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**Beyond Heuristics: A Data-Driven Approach to TOD Typologies in
the Milan Functional Urban Area**

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"There is, however, a fundamental dilemma when trying to make urban development less dependent on the car: the inability of most alternatives to match the quality of accessibility provided by private motorized transport."

Bertolini & Le Clercq (2003)

Abstract

As many contemporary urbanization problems and challenges are interconnected with the dominant car-dependent mobility pattern, including urban sprawl, infrastructure strain, environmental-related problems, and social exclusion, any solution must address the situation from a holistic perspective. Among urban paradigms, Transit-oriented Development (TOD) distinguishes itself because it seeks to reduce car dependency through local urban design while compensating for mobility needs by centering development within walking distance of transit hubs that provide sustainable accessibility. The argument for TOD as a viable solution to car-centric urbanization is further strengthened by studies indicating that the most important physical variable shaping mobility mode choice behavior is destination accessibility. This thesis thoroughly investigates the mode-choice behavior that shapes mobility patterns and tries to understand how TOD corresponds to them. The next step was to move from theory to practice. Given that each city has its own context and mobility infrastructure, adjusting it to TOD principles remains challenging. A critical review of the TOD typology methodologies literature indicated that the most prevalent methods rely on subjective and heuristic approaches, fail to account for human mobility behavior that shapes accessibility. Furthermore, the study highlighted that translating the quantitative results of these models into actionable, targeted policies is inherently complex. Based on these acquired knowledges, a data-driven TOD typology methodology using multivariate techniques (Exploratory Factor Analysis) was developed and implemented on the Milan Functional Urban Area, focusing on the train transit network. During the process, 129 stations were analyzed, and the results led to 7 different profiles with targeted policies and implications to help decision-making processes. The spatial mapping and investigation of the results later confirmed the accuracy of the clusters, which verifies the capability of the

developed model. Even though the model contributed to the methodology, future studies are still needed, as the thesis instructs how to build it further.

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1. Introduction

When talking about sustainability in urban planning, one of the most disputed topics is transportation. It is merely because transportation comes at the intersection of diverse topics like environmental pollution, economic vitality, quality of life, and social cohesion, exerting influence on both local and global scales. European Environment Agency (EEA) publishes a report on 6th November 2025 about the share of different sectors on greenhouse gas emissions in Europe, and according to them, the transport sector has the highest share of the pollution (EEA, 2025). Notably, among the EU countries, Italy exhibits the highest car ownership with more than 765 cars per 1,000 inhabitants. More detailed statistics also indicate that, between 2002 and 2022, the sustainable means of mobility, including walking, cycling, and public transportation, collectively only account for 33.3 % of the total number of trips (Agovino et al., 2025). Therefore, when it comes to sustainable cities, transportation is always one of the most debated topics.

The multifaceted relationship between transportation and urbanization makes the development of effective solutions inherently complex and necessitates interdisciplinary approaches. More broadly, considering the bigger picture, such as social and economic issues, the unsustainability of current transportation patterns is largely attributed to an automobile-dependent form of urbanization, which has its fingerprint on the face of twentieth-century metropolitan identity. Though one could argue that everything has started to change since the industrial era, another could attribute this new pattern to Fordist mass production and the widespread availability of cars for the middle and working classes of society, as it created a self-reinforcing cycle between urban development and car-centric travel, continually producing and sustaining one another. From this argument, it yet remained unsolved to address urban transportation and urban land-use planning in a way that urban development

nullifies the necessity of car-dependency with no or at least with minimum increase in car usage (Bertolini & Le Clercq, 2003).

Municipalities in real-world practices often must balance multiple objectives simultaneously, and sustainability is usually just one goal among others, such as economic competitiveness and social equity, and it is not necessarily even the top priority. Solutions are most likely to succeed when they are designed to achieve multidimensional outcomes, targeting several goals or influencing them positively in different aspects. One of the possible common frictions that provides multidisciplinary benefits in different aspects is improvement in accessibility in a sustainable way (Bertolini & Le Clercq, 2003). Given the various goals, accessibility stimulates economic vitality by providing reliable access to potential employees, suppliers, and a wider base of customers. It also directly influences citizens' welfare by offering a broader range of choices, access to essential services and jobs, and reducing social exclusion, which all address different aspects of the challenges municipalities try to deal with. Ultimately, when accessibility is achieved through sustainable solutions, it helps mitigate the discussed environmental pollution as well.

Examining the impact of car-based accessibility shows us how and why urban sprawl and car-dominated suburban areas emerged. These trends are a direct byproduct of the increased accessibility that cars brought to urbanization, as they effectively shortened perceived distances, making people able to live farther from their workplaces and travel farther to meet everyday needs for most of the society. At the same time, this fostered a self-reinforcing cycle: urban development increasingly stimulates the reliance on cars, as destinations became difficult to reach on foot, and PT does not sufficiently and effectively exist. Hence, this is the interplay between transportation and land-use that meaningfully influences the accessibility (Kenworthy & Laube, 1996), and this is where transit-oriented development (TOD) emerges (Calthorpe, 1993).

TOD, as an urban development and design strategy, provides a set of principles for integrating PT and land use to improve accessibility through sustainable modes of transport. The main idea behind TOD is to create mixed-use communities within walkable distances from transit hubs, where daily needs are accessible by AT and PT, ensuring convenient access to other parts of the city, by concentrating housing, jobs, and services around high-capacity transit hubs. Briefly, TOD coordinates transport infrastructure and land use. This approach is fundamentally different from car-centric urban development, often associated with single-use zoning. The core difference of TOD with Transit-Adjacent Developments (TAD) is to move beyond physical proximity to transit hubs, and instead foster a vibrant, diverse, and livable place where the PT is the regional backbone for mobility (Renne, 2009).

Within this framework, it remains necessary to carefully study and analyze people's mode choice behavior: understanding how individuals' socio-demographic characteristics, entrenched attitudes and preferences, and thresholds for walking or using PT, as well as the costs they are willing to bear, whether time, money, or comfort, shape their decisions (Bertolini & Le Clercq, 2003). Moreover, both the physical environment centered by transit hubs and the quality of transit service influence these dynamics and, in turn, alter the potential accessibility provided by PT and AT. As Bertolini & Le Clercq (2003) argue, to effectively shift reliance away from cars as the primary mode of transportation and toward more sustainable alternatives, the discussion must place the quality - in all aspects - of accessibility at its core. Ultimately, TOD alone does not necessarily guarantee improvement in PT ridership (Md. Kamruzzaman et al., 2013), but it provides the indispensable physical infrastructure that paves the road toward more sustainable transportation. Yet other complementary pieces are needed to move from a car-centric transportation system to a more sustainable one.

