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Redefining Choices. How Does Artificial Intelligence support decision-making in urban and architectural development?

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ABSTRACT

In response to the increasing complexity of urban and architectural projects and the need for informed, viable, and objective problem-solving processes, this research examines the decision-making processes in urban and architectural realms. It explores how artificial intelligence (AI) can enhance specific stages of decision-support approaches. Through a combination of theoretical analysis with practical application, this thesis explores the use of Multi-Values Appraisal Methodology (MuVAM) to support decision-making in architecture with or without the support of artificial intelligence (AI). MuVAM is a new tool that combines problem structuring methods (PSMs) and multi-criteria decision analyses (MCDAs), offering a framework to address complex problems and evaluate multiple criteria. The research examines two aspects of the application of MuVAM: its stand-alone use, focusing on its ability to structure and analyze problems, and its integration with AI, exploring how this digital technology enhances its functionality. By addressing these complementary perspectives, the thesis highlights the features of MuVAM and the potential of AI in decision support systems. In particular, the thesis draws upon the observation and reporting of participants interacting in the workshop's environment. The workshops were experimented with through three case studies at different scales: (i) the transformation of the district "Pointe Nord" in Geneva, (ii) the adaptive reuse of the former Paracchi carpet factory in Turin, and (iii) the requalification of the San Salvario neighborhood in Turin. Each case study illustrates how structured decision-making, guided by the integrated methodology, can be applied in architecture to address site-specific challenges and optimize urban decision outcomes. Also, since the first one was performed without using AI combined with MuVAM, the applications were compared in this sense. Accordingly, by connecting theoretical research with observation of practical experiments, the thesis highlights the challenges and opportunities of such integrations, incorporating decision-making processes and artificial intelligence into architecture.

Keywords Architecture / Decision-making process / Decision support / Artificial intelligence / Urban transformation

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AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
DM	Decision Maker
DSS	Decision Support System
GDSS	Group Decision Support Systems
MCDA	Multi-Criteria Decision Analyses
MuVAM	Multi-Values Appraisal Methodology
NLP	Natural Language Processing
PSM	Problem Structuring Method
SCA	Strategic Choice Approach

01

INTRODUCTION

Chapter 1. Introduction

The complexity of urban and architectural projects increasingly requires a traceable and comprehensive decision-making process. This research aims to investigate how decision-making processes are applied to address the challenges of urban transformation, focusing on integrating AI to enhance the results of these decisions. Indeed, this research explores the integration of AI in decision-making processes of urban and architectural projects as a resource to improve and support these contexts because the development and impact of its use in different fields of action have been evident, revolutionizing how to carry out activities, problem-solving, and process data.

This thesis is part of a larger research project called "*Decision Support in the Urban Context in the Digital Age: Interactions and Uncertainties*" (SUITE) for its acronym in Italian, whose scientific responsible is Prof. Lami. Supported by the *Interuniversity Department of Territorial Sciences, Projects, and Policies* (DIST) at the Politecnico di Torino, this project addresses the role of decision support tools in the urban context, specifically focusing on two key methodologies: Problem Structuring Methods (PSMs) and Multi-Criteria Decision Analyses (MCDA). Both methods are fundamental to structuring complex problems and evaluating options based on multiple criteria, which are essential in urban planning and transformation. Furthermore, the research uses new software, Multi-Values Appraisal Methodology (MuVAM), specifically designed to improve urban environments' evaluation and decision-making process. As part of this project, this research explores how these tools and approaches can be integrated into architectural and urban processes, especially when addressing the uncertainties and complexity of decisions in the digital age.

MuVAM is a methodological approach that uses software to support decision-making processes related to complex problems. It was developed by Prof. Lami and architects Bassan and De Nicoli. This software enables analysis, collaborative discussion, the development of shared solutions, and deliberation of decision-making problems through an interface designed to make the complexity of the components more accessible.

The research focuses on the central question: *How are decision-making processes implemented in urban and architectural contexts in the digital era, and how can the integration of AI improve their development?*

The framework of this research is built upon the following objectives, which aim to provide a clear and focused direction for the investigation:

(i) ***Theoretical Analysis to explore the key features of Decision-Making Processes****:* This involves reviewing decision-making processes in architecture and urban transformation. The aim is to examine their structure and guiding principles, drawing on theories and frameworks described in the literature. Through a review of academic sources, the study seeks to identify and assess the potential of AI to support decision-making in architectural contexts.

(ii) ***Application of MuVAM in Case Studies****:* This examines how the MuVAM software, which integrates mixed methodologies to evaluate alternatives systematically, is applied to three case studies in the urban and architectural fields. MuVAM, based on frameworks such as the Strategic Choice Approach (SCA) and the Analytic Hierarchy Process (AHP), offers a structure for decision-making, allowing for qualitative and quantitative assessment of alternatives.

(iii) ***Evaluation of AI's Influence on the Key Decision-Making Stages****:* This study studies how integrating AI tools and MuVAM influences key stages of the decision-making process, identifying its specific contributions and limitations and developing reflections based on the comparison of the different results.

The research methodology combines theoretical analysis with practical observation. The theoretical component aims to outline key features and characteristics of decision-making processes in the context of urban and architectural transformations and examine their potential relationship with AI. The practical component focuses on observing the role of AI in case studies, specifically within workshops, to understand how AI influences the dynamics and outcomes of decision-making.

The theoretical component was conducted through a literature analysis to identify key concepts, trends, and gaps in integrating decision-making processes and AI in urban and architectural contexts. The review focused on academic articles published in English between 2018 and 2024, sourced from Scopus, ScienceDirect, and Google Scholar databases. The search was guided by relevant keywords such as "artificial intelligence," "decision-making," "decision support," "urban transformation," and "architecture." These terms are selected to align with the research focus. Articles are evaluated based on their relevance and relation to the research topic. These findings help construct a theoretical framework for the subsequent analysis.

Indeed, based on the perspectives derived from the literature review, a theoretical framework was defined regarding the relationship between decision-making processes and AI. This framework identifies specific stages within decision-making processes where AI can be most beneficial. The theoretical framework provides a conceptual structure that guides the practical aspects of the research.

The practical component allows for observing how the integration of MuVAM and AI is applied (or not) in different workshops, observing the specific ways in which these methodologies are used, their impact on decision-making, and the results obtained in each case. The theoretical framework provides a structure for interpreting and analyzing the cases while giving perspectives on the challenges and opportunities of applying these concepts in practice.

To achieve this, the research addresses the selection of three case studies. The first is the transformation of *Le Pav – Pointe Nord* in Geneva, Switzerland, with the implementation of the MuVAM software without the support of AI. This workshop was carried out with a group of PhD students from Politecnico di Torino, providing an initial context to evaluate the stand-alone capabilities of the software. The second case study was developed at the *Former Paracchi carpet factory* in Turin, Italy. Where the interaction of the MuVAM software with AI tools was explored, in this case, the workshop sessions were implemented with Master students of the Architecture Construction City program as part of the "Economic Evaluation of Projects" course. This approach allowed us to analyze how the integration of AI influences the dynamics and outcomes of the decision-making process. Finally, a workshop was held, *Requalification of the San Salvario neighborhood*, also in Turin, where the interaction between MuVAM and AI was examined from a different perspective concerning previous cases. This workshop saw the participation of professionals from the architecture and urban planning field linked to the Urban Lab association, renowned for its activities related to urban planning in collaboration with the Municipality of Turin. In all the workshops, I played the role of an observer, documenting and analyzing their development to interpret the results and reflect on the impact of using MuVAM with and without the support of AI.

The case studies were selected for their diverse urban and architectural challenges, spanning transformations at different scales, from masterplans to districts and individual buildings. This diversity makes them well-suited to testing the effectiveness and adaptability of potentially AI-enhanced decision-making frameworks. In the context of urban transformation, these frameworks act as valuable tools to support and structure the decision-making process. They enhance architectural and planning practices' strategic and contextual relevance by providing methodologies to analyze complex situations, prioritize objectives, and align interventions with broader goals such as sustainability, functionality, and community impact. The integration of AI further strengthens this process, enabling more dynamic, data-driven, and adaptive solutions tailored to the unique demands of each scale.

The thesis is structured into five chapters, including this introduction.

Chapter 2 presents the theoretical framework, focusing on decision-making processes in architecture and the role of AI as a supporting resource. This chapter explores how digital transformation reconfigures architectural practices and urban planning by integrating AI technologies. Accordingly, it examines interconnected elements to establish a conceptual foundation for understanding how AI can enhance and support decision-making in addressing architectural and urban challenges. It delves into the growing influence of digital technologies on architectural practices, focusing specifically on the role of AI in urban and architectural decision-making. This exploration highlights AI's potential to optimize design processes, enhance efficiency, and address complex urban issues. Additionally, the chapter explores methodologies and systems that facilitate decision-making in architecture and urban planning, introducing Decision Support Systems (DSSs) as structured approaches for analyzing and solving complex problems, emphasizing PSMs.

Through these discussions, the chapter establishes a theoretical framework that highlights the role of AI in supporting decision-making processes within architectural and urban transformation projects. It connects theoretical concepts with practical applications, laying the groundwork for exploring AI-driven methodologies to address complex design and planning challenges.

Chapter 3 outlines the methodology and analytical framework used in the research, with an analysis of the three case studies in which these approaches are applied. First, MuVAM and its role in decision-making processes in urban and architectural contexts are introduced. Furthermore, it describes how the analytical framework, which combines MuVAM and AI, interprets and analyzes the practical applications of the case studies. This framework guides the structuring of the analysis and links to a theoretical framework, allowing one to read and understand the decisions made in each context. These case studies illustrate how applying the proposed analytical framework contributes to addressing complex problems in diverse urban and architectural settings. The relationship between the theoretical framework and the methodology in this research is essential, as the theoretical framework provides the conceptual foundation for the practical analysis of the case studies. It sets the context in which the integration of AI into decision-making processes in architecture and urban planning is explored, addressing fundamental principles, methodologies, and tools that can improve these processes. Through this framework, the specific roles that AI can play are identified, as well as how it can be effectively applied in urban and architectural environments. On the other hand, the methodology, which guides the process of analyzing the case studies and includes the use of MuVAM software and the integration of AI, is the practical means through which the reflections presented in the theoretical framework are applied and observed. Accordingly, the theoretical framework gives meaning to the methodological approach and ensures that the methods used are consistent with the research objectives and questions. Through this approach, the findings of the case studies are contextualized, offering some reflections on the possibilities and limitations of AI integration.

Chapter 4 presents the results obtained from applying the proposed methodological framework in the three case studies: *Le Pav – Pointe Nord in Geneva, the former Paracchi carpet factory in Turin, and the requalification of the San Salvario district in Turin.* Each case study offers a distinct perspective on applying AI-assisted decision-making and using MuVAM, considering differences in scale, stakeholder involvement, and contextual constraints. The analysis explores how these tools contributed to structuring decision options, engaging participants, and evaluating transformation strategies within each urban and architectural context.

The first three sections focus on the specific results of each case study, detailing the role of AI (where applied) and MuVAM in shaping decision-making processes. These sections highlight how AI-supported methodologies facilitated or influenced decision structuring, from identifying priorities and trade-offs to visualizing possible future scenarios. Differences between the three cases are highlighted, particularly in terms of stakeholder engagement, the adaptability of AI within diverse planning frameworks, and the extent to which AI-driven insights were integrated into decision outcomes. The final section summarizes the key findings across the three cases. It examines the dynamics developed in decision-making, AI integration, and the broader implications for architectural and urban transformation processes. Including a section on key findings, this synthesis assesses the relationship of MuVAM and AI in supporting urban and architectural decision-making and offers insights for future applications.

Chapter 5 presents the final reflections and conclusions derived from the research, summarizing the key insights gained from the theoretical part, the application of MuVAM, and AI-assisted decision-making in the three case studies. It synthesizes the findings discussed in the previous chapters, emphasizing the implications for architectural and urban transformation processes, the role of AI in supporting decision-making, and the broader methodological contributions of the study. It reviews the research objectives, assessing how the integration of AI tools influenced decision structuring, stakeholder engagement, and the evaluation of transformation strategies. The chapter concludes with considerations and recommendations for future research. By consolidating the findings of this research, the chapter provides a basis for continued exploration of the role of AI in shaping architectural and urban decision-making.

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THEORETICAL DEVELOPMENT

Chapter 2. Theoretical development

In this research, a literature search focused on academic articles published in English between 2018 and 2024. The reference time was set to cover the five years before the start of this research up to the present. This timeframe was chosen to ensure the inclusion of recent studies, considering the evolution of the topic and the need for up-to-date information. The bibliographic search was guided by specific concepts and keywords relevant to the central themes of the study, such as "artificial intelligence", "decision making", "decision support", "urban transformation", and "architecture"." This search used widely recognized academic databases, including Scopus, ScienceDirect, and Google Scholar. The results were subsequently re-elaborated and organized into key topics, such as "AI and architecture" and "AI and decision-making", to align with the research's specific focus on the role of AI in decision-making processes within architecture and urban transformation.

For each search term, the articles found were reviewed and evaluated based on their relevance and direct relationship with the research objectives. The articles were assessed according to their ability to contribute to constructing a solid theoretical framework, emphasizing how decision-making processes are developed in architecture and how AI can impact and support these processes.

All articles obtained during the search were selected to determine their relevance to the research objectives. During this process, the articles were classified into three categories:

In line with the research: Articles wholly aligned with the research focus, that is, those that directly addressed the use of AI to support decision-making in architecture and urban transformation.

Out of the specific scope, but in topic: Articles that, although not focused exclusively on architecture or urban transformation, addressed relevant issues related to AI and decision-making in other fields, such as engineering, business, or social sciences. These articles were considered useful to provide a broader and more contextual perspective.

Not related: Articles not associated with the key research topics were discarded.

Following this selection process, articles were chosen and reviewed for the research. Articles aligned with the central themes of the research were included, along with some articles that, although not directly related to architecture or urban transformation, addressed topics related to AI and decision-making in similar contexts. This selection of articles contributed to developing a theoretical framework, which provides the necessary basis for exploring the opportunities and challenges associated with integrating AI into architectural processes.

This section explores the theoretical foundations shaping the development of decision-making processes in architecture and urban transformation, focusing on integrating AI. It begins by providing an overview of the digital transformation within the field of architecture, analyzing the changes gendered by technological advances. These developments have revolutionized traditional practices, from design and construction methods to project management, improving the efficiency and sustainability of architectural practices. The section highlights how digital tools have become essential to optimize workflows, improve design accuracy, and foster more sustainable approaches in urban planning and architectural design.

This analysis considers the expanding influence of AI technologies across different sectors, emphasizing their growing role within architecture. The discussion explores recent advances in AI applications, focusing on their integration into decision-making frameworks in architectural and urban contexts. Special attention is given to how machine learning algorithms, data analytics, and predictive modeling techniques transform decisions. This section further investigates the potential of AI to improve efficiency, accuracy, and inclusiveness in decision-making, which is critical for addressing complex and dynamic challenges faced in modern urban environments.

The chapter then proposes an analysis of decision-making processes in architecture and urban transformation, examining traditional decision-making frameworks and the emerging need for more sophisticated systems to address the growing complexity of urban and architectural projects. The focus is on DSSs, with an exploration of PSMs essential to clarify complex problems and guide effective decision-making in these fields.

Finally, the chapter explores the fundamental role of AI in supporting decision-making processes in architectural and urban transformation projects. These tools help manage the complexity of urban systems, optimize resource allocation, and promote public participation in the planning process. The debate highlights the potential of AI to address urgent urban challenges, such as sustainability, climate resilience, and urban adaptability, by fostering more responsive and flexible urban environments capable of evolving with social needs.

2.1. Overview of Digital Transformation in Architecture

Digital transformation is the context in which the possibilities of integrating AI into architecture have emerged. AI is characterized by the capability of digital machines and computers to execute specific tasks that mimic the cognitive functions of the human mind and intelligent entities. These tasks encompass a range of abilities, including thinking and learning from past experiences and emulating various mental processes (Matter & Gado, 2024). At the same time**,** AI has permeated diverse sectors, revolutionizing multiple aspects of human life by automating tasks traditionally performed by humans. This includes manufacturing automation, specific educational methodologies, and the dynamics of social media (Matter & Gado, 2024). AI is used advantageously in different industries such as healthcare, agriculture, finance, and banking industries. Also, AI is already embedded in our lives in various applications such as Siri, Google Search, smartphones, and Amazon recommendations. People might not even realize that they are using AI in their daily life (Mohammadpour et al., 2019; Russell & Norvig, 2016).

Thanks to digital transformation, architects can incorporate data on environmental, social, and economic factors to make informed decisions, assess risks, and anticipate the future needs of urban spaces. Architects may now deal with ideas and notions beyond appearances thanks to AI programs, which provide various design solutions and ways of thinking (Almaz et al.,2024). Digital transformation also extends to urban planning, where AI-enabled tools analyze multimodal datasets, predict urban growth patterns, and simulate the effects of planning decisions on socioeconomic factors (Yigitcanlar et al., 2020). These technologies enable cities to adapt to evolving challenges, including climate change, population growth, and resource scarcity, with data-driven solutions.

Like in many other fields, AI in architecture presents opportunities and challenges. It requires a careful balance between embracing new technologies and preserving the distinct human vision that has always been vital to the profession. In this context, AI does not replace architects but complements their capabilities, creating a collaborative process where humans and machines work together.

The opportunities offered by AI can be considerable. Architects benefit from the relationship created by using AI as a resource to explore, optimize, and overcome design challenges in dynamic environments. AI enables them to process large amounts of data, predict outcomes, and test design scenarios. This creates a mix of human creativity and technical ability, enhancing architectural creativity and problem-solving skills. As Matter & Gado (2024) mention, the result is a fusion where human imagination works integrally with advanced AI tools, pushing the limits of architectural potential. In this context, AI enhances the work of architects rather than replacing them, fostering a collaborative process where humans and machines collaborate effectively.

Integrating AI into architecture offers many advantages but also presents challenges. The accelerated development of technology means that the architect profession must increasingly support a relationship between human experience and AI to design cities from a different perspective. The complexity of AI-driven systems also requires architects to acquire new skills, from data analysis to programming, and to change traditional architectural education and practice.

Figure 1 illustrates the division of responsibilities and competencies between humans and automated systems (computers) in the execution of tasks or decision-making (Almaz et al., 2024). This scheme is organized into three main blocks representing different functions according to their complexity and nature: *common sense*, *expertise*, and *straightforward*. In addition, it establishes an edge that delimits human and automated capabilities, marking the transition point between the two.

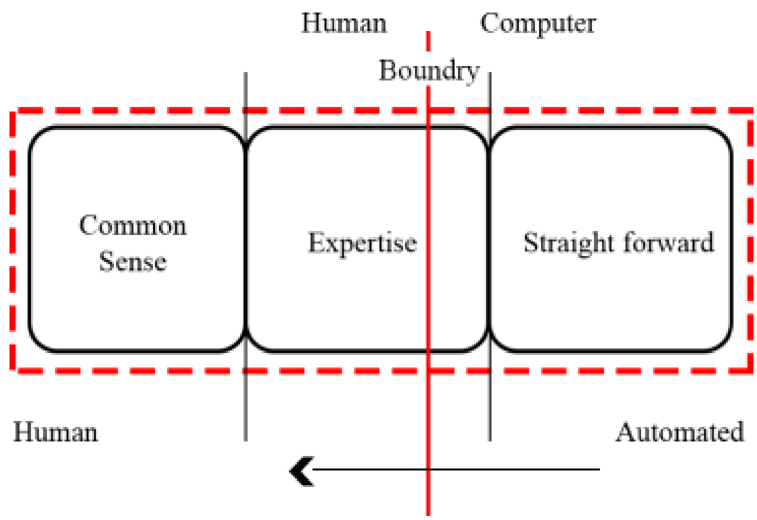

Figure 1. Problem-solving knowledge is ordered by complexity. Source: (Almaz et al.,2024).

In the *common sense* section, tasks specific to humans are grouped. These activities require intuition, everyday reasoning, and the use of previous experiences, aspects that are often challenging for automated systems. Human capabilities are essential here since machines do not have the context or flexibility necessary to address this type of task. The central section, referred to as *expertise*, represents a collaborative space between humans and automated systems. This task requires deeper specialized knowledge, which can come from human skills and advanced computer processing. In this zone, humans and machines can complement each other to achieve more efficient and accurate solutions. Finally, the straightforward direct tasks block includes routine, simple, and predictable activities that automated systems can completely manage. These tasks do not require significant human intervention, allowing computers to perform quickly and accurately.

The diagram also highlights progression, indicated by an arrow at the bottom, showing how tasks can move from the human domain to automation as they become more predictable and repetitive. The boundary establishes the limit between what humans and machines typically manage, although this limit can shift with technological advances or depending on the specific complexity of the tasks.

The diagram shows how humans and computers can effectively complement each other depending on the nature of the tasks. While humans excel at activities that demand intuition and judgment, machines are more efficient at repetitive and predictable tasks. In the intermediate zone, both collaborate using their particular skills to optimize processes and achieve better results.

The interaction between humans and machines, represented in the diagram, highlights the importance of understanding how each one's capabilities can complement each other in different scenarios. This collaboration optimizes processes in the present and opens the door to reflect on how technology, in constant evolution, redefines the boundaries of what is possible in different disciplines. In the case of architecture, this manifests itself in adopting digital tools such as parametric design, computational modeling systems, and, more recently, AI, which have transformed the way architectural projects are developed.

As technological tools advance, their influence extends beyond the simple automation of repetitive tasks. In the architectural field, this translates into an evolutionary process that can integrate innovative construction techniques into advanced computational systems such as AI. Chaillou (2019) suggests that technology is one of the central factors shaping the future of architecture, and it has left a profound and lasting impact on the field. Technological advances have influenced and driven significant changes. The design and conceptualization of buildings have already begun to evolve initially through adopting new construction techniques, then through the creation of specialized software, and now through the incorporation of robust statistical computing systems (such as data science and AI). This transition represents a steady, constant progression that has guided architectural evolution.

According to Hegazy & Saleh (2023), the digital transformation in architecture over time has been developed through key moments such as modularity, computational design, parametricism, and AI. *Modularity* involves using standardized, interchangeable parts in design to allow for flexibility and adaptability in construction. *Computational design* uses computers to assist in the design process, allowing for more precise and complex designs. *Parametric design* uses algorithms and variables to generate design options based on specific criteria. *AI* takes these concepts further by using advanced machine learning algorithms to assist in designing and creating even more complex and optimized designs.

Modularity in architecture is typically linked to a design method that organizes geometry, establishes a rhythm, and divides the space equally while also involving technical considerations related to the fundamental components of building systems, such as the production of elements, methods of assembly, and industrialization techniques (Lema, 2016). Modularity spans various fields and scales in the design process, from defining individual building parts to the entire systems of a building and from creating compact living units to designing intricate, adaptable environments. As a design principle, modularity offers flexibility, the potential for indeterminate design outcomes, and the precision required for efficient assembly. Influential figures like Le Corbusier and members of the Bauhaus, experienced in streamlining architectural designs, sought solutions to meet the large-scale needs of their time.

The post-war era encouraged visionary architects to experiment with projects and prototypes that emphasized adaptability, cost-effectiveness, and speed of construction (Lema, 2016). These developments also influenced urban planning, as exemplified by Archi Gram’s Plug-in City concept (Figure 2). Architectural and urban design adapted to efficient modular construction, similar to a Lego system, such as massive modular housing. Over time, modular systems became so complex, as seen in the case of the Sydney Opera House, that the use of applied computing became necessary. Indeed, one of the first applications of computer-aided design (CAD) was in the structural design of the Sydney Opera House in the early 1960s (Lukovich, 2023).

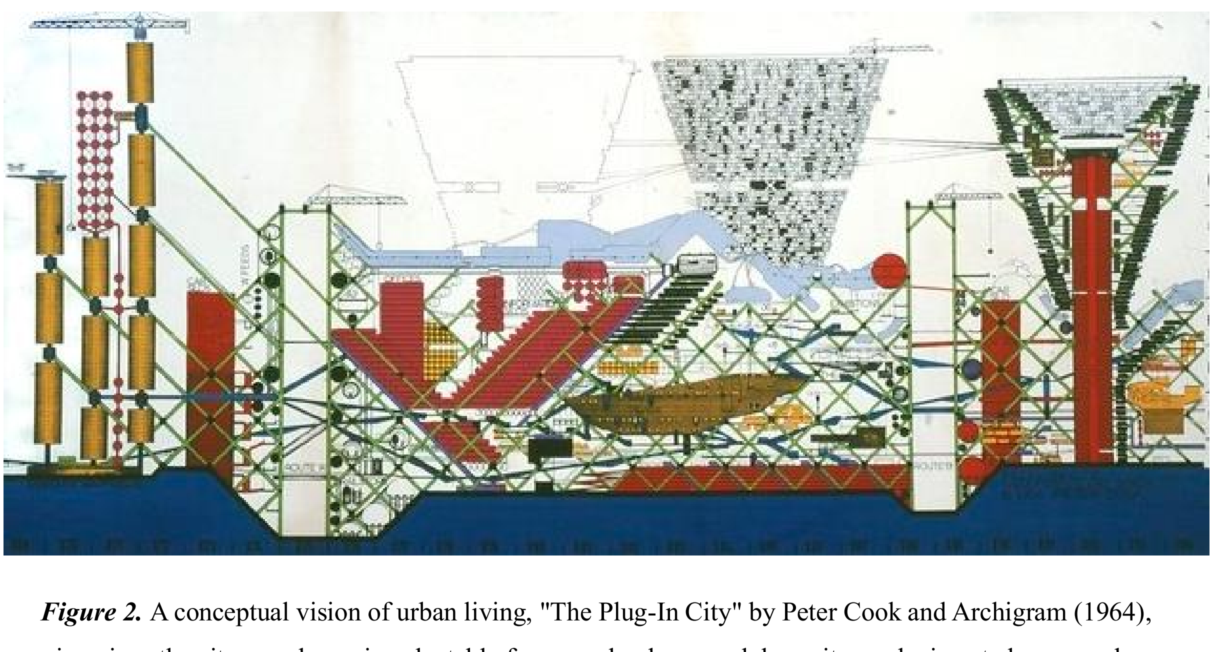

Figure 2. A conceptual vision of urban living, "The Plug-In City" by Peter Cook and Archigram (1964), reimagines the city as a dynamic, adaptable framework where modular units can be inserted, removed, or replaced, reflecting the futuristic optimism of the 1960s. Source: ArchDaily. Source: https://www.archdaily.com/399329/ad-classics-the-plug-in-city-peter-cook-archigram

Then, according to Lukovich (2023), the automation of architectural work began with the introduction of computational functions into CAD tools with *computational design*. This process started in engineering in the late 1950s when Patrick Hanratty released the prototype of CAD software (Chaillou, 2019). The potential offered by these tools soon caught the interest of architects. Christopher Alexander, the Austrian-born mathematician and architect working in the US, laid out the conceptual foundations for computational design in his influential book "Notes on the Synthesis of Form" (Alexander, 1964; Lukovich, 2023).

In the 1960s, this book became a required reading for computer science researchers. The principles described in the book still serve as a foundation for software programming today. According to Chaillou (2019), a generation of computer scientists and architects created a new field of research: "Computational Design." Professor Nicholas Negroponte guided the Architecture Machine Group (AMG) at MIT. Negroponte's book The Architecture Machine (1970) sums up AMG's mission: to investigate how machines can improve the creative process and, more specifically, architectural production.

The group's research culminated in projects such as URBAN II and its later iteration, URBAN V (Figure 3), which aimed to explore how human-computer interaction could shape design processes (Vardouli, 2011). Subsequent evaluation of these projects led Negroponte to shift the focus from attempting to replicate the architect's role to creating a more flexible and responsive tool: the "Design Amplifier." This new concept was conceived as a system that could enhance technical competence while adapting to the changing needs and intentions of the user, empowering them to make design decisions without being constrained by rigid parameters (Vardouli, 2011).

Negroponte's work was deeply influenced by contemporary debates on artificial intelligence, cybernetics, and learning technologies, which informed his approach to human-machine collaboration (Pertigkiozoglou, 2017). The Architecture Machine Group's research laid the groundwork for computational design and influenced the development of specialist software companies, such as Graphisoft, which introduced ArchiCAD in Budapest. While modern architects now use advanced computational tools to design complex forms with greater freedom, many digital design processes still rely on predefined commands. Consequently, there is growing interest in design methodologies integrating heuristic and rule-based decision-making approaches, allowing for more adaptive and interactive solutions (Cudzik & Radziszewski, 2018; Lukovich, 2023).

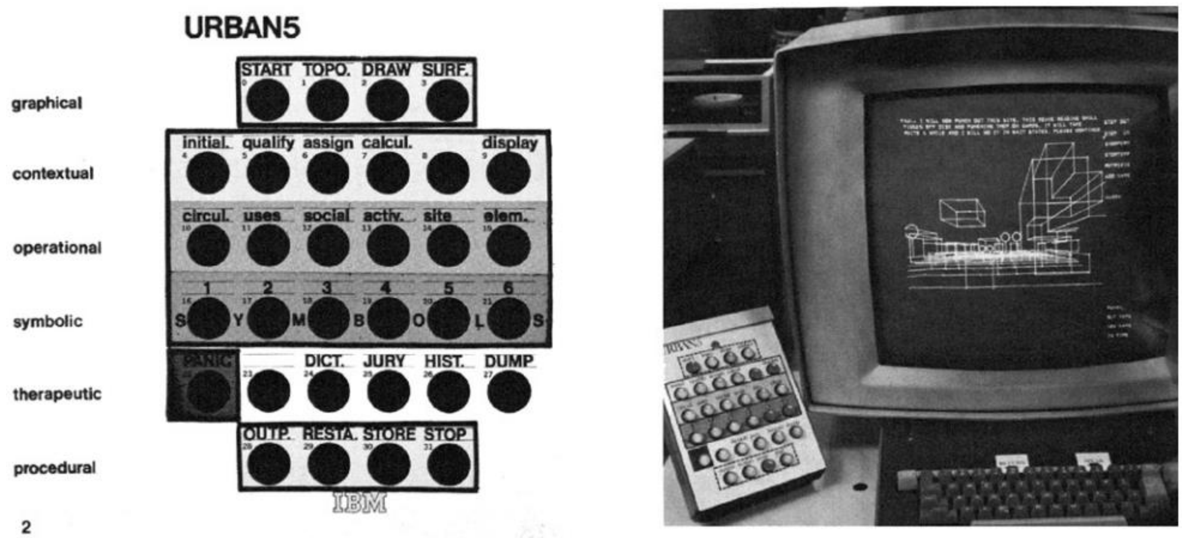

Figure 3. URBAN 5's overlay and the IBM 2250 model 1 cathode ray tube used for URBAN 5. Source: (Vardouli,2011)

In *parametricism*, both repetitive tasks and complex shapes can be managed effectively. The origins of parametricism date back to the early 1960s, with Luigi Moretti's theoretical stadium project, which used 19 parameters to create an unexpectedly organic yet rational form (Chaillou, 2019). Using computational tools, architects can adjust input parameters in software to produce a variety of shapes and configurations, allowing them to explore multiple design scenarios. This has become a "secret weapon" for many architects, allowing them to create surprising, sculptural forms in iconic buildings. Hegazy & Saleh (2023) referenced that parametricism is an approach to architectural design that uses computational algorithms to create dynamic and responsive forms. Famous architects who have used parametricism in their work include Zaha Hadid, Daniel Libeskind, and Rem Koolhaas. Examples of Parametricism in architecture include Zaha Hadid's design for the Guangzhou Opera House in China (Zaha Hadid Architects, 2010), which features interlocking panels that move in response to changes in the environment, and Rem Koolhaas's design for the CCTV

Headquarters in Beijing (West & Coad, 2020) which has an innovative and highly functional form created using computational design techniques. One of the most widely adopted tools today is software created by David Rutten in 2000. Grasshopper (*Figure 4)*, a visual programming interface, enables architects to identify and adjust the key parameters of their designs through iterative changes. Its user-friendly interface, combined with advanced built-in functions, has become central to the majority of building designs worldwide and has inspired an entire generation of "parametric" designers (Chaillou,2019). Beyond Grasshopper's immediate advantages for building design, a broader transformation initiated by parameterization since the early 2000s continues to progress with its use related to Building Information Modeling (BIM).

