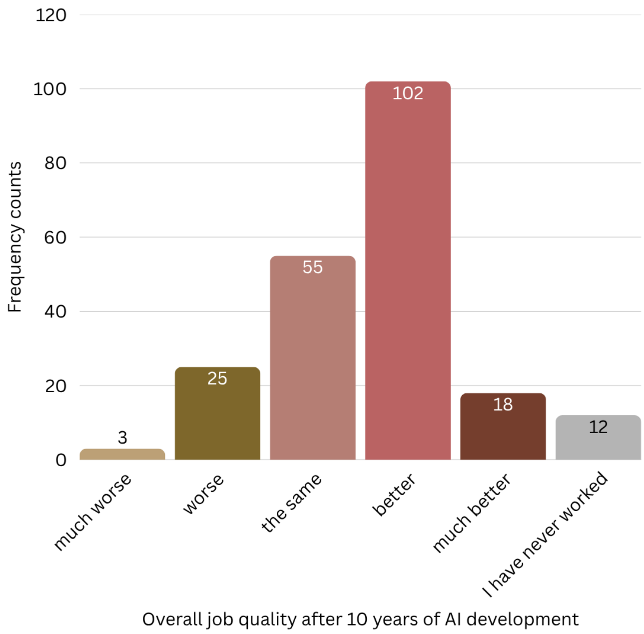

Figure 4.12. The histogram of the changes in overall job quality after 10 years of AI development – Online Survey 2

Clearly, the peaks of the distributions in both demographics seems to be at overall work quality becoming *better*. Grouping the "much better" and "better" categories and considering the respondents that have chosen them as having *a positive outlook* on the changes in job quality, the differences in terms of percentage points between the two age groups and sexes are plotted in Figure 4.13. Millennials have a higher positive outlook on overall job quality (64.7%) compared to Gen Z (53%), indicating a difference of 11.7 percentage points. Millennials generally have been in the workforce longer than Gen Z and may have more stable jobs, higher salaries, or greater confidence in their career trajectories, which could explain their more positive outlook. In terms of sex, females report a more positive outlook (62.7%) than males (55.4%), showing a moderate gender gap of 7.3 percentage points.

Last but not least, the respondents of Online Survey 1 were asked: *In today's society, paid work holds a central role in people's lives. Do you think that due to new technologies such as AI, society will be so profoundly transformed that work will no longer be a central component of people's lives within your lifetime? On a scale from 0 to 10, how likely is this to occur?* The histogram can be observed in Figure 4.14.

This distribution shows a clear peak in the middle range (values 5-6), with value 5 having the highest frequency (16) and value 6 close behind (15). There's a concentration of responses in the middle-to-lower-middle range (values 2-6), which account for most of the

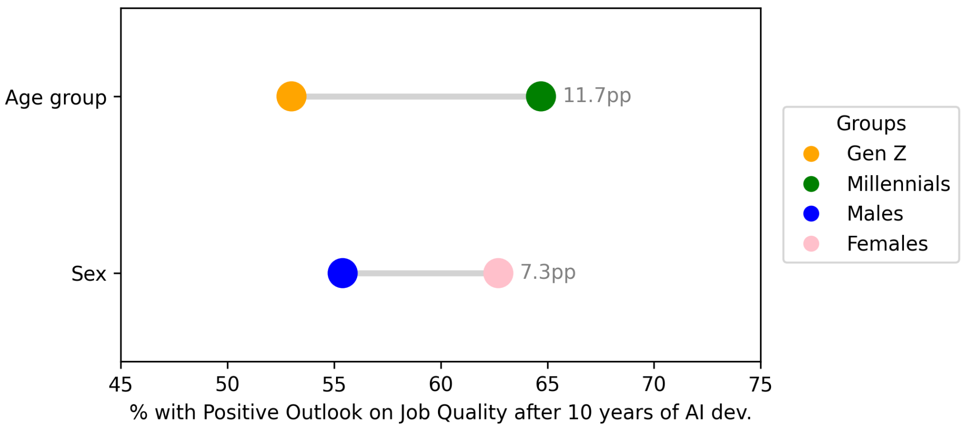

Figure 4.13. Dumbbell Chart: Positive Outlook (Better + Much Better) on overall job quality changes after 10 years of AI development by Age Group and Sex – Online Survey 2

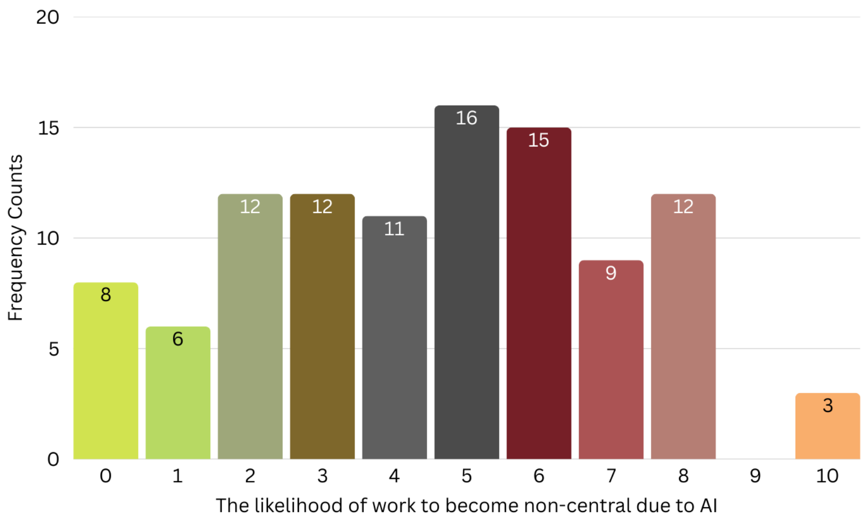

Figure 4.14. The histogram of the likelihood of work becoming non-central to people's lives within their lifetimes due to AI – Online Survey 1

data. The distribution then tapers off toward both extremes, with notably fewer responses at the low end (0-1) and especially at the high end (10). Thus, we can say that the sample of Online Survey 1 does consider it as a real possibility that work loses its centrality but they are moderate about it. The distributions in terms of sex and age groups can be observed in Table 4.19 and Table 4.20, respectively. Clearly, the majority of those who are the most pessimistic regarding work becoming non central within their lifetimes due to

AI, thus giving a score of 0, are males (87.5%). Interestingly, even those three individuals that have given a score of 10 are also males, illustrating how the group is quite spread with respect to their expectations. Likewise, Millennials appear to have higher counts on the more pessimistic level-0 and level-1, whereas Gen Z appears to be more spread across the levels. The Mann-Whitney U test reveals no statistically significant difference between males and females in their expectations about work becoming non-central in people's lives ($U = 1354.0$, $p = 0.992$), indicating that sex does not appear to influence these expectations in the sample. Likewise, the Mann-Whitney U test shows no statistically significant difference between Gen Z (18-26) and Millennials (27-35) in their expectations about work becoming non-central in people's lives within their lifetimes ($U = 1313.0$, $p = 0.926$), indicating that generational cohort does not meaningfully influence these expectations. The very high p-values (well above the conventional 0.05 threshold) suggest that both genders hold remarkably similar views on this potential societal shift regarding the centrality of work. Moreover, the correlation between the optimism people have about AI's impact in society and their expectations about work becoming non central in the near future is studied. The Spearman's rank correlation analysis reveals a weak but statistically significant positive relationship ($\rho = 0.219$, $p = 0.026$). This suggests that individuals who are more optimistic about AI's societal impact tend to anticipate a greater shift away from work-centricity within their lifetimes, though the modest correlation coefficient indicates this association explains only a small portion of the variance. The finding implies that positive attitudes toward AI may be *somewhat* linked to expectations of fundamental transformations in the role of work, though other factors likely play substantial roles in shaping these expectations. The distribution is shown in Figure 4.15, where darker dots indicate higher frequency of responses.

Scale	0	1	2	3	4	5	6	7	8	9	10
Female	1	3	6	9	6	10	7	3	7	0	0
Male	7	3	6	3	5	6	8	6	5	0	3

Table 4.19. Counts of work becoming non central within the respondents' lifetimes due to AI development perception scores by sex – Online Survey 1

Scale	0	1	2	3	4	5	6	7	8	9	10
18–26	3	2	7	5	6	5	6	4	6	0	1
27–35	5	4	5	7	5	11	9	5	6	0	2

Table 4.20. Counts of work becoming non central within the respondents' lifetimes due to AI development perception scores by age group – Online Survey 1

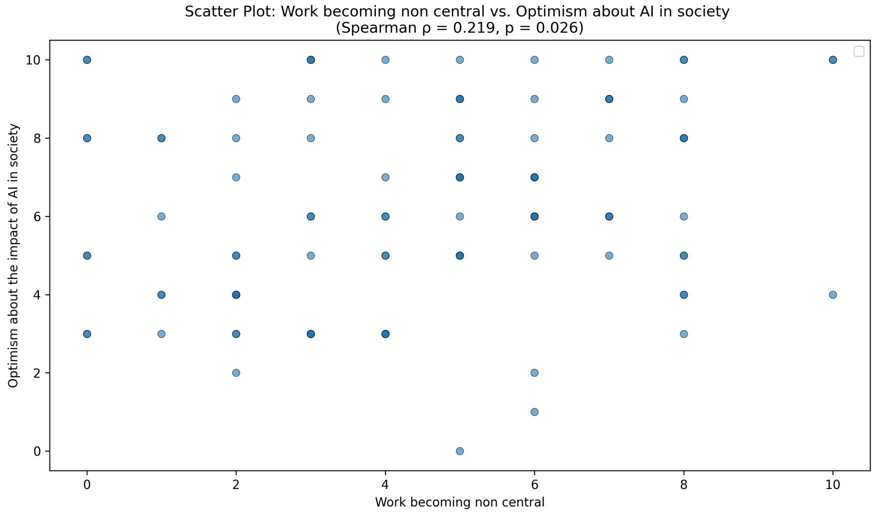

Figure 4.15. Scatter Plot: Work becoming non central vs. Optimism about AI in society (Spearman rho = 0.219, p = 0.026) – Online Survey 1

4.4.3 The impact of AI in unpaid household work.

In terms of the expected impact of AI in unpaid household work, the interviewees of Interview Set 2 were asked if in the next 10 years the time they spend on household related tasks will be: much more, more, the same, less, much less, taking into account potential developments in AI. The histogram of the responses can be observed in Figure 4.16. It clearly shows that the vast majority of interviewees, 20 out of 36, so 55.56% expect to spend *less* time in household tasks in the next 10 years.

When the analysis is performed on the basis of sex, both groups chose *less* as the dominant category, with 10 people from each sex. However, interestingly, the second-largest group for females is *much less* with $Frequency = 6$ whereas for males it is *the same* also with $Frequency = 6$. In terms of the distribution with respect to occupational groups, it can be observed in Table 4.21.

Group	Much More	More	The Same	Less	Much Less
g1 (Arts)	0	1	3	4	4
g2 (Politics)	0	0	2	8	2
g3 (Sciences)	0	1	2	8	1

Table 4.21. Distribution of the expected time to be spent on household tasks change after 10 years of AI development by occupational group – Interview Set 2

In order to see if there are statistically significant differences in the central tendencies of the three occupational groups with respect to changes in the time spent on household

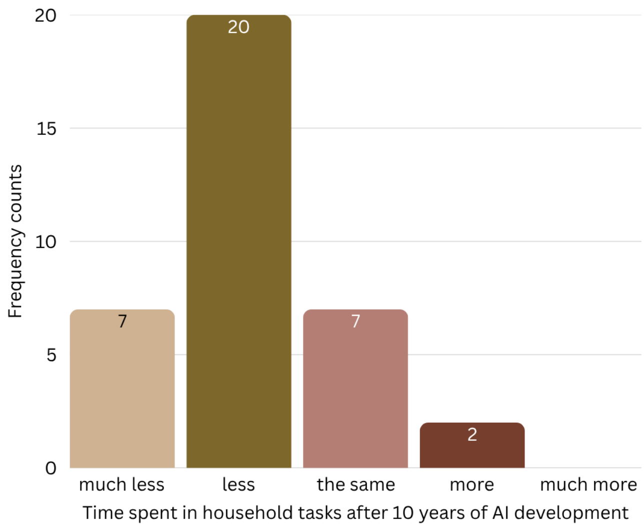

Figure 4.16. The histogram of the expected time spent on household tasks after 10 years of AI development – Interview Set 2

tasks, the non parametric The Kruskal-Wallis test (H test) is used. The results show $H - statistic = 0.837$ and $p - value = 0.658$, way above the 5% significance threshold. Thus, we fail to reject the null hypothesis and there appears to be no statistically significant difference among the distributions of the three occupational groups.

In terms of the rationales provided during the interviews, the most common expectation from those expecting that the time spent on household tasks will be either *less* or *much less* was the fact that the interviewees expected new gadgets to be created and to become commonly used in households. They bring the example of the clothes dryer, automatic floor sweeper, etc. Those that expect the time to remain *the same*, stated that AI will not be developed to such extent in the next 10 years that it can be integrated in household tasks and that. In those rare occasions ($Frequency = 2$) that people expected to spend *more* time in household-related tasks, the rationale of one of the respondents, for example, went as follows: *"...more because the respondent is imagining a scenario in which the respondent works from home and is connected to multiple computers and they are quite automated. Thus, the respondent will want to do something and the respondent claims they will turn to their home to be active to do stuff."*

4.5 Paradoxes, mon amour: The matter of productivity

Productivity, defined as the efficiency with which inputs are transformed into outputs, is widely recognized as a fundamental driver of economic growth. As highlighted by Kim et al. (2016), sustained improvements in productivity are central to the long-term development of economies, making it a key determinant of economic performance.

Widespread adoption of artificial intelligence technologies has generated substantial public and media expectations regarding their potential to boost productivity. Yet, empirical evidence often appears inconsistent with these expectations, leading to the re-emergence of the so-called **"The Productivity Paradox"** or **"The Solow Paradox"** (Wikipedia contributors, b). Solow famously noted in a book review in 1987:

> *"You can see the computer age everywhere but in the productivity statistics,"*

emphasizing the discrepancy between visible technological advances and measured productivity growth. More recently, Brynjolfsson et al. (2019) document that despite the transformative potential of AI, the expected productivity gains have not yet materialized at the aggregate level, marking a renewed manifestation of the paradox in the context of modern AI adoption. Figure 4.17 illustrates precisely that by showing how the rate of growth of productivity has been slowing down and if in the 70-s it was about 3.5% (considering the whole world), it has been continuously decreasing with a small increase after the commercialization of the internet but not enough to make up for the previous levels.

Current productivity growth statistics do not appear to be substantial, a conclusion that is supported by the observed trends in economic growth data. As Banerjee and Duflo note at the beginning of their chapter on growth in their best-selling book "Good Economics for Hard Times" (Banerjee and Duflo, 2019):

> *"Growth ended on October 16, 1973, or thereabouts, and is never to return, according to a wonderfully opinionated book by Robert Gordon."*

They proceed to offer their own assessment:

> *"What we can say with some confidence is that there is nothing in the available evidence promising a return to the kind of fast growth in measured GDP that characterized the Trente Glorieuses in Europe and the golden years in the United States."*

The *Trente Glorieuses* refers to the period following World War II up to the 1970s, during which remarkable rates of productivity and economic growth were observed in Western countries and beyond. The comparison underscores the stark contrast between that historical era of rapid growth and current subdued productivity trends.

Different economists offer a range of explanations for the apparent paradox between high expectations of productivity growth and relatively modest empirical outcomes. Just as in the film "Hiroshima, mon amour", there is a perfect fusion of two seemingly incompatible elements; the invariable blending of trauma and intimacy, destruction and affection, memory and forgetting. Likewise, as technologies are advancing, we find ourselves living with paradoxes where progress and uncertainty unfold side by side. Bootle (2019),

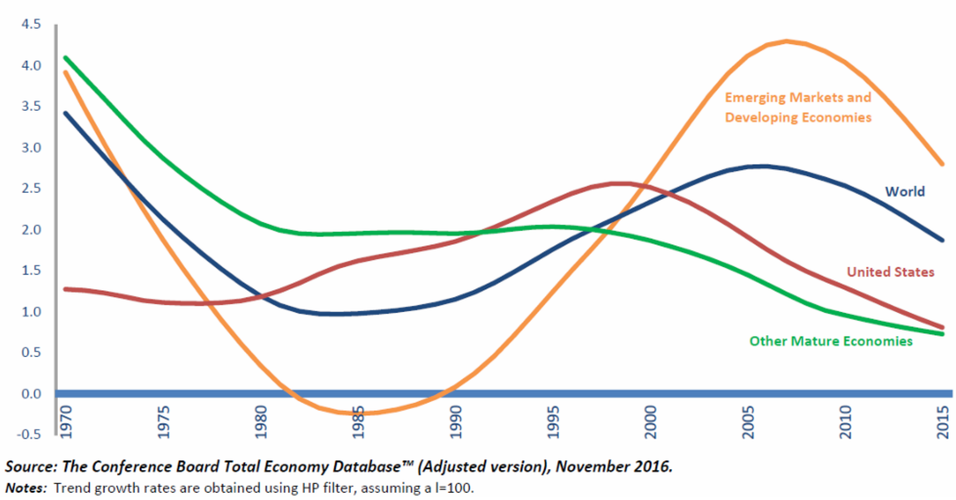

Figure 4.17. Smoothed Average Annual Labor Productivity Growth (Percent) by Region (Source: Brynjolfsson et al. (2019))

in "The AI Economy", identifies two main perspectives offered by economists to explain weak productivity growth. The demand-side explanation attributes slow productivity to weak aggregate demand, which has limited investment in plants, machinery, buildings, and software, thereby restricting workers' access to capital. The supply-side perspective, by contrast, is largely technological in nature, emphasizing that weak growth is due to insufficient technological progress. Economists such as Robert Gordon are often cited as proponents of this supply-side view. Bootle (2019) further discusses four counterarguments to the weak technological explanation. The first, the mismeasurement argument, suggests that official statistics may understate productivity gains, a point Bootle (2019) appears to support, noting that *"it is unlikely that the official data are telling the whole story"* (pp. 38). The second considers the lingering effects of the 2008 Great Financial Crisis, while the third emphasizes that the digital revolution still requires time to fully influence productivity. Finally, Bootle highlights that society is on the brink of new developments, which he expects will eventually boost productivity. He anticipates that robots and AI will reinvigorate the engine of growth, though he notes this depends on whether aggregate demand can absorb the rapid increases and whether increased supply capacity translates into output or leisure. Gordon (2018)'s analysis, particularly in his 2018 study *"Why has economic growth slowed when innovation appears to be accelerating?"*, focuses on the U.S., showing that productivity growth slowed after 2006 despite increasing patent activity. He attributes this to factors such as the maturity of the IT revolution, declining productivity of researchers, diminishing returns to drug innovation, the gradual rather than revolutionary impact of AI and robotics, low investment, and mismeasurement.

Brynjolfsson et al. (2019) propose four potential explanations for the current mismatch between expectations and observed productivity, particularly with respect to AI. First, *false hopes*, in which initial enthusiasm for AI leads to overestimated expectations and perhaps these technologies won't be as transformative as many expect, and although they might have modest and noteworthy effects on specific sectors, their aggregate impact might be small. Second, *mis-measurement*, acknowledging that conventional productivity metrics may fail to fully capture the effects of AI and digital technologies. This explanation implies that the productivity benefits of the new wave of technologies are already being enjoyed but have yet to be accurately measured. Third, *concentrated distribution and rent dissipation*, meaning that the gains from AI may be captured by a small set of firms or sectors rather than diffused broadly. For instance, two of the most profitable uses of AI to date have been for targeting and pricing online ads, and for automated trading of financial instruments, both applications with many zero-sum aspects. Finally, *implementation and restructuring lags*, which occur because the most advanced AI capabilities have not yet diffused widely and complementary innovations are required for their full productivity impact to be realized. This infers that it takes a *substantial amount of time* to see the gains from these new technologies.

It also must be noted, the rather different perspective is offered by Benanav (2020) in "Automation and the Future of Work". He challenges what he calls "automation theorists", a group he does not define with full precision, who attribute declining labor demand to rapid technological change. While he acknowledges that more output is indeed being produced with fewer workers, he argues that this phenomenon is not primarily driven by technological dynamism. Instead, Benanav (2020) contends that the underlying issue is a long-term slowdown in output growth itself (pp. 23). The statistical evidence he presents regarding weak labor demand does not, for him, support the idea that productivity is substantially rising in practice. As he writes: *"What automation theorists describe as the result of rising technological dynamism is actually the consequence of worsening economic stagnation, following on decades of manufacturing overcapacity and underinvestment"* (pp. 39). According to Benanav (2020), manufacturing and industrialization historically functioned as the "true" engines of growth because they allowed for steady, incremental productivity increases. This engine has weakened over recent decades due to the replication of technical capacities across countries, growing international redundancy, and increasingly fierce global competition for markets.

Crucially, Benanav (2020) argues that no comparable engine has emerged outside the manufacturing sector. As a result, workers have been reallocated into low-productivity activities, predominantly within the service sector. He rejects the idea that technological innovation is approaching exhaustion. Rather, he suggests that *"it is more likely that low rates of industrial productivity are the result of a slower pace of industrial expansion rather than the reverse"* (pp.34).

The matter of productivity was addressed in both Online Survey 2 and Interview Set 2. In Online Survey 2 the respondents were asked how "productive" AI made them *now* on a scale from 0 (not at all) to 10 (extremely) and how much productive they expected AI to make them after 10 years of development on the same scale. The distributions can be observed in Table 4.22. As it can be observed, the majority of the respondents (18.13%) report a level of 7 in terms of the productivity of AI *now* and the maximal level of 10 in terms of the expected productivity *after 10 years of AI development* (17.2%). However, it has to be noted that in both cases a substantial group still stick to a productivity level of 0. The Sankey diagram in Figure 4.18 further illustrates this stickiness property of the levels of productivity, particularly the extrema. All the 20 selections of a productivity level of 0 after 10 years of AI development come from a current productivity level of 0 and 48.64% of the selections of a productivity level of 10 after 10 years of AI development comes from an already level of 10 currently. The are only 2 cases of downgrading from a productivity level of 10 to that of 7 and 8.