Transitioning from theory to practice, TOD involves several key areas of focus, each necessary and complementary to its success (Global Platform for Sustainable Cities,

World Bank, 2018). Among these, the technical and analytical approach including TOD typologies and accessibility, seeks to understand the specific context of a case study before implementing any new interventions, identifying the area's baseline conditions in a regional perspective (Md. Kamruzzaman et al., 2013). This is often done through TOD typology studies, both qualitative and quantitative, which analyze the current transit system and urban context (Lyu et al., 2016). These studies aim to assess the current realities of stations and compare them with TOD norms, thereby guiding and informing the interventions needed to foster more Transit-oriented development (Zemp et al., 2011).

The second key aspect commonly addressed in TOD is urban design and physical planning (Cervero, R. et al., 2002). While creating compact, mixed-use communities near transit hubs forms the foundation of TOD, this must be paired with a high-quality urban environment that fosters both livability and active mobility (Jacobson & Forsyth, 2008). These enhancements in urban structure can help make sustainable transportation more attractive and competitive to car usage. Therefore, designers focus heavily on adjusting public spaces in a way that ensures that walking and cycling are safe, convenient, and desirable for pedestrians. Since TOD is based on mixed-use, high-density areas, effective urban design helps alleviate negative perceptions of density and mitigates issues such as noise pollution and crowding (Cervero, R. et al., 2002).

Governance, institutional, and financial approaches constitute the third key aspect of TOD implementation. Since TOD is inherently a regional solution for improving sustainable accessibility, its implementation requires a macro-level perspective that often spans municipal boundaries (Md. Kamruzzaman et al., 2013). This makes it a politically sensitive process that requires consensus among different types of stakeholders at various levels. To overcome these challenges, cities must establish robust institutional frameworks to align long-term visions across local, regional, and national governments. Financially, the high costs and risks associated with TOD call

for proactive Public-Private Partnerships (PPPs) and the adoption of innovative financial mechanisms, such as land value capture, density bonuses, and targeted TOD lending funds. All crucial for making TOD happen (Cervero, R. et al., 2002), and makes this aspect inherently different from the other two.

This research thesis focuses exclusively on the first aspect, employing a diagnostic regional approach to land use and transportation, specifically examining train stations as transit hubs, to develop targeted policies that inform the policymaking process through quantitative TOD typology analysis (Robillard et al., 2025) for the Metropolitan City of Milan (Italy) case study. However, the scope of the study extends further: with putting 'achieving sustainable transportation' as its central core, it requires a realistic examination of the urban dynamics that ultimately form travel and mobility patterns. Consequently, any analytical model must be designed to effectively capture and respond to these complexities. Yet, as there is no consensus on what the most correct approach is to conduct the analysis, and given that some conventional methods suffer from shortcomings, it is necessary to conduct thorough research about the methodologies in the literature. Eventually, a TOD typology model must be used to create targeted policies, as it is the ultimate goal of this tool (Ibraeva et al., 2020).

The main research question of this thesis is formulated as follows:

- What factors contribute to the success of TOD in achieving sustainable transportation, and which methodology is most effective for developing robust, targeted policies to facilitate TOD implementation within the functional urban areas of Milan?

According to the aforementioned research thesis question, the following sub-questions were developed to coordinate the study:

- What aspects influence mode choice behavior, and how TOD propels those dynamics toward sustainable transportation? And what is the role of accessibility in this regard?
- What are the TOD typology methodologies and how successful they are to capturing the reality of the transit-hubs?
- How can the application of this refined typology model to the Milan Functional Urban Area inform the development of targeted, context-specific urban planning and governance policies?

2. Literature Review

2.1. Introduction and Background of TOD

Transit-Oriented Development (TOD) is an urban planning strategy that has gained popularity since the 1990s to address the consequences of post-World War II urban development patterns. The term TOD was coined for the first time by architect and planner Peter Calthorpe in his book titled “The Next American Metropolis: Ecology, Community, and the American Dream” (1993). To understand the reasons behind the emergence of TOD, we need to understand the morphological shift that occurred in 20th century, exacerbated by ongoing trend of population growth in cities.

TOD and similar new urban design strategies have gained attention in recent decades largely due to the challenges and trends of modern urbanization. Rapid urban growth, combined with rising populations, means that in some regions, over 70% of people are expected to live in cities by 2035. For example, Melbourne, Australia, is projected to reach a population of 8 million by 2050, requiring 1.6 million new residential dwellings (Jeffrey et al., 2019). This is happening while cities are already facing serious problems.

Population growth in cities is not a new phenomenon. However, many cities are already at or beyond their limits. Severe traffic congestion and car-dependency, environmental degradation and climate vulnerability, socio-economic inequity and poor accessibility, transit financial shortfalls & economic inefficiency, and unmanaged urban growth that transforms the natural and agricultural lands surrounding cities into urban areas. In addition to environmental problems such as soil sealing and soil degradation, urban sprawl creates challenges for municipalities and increases costs, as they must invest heavily to expand infrastructure like water and sanitation systems, sewer lines, power grids, and road projects over large distances (World Bank, 2018).

In order to understand why and how cities are facing the aforementioned problems, it is needed to go back and see the urban development patterns that emerged since early 20th century. Urban sprawl, decentralization, car-centric suburbs and environmental pollutions must all be pinpointed as because of a fundamental change in the relationship between production, economy and the cities which is often attributed to the Fordism. Though these patterns had not entirely started by the Fordist system, it must be mentioned that how it turned the middle class into relatively well-paid consumers who could afford cars and more goods. This change directly fueled suburbanization. With car ownership, people were no longer confined to dense, walkable inner-city districts near their workplaces. This transition left a lasting mark on the geography of twentieth-century metropolises, transforming the urban landscape. Inter-urban freeways, sprawling suburban housing developments, separation of land-uses, and auto-centric commercial spaces are all examples of how cities transformed post-war (Jonas et al., 2015).