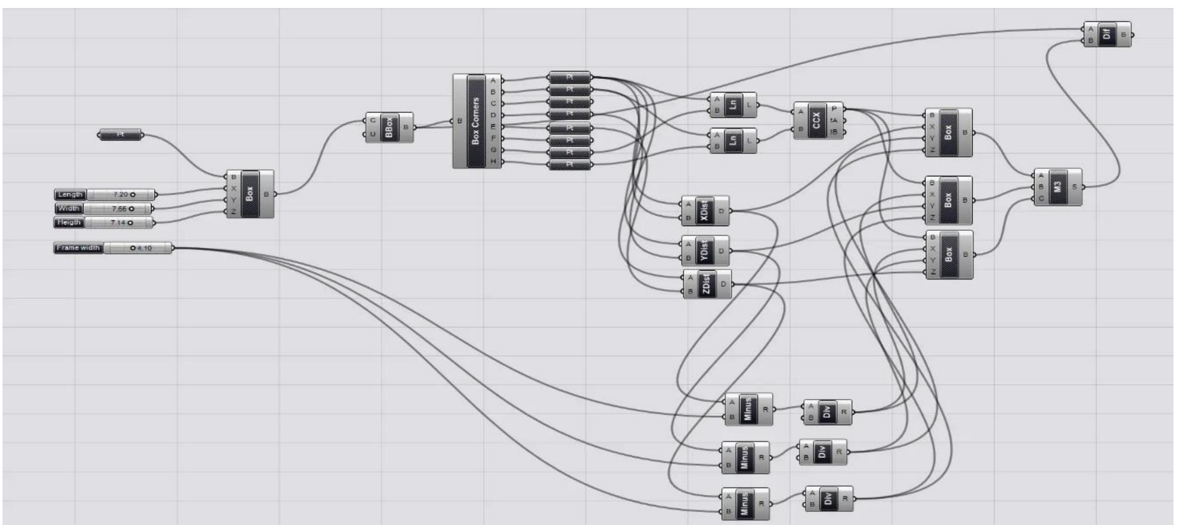

Figure 4. Grasshopper Interface. Source: *Parametric Architecture*. Source: https://parametric-architecture.com/grasshopper-3d-a-modeling-software-redefining-the-design-process/?srsltid=AfmBOopgepayppUsviaKK1gaLQKEzspxMeZHYJf0bP87qi4oEuE_-vTe

AI was first introduced in 1956 at Dartmouth College, where Marvin Minsky and John McCarthy organized the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) (Haenlein & Kaplan, 2019). However, development was slow until recently due to immature computational technologies. Recently, advances in hardware, software, and networking technologies have enabled us to design, develop, and deploy AI systems at scale (Yigitcanlar et al., 2020). AI, in the context of machine learning, refers to the ability of a computer or machine to simulate human cognitive abilities, such as learning and problem-solving, through the use of algorithms and statistical models. This allows the machine to learn from data and improve its performance over time without explicit programming (Hegazy & Saleh, 2023).

Unlike parametric models that depend on fixed parameters, AI offers a non-deterministic approach, allowing machines to process complex data and independently make autonomous decisions during design. Chaillou (2019) notes that this integration of AI enhances computational and parametric design, representing a significant shift in how architectural challenges are tackled and decisions are made. Recent research further underscores this change, pointing out the importance of generative AI models like generative adversarial networks (GANs) and diffusion probabilistic models (DDPMs) in broadening the possibilities of AI-driven architectural design (Li et al., 2024). As architecture progresses alongside technological advancements from modular principles to AI-driven methods, the equilibrium between technological growth and human sensitivity will determine its future influence on the field.

This concise overview of the progressive evolution of AI in architecture highlights the interconnections between four key paradigms: modularity, computational design, parametricism, and AI itself. Based on Chaillou (2019), a simplified diagram (*Figure 5*) illustrates important milestones in the integration of technology and architectural design from the 1930s to the present, showing how innovation and trends have influenced discipline.

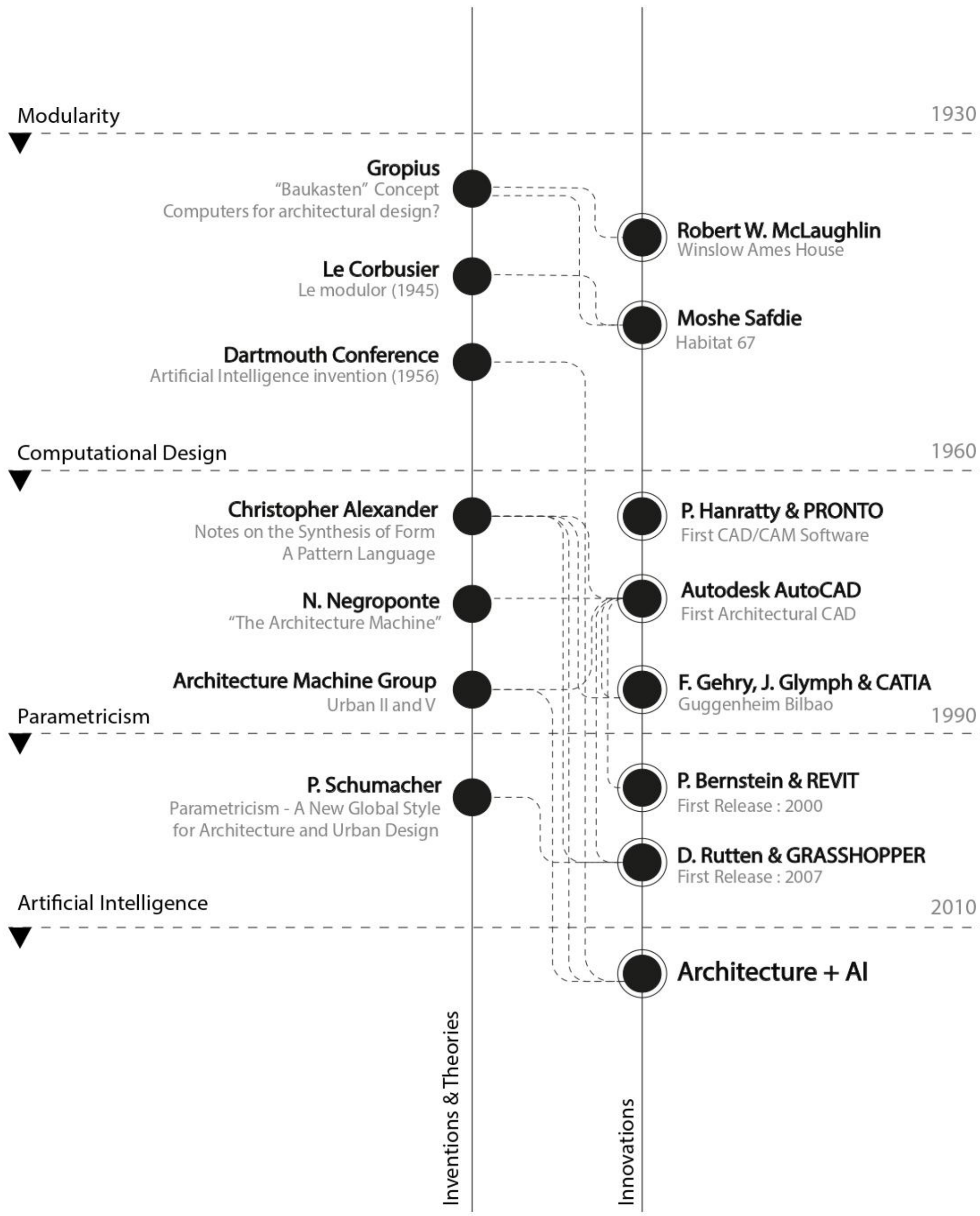

Figure 5. The historical evolution of AI in architecture and Interconnections between Modularity, Computational design, Parametricism, and AI, Simplified diagram based on (Chaillou, 2019)

This overview emphasizes the impact of digital tools on architectural practices. In conclusion, as shown through these milestones, the digital transformation in architecture reveals a discipline that is evolving and redefining. This opens up the possibility for architects to navigate this transformation by integrating technological innovations and maintaining their commitment to context-sensitive, human-centered, and sustainable design principles.

2.1.1. Artificial intelligence in urban and architectural decisions

The integration of AI into architectural practice has grown in recent years, marking a shift in how architectural and urban decisions are approached. Traditionally, architectural design has been a manual and iterative process where architects define problems, generate concepts, and evaluate solutions. However, the application of AI in architecture brings a new dimension to these processes, leveraging its algorithms, learning capabilities, and iterative nature to improve decision-making and problem-solving (Bölek & Özbaşaran,2023). AI introduces the ability to automate these complex tasks, allowing architects and urban planners to explore multiple optimal solutions within a reasonable timeframe, which would have otherwise required significant manual effort and time.

The intersection of AI and architecture is significant because it helps connect problem definition, concept generation, and evaluation. AI can analyze large data sets and spot patterns that might not be obvious to human teams, which is especially beneficial. It provides additional insights into the data, helping to uncover trends and relationships that may go unnoticed through conventional methods. This is especially significant when considering AI's role in urban planning, where large-scale data sets such as population density, energy consumption, and environmental impact need to be analyzed efficiently and accurately. As (Bölek & Özbaşaran,2023) points out, AI enables the exploration of numerous solutions simultaneously, allowing architects to evaluate different alternatives.

Furthermore, AI's applications extend beyond simply assisting architects in their design processes. AI has the potential to reshape urban landscapes and support the development of smarter cities. By automating the decision-making process in urban planning, AI can help planners address challenges such as land use optimization, transportation efficiency, and sustainability (Yigitcanlar et al.,2020). Its predictive capabilities can also help anticipate future urban needs, from changes in population to evolving environmental conditions.

As Rane (2024) mentioned, urban needs involve regulating, designing, and utilizing land, resources, facilities, and infrastructure to create sustainable, functional, and visually appealing environments for current and future generations. With the rapid advancement of technology, AI has emerged as a powerful tool with significant implications for urban planning (Peng et al., 2023; Wang et al., 2023; Zhang et al., 2023; Rane & Jayaraj, 2022).

Another notable advantage of AI in architectural and urban decisions is its ability to process data faster and more accurately than human teams alone. According to Mohammadpour et al. (2019), AI can analyze large amounts of data with a level of accuracy that would be difficult to achieve manually. Construction teams, for example, can rely on AI to gain insights into material performance, energy consumption, and other factors that can take much longer to assess using traditional methods. Not only does this speed up the decision-making process, but it also minimizes the risk of human error, leading to more reliable and effective outcomes.

Urban planning is also transforming with the integration of AI technologies. The rapid expansion of urban areas and the increasing complexity of urban challenges have created significant difficulties for urban planners (Peng et al., 2023). Authors such as Shrestha et al. (2019) propose a framework that describes the conditions under which AI can support decision-making; it can be implemented in a hybrid way (where AI provides input for human decisions or vice versa) or combined (where both humans and AI systems make decisions in parallel, and the optimal option is determined through a voting mechanism). The selection of the most appropriate approach depends on factors such as the specificity of the decision-making space, the number of alternatives available, the speed required for decision-making, and the need for interpretability and replicability.

A key advantage of AI in urban planning lies in its ability to analyze large data sets related to demographics, traffic patterns, and land use (Casali et al., 2022; Mora-García et al., 2022; Zhu et al., 2018). This capability allows planners to identify trends and patterns that improve decision-making processes. For example, the Urban Institute (https://www.urban.org/), a nonprofit research center in Washington, D.C., focuses on economic and social policy analysis. Founded in 1968 by the Lyndon B. Johnson administration, its original goal was to study the nation's urban problems and evaluate Society initiatives. Used machine learning to quantify, identify, and predict neighborhood changes, gaining insights into the impacts of gentrification and displacement in various city areas (Stern & Gilling, 2021).

While AI presents opportunities to revolutionize urban planning, its implementation also faces significant challenges, particularly during the stages of automated and autonomous planning using AI. According to Peng et al. (2023), these key challenges include:

- *Trust and transparency:* Lack of interpretability in AI models can undermine trust among stakeholders.
- *Data quality and quantity:* Accuracy and completeness of input data impacts AI model performance and reliability.
- *Cost and expertise*: Developing and deploying AI solutions requires substantial financial and technical resources, which may not be accessible to all municipalities

Moreover, as Haenlein & Kaplan (2019) explain, AI will become an integral part of daily life, much like the Internet and social media have in the past. Its influence will extend beyond personal experience, fundamentally reshaping how organizations make decisions and interact with stakeholders, including employees and customers. The key question is not whether AI will be involved but what role it will play and how it can coexist effectively with human decision-makers. Organizations must determine which decisions to delegate to AI, which to keep under human control, and which to make collaboratively.

In summary, while AI offers transformative potential for urban planning, addressing its challenges is critical to ensuring equitable, transparent, and effective outcomes. From automating design iterations to analyzing complex data sets, AI offers significant advantages in terms of efficiency and innovation. By leveraging AI, architects and urban planners can more effectively address complex challenges and contribute to developing more intelligent, more sustainable urban environments. As the field continues to evolve, AI's role in shaping the future of cities and architecture will likely expand, offering new opportunities for innovation and problem-solving in the built environment.

2.1.2. Recent applications of artificial intelligence in architecture

AI applications in architecture are diverse, ranging from design generation to performance optimization. Generative design is among the most significant advances, where algorithms produce multiple design solutions based on specific criteria. These solutions are evaluated for performance metrics such as energy efficiency, material usage, and structural stability (Bölek & Özbaşaran,2023)

For instance, AI has been employed to create complex geometries that were previously infeasible, integrating form with function to meet both aesthetic and practical requirements (Chaillou,2019). Moreover, tools enable architects to simulate a building's lifecycle, considering maintenance, energy consumption, and user behavior (Yitmen et al., 2021).

In urban contexts, AI-powered simulations predict the impact of urban regeneration projects, such as brownfield redevelopment, by analyzing environmental, social, and economic variables (Hammond et al., 2023). These simulations provide a comprehensive understanding of how interventions shape urban dynamics, aiding planners in crafting sustainable and inclusive urban spaces.

Looking at different categories of applications can provide an overview of how AI is used to optimize processes, improve decision-making, and foster new architectural and urban design solutions.

Generative Design

Generative design resources: Generative AI is rapidly reshaping architectural design by offering tools capable of creating diverse content, including text, images, music, videos, and 3D models (Li et al., 2024). Among its various applications, generative AI is particularly impactful during the initial phases of design exploration, where architects and engineers often brainstorm multiple concepts before finalizing their ideas (Rane, 2024; Jauhiainen & Guerra, 2023; Alshami et al., 2023). Software such as Autodesk Revit and Rhino integrated with Grasshopper have built-in generative design capabilities, allowing architects to define specific parameters such as costs, dimensions, and materials. This gives architects alternatives to selecting the most efficient design, reducing time, and proposing solutions that may not have been considered conventionally.

AI-assisted generative design uses algorithms to produce various architectural solutions, enabling architects to evaluate their aesthetic appeal and functionality efficiently. These algorithms can generate innovative and sustainable design options by setting specific parameters such as optimizing natural light, enhancing airflow, or reducing material usage (Meng et al., 2024). For architects, AI is a collaborative partner, expanding their creative possibilities and accelerating the design process. However, the effective integration of AI into architectural practices relies heavily on architects' decision-making skills. While AI can provide numerous alternatives, architects must be able to critically evaluate these options and ensure they align with project goals. Over-reliance on AI without a structured approach could lead to decision paralysis, diminishing the tool's potential to enhance design outcomes (Meng et al.,2024).

Generative AI, such as ChatGPT, represents a notable application of AI in this field. Utilizing advanced machine learning algorithms, this technology can revolutionize various aspects of urban planning, ranging from data analysis and simulation to citizen engagement and decision-making (Peng et al., 2023; Chaturvedi & de Vries, 2021).

Algorithmic Modeling

Optimization with algorithmic modeling: Exploring various application categories reveals how AI-driven algorithmic modeling enhances processes, aids decision-making, and inspires innovative architectural and urban design solutions. By leveraging data and algorithms, this method improves critical elements such as structural integrity, material allocation, and energy efficiency. Computational techniques allow designers to create optimized structural forms, minimize resource use, and boost environmental performance. For instance, a refined multi-objective optimization algorithm has been introduced to enhance building energy efficiency by balancing energy consumption, thermal comfort, and lighting levels (Li et al., 2024). These developments underscore the role of AI-driven modeling in promoting a more sustainable and effective architectural practice, integrating performance-oriented solutions while tackling emerging design challenges.

Predictive analysis and assessment

Predicting energy needs and sustainability: AI allows architects to simulate a building's energy consumption based on climate, orientation, and building materials. Tools that integrate with platforms such as Rhino and Revit allow simulations of how buildings will respond to different climate conditions. This enables the development of energy-efficient buildings and reduces the project's environmental impact. For instance, according to Nabizadeh Rafsanjani & Nabizadeh (2023), this can be useful for renovation and retrofitting; AI can help architects assess existing buildings for renovation and modernization opportunities, optimizing the reuse of materials and minimizing environmental impact.

Assessing environmental impact: AI makes it easier to model how a building and its design choices will influence the surrounding ecosystem. For instance, it can simulate sunlight movement, airflow, and water drainage, helping to ensure the design conforms to environmental guidelines and reduces adverse effects. Environmental impact is related to adaptive architecture; human-centered AI can enable buildings to adapt to changing environmental conditions and user needs. For example, AI-controlled building systems can optimize lighting and temperature based on occupancy and time of day (Nabizadeh Rafsanjani & Nabizadeh, 2023)

Urban Planning and Land Use Analysis

Urban growth modeling: AI can analyze urban data, such as population growth, land use, and transportation patterns, to assist in urban planning and designing sustainable and livable cities (Nabizadeh Rafsanjani & Nabizadeh, 2023). AI is recognized as one of the most transformative technologies of our time, and interest in its application in urban development continues to grow. One notable example is the emergence of smart cities, which are technology-enabled urban environments that support community participation. AI can analyze large data sets on urban growth, such as traffic patterns, population density, and the distribution of green spaces. Using AI prediction, it is possible to identify patterns of growth or densification in different areas, helping to make decisions about where to locate new services or infrastructure. This approach greatly helps to create sustainable cities and prevent uncontrolled urban sprawl. AI plays a crucial role in developing smart cities, where urban systems are interconnected, and data is continuously collected to enhance services like transportation and energy distribution. Yigitcanlar et al. (2020) highlight AI's dual role in creating smarter cities: it contributes to more efficient urban infrastructure and helps mitigate risks by anticipating potential challenges, such as environmental degradation and urban congestion. This proactive approach to urban management is essential for promoting sustainability and resilience in a rapidly changing environment.

Automated zoning and Land use analysis: AI-based tools can analyze zoning laws and land use data quickly and accurately, speeding up decision-making on projects that must align with local regulations. This helps quickly identify whether a site meets a specific project's requirements or suggests design or use adjustments. This dynamic adaptability is crucial as urban areas face increasing complexity and diversity capabilities beyond individual building design for broader urban planning applications. It enables data-driven decision-making to consider multiple variables, including environmental impact, social dynamics, and economic factors. Schubert et al. (2023) emphasize the role of AI in DSS for urban development. These systems help architects and planners to analyze complex data sets and predict outcomes, improving strategic planning for urban transformations.

Building Information Modelling (BIM)

Automated Conflict Detection: In complex BIM models, conflicts can arise between elements, such as pipes intersecting structural walls, etc. AI enables architects to identify and resolve these issues before the construction phase. This saves costs associated with construction errors, reduces time, and improves construction safety. BIM, for example, facilitates a holistic approach to design by integrating 3D modeling with data on material properties, energy efficiency, and cost projections. This enhances stakeholder collaboration and lays the groundwork for AI systems to optimize decision-making processes. Parametric design tools further complement these capabilities, allowing architects to explore countless design variations based on predefined parameters, such as structural integrity, material use, and environmental impact (Lukovich, 2023).

Lifecycle management and predictive maintenance: AI can predict the right time for building maintenance by analyzing historical data and real-time sensor data. This proactive maintenance approach extends the life of infrastructure and reduces the risk of critical failures in essential systems such as electrical or plumbing.

Virtual Reality (VR) and Augmented Reality (AR)

Real-Time Design Modifications: By incorporating AI-powered VR and AR technologies, architects can offer immersive walkthroughs of their designs, allowing users and stakeholders to interact with the space in real time. Users can provide instant feedback, suggesting modifications or adjustments, which improves collaboration and ensures the design aligns with their vision. This interaction fosters better decision-making and ensures the design process is more accurate, as real-time information allows architects to visualize how design changes will impact the overall space. AI-powered virtual reality and augmented reality tools can enable architects to visualize and experience their designs in immersive environments. This enhances the communication of design intent to clients and stakeholders, improving the overall design review process Nabizadeh Rafsanjani & Nabizadeh (2023).

Interactive Prototyping and Collaboration: Augmented reality tools allow virtual designs to be overlaid on the physical space, which is helpful for construction teams and users who want to see how a design will look in its real-world context. This allows for immediate feedback and quick adjustments.

Table 1 below summarizes key categories in which AI transforms architecture and urban planning. Each category includes key ideas, examples of tools or applications, and relevant references that support the claims.

Table 1. Key categories - AI transforms architecture and urban planning (Source: own elaboration).

Category / Application	Key Idea	Examples / Tools	Reference
Generative design	Algorithms generate multiple design solutions evaluated on performance metrics (e.g., energy efficiency, material usage).	Autodesk Revit, Rhino with Grasshopper: Optimize materials, costs, and dimensions.	Bölek & Özbaşaran (2023); Rane (2024); Meng et al. (2024); Li et al., 2024
	Designs integrate form and function, creating complex geometries.	Parametric design tools that explore structural integrity and material efficiency.	Chaillou (2019)
Algorithmic modeling	Enhances stability and material efficiency through AI-driven algorithms.	GIS-based AI tools (ArcGIS, UrbanSim), machine learning models, multi-objective optimization algorithms, energy simulation tools (EnergyPlus, DesignBuilder)	(Li et al., 2024).
Predictive analysis and assessment	AI simulates energy consumption and environmental impacts based on building parameters like climate and orientation.	Rhino, Revit: Tools for energy-efficient designs and environmental impact modeling (e.g., sunlight, airflow, water drainage).	Nabizadeh Rafsanjani & Nabizadeh (2023)
	AI enhances adaptive architecture by adjusting to user needs and environmental conditions.	AI-controlled systems for lighting and temperature optimization based on occupancy.	Nabizadeh Rafsanjani & Nabizadeh (2023)
Urban planning and	AI predicts urban growth patterns, helping optimize land use and reduce urban sprawl.	Smart Cities: Data-driven systems enhance services like transportation and energy distribution.	Yigitcanlar et al. (2020)

land use analysis	AI tools analyze zoning laws and facilitate data-driven decisions for urban development.	DSS: Aligns projects with environmental, social, and economic variables.	Schubert et al. (2023)
Building information modeling (BIM)	AI automates conflict detection in complex models (e.g., pipes intersecting walls).	BIM: Integrates 3D modeling with data on energy efficiency, cost projections, and material properties.	Lukovich (2023)
	AI-driven lifecycle management predicts maintenance schedules, extending infrastructure lifespan.	Predictive maintenance reduces risks of system failures (e.g., plumbing, electrical).	Lukovich (2023)
Virtual reality (VR) and augmented reality (AR)	Real-time design walkthroughs using AI-powered VR/AR enable interactive collaboration with stakeholders.	VR/AR tools overlay designs on physical spaces, fostering immediate feedback and improved construction planning.	Nabizadeh Rafsanjani & Nabizadeh (2023)
	Interactive prototyping aligns user feedback with design vision.	AI-enhanced virtual environments improve design communication and ensure accuracy in decision-making.	Nabizadeh Rafsanjani & Nabizadeh (2023)

Recent applications of AI in architecture and urban planning represent a breakthrough in how projects are conceived, optimized, and managed. Tools such as generative design, algorithmic modeling, and predictive simulations increase process efficiency and allow for exploring previously complex solutions due to their complexity and technological limitations. However, despite the apparent benefits, it is necessary to consider the practical challenges and limitations that arise with the incorporation of these technologies.

On the one hand, AI expands architects' creative capabilities and optimizes resource use, resulting in a more sustainable and efficient design. Examples such as the prediction of energy consumption, the optimization of materials, and the simulation of the life cycle of a building are proof of the transformative potential of these tools. Likewise, in urban contexts, AI facilitates informed decision-making by analyzing large data sets that cover social, economic, and environmental variables. This is crucial for developing more inclusive and resilient planning strategies, such as in the context of smart cities. However, this integration presents certain practical limitations. Over-reliance on algorithms can create a risk of uniformity in design, limiting the creativity and contextual identity that characterize traditional architecture. In addition, AI-based tools require accurate and up-to-date data to ensure reliable results, which is sometimes challenging due to the lack of technological infrastructure or accessible data in certain regions.

Although AI represents a unique opportunity to optimize processes and improve the quality of architectural and urban design, its implementation must be balanced and critical. Professionals in the sector must understand the capabilities and limitations of these tools, ensuring that AI complements and does not replace human judgment. Accordingly, collaboration between architects and technology must focus on generating innovative solutions that, without losing their humanistic approach, respond to the current and future challenges of the built environment.

2.2. Decision-making process in architecture and urban transformations

Decision-making in urban and architectural transformation projects is characterized by inherent complexity, mainly due to the involvement of multiple actors with diverse and, in many cases, conflicting objectives. These decisions are often unconventional, requiring balancing functional, aesthetic, environmental, and economic aspects. Furthermore, urban transformation processes are dynamic by nature, and decisions made at one stage can have long-term repercussions, influencing future outcomes and options (Omari et al., 2023). In such contexts, traditional experience-based decision-making approaches often prove insufficient, especially when tasks are unique or decision-makers lack the necessary expertise. This highlights the need for structured methodologies and tools to effectively address the multidimensional nature of real-world decision-making.

The complexity of decision-making in real-world scenarios, particularly in urban transformation processes, is influenced by several interrelated factors (Podvesovskii et al., 2021):

- *Multi-purpose nature of options and conflicting objectives:* Decisions in these contexts cannot be adequately captured by a single objective function, as they frequently involve multiple criteria that may conflict.
- *Sheer volume of alternatives:* Many practical problems present hundreds or even thousands of potential solutions, rendering traditional methods such as statistical analysis insufficient due to differences in measurement parameters and intervals between alternatives.
- *Incomplete and uncertain information:* Decision-makers often operate with limited or imprecise data regarding how the external environment will respond to their choices, introducing significant uncertainty into the process.
- *Dynamic nature of decision-making:* Decisions' consequences are not always immediate, and their effects may unfold over time, necessitating adaptive and flexible approaches to accommodate evolving circumstances (Omari et al., 2023).

Given the inherent complexity of these decisions, a structured decision-making process is indispensable to ensure informed, effective, and goal-oriented outcomes. A logical framework facilitates problem definition, exploration of alternatives, risk assessment, and justification of chosen solutions. This structured approach minimizes the likelihood of impulsive decisions, enhances the credibility of the decision-making process, and fosters transparency, which is critical to building trust and collaboration among stakeholders (Omari et al., 2023; Schubert et al., 2023).

Integrating technical, regulatory, and safety considerations early in the design process is essential to align project goals with user needs and environmental demands. This approach promotes sustainable, context-sensitive solutions that support adaptability and long-term success in urban environments (Chaillou, 2019). Furthermore, systematic evaluation and limitation of alternatives enable better risk mitigation and outcome prediction, ensuring that decisions are resilient and adaptable to changing conditions.

Decision Support Systems (DSSs) are designed to optimize decisions' quality, speed, and accuracy, facilitating access to relevant information, analysis of options, and support in complex decisions in various fields (Shim et al., 2022). They are powerful tools that support decision-making by providing analytical capabilities to assess data and evaluate alternatives. In urban transformation, where multiple stakeholders with diverse interests are involved, Group Decision Support Systems (GDSSs) are applied in collaborative decision-making processes, especially in complex urban contexts. GDSSs help manage the interaction between multiple actors and reduce biases and conflicts (Omari et al., 2023). In this context, DSSs and GDSSs have emerged as fundamental tools to address complex decision-making challenges. DSSs were initially developed to support decision-making by identifying the most appropriate methodologies for specific problems. These systems are designed to facilitate stakeholder consensus-building through negotiation, voting, and argument-based approaches (Omari et al., 2023). In this context, GDSSs enhance the quality of decisions, reduce biases, and help mitigate conflicts, ensuring that diverse stakeholder perspectives are considered.

In urban transformation processes, decision-making often involves complex problems requiring more than analytical support. Problem Structuring Methods (PSMs) and Multi-Criteria Decision Analysis (MCDA) are two essential methodologies that complement DSSs. While DSSs provide the technological framework for data analysis and decision evaluation, PSMs help identify and structure the underlying problems. PSMs ensure that all relevant factors are considered before decision-making begins. MCDA, on the other hand, is used to evaluate alternatives based on multiple criteria, which is especially important in urban transformation projects where decisions cannot be based on a single factor. MCDA allows decision-makers to weigh alternatives, prioritize them, and make more informed decisions (Cinelli et al., 2020; Podvesovskii et al., 2021).

The relationship between DSSs, PSMs, and MCDA can be considered complementary and sequential. PSMs structure the problem, DSSs provide the tools to analyze the data and evaluate alternatives, and MCDA helps select the best option considering multiple criteria. Together, these approaches enable more structured, collaborative, and effective decision-making, especially in complex contexts such as urban transformation. This integration allows for effective problem structuring, stakeholder collaboration, and systematic evaluation, ultimately leading to informed, sustainable decisions (Cinelli et al., 2020; Podvesovskii et al., 2021; Omari et al., 2023).

2.2.1. Decision support systems in architecture

In architectural practice, projects often encompass multiple dimensions, including technical, social, economic, and environmental factors. These complexities demand effective methods to coordinate interdisciplinary teams, manage limited resources, and ensure proposed solutions meet project objectives. Since the mid-1960s, DSS has been employed to assist in planning and decision-making for complex problems, becoming indispensable tools for addressing multifaceted challenges and optimizing design and planning processes (Schubert, Bratoev, & Petzold, 2023).