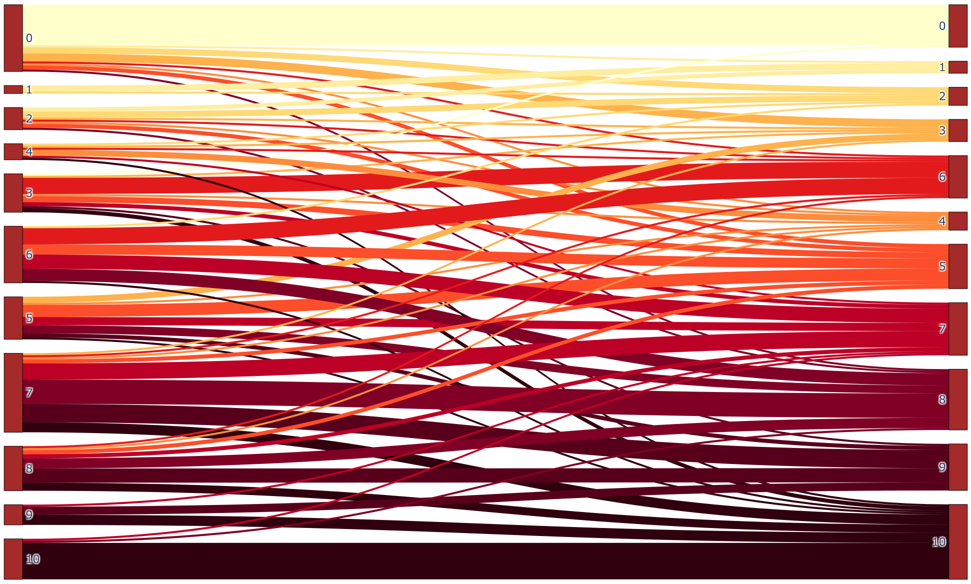

Figure 4.18. The Sankey diagram of the flows between the current levels of productivity and the expected one after 10 years of AI development – Online Survey 2

In terms of sex and age groups, the distributions can be observed in Table 4.23. Both females and males show upward-sloping distributions, indicating that respondents generally expect AI to improve productivity over the next decade. Male respondents show a slightly stronger concentration at the highest score (10), whereas female responses are more evenly distributed across the upper range. Overall, the pattern suggests broadly optimistic expectations across both groups, with men expressing slightly higher anticipated gains. In terms of age groups, the distributions differ much more. Clearly, Gen Z has an equal number of respondents that expect productivity to be 0 and 10 after 10 years of development displaying a bimodal distribution, whereas Millennials seem to exhibit a more positive outlook with the main frequency counts concentrated at the upper end of the productivity scores.

Score	Productive Now (Count)	Productive in 10 Years (Count)
0	33	21
1	4	6
2	11	9
3	19	11
4	8	9
5	21	22
6	28	21
7	**39**	26
8	22	30
9	10	23
10	20	**37**

Table 4.22. Comparison of productivity scores now and expected productivity after 10 years of AI development – Online Survey 2

Score	Female	Male	18-26	27-35
0	10	11	**17**	4
1	3	3	2	4
2	3	6	6	3
3	9	2	5	6
4	4	5	4	5
5	12	10	13	9
6	11	10	13	8
7	12	14	13	13
8	**17**	13	13	17
9	12	11	7	16
10	16	**21**	**17**	**20**

Table 4.23. Expected productivity after 10 years of AI development by sex and age group – Online Survey 2

In Interview Set 2, the interviewees were exposed to the four lines of thought noted by Brynjolfsson et al. (2019) with respect to the modern productivity paradox explained above. They were asked to choose the one theory they found to be most believable. The histogram of their choices can be seen in Figure 4.19. Clearly, most people find the "implementing lags" argument to be the most probable (36.11%) followed closely in the second place by the "concentrated distribution" argument (33.33%). The main rationales provided from the proponents of each argument were along the following lines:

- False Hopes: Interviewees who support the false-hopes explanation argue that society consistently overestimates technological progress, historically expecting innovations such as flying cars that never materialized. One explanation offered is that the exceptional post–World War II productivity boom was driven by massive reconstruction efforts and intense ideological competition, conditions that no longer exist today. They also highlight that modern technologies often affect only specific sectors and fail to diffuse widely; for example, entire industries in regions like Pakistan continue using very old machinery. As a result, the economic impact of recent AI developments may be more limited than the public narrative suggests, at least for now.

- Measurement: Several interviewees believe the productivity paradox is largely driven by mismeasurement, because today's digital and AI-driven activities are not properly captured by traditional productivity statistics. They point out that people now use tools like ChatGPT, YouTube learning content, instrument-tuning apps, and many other digital services that significantly improve efficiency but leave no trace in conventional economic indicators. Some argue that measurement tools remain rooted in an outdated, capital-centric worldview that ignores new forms of value creation, such as social-media-based income or intangible knowledge work. Others, coming from sciences, emphasize that classic models (like the Cobb-Douglas production function) introduce statistical errors that underestimate the economic contribution of modern technologies.

- Concentrated Distribution & Rent Dissipation: Interviewees supporting this argument believe that technological development today is highly uneven, with productivity gains and wealth concentrated in the hands of a few actors. Several note that although advanced technologies exist, they are often applied to trivial or low-impact areas, such as ads or entertainment, rather than sectors that matter for broad economic growth. Some argue that society misuses technology by over-investing in social media and other low-productivity activities, dissipating potential gains instead of reinforcing economic fundamentals. Others see this as consistent with current global patterns of capital accumulation, where technology amplifies existing inequalities rather than diffusing benefits widely. Some emphasize that technologies remain siloed in certain industries and fail to penetrate the broader economy, preventing widespread productivity growth.

- Implementing and Restructuring Lags: Interviewees who favor this explanation argue that AI technologies have evolved far faster than society, institutions, and labor markets can adapt. Because of this, productivity gains cannot yet appear: businesses need time to restructure, workers need to move into new roles, and complementary processes must be developed. Many point out that AI diffusion is still uneven, despite the popularity of tools like ChatGPT in some circles, most people and companies do not use AI extensively or effectively. Others stress that previous generations of AI also went through cycles of enthusiasm and stagnation, showing that long adjustment periods are normal and often slowed by risk aversion. Several respondents highlight that measurement systems themselves lag behind technological change, making it too early to judge AI's real productivity impact. Overall, they see this argument as the most historically grounded and persuasive, emphasizing that both human organizations and technological infrastructure require significant time to adapt before large productivity boosts can materialize.

In terms of occupational groups and sex, the distributions can be observed in Figure 4.20 and Figure 4.21, respectively. In terms of *false hopes*, the people coming from politics find it equally believable as those coming from sciences, with the arts group showing the smallest percentage (20%). In terms of sex, females seem to be more likely (60%) to support it as opposed to males. The *implementing lags* argument, which was the most supported one overall, seems to be a more common choice of males (61.5%) as opposed to females (38.5%) and of people coming from arts (38.5%), but not that far from those coming from politics and sciences, having both an equal representation (30.8%). With respect to the *concentrated distributions* argument and occupational groups, like in the case of implementing lags, the art group is the wider majority (41.7%), however, again followed closely by the politics group (33.3%) and the sciences group (25%). In terms of sex, females seem to be more likely to accept this argument (58.3%). Lastly, *the measurement* argument appears to have a perfectly equal representation from both sexes, but with respect to the occupational groups, the sciences group is the one that is the biggest proponent with 50% of the individuals who chose this argument being from this group. As noted previously, some respondents even denoted specific metrics or models.

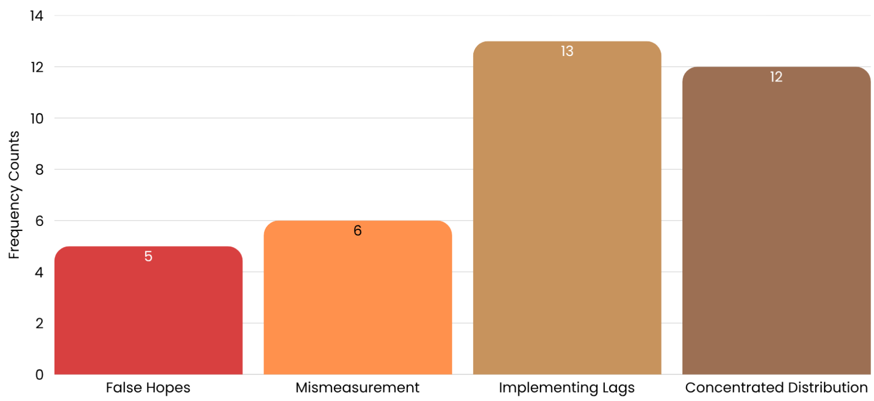

Figure 4.19. The histogram on the choices of the most believable explanation for the modern productivity paradox – Interview Set 2

Moreover, a positive outlook was taken as a mental exercise, namely one in which productivity actually does increase substantially in the near future due to AI. The economic question that presents itself then is whether people would use these productivity gains as *increased output*, meaning to keep on working at the same rate, or as *increased leisure*. This distinction is crucial because whether people use productivity gains for more output

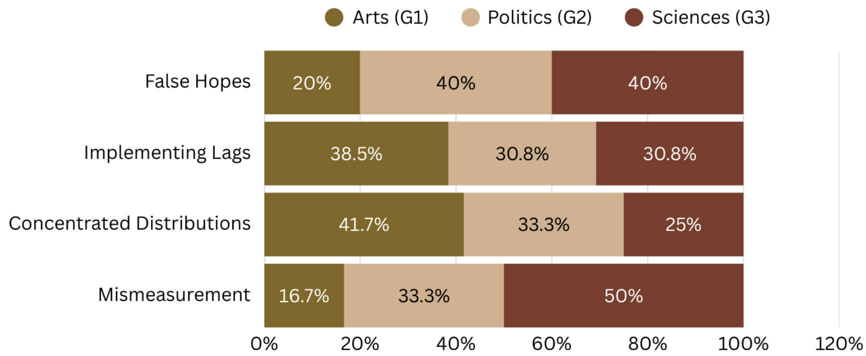

Figure 4.20. The histogram on the choices of the most believable explanation for the modern productivity paradox by occupational group – Interview Set 2

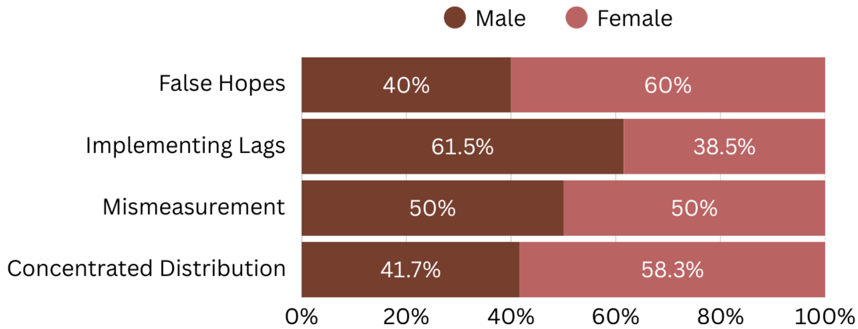

Figure 4.21. The histogram on the choices of the most believable explanation for the modern productivity paradox by sex – Interview Set 2

or more leisure fundamentally shapes how economic growth translates into living standards. If workers choose additional leisure, productivity improvements may not appear in aggregate output statistics even though well-being increases. Understanding this trade-off helps policymakers design labor, welfare and technology policies that align economic incentives with societal preferences. This matter is also discussed by economists like Bootle (2019) but also by technologists like NVIDIA's CEO, who anticipates that technology will unleash a wave of new ideas and unfinished projects, thus leaving people busier, not freer, as "everybody's jobs will be different" (Coacci, 2025).

In this case as well, the participants of Interview Set 2 were presented with the matter, and **20 out of 36 people expected that the majority of the population would opt for increased leisure.** Histograms in terms of sex and occupational groups can be observed in Figure 4.23 and Figure 4.22. While in terms of sex the distributions are perfectly equal, in terms of the occupations the matter changes dramatically with respect to the political group, making the widest majority of those who expect *increased leisure*. The rationales provided during the interviews were mainly along the following lines:

- Increased Leisure: many respondents who chose this argument expected people to want to "be free" as opposed to produce *more* things, particularly for *someone else*. In one case, the notion of *leisure* itself was not viewed in a positive connotation but rather associated with some form of *numbness*. One interviewee noted that after COVID people discovered (*or perhaps rediscovered?*) that there is more to life than work. Furthermore, the group from politics highlighted the *need for leisure as part of human nature*.

- Increased Output: on the other hand, those that chose this argument tend to believe this is *already* happening and, in a respondent's own words, it is "unfortunate", giving the clear indication that there is no true choice on the matter but rather what people will be forced to do. In a few cases, it was verbalized the notion of *the markets*, indicating that the interviewees believe markets behave in such way, and such approach appeared to be quite deterministic in their language. Others, for example in the case of an artist, anticipate the processes of production to become easier and therefore produce more. Some people from sciences mentioned that it would be due to competition that people would be constantly pushed to produce more, or as one interviewee put it: *"cut-throat ambition"*.

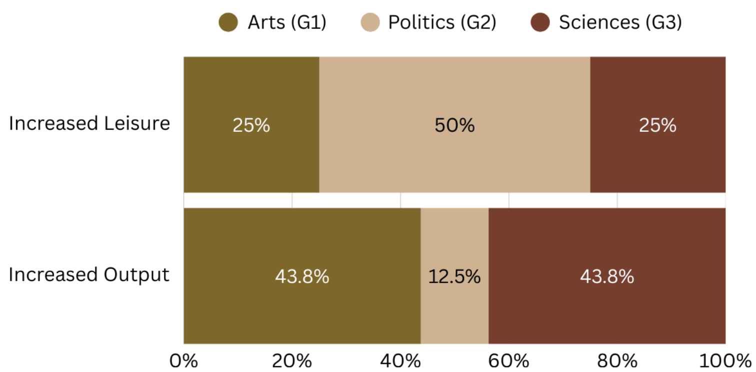

Figure 4.22. The distribution of increased leisure vs. output by occupational group – Interview Set 2

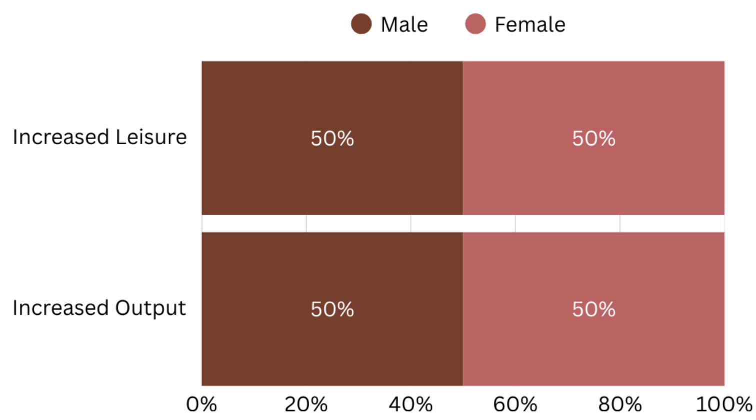

Figure 4.23. The distribution of increased leisure vs. output by sex – Interview Set 2

4.6 Tale in *brief*: AI's impact in work

As we are approaching the end of the journey in the *Mangalem* neighborhood of Berat, we come to one of the core parts of this work, namely: the expected impact of AI in the realm of work. Initially in Sub-chapters 4.2.1 and 4.2.2, an overview is made on how economists view jobs as *bundles of tasks*, their discussion on the historical and contemporary forces of *substitution* and *complementarity* that are associated with the impact technologies bring in the labor market and how there are different techniques to operationalize the task encroachment by AI. In Online Survey 2, respondents were asked if the entities for which they work are more likely to use AI to complement the workers' tasks or to substitute them. The results showed that the vast majority of respondents, about **75% believe in the complementary strategy**. Moreover, in Online Survey 2, the respondents were asked an alternative question which required the percentage of tasks that AI can automate in their current job at this moment in time. The data show that the peak is at "less than 50%", with 18% of the respondents choosing that alternative. This would be a normal distribution, if it were not for a substantial group believing that "90-100%" of the tasks could be automated. Lastly on this topic, the matter of *"Is this time different?"* was studied with the participants of Interview Set 2. The interviewees, after they were presented with the two forces of substitution and complementarity, were asked if they believe that this time is different and asked if the complementing force will prove weaker than the substitution one this time, leading perhaps to technological unemployment. The results show that 17 out of 36 interviewees or **47.2% believe that this time is different**, clearly illustrating how torn the sample was on the matter. It must be noted that multiple respondents explicitly stated they were choosing to be optimistic rather than making what they considered realistic estimations, and even when pressed on this point, they maintained their optimistic stance, with one expressing hope that the relationship with work would alter but that the complementary force would prevail if new generations were properly prepared.

Economists not only differ with respect to their expectations on what is to happen in the future of work due to AI, but also on what is happening right now due to AI and more generally information technologies. One of the most well-known discussions is the one between **Routine Biased Technological Change (RBTC)** and **Skills Biased Technological Change (SBTC)** analyzed in Sub-chapter 4.3. In very simplistic terms, the former proclaims that it is the occupations that are the most routine that are prone to be automated. The later states that the more skilled you are, the less likely you are to be impacted by technological change. The interviewees of Interview Set 2 were exposed to the two concepts of RBTC and SBTC and they were asked to pick the one they found strongest in *explanatory power* in terms of what is happening right now due to AI. The results show that 30 out of 36, so **83.4% chose RBTC**. In terms of sex, the situation is perfectly balanced and in terms of the three occupational groups, the differences were negligible. Interestingly, what came up during the interviews was that many people didn't find these two theories necessarily as mutually exclusive but rather complementary to one another, stating that while the highest skilled workers would have it easier, in any case, their routine tasks could simultaneously be substituted.

With respect to **wage-labor**, the impact of AI after 10 years of development, on its multiple dimensions was studied. In terms of wages, the expectations of the respondents of Online Survey 2 were such that the wide majority, **38.6% expect their real wage to remain the same.** In terms of sex and age groups, the peak is always at "the same" and the distributions hardly differ from one-another. In terms of expectations regarding job losses in the next 10 years due to AI, the respondents of Online Survey 2 expect limited job loss due to AI, with the majority choosing estimates below 40%. Only a small minority foresee extreme outcomes, either catastrophic job loss (90 to 100%) or an increase in jobs. This and the distribution on the expectation with respect to wages suggests generally **moderate expectations about AI's impact on the wage-labor in the next 10 years**. The Mann-Whitney U test was conducted to compare perceived AI-related job loss risk between younger (18-26) and older (27-35) age groups as well as between males and females. In both cases the test revealed no statistically significant difference, suggesting that those demographic groups, within themselves, perceive similar levels of threat to their employment from AI automation. Furthermore, the respondents of Online Survey 2 are asked to state on a scale from 0 to 10 how much they like their job now and how much they expect to like their job after 10 years of AI development on a 5-categories scale from much more to much less. The results show that if we consider a high level of liking their job if they give a score from 7-10, **81% of the people that expect to like their jobs "more" after 10 years of AI development come from an already high level of current job satisfaction**. The full flows from current levels of satisfaction to future ones can be observed in the Sankey diagram in Figure 4.9. The majority of the respondents that are in working-relations, specifically **52.15%, expect to like their job *the same* after 10 years of AI development.** With respect to the changes of job liking and sex, after 10 years of AI development, the distributions show that males and females have similar expectations, with the only exception that 9.1% of females expect to like their job "much less" after 10 years of AI development compared to only 2.8% of males. With respect to the age groups, while Gen Z appears more polarized or uncertain (more variability), both generations have similar average expectations about job satisfaction. The Mann-Whitney U test detected that the typical (median) Gen Z respondent doesn't differ significantly from the typical Millennial respondent, even though Gen Z shows more diversity of opinion within their group. Likewise, in terms of working hours respondents of Online Survey 2 were asked how many hours they work *now* and the expected change after 10 years of AI development. The results show that **most people expect to work less in terms of hours** and if we consider only those that have been in working relations, then 41.6% of the respondents expect to work less after 10 years of AI development. The Sankey plot in Figure 4.10 shows the flows between the current working hours and expected changes. As it can be observed, the respondents that work "maximum 12 hours" expect, interestingly, in their largest majority to work the same amount of hours after 10 years of AI development (62.5%).The most diversified group in terms of expectations is the one currently working "maximum 6 hours". In terms of wage-labor, the last aspect that was studied on how it would differ after 10 years of AI development was underemployment and its three types. The participants of Interview Set 2 were asked, for each of the three types of underemployment, if they expect it in the next 10 years of AI development to get: much better, better, the same, worse, much worse. In the sense that, for example, if skills-related underemployment gets better with AI development, that means that there will be less of that sort of underemployment and the young people interviewed will find it easier to find jobs that match their skill-sets. The results show that **the majority of people from Interview Set 2 expect all three types of underemployment to get worse** in more or less the same levels. A Friedman test was conducted to examine whether respondents perceived different levels of underemployment across three dimensions (time, skills, and income) after 10 years of AI development, revealing no statistically significant difference ($\chi^2 = 0.67$, $p = 0.717$).

Qualitative aspects of work were also studied, specifically: *work as a drudgery*, *work-life balance*, *overall work quality* and *the likelihood of work not becoming central in people's lives.*

In terms of the concept of work as a drudgery, the interviewees of Interview Set 2 were asked to determine for each dimension that makes work a drudgery if after 10 years of AI development it will become: much better, better, the same, worse, much worse. The results show that while **the vast majority of the interviewees expect their jobs to get less repetitive, in every other dimension the expectations are either reverted or expecting no changes**. In terms of sex and repetitiveness and the connection with the end product and the end user, the expectations among males and females appear to be similar. However, they differ with respect to the connection with the colleagues, most females expect it to get either worse or much worse at 72%, compared to 33% of males. Likewise, in terms of the belief in the inherent value of work, 61% of females expect it to get either worse or much worse compared to 27% of males. With respect to the three occupational groups and the expected changes in the work as a drudgery categories, the distributions can be observed in Table 4.13. Furthermore, the Violin plots in Figure 4.11, show how the medians differ among the three occupational groups and their medians.

With respect to the *work-life balance*, which as observed in Chapter 2.4.2, it was the first ranking dimension that made a job - a good job, for the respondents of Online Survey 1, the concept was further explored in Interview Set 2, specifically under the *spillover model* (Guest, 2002). The goal was to understand the expected change in this dimension after 10 years of AI development, if it will become: much better, better, the same, worse, much worse. The majority of males, 10 out of 18, expect the work-life balance to get better compared to only 6 out of 18 females. Furthermore, out of the 7 people that expect work-life balance to get worse, 6 out of 7 are female. The distributions across the three occupational groups are quite similar.

Furthermore, the respondents of Online Survey 2 were asked to take many factors into account and determine if **after 10 years of AI development their overall work quality** would be: much better, better, the same, worse, much worse. The vast majority of respondents expect the overall quality of their jobs to get *better*, about **47%**. In terms of the two demographic groups taken into account, when they are disaggregated, the peaks of the distributions in both demographics seems to be at overall work quality becoming better.

Moreover, the respondents of Online Survey 1 were asked to estimate **the likelihood of work becoming non-central in people's lives** in the near future, within their lifetimes due to AI development, on a scale from 0 to 10. The results showed that there was a concentration of responses in the middle-to-lower-middle range (values 2-6), which account for most of the data. Thus, we can say that the sample does consider it as a real possibility that work loses its centrality but they are moderate about it. The Mann-Whitney U test was used to check if there were statistically significant differences in the central tendencies between males and females and between Millennials and Gen Z. The results yielded high p-values, thus we can say there are no statistically significant differences in the expectations of work becoming non-central between genders or between generational cohorts. Moreover, the Spearman's rank correlation analysis between the optimism people have about AI's impact in society and their expectations about work becoming non central in the near future was studied. The results reveal a weak but statistically significant positive relationship ($rho = 0.219$, $p = 0.026$), suggesting that individuals who are more optimistic about AI's societal impact tend to anticipate a greater shift away from work-centricity, though the modest correlation coefficient indicates this association explains only a small portion of the variance.

In terms of the expected changes in **the unpaid household work**, the participants of Interview Set 2 were asked to estimate if the time they spend on those tasks after 10 years of AI development will be: much more, more, the same, less, much less. The data clearly shows that the wide majority of the interviewees, 20 out of 36, so **55.56% expect to spend less time** in household tasks in the next 10 years. With respect to sex, the second largest group for females was much less (Frequency = 6) whereas for males is the same (Frequency = 6).