While reliance on cars promised freedom and mobility, the resulting urban structure led to a crisis. It is widely accepted that car-centric cities are no longer economical or environmentally viable, as we can observe their negative impact every day, like traffic congestion, environmental problems, and the “commuting paradox” where some people want to live in farther locations, because they are looking for bigger housing options to improve their life quality, but they find themselves exhausted because of the long everyday commutes (Stutzer & Frey, 2008; Su et al., 2021a).

Furthermore, it is very important to emphasize the environmental impacts of current urban models. Though it is not the intention of this thesis to critically examine this course, this pattern of development causes high CO₂ emissions, air pollution, and soil sealing of agricultural lands (Su et al., 2021a). The causal effects of such a pattern are evident throughout the car-centric urban form. As cities move toward sustainability, including environmental, economic, and social sustainability, more attention and

efforts focus on alternative solutions to alleviate this paradigm of urbanization (Cervero, R. et al., 2002).

To achieve these goals, some new urban planning paradigms emerged in the 1980s and early 2000s. These paradigms share a common goal: to stop the car-centric pattern of urban development. New Urbanism (USA), Smart Growth, Green Urbanism, The Compact City (Europe), and Sustainable Mobility Paradigm are among the new approaches. These paradigms are not entirely distinct from each other and often overlap. For example, TOD can be considered the regional transportation component of the New Urbanism movement (Jacobson & Forsyth, 2008; Schwanen & Mokhtarian, 2005).

2.2. TOD Definitions and Interpretations

There are many different interpretations of TOD and various ways to define it. However, it is widely accepted that TOD is mixed-use development well-served by public transit. The integration of land use and transit infrastructure is the main principle of TOD (Cervero, R. et al., 2002). Peter Calthorpe defined TOD in his book as: “A Transit-Oriented Development is a mixed-use community within an average 2,000-foot walking distance of a transit stop and core commercial area. TODs mix residential, retail, office, open space, and public uses in a walkable environment, making it convenient for residents and employees to travel by transit, bicycle, foot, or car” (Calthorpe, 1993, p. 56). According to him, TODs can be implemented in both city and suburban contexts, the difference only derives from the density in two cases (Calthorpe, 1993).

Calthorpe, in his book, argues that the “walkable” environment is centered on this concept: if we want to build a solution to overcome car-oriented transportation, we need comfortable, viable pedestrian areas at both the origin and destination of trips (Calthorpe, 1993, p. 41). While such a strategy in development pattern has similarities

with other concepts that they also seek to overcome the negative consequences of car-centric development like Pedestrian Pockets, Traditional Neighborhood Developments, Urban Villages and Compact Communities, TOD's additional emphasis compare to other solutions is on the integration of transportation on a regional basis in a way that rail-transit network (or other transport means) provides the backbone of mobility, and this prevents the urban sprawl happening by the emergence of distant sites that are accessible only by highways (Calthorpe, 1993).

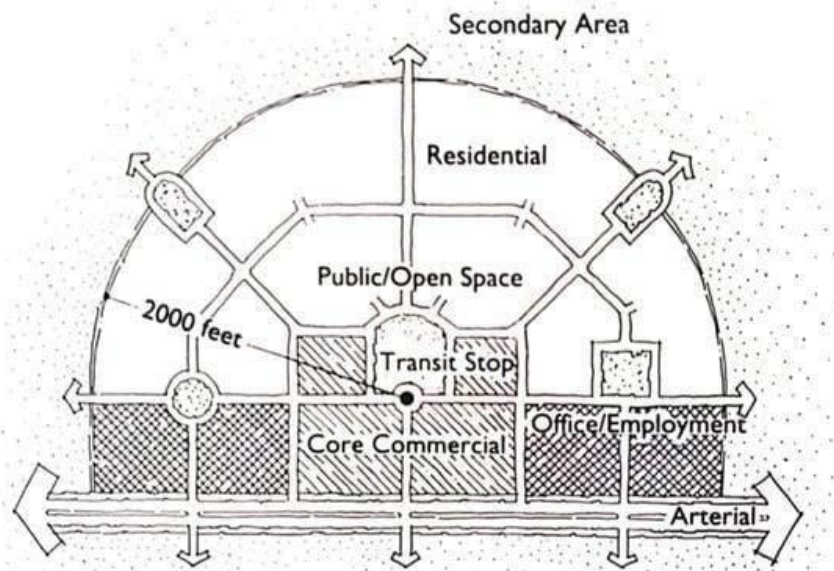


Figure 1 - TOD in place¹

The aforementioned definition of TOD primarily approaches it through a lens of the built environment (Calthorpe, 1993; Cervero, R. et al., 2002; M. Bernick & R. Cervero, 1997), though scholars define TOD from their specific perspectives as well. Another perspective is the functional coordination and planning perspective (Su et al., 2022). For instance, Bertolini (1999), by his foundational work that started the quantitative TOD typologies literature, viewed TOD as a strategy in which a station has a dual interconnected dimension of its status within the transit network, which is called “Node”, and the station's local, reachable by walking area, where diverse human activities occur which is called “Place” (Bertolini, 1999). Many other scholars later

¹ Note. From *The Next American Metropolis: Ecology, Community, and the American Dream* (p. 56), by P. Calthorpe, 1993, Princeton Architectural Press.

expand this definition on similar basis (Schlossberg & Brown, 2004; T. Parker et al., 2002; Vale et al., 2018).

Many TOD studies have also been significantly shaped by the development of the "Ds" concepts since its introduction. It was first introduced by Cervero and Kockelman (1997) through 3Ds: Density, Diversity, and Design. Their empirical study took place in San Francisco, where they examined how various aspects of the built environment affect travel behavior, proposing that these influences can be captured through the 3Ds headings. Their results showed that while each individual dimension had a relatively modest effect on reducing trip rates and promoting non-automobile travel (with elasticities ranging from 0.06 to 0.18) that does not make a difference, they collectively account for a significant impact. This research highlighted that simply increasing housing density near transit stations is not enough (Cervero & Kockelman, 1997), and instead, a collective approach that addresses multiple built environment factors is needed to fulfill the aims. Later, the framework expanded into 5Ds by adding Destination Accessibility and Distance to Transit (Ewing & Cervero, 2001). Later, the authors posit that the Destination Accessibility is the strongest predictor of travel behavior (Ewing & Cervero, 2010), this assertion is also in accordance with other scholars as well (Bertolini & Le Clercq, 2003). The Ds framework eventually influenced TOD literature as many scholars conducted their work around developing and assessing their case studies through this perspective (Jeffrey et al., 2019; Niu et al., 2021).