A DSS is a computer-based tool designed to assist decision-makers in analyzing data, evaluating alternatives, and making informed choices. DSS integrates data management, modeling, and user interfaces to provide structured frameworks for decision-making. Its primary purpose is to enhance the quality of decisions by processing complex information and presenting it in an actionable format. DSS is particularly valuable in fields like architecture and urban planning, where decisions must balance multiple criteria, such as sustainability, cost, and social impact (Shim et al., 2022).

DSS encompasses a variety of methods and tools tailored to different types of decision-making challenges. MCDA and PSMs are prominent members of the DSS "family." While

MCDA evaluates and ranks alternatives based on multiple criteria, PSMs are designed to help structure complex, ill-defined problems by clarifying objectives, identifying key factors, and fostering stakeholder collaboration. Both MCDA and PSMs share the common goal of enhancing decision-making processes. However, they address different aspects: MCDA is more analytical and quantitative, whereas PSMs are often qualitative and participatory.

Belton and Stewart (2010) explore how PSMs and MCDA complement each other in complex decision making. MCDA is a decision-support method designed to evaluate and prioritize a set of alternatives based on multiple, often conflicting criteria. Key features of MCDA include its quantitative focus, where alternatives are evaluated against pre-established criteria using numerical scores. Analytical tools such as the Weighted Sum Model, Analytic Hierarchy Process (AHP), and PROMETHEE are commonly employed to assess the performance of alternatives, applying mathematical and statistical models to facilitate the comparison. MCDA aims to support decision-makers in identifying relevant criteria to base their decisions on, thereby minimizing the potential for post-decision regrets by ensuring that all important issues are properly considered (Belton & Stewart, 2002; Lami & Todella, 2023).

PSMs focus on understanding and structuring complex problems through a qualitative and participatory approach, involving stakeholders in the process. They aim to frame the problem, identify uncertainties and explore different scenarios, using techniques such as Soft Systems Methodology (SSM) or Strategic Options Analysis (SODA) and SCA (Belton and Stewart, 2010). Unlike quantitative approaches, PSMs facilitate dialogue between participants to resolve conflicts and develop a shared understanding, which is crucial in complex decisions involving multiple actors and criteria that are difficult to quantify.

Evaluation techniques in urban decision-making have undergone significant transformation. Traditionally, they were perceived as “decisional tools” designed to deliver optimal solutions based on a rational-comprehensive model. As Lami & Moroni (2020) noted, “There was a rough idea that, after the important data had been collected, the technique in question would indicate the best decision by itself.” This approach, which downplayed the ethical, political, and subjective dimensions of decision-making, focused instead on technical expertise. This perspective has been criticized over time, particularly following Lindblom’s (1959) influential work, which questioned the simplicity of such models and introduced the concept of "muddling through" as a more realistic approach to decision-making.

In response to these critiques, evaluation techniques shifted toward a more inclusive and flexible role as "decision aids." This new paradigm recognizes urban transformations' complex, multi-actor nature, emphasizing the need to mediate between diverse priorities and uncertainties. Lami & Moroni (2020) highlight that tools like MCDA and PSMs embody this evolution, prioritizing stakeholder involvement and adaptive decision-making processes. These approaches help address urban challenges, where decision-making must balance environmental, economic, and social factors. MCDA methods, in particular, allow decision-makers to simultaneously consider multiple criteria while integrating diverse information and perspectives from stakeholders (Mecca, 2023).

In addition to individual DSS, GDSS have emerged as critical tools for facilitating collaborative decision-making among multiple stakeholders. GDSS methods enhance communication, resolve conflicts, and build consensus within interdisciplinary teams. These systems often incorporate techniques such as brainstorming, voting, and scenario analysis to ensure that diverse perspectives are considered. For example, in urban transformation projects, GDSS enables teams to evaluate different scenarios, align technical and social objectives, and identify critical aspects that may go unnoticed in conventional approaches (Schubert et al., 2023). The participatory and interactive design of GDSS ensures stakeholder involvement in all stages of the process, fostering collaboration and knowledge generation essential for sustainable strategies (Sala et al., 2013; Mecca, 2023).

One of the essential roles of a DSS is filtering information to transform raw data into actionable insights. As Ackoff's (1989) hierarchy, cited in Lami & Moroni (2020), explains, data are "products of observations that have no value until they are processed and transformed into information." DSS achieves this by employing classification, sorting, aggregation, and selection techniques, which help distill vast amounts of data into meaningful and relevant information. This capability is particularly critical in architectural and urban planning projects, where decision-makers must integrate diverse datasets ranging from spatial configurations and material properties to environmental impacts into a coherent framework. By filtering out irrelevant or redundant information, DSS allows professionals to focus on the most critical elements, enhancing the efficiency and accuracy of decision-making processes.

Another key function of DSS is structuring complex, ill-defined problems into manageable and actionable frameworks. Described as the “artistic part of decision analysis” (Lami & Moroni, 2020), structuring emphasizes creativity and systematic representation. PSMs, a subset of DSS tools, play a vital role in this process. PSMs enable decision-makers to translate vague or ambiguous concerns into clear objectives by defining boundaries, identifying key factors, and creating hierarchical frameworks. For instance, tools like decision graphs and option diagrams are often used to visualize relationships and build stakeholder consensus. As Von Winterfeldt (1980, as cited in Lami & Moroni, 2020) notes, structuring ensures that decisions are based on well-defined objectives and alternatives, leading to more robust and transparent outcomes. Moreover, the iterative nature of structuring methods allows decision-makers to adapt their frameworks as new data or stakeholder input emerges, ensuring flexibility and responsiveness in dynamic contexts.

Prioritization is another function of DSS, enabling decision-makers to rank alternatives based on quantitative and qualitative criteria. AHP is a widely used method for prioritization within DSS. In AHP, alternatives are compared pairwise using a predefined scale (typically 0-9), where higher scores indicate better performance relative to a specific criterion. Similarly, criteria weights are derived through pairwise comparisons, ensuring a systematic and transparent evaluation process. These values are then combined additively to calculate a final score for each alternative, facilitating their ranking (Saaty, 1990; Marttunen et al., 2018). This prioritization process is especially valuable in urban transformation projects, where competing interests and objectives often create complex trade-offs. DSS helps architects and urban planners align their decisions with project goals, resource constraints, and community values by providing a structured approach to ranking solutions. Furthermore, prioritization fosters transparency in resource allocation, ensuring that critical aspects of sustainability, such as energy efficiency, social equity, and environmental impact, are adequately addressed.

DSS are particularly useful in addressing the complexities of multicriteria decision-making, as real-world architectural and urban projects require evaluating multiple criteria simultaneously. Multicriteria decision support enables decision-makers to rank and select solutions based on their importance while considering various influencing factors such as sustainability, costs, and urban impact (Omari et al., 2023). This capacity to manage diverse and sometimes conflicting objectives makes DSS indispensable in creating resilient and adaptable urban environments. Tools like the AHP assist in ranking alternatives based on stakeholder preferences, ensuring balanced and well-informed decisions. PSMs are particularly effective in tackling “wicked problems” in architecture, such as reconciling historic preservation with modern functionality. These methods encourage participatory processes, exploring collaborative scenarios that engage stakeholders in developing solutions tailored to complex challenges (Cinelli et al., 2021).

Despite their transformative potential, implementing DSS presents challenges, including managing vast datasets, ensuring transparency, and addressing ethical concerns. Establishing systems that integrate databases, analysis models, and user interfaces is critical for practical scenario analysis and data visualization. By allowing decision-makers to handle complex, interconnected factors efficiently, DSS reduces risks, improves accuracy, and enhances the quality of decisions across all stages of architectural and urban projects (Omari et al., 2023). Additionally, fostering interdisciplinary collaboration and ensuring the inclusion of underrepresented stakeholder groups remain key areas for further development.

In synthesis, DSSs provide architects and urban planners with robust frameworks to navigate the complexities of modern projects. These systems promote informed and sustainable decision-making by filtering information, structuring problems, prioritizing options, and involving stakeholders. As Lami & Moroni (2020) conclude, “Evaluation cannot substitute the decision-making process; instead, it should enhance its clarity, efficiency, and inclusivity.” Future research should continue to refine these tools, ensuring they remain responsive to the evolving challenges of architecture and urban design while addressing ethical considerations and technological advancements.

2.2.2. Problem Structuring Methods (PSMs)

After exploring the general concept of DSS and briefly addressing PSMs and MCDA as key components in the decision-making process, this section will focus specifically on PSMs. This shift is motivated by their relevance in complex decision-making processes, especially in the context of urban transformation, where multiple variables and alternatives must be considered. Deepening the PSM, we can better understand their potential for integrating AI-based solutions within the architectural and urban domains.

PSMs emerged from the field of Operational Research (OR) as a response to the limitations of traditional, mathematically driven approaches in dealing with complex, ill-structured problems. While classical OR techniques focus on optimization and quantitative analysis, PSMs emphasize participation, qualitative reasoning, and iterative processes to support decision-making in uncertain and dynamic environments (Mingers & Rosenhead, 2004)

Rooted in Soft Operational Research (Soft OR), PSMs were developed to address real-world challenges where multiple stakeholders, conflicting perspectives, and subjective judgments play a central role. Seminal contributions, such as those of Mingers & Rosenhead (2004), trace the evolution of these methods, highlighting their foundations in earlier OR works, including Blackett's pioneering studies (1943). These approaches prioritize problem exploration over definitive solutions, making them particularly useful in strategic decision-making and complex urban and architectural transformations.

According to Tosunlu et al. (2023), most PSMs primarily serve a descriptive function, helping to identify the stakeholders involved, their respective concerns, and the underlying reasons for these issues. As a result, PSMs are primarily developed to support stakeholders in complex problem scenarios by facilitating thorough assessments and fostering a shared understanding among the parties involved (Hester et al., 2020).

Smith & Shaw (2019) highlight some characteristics of PSMs: these models are qualitative, promote participation, and enhance participants' understanding of the problem. Furthermore, they aim to provide a holistic view of the system based on participants' subjective perceptions of the world.

Other key aspects of PSMs include establishing the model's credibility by preserving participants' contributions, using rational procedures to foster trust, and structuring knowledge through several stages of analysis. Furthermore, these methods incorporate distinct phases for convergent and divergent thinking (Schramm & Schramm, 2018), which help the group involved in the complex problem negotiate a set of improvements and actions to address the situation (Ackermann, 2012; Gomes & Schramm,2022).

PSMs have been utilized across multiple fields (Gomes & Schramm, 2022), including business management (Hanafizadeh & Ghamkhari, 2019; Savage et al., 2019), environmental management (Hart & Paucar-Caceres, 2014; Santos et al., 2019), and healthcare (Cardoso-Grilo et al., 2019; Carter et al., 2019). They have also been applied to address social challenges (Brocklesby & Beall, 2018; Laouris & Michaelides, 2018) and other areas (Armstrong, 2019; Cloutier et al., 2015).

In architecture, PSMs offer a powerful tool for addressing complexities. By fostering collaboration, clarifying priorities, and enabling structured decision-making, these methods help architects and stakeholders navigate the multifaceted challenges of contemporary design and urban planning, paving the way for more inclusive and sustainable outcomes.

Architectural projects frequently encompass ill-defined problems that evolve. These challenges often transcend technical and design concerns, integrating broader social, economic, and environmental considerations that add significant complexity to the process. These tools enhance the iterative evaluation and refinement of designs and offer a structured framework to address the multifaceted nature of architectural decision-making, helping bridge gaps in understanding and coordination among diverse stakeholders.

PSMs serve as a framework for tackling the intricate challenges faced in architectural and urban projects. These methods emphasize the structuring of problems rather than their direct resolution, providing a participative and systematic approach particularly effective for managing "wicked problems." According to Rosenhead (1996; Lami & Moroni, 2020), wicked problems are characterized by complexity, uncertainty, and competing stakeholder interests. Examples include urban regeneration projects, historic preservation efforts, and the design of sustainable housing solutions.

PSMs, such as the Strategic Choice Approach (SCA), Soft Systems Methodology (SSM), and Strategic Options Development and Analysis (SODA) (Lami & Todella,2019), are particularly relevant to architectural practice (Gomes & Schramm, 2022):

- ***SCA*** supports collaborative decision-making by helping stakeholders manage uncertainty through a structured four-step process: shaping, where problems are identified; designing, which focuses on generating feasible solutions; comparing, where alternatives are evaluated; and choosing, the stage where the group reaches a consensus on the most suitable course of action.
- ***SSM*** is a learning-based approach that involves creating a visual representation of the problem, developing a conceptual model that reflects the perspectives and interests of decision-makers, comparing the actual situation with the conceptual model, identifying culturally and systemically acceptable changes, and implementing actions to address the issue.
- ***SODA*** facilitates problem-solving by using cognitive mapping to capture individual perceptions of a situation. This fosters a shared understanding among stakeholders and guides the group toward identifying solutions.

As Lami & Moroni (2020) note, PSMs are particularly effective in contexts where stakeholder participation is critical. For example, in redeveloping a historic district, methods like SSM can facilitate discussions around preserving cultural heritage while addressing modern infrastructure needs. Another case involves using SCA in architectural design (Todella et al., 2018). SCA is widely applied in public participation processes to manage uncertainties and support informed decision-making by integrating analysis, planning, and design. In this context, it provides a rational framework for comparing alternative solutions (Friend, 1993; Todella et al.,2018). This approach enables architects to navigate uncertainties by incorporating flexible decision pathways, allowing judges and stakeholders to prioritize innovative yet practical design solutions. Additionally, PSMs offer significant advantages in architectural and urban contexts. According to Lami & Moroni (2020), these advantages include:

- *Provide a structured framework for managing competing stakeholder interests:* PSMs allow structuring complex problems and resolving conflicts of interest between diverse stakeholders, a key feature when dealing with projects with multiple perspectives and competing objectives.

- *Enhance collaboration by fostering mutual understanding among participants:* These techniques promote participation and mutual understanding by involving different actors in all process phases, from problem identification to collective decision-making.
- *Enable the consideration of creative and unconventional solutions, broadening the scope of possibilities:* By emphasizing participation and flexibility in defining objectives, PSMs facilitate the generation of innovative solutions, particularly in scenarios of high uncertainty (Rosenhead, 1996; Lami & Moroni, 2020).
- *Clarify objectives and priorities, ensuring alignment between project goals and stakeholder expectations:* Through tools like "decision graphs" and "rich pictures," PSMs help clarify objectives and priorities, ensuring that final designs reflect client expectations and respect project constraints.

Despite their advantages, implementing PSMs is not without challenges. One common issue is the difficulty of aligning diverse stakeholder values, particularly in highly politicized or resource-constrained environments. Additionally, effectively using these methods often requires substantial expertise and facilitation skills.

Future research could explore the integration of PSMs with emerging technologies such as AI and big data analytics. For instance, AI-driven decision support systems could enhance PSMs by providing real-time analysis and predictive modeling, enabling architects to better anticipate the outcomes of various design choices. As Lami & Moroni (2020) suggest, such advancements could further refine the role of PSMs as decision aids, bridging the gap between technical evaluation and democratic decision-making processes. As Chaillou (2019) notes, this complexity makes architectural projects especially well-suited to the use of advanced problem-solving tools, including AI-assisted decision-making systems.

2.3. The role of artificial intelligence in supporting the decision-making process in architectural and urban process

In recent years, AI has emerged as a transformative force in industries that require complex decision-making, such as architecture and urban planning. These fields involve managing intricate relationships between design, human behavior, and environmental factors, which can lead to high levels of uncertainty and complexity. AI technologies offer an opportunity to help decision-makers navigate this complexity, enabling architects and urban planners to make more informed decisions.

According to Rane (2024), the potential applications of AI are changing the way architectural projects are conceived, designed, and executed (Bölek & Özbaşaran,2023). For example, generative AI, a subset of AI, promises to amplify the creative capabilities of architects and engineers (Budhwar et al., 2023; Kanbach et al., 2023; Ooi et al., 2023). These AI models, trained on extensive datasets, can produce human-like texts, providing insights, suggestions, and even design proposals (Chowdhary, 2020; Bölek & Özbaşaran,2023)

The role of AI in decision-making goes beyond automating repetitive tasks. It provides tools that help process large amounts of data, identify patterns, and predict future elements crucial in urban and architectural contexts. By leveraging machine learning algorithms and advanced analytics, AI can deliver data-driven insights, supporting decisions that consider current conditions and future implications. This makes AI a powerful ally in architectural design and urban development, where the balance between aesthetics, functionality, and environmental sustainability is critical.

A notable advantage of AI is its ability to predict energy consumption and material performance. As Matter & Gado (2024) point out, AI-based tools enable architects to optimize designs for sustainability. This improves the final product's quality and ensures that the decision-making process is based on measurable data. Architects can significantly reduce the uncertainty and risk associated with their decisions by relying on accurate data. This predictive capability enables architects to make more informed decisions, ensuring that designs are innovative and environmentally responsible.

The emergence of new technologies, particularly AI, presents exciting possibilities for overcoming traditional obstacles in the design process. AI can assist architects in generating design alternatives, performing cost analyses, and assessing environmental impacts. These AI-powered tools enable architects to test different scenarios quickly and accurately.

Furthermore, AI opens opportunities to address emerging architectural and urban decision-making challenges. For example, AI can mitigate the problem of data overload, helping professionals process and interpret large amounts of information from multiple sources. In doing so, AI enables architects to focus on the most relevant factors, streamlining the decision-making process. Furthermore, AI can play a pivotal role in resolving conflicts between stakeholders. By using data-driven insights, AI can identify potential areas of disagreement and offer solutions that promote collaboration and consensus-building. As Omari et al. (2023) indicate, intelligent agent-based systems can facilitate multi-criteria group decision support, making them particularly valuable in urban design's complex and multifaceted nature. This capability enables better land use management and more effective resolution of conflicts between competing priorities.

These applications highlight how AI can become a supporting tool, improving architects' ability to address complex, time-consuming, or previously difficult-to-manage challenges. Integrating AI into architectural and urban decision-making facilitates the optimization of designs and provides a structured approach to addressing problems at each stage of the process. As architects and urban planners face challenges related to sustainability, data analysis, and conflict resolution, AI-based tools enable them to assess and predict outcomes with unprecedented accuracy, reducing uncertainty and risk in their decisions.

These advancements are critical at stages of the decision-making process, such as problem identification, where AI helps define the most effective objectives and strategies to follow. AI's ability to analyze large volumes of information and predict the impact of different decisions offers valuable support for professionals to compare possible solutions and justify their choices, as suggested by the decision support systems (DSS)-based decision framework mentioned by Podvesovskii et al. (2021). Accordingly, as shown in *Table 2*, AI-based and human-based decision-making are compared (Shrestha et al., 2019) to highlight differences in their approaches and results. The authors compare their characteristics under five key conditions: specificity of the search space, interpretability of the process and the result, size of the set of alternatives, speed of decision-making, and replicability.

Table 2. Comparison of AI-Based and Human Decision Making (Source: Shrestha et al., 2019).

Decision-Making Conditions	AI-Based Decision-Making	Human Decision-Making
Specificity of the decision search space	Requires a well-specified decision search space with specific objective functions.	Accommodates a loosely defined decision search space.
Interpretability of the decision-making process and outcome	The complexity of the functional forms can make it challenging to interpret the decision process and outcomes.	Decisions are explainable and interpretable, though vulnerable to retrospective sense-making.
Size of the alternative set	Accommodates large alternative sets.	Limited capacity to uniformly evaluate a large alternative set.
Decision-making speed	Comparatively fast. Limited trade-off between speed and accuracy.	Comparatively slow. The high trade-off between speed and accuracy.
Replicability of outcomes	The decision-making process and outcomes are highly replicable due to standard computational procedures.	Replicability is vulnerable to inter- and intra-individual factors such as differences in experience, attention, context, and the decision maker's emotional state.

Moreover, *Figure 6* provides a framework for understanding the stages involved in decision-making for architectural and urban projects, focusing on AI integration. It outlines interconnected stages demonstrating how problems are identified, addressed, and resolved through human- and AI-driven approaches.

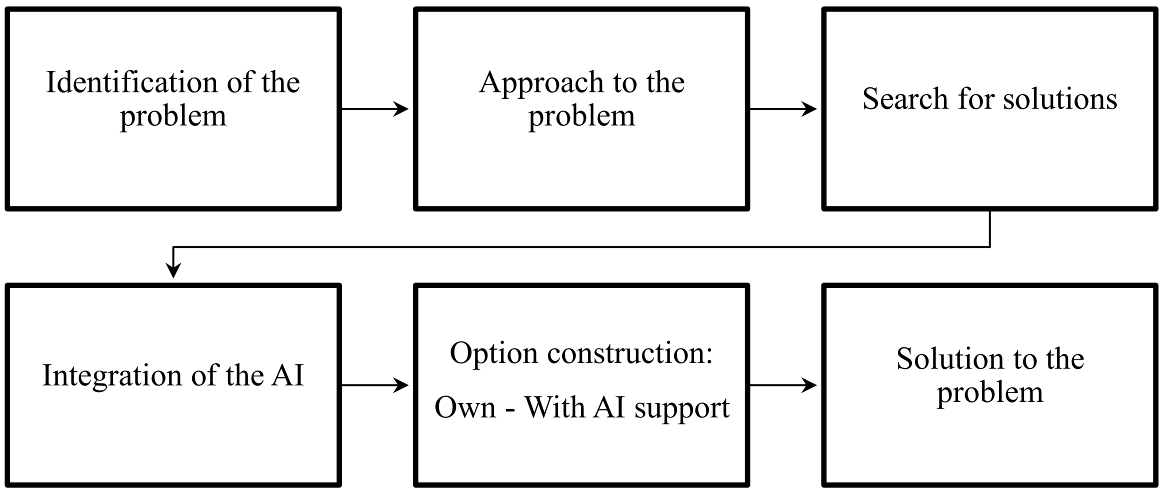

Figure 6. The decision-making process and the possible role of AI, Own elaboration based on Podvesovskii et al. (2021)

The process begins with problem identification, which forms the basis for all subsequent steps. At this stage, decision-makers recognize the problem or challenge that needs to be solved, defining the scope and objectives of the entire process. This stage is crucial as it sets the direction of the approach and the strategies to be developed. According to Podvesovskii et al. (2021), DSSs allow decision-makers to identify a variety of possible solutions, compare them, evaluate the consequences of their choice, and justify their selection, helping them to establish the foundations of the process.

The problem approach involves formulating strategies or methodologies to address the identified problem. This includes prioritizing tasks, assessing constraints, and evaluating available resources to address the problem systematically. Once the foundation is set, the process moves to solution-finding, a collaborative phase where stakeholders generate a variety of alternatives. At this stage, data-driven insights, brainstorming sessions, and stakeholder input are leveraged to identify potential solution pathways. Omari et al. (2023) highlight that DSSs often employ negotiation, voting, and argument-based systems to engage stakeholders and promote collaboration.

An important aspect is the integration of AI, which introduces tools to improve the analysis and evaluation of solutions. Integrating AI into architectural and urban processes transforms how solutions are evaluated, providing advanced tools to improve analysis, planning, and decision-making. This approach, proposed by Cugurullo et al. (2024) called "AI urbanism" represents a significant shift from traditional smart urbanism, going beyond data collection to autonomous decision-making capabilities. According to it, urban AIs like city brains and urban software agents directly influence the governance of cities by making decisions. City brains manage urban traffic and determine optimized mobility strategies independent of humans. These technologies are redesigning governance and planning processes, allowing urban planners to access new levels of information and control.

AI can contribute differently to the decision-making process related to architecture and urban transformations:

Predictive analysis: AI makes it possible to process large volumes of data to anticipate future patterns and trends, improving the ability to assess the long-term impact of proposed solutions. For example, technologies such as “city brains” integrate advanced sensors and digital platforms to generate predictions about future urban conditions, such as energy demand or mobility patterns. As the authors point out, city brains foresee how much energy a city will consume in the coming years and how much carbon dioxide will be emitted; algorithms predict the future value of a property or who is about to commit a crime (Cugurullo et al.,2024). This allows architects and urban planners to make more informed and sustainable project decisions while optimizing resources and reducing risks. AI can contribute by processing large data sets, running predictive models, and simulating scenarios, allowing decision-makers to evaluate alternatives more effectively and make evidence-based decisions. Schubert et al. (2023) noted that AI in DSSs are essential tools for urban planning, as they process complex data, run predictive models, and simulate scenarios to forecast outcomes and improve strategic planning. This integration is iterative, as AI feedback leads to the refinement of solutions, creating a dynamic and adaptive decision-making process.

Simulation and modeling: AI makes it possible to create sophisticated simulations that evaluate the impact of different designs or policies before implementation. These simulations optimize aspects such as energy efficiency or mobility and reveal potential risks associated with urban decisions. As the authors mention, urban AIs can produce narratives and accounts that define what is good or bad in and for the city. However, there is the risk that AI-generated idealizations of the city might not correspond to crucial human ideals such as justice and equity (Cugurullo et al.,2024). These capabilities underline the need to incorporate fair principles in evaluating urban solutions.

Efficiency evaluation: AI can also analyze the efficiency of solutions in real time, providing valuable data to optimize architectural and urban processes. For example, "city brains" monitor energy consumption and automatically adjust systems to improve performance. Sensors produce data on the city's metabolism regarding energy consumption, and human decision-makers manage energy production considering the insights that innovative technology has generated (Cugurullo et al.,2024). This allows for more precise and dynamic control in urban planning and design processes.

Complex data analysis: AI's ability to process complex data, such as satellite imagery, urban sensors, and social media, enables the identification of space use patterns, citizen preferences, and mobility dynamics. This analysis improves the evaluation of existing solutions and highlights areas for improvement. According to the authors, city brains are large-scale AIs residing in vast digital urban platforms capable of managing multiple urban domains in real-time, including transport, safety, health, environmental monitoring, and planning (Cugurullo et al.,2024). Urban planners can adopt more comprehensive and evidence-based approaches by integrating this data.

While AI offers powerful tools for evaluating architectural and urban solutions, its implementation must be ethical and responsible. Addressing the risks associated with algorithmic biases, privacy, and human autonomy is critical. As Cugurullo et al. (2024) point out, the successful integration of AI into these processes will depend on a balanced approach considering its transformative potential and potential negative implications, promoting more sustainable and equitable cities.

The solutions phase focuses on developing proposed resolutions. These solutions may depend entirely on human expertise or be supported by AI capabilities. As Podvesovskii et al. (2021) noted, DSSs assist decision-makers in excluding unfeasible options based on specific requirements by providing a structured framework for evaluating and justifying potential solutions. The process aims to deliver a feasible, data-informed outcome that aligns with the initial objectives. Incorporating AI can contribute to the efficiency and sustainability of the final solution, offering evidence-based support for the decision-making process.

The phase interaction underlines the feedback loop between AI integration and solution-finding. This iterative process allows continuously refining and adapting proposed solutions based on real-time data and information. AI plays a dual role in this framework: it acts as a support tool and a transformative element that redefines traditional problem-solving approaches.

Furthermore, AI integration improves problem-solving efficiency by reducing the time and effort required to address complex issues, particularly in urban planning contexts. This is critical in projects where decisions involve balancing sustainability, resource allocation, and community needs. Schubert et al. (2023) emphasize that AI improves efficiency and fosters collaboration between multiple actors, allowing everyone to participate in designing more equitable and sustainable solutions. Furthermore, AI's ability to simulate scenarios and anticipate potential risks helps stakeholders address challenges by minimizing the risks associated with planning and design.

AI's role in supporting decision-making processes goes beyond efficiency, including fostering inclusion, mitigating risks, and enhancing collaboration. Omari et al. (2023) highlight that AI redefines traditional approaches by facilitating consensus in complex contexts. Podvesovskii et al. (2021) highlight that its integration can mitigate risks by anticipating problems before they arise. These advances position AI as a resource to address the challenges of architecture and urban transformation.

Drawing on the research mentioned to support analysis, Table 3 describes some applications of AI in architecture, showing how it has been used in different areas of impact and emphasizing its role in the decision-making process.

Table 3. AI applications in architecture and its role in the decision-making process (Source: own elaboration).

Impact Area in Architecture	AI Applications	Opportunities	Contribution to the DM Process	Reference
Generative Design	Generative algorithms create multiple design versions based on specific parameters.	Greater creativity, space efficiency, and resource optimization.	Facilitates evaluation of multiple design alternatives based on optimized data.	Chaillou (2019) Rane (2024)
Urban Planning	Analysis of large sets of geospatial, demographic, and socioeconomic data for urban planning.	More efficient planning for innovative, inclusive, and sustainable cities.	Provides key insights for strategic urban development decisions based on data.	Yigitcanlar et al. (2020)
Environmental Sustainability	Evaluation of the environmental impact of architectural and urban projects.	Ensures environmental regulations and reduces environmental impact in urban and architectural design.	Aids in defining design strategies that maximize sustainability and minimize environmental impact.	Hammond et al. (2023)
Energy Optimization	Predictive simulation and analysis of energy performance and material efficiency in buildings.	Reduces carbon footprint and improves sustainability.	Enables informed decisions on materials and energy-efficient technologies.	Matter & Gado (2024)
Cost and Feasibility Analysis	Predictive AI tools for cost and financial risk analysis in projects.	Optimizes budgets and minimizes financial risks during project development.	Enables more precise budget adjustments and cost forecasting, reducing financial risks.	Omari et al. (2023)

2.3.1. Conversational Challenges in the Use of Artificial Intelligence

To facilitate the interaction between AI and decision-making processes, it is crucial to understand how AI processes text and the general techniques for supplying it with the required inputs. This section focuses on the technical aspects of using AI, such as input cues and practical strategies for adapting AI solutions to architectural and urban applications. As previously mentioned, AI reshapes how architects and urban planners make decisions in design processes. This leads to a discussion on how AI can be applied to architectural design and urban planning, mainly through conversational interfaces.

According to Matter & Gado (2024), Natural Language Processing (NLP) is an area of AI research that enables machines to learn and create human language. This is crucial when categorizing and achieving significant amounts of textual information. In architecture, NLP can be applied to directly index regulations, historical articles, case studies, and other sources to create a ready list of information sources for a given project.

Natural language data is analyzed by converting human language into a form a computer can understand. Textual structure dissection techniques include dependency analysis and a sentence's structure aspect. As the use of NLP increases, machines can read and write words and text, thus improving communication between humans and machines (Nabizadeh Rafsanjani & Nabizadeh, 2023). Natural Language Generation (NLG) is the systematic approach to generating human-understandable natural language text from non-textual data or meaning representations. This area is key to improving human-computer interaction (Perera & Nand, 2017; Miró et al., 2024). These systems can translate data sets or tables containing structured information into natural language. Large volumes of data are used to train text generation algorithms, which allow them to identify linguistic trends and predict the most likely sequences of words, phrases, and even paragraphs. That way, AI text generators generate readable content using algorithms to sort the content generated by context analysis. Such systems are usually designed to incorporate contextual generation, grammar, and spell check to support producing high-quality content.) These advancements enable AI to create syntactically correct text and contextualize relevant content. In short, automatic text generation and NLP revolutionize how machines communicate with human language (Miró et al., 2024)

Why is it important to understand how to communicate with AI? Communication between humans and AI is crucial to unlocking the benefits of the new world of digital computing, and it goes beyond simple optimism. As argued in Acar (2023), problem formulation is a more enduring and adaptable skill to harness the potential of generative AI. Detailed information is required in creative and other professions that use AI systems. Knowing how to interact with AI, what to input, what words to use, and how to adjust settings allows the output to be helpful for the user's goals. Furthermore, the effectiveness of prompts is limited to specific algorithms, making their applicability lower across different AI models and versions. Proper problem formulation is essential to achieving practical solutions, even when using sophisticated prompts.