Last but not least, the matter of the expectations on productivity and the **modern productivity paradox** was discussed, basing it on work from Brynjolfsson et al. (2019), Acemoglu and Restrepo (2019), Bootle (2019), Gordon (2018) and others in Sub-chapter 4.5. The key idea is that while these new technologies like AI are being developed, the impact on the rate of growth of productivity is not particularly meaningful. This echoes observations from Solow from the late 80s, stating: *"We see computers everywhere, except in productivity statistics."* Four schools of thought were taken into account that try to make sense of this phenomena, as complied by Brynjolfsson et al. (2019): **false hopes**, where initial enthusiasm for AI leads to overestimated expectations and perhaps these technologies won't be as transformative as many expect; **mis-measurement**, acknowledging that conventional productivity metrics may fail to fully capture the effects of AI and digital technologies; **concentrated distribution and rent dissipation**, meaning that the gains from AI may be captured by a small set of firms or sectors rather than diffused broadly. For instance, two of the most profitable uses of AI to date have been for targeting and pricing online ads, and for automated trading of financial instruments, both applications with many zero-sum aspects; **implementation and restructuring lags**, which occur because the most advanced AI capabilities have not yet diffused widely, and complementary innovations are required for their full productivity impact to be realized. Then, the participants of Interview Set 2 were confronted with these ideas and they were asked to chose the one they find the most believable. The results show that most people find the "implementing lags" argument to be the most probable (36.11%) followed closely in the second place by the "concentrated distribution" argument (33.33%). In addition, in terms of the expectations on productivity, in Online Survey 2 the respondents were asked how "productive" AI made them now on a scale from 0 (not at all) to 10 (extremely) and how much productive they expected AI to make them after 10 years of development on the same scale. The results showed that the majority of the respondents (18.13%) reported a level of 7 in terms of the productivity of AI now and the maximal level of 10 in terms of the expected productivity after 10 years of AI development (17.2%). However, it has to be noted that in both cases a substantial group still stick to a productivity level of 0.

Moreover, a positive outlook was taken as a mental exercise, namely one in which the productivity actually does increase substantially in the near future due to AI. The economic question that presents itself then is whether people would use these productivity gains as **increased output**, meaning to keep on working with the same rate, or as **increased leisure**. Also in this case, the participants of Interview Set 2 were presented with the matter and **20 out of 36 people expected that the majority of the population would opt for increased leisure**. While in terms of sex the distributions were perfectly equal, in terms of the occupations the matter changes dramatically with respect to the political group, making the widest majority of those that expect increased leisure.

Part II

Gorica

Chapter 5

A *digressive* brief tale: AI Labor and The Fabrication of Desires

Figure 5.1. Tale 4: Gorica - Tales of Desires and AI Labor.

5.1 Tale 4: Gorica - Tales of Desires and AI Labor.

So far, the tale-teller, the chronicler, has not intervened in the mythical-real city. The elders, the residents, the blind watchmakers have all been presented with some religious truthfulness, refraining herself from taking sides and with no deus-en-machina maneuvers whatsoever. However, it will all alter now that we cross the seven-arched Gorica Bridge built in the 1780s and situate ourselves in the Gorica neighborhood for the next two chapters. The chronicler, like many other chroniclers before her, will become treacherous to the written word as merely descriptive, and more like the archetypal novelist Fielding, the absolutist power of the storyline will be interrupted, "as often as I see occasion" with one's own comments and thoughts. Through the usage of the sidewalks of the Gorica bridge, that are common rendezvous points for our residents and for the blind watchmakers to gather insights from them (read: through the case study of social media), the perfidious chronicler will try to convince us of two things: that the blind watchmakers, to exist, feed on the free labor of our residents and that they fabricate the desires of our residents. Arguments have also been made before by the elders on whether data should be denoted as labor or capital and that point will be explored. Furthermore, the tales-teller, just as the ancient Greek gods, will mingle with the affairs of the residents and try to convince them of this case (read: the interviewees will be asked if they are convinced of the two arguments posited before). However, these arguments are not entirely disconnected from what's already in the city, and build upon the houses of commodification of communication and behavior, which engulf the byzantine Church of Saint Thomas. They are intricately connected to theories of value, that since the neoclassicists stepped foot on the town, value has forever been coupled with price and a subjective notion of preferences. However, that was not always the case and the predecessors of the house of theory of value will be explored all the way back to their far origins. This then, will allow us to explore the mismeasurement argument, that might help us assess the productivity paradox we observed in Mangalem.

The commodification of communication has gradually expanded into the commodification of behavior through a set of mutually reinforcing processes. As Fleissner (2009) explains, commodification advances whenever forms of human activity or knowledge that were previously shared, relational or collectively produced become reorganized into measurable and tradable units that can be circulated within markets. In digital communication environments this means that everyday acts of expression, interaction and information sharing are increasingly captured, structured and sold as valuable informational commodities. Thus far, nothing new. The idea of going to such a deep level of granularity in order to "engineer" behavior goes way back in time. B.F.Skinner, an American psychologist, the one who developed behavior analysis, especially the philosophy of radical behaviorism, and founded the experimental analysis of behavior, said in a symposium (Zuboff, 2019): *"It is not a matter of bringing the world into the laboratory, but of extending the practices of an experimental science to the world at large."* This imagination derived from a world torn apart by war and hoping to achieve what Skinner called "radical behaviorism" and "technology of behavior". In this vision we were to surrender our freedom (since "free will" is simply an illusion) and through the scientific process to gain knowledge on our behavior and be able to engineer it in such a manner that problems like crime, pollution, poverty etc., would be solved. However, quite differently from Skinner's goals and as Zuboff (2019) notably observes: *"The knowledge that now displaces our freedom is proprietary. The knowledge is theirs (of surveillance capitalists or platforms) but the lost freedom belongs solely to us."*

Social media platforms intensify this dynamic because, as Herman (2013) argues, they operate simultaneously as tools of communication and tools of production, blurring the boundary between leisure, creativity and labor. Users create content, maintain networks and generate attention while also supplying the continuous streams of data that the platforms require in order to produce value. These platforms further concentrate power because they develop and control some of the most advanced artificial intelligence systems, which depend on massive quantities of user generated input in order to refine predictions and optimize engagement. More on the matter of power, specifically business power, will be discussed in Chapter 4. Social media platforms serve as exemplary case studies for examining how AI creates new forms of unpaid labor, fabricates desires, and establishes novel power structures in the digital economy. These platforms are uniquely positioned as both **AI-driven and AI-driving entities**: they deploy sophisticated machine learning algorithms to shape user behavior while simultaneously operating at the forefront of AI research and development. This dual role is evidenced by the fact that two of the most widely-used deep learning libraries, TensorFlow (developed by Google)[1] and PyTorch (developed by Meta/Facebook)[2], the very "languages" of creating many of the current AI algorithms, originated from the technical infrastructure of major social media companies.

[1] TensorFlow Guide: `https://www.databricks.com/glossary/tensorflow-guide`

[2] More on PyTorch and its creators: `https://en.wikipedia.org/wiki/PyTorch`

Zuboff (2019) deepens this argument by showing how what she demarcates as *surveillance capitalism* turns behavior itself into a raw material that can be analyzed, predicted and shaped for commercial gain, leading to systems designed not simply to observe actions but to modify them in profitable directions. Through these intertwined developments, communication becomes an arena for the systematic extraction of behavioral data and behavior itself becomes a commodity that platforms can package, forecast and sell, thereby transforming social interaction into a continuous source of economic value. As Varoufakis (2023) notes, this results in a circular and extractive process in which users train the models, the models train the users, and the entire cycle becomes a form of capital accumulation based on behavioral capture rather than on traditional production.

Two arguments are to be made in this *digressive* chapter, through the commodification of communication and consequently to the commodification of behavior:

- These processes have led to the creation of a new form of unpaid work that in this work will be called *AI work*.
- The ability to create *false desires* at the most granular level is for the first time possible.

Both of the two above-mentioned notions have fundamental effects in society overall and in the matters of political economy in particular, by challenging the widely accepted neoclassical theory of value.

Through our very presence in social media, through every interaction, like, click, scroll, we are generating data and consequently training AI algorithms, whose value, without the vast and granular data provided by us, would be greatly diminished, if not rendered useless. This is called for the purposes of this work "AI Labor", as a new form of unpaid work. This phenomenon has not gone unnoticed by scholars in social sciences and beyond. Schau (2023) uses the now-famous analogy "data is new oil", to analyze data as a resource, metaphorically separated from that which it represents (a person or an artifact). However, Schau (2023) clearly points out that this resource is the product of *digital labor*. Building on work from Fuchs (2010) who conceptualizes "digital labor" as: *"...the dominant capital accumulation model of contemporary corporate Internet platforms is based on the exploitation of users' unpaid labour, who engage in the creation of content and the use of blogs, social networking sites, wikis, microblogs, content sharing sites for fun and in these activities create value that is at the heart of profit generation."* Moreover, critics of the current data economy argue that a fundamental problem lies in treating data as capital rather than labor (Ibarra, 2017). Under a "data as labor" paradigm proposed by Ibarra (2017), data would be recognized as user possessions that primarily benefit their creators rather than being treated as mere exhaust from consumption to be collected by firms, with compensation flowing to individual data producers to incentivize quality and quantity rather than channeling profits exclusively to AI companies and platforms. For Ibarra (2017) this could even address the matter of the productivity paradox, which was elaborated at length in Sub-chapter 4.22.

It is worth highlighting the matter raised by Fleissner (2009) on the complex matter of the commodification of services by stating: *"It is worth while to mention that commodification of services is a contradictory process, it can be demeaning and dehumanising, but also liberating and progressive, giving room for social innovation by destroying traditional bounds. Also, with commodification one can see a change from personal relationships towards often anonymous market relations. The relations between people are replaced by relations between people and things."* One can only imagine how much more contradictory is the fact of the exploitation of AI Labor rising from the commodification of our social knowledge and behavior, leading to the dual result of generating new granular knowledge like never before and likewise creating people-things.

Moreover, employing the same line of reasoning and deconstruction used by Himmelweit (1995) and Miranda (2011), with respect to why household and care tasks ought to be considered as work, below are my arguments as to why the sort of activities described above, namely "AI Labor", ought to be considered as work:

- The first argument to make and probabliy the hardest is that social media engagement is a *purposeful activity* that generates value and cannot be dismissed as mere leisure. Just as housework involves intentional actions that produce necessary outcomes, activities on social media such as scrolling, liking, sharing, and commenting are systematically harvested by platforms and converted into data for training algorithms. Users invest time, attention, and cognitive effort. These inputs have an opportunity cost because time spent generating data for platforms is time not spent on paid work, education, or rest. Although users may experience entertainment or social connection, the *purposeful outcome* for the platform is clear: these activities are exploited to refine algorithms, predict behavior, and create economic value. Social media engagement therefore constitutes productive labor rather than just consumption. The challenging part here is the purpose on the end of the user in their engagement process. Even if for the beneficiary end, the platform, there is an explicit purpose to keep users engaged and some would argue addicted, can we really consider this purposeful from the user's point of view? This goes back to more fundamental matters such as choice, which ought to be studied more in depth, beyond the mere psychological mechanisms of keeping users addicted to their economical foundation as work activities.

- Second, data-generating online activity is a part of a broader *division of labor* in the digital economy. In industrial capitalism, domestic labor was largely performed by women while men occupied wage labor, creating a two-track economic system. In the digital economy, a similar structural division emerges. Paid labor is performed by engineers, data scientists, and platform employees, while unpaid labor is performed by ordinary users who provide the raw material for machine learning and algorithmic development. Users are framed as consumers enjoying a free service, yet their activity is foundational to the function and profitability of AI systems. By recognizing this structure, we can understand that social media engagement is not merely entertainment but a form of labor that sustains the digital economy.

- Finally, distinguishing between the *tasks users perform* and the *individuals performing them* clarifies that data generation is neither natural nor inevitable. Just as feminists argued that housework was not an expression of femininity, social media activity is not an intrinsic behavior but a source of economic value for platforms. Platforms instrument these actions to convert them into signals that improve AI performance. The separation highlights two points: the task of generating data creates value independently of the users intentions or identity, and anyone performing these tasks contributes to the system. This insight challenges the notion that user engagement is harmless or inevitable and opens space for discussions of compensation, data rights, and democratic control over AI systems.

- In conclusion, applying the same framework used to conceptualize housework as labor, social media participation can be understood as *a new form of unpaid work*. It is purposeful and produces economic value, it fits into a structured division of labor that benefits platforms at the expense of users, and it depends on the distinction between tasks and individuals to naturalize the labor. Recognizing this form of labor is essential for debates about fairness, ownership, and control in the digital economy.

Not only we have a new form of unpaid work but also these platforms are *fabricating false desires in us*. Echoing the line of argument from Varoufakis (2023), he argues the creation of false desires, by (of course) taking into account a story, more specifically that of "Mad Men", the serial from the 1960s that due to the "Don Dapers" of the time the "mass commercialisation of nostalgia"(pp. 30) took place. Utilizing desire, nostalgia, fear is nothing new but, as Varoufakis (2023) argues, it has gotten to unforeseen terms with the usage of these cloud-based AI empowered systems. Before, this would only be the realm of science fiction. Clearly stated in "Brave new world" by Huxley (1932): *"The principles underlying propaganda are extremely simple. Find some common desire, some widespread unconscious fear or anxiety; think out some way to relate this wish or fear to the product you have to sell; then build a bridge of verbal or pictorial symbols over which your customer can pass from fact to compensatory dream, and from the dream to the illusion that your product, when purchased, will make the dream come true. They are selling hope."* However, whatever amazing things were achieved through the cleverness of the Don Draper's of the time, again, is nothing compared to now. Or, in other words: traditional commercials and advertisements are drastically different to what is being experienced now in the social media platforms in particular but also elsewhere in general. In Varoufakis (2023)' words (pp. 63): *"Don had a talent to invent ways to instill manufactured desires in us. But it was a one-way street. Through the medium of television, or large billboards in cities and along highways, Don would implant longings into our subconscious. That was that. However, with cloud-based Alexa-like devices in Don's place, we find ourselves in a permanently active two-way street between our soul and the cloud-based system hiding behind Alexa's soothing voice. In the words of the philosophers, Alexa ensnares us in the most dialectical of infinite regresses."*

Here we are to tackle "economic preferences" for products and services, as well as to a lesser extent, preferences for political views. However, the word "desire" is used in a paradoxical and provocative fashion, to refer to something more intimate, more personal and more archaic, as is the very nature of what these algorithms tackle in the personas that use them.

The two matters of the new unpaid work due to AI and the fabrication of desires were presented to the participants of Interview Set 2. They were presented with the argument that the time they spend on social media effectively generates data that are subsequently repackaged and sold. These data, in turn, are used to train AI algorithms; without them, the capabilities of such algorithms would be significantly diminished, if not altogether absent. Then they were asked when the matter was presented in such a way, if they consider the time that they spend on social media as unpaid work, given the fact that it is part of a production system. Out of the 36 participants of Interview Set 2, **25 so 69.4% consider such activities as unpaid work**, and the remaining part did not. In terms of sex and occupational groups the distributions can be observed in Figure 5.2 and Figure 5.3. The difference between males and females is not particularly meaningful, with only 1 more female considering it work compared to males. Neither is the difference meaningful between people coming from arts and those coming from politics, having the same exact distribution, with only 3 individuals from each group not considering such activities as work. However, people coming from sciences compose the largest group of "naysayers", with 5 people out of 12, so 41.6% not considering those activities as work. Interestingly, only 2 out of the 7 people that did not consider unpaid household tasks as work, analyzed in Chapter 2.2, also disagree with the fact that the time spent on social media and consequently training the AI algorithms is work. This shows that the refusal to recognize these activities as work is not necessarily consistent across domains and may depend on how visible or socially acknowledged the underlying labor is. It also indicates that this perception has little to do with a narrow focus on wage-labor or the presence of direct monetary compensation, suggesting instead that social recognition of the activity and other factors play a larger role in whether something is classified as work.

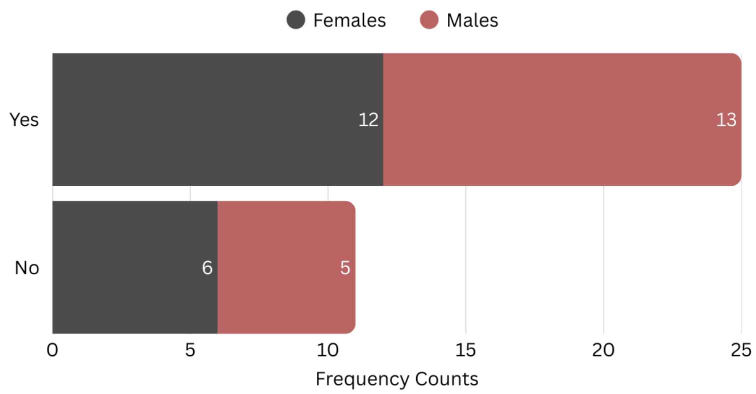

Figure 5.2. The histogram of agreeing or not with the notion that time spent on social media is unpaid AI labor based on sex – Interview Set 2

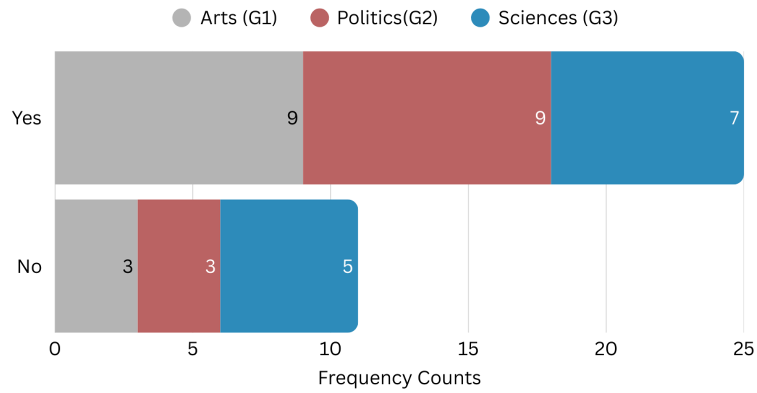

Figure 5.3. The histogram of agreeing or not with the notion that time spent on social media is unpaid AI labor based on occupational groups – Interview Set 2

When participants in Interview Set 2 were asked regarding the reasoning behind their choices, the following rationales emerged:

- For most people their presence and activities on social media are work because they are directly used to build or improve a service and thus produce value for *someone*.
- Even among the respondents that did consider it as work, they didn't see much *value* in it. In the words of one of the respondents from the politics group: *"I agree it is work but I don't think of it, there is a lack of intention of it but still even with the lack of intention it is still work because it is used as such. I think of Dostoyevski's "Notes From Underground" where somewhere it is mentioned that the most useless thing I have done is to move rocks from one place to another, again and again. One thinks of it as the worst possible thing due to its lacking in utility. In this case, having some utility but that you do not care about, that you do not value."*
- For the opponents to the idea that this is work the two main arguments were:
  - The fact that one is not consciously aware they are involving themselves in a production system but rather that they see it as a leisure time activity. The very existence of a sense of awareness is fundamental to it.
  - For others, the fact that you have "a choice" in engaging into what is mainly a "social" activity, is what becomes a decisive factor in it not being work.

In terms of the ability of social media AI driven-algorithms to *fabricate false desires* in them, participants of Interview Set 2 were asked if they believed that false desires were fabricated in them. The results show that 29 out of 36 interviewees, **or 80% agree with the statement that those algorithms have the ability to produce false desires**. When the analysis is made based on sex, interestingly, the wide majority of those that did not agree with the statement, specifically 85.71% were males, as it can be observed in the histogram in Figure 5.4. With respect to the occupational groups, the differences are minimal and can be observed in Figure 5.5.

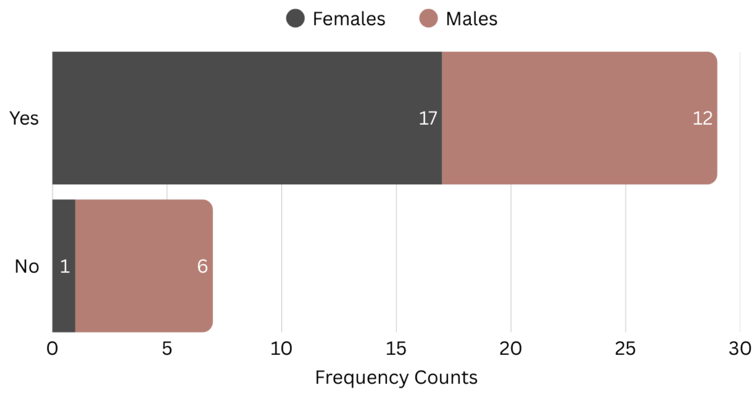

Figure 5.4. The histogram of agreeing or not with the notion that AI-driven social media platform's algorithms produce *false desires* in them based on sex – Interview Set 2

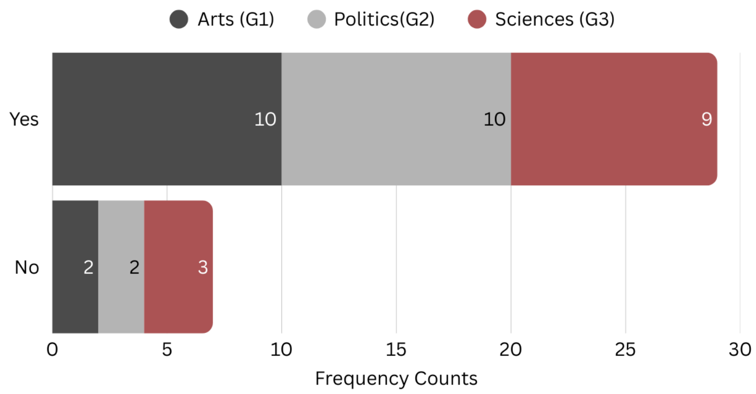

Figure 5.5. The histogram of agreeing or not with the notion that AI-driven social media platform's algorithms produce *false desires* in them based on occupational groups – Interview Set 2

Regarding the rationales offered in the case of the development of false desires, some proponents expressed that not only do social media algorithms produce false desires in them but they recognize this as their very *raison d'être*.

With respect to the opponents to this idea, the two main lines of thought were:

- Yes, social media algorithms may have the ability to produce false desires in *other people* but not *in them*, thus exhibiting some form of exceptionalism. The line of reasoning was similar to the well-known optimism bias (Nikolopoulou, 2023), where people underestimate the likelihood of negative events and the false-uniqueness effect (Wikipedia contributors, a), where people tend to believe their own traits or behaviors are more unique than they really are.

- Another interesting line of thought, was the fact that social media for some of the respondents just went "deeper" onto their already existing desires or made surface what was already present in them, thus not really creating false ones but rather bringing to the forth already-existing ones.