There are other perspectives toward TOD as well, for instance: the behavioral, economic, and social perspective (Su et al., 2022). Boarnet and Crane (1997, 1998) articulate TOD as a tool for urban investment, defining it as a "Practice of developing or intensifying residential land-use near rail stations" to increase public investment and promote public transport use. Still (2002) focused on commuter behavior and defined TOD as a tool to encourage people to live near transit hubs to decrease their dependence on driving. Salvensen (1996) focused on real estate and development

aspects and framed it as "Development near transit hubs with a variety of land uses and a multiplicity of landowners". Also, Olaru et al. (2019) articulated TOD as a sustainable strategy near public transport hubs.

Lastly, we can observe institutional perspectives that mostly occur within the framework of governance. Different state agencies, such as the California and Maryland Departments of Transportation (Su et al., 2022), define TOD as a moderate-to-high-density development located within an easy walkable distance of transit hubs. They emphasize development features like the rest of the approaches that are pedestrian- and bicycle-friendly, while not entirely excluding automobile use.

2.3. Role of TOD in Modal Shift from Private Cars to Active Transport and Public Transport

In order to be able to enable the modal shift within urban transportation, it is needed to understand what cars and public transport (PT) offer. Technically, cars have high speed and high flexibility, meaning that people can use cars whenever they want (as they usually own one) and go quickly wherever they need (as the urban structure allows them). The current urban structure lets you pick up your car, usually next to your door, and drive to your destination. In contrast, using public transport involves taking several steps: first, you need to walk to the station, wait for the vehicle, and ride to the nearest stop to your destination. You might need to transfer lines or switch modes, and often you'll have to walk the final stretch. It's also important to note that even when the network is extensive, public transport stops are not always conveniently located near the start or end of every trip. These characteristics of public transportation compared to cars translate to lower flexibility, where you cannot get off the vehicle at the door of your destination. Also, in urban planning point of view, it is important to consider that public transportation has a high capacity for carrying people, while private vehicles do not have such capacity. Lastly, active transportation

(AT) or walking and cycling are the most flexible means of mobility but the least fast (Gan et al., 2021; L. Bertolini et al, 2009).

This introduction was conducted to clarify what TOD does. With respect to accessibility, TOD combines the AT and PT together to benefit from the speed and capacity of PT and the flexibility of AT to improve their collective accessibility. TOD concentrates most of the daily destinations and origins within a walkable friendly distance from transit-hubs, where people can access to the daily needs within a walkable range of distance, and when they need to go somewhere farther, they can easily access the PT which takes them to a station that is close to destination, where they only need to take an acceptable amount of walk to reach there (L. Bertolini et al, 2009). However, given that people may go from anywhere to anyplace (Bertolini et al., 2005), the argument for regional accessibility for public transportation remains vital on top of flexibility and speed in this competition .

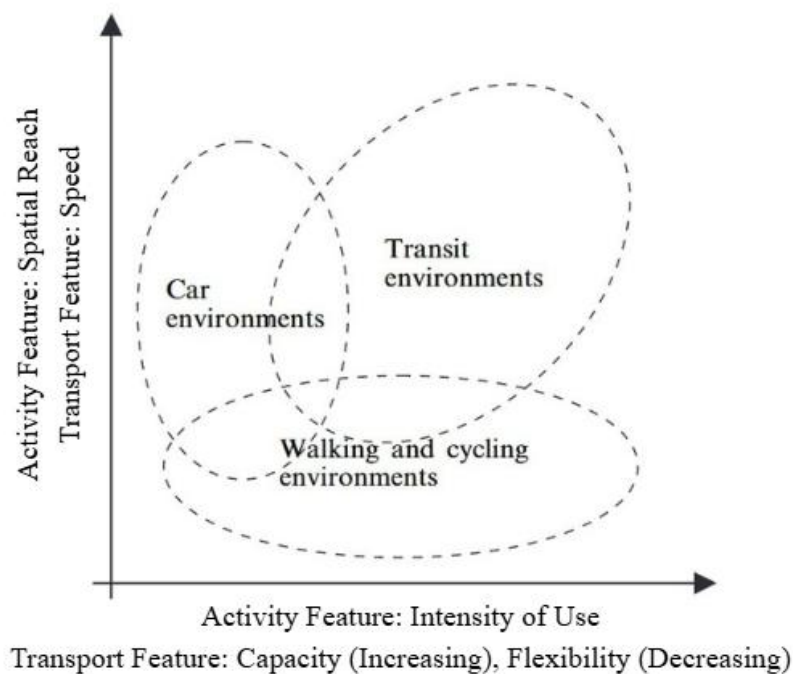


Figure 2 - Principles of multimodal urban / regional development: conceptual scheme. Adopted from (Bertolini & Le Clercq, 2003).

Ultimately, it is crucial to note that while TOD provides necessary physical and spatial foundation for enabling the modal shift toward more sustainable transportation, it

alone does not make it happen, as it is only one of the pieces needed to achieve this goal (Md. Kamruzzaman et al., 2013; Phani Kumar et al., 2018; Robillard et al., 2025). Policy interventions that aim for this modal shift are categorized in two groups of Push and Pull where in one you discourage people to use their cars or make it less desirable and where you use incentives and interventions by which you persuade people to shift toward more usage of public transportation (Cools et al., 2009). In conclusion, as Kamruzzaman (2013) points out, these can be classified also as soft (psychological) and hard (structural) interventions. In this context, TOD seeks to facilitate a modal shift toward PT and AT by improving the station environment, then it is classified as a hard intervention.

Besides the inherent differences in the characteristics of each transportation mode, a body of literature on the impact of urban form on travel behavior suggests that residential location and travel mode choice are interconnected (Schwanen & Mokhtarian, 2005). Scholars empirically claim that living in dense, mixed-use neighborhoods is associated with lower car dependency than in low-density, suburban environments (L. D. Frank & G. Pivo, 1994). This finding affirms that TOD can benefit the modal shift, however still some doubts persist.