As Almaz et al. (2024) explain, the ability of AI to produce high-quality results is highly linked to the quality of the cues provided to the models. To enhance the design process's accuracy, efficiency, and creativity, it is crucial to understand how to utilize AI effectively. Without a proper understanding of how to interact with the AI system, professionals may end up with misleading or irrelevant information. The use of prompts and fine-tuning AI parameters can help architects, urban planners, and other coworkers enhance the quality of the materials produced: ideas for designs, reports on analyses, and visualizations.

Users must provide clear and specific prompts to communicate effectively with AI systems, particularly those used in architectural design. Prompts are commands or queries that tell the AI engine what to generate. Whether the output is text, an image, or another type of content, these prompts are essential to determining its form. As mentioned by Almaz et al. (2024), to attain mastery of the ability to utilize functions that analyze text effectively, the end user must comprehend how text functions when implemented in AI systems. The AI model reads the input or the message, processes the language, and provides the response or content to fit the instructions. The interchanged message's tone, clarity, and content influence this interaction. The specificity of a message has a positive correlation with the likelihood of achieving results corresponding to the user's intentions.

The technique of effective prompting is iterative and can be improved with time. According to Almaz et al. (2024), key strategies for improving the quality of AI-generated responses include:

- *Be explicit:* Clarity is paramount when providing a prompt. To guarantee that the final product reflects the intended vision, for instance, color, texture, and architectural style must be defined if pictures of a building are needed. The AI system can only work with the information provided, so the more precise the prompt, the more accurate the result.
- *Experiment with prompts:* AI-generated results often evolve through trial and error. Users might find original and imaginative solutions by experimenting with various prompt combinations. Unconventional thinking and combining seemingly unrelated concepts can lead to innovative designs and unexpected results. This open-minded approach is especially useful when exploring new architecture and urban planning ideas.
- *Parameter tuning:* AI models allow users to adjust parameters such as randomness or diversity in the output. These settings influence the generated content, allowing for greater creativity or controlled consistency. For example, adjusting randomness can lead to more diverse design concepts, which can be particularly useful when exploring alternative architectural styles or urban plans.

Designing architectural structures is a creative endeavor that is aided by good communication. If the design ideas are specific enough, an architect chooses the virtual design's building interactions with the real-world constraints that he addresses in his projects more accurately. Notably, keywords and AI interface descriptions can produce visual content for space construction in architectural design. For example, an architect needs to create an interior design concept with the help of AI technology. In this way, if the AI system is given details such as "modern minimalist interior with soft natural lighting, white walls, and modern furniture," it can generate the above image. Almaz et al. (2024) emphasize combining explicit language with experimentation to achieve optimal results. As the authors note, these techniques are not confined to image generation but also encompass text-based outputs, equally crucial in urban planning. For instance, posing questions such as, "As an urban planner, could you provide details on the environmental impacts of high-density housing in urban areas?” guides AI in producing professional information and materials tailored to the needs of urban planners and architects.

Incorporating AI into architectural and urban planning designs of cities involves adopting the basic knowledge of approaching an AI system. It is important to establish that the technical competence of interaction, regardless of other characteristics, allows the stated goal to be achieved. Therefore, through the commitment to learn the appropriate use of language input data, change the sequence of words used in prompts, and continuously analyze and test to improve prompts, a professional can realize the full potential of AI tools. These approaches will become much more important in shaping this construction of architectural design. About AI, descriptive language, and sensitive parameter changes, AI can become a helpful tool in architecture's creative and decision-making processes.

2.4. Theoretical Framework

This framework is based on the literature analysis (Table 4) and represents an original synthesis of theoretical findings on AI integration in urban and architectural decision-making. The division into four main categories (*technical, social, implementation, and impact*) stems from the author's elaboration based on the literature review. These categories structure the theoretical premises and form the foundation for the methodological investigation of AI applications in urban transformation projects.

The category “Technical” focuses on understanding AI technologies in urban and architectural contexts. It examines criteria for assessing their effectiveness in data collection and analysis, subsequently informing methodological strategies for evaluating their practical applications.

The “Social” one explores theoretical frameworks on the interaction between AI and various stakeholders, emphasizing collaboration, inclusion, and participatory decision-making. This provides a basis for developing methods to analyze how AI enables diverse perspectives in architectural and urban contexts.

The “Implementation” analyses the theoretical principles behind adapting AI models to specific urban contexts. This category bridges the gap between theoretical knowledge and practical methodologies for adapting AI tools to diverse environments by understanding the underlying dynamics, limitations, and potential solutions.

Finally, the “Impact” category explores the effects of incorporating AI into project results, emphasizing how it can enhance resource efficiency and effectiveness. This category establishes a foundation for developing methods to assess and evaluate AI's role in the success of urban and architectural projects.

The repetition of references across multiple categories reflects the interconnected nature of theoretical knowledge, as the same studies often address various dimensions of AI's role in decision-making processes. This connection emphasizes the necessity for a multidisciplinary approach, in which theoretical frameworks inform the creation of methodologies that effectively tackle the challenges and opportunities AI brings in urban transformation. By establishing a theoretical foundation, the framework facilitates a transition to the methodological phase of research.

Table 4. Theoretical Framework (Source: own elaboration).

Category	Approach	Analysis	References
Technical	Study of specific AI technologies and their implementation in urban or architectural contexts.	Which AI technologies were implemented?	Bölek & Özbaşaran (2023); Cugurullo et al. (2024); He & Chen (2024); Lami & Moroni (2020); Lami & Todella (2019); Lukovich (2023) ; Omari el al. (2023); Peng et al. (2023)
	Methods to analyze the effectiveness of AI tools in supporting data collection and decision-making.	How did these tools support information collection, analysis, and synthesis?	Rane, (2024); Schubert et al. (2023); Shrestha et al. (2019); Strich et al. (2021); Yigitcanlar et al. (2020); Yigitcanlar & Cugurullo (2020)
Social	Case studies analysis where AI facilitates collaboration and interaction with various stakeholders.	How were stakeholders (students, architects, planners, etc.) involved in AI use?	Castro et al. (2021); Cugurullo et al. (2024); Chaillou (2019); Hegazy & Saleh (2023); Hammond et al. (2023)
	Participatory research and analysis of how AI enables the inclusion of diverse voices in decision-making.	Did AI facilitate the inclusion of diverse perspectives in the decision-making process?	Lami & Moroni (2020); Matter & Gado (2024); Meng et al.(2024); Mohammadpour et al. (2019); Nabizadeh Rafsanjani & Nabizadeh (2023) ; Ogrodnik, (2019); Omari et al. (2023); Podvesovskii et al.(2021); Raj et al. (2023); Schubert et al. (2023); Volk et al. (2021); Yitmen et al. (2021)

Implementation	Application of adaptive models to integrate AI into specific urban contexts, adjusting to the social dynamics of each case.	How were decision-making tools applied to adapt AI to each case's urban and social context?	Bölek & Özbaşaran (2023); He & Chen (2024); Lami & Todella (2019); Lukovich (2023); Mecca (2023); Peng et al. (2023)
	Study technological and social limitations, with practical solutions applied in specific cases.	What limitations were encountered, and how were they addressed?	Kizielewicz et al. (2020); Rane (2024); Schubert et al. (2023); Shrestha et al. (2019); Strich et al. (2021); Yigitcanlar et al. (2020); Yigitcanlar & Cugurullo (2020)
Impact	Evaluation of project outcomes with and without AI use, analyzing its impact on results.	How did AI influence the project's outcomes?	Bölek & Özbaşaran (2023); He & Chen (2024); Lami & Todella (2019); Lukovich (2023); Mecca, (2023); Peng et al. (2023)
	Efficiency analysis in resource use through AI integration, comparing cases with and without AI.	Were resources optimized through AI integration?	Kizielewicz et al. (2020); Rane (2024); Schubert et al. (2023); Shrestha et al. (2019); Strich et al. (2021); Yigitcanlar et al. (2020); Yigitcanlar & Cugurullo (2020)

This approach allows us to observe how AI supports decision-making, adapts to diverse architectural contexts, and evolves to meet the demands of complex and dynamic environments.

The *framework's technical level* examines AI technologies, their implementation, and their role in supporting information gathering, analysis, and synthesis processes. This relates to the first research objective, which explores how AI can support decision-making processes in architecture and urban transformations, as outlined in the theoretical analysis. By addressing these aspects, the framework establishes a basis for understanding the capabilities and potential of AI tools within the contexts under study.

The *implementation* level focuses on how AI tools adapt to each case study's specific urban and social contexts, the challenges encountered, and the strategies to overcome them. This component directly corresponds to the second research objective, which emphasizes the application of the MuVAM software multi-methodology in the selected case studies. By considering these factors, the framework assesses the technical feasibility of AI tools and their ability to respond to the unique demands of each environment.

Finally, the *social* and *impact* levels are linked to the third research objective, which aims to assess how AI integration influences key stages of the decision-making process by identifying its specific contributions and limitations. The social level addresses the inclusion of key actors and diverse perspectives in the decision-making process. In contrast, the impact level investigates how AI intervenes in project outcomes by optimizing resources and improving processes. Together, these dimensions allow for assessing the outcomes and challenges associated with AI integration.

Based on these findings, the theoretical framework was developed to address the specific challenges observed in the case studies. By linking the AI applications described in *Tables 3 and 4* with observations from the case studies, the framework provides a structure for assessing the interaction of AI tools in real-world urban contexts. This approach connects theoretical knowledge with practical applications. It demonstrates how AI can contribute to the decision-making process by supporting the development of design alternatives, stakeholder engagement, and sustainability, as explored further in the case studies.

03

METHODOLOGY AND CASE STUDIES

Chapter 3. Methodology and Case Studies

This chapter explores the methodological framework and selected case studies, emphasizing the processes of architectural decision-making and urban transformation facilitated by MuVAM. It examines how this tool, and in some cases, AI technologies such as ChatGPT (https://openai.com/index/chatgpt/) and Replika (https://replika.com/), enhance problem structuring and solution generation in complex urban environments, addressing challenges across diverse contexts and cities.

To achieve this, the chapter is organized into four main sections. The first section establishes the research setting, providing the context and scope of the study. Here, the research objectives and the rationale for selecting the case studies are outlined. This section sets the foundation for understanding the practical and theoretical relevance of the work. Building on this foundation, the chapter introduces the methodological framework, which details the theoretical and practical approaches guiding the research. This section not only explains the overall methodology but also touches on the role of AI tools in supporting decision-making processes (where applicable).

The subsequent section explores MuVAM and its application, presenting the software as a central decision-support tool. It examines its use in architectural and urban decision-making processes, highlighting its strengths and potential limitations. It also examines how MuVAM, combined with AI technologies, can address complex urban challenges, offering a nuanced understanding of its practical implementation.

Finally, the chapter delves into case studies that illustrate the real-world application of MuVAM and AI in architectural and urban transformations. Each case study is structured into two parts: "Project Overview and Context," which provides background information and explains the project's significance, and "Decision-Making Process," which analyzes how MuVAM (and AI, where applicable) was integrated into the decision-making process.

The chapter aims to comprehensively understand the methodology and its application, demonstrating how MuVAM and AI technologies can address complex architecture and urban planning challenges across diverse contexts. Through this exploration, the chapter contributes to the ongoing discourse on digital transformation and its impact on the built environment.

3.1. Research setting

The studies conducted by Prof. Lami and Dr. Elena Todella within the framework of the SUITE project (*Decision Support in an Urban Context in the Digital Age: Interactions and Uncertainties*) provide a key foundation for formulating hypotheses on AI's potential contributions in different decision-making phases. SUITE explores the relevance of structuring and decision-support methods in urban environments in the digital age, acknowledging how contextual changes, particularly the digital revolution, may have influenced their use and objectives (Lami & Todella, 2023).

The methodology proposed by SUITE, especially the organization and sequence of workshop activities, has served as a foundational basis for the observations made in this thesis. A crucial aspect of this approach is the use of MuVAM (https://demfuture.com/progetto/muvam/), a software developed by Isabella Lami and DEM Future srl, which facilitates multi-criteria evaluations in complex decision-making contexts. The reflections and subsequent analysis derived from observing the development of these workshops, combined with a literature review, constitute the original contribution of this thesis.

My role in this research focused on observing and documenting the use of AI tools, in particular ChatGPT and Replika, in combination with MuVAM in the workshops and the case study applications in the SUITE research. Specifically, my responsibilities included:

- *Observing* how participants utilized the tools and their understanding of each tool's capabilities and limitations.
- *Documenting Findings* through noting the results generated at each process stage.
- *Evaluating AI Integration* and analyzing how these tools influenced collaboration, problem structuring, and solution generation.

Through these tasks, my role contributed to understanding how AI can facilitate decision-making in architectural and urban contexts, shedding light on the potential of AI to streamline processes, improve collaboration, and provide solutions to complex urban challenges. This research, by combining theoretical analysis, practical applications, and AI integration, aims to offer an understanding of the evolving role of AI in decision-making processes and provide a comprehensive framework for future urban transformation projects.

The central research question guiding this investigation is: *How are decision-making processes implemented in urban and architectural contexts, and how can the integration of AI improve their development?* To address this question, the research is structured around three key objectives:

(i) ***Theoretical Analysis to explore the key features of Decision-Making Processes****:* This involves reviewing decision-making processes in architecture and urban transformation. The aim is to examine their structure and guiding principles, drawing on theories and frameworks described in the literature. Through a review of academic sources, the study seeks to identify and assess the potential of AI to support decision-making in architectural contexts.

(ii) ***Application of MuVAM in Case Studies****:* This examines how the MuVAM software, which integrates mixed methodologies to evaluate alternatives systematically, is applied to three case studies in the urban and architectural fields. MuVAM, based on frameworks such as the Strategic Choice Approach (SCA) and the Analytic Hierarchy Process (AHP), offers a structure for decision-making, allowing for qualitative and quantitative assessment of alternatives.

(iii) ***Evaluation of AI's Influence on the Key Decision-Making Stages****:* This study studies how integrating AI tools and MuVAM influences key stages of the decision-making process, identifying its specific contributions and limitations and developing reflections based on the comparison of the different results.

MuVAM is a methodological approach that uses software to support decision-making processes related to complex problems. MuVAM was developed by Prof. Lami and architects Bassan and De Nicoli. This approach facilitates analysis, discussion collaboration, the development of consensus solutions, and deliberation on decision problems through an interface that simplifies understanding of the complex elements involved. The software combines SCA methodology with AHP, analyzing variables and evaluating solutions collaboratively. Users, guided by a moderator, progress through stages such as defining decision areas, options, incompatibility, and the weighted comparison of alternative solutions. Finally, the application generates collective and individual results for further analysis (Lami & Todella, 2023).

As mentioned in the second objective, from a qualitative perspective, MuVAM stands out as a tool that facilitates the integration of contextual factors, such as social dynamics and local needs, into urban planning. According to Hammond et al. (2023), understanding and aligning stakeholders' perspectives with project objectives is key to building legitimacy and local acceptance. The qualitative component allows for exploring stakeholders' priorities and preferences, significantly influencing the decision-making process.

In quantitative analysis, using mathematical models, MuVAM creates objective scores and rankings for suggested alternatives. Informed decision-making is supported by this methodical, data-driven approach, which ensures that all options are evaluated openly and consistently (Hammond et al.,2023). Furthermore, AI systems such as ChatGPT can support quantitative analysis by processing large amounts of data and producing design optimizations such as increased structural integrity and energy efficiency (Xue et al., 2023). By integrating the two methods, practical knowledge can be gained while minimizing potential biases and enhancing stakeholder engagement. Incorporating theoretical frameworks such as SCA and AHP is essential to the organization and evaluation of the research decision-making process. These frameworks ensure that AI tools have a theoretical foundation and offer practical alternatives.

On the other hand, AHP supports a structured, data-driven approach to decision-making, providing a systematic method to compare alternatives based on clearly defined criteria. This method enhances the transparency and consistency of the decision-making process, ensuring that all proposed alternatives are evaluated consistently. The use of AHP within MuVAM ensures that the decision-making process is objective and measurable, reducing biases and improving the accuracy of evaluations. The combination of SCA and AHP ensures that the

AI tools used in this research, such as MuVAM, not only enhance efficiency and collaboration but are also aligned with established decision-making theories, increasing the reliability and breadth of the solutions generated.

The last objective refers to AI tools incorporated into this research to observe and analyze whether they support and optimize the decision-making process. Rane (2024) underlines how ChatGPT is used in the architectural workflow, serving as a creative assistant during the conceptualization phase by generating design ideas based on parameters such as site specifications, budget constraints, and client preferences. Furthermore, ChatGPT improves stakeholder communication by translating technical jargon into easily understandable terms and automates tasks such as generating architectural drawings and specifications, reducing human error, and increasing project efficiency (Rane, 2024).

Another AI technology, Replika, simulates stakeholder conversations to investigate various viewpoints and priorities. By facilitating cooperative dialogues, Replika allows project participants to express their opinions and reach a consensus on important issues.

3.2. Methodological Framework

As mentioned, the central focus of the research examines the implementation of decision-making processes within urban and architectural contexts in the digital age, with a particular emphasis on understanding how AI integration can contribute to their advancement. This approach is addressed through the four levels of analysis proposed in the theoretical framework. The technical level explores AI tools' role in supporting the development of these processes. The social level highlights the involvement of key stakeholders and the inclusion of diverse perspectives in decision-making. The impact level assesses the extent to which AI improves project outcomes by optimizing resources and improving workflows. Finally, the adaptive level considers how these tools are customized to meet the unique demands of specific contexts, emphasizing the importance of contextualization in urban and architectural transformations.

Table 5 analyzes the use of AI in the selected case studies related to urban transformation and architecture projects. Derived from the theoretical section framework, it provides a methodology focusing on its application and its impact at each stage of the project. It is organized into four categories (Technical, Social, Implementation, and Impact), each addressing key aspects of the role of AI in decision-making processes:

- *Technical:* This category investigates AI technologies implemented in different case studies, including details about the case study context, participants, tools used, and the stages at which AI is integrated into the decision-making process. It is important because it provides insights into AI tools and technologies that drive innovation and transform decision-making processes. Understanding the technical application of AI helps to identify best practices, evaluate different solutions, and ensure that the right tools are used at the appropriate stages of urban projects. As urban challenges evolve, selecting the most suitable AI technologies becomes key to the successful integration of AI into urban transformation processes.
- *Social:* The focus is on stakeholder engagement, mainly how students, architects, planners, and communities interact with AI in the decision-making process. This category is important because it highlights the human aspect of AI integration. Involving a wide range of stakeholders ensures that the decision-making process is inclusive and democratic and considers the needs and concerns of different groups. It also helps to assess how AI can facilitate more equitable participation and avoid bias in decision-making by ensuring that different perspectives are included. By fostering collaboration, AI can strengthen the social fabric of urban planning, ensuring that all voices are heard and considered in transformative urban projects.
- *Implementation:* This category focuses on how the decision-making tool was applied to each case study, concerning how AI was adopted for each Case Study's urban and societal environment. It also considers the issues encountered while deploying AI and the methods to solve these difficulties. The importance of this category is founded on the exploration of possibilities of how deep learning tools and the formulation of AI frameworks can be used for designing approaches for actual and context-based issues. Essential features for AI tools and frameworks are stressed, including that due to context changes, extensibility and adaptability may be necessary, alongside possible challenges and how to navigate them.

- *Impact:* An evaluation of the role of AI in determining project results previews footprints that define AI’s contributions, benefits, challenges, and ways in which AI optimized (or not) resources in the decision process. This category is important because it can potentially establish AI's value in producing results. It enables one to ask whether AI enhances the decision-making process with enhanced results on the project in question and efficient resource use, resulting in improved urban transformation projects. Learning the effects of AI integration is a crucial factor that enables stakeholders to prove the worth of the technology in real-time operations and ascertain the efficient utilization of resources, hence the effectiveness of transformation that brings about outcomes about developments that align with the stakeholders' expectations.

By analyzing these four dimensions (technical, social, implementation, and impact), the proposed framework aims to offer a holistic view of AI's potential and limitations in urban transformation projects. Each category contributes to understanding how AI can be used in decision-making, stakeholder engagement, and resource optimization, offering insights into their broader implications.

Table 5. Base Table, a methodological framework for AI Integration in Decision-Making Processes (Source: own elaboration).

Category	Sub-category	Relevance	Description / Observation
Technical	Case study	Offers a reference point for understanding the implementation and outcomes of AI use in architectural or urban projects.	The specific case studies analyzed, providing their name or title (e.g., "Le Pav—Pointe Nord"), allow analysis of how AI tools were applied in a specific urban context.
	Project Context	Provides a general framework to evaluate how contextual characteristics affect AI implementation and impact.	The project's environment, including location, objectives, and key challenges. This helps to understand the initial conditions and external factors influencing AI.
	Participants	It helps understand who is involved in the process and how their roles or perspectives influence decision-making processes.	The type and number of participants involved (e.g., students, architects, urban planners, local communities, etc.).
	Tools used	Identifies the technical resources used and their contribution to the design and decision-making process.	The tools employed in the process include AI, collaborative platforms, or manual tools.
	Use or not of AI	Evaluates the relevance and scope of AI usage at different project phases.	Whether AI was used and at which stage of the project (e.g., initial design, analysis, feedback).
	Stage of Decision-Making with AI	Analyzes how and when AI influences the project flow and key decisions.	The specific moment in the decision-making process when AI was employed.
Social	Types of interaction	Assesses how AI fosters new interaction among participants and facilitates collaborative work.	Description of AI-facilitated interactions, such as group collaboration or data analysis.

	Inclusion of stakeholders	Examines equity and diversity in project participation, ensuring relevant voices are heard.	Explanation on how stakeholders (students, architects, planners, communities) were involved in the use (or non-use) of AI.
Implementation	Key examples	Offers concrete evidence of AI's impact and application, allowing for a better understanding of the case.	Specific examples illustrating the role of AI in the case, such as textual quotes or highlighted excerpts.
	Application of MuVAM	Analyzes the flexibility and effectiveness of the MuVAM in addressing specific contextual challenges.	Explanation on how MuVAM was applied to adapt AI to the urban and social context of the case.
	Limitations and solutions	Evaluates practical challenges in AI implementation and the strategies developed to overcome them.	The limitations encountered in using AI, how they were addressed, or how future issues might be resolved.
Impact	Contributions of AI	Explores the added value of AI in the efficiency and quality of the decision-making process.	Categorizations of AI's contributions to the process, such as improved communication or increased precision in analysis.
	Observed benefits	Highlights the positive aspects of AI usage in urban and architectural projects.	Benefits identified from using AI include time reduction and more informed decisions.
	Observed challenges	Identifies areas for improvement and potential barriers to the effective integration of AI in future projects.	Challenges or limitations encountered in using AI in the case.

3.3. Multi-Values Appraisal Methodology (MuVAM) and its application

The development of MuVAM is based on a multi-methodological framework that combines elements of the SCA and the AHP to address different phases of the decision-making process in a structured and efficient way (Lami &Todella, 2023).

SCA (Friend and Hickling 1987, 2005) is a PSM and aims to assist in identifying relationships between seemingly unconnected sectors; moreover, to start from an awareness of the complexity of problems to be faced means also accepting the consequent uncertainty related to future actions. The SCA (*Figure 7*) generally begins with the identification of a series of related decision problems and consists of four key phases: *Shaping Mode, Designing Mode, Comparing Mode, and Choosing Mode* (Friend & Hickling, 2005; Lami & Todella, 2019):

- *In shaping Mode*, decision-makers define and structure decision areas by identifying key issues, their interrelations, and urgency. This step establishes connections between different decision fields and lays the foundation for subsequent choices.
- *Designing Mode* focuses on developing feasible alternatives for each decision area while assessing their compatibility and interdependence. A decision tree is created to structure possible courses of action and ensure coherence in planning.
- *Comparing Mode*, alternative decision schemes are evaluated using qualitative criteria that reflect diverse stakeholder perspectives. A comparison grid helps analyze advantages, risks, and uncertainties, offering a rational basis for decision-making.
- Finally, the *Choosing Mode* involves negotiation, resolving uncertainties, and committing to action. Stakeholders establish agreements, define a flexible action plan, and outline strategies to adapt to evolving circumstances. This structured approach supports informed decision-making while allowing adaptability in complex urban and architectural contexts.

The first two (*Shaping Mode, Designing Mode*) are applied in MuVAM. Participants try to clarify situations and resolve uncertainty by raising and comparing alternatives for strategic decisions (Lami & Todella, 2019).

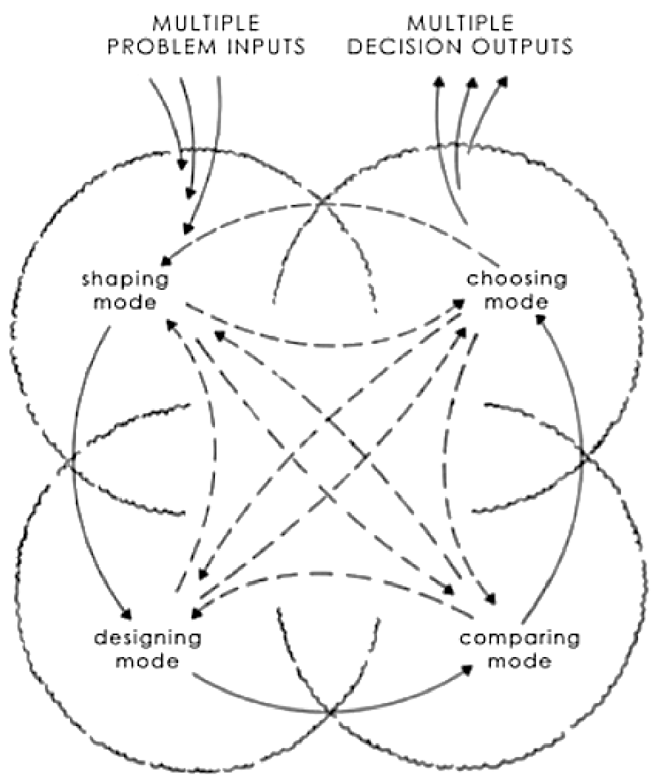

Figure 7. The process of Strategic Choice Approach. Source: (Friend and Hickling 2005; Lami & Todella, 2019)

In urban and territorial contexts, through the application of SCA, the planning choices and the projects are elaborated and selected only after identifying and evaluating different possible alternatives (as options); the need to operate quickly is consistently pursued to maintain maximum flexibility and effectiveness for future choices. This method does not lead to the drafting of plans as rigid systems of prescriptions; instead, it identifies the actions and the projects to be carried out in the successive phases of an incremental and continuous process. The choice of actions to address some parts of the problematic situation will leave other choices open for the future, creating opportunities for future remodeling of problems such as the occurrence of unforeseen events and the appearance of new connections (Friend, Hickling 2005; Lami & Todella, 2019).

AHP is an MCDA-structured technique developed by Thomas L. Saaty in the 1970s for decision-making in complex, multi-criteria environments. It is advantageous when decision-makers must evaluate multiple options based on various criteria, incorporating quantitative data and subjective judgments. The AHP methodology (Saaty, 1980) is based on mathematical principles and psychological insights and offers a systematic framework for prioritization and decision-making. This algorithm follows key steps, including criteria definition, pairwise comparisons, matrix construction, and results synthesis to rank alternatives based on calculated weights. Its strength is integrating both qualitative judgments and quantitative data, making it particularly relevant in areas where uncertainty and competing objectives coexist (Amador et al., 2018; Bölek & Özbaşaran,2023).

In urban transformation projects, AHP has demonstrated significant value in helping to balance objectives such as sustainability, efficiency, and stakeholder interests. For example, Hammond et al. (2023) highlight its application in land use management, where it helps prioritize redevelopment options based on environmental, economic, and social criteria. AHP has gained widespread attention globally due to its versatility and applicability across various fields (Ogrodnik, 2019). One of its primary strengths lies in its ability to decompose complex decision problems into a hierarchical structure, allowing for a more systematic and organized analysis. This method also enables pairwise comparisons of elements within the hierarchy, facilitating precise evaluations and prioritization. Furthermore, using a consistency ratio in AHP helps assess the reliability and coherence of these comparisons, ensuring logical consistency throughout the decision-making process. However, AHP has also been subject to criticism. A notable limitation is its assumption of independence among the elements analyzed, which does not always reflect real-world conditions. Additionally, the method heavily relies on subjective judgments, which can introduce bias and affect the validity of the results. Another challenge is its limited ability to handle uncertainties inherent in human decision-making, making it less robust in scenarios where ambiguity plays a significant role (Ogrodnik, 2019). AHP is a widely adopted decision-making tool valued for its structured approach and capacity to address complex problems effectively.

Figure 8 shows the interface of MuVAM and, specifically, the steps through which it is applied through the software.

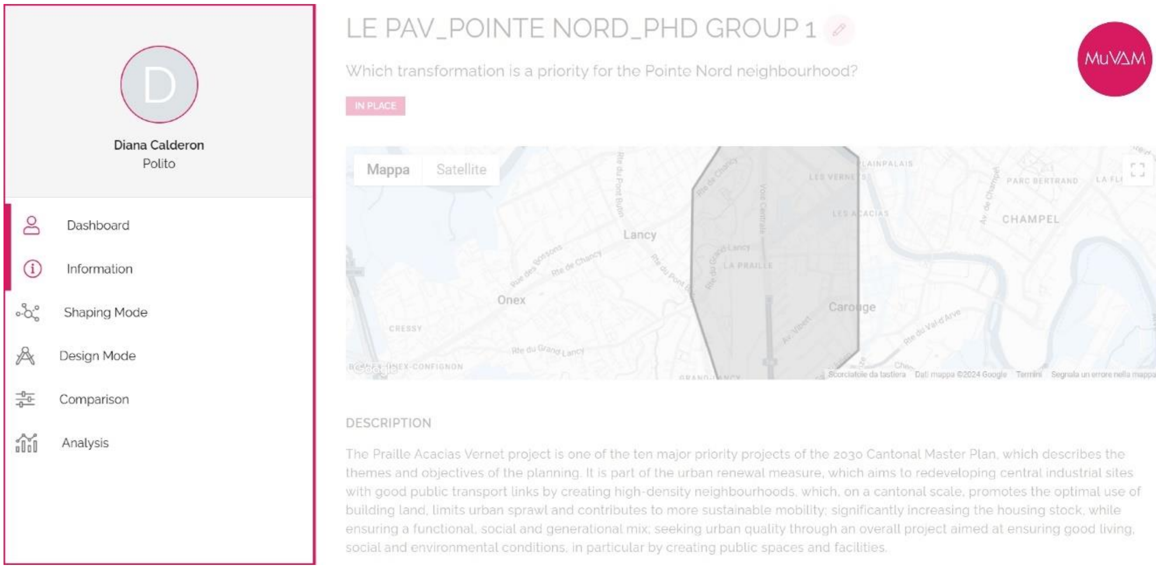

Figure 8. Shaping Mode, Designing Mode, Comparison and Analysis - MuVAM interface

Shaping Mode and Designing Mode (SCA)

The SCA guides the initial stages of the process, specifically in Shaping Mode, where key issues are identified and structured, and in Designing Mode, which focuses on generating and exploring strategic alternatives. At these stages, the software organizes information, clarifies priorities, and defines the scope of decisions through interactive and participatory tools. This approach ensures that multiple perspectives are integrated and complex problems are broken down into manageable parts.