Moreover, participants in Interview Set 2 were also asked whether they consider the advertising and marketing strategies used on social media platforms to differ from those found in more traditional media such as television, newspapers, or even earlier, pre–AI-driven forms of the internet. A substantial majority, 30 out of 36 respondents, answered affirmatively. The distribution by sex mirrors this overall pattern, with only three males and three females disagreeing, as shown in Figure 5.6. Looking across the three occupational groups, disagreement follows a decreasing gradient: no participants from the arts expressed disagreement, while two participants working in politics and four participants in the sciences did so, as shown in Figure 5.7. With respect to the rationales that surfaced during the interviews, almost all proponents of the idea that these sort of platforms are different from traditional marketing highlighted *the granularity* and *pervasiveness* of these platforms. As one interviewee put it: *"Yes, they fabricate false desires due to how often you see them and thus you get a sense of necessity and urgency for whatever you see there."*

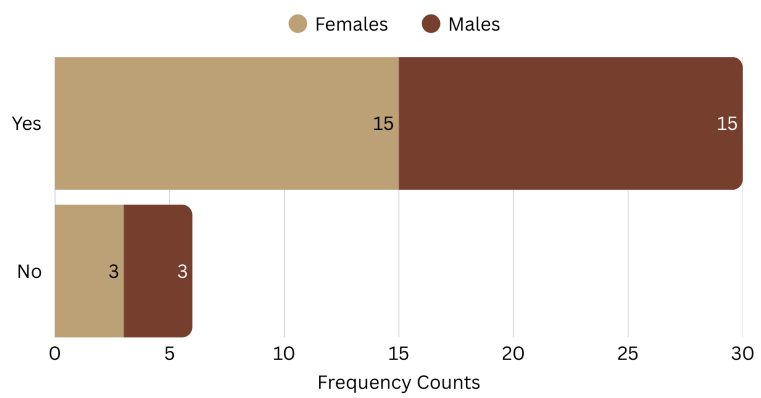

Figure 5.6. The histogram of agreeing or not with the notion that ads on AI-driven social media platforms are different from traditional marketing based on sex – Interview Set 2

The concept was further studied in Online Survey 1, during which the 104 respondents were queried regarding the impact social media platforms have in influencing: their preferences for products, their preferences for services and their political opinions. The scale was from 0 (not at all) to 5(extremely) and the purpose was to be able to draw some

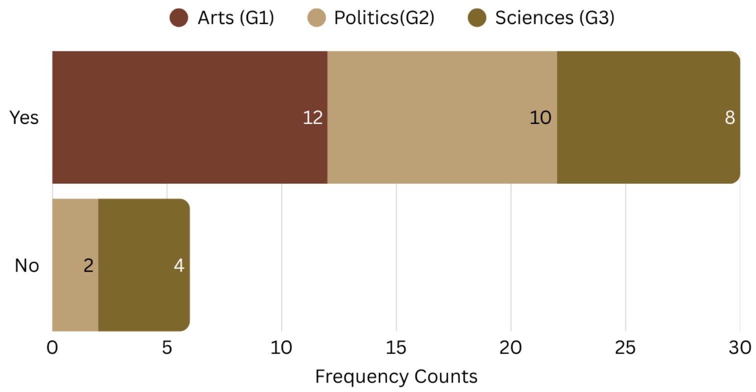

Figure 5.7. The histogram of agreeing or not with the notion that ads on AI-driven social media platforms are different from traditional marketing based on occupational groups – Interview Set 2

comparisons across the categories. The three line charts can be observed in Figure 5.8. As it can be observed, the impact that AI-driven social media have on the preferences for *services* follows a normal distribution with a peak at a level-2 of impact, with 29 out of 104 respondents of Online Survey 1 choosing that alternative. In terms of the impact these platforms have on the preferences for *products*, the distribution leans towards the higher-values with the peak being at level-3 of impact with 29 out of 104 choosing that. The impact on the *political opinions* is the one the young people that participated in Online Survey 1 seem to consider as the least influential, with the distribution clearly being very right-skewed and the peak being at level-1 of impact with again 29 respondents choosing that. Due to the fact that the three questions are ordinal (0–5) and were answered by the same respondents, I applied the non-parametric Friedman test, which does not assume normality and is appropriate for comparing related ordinal measures. The test revealed statistically significant differences among the three items ($\chi^2 = 43.16, p < 0.001$), indicating that participants rated the impact AI-driven social media platforms have on their preferences differently on average in a statistically significant way.

This broad consensus further reinforces the idea that AI-driven social media platforms are not only deploying fundamentally novel marketing strategies unlike those of earlier media environments but it goes as far as manufacturing new, potentially artificial desires. However, the impact is not equal among different categories.

The implications of this matter can be quite meaningful, particularly to the *theory of value* in economics. Even though contemporary economic discourse often accepts the neo-classical formulation of value[3] with little debate, revisiting alternative conceptions remains

[3] The neoclassical economics considers the value of a good or serice to rely on the utility maximization

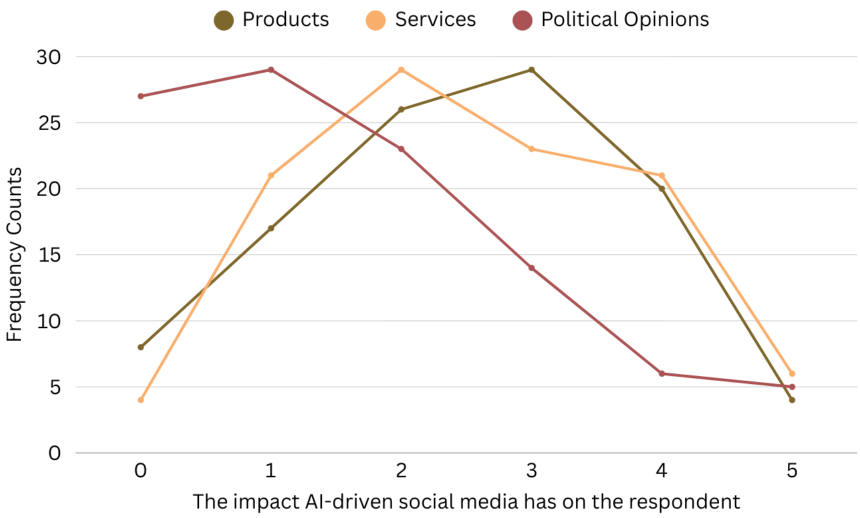

Figure 5.8. How much do AI-driven social media platforms impact the *preferences* for products, services and political opinions – Online Survey 1

crucial for understanding how value is actually generated in digital economies. The rise of data-driven platforms challenges the idea that value is solely created through market exchanges, highlighting instead the role of user activity, attention, and behavioral data as productive inputs. Moreover, acknowledging these dynamics opens space for reconsidering who contributes to value creation and who benefits from it, in increasingly automated and algorithmic systems.

In the latest book of Mazzucato (2018), "The Value of Everything", the historical evolution of the concept of value is traced as economists sought to depict the "wealth of nations". The book urges readers to rethink the origins of wealth. Central to Mazzucato (2018)'s argument is a distinction between "value creation" and "value extraction", challenging current assumptions about who constitutes the true creators of wealth. A similar conceptual move is made by the Nobel Prize winner Joseph Stiglitz in "People, Power, and Progress" (2019), where he likewise differentiates between "wealth creation" and "wealth extraction", arguing that contemporary capitalism often rewards activities that redistribute or capture value rather than generate it. Both authors therefore call for a re-evaluation of what counts as productive, and both highlight the inadequacy of current economic frameworks for distinguishing socially beneficial activities from merely lucrative ones. The conflicts on the varieties of not only creating value but also the very nature of value have had historical importance, exemplified by Varoufakis (2017) highlighting the tension between "experiential value" and "exchange value", in his chapter on

for individuals and profit maximization for firms. See more here Neoclassical Economics.

the "Commodification of everything", noting *"the unstoppable victory of exchange value over experiential value"*. The notion of value is closely linked to the process of commodification, as Fleissner (2009) observes: *"Since Aristotle, the dialectic face of commodities, later elaborated by Karl Marx, is well known: they carry value in use and value in exchange. Nowadays, even as we understand the economy as a social construction and are aware of the relativity of value given to objects, we are still confronted with the same distinction and with the transition of objects into commodities."*

For the purposes of this work, the first chapters of Mazzucato (2018) are particularly relevant, as they outline four historical schools of thought on value:

- The Mercantilists: They argued that the accumulation of precious metals was the path to national prosperity (Mazzucato (2018), pp. 23). For the first time, wealth was considered at a national rather than an individual level. Key figures include Sir William Petty and Gregory King.

- The Physiocrats: Responding to early industrialization, they emphasized the value of the soil and agriculture. François Quesnay, often regarded as the father of economics, included only farmers and land-related occupations within the productive sphere, excluding household production, industry, services, and government.

- Classical Economics and the Labor Theory of Value: Here, value was grounded in the objective conditions of production, and market prices were seen as reflective of the labor required to produce goods (Mazzucato (2018), pp. 57). Figures such as Adam Smith, Ricardo, and Marx offered varying perspectives on how to draw the production boundary, for instance, whether to include services as productive labor (Marx included them, Smith did not). All, however, agreed that value was proportional to the time spent in production (Mazzucato (2018), pp. 37).

- The Neoclassicists: Influenced by utilitarian ethics, Jean-Baptiste Say argued that "the value of a commodity resides in its utility to a buyer and, therefore, productive labor is labor which produces utility" (Mazzucato (2018), pp. 61). With the rise of marginalist thought, price became the primary measure of value, determined by the subjective notions of scarcity and utility (Mazzucato (2018) pp. 62, 65). More consequently, this approach complicates distinctions between rent and profit.

The last two theories of value can be observed in a summary mind-map in Figure 5.9. The neoclassical notion of value has become the contemporary standard, to the point that the very idea of "theories of value" has largely disappeared from mainstream discourse, replaced by the study of prices and wages in Microeconomics 101. As mentioned by Mazzucato (2018), price became the very measure of value during the intersection of the "rational"[4] choices through which the consumers try maximize the utility subject to income and firms try maximize profits subject to costs. In simplistic terms, that which fetches

[4] Also the very idea of rational choice is fundamental in this line of argument and is challenged, particularly with the rise of behavioral economics.

a price is productive and its value lies on the price which in itself lies of some subjective preferences and utility of individuals. In fact, there is a very famous economics paper entitled "De gustibus non est disputandum" by Stigler and Becker (1977), both Nobel Prize winners and founders of the Chicago school of economics. Stigler and Becker (1977) make their case why economics shouldn't trouble itself with the notion of preferences and what lies behind them. If two individuals have all the necessary information they argue, and in the end one prefers apples and the other oranges, there must be something innate, intrinsic in the individual that reflects their judgment on what they value (Stigler and Becker, 1977). However, as it was previously argued, AI-driven and AI-driving social media platforms have the ability to *fabricate desires*, and moreover, their functionality often relies not on traditional market exchanges or pricing mechanisms but on the active participation of users themselves. Platforms such as social media networks or AI language models like ChatGPT derive their value from user-generated data, interactions, and content that train and refine the algorithms, rather than from direct payment for a good or service. In this sense, the standard link between price, utility, and individual preference becomes tenuous: the "consumers" simultaneously act as unpaid contributors, effectively co-producing the value of the platform. Consequently, the subjective preferences at the core of the neoclassical price-based theory of value no longer provide a reliable foundation under these business models. Such phenomena further challenge the neoclassical theory of value, which has been lately challenged by economists like Stiglitz (2019), Mazzucato (2018). Furthermore, current issues with productivity statistics, as discussed in Chapter 4.5, underscore the need to critically reassess what constitutes productive work. Indeed, the rise of AI-driven unpaid labor forces a reconsideration of assumptions about value that have long been taken for granted but have not always reflected historical or conceptual realities. Are we to say that it is time to forgo that model altogether? This question will remain open in this paper and no definite answer will be provided, but certainly the two bases that hold together the neoclassical theory of value that we have inherited and now take for granted are not solid, particularly in the case of AI empowered and AI empowering social media.

On this matter, the respondents of Online Survey 1 were questioned to asses the value-generation of their presence in AI-driven social media platforms and how much value they are generating, comparatively for: themselves, friends/family, the owners of the platforms and society overall, on a scale from 0 (not at all) to 5 (extremely). The distributions can be observed in Figure 5.10. As shown in the graph, the distributions for the value produced for oneself, friends/family and the society follow a similar distribution, though for society the peak at 0 makes a difference, with 22.11% choosing that. With respect to the value created for the owners of the platforms, the peak is at 5 with 44.23% of the respondents assigning level-5 value. A Friedman test was conducted to examine whether there were significant differences in participants' perceptions of how much value was being created for the different beneficiaries (themselves, friends/family, platform owners, and society) through their social media participation. The results revealed statistically significant differences among these groups, $\chi^2(3) = 45.09$, $p < .001$, indicating that participants perceived varying levels of value creation depending on the beneficiary category. Clearly, the young people that were part of the sample for this study are very aware of the dynamics

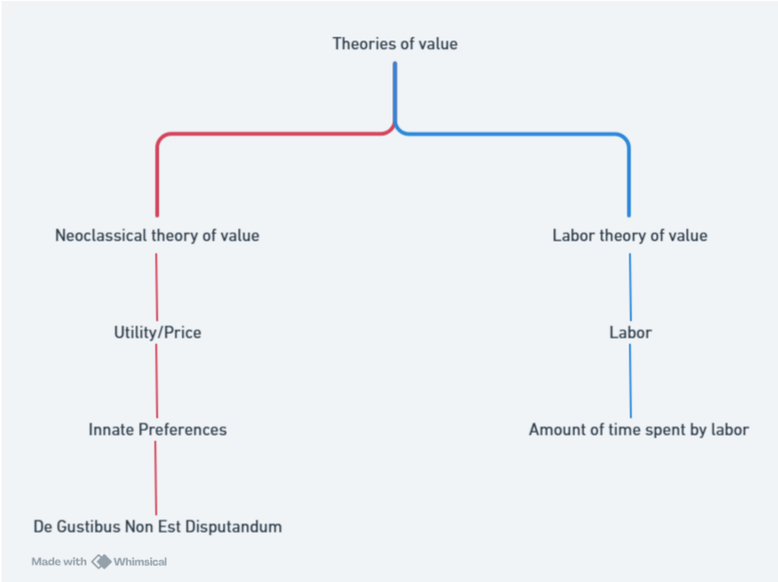

Figure 5.9. Theories of Value: Neoclassical and Labor ones, mainly based on the summary from Mazzucato (2018)

involved in the value-creation process. This was not pushed further to test it in more economic terms and linking it to the theories of value due to the complexity of the matter. It should, however, be part of future research.

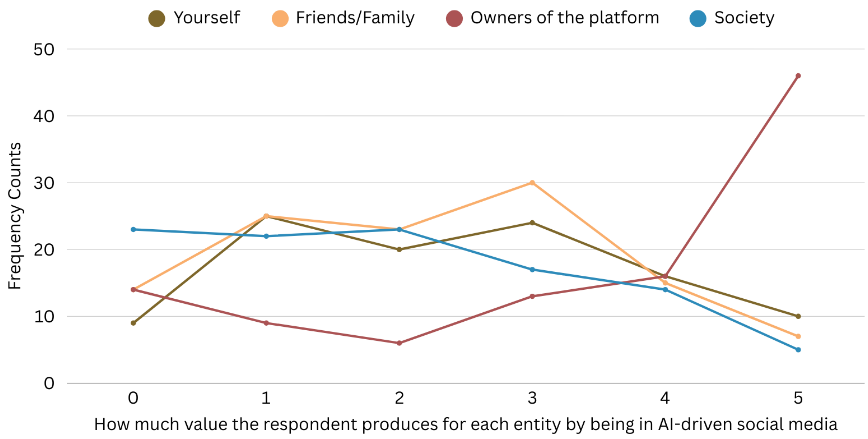

Figure 5.10. How much value the respondent produces for oneself, friends/family, owners of the platform and society by being present in AI-driven social media platforms – Online Survey 1

5.2 Tale *in brief*: AI Labor and Fabrication of Desires

Having crossed the physical and theoretical bridge of Gorica in our mythical-real city we got to this chapter. The goal of this short chapter was to highlight the potential existence of **a new form of unpaid work - AI Labor** and **the new ability to fabricate false desires like never before**. Both of these arguments were laid out using the AI-driven and AI-driving social media platforms, given the fact that they are at the forefront of AI development and have AI embedded in their very structure. The implications of this matter can be quite meaningful, particularly to the *theory of value* in economics. Even though, the neoclassical notion of value has become the contemporary standard, to the point that the very idea of "theories of value" has largely disappeared from mainstream discourse, replaced by the study of prices and wages in Microeconomics 101 (Mazzucato, 2018), the two above-mentioned notions have the potential to weaken further its explanatory power.

The two notions are studied by many scholars, like but not limited to: Zuboff (2019), Varoufakis (2023), Fleissner (2009), Schau (2023), Ibarra (2017), etc., and it is upon their work that these concepts rely on. Furthermore, this work contributed by reusing the arguments made back in the 60s and later on with respect to considering household work as work, in the realm of AI labor. The idea is that through our very presence in social media, through every interaction, like, click, scroll, we are generating data and consequently training AI algorithms, whose value, without the vast and granular data provided by us, would be greatly diminished, if not rendered useless. Re-employing the arguments from Himmelweit (1995) and Miranda (2011), the case was made that "AI Labor" ought to be considered as work, given that: it is a purposeful activity, at least on the side of the platform; it is part of a broader division of labor; one can distinguish between the tasks and the individual performing them. Furthermore, focusing specifically on the work from Varoufakis (2023), the argument was made that AI-driven and AI-driving social media algorithms have the power to fabricate false desires in us. Here, what were mainly tackled were "economic preferences" for products and services, as well as to a lesser extent, preferences for political views. However, the word "desire" was used in a paradoxical and provocative fashion, to refer to something more intimate, more personal and more archaic, as is the very nature of what these algorithms tackle in the personas that use them.

The two matters of the new unpaid work due to AI and the fabrication of desires were presented to the participants of Interview Set 2. Out of the 36 participants of Interview Set 2, **25 so 69.4% consider such activities as unpaid work**, and the remaining part did not. The difference between males and females is not particularly meaningful, with only 1 more female considering it work compared to males. Neither is the difference meaningful between people coming from arts and those coming from politics, having the same exact distribution, with only 3 individuals from each group not considering such activities as work. However, people coming from sciences compose the largest group of "naysayers", with 5 people out of 12, so 41.6% not considering those activities as work.

Interestingly, only 2 out of the 7 people that did not consider unpaid household tasks as work, analyzed in Chapter 2.2, also disagree with the fact that the time spent on social media and consequently training the AI algorithms is work. This shows that the refusal to recognize these activities as work is not necessarily consistent across domains and may depend on how visible or socially acknowledged the underlying labor is.

In terms of the ability of social media AI driven-algorithms to fabricate false desires in them, participants of Interview Set 2 were asked if they believed that false desires were fabricated in them. The results show that 29 out of 36 interviewees, or **80% agree with the statement that those algorithms have the ability to produce false desires**. When the analysis is made based on sex, interestingly, the wide majority of those that did not agree with the statement, specifically 85.71% were males. One of the main rationales provided during the interviews from the "naysayers" to this idea was: *Yes, social media algorithms may have the ability to produce false desires in other people but not in them, thus exhibiting some form of exceptionalism.*

Moreover, participants in Interview Set 2 were also asked whether they consider the advertising and marketing strategies used on social media platforms to differ from those found in more traditional media such as television, newspapers, or even earlier, pre–AI-driven forms of the internet. A substantial majority, 30 out of 36 respondents, answered affirmatively. With respect to the rationales that surfaced during the interviews, almost all proponents of the idea that these sort of platforms are different from traditional marketing highlighted the **granularity** and **pervasiveness** of these platforms.

The concept was further studied in Online Survey 1, during which the 104 respondents were queried regarding the impact social media platforms have in influencing: their preferences for products, their preferences for services and their political opinions, on a scale from 0 (not at all) to 5(extremely). The non-parametric Friedman test, which does not assume normality and is appropriate for comparing related ordinal measures was used to see if there were any differences on how the three categories were being impacted. The test revealed statistically significant differences among the three items ($\chi^2 = 43.16, p < 0.001$), indicating that participants rated the impact AI-driven social media platforms have on their preferences differently on average in a statistically significant way.

Lastly, the respondents of Online Survey 1 were questioned to asses the value-generation of their presence in AI-driven social media platforms and how much value they are generating, comparatively for: themselves, friends/family, the owners of the platforms and society overall, on a scale from 0 (not at all) to 5 (extremely). The distributions for the value produced for oneself, friends/family and the society follow a similar distribution, though for society the peak at 0 makes a difference, with 22.11% choosing that. With respect to the value created for the owners of the platforms, the peak is at 5 with 44.23% of the respondents assigning level-5 value. A Friedman test was conducted to examine whether there were significant differences in participants' perceptions of how much value was being created for different beneficiaries (themselves, friends/family, platform owners, and society) through their social media participation. The results revealed statistically significant differences among these groups, $\chi^2(3) = 45.09$, $p < .001$, indicating that participants perceived varying levels of value creation depending on the beneficiary category.

This broad consensus further reinforces the idea that AI-driven social media platforms are not only deploying fundamentally novel marketing strategies unlike those of earlier media environments but it goes as far as manufacturing new, potentially artificial desires. However, the impact is not equal among different categories.

Chapter 6

Tales of Power

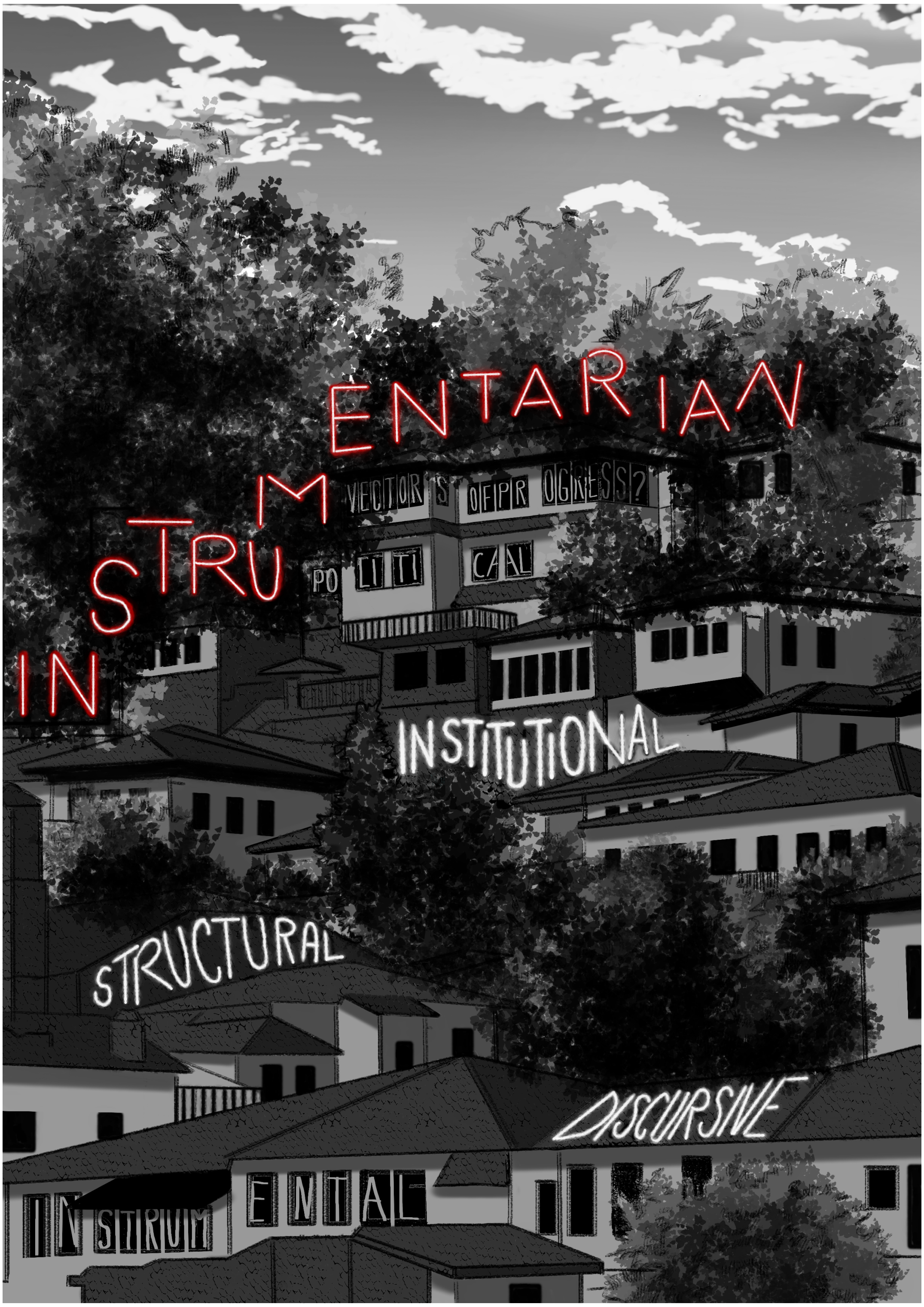

Figure 6.1. Tale 5: Gorica - Tales of Power in Palaces of Dreams.