2.4. Individuals' Characteristics in Mode Choice Behavior in TOD areas

Schwanen and Mokhtarian (2005) argue that although the literature affirms that urban structure can affect the reduction in car usage, it is unclear what the magnitude of land-use's role in influencing commute behavior is. In continue, they argue that other factors like sociodemographic factors, like gender, household size, and income have a relatively higher importance in shaping the commute behavior compare to land-use and furthermore travel-related attitudes or lifestyle variables may be even more

important than socio-demographics in explaining this behavior (Schwanen & Mokhtarian, 2005).

Given that one of the primary goals of TOD is to increase ridership of PT (Su et al., 2022), it is crucial to better understand the factors that can influence mode choice to make sure the TOD corresponds to those variables effectively (Md. Kamruzzaman et al., 2013; Phani Kumar et al., 2018). This matter is of great importance because some scholars argue that residing in a TOD area helps adjust attitudes to eventually use PT more than before (Phani Kumar et al., 2018; Schwanen & Mokhtarian, 2005). Hence it is important to understand what the relationship between the neighborhood environment, demographic characteristics and mode choice is.

One of the greatest challenges to understanding whether TOD is efficient is the Residential Self-Selection argument. The residential self-selection argument holds that households choose to live in places that align with their preferred travel modes (Schwanen & Mokhtarian, 2005). A group of scholars later the same basis articulated the relationship between the living environment and residents' attitudes using the terms "TOD Consonance" and "TOD Dissonance": people who are already inclined to use PT live in TOD areas are TOD consonants, and when they live in non-TOD areas, they are non-TOD dissonants. On the other hand, people who are inclined to use their cars are TOD-dissonant when they live in TOD areas and TOD-consonant when they live in non-TOD areas (Md. Kamruzzaman et al., 2013). Therefore, it is important to understand whether living near good transit hubs over time transforms people to use PT more, or whether people who already prefer to use PT come to areas with good PT access.

To understand this, Kamruzzaman et al. (2013) conducted a longitudinal analysis in Brisbane, Australia, to determine whether preference change occurred in the short term (2009) and the mid-term (2009 – 2011). In their analysis, they first identified TOD and non-TOD areas by using 5 environmental indicators (residential density, land use diversity, intersection density, cul-de-sac density, and public transport accessibility

level) and conducting a cluster analysis, and then 16 variables used to measure whether 3957 residents in those neighborhoods were dissonant or consonant. The result of the analysis has an important implication: the entrenched attitude problem. Meaning that even though having a high-quality TOD area, it does not necessarily change the travel preference of people, and TOD dissonants often continue to rely on cars (Md. Kamruzzaman et al., 2013). It is obtainable that TOD does not increase total PT ridership as the author justified that by explaining TOD dissonants often move to the suburbs, where they can more easily use their cars, while non-TOD dissonants rarely move into TODs, often because of housing costs or constraints due to the need to be in proximity to specific jobs or schools (L. Kamruzzaman et al., 2013).

Based on the mentioned literature, while TOD alone may not directly prompt a modal shift from car use to public transport among TOD dissonants, it serves as essential infrastructure. TOD creates high-quality, walkable areas with excellent access to public transport, but additional interventions are needed to encourage changes in travel behavior for this group (Agovino et al., 2025; Md. Kamruzzaman et al., 2013; Phani Kumar et al., 2018).

Regarding the factors that influence mode choice behavior, there are many studies, most of which are cross-sectional. Age, gender, car ownership, attitudes, self-efficacy, social norms, trip purpose, trip start time, and locational characteristics can influence mode choice behavior. More importantly, longitudinal analysis revealed that the factors that may cause behavioral change are relatively rare (Md. Kamruzzaman et al., 2013). Kamruzzaman (2013) in his article also points out that there are dynamics that influence trip behavior, like micro-dynamics (daily changes), macro dynamics modifiers (several years), and macro dynamic processes (lifespan changes).

Demographic studies on mode choice behavior confirm that women, younger people, low-income groups, singles, and those without cars are less likely to drive than other groups, including larger families, wealthier people, and car owners (Limtanakool et al., 2006). Moreover, studies show that women have more environmental concern,

weaker car habits and more willing to reduce car usage (Md. Kamruzzaman et al., 2013). Eventually, Thøgersen (2006) asserts that past behaviors (long-established habits) are a strong predictor of today's choices.

This body of literature studying individuals' preferences and attitudes toward mode choice also asserts that individual-level changes (e.g., car ownership) are not the only influential factors in mode choice, but that systematic changes (e.g., land-use) are also influential. For instance, during the 2002 Olympic Games, as a countermeasure to the shortage of car parking, the University of Utah opened a new light-rail line. Later, the surveys indicated that while people were reluctant to use PT, when they started to use light rail because of necessity, and they experienced the ease of using it, they gradually showed interest in continuing their use when the restrictions were lifted (Brown et al., 2003). There are other studies on the system-level changes, like a report on significant change from cars to PT after the opening of Manchester's Metrolink (Knowles, 1996), and other studies showed that the shift from cars to metro is smaller than shifts from other modes (Golias, 2002).

Ewing & Cervero (2010), in their article "Travel and Built Environment: A Meta-Analysis" identified over 200 studies examining the relationship between the built environment and travel behavior. They conclude that though the relationship between these two is statistically significant, the magnitude of the effect is very different. They argue that destination accessibility is the dominant environmental influence on travel behavior (Cervero & Kockelman, 1997; Ewing & Cervero, 2010).

Eventually, Golias (2002) showed that travel time and cost are the strongest predictors of commute mode choice. Kamruzzaman et al. (2013) conclude that changes in attitudes and intentions are crucial for shifts in travel behavior, still more confirmatory studies on longitudinal changes are needed.

2.5. Importance of Destination Accessibility and Travel Cost in TOD

Bertolini et al. (2005) offer a distinct perspective on the critical role of accessibility in achieving sustainable transportation objectives. While the integration of land use and transportation is widely regarded as an effective strategy for promoting sustainability, the authors contend that accessibility is the key concept for understanding the functional benefits of this integration. According to him and a handful of other scholars, understanding the role of accessibility provided under TOD as a competitive tool that matches the accessibility of non-sustainable modes of transportation is often neglected (Bertolini et al., 2005; Cao et al., 2020; Robillard et al., 2025; Vale, 2015).