Shaping mode *(Figure 9):* The decision-makers will consider and study the various decision areas regarding their interrelation and relative importance or urgency. Decision areas address the practical and specific problems identified in the general problematic situation. The goal in shaping is to select a subset of problems that will form an appropriate focus or outline for the process. It is, therefore, a moment related to the shaping of problems, with the task of beginning to build up a set of choices to deal with; moreover, it constitutes a crucial way of investigating linkages between the decision areas and the possible connections between one field of choice and another (Lami & Todella, 2019).

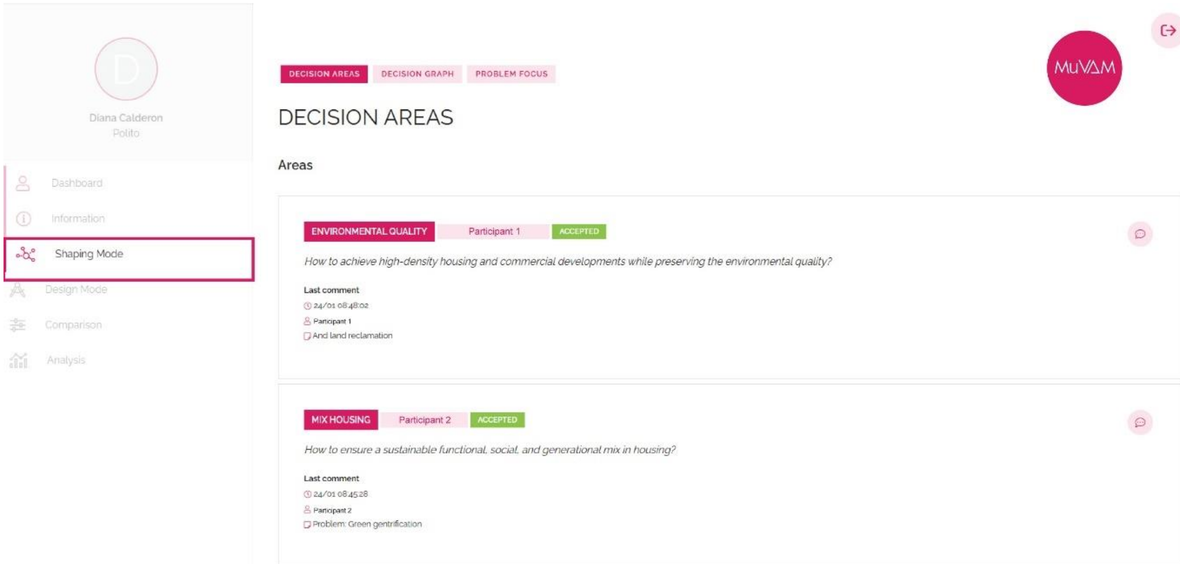

Figure 9. Shaping Mode: Decision areas, decision graph, problem focus - MuVAM interface

Design mode *(Figure 10):* Within each decision area, options are identified and discussed as feasible alternative solutions and possible courses of action are available. The possibilities are examined in pairs to see which ones are incompatible; it is possible to consider all the combinations of options to arrive at a series of potentially feasible decision-making schemes that cover all decision-making areas. Ultimately, a decision tree is built, with the choice of sequence in which decision options (and relative courses of action) should be considered. Each sequence of options gives birth to a specific decision scheme, a scheme of actions to carry out (Lami & Todella, 2019).

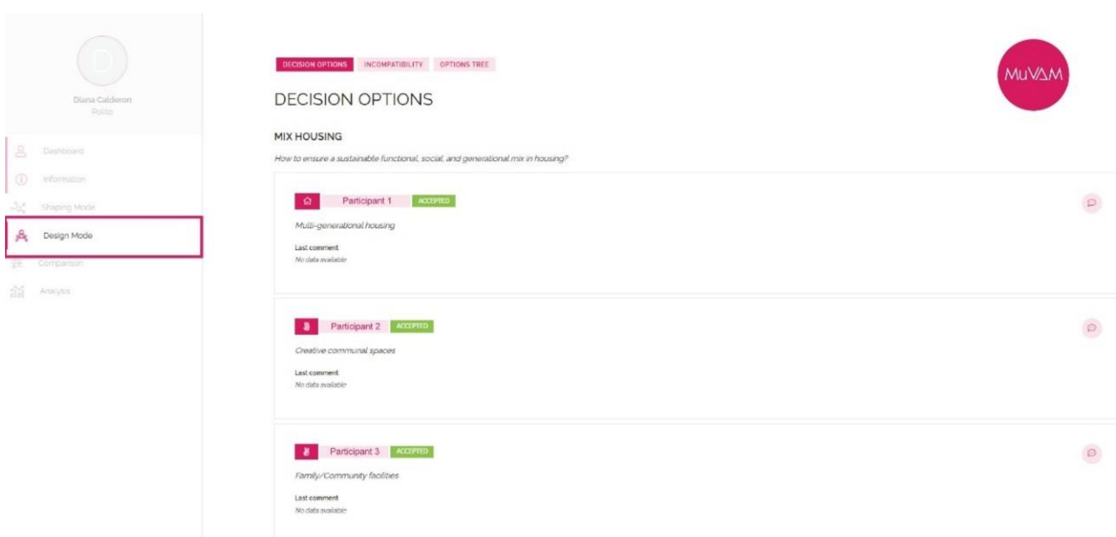

Figure 10. Designing Mode: Decision options, incompatibility, options tree - MuVAM interface

Comparison and Analysis (AHP)

For the comparison *(Figure 11)* and analysis phase *(Figure 12)*, AHP is used as a methodology that allows alternatives to be evaluated and prioritized based on quantitative and qualitative criteria. The AHP provides a framework for hierarchically structuring decision criteria and assigning relative weights to each, which facilitates comparing options and identifying the best solution. Integrating AHP into the software allows for systematic, transparent, and replicable multi-criteria analysis.

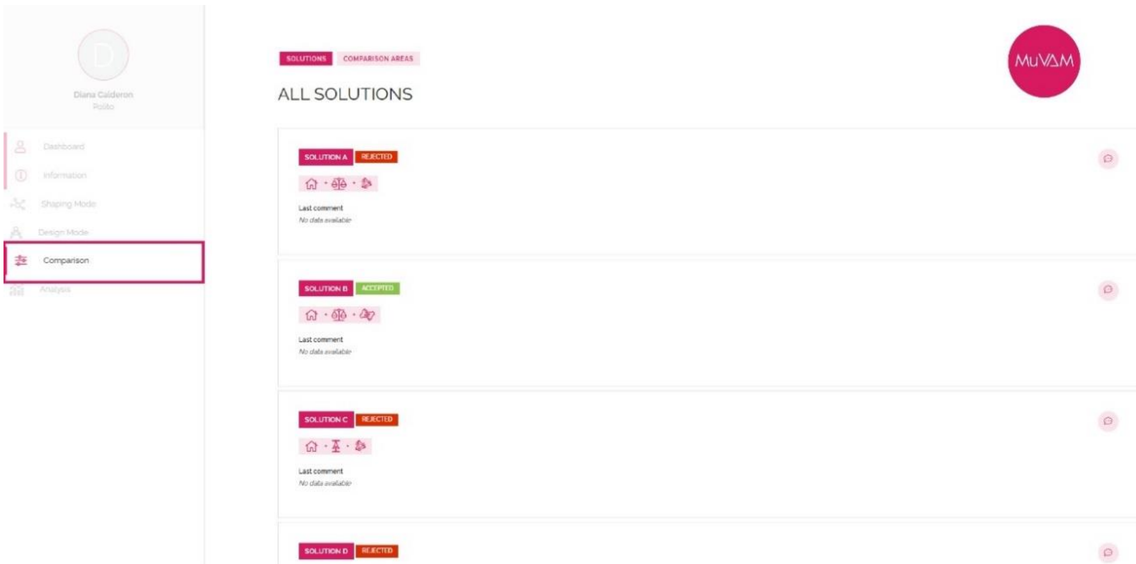

Figure 11. Comparison: Solutions, comparison areas - MuVAM interface

Figure 12. Analysis: Results - MuVAM interface

The development of software based on the combination of SCA and AHP represents a significant advance in decision-making for urban transformation (Lami & Todella, 2023). With its participatory and flexible approach, the SCA methodology allows for the effective structuring of complex and uncertain problems that often characterize urban processes, facilitating the identification of key problems and exploring diverse solutions (Lami & Todella, 2019). This approach is crucial in urban contexts where uncertainty and the multiplicity of actors and perspectives require an adaptive methodology that integrates different viewpoints and generates viable strategic alternatives.

On the other hand, the AHP complements this process by providing a solid tool for evaluating and prioritizing alternatives through a multi-criteria analysis, which helps decision-makers select the options most aligned with the established objectives. This ability to sort and weigh different criteria is beneficial in contexts where complex decisions must be made under multiple constraints and goals, such as in the case of urban regeneration projects or sustainable infrastructure planning (Volk et al., 2021; Bölek & Özbaşaran,2023). The integration of both approaches allows the software to not only manage the uncertainty inherent in urban decision-making but also facilitate the active participation of stakeholders, promoting a more inclusive and transparent decision-making process.

Overall, this multi-methodologic approach offers a robust and flexible framework that not only optimizes urban planning and design processes but also improves the ability to adapt to changes and disruptive events, something crucial in today's dynamic and constantly evolving urban environment (Hammond et al., 2023; Yigitcanlar et al., 2020). This methodological advance, therefore, opens up new opportunities for the possible integration of AI into urban planning to build more resilient, adaptive, and sustainable urban transformations.

3.4. Case Studies

This section analyzes the development of decision-making processes and the role of AI in these processes, with a particular focus on its application in urban transformation projects at different scales: (i) Le Pav – Pointe Nord in Geneva, (ii) the former Paracchi carpet factory in Turin, and (iii) the requalification of the San Salvario district in Turin.

In all cases, MuVAM is used to structure and analyze decision-making processes (Table 6). Le Pav – Pointe Nord addresses transformation at an urban scale, using MuVAM to guide strategic decisions without AI intervention. The second case study, the former Paracchi carpet factory, focuses on adaptive reuse at the building scale, integrating AI with MuVAM to support the preservation and reinterpretation of this structure. Finally, the workshop in San Salvario operates at a local scale, where MuVAM and AI combine to strengthen participatory planning and community interventions in design.

The evaluation of these projects is conducted using the proposed methodological framework (Tables 7-8-9), which is applied to each case study, offering a structured framework to analyze key aspects such as decision-making processes, the degree of AI integration, and some reflections on development at each scale. This approach ensures the coherence of the analysis and allows for the identification of patterns, challenges, and opportunities in various contexts. Through the study of these cases, the chapter explores the implications of integrating AI into decision-making processes and assessing its capacity to transform urban environments, promoting data-driven strategic decisions.

Table 6. Overview of Case Studies, Scales, Dates of Application, and Participants (Source: own elaboration).

Case study	Scale	Date of application	Number of participants	Participants
Le Pav -Pointe Nord, Geneva	**District (Urban Scale)**: This refers to larger urban areas or regions encompassing multiple buildings, streets, and other infrastructure elements, addressing broader urban issues such as transportation, zoning, and utilities. It includes business districts, residential areas, and mixed-use zones.	24/25 January 2024, Turin - Italy	4/5	PhD students from the Politecnico di Torino (Members, Moderator, Observer, External observer)
Former Paracchi Carpet Factory, Turin	**Building:** Focuses on individual structures in a specific neighborhood. This scale addresses the buildings' design, function, and construction.	29 April 2024, Turin - Italy	5	Students of the master's degree in "Architecture, Construction City" at the Politecnico di Torino (Members, Moderator, Observer, External observer)
Requalification of the San Salvario neighborhood, Turin	**Neighborhood (Local Scale):** This scale focuses on smaller, community-level areas within the city. It includes the interactions between residential buildings, local services, parks, and streets and emphasizes social dynamics, local infrastructure, and community participation.	08 July 2024, Turin – Italy	5	Architects with urban development experience from Urban Lab. (Members, Moderator, Observer, External observer)

CASE STUDY

LE PAV- POINTE NORD

Photograph by Fred Merz,2025.© PAV Official Website

Application of MuVAM

GENEVA

3.4.1. Le Pav - Pointe Nord, Geneva

The **Pointe Nord** project is integral to the **Praille Acacias Vernets (PAV)** initiative (Figure 12), one of Switzerland's most significant urban renewal projects, as outlined in the **Cantonal Master Plan 2030** (https://www.ge.ch). This initiative, which aims to revitalize some of Geneva's most underused spaces, represents the city's largest opportunity for housing development. It aims to address several of Geneva's urban challenges, such as optimizing land use, containing urban sprawl, and promoting sustainable mobility. As one of the key sites of the PAV program, Pointe Nord is an example of how former industrial zones can be transformed into high-density, mixed-use neighborhoods that provide access to public transportation (https://www.ville-ge.ch)

Located in the Queue-d'Arve area, within the Les Acacias neighborhood, Pointe Nord occupies a strategic position between Geneva's historic center and its industrial sectors. This location is particularly significant as it allows the project to function as a transitional space bridging the old and new parts of the city, connecting the historic city center with the rapidly evolving areas to the south. The site is well connected to the city's transport networks, further enhancing its potential for urban renewal.

The project is overseen by the Praille-Acacias-Vernets Foundation (FPAV), in collaboration with the State of Geneva and the Caisse de Prévoyance de l'État de Genève (CPEG). This partnership brings together public and private actors, each playing a role in ensuring that the project meets economic and social objectives. One of the project's main objectives is to meet the city's housing needs while simultaneously creating multifunctional urban spaces that encourage social interaction and cultural development.

Historically, Pointe Nord was an industrial area with several buildings dating back to the early 20th century. The transformation of this area into a residential and mixed-use district aims to preserve the historic character of the site while integrating new residential, commercial, and public spaces. The project envisages the construction of approximately 250 housing units. However, the project is not limited to housing but also seeks to foster functional diversity by incorporating spaces for local businesses, community services, and cultural activities. Cultural landmarks such as the Théâtre du Loup and La Parfumerie will be integrated into the project, adding a cultural dimension to the urban renewal.

The project also aims to improve the quality of urban life by creating public spaces. These areas will serve as places of social interaction and be designed with environmental sustainability. Public parks, green spaces, and pedestrian paths are central to the design, allowing residents and visitors to experience both urban life and nature in a balanced environment (Geneva Environment Network, n.d.).

Figure 13. "Pointe Nord". *PAV - Praille Acacias Vernets*. Genève. Retrieved from www.ge.ch.

3.4.1.1.Project Overview and Context.

The Pointe Nord project covers an area of 230 hectares, of which 140 are intended for mixed-use developments. The size of the site is one of the project's defining characteristics and underlines the importance of land management in the urban renewal process. The project's phased development began in 2021, with the first stages focusing on the renovation of key historic buildings and the relocation of the state administrative offices, which were completed in October 2023.

The overall design of Pointe Nord prioritizes sustainable mobility and takes advantage of its location near the Arve River and the Bois-de-la-Bâtie to promote ecological integration. Including pedestrian and cycling paths and a new bridge over the Arve further emphasizes the commitment to improving accessibility while promoting low-impact forms of transport.

This infrastructure will not only improve connectivity between the Les Acacias neighborhood and other parts of the city. However, it will also serve as a model for sustainable urban mobility.

In addition to mobility, the project's environmental sustainability is a key focus. Integrating green spaces, efficient waste management systems and sustainable building practices aligns with Geneva's broader urban policies to mitigate climate change and promote green management. The project contributes to a greener and more resilient urban future by reducing the carbon footprint and improving air quality.

From a research perspective, Pointe Nord represents a significant case study in urban redevelopment. The scale and complexity of the project provide valuable insights into how urban renewal can balance the preservation of industrial heritage with the need for modern residential and commercial infrastructure. Through its integration of diverse, sustainable needs and practices, Pointe Nord stands as an initiative within the broader framework of the Praille Acacias Vernets (PAV) renewal program, offering a comprehensive approach to urban transformation.

3.4.1.2. Application of MuVAM

Workshop No. 1 was held with PhD students from the Politecnico of Turin to explore transformation priorities in the selected neighborhood using MuVAM software. During this workshop, participants, organized into groups of 4/5 people (Figure 14, anonymized), worked together to identify and analyze relevant problems, develop solutions, and reach conclusions based on the software's use.

The workshop started with a clear assignment of roles within each group. The work dynamic was facilitated by a combination of English and Italian languages, allowing all members to participate. The first part of the workshop consisted of an introduction to the MuVAM software, in which topics such as registration, familiarization with the interface, and loading of pre-data were addressed. This initiative was essential to ensure that all participants had a basic understanding of the software.

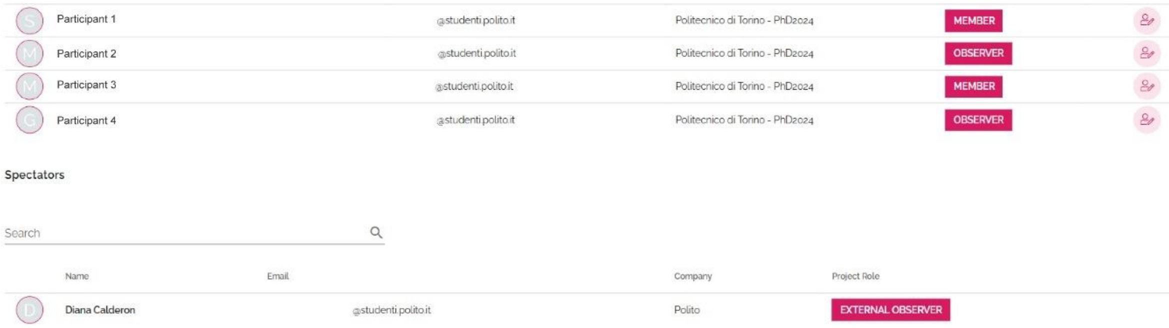

Figure 14. Workshop participants—MuVAM interface. This is one of the two groups involved in the session, with the researcher listed as an external observer.

In this case, participation was good in the group's proposed topics and the workshop's purpose. Within the group's organization, designated which person will carry out a defined activity for its development; the moderator has important functions in decisive moments concerning the software since only this person accepts or denies the process' prosecution after discussing it with his colleagues.

Shaping mode

The participants focused on identifying the main decision areas and problems affecting the selected community in the case study. Through a series of discussions guided by the participants, they were directed to reflect on the community's issues and needs critically. The moderator structured the conversations using key questions and dynamics that encouraged collaboration, ensuring that all relevant areas for developing solutions were addressed, fostering an environment of idea exchange, and encouraging participants to share experiences and perspectives to enrich the discussion.

This approach allowed the participants to delve deeper into the different dimensions of each area, generating a more comprehensive analysis. The group identified seven key areas: environmental quality, mixed housing, stakeholder engagement, cultural capital, diverse economy, sustainable mobility, and ecological resilience. Each of these areas was analyzed in detail, and MuVAM software was used to organize the information and facilitate the visualization of the relationships between the problems. Additionally, the participants complemented this activity with references to examples from other places, which allowed them to contextualize the solutions within a broader framework. This analysis stage was crucial, as it helped to define the problems that needed to be solved clearly and ensured that all participants were aligned before moving on to the next phase.

Although identifying the problem areas was developed effectively, the discussion dynamics could have been further enriched with a broader focus on socioeconomic and cultural factors. However, areas such as “stakeholder engagement” and “diverse economy” were addressed.
Up to this point, the group members were rapid in their organization, there was good communication and leaders who facilitated the development of the workshop, and everyone remained very focused and worked not only on the platform but also on their report. It was also important to explain the previous steps before being able to use the software. This way, the first approach emerged more organized without technical conflicts since the steps were explained to enter the platform, registration, and interface familiarization. Although it takes a few minutes, it is very intuitive. Once entered, the information can begin to be uploaded, and the group takes previous analyses to organize the data and the information appropriately.

Decision Areas. The group takes the guides uploaded to the course platform as good support material, facilitating interaction with the software and explaining the following steps. Later, within the topic, discussions are presented on issues such as gentrification, activities carried out in the place, uses and facilities thinking about the local community, and economic resources thinking about later problems. Then, to reach an agreement, a classification of the decisions is presented to know which aspects are helpful and which are not, where the problems are specified, and a joint model is created for their solution. They also take references from other places/cities to relate them to the project they were developing. As a teaching aid, they use the resources to write their ideas on the board to give everyone an overview of what is being defined.

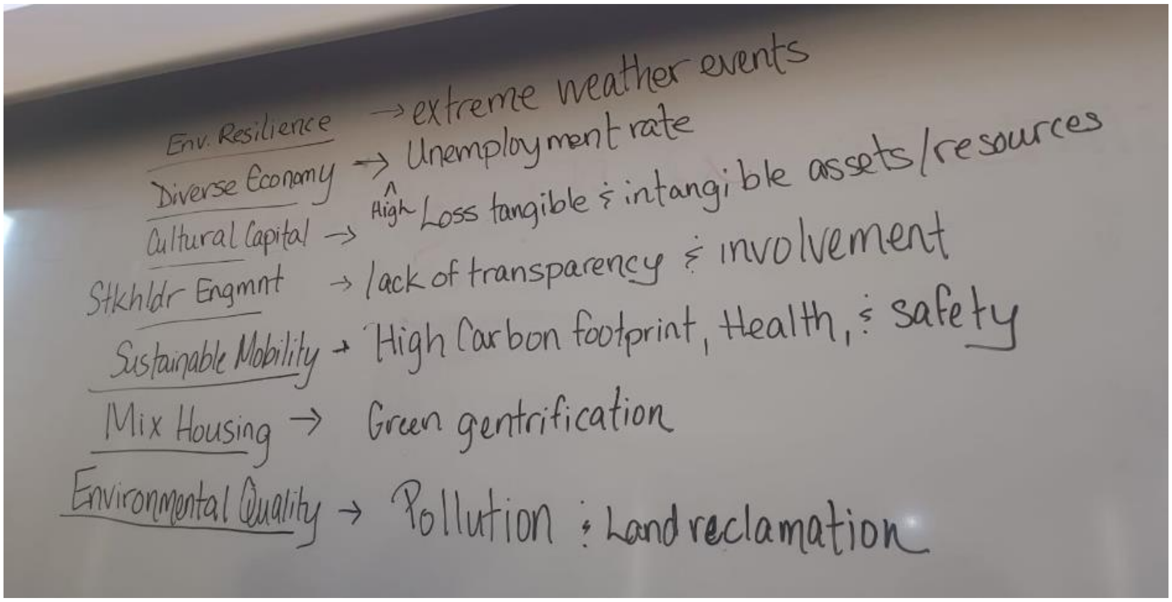

Figure 15. Decision Areas, group construction. Source: Photo by the author, 2024

After the previous analysis, the information is entered into the software, which defines seven problem areas (Environmental quality, mixed housing, stakeholder engagements, cultural capital, diverse economy, sustainable mobility, and environmental resilience). *Figure 16* shows some of the defined areas. It was decided to use the comments resource, which briefly describes the problem.

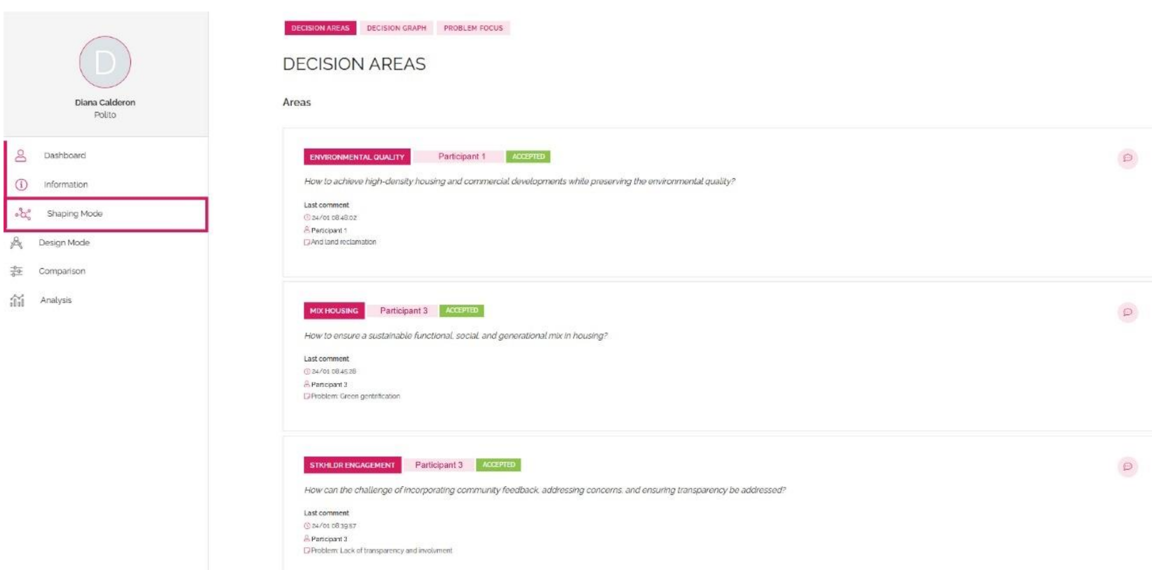

Figure 16. Decision areas - MuVAM interface

Decision Graph. After the previous step, the next one was to graphically show which areas are related and which are the relationships/unions. In this case, the area with the most relationships is "Stakeholder engagement." MuVAM facilitated the visualization of these previously proposed relationships, with which the group participants were satisfied, and some were surprised at the ease with which the results could be seen graphically; they quickly moved on to the next point.

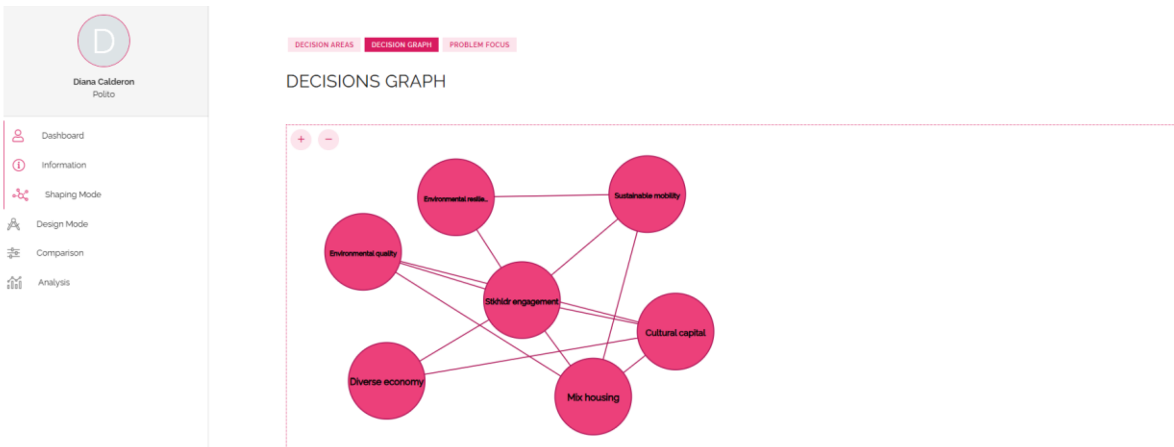

Figure 17. Decision Graph - MuVAM interface

Problem focus. Figure *18* shows the areas with the most relationships between them, and according to this, it marks them as urgent, important, and secondary. The group could modify and choose more urgent or important areas, but it was decided to continue in this case with those marked by the program. They reanalyzed these previous results, and everyone thought they were good. Finally, it was finished thanks to the agreements within the group that allowed decisions to be made quickly.

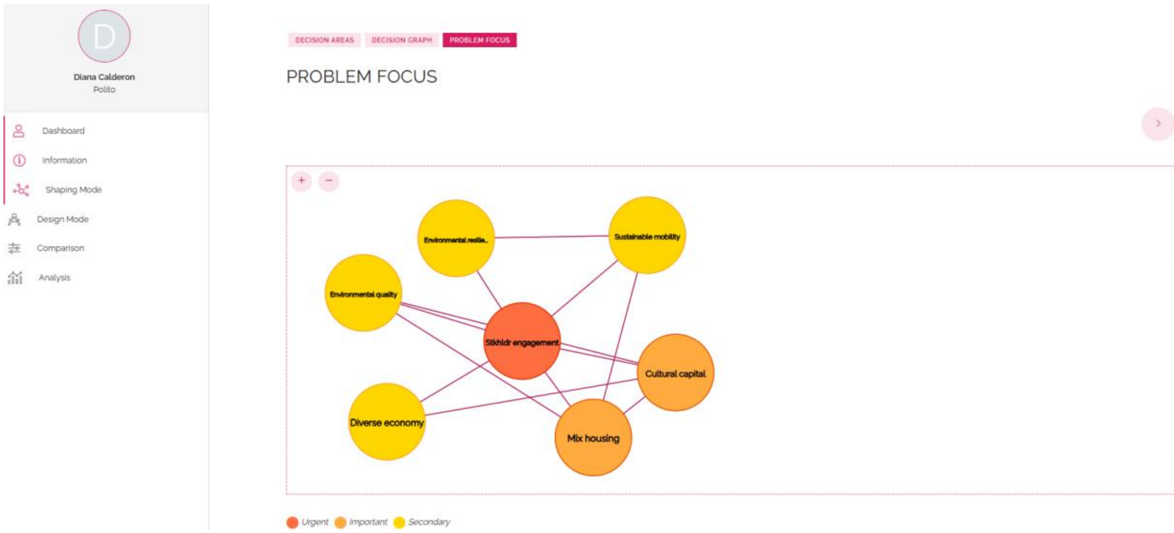

Figure 18. Problem Focus - MuVAM interface

Design mode

Decision options (Figure 19). In the next phase of the workshop, participants generated solutions for the previously identified decision areas. Then, a brainstorming session was held in which each group member presented proposals to define the options for each area. Some wrote the proposals directly in the program, one person wrote on the board, and another waited for the information to be uploaded. This stage ensured that each area had three proposals to solve the question.

After this process, the group identified some incompatibilities between the proposals, such as social problems, community links, and the relationships between the public and private sectors. These incompatibilities were analyzed in depth since some solutions could prove unfeasible due to economic restrictions or technical problems. The elimination of less viable options culminated in creating a decision tree that showed the solutions closest to the reality of the context. However, the accumulated fatigue of the previous sessions affected the group's ability to make quick and effective decisions. The brainstorming session was a good approach, and the proposals were sometimes ideal on paper but unrealistic in implementation due to budgetary or technological limitations.