6.1 Tale 5: Gorica - Tales of Power in Palaces of Dreams

Power. One would think that after more than two thousand years of being conquered, destroyed and rebuilt, our residents would be used to it. Since its inception, the city has changed many handlers and many names. The ancient Illyrian settlement of "Antipatrea", the ancient Macedonians labeled it "Dassaretia", the Romans after invading it and later the early Byzantine empire renamed it to "Albanorum Oppidum" and "Pulcheriopolis". Then, with the conquering by the First Bulgarian Empire, the city was known as "Bel[i]grad" ("White City"), with the transliteration with greek characters "", which persisted throughout the medieval period, changing to "Berat" under Ottoman rule. Whenever something metamorphic occurred, a new denomination came along. Could one argue that something so metamorphic is happening now, with the presence of these Blind Watchmakers, that the city ought to change its name? Perhaps. However, for sure a different dimension of power is being yielded in our legendary-true city, and that is one the residents have not experienced before. It is neither instrumental, nor discursive, nor structural or institutional, powers which have been written about at large and will be explored in this chapter. Something else is happening and a name is needed for it. The chronicler will borrow Zuboff's term "instrumentarian power". Will our citizens be convinced of it? "The object of power is power", as Orwell notes in "1984" and one of the main things that power does is to legitimize itself. We will then try to understand how this new power legitimizes itself through the usage of two mechanisms: self-proclaimed vectors of progress and a political one. Be not mistaken: the blind watchmakers (read: the businesses that develop the state of the art AI seen through the case study of social media), yield all the powers, old and new. However, the new has to be understood and for it to be understood it has to be named.

6.2 (New) Business Powers and Palaces of Dreams

The barbarous gold barons - they did not find the gold, they did not mine the gold, they did not mill the gold, but by some weird alchemy all the gold belonged to them - Big Bill Haywood, founder of The United States' first industrial union, 1929.

Power is one of the most controversial concepts of political science and by extension of comparative political economy, due to its relationally and sociologically amorphous nature, as Weber pointed out (Fuchs and Lederer, 2007). The current political debate is largely focused on the power accumulated by platforms such as Google, Facebook, and even those part of the ever-shifting in terms of semantics of "sharing/gig/collaborative" economy such as Uber, Airbnb, etc. While these businesses encompass the conventional forms of power, they also yield a specific form of power that is unprecedented. In fact, they are at the forefront of AI development, as duly noted in Chapter 5. We must therefore surpass the syndrome of the horseless carriage, in which we associate old, familiar concepts with novel dangers, rendering ourselves unable to deal with them. Thus, the purpose of this chapter is to illustrate the very existence of this new form of business power, given the rise of AI and its deep-integration in social media platforms, deconstructing it onto its characteristics and mainly the manner in which it legitimizes itself. This is strongly connected with what was discussed in Chapter 5 above, in which it was argued how strong data platforms, particularly the social media ones, that are at the forefront of AI development, have led to the creation of a new form of unpaid AI work and the fabrication of desires. It is upon these fundaments that we built the structures necessary to individuate and denominate the new business power.

Jean-Luc Godard once said: *"Sometimes reality is complex. Stories give it form."* (Godard, n.d.) In terms of technological futuristic dystopias and the themes of power and control, people tend to refer, in terms of books that evoke the popular imagination, to either Orwell (2013)'s "1984" or Huxley (1932)'s "Brave New World". These two works fill the popular imagination when it comes to how much power entities that can develop AI can obtain. Both Brave New World and 1984 depict power as a force that seeks total control over the individual, extending into thoughts, emotions, and even desires. They reveal how true power lies not just in ruling people's actions, but in shaping their perception of reality itself. In both worlds, the greatest strength of power is its ability to make people accept, or in fact not even recognize, their own oppression. However, the distinctions among these two dystopias in how power is exercised and its goals are achieved couldn't be more stark. Best depicted by the analysis of Neil Postman in "Amusing ourselves to death" (1985):

"What Orwell feared were those who would ban books. What Huxley feared was that there would be no reason to ban a book, for there would be no one who wanted to read one. Orwell feared those who would deprive us of information. Huxley feared those who would give us so much that we would be reduced to passivity and egoism. Orwell feared that the truth would be concealed from us. Huxley feared the truth would be drowned in a sea of

irrelevance. Orwell feared we would become a captive culture. Huxley feared we would become a trivial culture, preoccupied with some equivalent of the feelies, the orgy porgy, and the centrifugal bumblepuppy. As Huxley remarked in Brave New World Revisited, the civil libertarians and rationalists who are ever on the alert to oppose tyranny "failed to take into account man's almost infinite appetite for distractions." In 1984, Huxley added, people are controlled by inflicting pain. In Brave New World, they are controlled by inflicting pleasure. In short, Orwell feared that what we hate will ruin us. Huxley feared that what we love will ruin us."

A whole line of arguments can be made on who, essentially, was right. This is indeed a very popular thematic. Are we drowning in a sea of "irrelevance" by being inundated in algorithmic-chosen social media materials or is the very fact that we all have a personalized homepage infers that "truth" is being "hidden/altered"? Many social sciences researchers have focused on these matters, inspired by the phraseology and the imagination that Huxley and Orwell ignite.

However, when reflecting on the power accumulated by current platforms, I couldn't think of a better story to draw parallels with than Kadare (2011) a many-times Nobel Prize nominee. Ismail Kadare is a renowned Albanian novelist, poet, and essayist. He's widely regarded as one of the most important literary figures in Eastern Europe and has been a prominent voice in Albanian literature since the mid-20th century. Kadare tends to blend myth, history, and politics, often using allegory and symbolism. One could make an argument that his focus was to critique totalitarian regimes, especially the communist dictatorship of Enver Hoxha in Albania. However, there are those that have questioned this claim based on his continued prominence as a leading author within and throughout the duration of the regime. He's known for navigating censorship while embedding powerful political commentary in historical or fantastical settings. The work taken into consideration here, **"The Palace of Dreams"**, was originally published in 1977 as "The Clerk of the Palace of Dreams" *(original title: "Nëpunësi i Pallatit të Ëndrrave")* as part of a collection of stories, in order not to attract attention. However, once republished in 1982, the book generated harsh criticisms[1] and in a special plenum of the then "The Writers' League", the work was considered as against the regime and was banned, only to be republished after the fall of communism. What actually takes place in the story-line and why is it relevant as the best possible metaphor for the power of AI-driven and AI-driving, social media platforms?

Mark-Alem, an Ottoman-Albanian, a descendant of the influential Köprülü family finds himself employed in Tabir Saraj, one of the most important and mysterious institutions of the mythical-real empire. His family is at times a friend of the mythical-real regime depicted in the book and at other times repressed and an enemy, highlighting the volatility of the regime as well as that of even the main actors within the regime. Tabir Saraj is this mystical institution of the empire that deals with the collection, selection and

[1] See more here: The palace of dreams.

interpretation of dreams *(read: essentially a data processing institution).* The dreams take paramount importance for the regime *(read: the data is crucial for maintaining control and power).* Just as in modern tech systems, where every click, scroll, and post contributes to an endless stream of data, the dreams of citizens are constantly collected, analyzed, and categorized. The system sorts and interprets these dreams, seeking hidden meanings or threats that can affect the empire's stability *(read: AI algorithms constantly analyze user data to predict behaviors, trends, and even potential risks).* In the empire, citizens' dreams are "voluntarily"[2] submitted to the palace, much like how users today submit data to tech platforms through their online interactions *(read: digital participation is often unavoidable in today's society, it's just the state of affairs).* Even in the most totalitarian dystopian imagination, the handing out of "dreams" *(read: access to some deeply intimate aspect of the self)* would happen, as the narrative goes, by the free will of the dreamer. The equivalence of "free will" in these platforms is accepting the terms & conditions, and multiple studies have shown that people can agree to anything without reading them, even handing out their first-born child to access a fictitious network (Obar and Oeldorf-Hirsch, 2020), showing the limitations of this from of consent. This highlights the disturbing reality that, just like in Kadare's empire, individuals unknowingly surrender their most personal information under the guise of voluntary consent. The paper underscores how this "consent" is often obtained through manipulation and a lack of true awareness, which shifts the power balance entirely in favor of those controlling the platforms. In both cases, what is presented as voluntary submission is, in fact, a coercive act hidden beneath layers of convenience and ignorance. The authors in the paper, Obar and Oeldorf-Hirsch (2020), argue that users are often unaware of the extent to which they surrender their privacy and autonomy because they are either overwhelmed by complex legal jargon or because they simply accept these terms in exchange for free access to services. The most alarming and ironic example from that research would be that 98% of the participants missed NameDrop's (a fictional platform used for the study) "gotcha clauses" about data sharing, and about providing a first-born child as payment for access. Obar and Oeldorf-Hirsch (2020) also emphasize the illusion of control, noting that users believe they have the ability to manage their privacy, but in reality, they are entrapped in a system that capitalizes on their ignorance and lack of alternatives. Indeed, as mentioned by one of the forwards in the republication of "The Palace of Dreams"(2011), by the french critic Alain Bosquet: *"The temporary power relies upon the invisible, the random and the involuntary - for everyone. One does not have to prefer "njëmendtën" or "panjëmendtën" (an effortful translation: the real-one, genuine-one, true-one, versus its negation). Duality is necessary."*

This data is then processed by unseen forces, the interpreters in the case of the palace, algorithm and algorithm designers in the case of big tech platforms *(read: both are hidden layers that control what is considered relevant or useful based on rarely transparent processes).* In big data AI algorithms, particularly black-box models, the interpretation of data is often opaque and difficult for users to fully understand. This mirrors Tabir

[2] Given the fact that a "good citizen" was one that contributed to the empire and it was also the social expected behavior.

Saraj, where the interpretation of dreams is conducted by unseen forces within the empire, controlling the actions and policies based on data that is not fully transparent to the people. Just like the empire's reliance on mysterious dream analysis to maintain power, modern AI platforms use complex, often inscrutable algorithms to shape user behavior, making decisions that are outside the user's awareness or control. The interpretation of these dreams, much like the interpretation of user data, is used to shape the actions and policies of those in power. For instance, the insights drawn from dreams could dictate how the empire reacts to social changes or threats *(read: targeted content, political ads, and behavioral nudges are used to influence individuals' decisions)*. Dreams, so intimate and personal, not only have their semantics[3] exposed for the community to witness but are also processed by a vast bureaucratic system that interprets, utilizes and "sells" them (in this case for political favors, in the actual cases of data processing entities for profit). Similarly, today, our deeply personal behavioral data, from private conversations with loved ones to health concerns and even existential questions, are transformed into data points. These data points are then commodified and processed by corporate and political systems, shaping everything from targeted ads to social influence. What was once private and intimate becomes part of a larger, impersonal bureaucracy that exploits personal information for profit and power.

In a Kafkaesque-like bureaucracy, Mark-Alem navigates his days and the dreams of the world, not necessarily in search of truth or future predictions *per se*, but trying (and perhaps not always succeeding) to not get himself entangled in the political webs. Indeed the dreams-foresight *(read: the ability to predict & shift behavior)* had existed for thousands of years, from the Oracle of Delph, the Romans, assyrians, etc., but these all fainted compared to Tabir Saraj, since this empire was the first in the history of the world to level-up the dreams-foresight by institutionalizing it. The same parallels can be imagined when people often note how advertising, lobbying and business persuasion has existed before as well. So, these platforms are nothing new. However, the very idea of building an entire institution around the exploitation of people's most inner and intimate things, such as dreams *(read: behavior, fears, political opinions etc)* is another power altogether. Summarizing the key parallel-lines in a table comparing the dimensions of Tabir Saraj and AI-driven big social media platforms, Table 6.1 is obtained.

Thus, how new are the modern Tabir Saraj-s or palaces of dreams in terms of the nature of the power they exert and how do they differ from the older versions, the other Oracles and predecessors? Let's take a look at the conventional classifications of business power and investigate where this one fits, if it does, or whether it is *that* different that it merits its own category.

Many researchers have addressed the issue of business power, in particular recently that of transnational corporations (TNC) in a globalized world setting, in such a manner that compares these companies to small national economies, their dominance in entire

[3]Presumed semantics, who knows the true ones?!

markets etc„ so, mainly in numerical terms (Thomas, 2000). However, this comes at the expense of understanding the political process, meaning how these values translate into political influence. Thus, driven by this lack of systematic research, Fuchs and Lederer (2007) came up with a study of the facets of business political power and provided 3 categories:

- Instrumental - focuses on the concept of direct influence from an actor to another. It utilizes an actor-centered and relational notion of power based on the concept of individual voluntary action. It tends to explore the way actors influence decisions by formal political decision-makers, that is policy output. As an illustration, lobbying and campaign finance activities are the main ways business invests resources in order to exercise influence on the political process.

- Structural - in juxtaposition to instrumentalists, it underscores the significance of the input side of policy, focusing on the predetermined options of political decision-makers. Power and its use must be studied in the context of socio-economic and ideational institutions and structures. In other words, A devotes his/her energies to creating or reinforcing social and political values and institutions of only those issues which are comparatively innocuous to A and not to some other actor B. To illustrate, as mentioned by Busemeyer and Thelen (2020), market economies rely on private investment decisions (by business actors), to support and foster growth and employment.

- Discursive - it encompasses a sociological standpoint when analyzing power dynamics in society. Power is seen as a product of prevailing norms, ideas, and societal institutions. Its influence is noticeable in the frameworks of discourse, communicative practices and cultural values. Discursive power exerts influence over the framing of policy issues & solutions. For example, business promotion of consumer/entertainment culture exerts political influence broadly, as it shapes public desires and attention.

Dimension	Tabir Saraj (Empire)	AI-driven Social Media
Data Collection and Analysis	Dreams are constantly collected, analyzed, and interpreted to predict political or social outcomes.	User data (clicks, posts, likes, etc.) is collected and analyzed to predict behaviors, trends, and interests.
Involuntary Data Submission	Dreams are "involuntarily" submitted to the palace, like how users unknowingly provide personal information.	Users often "unknowingly" submit personal data by accepting terms and conditions without full awareness.
Use of Data for Larger Entities	Interpreters use dreams to shape the empire's political decisions and control stability.	Algorithms process user data to target ads, influence decisions, and sway political or social behavior.
Interpretation Based on Unseen Forces	The interpretation of dreams is managed by unseen bureaucratic forces, similar to an opaque system of governance.	Algorithms and platform designers control the interpretation of user data, shaping what is visible and relevant to users.
Exploitation of Intimate Information	Dreams, a deeply personal and intimate aspect of self, are exploited for political power and control.	Personal data (e.g., behavior, opinions, health) is commodified and used for profit and influence.
Illusion of Free Will	Citizens "freely" submit their dreams, much like users accept terms without fully understanding the implications. It is just the state of normal affairs.	Users believe they control their privacy, but are often trapped in a system that capitalizes on their ignorance.

Table 6.1. Comparison between *Tabir Saraj* (Empire) and AI-driven social media platforms.

Busemeyer and Thelen (2020) identify a fourth, "institutional power", which arises when policymakers delegate public functions to private actors. Gradually, this leads to asymmetrical dependence of the state on private business actors. This power was also previously identified by Fuchs and Lederer (2007), but was categorized as an extended part of structural power.

Is the power that is exerted by the large social media platforms, described along the lines of the Palace of Dreams, merit its own category or does it belong to one of the above mentioned ones?

These reflections are not entirely new and Zuboff (2019), in her pioneering work "Surveillance Capitalism", highlights that not only there exist some new business powers but a whole new economic order and defines Surveillance Capitalism as *"a new economic order that claims human experience as free raw material for hidden commercial practices of extraction, prediction, and sales"*. For example, Google collects immense amounts of data on the search history of users, email content, and online activities in order to personalize advertisements. The ad targeting algorithms analyze the most intimate interests, desires, and behavior of users yielding an unprecedented power over them. Similarly, Facebook collects extensive data on its users, to create meticulous user profiles using advanced algorithms that advertisers leverage to target specific demographics but also impact civic life, especially in elections times.

Aside from conventional power categories, she identifies "instrumentarian power", defined as the instrumentation and instrumentalization of behavior for the purposes of modification, prediction, monetization, and control. It is important that this power defined by Zuboff (2019) should not be confused with the above mentioned "instrumental power" due to paronymy. "Instrumentation" pertains to the material architecture of computation that influences human experience, while "instrumentalization" refers to the social dynamics where surveillance capitalism utilizes machines to take advantage of individuals for market purposes.

The central question remains: how is this power, predominantly the one described above by Zuboff, different from the conventional categories?

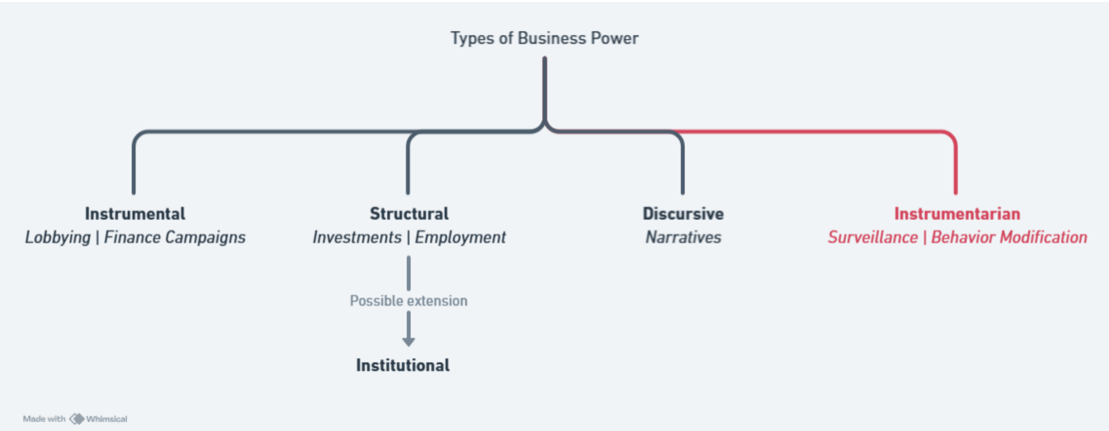

Figure 6.2. Types of Business Power

Aside from conventional power categories, instrumentarian power represents a distinct form of control that cannot be neatly classified as instrumental, structural, or discursive. It goes beyond instrumental power, which typically involves direct influence of one actor (A) over another (B) to the point that B does something they wouldn't have otherwise done. While instrumental power focuses on influencing decision-making, instrumentarian power is more intrusive, as it does not simply seek to change actions or decisions but manipulates and controls behavior at a deeper, more foundational level. It's about shaping B's very nature, behavior, and thought processes to serve the interests of A, often through predictive algorithms, surveillance, and behavioral engineering. The key difference is that instrumentarian power doesn't assume an equal or dynamic relationship between A and B; instead, it erases B's autonomy, leaving them not as a subject of power, but as an object entirely shaped by it. Similarly, instrumentarian power does not align with structural power, which is concerned with shaping and reinforcing broader socio-economic and political structures that influence decision-making. In structural power, A creates or reinforces values and institutions, but these actions are limited to specific areas or issues that are strategically advantageous or neutral to A. In contrast, instrumentarian power goes beyond influencing external structures to directly mold individual behavior. It's not about influencing policy or institutions from a distance; it's about embedding mechanisms of control within the very fabric of individual experience, manipulating behavior on a granular level. Finally, instrumentarian power is also distinct from discursive power, which involves shaping the ideas, norms, and discourse through communication. Discursive power works through persuasion, where A seeks to influence B's beliefs or ideas through shared social frameworks. However, in the case of instrumentarian power, the relational dimension of influence breaks down entirely. Instead of engaging in dialogue, A exercises control over B through mechanisms like data manipulation, surveillance, and algorithmic prediction. The aim is not to persuade B's ideas or opinions, but to reshape their behavior to the point where B no longer retains autonomy or independent agency. In this sense, instrumentarian power mirrors the control seen in Tabir Saraj, where the very essence of the individual (in this case, their dreams) is collected, analyzed, and manipulated to serve the regime's interests. Just as the empire in Tabir Saraj controls the interpretation of citizens' most intimate experiences (their dreams) for political purposes, instrumentarian power works similarly by gathering and analyzing vast amounts of personal data to predict and shape individual behavior. The relational dynamic shifts fundamentally in both cases, as the subject (B) is no longer a free actor but is shaped, controlled, and commodified. In this way, instrumentarian power reflects a totalizing form of very intimate control, transcending the conventional frameworks of instrumental, structural, and discursive power to create a new, more invasive form of dominance.

To sum up, it is not instrumental as it's not simply *"A has power over B to the extent that he/she can get B to do something they wouldn't otherwise do"*, nor structural as in *"A devotes his/her energies to creating or reinforcing social and political values and institutions of only those issues which are comparatively innocuous to A"*(Bachrach and Baratz, 1962). Instead, the very relational dimension between A and B breaks down as A has (ideally) total knowledge over B and can (ideally) shape the very nature of B to the extent that B no longer is a subject but becomes an object, similar to the ideal study as an "organism" of the radical behaviorism approach envisioned by Skinner. Thus, it is not discursive either as the ability to mold someone's ideas through dialogue also requires a relational dimension, which breaks down when A knows and manipulates B mind & behavior.

This new category of power is not an is-a but rather a has-a relationship for these businesses. Platforms such as Google and Facebook fully exercise also the other categories of power. In fact, as the journal POLITICO (2022)notes, Meta (Facebook) set a record in 2021 on spending more than $20 million making it one of the biggest spenders in Washington. Reuters (2022) notes how Alphabet (Google) had a 27% higher U.S. lobbying expenditures for 2021 compared to 2020, clearly exercising instrumental power. These companies also exercise structural power, as research from Khan (2017) indicates. They are gatekeepers, building and controlling the infrastructure for digital markets and the de facto owners of digital commerce routes on which other companies as well as citizens and governments depend on. In fact, 55% of online shopping searches are now in Amazon and Google & Facebook, which together now capture 73% of all digital advertising in the U.S. They also exercise institutional (or extended structural- if you will) power by constantly engaging in public-private partnerships with governments, for example Google's Partnership with the United States Department of Defense in 2017 having the latter make use of Google's AI in their drones (Gibbs, 2018). Thus, this new power facet these companies encompass is yet another added weaponry in their arsenal and certainly not the only one. Furthermore, these entities definitely exercise their discursive power when engaging with the public on numerous occasions. For example, when faced with criticism from civic society they use the neutrality of their technology as a rhetorical move that hides vast policy influence and economic imperatives (Gillespie, 2010). Another example that exhibits the discursive power of the social-media platforms, is in their definition of the "fake news problem" as a mainly technical as opposed to a socio-technical one, thus, *"by proposing technical solutions to social problems, such formulations forward the idea that technology companies as can be the responsible wielders of their own power"* (Creech, 2020).