There are different approaches toward how to define and conceptualize accessibility (Bertolini, 1999; Bertolini et al., 2005; Cao et al., 2020; Cascetta et al., 2013; Coelho et al., 2025; Ewing & Cervero, 2010). Cascetta et al. (2013), at the start of their paper, point out that accessibility is related to the interplay between activities within a territory and the transportation system that supports them. Later in their article, Cascetta et al. (2013) quote a definition by Hansen (1959 as cited in Cascetta et al., 2013), who defined accessibility as the number of opportunities individuals in a certain location can participate in. This perspective later diverged into two different points of view (Cascetta et al., 2013).

Another view, with a systemic lens, defines accessibility as the extent to which land-use and transportation systems enable an individual to reach activities and opportunities by transportation modes (Cao et al., 2020). The systematic view can also be refined into two perspectives: Active (or Person) Accessibility, and Passive (or Place) Accessibility. Where the former implies the ease with which an individual can access potential activities such as shopping, entertainment, education, etc. While the latter refers to how destinations are reachable by potential users (Cascetta et al., 2013). Specifically, in evaluating public transportation and TOD, accessibility refers to two distinct spatial aspects. First, local access enables an individual to reach transportation

stops from the origin of the trip, which, under TOD, is expected to be done often by walking, cycling, or feeder-mode travel. And destination accessibility, which refers to the effectiveness of desired destinations and opportunities within the TOD, as well as the transit hubs that connect to them (Coelho et al., 2025).

The definitions and significance of destination accessibility become particularly salient when recognizing that, within the context of TOD, it is not feasible to situate all desired destinations within walkable areas. This limitation necessitates viewing TOD and its associated stations as components of a complementary network (Huang et al., 2018). This understanding channels us toward placing greater importance on Passive Accessibility, as we recognize the strategic importance of planning to ensure public needs are regionally accessible through the network of TOD (Cascetta et al., 2013). This understanding of Passive Accessibility explicitly addresses the “Optimal Location Problem” discussed by Cascetta et al. (2013), who stated that, despite limited attention to Passive Accessibility, it is designed to solve “the problem of optimal displacement of Public Utilities and Services”. This again aligns with Ewing and Cervero (2013) assertion that empirical findings prove that destination accessibility is the ultimate mode choice behavior.

Back to Bertolini et al. (2003), they directly address the failure of urban development to replace car-dependency for mobility with public transportation, as the alternatives fail to match the quality of accessibility provided by cars. According to them, accessibility is the central argument in this competition (Bertolini & Le Clercq, 2003). Therefore, it is essential to advance our understanding and analysis using precise measures of multimodal potential accessibility, as enabled by the integration of active transportation (AT) and public transportation (PT) modes. This includes evaluating trips with a combination of different modes like walking and train transport, cycling and bus transport, etc. Also, systematically comparing these combinations with the accessibility that is provided by private automobiles. Furthermore, incorporating the cost associated with each mode is a critical factor in explaining and predicting mode

choice (Agovino et al., 2025; Beria et al., 2017; Bertolini et al., 2005; Cascetta et al., 2013). This premise also hints for how underserved areas within potential destinations can deteriorate the overall effectiveness of TOD in reducing car-dependency and modal shift (Agovino et al., 2025).

2.5.1. Methodologies on Accessibility Calculations

Accepting that the discussed accessibility is very important in the urban context, then we need to answer this question: How to assess the accessibility? A common approach involves the use of isochrone models (Euclidean), which rely on straight-line distances to delineate catchment areas. This approach is very simple and easy to use, however actual movement within cities is profoundly shaped by the urban context, including streets configuration, topography, safety, travel time (day vs. night), individual characteristics, and urban design factors, which such models fail to properly capture (Biba et al., 2010; Coelho et al., 2025; Verma & Ukkusuri, 2025).

Isochrone models use rigid, binary cost thresholds, such as fixed time limits. The primary failure of this method is that it cannot reflect the complexity of real-world mobility systems. For instance, these models simply exclude all the destinations that just fall outside the defined range. If the standard threshold is set to 15 minutes' walk or an 800-meter radius, they simply exclude an important destination within 810 meters (Cascetta et al., 2013). Such oversimplification can result in significant behavioral overestimations or underestimations. One of the most enlightening examples in literature is the work of Cascetta et al. (2013), who compare two models: an isochrone-based model, where the model identifies 2,150 shops within the range of access, while a more sophisticated model, like a behaviorally calibrated model, demonstrates access to only 175 shops. This is a huge difference between the results of these two models.

A more accurate alternative to isochrone models is gravity-based (potential) accessibility that uses an impedance function (Beria et al., 2017). The key innovation of this model lies in the application of distance decay, such as negative exponential or power-law curves, which avoid binary inclusion or exclusion of destinations (Verma & Ukkusuri, 2025). Such an approach uses a function where the potential accessibility of destinations diminishes with an increase in the general cost, which can be time or distance. However, the traditional Gravity-based models, as Verma & Ukkusuri (2025) discussed, have limitations. These models used a generalized (fixed) impedance function for all types of trips, without accounting for factors that drastically affect accessibility, such as socio-economic factors, means of travel, destination, and purpose. Therefore, using a fixed impedance function for everyone is not accurate as well. Studies show that using a generalized impedance function can lead to up to 80% overestimation of public transit accessibility. Consequently, factor-specific impedance functions are necessary (Verma & Ukkusuri, 2025).

$$A_i = \sum_{j=1}^n M_j f(\beta, x_{ij})$$

Equation 1: Location-based Potential Accessibility, where A_i measures of accessibility from the origin i , M_j is the mass of opportunities, β is the sensitivity parameter to x_{ij} which is the impedance variable of the trip from i to j (This formulation is general and both M and x can be defined differently) (Beria et al., 2017).

There are also different functional approximations of impedance functions, like the Gravity Model (Power Law), Negative Exponential, and Power Exponential & Truncated Polynomial (Cheng & Bertolini, 2013; Halás et al., 2014; Wittowsky et al., 2020). In any case, this is the shape and the parameters of the impedance function that determine the potential accessibility. Verma & Ukkusuri (2025) among all the families of impedance functions, modeled their impedance distribution using Complemented Cumulative Density Function (CDF), because this model as it inherently conforms to the principles of impedance decay as the probability starts at 1 when the distance (or time) is 0, and the probability goes toward 0 when the distance goes toward infinite. Then to functionally approximate these CDF curves, they applied Negative

Exponential Function (Eq. 2) because it relies on a single parameter, and it enabled them to measure and compare the individual impact of various covariates on travel impedance.

$$f(x) = \exp(-\beta x) \quad (\text{Eq. 2})$$

In the function above, the β is decay rate parameter, determined by four key categorical factors: Travel mode, trip purpose, urbanity status, and traveler's socio-economic status (Verma & Ukkusuri, 2025). These parameters, as previously mentioned before have a substantial role in determining the travel time, mode choice and accessibility (Cascetta et al., 2013; L. Kamruzzaman et al., 2013). Verma & Ukkusuri (2025) calculated the decay rate parameter for the following specific factors: travel modes, purposes, urbanities, and socio-economic status (See Table 3 in Verma & Ukkusuri, 2025).