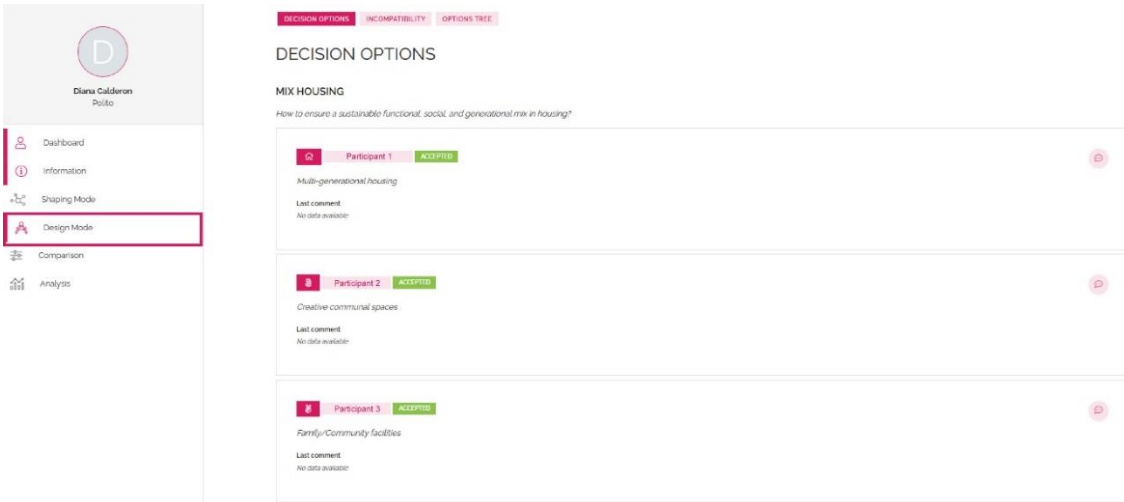

Figure 19. Decision options - MuVAM interface

Incompatibility (Figure 20). Again, all the previous points are reviewed to find some incompatibilities; even if progress is made, the previous concepts are continuously reviewed to get a clear idea of what is being evaluated and what the community's needs are, to define what is related, what is not feasible due to a technical issue, and what is available economically, among other things.

The relationships that may have a problem are defined, and the concepts do have relationships or, on the contrary because they could not have one; some of the options that appeared in their analysis were social problems, social links, Relations between private and public sectors, and Local community. Most relationships that were proposed are feasible. However, their combination may be unfeasible, it may be costly to carry out the two interventions considering the economic value, or they had many proposals that refer to the activities carried out directly with the community.

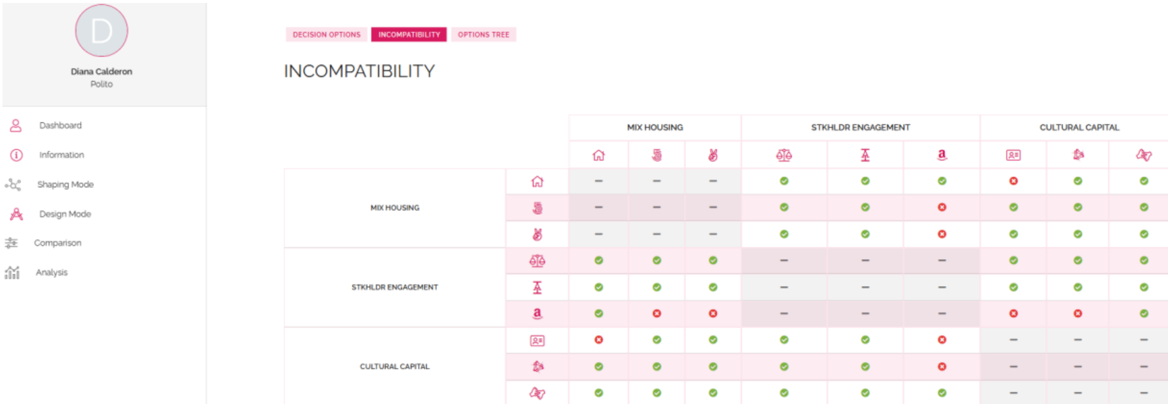

Figure 20. Incompatibility - MuVAM interface

This phase was crucial for refining the solutions. While some incompatibilities, such as those related to economic resources or interaction between sectors, were considered, there was not enough depth into more specific aspects, such as potential conflicts between the local community and the proposed projects (*Figure 21*). The lack of more significant interaction with local actors or experts in the analysis phase could have provided more realistic feedback on social or cultural tensions that might arise during the implementation of the solutions. Integrating local actors or experts more directly in the analysis and diagnosis phases would be helpful.

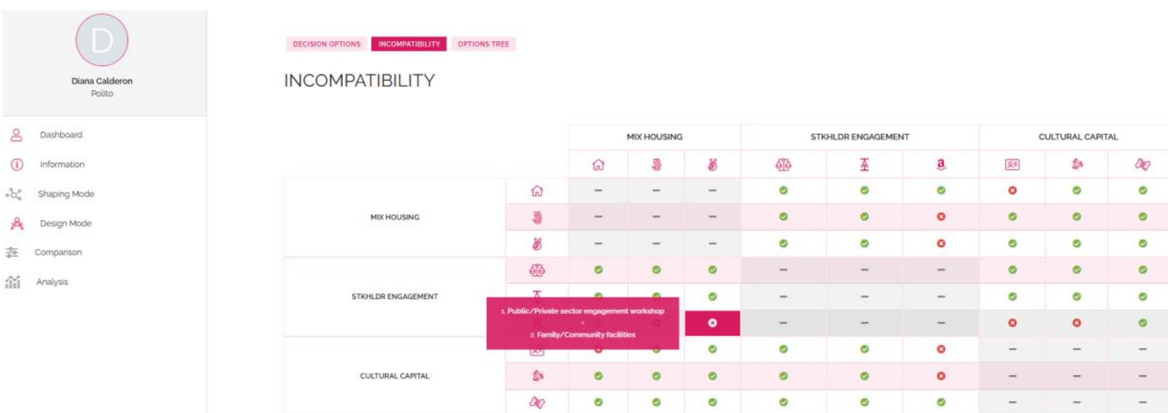

Figure 21. Example of Incompatibility - MuVAM interface

The review is presented midway through the process, and the concepts are clarified before proceeding to the final step (*Figure 22*).

Figure 22. Workshop development. Source: Photo by the author, 2024

Options tree. A process of eliminating some options is carried out to form a tree; at this point, cutting the number of possibilities was tough because they all seemed like they could be a good option. However, they reached an agreement with the choice of the options, and in this phase, you can also see the incompatibilities with this tree; by this point in the workshop, the group was already tired and did not advance as quickly as in the previous points.

Although creating the decision tree (Figure 23) allowed participants to visualize viable options, eliminating solutions was complex, indicating that all proposals seemed to have merit. However, the accumulated fatigue from the previous sessions affected the pace of work, slowing down the decision-making process. This point underlines the importance of maintaining efficient time management throughout the workshop. In addition, better planning of priorities and evaluation criteria, such as urgency or feasibility, would help make the elimination process more streamlined and more straightforward, preventing the group from getting stuck in indecision.

Figure 23. Option tree - MuVAM interface

Comparison

Finally, in this last part, 17 possible solutions are defined. Thanks to the fact that they had many solutions, it was necessary to choose four options to be taken, preferably the most different ones, so that they could be compared. Within the group, the mechanism used was that each member of the group individually chose their four options, then everyone showed their answers, and those that were most repeated within this selection were at the end as the possibilities to compare; after this, a comparison of the options was made to determine their similarities.

The criteria were established through group discussions, which facilitated a collaborative effort to identify the most relevant aspects and key elements for decision-making. Each team member shared their insights and experiences throughout the sessions, leading to criteria that captured a collective vision of the project's needs and goals. This group dynamic allowed for a diverse range of opinions to be considered when selecting the criteria. Afterward, participants chose four options for comparison, utilizing the MuVAM software (Figure 24).

The results were presented at the global and individual levels, allowing for differences and similarities in participants' preferences to be observed. This approach also allowed for assessing how each option aligned with the group's priorities and identified problems. The use of graphs facilitated understanding of the results but also underlined the need to complement them with more specific and detailed data to strengthen the conclusions obtained.

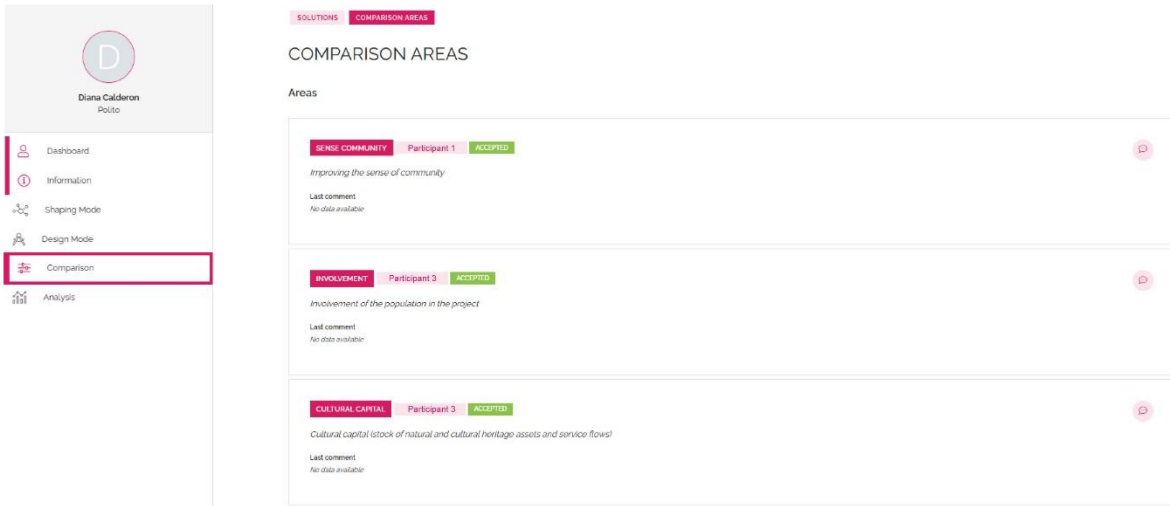

Figure 24. Comparison areas - MuVAM interface

Analysis

The final phase showed a democratic approach. Participants individually assigned weights to the criteria, which were then used to evaluate each pair of solutions using a pairwise comparison. Each participant assessed the relative importance of each criterion, assigning numerical values to reflect their priorities. These individual weights were then applied in the pairwise comparison method, where solutions were evaluated based on their alignment with the selected criteria. This approach allowed for a systematic comparison of solutions, providing a clearer understanding of their feasibility and benefits.

However, the comparison framework was rigorously structured through pairwise comparisons, applying a structured scoring system based on the Saaty scale (1-9) (Saaty, 1980). This approach helped ensure that the final selection was grounded in a thorough analysis of the solutions' potential impacts rather than being influenced by personal preferences. Key factors such as social impact, sustainability, economic viability, and local acceptance were systematically considered to enhance objectivity and support informed decision-making.

The information is shown quickly and graphically. Each group member's participation is important for discussing the information being handled and the best options for carrying out a specific action. Finally, the global results show the best options. Also, there is the option to show individual results that have similarities and differences in the scores of each participant, whether carried out from the computer or using other electronic devices such as mobile phones.

Figure 25. Analysis - MuVAM interface

The workshop concluded with a review of the proposed solutions, and a consensus was reached on the best options. Despite the difficulties, participants defined clear and relevant solutions to the identified problems. The results were displayed graphically, allowing for easy visualization of progress and decisions. In addition, the possibility of observing individual results provided a more detailed analysis of participants' preferences.

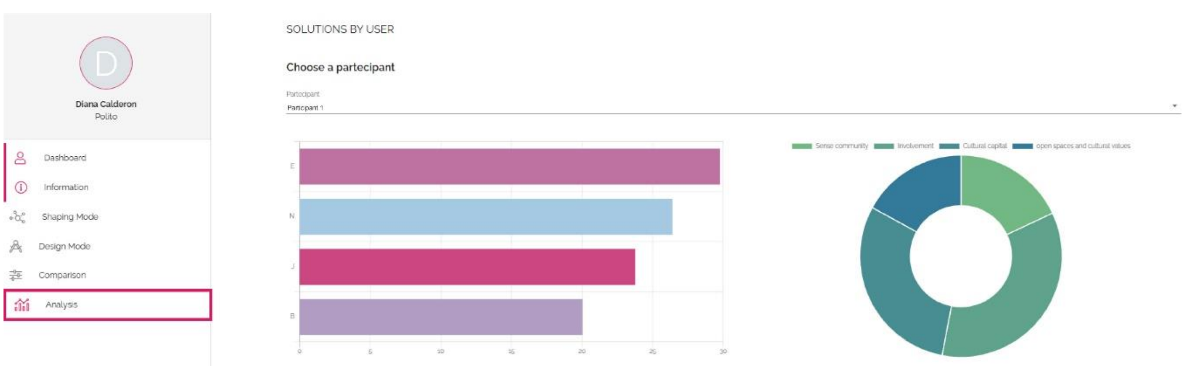

Figure 26. Analysis, induvial results - MuVAM interface

CASE STUDY

FORMER PARACCHI CARPET FACTORY

Photograph by Francesca Talami,2015. © Historical Archive of the City of Turin

Application of MuVAM + AI

TURIN

3.4.2. Former Paracchi carpet factory- Torino

The Paracchi Carpet Factory, which is in Torino, is a large industrial building that has a history dating back to the early 20th century. Historically, the place was a textile production factory, but over the years, the building became abandoned as the industry progressed. Today, it is used as a park as a part of the attempt to revitalize urban regions of the city. Thus, the project's goal is to add the historical details of the building to the useful spots of today's functional environment, which is necessary for the city's current requirements. In this respect, the envisioned transformation supports the broader objectives of Torino's development agenda, which seeks to transform the city while conserving its industrial past.

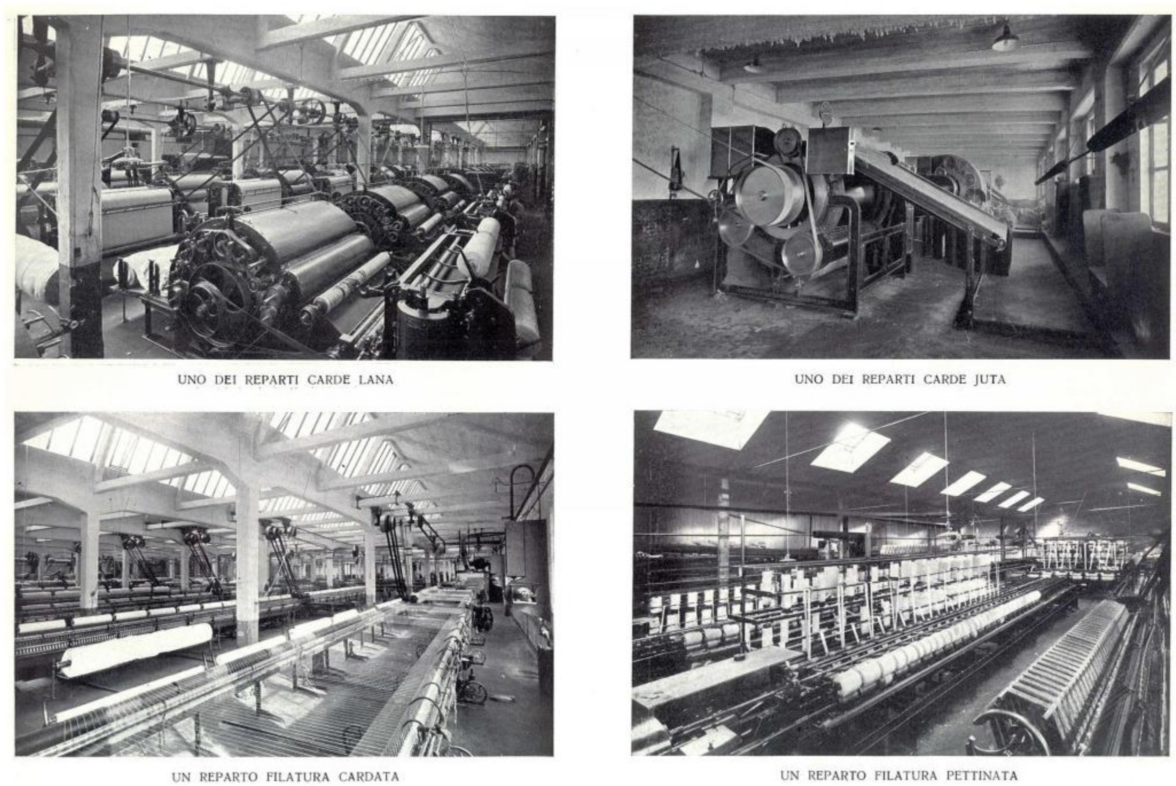

Figure 27. Historical photograph of factory departments, 1934 Source: https://www.museotorino.it/view/s/2fd7c953ee7f449296356b5192dc31d7

3.4.2.1.Project Overview and Context.

The former Paracchi Carpet Factory is a significant historical building in Turin. It was constructed at the beginning of the 20th century (https://www.museotorino.it/view/s/2fd7c953ee7f449296356b5192dc31d7), was the center of the Turin textile industry and helped the city's economy grow. However, as the city's industrial landscape changed, the factory lost significance and stopped producing products. As a result, the location is currently being redesigned as a component of an extensive urban renewal initiative meant to bring life to the neighborhood. The project's primary goal is to preserve the factory's industrial look while adding contemporary commercial, cultural, and residential features.

The factory's adaptive reuse illustrates how old industrial sites can be integrated into contemporary urban fabric, balancing heritage conservation with the needs of a growing city.

The ongoing transformation is expected to serve as a model for future urban regeneration efforts, showing how industrial heritage can be preserved and repurposed for new purposes. The project contributes to revitalizing the area, preserving Torino's industrial past, and promoting sustainable development by creating mixed-use spaces that serve the community's evolving needs.

3.4.2.2. AI Integration in MuVAM Application

This workshop was held with students of the master's degree in "Architecture, Construction City" at the Politecnico di Torino during "Economic Evaluation of Projects." It aimed to explore the application of MuVAM software combined with AI tools. The former Paracchi factory, a historic industrial site in Turin, Italy, was used as a case study. That is being considered for redevelopment as a residential healthcare facility (RSA) with secondary functions. Participants analyzed possible future uses of the site while incorporating AI into decision-making processes. The main objective was to assess how AI could enhance or limit collaborative decision-making and project development in the context of the renovation of this former factory.

For the development of this workshop, the students of the course were divided into 10 groups of approximately 4/5 participants each to be able to analyze the same case study with different AI tools or without them:

Type 1: MuVAM without the use of AI

Type 2: MuVAM with Chat GPT

Type 3: MuVAM with Replika

The methodology employed in this workshop was designed to integrate structured decision-making with AI's exploration potential. This section describes the information collected in group type 3: MuVAM with Replika as AI.

Replika AI was employed to generate complementary ideas and enrich the discussions. Interactions were conducted in both English and Italian, allowing an assessment of linguistic coherence in the AI results. The workshop was divided into two main phases. The Shaping Mode focused on the initial generation of ideas, where students proposed redevelopment concepts based on personal knowledge and group discussions. These ideas were complemented and compared with the results of the AI tool Replika; during the exploration of this tool, the students evidenced that it offers information in both an "AI Model" and a "Human Model modes. Based on the observation of this workshop, these are framed as:

- AI Model Mode: In this mode, Replika likely operates like a traditional AI tool, responding based on patterns, data analysis, and so on. The AI model can provide data-driven insights, predictions, or recommendations, operating purely on its computational capacity without incorporating human biases, emotions, or experiences. This could include automated suggestions for design or decision-making that are based on data or trends identified by the AI.
- Human Model Mode: In contrast, when Replika is in "human model" mode, it can simulate or integrate human-like responses, which could reflect subjective judgment, emotion, or more personalized information. In this mode, the tool can offer responses or insights that consider human experiences, cultural context, and so on, making it more aligned with how a human might approach the same problem or question. This could involve tailoring responses based on the tone of the conversation or recognizing a user's personal preferences and adjusting your responses accordingly.

Figure 28. Workshop development. Source: Photo by the author, 2024

Shaping mode

In this first phase, students based their discussions on their interests. According to their knowledge, they decided to choose the use that could be feasible for the renovation of this former factory be Residential Sanitary Assistance (RSA); after sharing all their options, when no more ideas arose, we resorted to the use of AI to be able to make a comparison with the previous information that they had already built and perhaps be able to obtain information that is not being taken into account at that moment. However, despite being asked differently, AI often provided too generic responses. In some cases, the answers were correct. However, even when the queries were framed clearly with all necessary instructions and context, the AI focused on delivering the "correct" response. This approach sometimes tried to convince the students that this was the best option rather than offering a more thoughtful or adaptable solution.

They were asked for different data to arrive at a more specific compilation of information, but the AI continued repeating the same information. In this case, they were asked what new use the former factory could have. The students proposed an RSA. However, all the information provided by the AI was focused on new uses that mainly serve students, such as university residences or workspaces, far from the expected answers since it had previously been described that the use would be a specific population different from that proposed by Replika.

Within this process, the structure and how the question is formulated must be considered to have an accurate conversation with the AI; even so, in most cases, the answers were too generic and did not generate interest in the students for this reason. Group members preferred to use the construction of their information for the construction of their areas and not rely on that provided by Replika.

The lack of precision in Replika's responses limited the added value that AI could offer in this phase. Although the software generated answers quickly, the suggested options were inconsistent with the project's specific context. Accurate question formulation is key to obtaining valuable responses from AI.

Design mode

In the next part of the workshop, the AI was consulted again; at this point, it is recommended to give it a context about what is expected with that search and also provide the AI with previously verified information to start the conversation, in this step, like the previous one, the initial options are prioritized. Then, the information that resulted from AI can be considered; however, what specific actions could be carried out during the construction of this information? A point in its favor is that the responses provided are fast and almost immediate, which allows fluidity when working in information discussion spaces.

It was also mentioned and compared with other AIs, such as Gemini or Chat GPT, which have a much more extensive and developed database for obtaining data; however, with any of these options, clear instructions must be given about what information is to be collected. It is looking for and that it is helpful to continue with the development of the MuVAM phases.

While Replika's quick responses can be helpful in some contexts, its lack of accuracy and consistency makes it difficult to rely on critical decision-making in complex projects. Compared with other, more robust tools, it highlights the need for more advanced AI tools to support collaborative decision-making.

Figure 29. Workshop development. Source: Photo by the author, 2024

During their exploration of Replika, the students noted that the tool's responses seemed to differ depending on the input type, which they described as being either aligned with an "AI Model" or a "Human Model." These observations were framed by the students as follows:

- *AI model:* generic answers, paraphrase the answers repeatedly.
- *Human model:* It is more sufficient and complete, and even in its AI mode, its responses are more accurate; even so, it tries to change the idea of the project with its preferences.

To cover Replika's options, the group was subdivided into two groups: the human AI model asking in English and Italian, and the AI model also asking in English and Italian. The results showed no consistency in the data; asking the same question with each described mode results in different results.

To give examples, as explained previously, the project they were developing was Residential Sanitary Assistance. Regarding the question about the number of rooms that can be developed in the RSA:

AI model

Student 1	No response
Student 2	30-90
Student 3	250
Student 4	50-60

Human model

Student 1	150
Student 2	30-40 / 50-60
Student 3	No response
Student 4	150

Regarding the activities that can be carried out within the RSA:

Student 1	Mensa, social events
Student 2	Asylum
Student 3	Rehabilitation
Student 4	Clinic

Regarding the proportions that the RSA must have in terms of activities carried out:

Student 1	70%	30%
Student 2	70%	30%

Student 3	70%	30%
Student 4	50%	50%

Inconsistent responses regarding the number of rooms and activities within the RSA reflect the lack of accuracy and consistency of Replika's AI model. Although some students adjusted the AI's responses based on their judgment, the inconsistent results hampered the workshop's progress.

Comparison

At this time, when the areas of this exercise had already been established, the group members decided on the incompatibility, considering that it was feasible both at the project's development level and its economic feasibility.

At the end of the workshop, a comparative evaluation of the proposed solutions was carried out, considering technical and economic feasibility. Despite AI's limitations, MuVAM allowed participants to structure their analysis effectively, achieving a hierarchical order of options based on objective criteria. In this context, AI was more beneficial for generating initial ideas but less helpful in making critical decisions. The lack of consistency in Replika's results highlights the importance of more developed AI tools to provide more accurate and consistent information.

Analysis

In this phase, AI was used operationally; each participant gave their autonomous evaluation. For ranking the analysis, Replika was very useful for achieving a hierarchical order by comparing the scenarios that emerged from the entire previous process and being more objective regarding the result they expected.

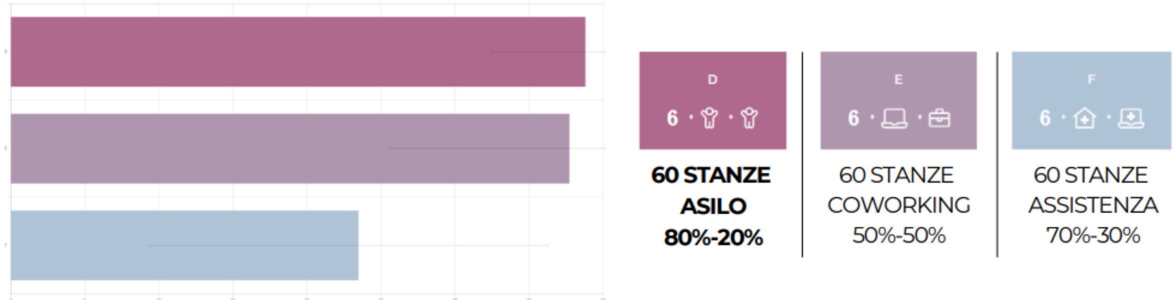

Figure 30. Analysis - MuVAM interface Source: Student report

At the end of the activity, the students' level of satisfaction concerning the MuVAM was positive; they liked its structure, and, in the end, they were able to compare their results among themselves, being transparent about the information that had been considered. However, the use of AI was not very satisfactory since, in many cases, the information it generates does not have solid bases or sources, nor is there a constant result that allows them to verify the veracity of the data/answers, so in many cases, they chose to use their information.

CASE STUDY

REQUALIFICATION- SAN SALVARIO NEIGHBORHOOD

Photograph by Michele D'Ottavio, 2025.© Torino Cambia Official Website

Application of MuVAM + AI

TURIN

3.4.3. Requalification of the San Salvario neighborhood in Turin.

The requalification of the San Salvario neighborhood in Turin is part of a broader urban renewal effort to address several urban challenges, including improving infrastructure, promoting social inclusion, and ensuring environmental sustainability. Once an industrial district, San Salvador has become known for its cultural diversity and creative industries. However, according to information provided by the city through the "*Torino Cambia*" project (https://www.torinocambia.it/), the neighborhood still faces issues such as urban decay and the need to improve public spaces and mobility.

The project aims to address these challenges by focusing on urban renewal efforts that improve the quality of life for residents and visitors. Sustainable development is a central element of the plan, with initiatives aimed at reducing the district's environmental footprint, improving the energy efficiency of buildings, and increasing green spaces. Integrating these strategies into the urban fabric aims to create a more resilient and sustainable urban environment.

Additionally, the project focuses on revitalizing public spaces, improving pedestrian and cycling infrastructure, and making the neighborhood more accessible. This comprehensive approach enhances the physical environment and fosters community and belonging.

3.4.3.1. Project Overview and Context.

The *San Salvario* project is a participatory urban regeneration initiative that aims to transform the neighborhood into a more sustainable, inclusive, and resilient area. This project focuses on the local community's active participation, integrating residents' needs and cultural heritage into the design of the neighborhood's future. In this way, the project aims to ensure that the redevelopment is aligned with the aspirations of those who live and work in the area.

An important feature of this initiative is its commitment to sustainability. The project includes improving energy efficiency, reducing environmental impacts, creating green spaces that promote biodiversity, and improving residents' quality of life. These efforts align with the goals of European initiatives to foster more sustainable cities. Furthermore, the project integrates innovative urban planning methods, such as agent-based models, to assess the potential impacts of various redevelopment strategies.

Preserving San Salvario's historical and cultural identity is another key aspect of the project. The area's industrial past, which has shaped its character, will be integrated into the transformation process. Public participation is central to this effort, ensuring the community's history is considered while leaving room for modern interventions. In this way, the neighborhood aims to preserve its unique identity while adapting to contemporary needs and future challenges.

3.4.3.2. AI integration in MuVAM Application

The MuVAM Workshop, with the support of Urban Lab in July 2024 in Turin, Italy, focused on how AI can propose solutions in urban decision-making. Five architects with experience in urban development participated in this workshop. The case study addressed the redevelopment of the San Salvario neighborhood, focusing on key aspects that participants had with information collected in the development of activities carried out in this neighborhood, focusing on four factors: housing, services, public spaces, and mobility within the neighborhood. The MuVAM software and AI, particularly Chat GPT, were used throughout the workshop to structure the decision-making process.

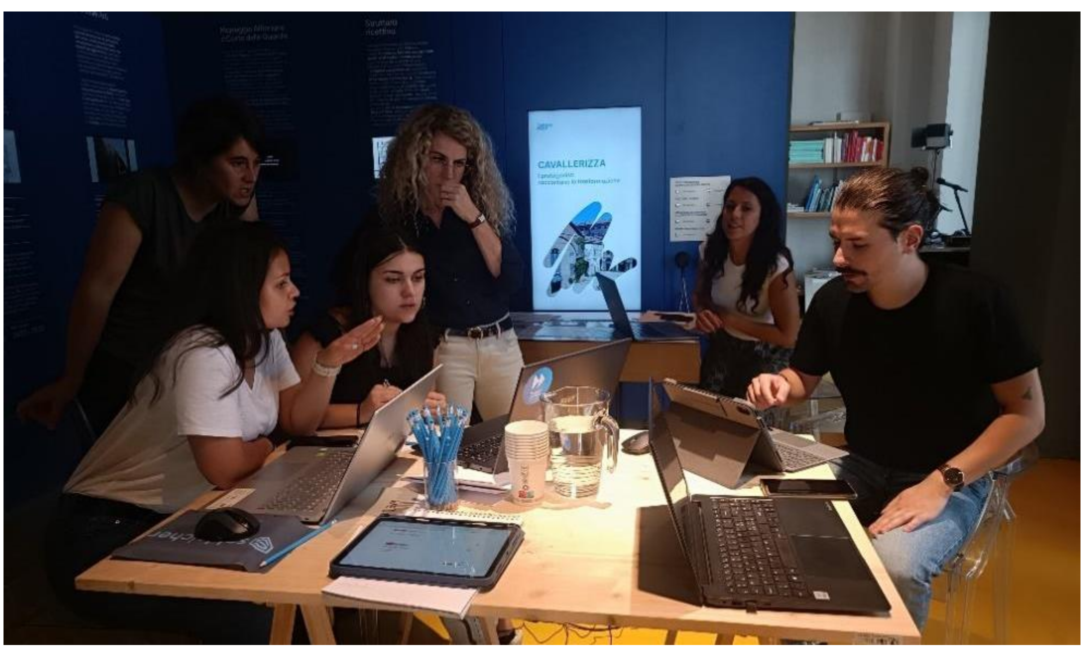

Figure 31. Workshop development. Source: Photo by the author, 2024

Shaping Mode

In the initial Shaping Mode phase, AI was vital in organizing and structuring data, allowing participants to identify specific challenges more efficiently. AI provided valuable insights into public spaces, green spaces, and urban mobility, helping participants focus on critical issues. For example, AI suggested “ways to enhance socializing spaces within Valentino Park and the San Salvario neighborhood by adding benches, recreational areas, and urban furniture, and recommended optimizing public lighting for safety, particularly in green spaces.”