"The object of power is power", as Orwell (2013) notes in "1984", so how does the power exercised by these companies, in its multitude of dimensions, legitimize itself? Yates (2020) comes up with two key tactics which platforms use to legitimize themselves in front of pressure (but not only):

- "Discursive vectors of progress" - these platforms self-declare as "the future", consequently making any attempt to regulate them sounding "backward". Authors who have looked at social movements have noted the strategic importance of our collective imagination about the future and how movements inspire in their combination of disruption, insurgency and innovation (Eyerman and Jamison, 1991). Platforms have appropriated this approach and often legitimize themselves as the inevitable future. However, as Yates (2020) clearly observes: *"Platform economy businesses invoke vacuous or controversial future visions but their future visions are still potent because states have largely abandoned this discursive terrain."* Thus, this ecompasses a dual usage: the exertion of their discursive power to impact society at large and the employment of their discursive power as a technique to maintain all the power dimensions.

- "Political" - through the direct mobilization of platform users, alliances with existing "grassroots" associations, and the creation of front groups. In this case, civil society pressure is fabricated (sometimes co-opted) to influence the public opinion at large and consequently regulators. Among these, user mobilization is one of the most used sub-tactics. For example, Uber added a "De Blasio" button on their app as a reaction to Mayor Bill de Blasio who introduced a new bill which would restrict Uber and even offered free UberPool rides to its New York customers to attend a pro-Uber protest at New York's City Hall (Kosoff, 2015). Also, as Thelen (2018) notes, users can be mobilized either as consumers or as taxpayers, and it turns out this difference is consequential in terms of policy making.

In Interview Set 2 (see Appendix .1.12), participants were asked to reflect on whether the described power represents a new form, after being presented with an overview of the established categories of power, or if it fits within one of those existing categories. The results show that the interviewees were torn, with the majority (21) responding this is a new power and the rest (15) responding they think it belongs to one of the more "traditional" (other three) power categories. When disintegrating in terms of sex and occupational groups, the following are observed:

- Females are more likely to believe that the described power is new, while males are more inclined to think that the power is not new, aligning it with one of the established categories (see Figure 6.3).

- Respondents from arts show a clear inclination towards the belief that this is a new business power; Those from sciences show a slight preference for the power being new but not as strong as those from arts; Respondents from politics demonstrate a neutral stance, being divided in half if this is a new power or not (see Figure 6.4).

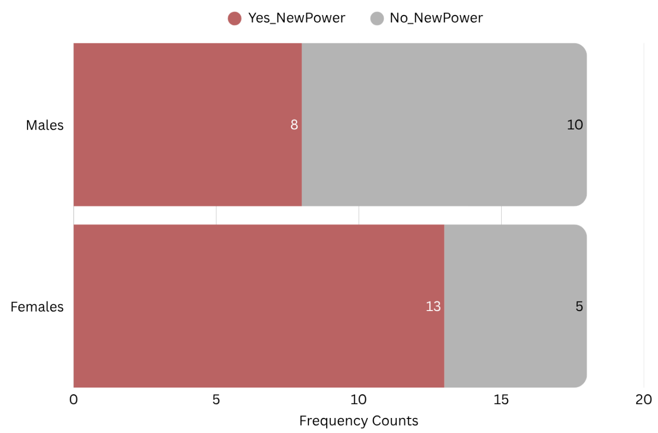

Figure 6.3. Frequency Counts on considering the "instrumentarian" power as new based on sex - Interview Set 2.

When the interviewees were asked to provide a rationale for their choices. Those that argued that the "new power" emerging from social media platforms and AI is fundamentally distinct from the traditional business powers, namely instrumental, structural, and

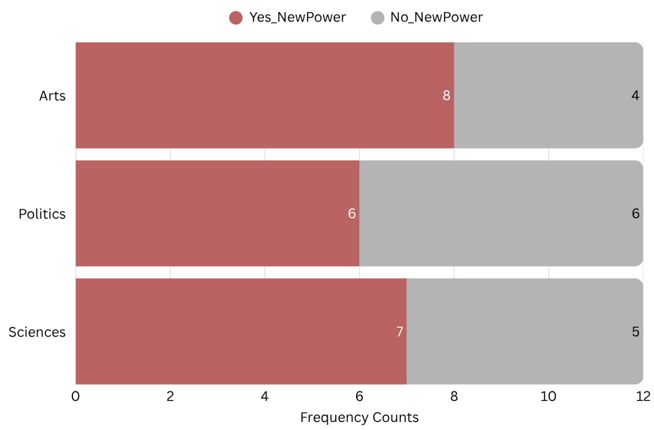

Figure 6.4. Frequency Counts on considering the "instrumentarian" power as new based on occupational groups - Interview Set 2.

discursive and merits its own category, emphasized its deep, subconscious influence on individuals. They noted that it shapes behavior without overt consent or awareness, unlike lobbying or advertising. This power operates through algorithmic prediction, behavior modification, and data-driven personalization, making it far more invasive and harder to detect. It does not just frame issues or set agendas but it actively molds preferences, choices, and even identity, often bypassing rational thought and critical reflection.

Beyond its psychological depth, this new power is also seen as unique in scope and structure. It is not confined to a specific location or market, and it transcends traditional categories by blending and amplifying aspects of all three. Some described it as a new form of oligarchy, with tech giants wielding influence beyond national governments, while others highlighted its predictive and pervasive nature that affects virtually every part of life. Because it manipulates users in ways they don't recognize, lacks clear regulation, and redefines the boundaries of agency, many concluded it represents a new, more extreme dimension of business power that cannot be fully explained within existing frameworks.

In terms of opponents, so those who claim that this power merits its own category, the 15 people labeled it as either part of discursive or structural, with the majority being in the discursive camp as it can be observed in Figure 6.5. When analyzing in terms of groups, for the people who oppose the idea that this is a new power, those coming from arts and politics mainly label it as discursive, whereas those coming from sciences mainly label it as structural (see Appendix .4.1). When disintegrating in terms of sex, the females largely chose discursive (4 out of 5), whereas the males were torn in half between it being a structural or a discursive power (see Appendix .4.2).

In terms of the rationales the opponents provided, many identified it as a more sophisticated form of discursive power, given its role in shaping culture, framing desires,

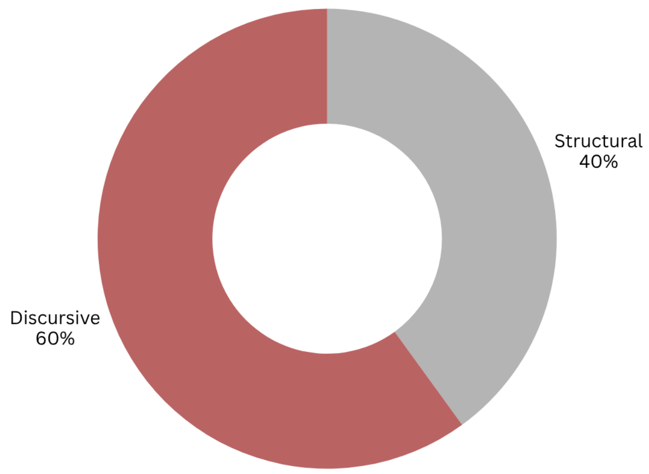

Figure 6.5. Distribution of the opponents to the idea that the instrumentarian power is new based on the traditional power they think it belong to - Interview Set 2.

and influencing public will. Several pointed to historical precedents such as TV advertising and behaviorist marketing (e.g., smoking campaigns) to argue that the manipulation of behavior is not new. It is only more personalized and technologically advanced now. Even though AI allows for targeting at the individual level rather than the collective, they maintain that this is an intensified evolution of discursive influence rather than a fundamentally new kind. Some mentioned the Cambridge Analytica case as an example of business-led cultural and political hegemony that still aligns with discursive frameworks. Others placed this power under the structural category, reasoning that it stems from businesses' pre-existing economic influence and long-standing goals. They argued that tech companies' ability to collect and exploit data for behavioral control is made possible by their structural position, which is essentially accumulated wealth and market dominance developed over time. From this perspective, AI and algorithmic influence are seen as new tools within the same structural ambitions that have defined business power since the industrial revolution. Though some acknowledged that this power may have acquired greater depth and reach, they viewed it as a natural extension or intensification of existing structural logic rather than something categorically new.

6.3 Tale *in brief* - Power

Power in today's digital age, exemplified by AI-driven and AI-driving social media platforms like Google, Facebook etc, presents a new, unprecedented form tied to AI and data manipulation. This power, while rooted in traditional categories, necessitates a deeper understanding of how it shapes individual behavior through mechanisms of consent and data exploitation. Drawing a parallel with Kadare's "Palace of Dreams," the collection and interpretation of personal data by modern platforms mirrors the control mechanisms in a totalitarian regime, where individuals unknowingly submit their most intimate information, often under the illusion of free will (see Kadare (2011)). In Kadare's The Palace of Dreams, the collection and interpretation of citizens' dreams by the Tabir Saraj institution serve as a powerful metaphor for the control exerted by modern AI-driven platforms like social media and tech giants. In the novel, individuals unknowingly submit their most intimate dreams, which are processed by a Kafkaesque bureaucratic system to maintain political control, mirroring how modern platforms gather vast amounts of personal data, from clicks, likes, and searches, in order to predict and influence user behavior. Both systems create an illusion of voluntary submission, as users "consent" to terms and conditions without fully understanding the consequences, much like how citizens in the novel submit their dreams under the guise of free will. The unseen forces, *interpreters* in the palace and *algorithmic designers* in tech platforms, use this collected data to shape decisions and actions, steering political, social, and commercial outcomes. Just as the empire's stability in the novel depends on dream analysis, the power of modern platforms relies on the manipulation of personal data to guide everything from content recommendations to political ads, thereby controlling and shaping public opinion and behavior.

In exploring conventional categories of business power, namely the instrumental, structural, and discursive ones, using the analytical model of Fuchs and Lederer (2007), this analysis uncovers how these platforms fit into or challenge these frameworks. Inspired by the concept of "Surveillance Capitalism" from Zuboff (2019) that introduces a new form of power, "instrumentarian power", which transcends traditional classifications by not only influencing but actively shaping and controlling individual behavior for profit. This power, much like the dream-collecting institution in Kadare's novel, operates through opaque systems that commodify personal data and transform it into a tool for manipulation, subtly undermining individual autonomy. This constitutes a new business power because it is not instrumental as it's not simply "A has power over B to the extent that he/she can get B to do something they wouldn't otherwise do", nor structural as in "A devotes his/her energies to creating or reinforcing social and political values and institutions of only those issues which are comparatively innocuous to A" (Bachrach and Baratz, 1962). Instead, the very relational dimension between A and B breaks down as A has (ideally) total knowledge over B and can (ideally) shape the very nature of B to the extent that B no longer is a subject but becomes an object, similar to the ideal study as an "organism" of the radical behaviorism approach envisioned by Skinner. Thus, it is not discursive either as the ability to mold someone's ideas through dialogue also requires a relational dimension, which breaks down when A knows and manipulates B mind & behavior. However, this new category of power is not an is-a but rather a has-a relationship for these businesses, which also yield all the other categories of business power. Furthermore, they legitimize themselves using multiple techniques most notably: these platforms self-declare as "the future", consequently making any attempt to regulate them sounding "backward" and through the direct mobilization of platform users, alliances with existing grassroots associations, and the creation of front groups.

Interviewees from Set 2 were divided on whether the power exerted by tech platforms like Google and Facebook represents a new form of business power. A majority believed it was indeed a new category, 21 out of 36 interviewees, emphasizing its deep, subconscious influence on individuals through mechanisms like algorithmic prediction and behavior modification, which shape preferences and identities without overt consent. This form of power was seen as more invasive, personalized, and difficult to detect compared to traditional lobbying or advertising. However, others viewed it as an intensified version of existing forms of power, particularly discursive (60%) and structural (40%) power.

Chapter 7

Conclusions

The following can be considered as the main conclusions springing up from this work:

- One of the major conclusions of this study is that there is a clear need for **improved science communication**, both in terms of *breadth* and *depth.* This conclusion is supported by multiple findings. For instance, when participants in Interview Set 2 were asked whether they were familiar with the concept of *underemployment*, only 22.2% responded affirmatively. Moreover, even among those who indicated familiarity, the descriptions provided were partial and did not capture the full scope of the concept. This suggests that awareness of key economic and labor-related concepts remains limited and that deeper engagement with these topics is lacking.Similarly, results from Online Survey 2 further underscore the importance of enhancing scientific literacy. When respondents were asked to define *artificial intelligence*, the most frequently occurring words and the descriptions themselves were largely consistent with a *symbolist* understanding of AI. This contrasts sharply with the *connectionist* approaches that dominate current AI research and application. In other words, the respondents' conceptualizations appear to reflect outdated or simplified models rather than the state of the art technologies. These findings indicate not only a gap in general awareness but also a deficit in nuanced understanding of rapidly evolving scientific and technological domains. Hence, this would be an important point to be explored by those that guide public education and science communication for the general audience, as well as the relevant policy makers. Furthermore, this highlights the need for "AI literacy programs", also in alignment with the EU Act, Article 4 (European Union, 2021). Taken together, these results show an urgent need for science communication strategies that reach wider audiences while also conveying the complexity and current developments of concepts in labor economics and artificial intelligence. Without such efforts, there is a risk that public understanding will remain superficial, potentially influencing policy, education, and public discourse in ways that do not align with contemporary knowledge.

- Moreover, on a macro-scale, one thing that was noticed throughout this thesis, particularly during the second set of interviews, was the fact that many respondents explicitly acknowledged that they were *choosing optimism* rather than providing what they themselves considered realistic or grounded estimations of the phenomena under investigation. This deliberate framing of their responses as aspirational rather than predictive suggests that discussions about AI's impact on work and society are deeply entangled with normative preferences and psychological coping mechanisms, complicating efforts to distinguish between evidence-based forecasts and wishful thinking. Even when pressed to separate their hopes from their expectations, several interviewees maintained their optimistic stance, indicating that for many individuals, optimism may serve as a deliberate strategy for engaging with uncertain and potentially anxiety-inducing futures rather than as a straightforward assessment of probable outcomes. A clear illustration of this is the matter of *"Is this time different?"* discussed in Sub-chapter 4.2.1, with respect to the two forces at play: the complementary vs. substitution one. The results showed that 17 out of 36 interviewees or **47.2%**, believe that this time *is* different and the remaining part didn't. Many of those that did not accept that view, stated they wanted to be optimistic and even when pushed to provide their realistic expectation, whichever that was, as opposed to wishful thinking, many still resisted the idea.

- Mann-Whitney U tests were conducted across multiple instances throughout the analysis to examine potential differences between Millennials and Gen Z, as well as between males and females, on various attitudes toward work and AI. This statistical approach is particularly important because it allows for non-parametric comparison of central tendencies without assuming normal distributions,a crucial consideration given the ordinal nature of many survey responses and the potential for skewed distributions in attitudinal data. The majority of these tests yielded no statistically significant differences between demographic groups, a finding that warrants careful interpretation. This absence of significant results could be attributed to limited sample sizes, which may have reduced the statistical power of the tests to detect true differences. Mann-Whitney U tests are sensitive to sample size, and with insufficient observations, even meaningful differences in central tendencies may fail to reach statistical significance. However, it is important to note that these tests specifically measure differences in central tendencies (medians) and do not capture the full distributional characteristics of the data. As illustrated in the violin plots and descriptive tables throughout the analysis, there are observable differences in variances and distributional shapes between demographic groups, even when central tendencies do not differ significantly. These distributional differences, such as greater spread or multimodality in certain subgroups, may reflect meaningful heterogeneity in attitudes that the Mann-Whitney U test is not designed to detect. Alternatively, the lack of statistically significant differences may genuinely reflect the empirical reality that attitudes toward work and AI are remarkably homogeneous across these demographic categories among young Europeans. This interpretation challenges common assumptions about pronounced generational and gender divides in technology attitudes and labor perspectives.

- When set against the emerging dynamics of AI driven and AI driving social media platforms, three novel phenomena were presented to the respondents of Interview

Set 2: the idea of unpaid AI work, the fabrication of desires by algorithmic systems, and the rise of a new form of business power. The responses reveal a clear tendency to acknowledge these shifts. A substantial majority, **69.4%**, consider the time spent training algorithms through everyday platform use to constitute a form of unpaid work. An even larger share, **80%**, agree that these algorithms are capable of generating false desires. Finally, **58.33%** believe that such platforms exercise a new form of business power. Furthermore, the results show that when the participants of Online Survey 1 were queried regarding the impact social media platforms have in influencing: their preferences for products, their preferences for services and their political opinions, on a scale from 0 (not at all) to 5(extremely), applying a Friedman test, the results yield statistically significant differences among the three items ($\chi^2 = 43.16$, $p < 0.001$). The same test was used to to examine whether there were significant differences in participants' perceptions of how much value was being created for different beneficiaries (themselves, friends/family, platform owners, and society) through their social media participation. The results again revealed statistically significant differences among these groups ($\chi^2 = 45.09$, $p < 0.001$). Taken together, these findings suggest that respondents not only recognize the transformative nature of AI mediated environments but also perceive them as reshaping fundamental relations between labor, preferences, and economic power.

- Overall, it can be said that particularly for the samples of Online Survey 1 and Online Survey 2, the expectations of young people aged 18 to 35 in Kosova, Albania and Italy range from neutral to positive with respect to AI's impact in the world of work, in a 10 year time-frame. Whether that will materialize in the actual reality, remains to be seen.

Chapter 8

Limitations and Future Work

This study has several limitations that present opportunities for future research. First, the use of **snowball sampling** may have introduced selection bias, as participants were recruited through existing networks rather than through probability-based methods. While maximal effort was made to ensure diverse demographics in terms of sex, age, political orientation, religious belief, and field of study, it must be noted that most participants are highly educated and the vast majority live in large urban areas. This limits the generalizability of the findings to the broader population, particularly to individuals with lower educational attainment and those residing in rural or semi-urban settings. Future studies should employ stratified random sampling or other representative sampling techniques to ensure more diverse and generalizable results across all demographic and geographic segments.

Second, the reliance on correlation and regression-based techniques limits the ability to make causal inferences or provide direct policy recommendations. While these methods effectively identify associations and patterns in the data, they cannot establish causality. Future research should incorporate causation-based techniques that build upon survey and interview methods. Randomized controlled trials (RCTs) could provide valuable insights into the causal mechanisms underlying young people's perceptions of AI and work in Europe, offering more actionable evidence for policymakers.

Third, while a subset of analytical methods appropriate for the research questions was applied, the field offers numerous additional approaches that could yield complementary insights. Future work could incorporate alternative methodologies such as ensemble methods to provide a more comprehensive analysis.

Fourth, as highlighted in the conclusions, many participants exhibited **response biases** in certain questions, such as *"trying to be optimistic"* rather than providing realistic estimations of what they were actually being asked. This social desirability bias or optimistic framing may have influenced the accuracy of self-reported perceptions and expectations. Future research could employ more sophisticated psychological techniques, such as implicit association tests, forced-choice paradigms, or indirect questioning methods, to better capture genuine attitudes and beliefs while minimizing the influence of response biases.

Fifth, **the limited number of data points** represents another constraint of this study. However, it should be noted that the entire data collection process, encompassing Interview Set 1, Online Survey 1, Online Survey 2, and Interview Set 2, totaling approximately 254 hours of monitored surveys and interviews, was conducted solely by the author. This resource limitation, while constraining sample size, ensured consistency in data collection procedures. Future research with larger research teams could achieve greater sample sizes and broader geographic coverage.

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Appendices

.1 Data Collection Process

.1.1 Demographics of the interviewees of Interview Set 1 - City of Residence

City	Country	Count
Tirana	Albania	23
Torino	Italy	10
Prishtina	Kosova	7
Firenze	Italy	5
Vienna	Austria	5
Milan	Italy	3
Budapest	Hungary	3
Munich	Germany	2
Durres	Albania	2
Lisbon	Portugal	1
Nice	France	1
Osnabrück	Germany	1
Kërçovë	North Macedonia	1
Ankara	Turkey	1
Graz	Austria	1
Mitrovica	Kosova	1
Bruxelles	Belgium	1
Ljubljana	Slovenia	1
Johannesburg	South Africa	1
Berlin	Germany	1
Porto	Portugal	1
Toronto	Canada	1
Kristiansand	Norway	1
Luxembourg	Luxembourg	1
London	United Kingdom	1

.1.2 Demographics of the interviewees of Interview Set 1 - Age

Age	27	29	28	23	25	30	22	32	24	26	31	21	33	20	34	19
Count	10	7	7	7	7	5	5	5	5	5	4	3	2	2	1	1

.1.3 Demographics of the interviewees of Interview Set 1 - Political Orientation

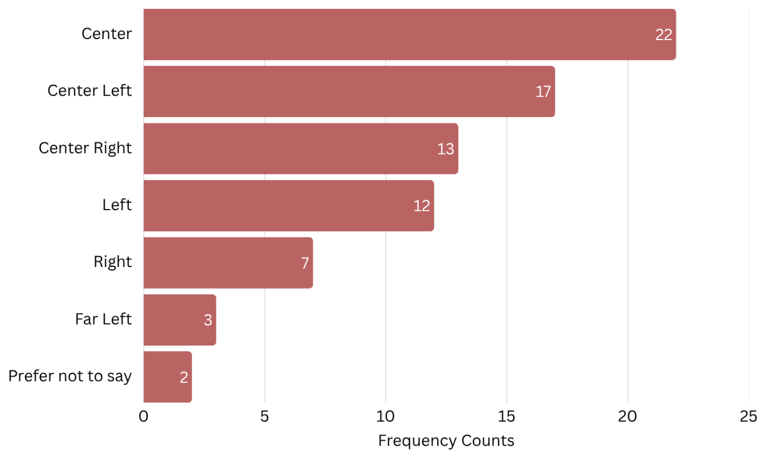

Figure 1. Distribution based on political orientation - Interview Set 1

.1.4 Demographics of the respondents of Online Survey 1 - City of Residence

City	Country	Count	City	Country	Count
Tirana	Albania	22	London	UK	2
Torino	Italy	16	Shkoder	Albania	2
Prishtina	Kosova	13	Zagreb	Croatia	1
Firenze	Italy	8	Munich	Germany	1
Vienna	Austria	6	Geneva	Switzerland	1
Milan	Italy	3	Siena	Italy	1
Budapest	Hungary	3	Bari	Italy	1
Brussels	Belgium	3	Brescia	Italy	1
Berlin	Germany	3	Lisbon	Portugal	1
Saranda	Albania	1	Vlore	Albania	1
Luxembourg	Luxembourg	1	Osnabrück	Germany	1
Liège	Belgium	1	Graz	Austria	1
Porto	Portugal	1	Tetovë	North Macedonia	1
Stockholm	Sweden	1	Sarajevo	Bosnia and Herzegovina	1
Gothenburg	Sweden	1	Göttingen	Germany	1
Bologna	Italy	1			

Table 1. Cities and countries of the interviewees - Interview Set 1.