It is essential to acknowledge that the parameter beta is not scale independent. In other words, it is completely context-dependent and cannot be transferred to other areas. Even within the same country, and for the exact factor (like the purpose of the trip), the resulting beta value can fluctuate significantly city by city (Beria et al., 2017; Halás et al., 2014). Halás et al. (2014), conducted a massive study to calculate specific distance-decay functions for 144 different regional centers in the Czech republic, they concluded that each city has its own specific conditions, that is determined by its location, and geographical context (Halás et al., 2014). Furthermore, beta parameters are completely dependent on how the "cost" is defined, which is an originally context-dependent factor (Beria et al., 2017).

There are a few attempts to improve the accessibility calculations in Italy. One of them is Beria et al. (2017) who criticize the use of simple physical distance or travel time as impedance variables, highlighting their inability to account for factors such as network connectivity, congestion, and fares. In response, they conducted a comprehensive study on the calculation of generalized cost as an impedance variable across the country. They used an exponential decay function, to approximate how

individuals' willingness decreases as the cost increase, however they did not have an empirically calibrated beta value, and they performed a sensitivity analysis on the beta parameter by testing various other beta values (0.1, 0.03, and 0.005) to see how it alters the map of Italy. Eventually they used 0.01 for beta. The authors eventually admit that scientifically calibrating this parameter for national level is "virtually impossible" (Beria et al., 2017).

Beria et al. (2017), however, argue that calibrated factor-specific impedance functions are generally more feasible at the regional scale, where it is possible to gather detailed survey data. For example, Bifulco, Cartenì, and Papola (2010) conducted a survey of 300 individuals to empirically develop activity-based models for commuting workers in Naples. Building on this, Cascetta et al. (2013) utilized the calibrated parameters to build a gravity-based model. Also, to propose and test the new Perceived Opportunities model (Another form of assessing the accessibility), they conducted a survey of 100 students. They acknowledged, however, that the results were only partially reliable and ultimately chose not to publish the specific values of the new model (Beria et al., 2017; Bifulco et al., 2010; Cascetta et al., 2013).

As this thesis has a special focus on Metropolitan City of Milan, it is crucial to note that there is a notable absence of literature on empirically calibrated generalized cost or factor-specific impedance functions for the case study.

2.6. TOD Typologies

In almost all of the areas where TODs are proposed, planning does not begin with designing neighborhoods from the ground up. Rather, there are pre-existing neighborhoods and developments do not start from zero (Huang et al., 2018), train stations, and transit lines, each characterized by its own distinct situations and dynamics. This urban status quo renders every city a unique case, requiring tailored strategies and adaptations to shift toward TOD principles if the area is not already

transit oriented. The conclusion here is that we need to understand and comprehend the context in order to put forward any adjustments toward making the current areas transit-oriented (Singh et al., 2017).

This is where TOD typology methodologies emerge, a viable tool in order to evaluate the existing conditions (Huang et al., 2018; Robillard et al., 2025). By systematically analyzing train stations and their surrounding urban catchment areas, TOD typology categorizes stations based on key characteristics and classify them into distinct clusters (Li et al., 2019; Robillard et al., 2025). This approach facilitates targeted planning and policy interventions tailored to the specific needs and opportunities of each cluster considering the fact that there is no one-fits-all model for any city (Huang et al., 2018; Lyu et al., 2016; Su et al., 2021).

Given the benefits of TOD typologies in enabling target policies, it is worth noting that many cases in which TOD policies are implemented or considered for implementation often involve a high number of stations. For instance, Chengdu (China) with 213 stations, Lisbon (Portugal) with 83 stations, Beijing, Shanghai, Shenzhen, Hangzhou, and Wuhan (China) with 1294 stations, Austin (USA) with 133 stations, etc. (Liu et al., 2025; Su et al., 2021a; Vale, 2015; Zhao et al., 2024). Understanding the magnitude of the work and the interconnected nature of TOD, which functions as a network rather than isolated transit hubs, it is important to analyze and group these stations into clusters that share similar characteristics. Therefore, TOD typologies at least enable: 1- Assessing the base situation, 2- Reducing complexity, and 3- Targeted policy packaging (Ibraeva et al., 2020; Robillard et al., 2025; Singh et al., 2017). Traditionally, rail infrastructure companies, such as SBB infrastructure in Switzerland, DB Station & Service in Germany, and Network Rail in the UK relied almost exclusively on passenger frequency to classify their stations. However, the literature suggests several other approaches that more comprehensively can capture the context of the sites (Zemp et al., 2011), there are two main approaches within TOD typologies literature: Qualitative and Quantitative (Lyu et al., 2016; Wu et al., 2024).

2.6.1. TOD Typologies: Qualitative Approach

Qualitative TOD typologies, or Normative TOD typologies, are divisions of TOD typology methodology based on the abstract, ideal characteristics of what different contexts of TOD should look like. It can address characteristics based on target description. Considering that each city has its own unique context, generally there is no definite number of typologies.

It was also Peter Calthorpe (1993) who provided a preliminary normative category of TODs by distinguishing between “Urban TODs” and “Neighborhood TODs”, in which the primary difference between these types lies in their urban morphology, land-use activity, and densities. Urban TODs are used along major transit hubs and are characterized by high commercial intensity, job clusters, and moderate-to-high residential density. Neighborhood TODs also refer to areas located along feeder bus routes and are characterized by a residential focus paired with local-serving shops and other amenities (Calthorpe, 1993).

While Calthorpe created the initial foundation for TOD typologies with his urban and neighborhood divisions, other scholars expanded it like Dittmar and Poticha (2004), create a distinction between urban and suburban TODs by categorizing them into Urban downtown, Urban neighborhood, Suburban town center, Suburban neighborhood, Neighborhood transit zone, and commute town. This classification itself inspired emergence of more nuanced types as well.