However, while AI’s ability to organize data was valid, it struggled to fully capture the complexities of the local context, particularly the social and cultural dynamics of San Salvario. This limitation required participants to engage actively with the data, adjusting and interpreting it based on their local knowledge. It highlighted one of AI's primary weaknesses: its inability to understand a place's social and cultural complexities.

Design Mode

During the Designing Mode phase, AI proposed alternatives to address the neighborhood's challenges, such as expanding pedestrian areas, creating new green zones, and introducing the Superblock (Superilla) concept to improve urban mobility.

“Superilles” or “Superblocks” are an innovative urban planning strategy implemented in Barcelona to transform public space and promote sustainability. They consist of grouping traditional urban blocks into 400 x 400 meters units, restricting vehicular traffic on interior streets, and prioritizing pedestrians, cyclists, and public transport. This approach seeks to recover spaces for the community, improve biodiversity, and foster social cohesion (CitiesForum, 2021; PublicSpace, 2020).

While these suggestions aligned with the general goals of enhancing public spaces and mobility, they were often too general and lacked the specificity needed for the San Salvario context. For instance, the idea to [Expand the pedestrianization of Corso Marconi] * was promising, but adjustments were required to account for the neighborhood's urban conditions and mobility patterns. Similarly, proposals to reduce impermeable asphalt surfaces and add small green areas require further refinement to ensure their feasibility within the existing urban framework.

This phase revealed AI's limitations in generating context-specific solutions. Although AI is effective in generating preliminary ideas, human expertise is necessary to refine these alternatives and adapt them to the unique characteristics of each urban context. AI’s role is particularly valuable in the early stages of the decision-making process, but it cannot replace the depth of understanding that professionals bring to the workshop.

Figure 32. MuVAM Use. Source: Photo by the author, 2024

Decision Options.

During the design phase, AI was consulted to define decision options. This step structured the available options before proceeding to the next stages of the decision-making process.as an example of the interaction with AI in this workshop:

Question: [Socializing spaces: How can socialization spaces be increased within Valentino Park and the neighborhood?] * Some examples of the choices that were construction personal experience and AI:

- [Open some private courtyards to public use

- Increase spaces for relaxation and recreation in Parco del Valentino by increasing the number of benches, games, and street furniture
- Expand the pedestrianization of Corso Marconi
- Reduce the impermeable surfaces occupied by asphalt and create small green areas in squares and along streets
- Work with schools to create school gardens that are accessible even outside of school hours.
- Create linear parks or green strips along railway lines to isolate noise and improve the environment.
- Organizing community events, markets, festivals, and cultural activities in public spaces can increase their positive use and strengthen the sense of community.
- Optimize public lighting to improve safety, especially in green areas
- Creating and maintaining attractive and popular public spaces can deter criminal activity. The constant presence of residents, families, and children makes it more difficult for drug dealers to operate unnoticed.
- Make the cycle path a capillary network and increase the number of spaces for parking bicycles
- introduce the superillas model in San Salvario] *

Then, the options provided by AI were analyzed, and MuVAM was used to organize them using the decision graph, as shown in Figure 33, to later work on Problem Focus Figure 34, which highlights the options of green areas, slow neighborhoods, security, and pedestrianization.

*Translation by the author from Italian

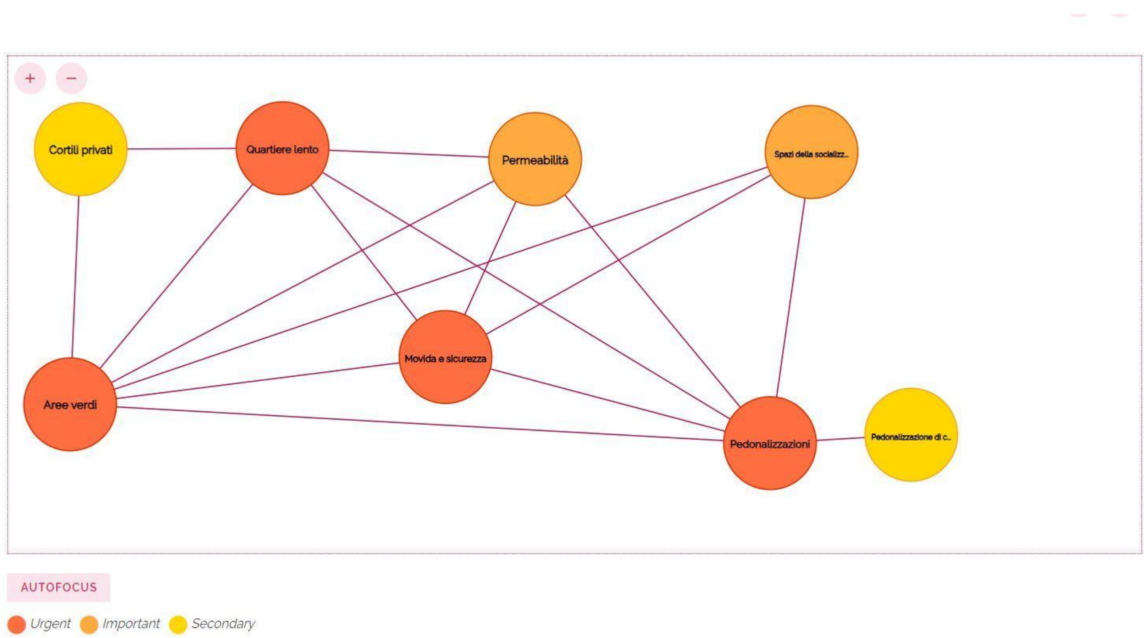

Figure 33. Decisions Graph- MuVAM interface

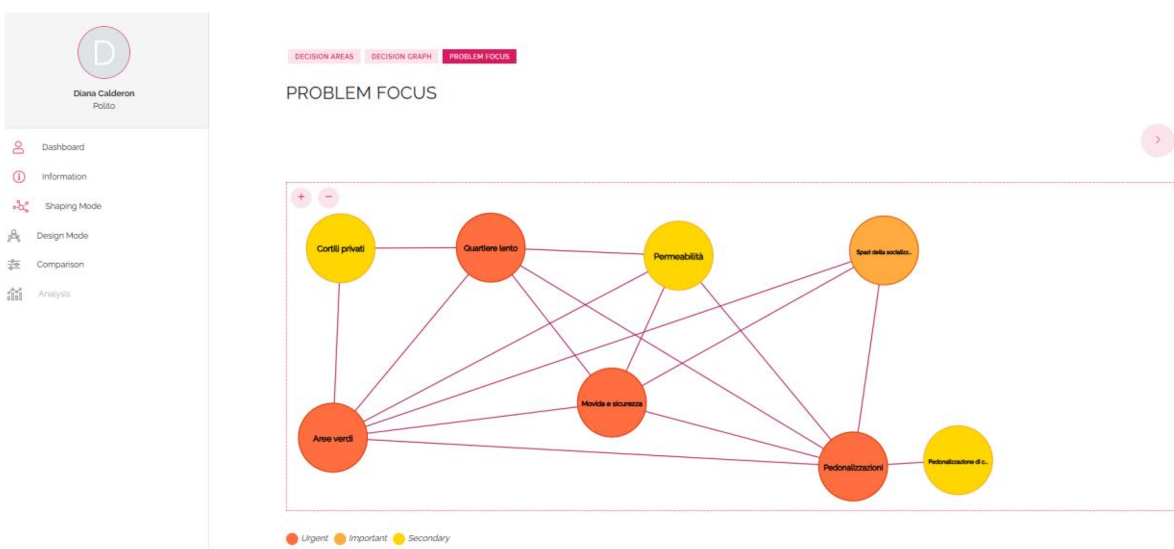

Figure 34. Problem Focus- MuVAM interface

Participants compared AI-generated alternatives and discussed their feasibility, potential impact, and alignment with specific neighborhood needs. This phase was carried out manually by the workshop participants in an orderly and well-structured way; taking this professional experience as a reference, some unrealistic actions were identified. Finally, when completing this table, its results are one answer.

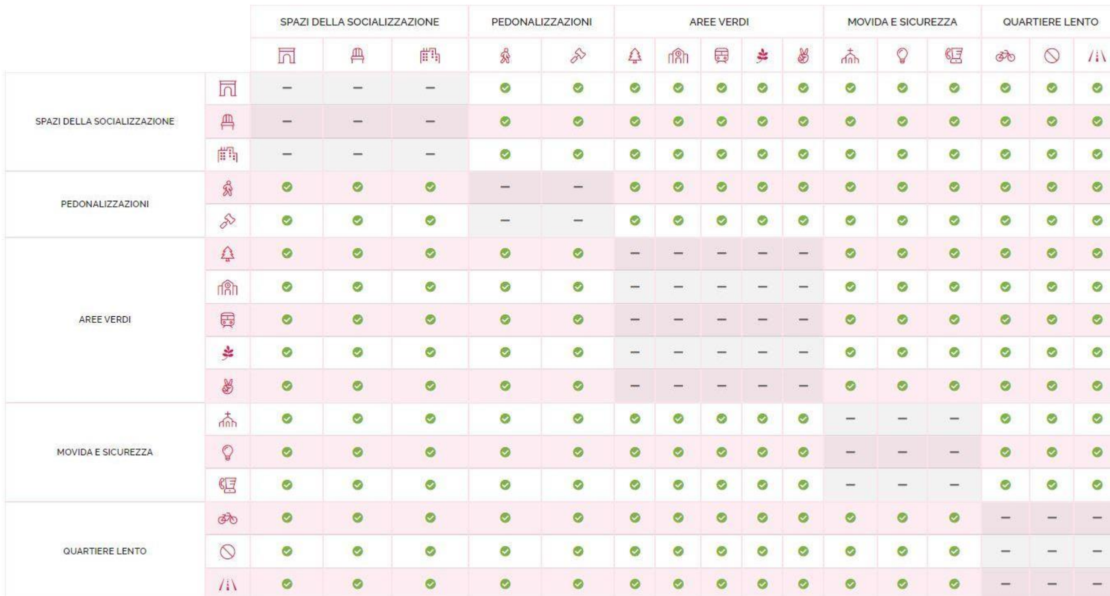

Figure 35. Incompatibility - MuVAM interface

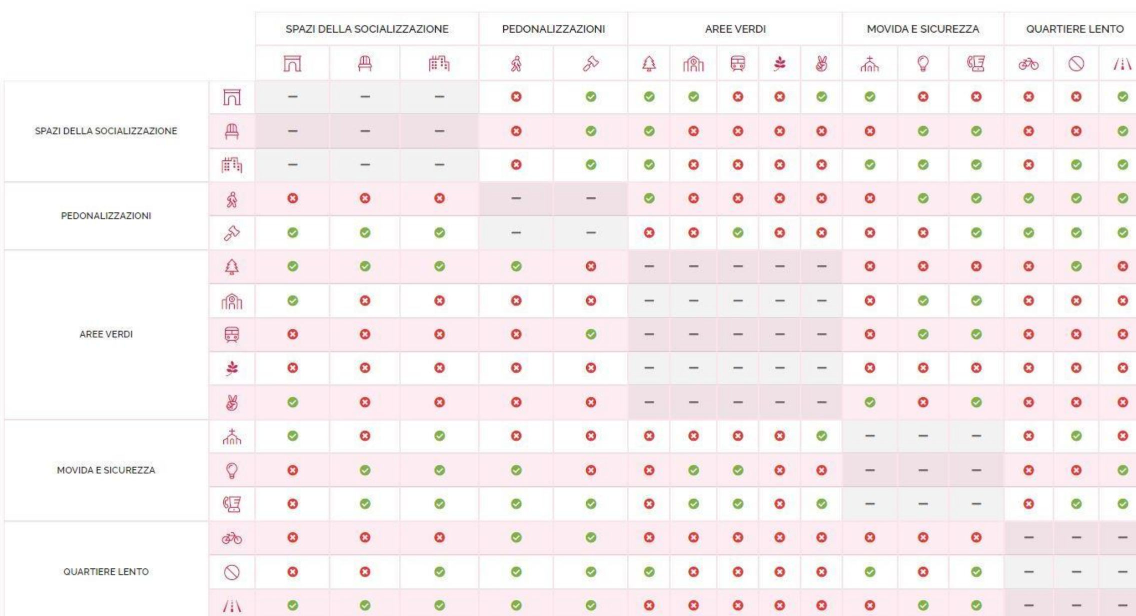

Figure 36. Incompatibility after manual adjustment by participants - MuVAM interface

Comparison and Analysis

The phases of Comparison and Analysis were not carried out because the result was unique after the designing phase, namely: “In Valentino Park, increase the spaces for relaxation and recreation through the benches, Games, and urban furniture + Expand the pedestrian area of the Marconi course + Reduce the impermeable surfaces occupied by asphalt and create small green areas in squares and along roads + Optimize public lighting to improve safety, especially in green areas + to introduce the Superblock (Superilla) model in San Salvario” (author’s translation).

Figure 37. Solution **-** MuVAM interface

04

RESULTS AND DISCUSSION

Chapter 4. Results and discussion

The results from the case studies shed light on the different ways AI is integrated and its effects on decision-making processes. Each case study offers distinct insights into AI's role in urban and architectural contexts, emphasizing its ability to improve efficiency, meet local needs, and adapt to complex environments. Analyzing these cases reveals that integrating AI in various settings produced different outcomes, highlighting both the advantages and challenges of using AI in decision-making frameworks. These findings provide a clearer understanding of the AI's practical uses and limitations in transformation processes.

The data collected in the case studies were analyzed to identify trends, challenges, and key outcomes associated with the use of AI in decision-making processes in urban and architectural contexts. This analysis aimed to uncover the impact of AI integration in the decision-making process, its adaptability to different urban environments, and its ability to respond to local conditions and stakeholder priorities.

4.1. Le Pav – Pointe Nord: Results and Data Analysis

Workshop No. 1 emerged as a valuable experience for participants and organizers. The MuVAM software allowed students to apply their knowledge practically and obtain visually clear results that facilitate decision-making in a collaborative environment. The main strengths of the workshop included the precise specification of roles and tasks and the ease of use of the platform, which facilitated collaboration between group members.

However, areas for improvement were also identified. The time spent on the technical introduction could have been optimized, and it is suggested that a deeper analysis of the solutions' feasibility and social implications be integrated. Furthermore, fatigue at the end of the workshop affected the speed of decision-making, underlining the importance of better managing time and breaks in future seminars.

Overall, this workshop showed the potential of tools such as MuVAM to facilitate urban decision-making in urban contexts. However, adjustments need to be made to ensure that the technical approach is accompanied by deeper reflection on the social, economic, and cultural context, improving the quality of the proposed solutions.

The table summarizes the analysis of Workshop No. 1 as part of a case study evaluating the application of MuVAM software. In this context, the workshop aimed to observe and understand how participants work together, without relying on AI tools, to identify, analyze, and prioritize solutions, relying on practical, non-digital methods for collaboration and problem-solving. Participants aimed to actively identify challenges, explore potential solutions, and prioritize them about urban transformation goals. This allows direct human interaction and physical materials to facilitate discussions and decision-making.

This workshop offered an opportunity to examine how decision-making unfolds with MuVAM without relying on AI tools, allowing for a focused exploration of group dynamics, interaction, and the advantages and challenges of a human-based approach to each phase. The workshop involved PhD students from the Polytechnic of Turin, divided into groups of 4/5 participants each. Specific roles were assigned to enhance the structure of the activity, including observer, moderator, and external observer. These roles ensured that all aspects of the process were monitored and evaluated; by not incorporating AI tools, the structured approach allowed participants to focus on problem analysis, relationship definition, and solution prioritization through self-produced frameworks, contributing to a deeper understanding of these processes without AI.

Table 6 presents some key insights emerging about the positive outcomes and challenges faced during the workshop. One of the observed strengths was improved collaboration and organization, which facilitated understanding the complex relationships between various decision areas. This approach allowed participants to engage actively in brainstorming and decision-making, resulting in a systematic approach to problem-solving. However, the table also reveals some of the challenges faced by participants, including fatigue during the later stages of the workshop and difficulties in managing the complexity of combining diverse proposals with limited resources.

These challenges underline the methods' limitations, especially regarding time constraints and the need for a continuous approach. The table also highlights the adaptive strategies implemented during the workshop in response to these challenges. Task division and regular reviews were employed to manage time and maintain participant engagement. These adaptations were essential to ensure that the decision-making process remained organized and focused despite the difficulties encountered. These insights provide valuable lessons for future workshops and decision-making scenarios, both with and without the integration of AI tools.

Table 7. Case Study Analysis - Le Pav - Pointe Nord, Geneva - application of MuVAM (Source: own elaboration).

Category	Sub-category	Description / Observation
Technical	Case study	Workshop N°1: MuVAM Software Application (24/25 January 2024, Turin - Italy)
	Project Context	The Pointe Nord Project, part of the PAV program in Geneva, transforms former industrial areas into a mixed-use district with housing, commercial spaces, community services, and cultural areas. This project combines the preservation of industrial heritage with modern solutions to revitalize urban spaces under social, economic, and environmental objectives.
	Participants	Group of 4/5 people PhD students from Politecnico di Torino. Their roles included observer, moderator, and external observer.
	Tools used	MuVAM software, whiteboard for brainstorming, laptops, mobile devices.
	Use or not of AI	This workshop was conducted without AI.
	Stage of Decision-Making with or without AI	No AI was used; decisions were made by human-based approaches, focusing on problem analysis, defining relationships, and prioritizing solutions.
Social	Types of interaction	Collaborative discussions, brainstorming, human-based organization of concepts, and group decision-making.
	Inclusion of stakeholders	Stakeholders (students, observers, moderators) actively participated in defining decision areas, brainstorming, and organizing data collaboratively.
Implementation	Key examples	Definition of seven problem areas (e.g., environmental quality, sustainable mobility), creation of decision graphs, and formation of an options tree to evaluate solutions.

	Application of MuVAM	MuVAM was a framework to support data organization, visualization, and solution prioritization without AI functionalities.
	Limitations and solutions	Time constraints and reduced focus were managed by dividing tasks and reviewing steps to maintain clarity and engagement.
Impact	Contributions of AI	Not applicable; contributions were based on the group work and structured frameworks.
	Observed benefits	Facilitated the organization and understanding of complex relationships, supported collaboration, and provided a systematic approach to decision-making.
	Observed challenges	Fatigue during later stages of the workshop, difficulty in eliminating options, and managing the complexity of combining proposals with limited resources.

Several conclusions emerge from the analysis of Table 7 that allow us to understand the essential aspects of this case study. These conclusions can be summarized as follows:

- ***Human-based decision-making process:*** The workshop's reliance on manual decision-making allowed participants to engage deeply in problem analysis and solution prioritization. While this approach fostered deep understanding, it also required more time and careful management of resources and tasks.

- ***Collaborative and structured approach:*** Collaborative discussions, brainstorming sessions, and human-based organization of concepts promoted active participation among stakeholders (students, observers, moderators).

- ***Use of MuVAM:*** MuVAM was effectively used to structure data, visualize relationships, and prioritize solutions. Despite the absence of AI, the tool's framework facilitated decision-making by providing a clear and systematic approach to handling complex problems.

- ***Time and task management:*** Time constraints presented a challenge, especially in the later stages of the workshop, leading to fatigue in participants and difficulty eliminating options. Dividing up tasks and reviewing steps ensured that the group remained focused and engaged, but it highlighted the need for time management strategies to avoid burnout and decision fatigue.

- ***Challenges in managing complexity:*** Combining diverse proposals and managing multiple decision areas with limited resources was challenging. Participants had to carefully weigh competing priorities, which, while valuable for developing decision-making skills.

- ***Group dynamics and stakeholder engagement:*** Stakeholders played an active role throughout the workshop, contributing significantly to defining decision areas and generating solutions. This engagement was essential to ensure outcomes aligned with project objectives and context.

4.2. Former Paracchi Carpet Factory: Results and Data Analysis

Workshop No. 2 allowed participants to examine the same case study using different methodological approaches, either integrating AI tools or working without them. The three groups were structured as follows: *Type 1*, utilizing MuVAM without AI; *Type 2*, integrating MuVAM with ChatGPT; and *Type 3*, combining MuVAM with Replika.

This section focuses on the results obtained from *Type 3*, where MuVAM was used alongside Replika AI. The collected data indicate that Replika contributed to generating complementary ideas, enriching discussions, and expanding the scope of explored solutions. However, its effectiveness varied depending on how participants engaged with the tool. The analysis highlights patterns in AI-generated suggestions, their relevance to the decision-making process, and the extent to which human intervention was required to refine or adapt AI-driven insights.

During the Shaping Mode, participants initially proposed an RSA facility for the site. However, AI responses were often generic and inconsistent, suggesting options like university residences or coworking spaces that deviated from the intended purpose. This pushed participants to rely more on their discussions and critical analysis.

In the Designing Mode**,** participants refined their proposals by reintroducing AI with more explicit prompts and specific contextual information. While Replika provided faster responses, it often paraphrased inputs or introduced unrelated suggestions. Comparisons with other tools, such as ChatGPT and Gemini, revealed that these alternatives offered more robust and context-aware outputs, underscoring Replika's limitations in this scenario.

A comparative analysis demonstrated significant inconsistencies in AI-generated outputs. For example, the number of RSA rooms proposed ranged from 30 to 250 in the AI Model but was narrower and more realistic (30 to 150) in the Human Model. Similarly, the AI Model suggested overly broad activities like "social events," while the Human Model proposed contextually relevant functions such as a canteen or clinic.

Integrating AI into decision-making presented notable contributions and challenges that contributed to the process by providing rapid responses, stimulating idea generation, and enabling scenario comparisons. However, its benefits were tempered by challenges, including generic outputs, language inconsistencies, and reliance on precise prompts. Replika's limitations as a companion AI rather than a decision-support tool became apparent, as its production often lacked depth or relevance.

Despite these challenges, the workshop demonstrated MuVAM's effectiveness in structuring discussions and enabling participants to reconcile differing opinions. It also revealed the potential for more advanced AI tools to enhance collaborative decision-making, provided users are trained in prompt engineering and contextual alignment.

For instance, a question about RSA room capacity yielded highly varied responses from AI, highlighting the need for consistent inputs. Participants noted discrepancies between AI's suggestions and project requirements, prompting more precise instructions. AI's suggestion of "university residences" prompted other participants in the same group to refine their context, illustrating how AI can inspire deeper discussions.

MuVAM's structured framework enabled participants to finalize a feasible RSA proposal by combining diverse perspectives. The team collectively agreed on a 70% -30 % split for primary and secondary activities, reconciling differing priorities through collaborative analysis.

This workshop underscored the potential and limitations of integrating AI into decision-making processes using MuVAM. While the software effectively structured discussions and supported prioritization, the AI tool Replika often fell short of providing meaningful, contextually relevant insights. Using MuVAM and Replika allowed participants to structure decision-making, although the integration of AI into the design process was limited. While the MuVAM platform facilitated discussion and comparison of options, the Replika AI tool did not meet expectations regarding response quality and consistency. Although satisfied with the structure of MuVAM, participants preferred to rely on their analysis rather than on the responses provided by AI.

This workshop demonstrated the potential of integrating MuVAM with AI tools such as Replika, although its limitations prevented it from fully exploiting its potential. The lack of consistency and depth in Replika's responses shows the need for more advanced AI tools for collaborative decision-making. Despite this, MuVAM proved to be an effective tool for structuring discussions and facilitating the comparison of solutions, allowing students to arrive at a viable proposal for rehabilitating the former Paracchi factory. As a suggestion, the students, through the workshop reports, established that for future activities, it is essential to explore the use of more robust AI tools, such as Gemini or Copilot, which offer better results by being more contextualized.

Table 8 provides a breakdown of the criteria and observations derived from Workshop No. 2. This workshop aimed to assess the integration of MuVAM and AI tools into decision-making processes, focusing on the redevelopment of the former Paracchi carpet factory. The table highlights the interaction between human-driven and AI-supported methodologies.

The table is organized into four categories, each addressing key aspects of the methodology and workshop outcomes. These categories examine specific criteria such as project context, participants, tools used, decision-making stages, and AI contributions. Descriptions and observations illustrate the findings, challenges, and lessons learned during the workshop for each sub-category.

This table not only summarizes the findings of the group described above but also expands its scope to include three distinct methodologies employed during the workshop:

- Type 1, using MuVAM without AI.
- Type 2, integrating MuVAM with ChatGPT.
- Type 3, combining MuVAM with Replika.

The table compares these approaches to provide insight into how AI tools influence and improve decision-making processes in different scenarios.

In the Technical category, the table details the tools employed, including MuVAM, ChatGPT, and Replika, and their role in shaping and refining ideas for repurposing the Paracchi factory. The decision-making stages are analyzed, revealing the levels of AI effectiveness, particularly in the shaping and design phases. Also, the participants' reliance on human validation when AI results were inconsistent or not aligned with the project objectives.

The Social category delves deeper into the types of interactions facilitated during the workshop. It highlights the collaborative dynamics between participants and AI tools, showing how group discussions and comparisons between human- and AI-generated results enriched at some specific phases and moments in the decision-making process. Including human and AI stakeholders is assessed, underlining AI's limited but valuable contributions in fostering alternative perspectives.

The Implementation category emphasizes the dynamic and flexible decision-making processes observed during the workshop. This dimension focuses on how participants adapted to changing challenges by interacting with their constructions and AI-generated outputs, readjusting project goals to align with contextual objectives, and reconciling conflicting priorities among stakeholders.

Specific examples include adjusting MuVAM workflows to integrate AI tools such as ChatGPT and Replika and others proposed by students during the workshop, such as Copilot and Gemini. These adaptations underscore the value of MuVAM as a tool capable of fostering responsiveness and strategic adjustments in complex urban projects.

The Impact category examines the contributions, benefits, and challenges associated with AI. While ChatGPT provided structured data sets and rapid responses, Replika's outputs were often generic and required significant refinement. Examples of these challenges, such as discrepancies in the AI-generated RSA space estimates in this case, illustrate the importance of contextual understanding and human validation.

Table 8 also emphasizes the role of MuVAM in effectively structuring discussions and mapping relationships between proposed solutions. The information in the table is presented to provide a clear and structured analysis of the workshop findings. It serves both as a summary and an exploration of how AI tools and human decision-making interact in the context of urban transformation. This information helps to understand the methodologies used, assess the role of AI, and reflect on practical applications of MuVAM and AI in collaborative decision-making frameworks.

The results of this workshop focused on the use of MuVAM and Replika. However, to get a broader view of what was developed, the reports of the other two groups have been taken as reference: Group Type 1, which used MuVAM without AI, and Group Type 2, which integrated MuVAM with ChatGPT. These reports have been analyzed in Table 9.

Table 8. Case Study Analysis – Former Paracchi carpet factory- Torino - MuVAM + AI (Replika) (Source: own elaboration).

Category	Sub-category	Description / Observation
Technical	Case study	Workshop N°2: MuVAM Software Application + AI (29 April 2024, Turin - Italy)
	Project Context	Analysis and transformation proposal for the former Paracchi carpet factory in Turin, focusing on potential reuse and redevelopment strategies.
	Participants	5 Students of the master's degree in "Architecture, Construction City" at the Politecnico di Torino, as part of the "Economic Evaluation of Projects" course.
	Tools used	MuVAM, ChatGPT, Replika AI, whiteboard, and laptops.
	Use or not of AI	AI was combined with MuVAM to compare traditional and AI-supported decision-making processes. ***Use AI- Replika:*** (AI model and Human model): The AI model generated generic and inconsistent responses, requiring significant refinement or alternative approaches. The Human model produced relatively more coherent answers but still tended to shift project goals based on its internal logic.
	Stage of Decision-Making with or without AI	***AI- Replika:*** AI was integrated into shaping and designing modes but failed to provide consistent or sufficiently specific outputs
Social	Types of interaction	***AI- Replika:*** Participants divided tasks, compared AI-generated results with manually derived ones, and discussed outcomes to improve understanding and refine decisions.
	Inclusion of stakeholders	Stakeholders (students and AI) contributed to the decision-making process, though AI's role was limited due to its lack of relevant and consistent outputs.

Implementation	Key examples	***AI- Replika:*** AI suggested generic uses for the RSA (e.g., student housing, workspaces), conflicting with the group's target context (Residential Sanitary Assistance for a specific population). Examples include discrepancies in RSA room count estimates, where AI responses lacked coherence across Replika's models, and participants relied on their expertise.
	Application of MuVAM	MuVAM facilitated structured discussions, relationship mapping, and scenario analysis, effectively organizing participant-generated and AI-generated inputs.
	Limitations and solutions	AI limitations included generic outputs and a lack of contextual adaptation. Solutions involved participant-driven data validation and iterative question refinement.
Impact	Contributions of AI	***AI- Replika:*** AI facilitated rapid response generation and scenario comparisons but often provided inconsistent or generic data, reducing its effectiveness in supporting decision-making.
	Observed benefits	***AI- Replika:*** AI responses were quick, allowing some level of fluidity in discussions, and Replika's hierarchical ordering feature proved helpful in scenario ranking.
	Observed challenges	***AI- Replika:*** Inconsistent AI outputs, generic answers, and unreliable sources limit utility. AI responses often do not align with the project's context or goals.

Table 9. Case Study Analysis – Former Paracchi carpet factory- Torino - MuVAM and MuVAM + AI (ChatGPT) (Source: own elaboration).

Category	Sub-category	Description / Observation
Technical	Case study	Workshop N°2: MuVAM Software Application + AI (29 April 2024, Turin - Italy)
	Project Context	Analysis and transformation proposal for the former Paracchi carpet factory in Turin, focusing on potential reuse and redevelopment strategies.
	Participants	5 Students (by group) of the master’s degree in "Architecture, Construction City" at the Politecnico di Torino, as part of the “Economic Evaluation of Projects” course.
	Tools used	MuVAM, ChatGPT, Replika AI, whiteboard, and laptops, Gemini, CoPilot
	Use or not of AI	AI was combined with MuVAM to compare traditional and AI-supported decision-making processes. ***Use AI- Chat GPT:*** Provided a larger, more structured dataset and responded to explicit, context-specific queries more effectively than Replika. However, participants noted detailed instructions and context were critical to achieving valuable outputs.
	Stage of Decision-Making with or without AI	***AI- Chat GPT:*** AI was used during the shaping and designing phases to generate ideas, analyze relationships, rank potential solutions, identify challenges, and organize relevant data, helping participants focus on specific problems. AI-generated multiple alternative solutions, accelerating the brainstorming process and structuring proposals. ***Without AI:*** Participants manually analyzed data, relying on their professional experience to define challenges, which was more time-consuming but with context-specific results.