.1.5 Online Survey 1 Question Set - Part 1: Demographic Data

Demographic Survey Questions

1. Age: from 18 to 35 with an option other
2. Sex: male | female | prefer not to say|other
3. City/Country where you live at the moment: Current city and country of residence - a list was provided.
4. Were you born in the country that you live in?Whether the respondent was born in their current country of residence - yes or no question.
5. If not, please state your country of birth: Country of birth if different from current residence - Open ended question.
6. Choose all that apply from the following, you are: Employed/Self-Employed/Student/Unemployed (multiple-choice)
7. The highest level of education attained: High School | Bachelor | Masters | PhD |Other: _____
8. Please write down the field of study of the last degree you obtained: Open ended, leave blank if high school was last completed.
9. If you are currently studying, please write down the field of study and the level of studying: Current field and level of study, e.g., Law School, Bachelor degree.
10. Please choose your political orientation from the following alternatives: Far Left | Left | Center Left | Center | Center Right | Right | Far Right
11. Your marital status: Married | Single | Divorced | Widowed | Separated | Other-Prefer Not to Say
12. Do you have children? Whether the respondent has children, Yes/No/Other-Prefer Not to Say
13.Your religious views: Religious affiliation or personal views of the respondent, a list was provided together with the options of atheist/agnostic and prefer not to say.

.1.6 Online Survey 1 Question Set - Part 2: Perceptions and Attitudes about AI, Work

A: Perceptions and Attitudes about AI, Work

1. How optimistic are you about the future of society on a scale from 0 to 10, in general?
2. How interested are you in politics on a scale from 0 to 10?
3. How interested are you in economic affairs on a scale from 0 to 10?
4. How interested are you in technology in general on a scale from 0 to 10?
5. How interested are you in AI (artificial intelligence) in particular on a scale from 0 to 10?
6. How optimistic are you regarding the impact that AI (artificial intelligence) will have on society on a scale from 0 to 10?
7. Do you think your life will be better than your parents? Much better...Much worse (5 scales)
8. Do you think your life will be easier than your parents? Much easier ... Much harder (5 scl)
9. Do you think your generation is working more in terms of time than your parents' generation did on average?Much more...Much less (5 scl)
10.How much do you trust the government of the country that you currently live in to handle matters of AI on a scale from 0 to 10?
11. How much do you trust the media of the country that you currently live in to handle & inform on matters of AI on a scale from 0 to 10?
12.New technologies, like AI, may be implemented for many reasons and one of them is to improve the well-being of the average citizen. How committed from 0 (not at all) to 5 (completely committed) are the following parties to do that: a) The government of your country | b) The companies in your country | c) The nongovernmental organisations in your country | d) The European Union 13. Do you think AI can be more "fair" than people?
14.Have you ever used AI tools like ChatGPT?
15. If yes, how often have you used them on average last week, in terms of days per week?
16. Assume you see an ad in a newspaper about a job and you think "That's a good job!". For each of the following, please give a score from 0 to 5 on how important they are for you to think of a job as a good job: a) A good salary | b) Ability to learn new things / self-development | c) Opportunities to get higher up in the career | d) Agreeing with company's mission & values | e) Nice office spaces | f) Complete online job - always working from home | g) Ability to work from home some of the time | h) Good work-life balance | i) Using cutting-edge technology, like AI | j) Working for a well-established company/institution | k) Working for a startup | l) Traveling as part of the job | m) Private health insurance | n) Flexible working hours | o) The office is close to your home

B: Perceptions and Attitudes about AI, Work

17.In today's society, paid work holds a central role in people's lives. Do you think that due to new technologies such as AI, society will be so profoundly transformed that work will no longer be a central component of people's lives within your lifetime? On a scale from 0 to 10, how likely is this to occur?
18. In general, how willing are you, on a scale from 0 to 5, to learn more (not formal education but through upskilling/reskilling courses): a) Mathematics | b) Coding | c) Soft skills, like communication, leadership, conflict resolution
19. Have you ever taken a coding course in the last two years?
20.Overall, do you think that due to AI, inequality in society in the next 10 years will be: Much more - more - the same - less - much less
21. Some countries are currently talking about introducing a basic income scheme. The idea is this: The government pays everyone a monthly income to cover essential living costs - it replaces many other social benefits - the purpose is to guarantee everyone a minimum standard of living - everyone receives the same amount regardless of whether or not they are working - people also keep the money they earn from work or other sources. Overall, would you be against or in favor of having this scheme in the country that you live in?
22. Now imagine that the above mentioned "basic income" can only be received if you fulfill some social conditions. These conditions are not based on wealth or need but on doing things that are considered "good for society", for example: learning to read and write, periodical medical check-ups, taking their kids to school, etc. How much would you support this from 1 to 4?
23. How do you define "work"? What is "work" for you? - Open ended question [a]
24. How do you define "AI"? What is "AI" for you? - Open ended question [b]

[a]Present in Online Survey 2

[b]Only present in Online Survey 2

.1.7 Online Survey 1 Question Set - Part 3: Perceptions Work and AI's impact in work

A: Work and AI's impact in Work

1. Provide your exact current job title: (If unemployed, the last job title — if you never worked, write *not applicable*).
2.In which sector do you work in? (If unemployed, the last sector you worked in — if you never worked, choose *not applicable*).
3. Describe what you do in your job in a few sentences:(If unemployed, the last job you did — if you never worked, write *not applicable*).
4.On average, how many hours per day do you work? (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
5.Do you think due to the developments in AI, people doing the same exact job as you declared above will work more or less, in terms of hours of work, in the next 10 years? (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
6. Do you think the real wage (adjusted for inflation) in the same job you declared above due to the developments in AI, in the next 10 years, will be: (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
7. How much do you like the job you declared above on a scale from 0 to 10? (If you don't currently work, please respond for the last job you did — if you have never worked, choose 0).
8.Do you think that due to the developments in AI, in the next 10 years, you will like the job you declared above:(If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
9.How much more productive do you think the usage of the current state of AI tools can make you in the job position you declared above on a scale from 0 to 10?(If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
10. What about after 10 years — how much more productive do you think the usage of AI tools can make you in the job position you declared above on a scale from 0 to 10? (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
11. In your opinion, what percentage of people in the same job position you declared above are going to lose their job in the next 10 years due to AI? (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).

B: Work and AI's impact in Work

12.Let's envision your job as a set of tasks. For example, if you were a secretary, you might: 1. Write emails, 2. Set up appointments, etc. In your opinion, what percentage of the tasks within the job position you declared above can be automated using AI? (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
13. Do you think the company or institution that you work/ed at is more likely to use AI to: (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option). Substitute the workers | Complement the worker's jobs
14.Does your company or institution use AI tools in their daily practices? (If you don't currently work, please respond for the last job you did — if you have never worked, choose that option).
15.Rank the reasons below from 1 (most important) to 7 (least important) as to why you work in the job position declared above. *IMPORTANT: Unlike previous questions, this is a ranking — two reasons cannot both be number 1. If you don't currently work, please don't respond to this question.* [i. Make money | ii. Structure your days | iii. Give meaning to life | iv. Acquire skills to become self-employed | v. Socialize/Network | vi. Social status | vii. Help people / contribute to society]
16.Rank the following phenomena from 1 (most risky) to 7 (least risky) as to why you might lose your job, the exact job you declared above. *IMPORTANT: Two reasons cannot both be number 1 in terms of risk. If you don't currently work, please don't respond to this question.* [i. Automation | ii. Corruption | iii. Bad management | iv. Offshoring (e.g., call center jobs from Italy offshored to Albania) | v. Political instability in your country | vi. A migrant takes your job | vii. Clashes with colleagues' values & opinions]
17. Overall, due to the developments in AI in the next 10 years, when you consider working time, wage, job quality, etc., in the job position you declared above, do you think your job will be: Much Better...Much Worse
18.How do you imagine the future of work in general in the next 10 years? (*Not only in your specific job but in general.*)
19.How do you imagine the future of work in general in the next 100 years? (*Not only in your specific job but in general. You may draw comparisons with literature or movies.*)
20. We want to know if people are paying attention to the survey. To show that you have read this much, please select option 3. 1_National Newspaper | 2_National TV | 3_National Radio | 4_Social Media — This is the ATTENTION-CATCHER QUESTION.

.1.8 Online Survey 1 Question Set - Part 4: Perceptions about Social Media and Cultural Products & Services

Section D: Social Media Questions

1. How many hours per day on average do you think you spend on social media?
2. Do you consider YouTube a social media?
3. Do you use social media for work purposes?
4. How many social media accounts have you got on different apps that you proactively use?
5. Do you think the existence of social media improves your life?
6. On a scale from 0 (not at all) to 5 (a lot) how much value do you think you are creating/generating as you are using social media for: Yourself | Your friends and family | The owners of the platform | Society
7. Do you think you are accumulating social capital while being on social media?
8. How much are you willing to pay (in euros) for your access to social media per month, given that no ads would be shown to you: Instagram | TikTok | Facebook | Twitter | YouTube | SnapChat | LinkedIn | Whatsapp | Reddit | Telegram | BeReal | Pinterest | Tinder
9. How addicted do you think you are to social media on a scale from 0 to 10?
10. If there was a publicly owned version of a social media and the other social media are still available, how willing would you be to use the public one (0-10)?
11. How much power do you think you personally have (0-10) to impact the decision-making of big tech companies like Google, Facebook, etc.?
12. From 0 to 5, how much does the content in social media impact: Your preferences for products | Your preferences for services | Your political opinions
13. Assume you are the CEO of the following companies and want to charge in the country you live in for the usage per month. How much would you charge: Instagram | TikTok | Facebook | Twitter | YouTube | SnapChat | LinkedIn | Whatsapp | Reddit | Telegram | BeReal | Pinterest | Tinder
14. For the following questions, please state your interest on a scale from 0 (not at all) to 5 (very interested) to: Listen to music generated by AI | Read books generated by AI | Watch movies/series generated by AI
15. For the following questions, please state your interest on a scale from 0 (not at all) to 5 (very interested) in having an AI service, like ChatGPT but also with audio like Siri or Alexa, to: Be your customer service agent | Teach you stuff | Be your personal assistant
16. For the following questions, please state your interest on a scale from 0 (not at all) to 5 (very interested) in having robots empowered by AI to: Serve you food or drinks in a bar/restaurant | Take care of you like a nurse | Clean your housing/office spaces

.1.9 Demographics of the respondents of Online Survey 1 - Field of Study

Field	Count	Field	Count
Computer Engineering	7	Criminal Law	2
Computer Science	3	M.Sc. Communication Science	1
Economics	4	International Commercial Law	1
Software Engineering	3	Law	1
Architecture	2	Physics	1
International Relations	1	Master of European Affairs	1
Information Technology	4	Mathematics	2
Communication and Tourism	1	Health Economics	1
International Cooperation	1	Sociology and Philosophy	1
Clinical Psychology	1	Industrial Engineering	1
Bachelor in Law	1	Business Management	1
Master in Finance	1	Transportation Design	1
Data Science	3	Risk Management	1
Fine Arts, Painting	2	Double Major in Economics	1
Applied Chemistry	1	Automotive Engineering	1
Philosophy	1	Nursing	1
Science and Technology	1	Medical Studies	2
Journalism	1	International Communication	1
English Language	2	Gender Studies	1
Education Studies	1	Biomedical Engineering	1
Accounting	1	LLM in International Law	1
Translation	1	Psychology	2
Business Administration	1	Entrepreneurship	1
Political Science	4	Fashion Design	1
Banking and Finance	1	Structural Engineering	1
European Politics	2	Faculty of Education	1
Software Engineering	2	Painting Studies	1
Linguistics	1	Business Informatics	1
Sports Management	1	Engineering	1
Industrial Engineering	1	Humanistic Studies	1

Table 2. Frequency of respondents by field of study -Online Survey 2

.1.10 Demographics of the respondents of Online Survey 2- City of Residence

City - Country - Count	City - Country - Count
Tirana, Albania - 48	Milano, Italy - 3
Torino, Italy - 19	Istanbul, Turkey - 3
Vienna, Austria - 17	Thessaloniki, Greece - 2
Prishtina, Kosova - 17	Bologna, Italy - 2
Budapest, Hungary - 14	Berlin, Germany - 3
Firenze, Italy - 12	Lisbon, Portugal - 1
Sofia, Bulgaria - 7	Pristina, Kosova - 1
Brussels, Belgium - 5	Bari, Italy - 1
London, UK - 5	Brescia, Italy - 1
Munich, Germany - 6	Saranda, Albania - 1
Shkoder, Albania - 3	Vlore, Albania - 1
Zagreb, Croatia - 1	Luxembourg, Luxembourg - 1
Graz, Austria - 1	Porto, Portugal - 1
Osnabrück, Germany - 1	Liège, Belgium - 1
Stockholm, Sweden - 1	Tetovë, North Macedonia - 1
Sarajevo, Bosnia and Herzegovina - 1	Gothenburg, Sweden - 1
München, Germany - 1	Göttingen, Germany - 1
Siena, Italy - 1	Geneva, Switzerland - 2
Ljubljana, Slovenia - 1	Cardiff, Wales - 1
Hamburg, Germany - 1	Skopje, North Macedonia - 1
Netherlands - 1	Bielefeld, Germany - 1
Utrecht, Netherlands - 1	Trbovlje, Slovenia - 1
Dubai, UAE - 1	Chicago, USA - 1
Padova, Italy - 1	Frankfurt, Germany - 1
New York, USA - 1	Durres, Albania - 1
Basel, Switzerland - 2	Lorient, France - 1
Athens, Greece - 1	Amsterdam, Netherlands - 1
Kristiansand, Norway - 1	Miami, USA - 1
Bucharest, Romania - 1	Toronto, Canada - 1

Table 3. Frequency of respondents by city of residence - Online Survey 2

.1.11 Demographics of the respondents of Online Survey 2 - Field of Study

Field of Study	Count	Field of Study	Count
Computer Engineering	9	Political Science	9
Software Engineering	8	Information and Communication Technology	7
Economics	7	Architecture	6
Computer Science	6	Medical Studies	5
Business Informatics	5	Physics	3
Painting Studies	3	Law	3
Accounting	2	Linguistics	2
Criminal Law	2	Industrial Engineering	2
Engineering	2	Civil Engineering	2
International Relations	2	International Commercial Law	2
Mathematics	2	Communication Science	2
English Language and Literature	2	Data Science and Engineering	2
Finance and Banking	1	Business Management Studies	1
Applied Chemistry	1	Clinical Psychology	1
Sociology and Philosophy	1	Health Economics	1
International Cooperation	1	European Affairs	1
Communication and Tourism	1	Science and Technology	1
Nursing	2	Automotive Engineering	1
Biomedical Engineering	1	Medical Studies, Speech	1
Psychology	2	Gender Studies	1
Entrepreneurship and Innovation	1	Fashion Design	1
Banking and Finance	1	Journalism	1
International Communication	1	Risk Management	1
Structural Engineering	1	European Politics	1
Economic Studies	1	Humanistic Studies	1
Industrial Engineering	1	Sports Management	1
Transportation Design	1	Biophysics	1
Business Economics	1	European Studies	1
Education	4	Mechanical Engineering	1
Chemical Engineering	1	Philosophy	1
Literature	1	Biology	2
Music Pedagogy	1	Sociology	1
Legal Psychology	1	Management and Leadership	2
Foreign Languages	1	Accounting and Finance	1
Finance and Accounting	1	Electronic	1
Economic Engineering	1	Business School Project Management	1
Art Design	1	Banking	1
Biochemistry	1	Statistics	1
Business Development	1	Supply Chain Management	1
Industrial Biotechnology	1	Pharmacy	1
Architectural Engineer	1	Performing Arts	1
Electronics Engineering	1	Violin Specialization	1
Environmental Economics	1	Industrial Design	1
Civil Engineer	1	Food Analytics	1

Table 4. Frequency of respondents by field of study - Online Survey 2

.1.12 The Interview Set 2 Questions

Section 1: Unpaid Work and Underemployment

1. Do you consider unpaid work (care work, household tasks, volunteering) to be "work"?

2. Have you ever heard the term "underemployment"? What do you think it means?

   Definition Prompt (Read Aloud):

   Underemployment refers to the underutilization of the productive capacity of persons in employment in relation to an alternative employment situation in which individuals are willing and able to engage.

   - *Time-related underemployment:* Willing and available to work more hours, but current hours are below their desired threshold.
   - *Skill-related underemployment:* Possessing more skills than required by the current job.
   - *Income-related underemployment:* Being underpaid compared to others in the same occupation.

3. Have you personally experienced any of these types of underemployment?

4. Please rank the three types of underemployment in order of relevance for young people like you in Europe today.

Section 2: Work as Drudgery (for Young People in Europe Today)

Rank the dimensions below on what makes work a drudgery for young people like you in Europe today.

- Repetitiveness
- Lack of connection with colleagues
- Lack of connection with the end-product and end-user
- Lack of belief in the inherent value of the work

Section 3: Meaningful Work (for Young People in Europe Today)

Rank the dimensions below on what makes work meaningful for young people like you in Europe today.

- *Task integrity:* the tasks an individual does and the opportunity to complete a whole piece of work.
- *Skill cultivation and use:* the ability to use and develop a range of skills at work.
- *Task significance:* how one's work contributes to improving others' lives.

- *Task autonomy:* how freely individuals can determine their work approaches.
- *Belongingness:* how work can make one feel connected to a wider group.

Section 4: Technological Shifts

SBTC vs. RBTC: There are two "competing theories":

- **Skill-Biased Technological Change (SBTC):** Technological advancements increase demand for high-skilled workers and reduce demand for low-skilled workers.
- **Routine-Biased Technological Change (RBTC):** Technology mainly replaces routine-based tasks, whether manual or cognitive, while non-routine tasks are less affected.

Which one do you believe to be most "true" if you have to choose one?

Underemployment & AI Impact (Next 10 Years) For each type below, do you think the situation will be: much better, better, the same, worse, or much worse, given the impact of AI development in the next 10 years?

- Time-related underemployment
- Skills-related underemployment
- Wage-related underemployment

Unpaid Household Work & AI Impact Do you think the time you will spend on these tasks will be: much more, more, the same, less, or much less, given the impact of AI development in the next 10 years?

Section 5: Work-Life Balance and AI Impact

Work-life balance can be seen through the "spillover effect" — one world influencing the other positively or negatively. How do you expect the work-life balance to change in the next 10 years given AI's impact: much better, better, the same, worse, or much worse?

Section 6: Work as Drudgery – AI Impact

For each type below, do you think the situation will be: much better, better, the same, worse, or much worse, given AI's impact in the next 10 years?

- Repetitiveness
- Lack of connection with colleagues
- Lack of connection with the end-product and the end-user
- Lack of belief in the worth of what is being produced

Section 7: Is This Time Different?

Explore views on:

- **Substitution effect:** Automation replacing labor
- **Complement effect:** Automation enhancing labor

Section 8: Productivity & the Future

Do you think people will be more productive in the next 10 years: much more, more, the same, less, or much less? Why?

Prompt for Discussion – Possible Explanations for the Productivity Paradox:

- False Hopes: Technologies may not be as transformative as expected.
- Mismeasurement: Productivity gains are real but not accurately captured.
- Concentrated Distribution & Rent Dissipation: Gains are captured by few.
- Implementation and Restructuring Lags: Time is needed before full benefits are realized.

Assuming productivity increases due to AI, how should the gains be used?

- Toward increased output?
- Toward increased leisure?

Section 9: AI Work is Work Fabrication of Desires

Particularly in terms of AI-driven social media, the definition is provided to "AI Labor" and the participants are asked if they agree. Also, if they believe social media algorithms create false desires in them and if the ads they see there differ from traditional marketing.

Section 10: Business Power Dimensions - Social Media

Being provided with a description for the three “established” business powers, the interviewees are asked whether the fourth—arising mainly from social media platforms at the forefront of AI development—merits its own category.

Definitions:

- **Instrumental:** lobbying and campaign finance to influence politics.
- **Structural:** reliance of economies on private investment decisions.
- **Discursive:** influence over the framing of policy issues and public desires.
- **New Power:** the instrumentation and instrumentalization of behavior for modification, prediction, monetization, and control.