		Participants brainstormed solutions independently, relying entirely on expertise and prior knowledge, which ensured relevance but took longer to develop alternatives. They also compared solutions using structured discussions, ensuring alignment with local needs but requiring more effort and time.
Social	Types of interaction	***AI—Chat GPT: The interaction*** involved structured group discussions, AI-supported brainstorming, and comparisons between human and AI-generated outputs. ***Without AI:*** Group discussions and manual brainstorming, focusing on individual contributions, refining ideas without AI-generated input, and comparing personal outcomes.
	Inclusion of stakeholders	Stakeholders (students and AI) contributed to the decision-making process, though AI's role was limited due to its lack of relevant and consistent outputs.
Implementation	Key examples	***AI—Chat GPT: AI suggested generic uses for the RSA (e.g., student housing, workspaces), which conflicted*** with the group's target context (Residential Sanitary Assistance for a specific population). ***Without AI:*** Participants relied on their knowledge and expertise to suggest more context-specific uses for the RSA, focusing on meeting the needs of the specific population. Discrepancies in room count estimates were resolved through detailed analysis and discussions.
	Application of MuVAM	MuVAM facilitated structured discussions, relationship mapping, and scenario analysis, effectively organizing participant-generated and AI-generated inputs.
	Limitations and solutions	AI limitations included generic outputs and a lack of contextual adaptation. Solutions involved participant-driven data validation and iterative question refinement.

Impact	Contributions of AI	***AI- Chat GPT:*** Provided alternative perspectives, rapid responses, and hierarchical comparisons of solutions. ***Without AI, it*** relied on human expertise and in-depth discussions, resulting in more tailored and context-specific insights. Although decision-making was slower, it was often more coherent and consistent in addressing the issue.
	Observed benefits	***AI- Chat GPT:*** Speed of generating initial ideas and structured comparisons facilitated ranking of options. ***Without AI,*** Discussions were more deliberate and thoughtful, providing deeper insights but requiring more time for idea generation and ranking.
	Observed challenges	***AI- Chat GPT:*** AI-generated outputs were inconsistent and overly generic, and significant participant validation was required to ensure relevance and accuracy. ***Without AI,*** Decision-making took longer and depended more on individual knowledge, but it often lacked the efficiency and breadth of AI-generated suggestions.

Some insights can be highlighted from the analysis of the *tables 8* and *9*, which help to better understand the key aspects in this case study. These insights include the following points:

- ***Complementing AI and Human Expertise:*** AI can accelerate idea generation and broaden perspectives, but it always requires human validation and adjustments to ensure contextually accurate results. Human expertise remains crucial for adapting solutions to the project's specific needs.
- ***Limitations of AI:*** While AI can offer quick solutions, the results are often generic or inconsistent, especially with Replika, requiring human intervention to make them useful. This highlights the importance of improving the contextual adaptability of AI models.
- ***Social Role and Collaboration Dynamics****:* AI facilitates discussion and analysis of alternatives, but it does not replace the need for human collaboration. Interaction with AI speeds up some processes, but human judgment and experience are essential for refining the generated solutions.
- ***Challenges in AI Application****:* AI faces difficulties in tasks that require precision and adaptability, such as decision-making in complex and context-specific situations. This limits its applicability in large-scale architectural projects where consistency and accuracy are vital.

4.3. Requalification of San Salvario neighborhood: Results and Data Analysis

Throughout the last workshop, the integration of AI influenced group dynamics; AI facilitated the discussion by providing a structured basis for decision-making. However, the influence of AI on group dynamics was mixed. It accelerated certain phases by delivering options quickly; on the other hand, participants had to invest significant time in refining and contextualizing these options. For example, when AI proposed increasing green spaces in certain areas, the participants had to assess whether those suggestions were feasible given the urban layout of San Salvario. This need for re-organization of information sometimes led to disapproval among participants, as the choices generated by AI did not always fit local conditions.

One of the key elements explored during the workshop was how AI affected consensus-building among participants. AI played a supportive role by presenting neutral, data-driven alternatives that facilitated discussions and helped structure debates. This objective allowed participants to focus on the merits of each proposal. Disagree was expressed, notably when the IA proposals lacked the specificity necessary for local implementation.

Participants had to manage these disagreements by re-evaluating the AI recommendations and integrating their professional experience to reach a consensus. For example, AI's suggestions for improvements in public space or zoning regulations sometimes clashed with realities in the San Salvario neighborhood, forcing participants to adjust or reject specific proposals provided by AI.

One of the most notable effects of AI on decision-making was its ability to accelerate specific actions. In particular, AI accelerated the initial stages of organizing data and presenting potential solutions. Instead of manually generating various alternatives, AI could quickly produce options for participants to evaluate. This saved time in the early stages of the process, allowing for a more focused discussion on the feasibility and implementation of specific proposals.

Regarding the results, if we talk about what AI provides, they may become a little bit lacking in information and inconsistent because participants working in the search area had information based on their previous experiences that, when compared with that provided by AI, was not specific enough and sometimes redundant so the search was carried out information by asking different questions which can give as answer options which the participants think are feasible to carry out.

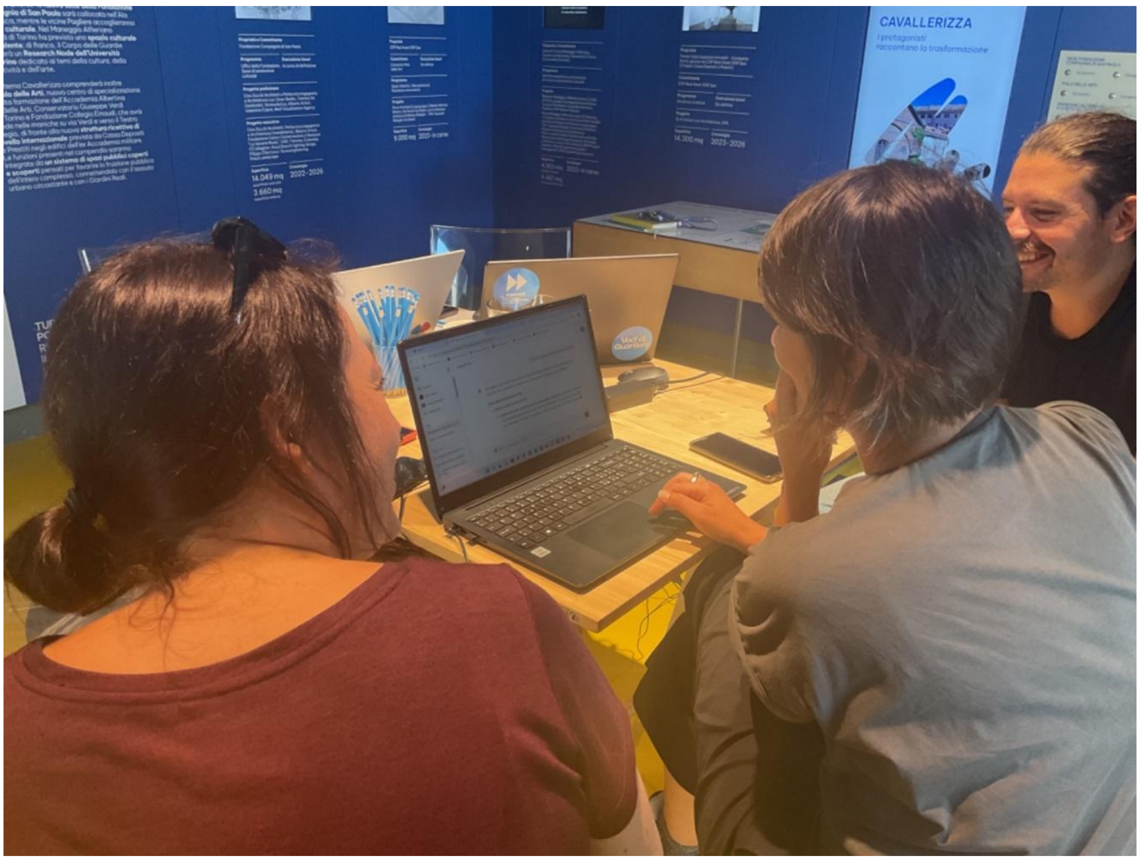

Figure 38. Participants Workshop N° 3. Source: Photo by the author, 2024

A crucial aspect of the workshop was how AI facilitated the decision-making process by presenting neutral, data-driven options, which helped structure discussions more organized and reduce biases. However, the impact of AI on consensus-building was mixed. Although the possibilities proposed by AI helped participants focus on the merits of each alternative, disagreements arose when the proposals were not specific or suitable for the San Salvario context. Participants managed these disagreements by re-evaluating the AI recommendations and integrating their local knowledge.

AI can be a useful tool for structuring debate and offering alternatives that facilitate discussion. However, in this investigation, the decision-making process requires active human intervention to ensure the proposed options are feasible and relevant. In this sense, AI should be seen more as a support tool than an authority in the consensus-building process.

The interaction between AI and the participants' professional experience was essential to the workshop's success. The architects and urban planners present had to combine their local knowledge with the solutions proposed by AI to create viable and specific options for San Salvario. This collaboration underscores that while AI can be a powerful tool for generating alternatives and organizing data, expert knowledge remains crucial for contextualizing and adapting those solutions to real-world conditions. AI should be viewed as a complementary tool rather than a substitute for human understanding. Professionals are still needed to ensure that the proposed solutions fit the characteristics of each urban area and that factors AI cannot capture, such as social dynamics and community needs, are considered.

The MuVAM workshop provided valuable insights into the role of AI in urban transformation processes. While AI proved useful for accelerating certain phases of the decision-making process, such as data organization and alternative generation, its limitations in providing context-oriented and specific solutions were evident. Despite these limitations, the collaboration between AI and human experts was key to adapting the proposals to local realities and ensuring the solutions were feasible and sustainable. In future urban transformation projects, AI must be a supportive tool, not a definitive solution, and always combined with human knowledge and expertise.

Table 10 presents the analysis of Workshop No. 3, which focused on the application of MuVAM software together with AI. This workshop aimed to explore how AI can improve decision-making processes in urban planning, particularly in the rezoning of urban areas, specifically focusing on the San Salvario neighborhood in Turin. Integrating AI tools, such as Chat GPT, allowed them to assess their role in identifying urban challenges, generating solutions, and organizing data during the early decision-making stages.

The workshop included architects with experience in urban development from the Urban Lab Association, who brought their professional expertise to evaluate AI solutions.

MuVAM software and AI facilitated an organized approach to the workshop phases, from problem identification to design refinement. AI was employed to propose data-driven alternatives for urban planning, particularly in the shaping and design stages of the decision-making process. This approach provided a basis for human participants to evaluate, refine, and adapt the AI-generated suggestions to the specific context of the San Salvario neighborhood.

Each category in this table is designed to offer insight into key components of the workshop, such as the project context, the tools used, the role of AI in the decision-making process, and the interactions between participants. This structure allows for a detailed examination of how AI was integrated into the decision-making process, highlighting the advantages and challenges it introduced. By categorizing the various elements of the workshop, a systematic overview of the processes involved in combining human expertise with AI in urban planning is provided.

The table reveals several essential insights from the workshop. One of the main benefits of AI was its ability to accelerate the identification of urban challenges and the idea generation phases. AI supported the initial stages of the workshop by presenting alternatives and organizing data, offering a neutral and data-driven perspective. However, the table also highlights some challenges, such as the generic AI responses, which required significant human involvement to tailor solutions to the specific needs of the San Salvario neighborhood. These insights emphasize the complementary role of AI in urban planning, where human expertise is crucial to refining and localizing AI-generated proposals.

Furthermore, the table highlights the adaptive strategies used during the workshop. AI-generated proposals, such as expanding pedestrian areas, adding green spaces, and optimizing lighting, were useful starting points but required significant adjustments based on the local context. This dynamic interaction between AI and human participants demonstrated a critical interplay in developing this urban planning, where AI can provide significant support. However, it must constantly be refined and carefully studied through professional judgment.

Table 10. Case Study Analysis - Requalification of the San Salvario neighborhood in Turin- MuVAM + AI (Source: own elaboration).

Category	Sub-category	Description / Observation
Technical	Case study	WORKSHOP N°3 MuVAM software application + AI Workshop carried out with Urban Lab (08 July 2024 Turin – Italy)
	Project Context	San Salvario neighborhood, Turin - Italy, focusing on the requalification of urban areas.
	Participants	Architects with urban development experience from Urban Lab.
	Tools used	MuVAM software, Chat GPT
	Use or not of AI	AI was used to identify urban challenges, propose solutions, and organize information.
	Stage of Decision-Making with or without AI	Shaping Mode: Identification of urban challenges. Designing Mode: AI-generated solutions were later refined.
Social	Types of interaction	AI facilitated group discussions by providing data-driven, neutral alternatives for urban planning.
	Inclusion of stakeholders	Based on professional experience, participants evaluated AI-generated solutions and refined them based on local context.
Implementation	Key examples	AI proposed actions like expanding pedestrian areas, adding green spaces, and optimizing lighting, but they needed refinement for the local context.
	Application of MuVAM	The workshop followed MuVAM phases: Shaping, Design, Comparison, and Analysis (the last omitted as a result was unique).

	Limitations and solutions	AI provided generic proposals that lacked specificity, but human input was key to adapting them to local conditions.
Impact	Contributions of AI	AI supported the initial stages by organizing data and presenting alternatives.
	Observed benefits	AI accelerated the problem identification and idea generation phases.
	Observed challenges	AI's responses were sometimes too generic, requiring significant human adjustment.

Several key insights emerge from the analysis of Table 10, providing a deeper understanding of the essential aspects of this case study. These insights can be summarized as follows:

- ***Complementarity Between AI and Human Experts:*** AI demonstrated its ability to generate ideas and structure information in the initial stages of the process. However, the need for human intervention highlights its role as a complement, not a substitute. Local experts' ability to adapt solutions to the specific characteristics of the urban context is crucial.
- ***Rapid Solution Generation:*** AI-accelerated problem identification and solution proposal are particularly useful in urban projects where quick decision-making is essential. However, initial results were too generic, emphasizing the importance of integrating local expertise to refine the proposals.
- ***Contextualization Challenges:*** One key challenge was the lack of specificity in the AI-generated proposals. This underscores the difficulty of creating solutions that consider the complexities of each local environment and the need to train AI models to be more sensitive to these contextual variations.
- ***Social Interaction and Collaboration:*** AI facilitated group discussions by providing neutral, data-driven alternatives, allowing participants to focus on analyzing options. However, human participants evaluating and refining those alternatives was essential to ensure that the proposed solutions were viable and contextually appropriate.
- ***Limitations in Solving Complex Problems:*** While AI is useful for well-defined urban problems, it still faces limitations when addressing more complex and specific issues in a neighborhood or community. Proposed solutions require continuous adjustment to be effective in complex contexts.
- ***Evolution of AI's Role in Urban Design:*** Although AI is still experimental in urban transformation, its potential to enhance decision-making is transparent. In the future, as its ability to understand broader contexts evolves, AI could play a more integral role throughout the entire project lifecycle, from planning to implementation.
- ***Omitted Analysis Phase:*** The omission of the analysis phase in this workshop points to a potential limitation in AI integration. The analysis phase is crucial for evaluating the long-term consequences of proposed decisions. It is important to ensure that AI tools are set up to cover all aspects of the decision-making process.

4.4. Discussion and comparative analysis

The results of the case studies provide valuable insights into the practical applications and limitations of AI in urban transformation. While AI integration supports the efficiency of the decision-making process in some contexts, challenges related to the interaction and responses generated by AI emerged, causing these results to need further refinement to fully exploit the potential of AI in such dynamic and diverse environments. The discussion highlights strengths and areas for improvement, offering reflections on future advancements in applying AI-supported decision-making processes.

A comparison (Table 9) can be proposed on three case studies that explore the application of MuVAM software in combination with AI and its implications for decision-making processes in urban and architectural contexts. Each case highlights different approaches regarding methodology, stakeholder engagement, and integrating emerging technologies, offering insights into these tools' strengths, limitations, and key learnings in collaborative environments.

This critical comparison provides insight into AI's changing role in urban and architectural decision-making while highlighting the indispensable role of human expertise at every stage of the process.

Table 11. Comparative analysis of three case studies exploring the application of MuVAM and AI (Source: own elaboration).

Category	Sub-category	Case 1: Pointe Nord	Case 2: Paracchi Factory	Case 3: San Salvario Neighborhood
Technical	Case Study	Workshop N°1: MuVAM Software Application (24/25 January 2024, Turin - Italy)	Workshop N°2: MuVAM Software Application + AI (29 April 2024, Turin - Italy)	Workshop N°3: MuVAM Software Application + AI (08 July 2024, Turin - Italy)
	Project Context	Transformation of former industrial areas into a mixed-use district under social, economic, and environmental objectives.	Redevelopment strategies for the former Paracchi carpet factory in Turin.	Urban requalification proposals for San Salvario, focusing on pedestrian areas, green spaces, and lighting optimization.
	Participants	PhD students are divided into groups of 4-5, with roles such as observer, moderator, and external observer. Participants had a more theoretical and structured approach, influencing how they organized information without AI.	Master's students from the Architecture Construction City program, Politecnico di Torino. Participants had an intermediate level of experience, allowing them to explore AI but requiring manual validation of outputs.	Architects from Urban Lab with expertise in urban development. Participants were urban planning professionals, making it easier to adapt AI-generated responses while highlighting their limitations.

	Tools Used	MuVAM, whiteboard, laptops, mobile devices.	MuVAM, ChatGPT, Replika AI, whiteboard, laptops, Gemini, CoPilot.	MuVAM, ChatGPT.
	Use or not of AI	AI was not used.	AI was combined with MuVAM to compare traditional and AI-supported processes.	AI was used to identify urban challenges and propose solutions, with participants refining AI-generated outputs.
	Decision-Making Stages	Problem analysis, relationship definition, and prioritization.	AI (ChatGPT and Replika) supported idea generation and ranking, but significant manual intervention was required.	AI supported the shaping and designing modes with the human refinement of AI-generated solutions.
Social	Types of Interaction	Collaborative brainstorming and manual organization of concepts.	AI-facilitated discussions compared with manual outputs to improve understanding and refine solutions.	AI-assisted group discussions offer data-driven alternatives for urban planning.
	Inclusion of Stakeholders	Active participation from all stakeholders (students).	Stakeholders engaged in discussions, though AI's contribution was limited by its generic outputs.	Stakeholders evaluated AI proposals and refined them based on professional expertise and local context.
Implementation	Key Examples	*Example:* Seven problem areas were identified, decision graphs were created, and	*Example:* AI outputs included generic RSA use proposals and room count estimates, which required participant refinement.	*Example:* AI suggested urban actions (e.g., pedestrian areas, green spaces) but lacked context-specific detail,

		solutions were prioritized using manual methods.		necessitating participant adjustments.
	Application of MuVAM	Used as a framework to organize data and prioritize solutions manually.	Facilitated data structuring and scenario analysis, integrating participant and AI-generated inputs. AI was integrated into data structuring, but human validation was necessary.	Followed structured phases (Shaping, Design, Comparison) with localized refinement of AI-generated alternatives.
	Limitations & Solutions	Time constraints and participant fatigue were managed through task division and step reviews.	AI's generic responses required iterative refinement and validation by participants.	AI-generated outputs were too broad, but human intervention ensured alignment with local needs and needed to be adapted to the actual urban context.
Impact	AI Contributions	Not applicable; decisions were based on traditional collaboration and structured frameworks.	ChatGPT accelerated idea generation and solution ranking; Replika provided inconsistent and generic outputs, limiting its effectiveness.	AI-supported data organization and initial problem identification but required refinement for specificity. AI facilitated the initial diagnosis of urban challenges, but participants found its solutions too general.
	Observed Benefits	Enhanced collaboration, systematic decision-making,	AI accelerated comparisons and provided alternative perspectives,	AI sped up the identification of urban challenges and initial solution generation.

	and a better understanding of complex relationships.	though limited by consistency and relevance.	
Observed Challenges	Participant fatigue during the later stages; difficulties prioritizing solutions under limited resources. The dependence on participants' prior knowledge is important for decision-making in a structured manner.	AI’s generic outputs, inconsistencies, and lack of reliable sources required significant participant intervention to validate and adjust.	AI's generic proposals lacked specificity and required human adjustments to align with project goals and local context.

From *Table 11*, it can be highlighted that the *complementary role of AI* became evident as it contributed to certain stages, such as the initial generation of ideas and the organization of data. However, its effectiveness seemed limited in addressing specific contexts or providing customized solutions. This reinforces the perspective that AI should be seen as a support tool rather than a replacement for human judgment. The importance of *human perspective* in all three cases, as well as participants' knowledge and experience, was crucial to interpreting data, refining proposals, and ensuring the relevance of solutions. Without human intervention, AI struggled to deliver satisfactory levels of specificity and adaptability.

Furthermore, *technological integration* presented some difficulties, particularly in the second and third cases, where participants encountered challenges in effectively incorporating AI into their processes. Understanding how to interact with the tools and adjusting their outputs to align with project objectives requires additional effort. These aspects indicate the need for specific training and specialized tools to address local complexities.

Finally, a *collaborative approaches* appeared valuable regardless of the use of AI; teamwork and structured collaboration emerged as essential factors for achieving strong outcomes, especially in contexts where solutions must be validated and fine-tuned collectively.

Table 12 presents some key findings that synthesize the insights and conclusions drawn from the previous case studies, workshops, and application of MuVAM combined with AI. Considering all the data, feedback, and results presented above, this section highlights the most significant learnings that emerged throughout the research. These findings reflect the use of the tools in urban and architectural decision-making, the challenges encountered in integrating AI, and the potential of these technologies to improve collaborative processes. Furthermore, they emphasize the importance of combining technical tools with professional expertise to ensure the relevance and contextual alignment of the proposed solutions.

Table 12. Key Findings. Comparative Analysis of Three Case Studies: Application of MuVAM and AI in Urban and Architectural Decision-Making (Source: own elaboration).

Case 1: Pointe Nord (MuVAM)	Case 2: Paracchi Factory (MuVAM + AI)	Case 3: San Salvario (MuVAM + AI)
	Key Findings	
Workshop Efficiency and Collaboration: The clear specification of roles and tasks enhanced collaboration and decision-making during the workshop. MuVAM allowed participants to visualize and prioritize solutions collaboratively, but the manual process was time-consuming.	**AI's Contribution and Limitations:** AI tools like Replika provided rapid suggestions, but their outputs were often generic and inconsistent, requiring significant human refinement. Despite this, AI stimulated idea generation and helped accelerate scenario comparisons.	**Accelerating Initial Phases:** AI helped accelerate data organization and the generation of potential solutions in the early stages. However, the relevance of these solutions depended heavily on participants' ability to refine and contextualize AI suggestions based on local needs.
Challenges in Time Management: While MuVAM facilitated structured decision-making, time constraints and participant fatigue slowed down the later stages of the workshop. Future workshops should consider optimizing time allocation and integrating more breaks.	**Prompt Challenges:** The varying quality of AI outputs highlighted the importance of precise and well-constructed prompts. Inconsistent AI responses (e.g., proposing irrelevant uses like university residences) forced participants to refine and align suggestions with the project's goals.	**Role of AI in Consensus-Building:** AI provided neutral, data-driven alternatives, which helped structure discussions and reduce biases. However, disagreements arose when AI suggestions lacked specificity or were not feasible in the San Salvario neighborhood context.

Social and Contextual Considerations: Although MuVAM supported the process, it lacked a detailed analysis of the proposed solutions' social, economic, and cultural implications. This gap indicates the need for deeper context integration alongside the tool's technical capabilities.	**MuVAM as a Framework for AI Integration:** MuVAM helped structure discussions, enabling participants to compare AI-generated outputs with human-generated solutions. However, AI was not always fully effective as a decision-support tool, underlining the need for more advanced, context-aware AI systems.	**Human Expertise Remains Crucial:** The collaboration between AI-generated ideas and human expertise was essential to contextualizing and adapting proposals to the real-world context. AI was useful for brainstorming, but human input ensured that solutions were viable and aligned with local dynamics.

In conclusion, comparing the three case studies provides interesting insights into integrating MuVAM and AI in urban and architectural decision-making. Each case highlighted distinct advantages and challenges of these tools, stressing the need to tailor technological solutions to specific local contexts and requirements.

In *Case 1: Pointe Nord (MuVAM)*, clearly defined roles and task distribution fostered collaboration, yet time constraints and fatigue affected the efficiency of decision-making. While technical tools contributed to structuring the process, a more profound contextual reflection was necessary to achieve a well-rounded approach. These observations emphasize the importance of balancing structured methodologies with a broader contextual understanding.

In *Case 2: Paracchi Factory (MuVAM + AI)*, AI played a role in accelerating idea generation but struggled with consistency, highlighting the necessity of practical prompt engineering to obtain meaningful results. Although MuVAM provided a structured decision-making framework, AI did not fully support the process. This demonstrates that further refinement is needed for these technologies to be effective in urban and architectural planning.

In *Case 3: San Salvario Neighborhood (MuVAM + AI)*, AI contributed to early decision-making by rapidly generating initial ideas. Still, human intervention was crucial to refine and validate their feasibility. AI also helped structure discussions and mitigate biases, yet it lacked specificity in addressing local conditions. This case reaffirmed the essential role of human expertise in adapting AI-generated suggestions to real-world applications.

Overall, the key findings (Table 12) highlight the need for a balanced approach that combines technological tools with human judgment to ensure the practicality and effectiveness of proposed solutions. While AI can potentially expedite idea generation and organizing data, its limitations in providing context-aware solutions remain apparent. Integrating AI in urban planning and architecture must involve ongoing refinement, including advancements in AI capabilities, enhanced user training, and a more comprehensive consideration of social, economic, and environmental factors in the decision-making process.

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CONCLUSIONS

Chapter 5. Conclusions

This research has explored the question: How are decision-making processes implemented in urban and architectural contexts in the digital age, and how might the integration of AI support their development? Through a theoretical analysis, the application of MuVAM in case studies, and the evaluation of AI's impact on key decision-making stages, several insights have been gathered that could contribute to a better understanding of the relationship between AI and decision-making processes.

As a starting point, the *theoretical analysis* helped identify the fundamental principles of decision-making processes in architecture and urban transformation. Reviewing the literature on DSS, MCDA, PSM, and SCA allowed me to explore the potential of AI in supporting decision-making. Additionally, this exploration enabled me to propose a theoretical framework for reading and interpreting the selected cases.

Moreover, the *application of MuVAM* in the case studies demonstrated how this structured tool facilitates the evaluation of alternatives in urban and architectural environments. The results suggest that MuVAM helped organize the decision-making process, providing a methodology for evaluating options qualitatively (with different problem-solving alternatives) and quantitatively (through voting to solve the issues posed in each case). However, the effectiveness of this tool may largely depend on the participant's experience and the quality of the information input into the system, which may not always be guaranteed in all scenarios.

Finally, *Evaluation of AI's Influence on the key decision-making stages* revealed that tools such as ChatGPT and Replika influenced the generation of ideas and the structuring of discussions. AI accelerated certain phases of the process and helped reduce bias, although the results generated were sometimes inconsistent and, at times, not very contextual. Despite these limitations, AI could improve decision-making efficiency if an appropriate balance is found with human intervention. The comparison between the approaches showed that, while AI could improve efficiency, its implementation is likely to need to consider the interaction with human expertise to ensure that solutions are viable and aligned with urban and architectural objectives.

Several key findings can be highlighted on how the integration of AI supports decision-making processes implemented in urban and architectural contexts. An important aspect is that the collaborative and structured approach is key in decision-making. Collaborative discussions, brainstorming sessions, and human organization of concepts promoted active participation among participants, allowing problems to be addressed more coherently and contextualized. For example, without using AI, participants analyzed the data based on their professional experience to define the problems. Although this process was slower, the results obtained were more specific and relevant to the context, suggesting that a traditional approach might suit certain aspects. Also, the integration of AI accelerated some phases of the process, particularly in the organization of data and the generation of initial options. AI allowed participants to save time in the early stages of the process, making it easier for discussions to focus more on the feasibility and implementation of specific proposals. However, some results generated by AI presented inconsistencies. For example, in the Former Paracchi carpet factory-Torino case, the number of RSA rooms suggested by AI fluctuated between 30 and 250. At the same time, in the human model, it remained in a narrower range of 30 to 150. In addition, limitations in AI were identified, such as the generation of generic responses, inconsistencies in language, and the need for precise instructions to obtain useful results. In particular, using Replika as a complementary AI showed that its capabilities as a conversational assistant were insufficient to generate decision-support solutions with the necessary depth. The integration of AI also influenced group dynamics. While AI helped structure discussions and reduce some biases, participants still needed to invest time in fine-tuning and contextualizing the suggestions generated by AI to make them more applicable to their needs. This highlights the importance of balancing AI and human expertise in decision-making processes.

These findings suggest that AI has potential as a support tool in architectural and urban decision-making. AI could be useful in structuring problems, assessing multiple criteria more accurately, and fostering collaboration between those involved. AI-powered interactive platforms could promote more inclusive and dynamic participation in decision-making processes, consistent with broader digital transformation trends in architecture and urban planning. Still, its implementation needs to be carefully tailored to local contexts, and its integration must be fine-tuned to ensure that solutions are viable, contextualized, and aligned with sustainability goals, functionality, and community impact.

This study also opens the way for future explorations. Indeed, it focuses on three specific case studies, nevertheless, the methodological framework could be applied to similar contexts, and then further research could extend these findings to other settings and scales. While useful, the AI tools used, such as ChatGPT and Replika, present areas for improvement, especially in generating more contextualized and relevant solutions. Accordingly, the need for accurate inputs and adaptation to local contexts are aspects to be further investigated. Another relevant aspect is that, since AI tools are constantly evolving, the results of this study could be limited by current technological capabilities. As AI advances, the findings must be revised and adapted to new versions of these tools. Also, the effectiveness of AI integration depends on the participant's level of knowledge and familiarity with the technologies, which may have influenced the results. In this sense, the interaction between AI and human participants was crucial to obtaining useful results, highlighting the importance of further developing training and experience in using these technologies.

In conclusion, this research has provided some first insights into the potential for integrating AI to support architecture and urban planning decision-making processes, highlighting the benefits and challenges associated with their evolution in the digital age. The analysis of the three case studies has shown how tools such as MuVAM and AI can optimize data organization, facilitate the generation of alternatives, and promote collaboration between the different actors involved. However, some inherent limitations of these tools have also been identified, especially in their capacity to generate solutions that fully fit local realities and needs. Accordingly, this work highlights the importance of combining such tools with human judgment, showing that, while emerging technologies offer great potential, it is essential to ensure their integration in a way that complements and enriches traditional decision-making processes. The research invites then further research into this field, considering how innovative methodologies can improve decision-making processes without replacing the complexity and understanding that human professionals bring to these processes.

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