.1.13 Demographics of the Interviewees from Arts - Interview Set 2

Nr	Date Int.	Specific Art	Sex	Country (Born)	Country (Current)
1	29-Oct	Violinist	F	Albania	Norway
2	27-Oct	Violinist	F	Albania	Norway
3	30-Sep	Writer & Content Creator	F	Kosova	Kosova
4	26-Oct	Graphic Designer	M	Albania	Albania
5	24-Oct	Material Designer	F	Turkey	UK
6	31-Oct	Painter	M	Albania	Albania
7	5-Nov	Violinist	F	Albania	Albania
8	4-Nov	DJ & Graphic Designer	M	Albania	Albania
9	11-Nov	Tenor	M	Albania	Austria
10	11-Nov	Sculptor	M	Albania	Albania
11	2-Dec	Multimedia: Painting and Photography (mainly)	M	Albania	Albania
12	4-Dec	Flute Player and Music Teacher	F	Albania	Norway

Table 5. Demographics of individuals in the specific arts sector - Interview Set 2 (Year:2024)

.1.14 Demographics of the Interviewees from Sciences - Interview Set 2

Nr	Date Int.	Specific Domain in Sciences	Sex	Age	Country (Born)	Country (Current)
1	10-Sep	Data Science	F	24	Turkey	Italy
2	11-Sep	Informatics	F	21	Albania	Albania
3	17-Sep	Bio Engineering	M	31	Albania	Italy
4	12-Oct	Cell Biology	F	28	Albania	Switzerland
5	22-Sep	Artificial Intelligence for Medical Sciences	M	27	Albania	Albania
6	15-Oct	Medicine	F	20	Albania	Albania
7	13-Oct	Evolutionary Biology	M	28	Albania	Germany
8	1-Oct	Astrophysics	F	29	Spain	Italy
9	19-Sep	Nutrition Sciences	F	27	Albania	Kosova
10	11-Oct	Bio Tech	M	26	Italy	Italy
11	23-Oct	Research in Banking and Finance	M	29	Albania	Italy
12	24-Oct	Statistics	M	33	Kosova	Germany

Table 6. Demographics of individuals in the sciences sector - Interview Set 2 (Year:2024)

.1.15 Demographics of the Interviewees from Politics - Interview Set 2

Nr	Date Int.	Specific Role in Politics	Sex	Age	Country (Born)	Country (Current)
1	15-Sep	Student Assistant in Political Science Studies	M	30	Albania	Germany
2	15-Sep	Political Analyst & TV Commentator	M	33	Kosova	Italy
3	5-Oct	Coordinator in a Political Movement	M	32	Albania	Albania
4	6-Oct	Political Advisor in a Municipality	M	25	Italy	Italy
5	16-Sep	Political Communicator	F	26	Romania	Romania
6	5-Oct	Political Journalist	F	21	Kosova	Kosova
7	2-Nov	Political Advisor in Transnational Politics Matters	F	26	Hungary	Italy
8	20-Nov	Political Consultant	F	24	Italy	Italy
9	1-Oct	Political Activist	M	24	Kosova	Kosova
10	13-Oct	Student Assistant in Political Science Studies	M	29	Albania	Austria
11	13-Oct	Political Activist	F	21	Kosova	Kosova
12	30-Nov	Political Sciences and Development Student	F	22	Norway	Norway

Table 7. Demographics of individuals in the political sector - Interview Set 2 (Year:2024)

.2 Chapter 2

.2.1 The distribution of familiarity with the term "underemployment" by sex - Interview Set 2

Sex	Heard of Underemployment	Count
Female	No	16
Female	Yes	2
Male	No	12
Male	Yes	6

Table 8. Awareness of underemployment by sex – Interview Set 2

.2.2 The distribution of familiarity with the term "underemployment" by occupational group - Interview Set 2

Group	Heard of Underemployment	Count
Arts	No	11
Arts	Yes	1
Politics	No	9
Politics	Yes	3
Science	No	8
Science	Yes	4

Table 9. Awareness of underemployment by occupational group – Interview Set 2

.2.3 Classification Report with unbalanced classes - ESS Data - Job Satisfaction classification

Class	Precision	Recall	F1-score	Support
Low	0.00	0.00	0.00	201
High	0.80	1.00	0.89	794
Accuracy	0.797			
Macro avg	0.40	0.50	0.44	995
Weighted avg	0.64	0.80	0.71	995

Table 10. Classification report for logistic regression model on imbalanced dataset- ESS Data - Job Satisfaction classification

.2.4 Classification Report with unbalanced classes using undersampling - ESS Data - Job Satisfaction classification

Class	Precision	Recall	F1-score	Support
Low	0.57	0.68	0.62	190
High	0.58	0.45	0.51	182
Accuracy		0.57		
Macro avg	0.57	0.57	0.56	372
Weighted avg	0.57	0.57	0.56	372

Table 11. Classification report for logistic regression model after undersampling the majority class - ESS Data - Job Satisfaction classification

.2.5 Classification Report with unbalanced classes using SMOTENC - ESS Data - Job Satisfaction classification

Class	Precision	Recall	F1-score	Support
Low	0.21	0.74	0.33	186
High	0.86	0.37	0.52	809
Accuracy		0.44		
Macro avg	0.54	0.56	0.42	995
Weighted avg	0.74	0.44	0.48	995

Table 12. Classification report for logistic regression model using SMOTENC the majority class - ESS Data - Job Satisfaction classification

.2.6 Distribution of the Sum of Scores of the dimensions of what makes a job - a good job - Online Survey 1

Category	Count
good salary	438
learn and gain new abilities	443
good career prospects	426
agree with mission and values	377
good office space	307
work from home - always	250
work from home - sometimes	366
work-life balance	**456**
use high tech	318
established institution	330
startup	235
travel on the job	311
private health insurance	357
flexible working hours	408
vicinity to residence	337

Table 13. Sum of Scores of factors contributing to a good job - Online Survey 1

.2.7 Distribution of the Sum of Scores of the dimensions of what makes a job - a good job by sex - Online Survey 1

Category	Female Count	Male Count
good salary	224	214
learn and gain new abilities	226	217
good career prospects	208	218
agree with mission and values	206	171
good office space	166	141
work-from-home (always)	124	126
work-from-home (sometimes)	184	182
work-life Balance	**230**	**226**
use high tech	154	164
established inst	173	157
startup	121	114
travel	160	151
private health insurance	188	169
flexible working hours	209	199
vicinity to residence	168	169

Table 14. Counts of factors contributing to a good job by sex - Online Survey 1

.2.8 Distribution of the Sum of Scores of the dimensions of what makes a job - a good job by age group - Online Survey 1

Category	18–26 Count	27–35 Count
good salary	193	245
learn and gain new abilities	188	255
good career prospects	186	240
agree with mission and values	164	213
good office space	132	175
work-from-home (always)	115	135
work-from-home (sometimes)	165	201
work-life balance	**196**	**260**
use high tech	136	182
established inst	137	193
startup	102	133
travel	135	176
private health insurance	146	211
flexible working hours	171	237
vicinity to residence	135	202

Table 15. Counts of factors contributing to a good job by age group (18–26 vs. 27–35) - Online Survey 1

.2.9 Tolerance and VIF scores for the determinants of the work-life balance index - ESS Data - Round 10

Feature	Tolerance	VIF
trdawrk	0.1787	5.5594
jbprtfp	0.1213	8.2394
pfmfdjba	0.2592	3.8568
wrklong	0.0864	11.5660
wrkresp	0.1089	9.1814

Table 16. Tolerance and Variance Inflation Factor (VIF) in the dimensions of the Work-Life Balance Index - ESS Data Round 10

Notes.
trdawrk = Too tired after work to enjoy things like doing at home, how often;
jbprtfp = Job prevents you from giving time to partner/family, how often;
pfmfdjba = Partner/family fed up with pressure of your job, how often;
wrklong = Employees expected to work overtime, how often;
wrkresp = Employees expected to be responsive outside working hours, how often.

.2.10 The breakdown of PC3, PC4, and PC5 of the work-life balance index - ESS Data - Round 10

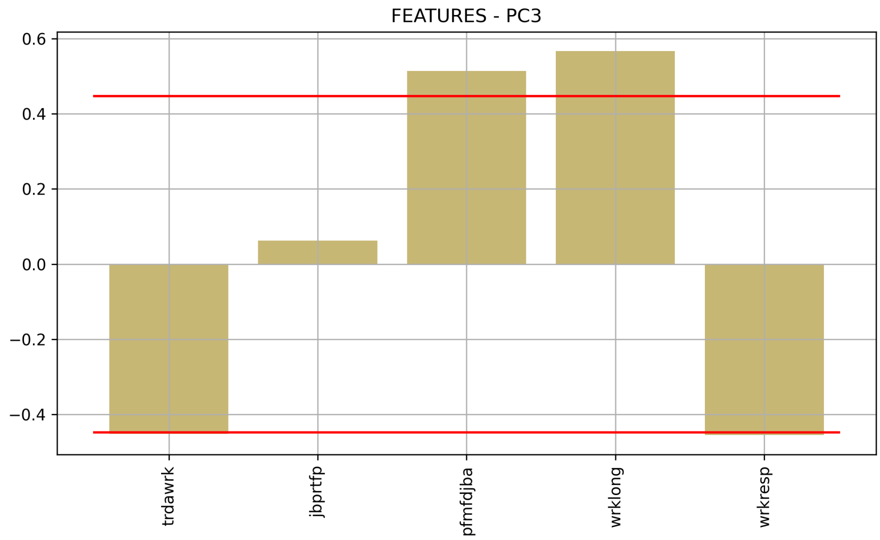

Figure 2. The breakdown in terms of dimensions of PC3 - Work Life Balance Index Creation.

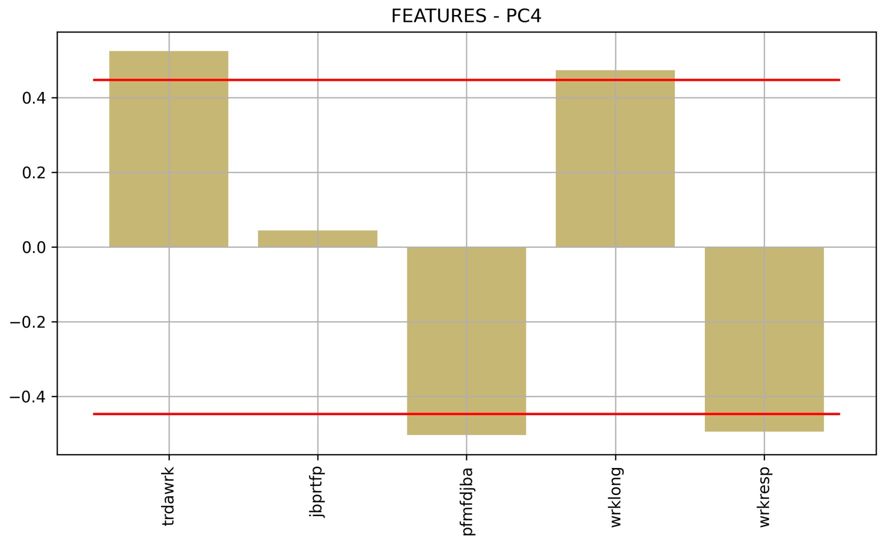

Figure 3. The breakdown in terms of dimensions of PC4 - Work Life Balance Index Creation.

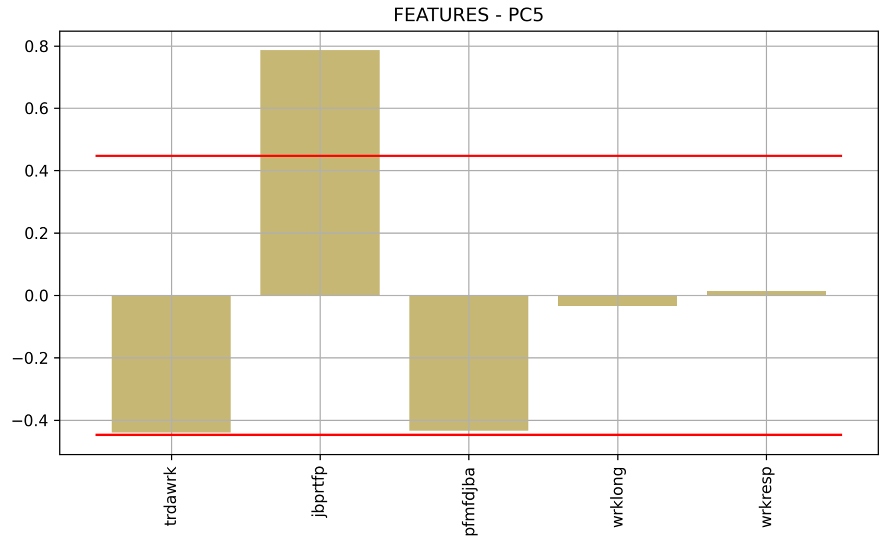

Figure 4. The breakdown in terms of dimensions of PC5 - Work Life Balance Index Creation.

.2.11 Heatmap of the rankings of the dimensions of what makes work a drudgery by sex - Interview Set 2

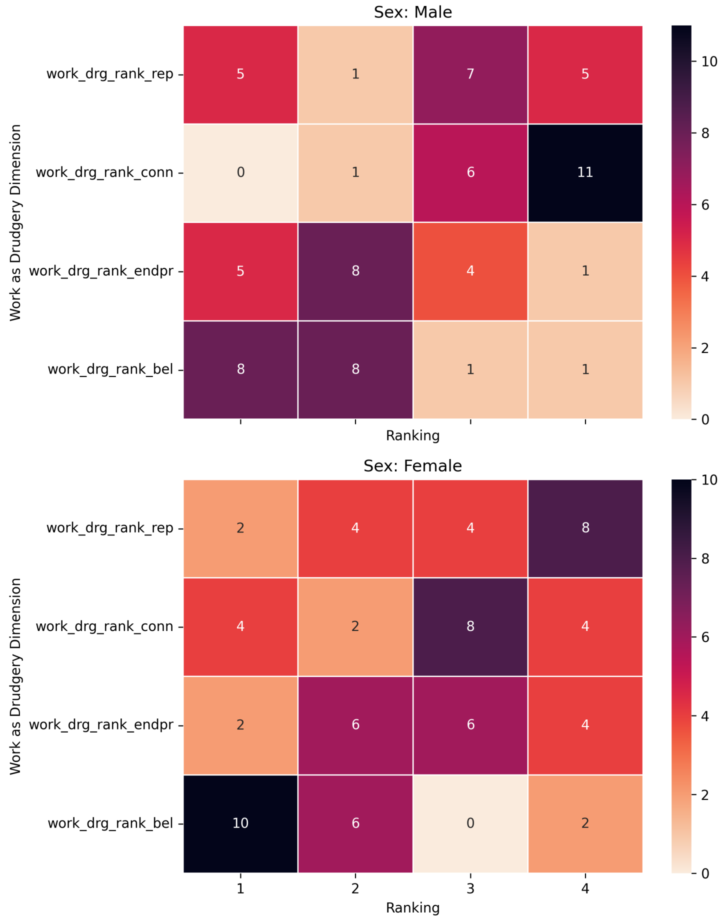

Figure 5. Heatmap of the rankings of the dimensions of what makes work a drudgery by sex - Interview Set 2

.3 Chapter 3

.3.1 WordCloud on AI definitions without custom stop words removed - Online Survey 2.

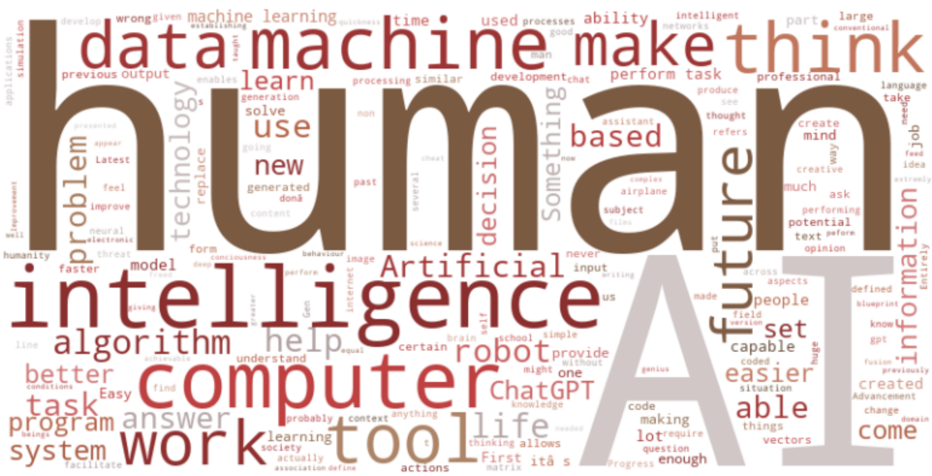

Figure 6. WordCloud of the definition of AI - without filtering out stop words - Online Survey 2

.3.2 Frequency word list on AI definitions without custom stop words removed - Online Survey 2 - based on sex.

Male	Freq.	Female	Freq.
human	10	like	10
think	8	**human**	9
machine	8	computer	8
data	8	tasks	8
tool	7	think	8
able	6	perform	5
use	6	easier	5
answers	5	tool	5
based	5	make	5
humans	4	also	5
better	4	machine	4
learning	4	use	4
it's	4	information	4
make	4	help	3
algorithms	4	set	3
created	4	comes	3
new	4	program	3
computer	3	things	3
helps	3	machines	3
would	3	humans.	3
-	3	Something	3
tasks	3	humans	3
could	3	robots	3
much	3	work	3
learn	3	future	3

Table 17. Top Words based on Frequency in defining AI by Sex - Online Survey 2

.3.3 Histograms of Optimism and Interest in AI filtered by sex - Online Survey 1

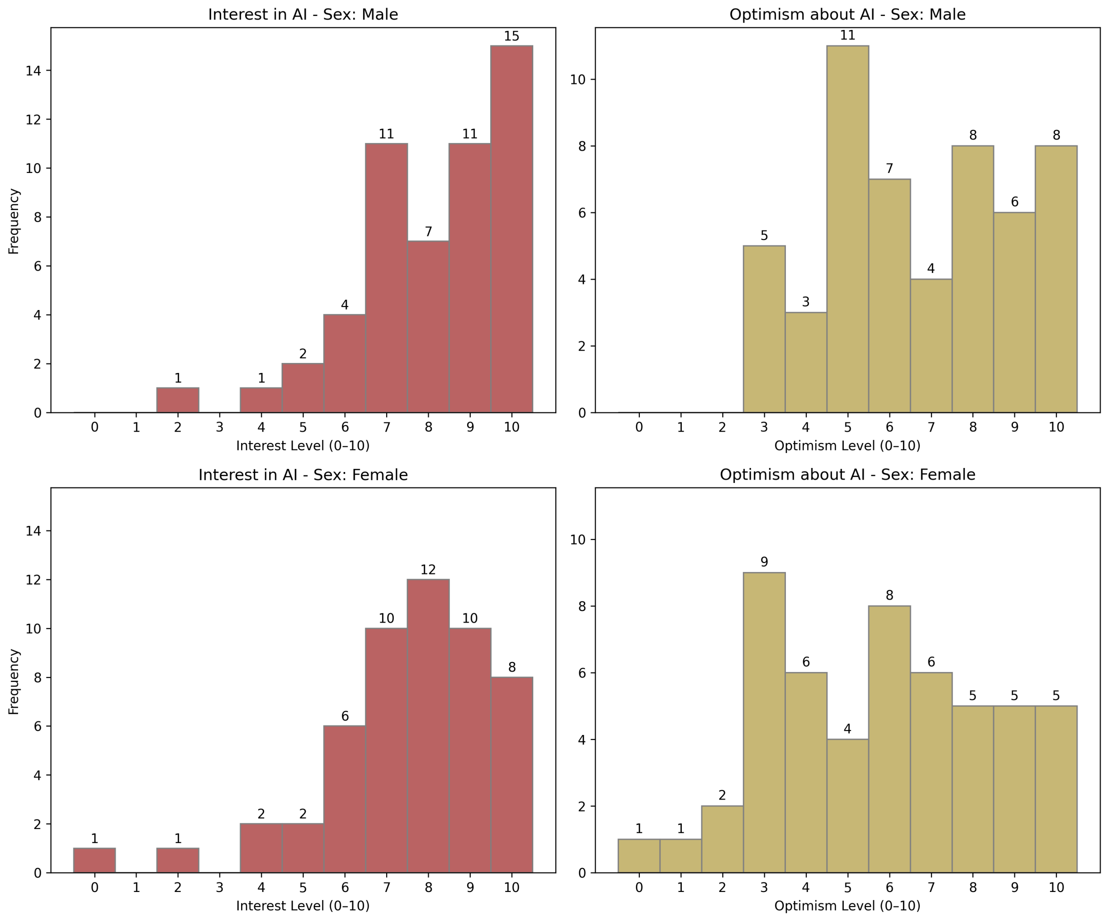

Figure 7. Histograms of Optimism and Interest in AI filtered by sex - Online Survey 1

.3.4 Histograms of Optimism and Interest in AI filtered by sex - Online Survey 1

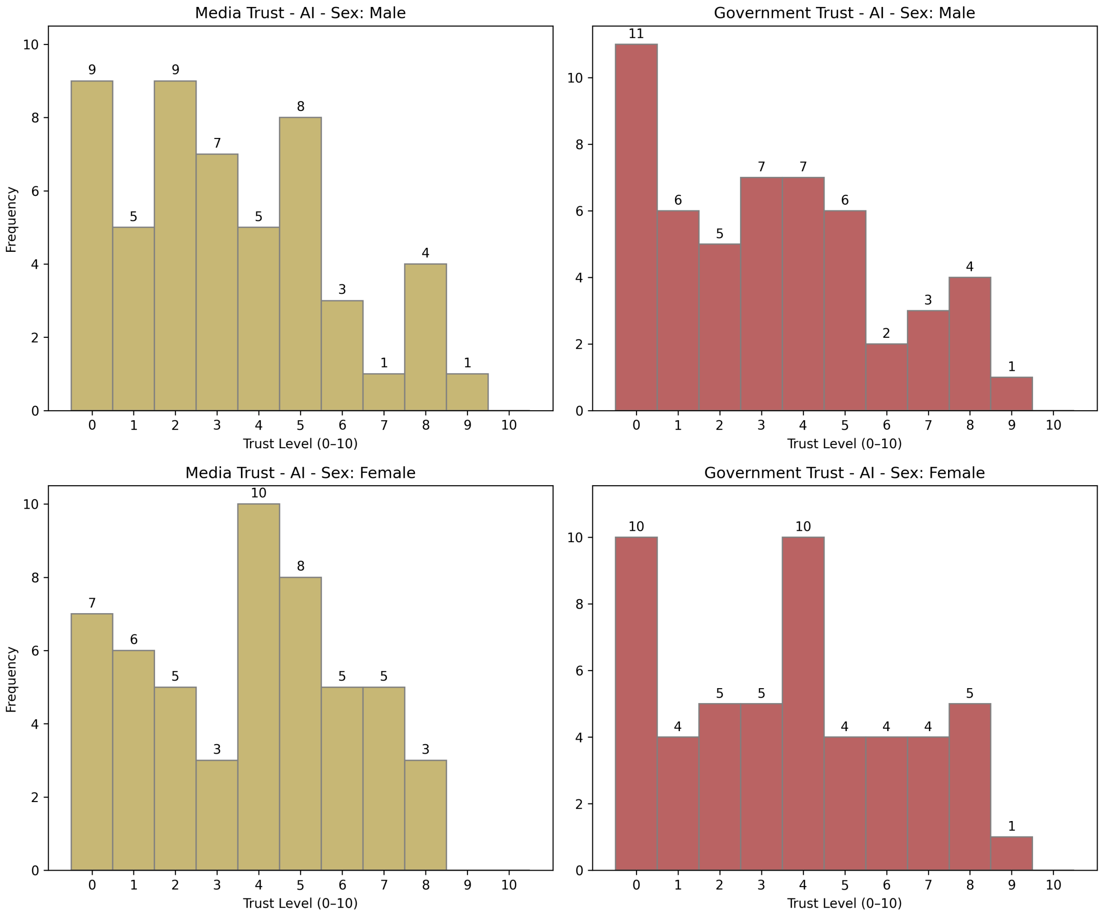

Figure 8. Histograms of trust in government and media in handling AI filtered by sex - Online Survey 1

.4 Chapter 6

.4.1 The distribution of the opponents to the idea that instrumentarian is a new business power based on occupational groups - Interview Set 2

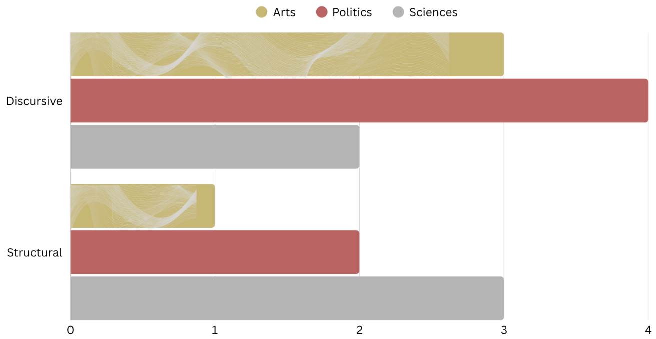

Figure 9. Distribution of opponents to "instrumentarian power" based on occupational group - Interview Set 2

.4.2 The distribution of the opponents to the idea that instrumentarian is a new business power based on sex - Interview Set 2

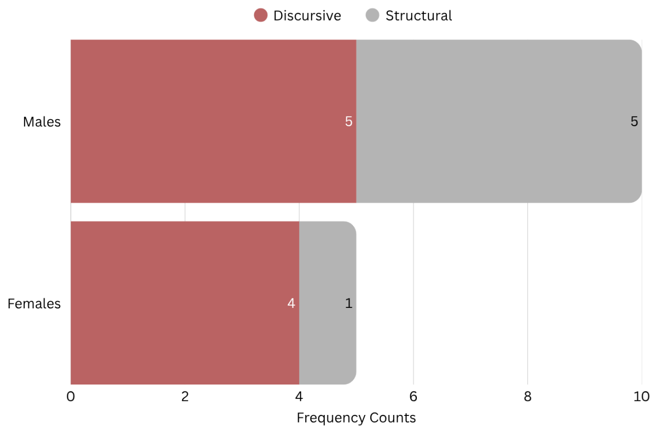

Figure 10. Distribution of opponents to "instrumentarian power" based on sex - Interview Set 2