2.6.2. TOD Typologies: Quantitative Approach

Quantitative TOD typology analysis is another solution for assessing the context of the transit hubs that rely on numeric measurements and empirical data that support clustering the stations into different scenarios. This enables scholars to systematically assess the potential for implementation or the effectiveness of existing TOD networks.

The earliest approach in quantitative analysis of TOD can be attributed to Bertolini (1996), in his seminal articles "Nodes and places: complexities of railway station redevelopment" and "Spatial Development Patterns and Public Transport: The Application of an Analytical Model in the Netherlands" (Bertolini, 1996, 1999), by distinguishing a dual nature for transit hubs, which later has been started to be used in literature and called the Node-Place Model and since then, it has been 30 years that TOD literature has been using various methods to conducting TOD typologies in quantitative way to support policy making (Kang & Miwa, 2025).

Bertolini observed that modern cities are simultaneously expanding outward and also becoming more compact. As the cost of living rises in urban centers, people and businesses are drawn to more affordable areas. At the same time, advances in communication technology facilitate the decentralization of activities. On the other hand, despite this decentralization, many industries and activities still and will rely on face-to-face interaction, like finance, media, culture, and sports events. This paradoxical dynamic creates a need for specific hubs where physical convergence can occur. (Bertolini, 1999).

He also concludes by asserting that the convergence of people at a node does not necessarily increase interaction, though it increases the "potential" for interaction. If a transportation node is not treated merely as a transit node but as a "place" integrated into its urban surroundings, it can foster sustainable and economic growth. He believes that to exploit this potential, it is necessary to stop seeing transportation infrastructure in isolation. Instead, the node (transit quality) must be balanced with place (local characteristics such as diversity of activities and land use) (Bertolini, 1999). The node-place model of his is based on these principles.

In Node-Place Model, Bertolini (1999) argues that the accessibility provided by the transport it is not just about "How many destinations we can reach", but also "How many, and how diverse are the activities that can performed in an area?" (Bertolini, 1999). So, it is understandable, it is not only about where can go, but also what can do.

Though understanding the dynamics between this Node and Place is essential for assessing the TOD potentials. To assess this interplay, at the Universiteit Utrecht a model was developed that mapped this relationship between these two dimensions.

According to Figure 3, the Node dimension evaluates a station's transport supply through variables such as daily service frequency, number of directions, and the number of stations served. The Place dimension encompasses factors that assess urban development within a 700-meters radius around the transit hubs, by measuring variables like population density, employment levels, and the degree of functional land-use mix. After measuring these indicators, stations are mapped and classified into five distinct groups: Dependent Areas, Balanced Areas, Stressed Areas, Unsustained Nodes, and Unsustained Places (Bertolini, 1999). Notably, Bertolini (1999) argues that, over time, stations will tend to move toward the central "equilibrium" line. For example, an Unsustained Node may eventually develop or lose its transit service.

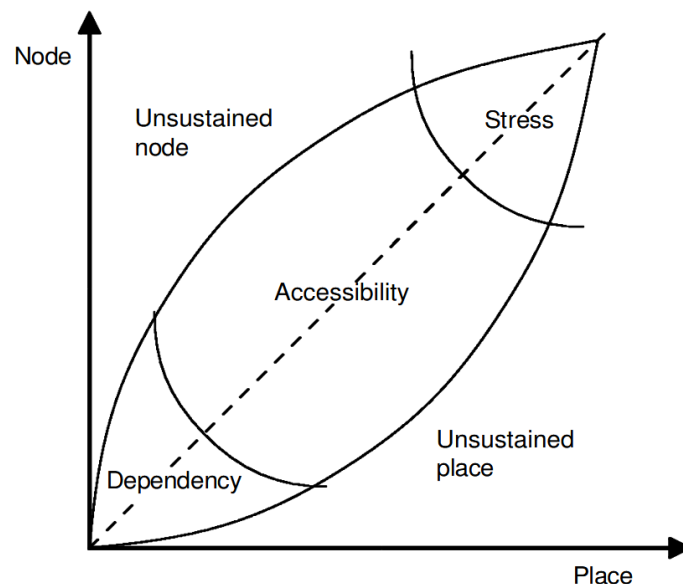


Figure 3 – Node-Place Model.²

² This diagram illustrates the four situations based on the relationship between transportation accessibility (node) and activity intensity (place). From "Nodes and Places: Complexities of Railway Station Redevelopment," by L. Bertolini, 1996, *European Planning Studies*, 4(3), p. 335. Copyright 1996 by Taylor & Francis.

Evolution of Quantitative TOD typologies

2.6.2.1. Dimensions: Heuristic Approach Problems

This section aims to critically review the literature to address the following question: *How has the methodology of TOD typologies evolved over time, and what constitutes the most robust framework?* Emphasis is placed on the selection of dimensions.

Node-Place assessment of TOD typologies soon gained lots of recognition and attention from the body of the literature and scholars. Over time, it has been refined and enhanced through various academic contributions. Kang & Miwa (2025), through their systematic review of 65 papers in this field, categorize the methodologies into five groups: (1) NP models, (2) Mixed NP models, (3) Validated NP models, (4) Visually Supported NP models, and (5) Extended NP models. Notably, the authors emphasized that the types are not distinct and many methods in the papers fall under several types, so overlaps are explicitly acknowledged (Kang & Miwa, 2025). It is also important to mention that this type of categorization of the methodology is not universally accepted between the scholars and divergences appear through other assessments as well. In this section of the literature review, an attempt is made to identify articles that introduced innovative approaches and to critically scrutinize the procedures they employed and the improvements they made.

It was Vale (2015), who *conceptually* added for the first time a third dimension to this model. In his article, “Transit-oriented development, integration of land use and transport, and pedestrian accessibility: Combining node-place model with pedestrian shed ratio to evaluate and classify station areas in Lisbon”, he posited that essentially a balanced node-place station does not represent a functional TOD, since the activities within the catchment area must be supported by walkable friendly streets (Vale, 2015). He argues that, to enhance the Node-Place model for better TOD planning, it is essential to assess the urban design characteristics of the catchment area (Vale, 2015), as it greatly influences TOD success.

Vale (2015) influenced the Node-Place methodology by introducing the concept of walkability and by discussing the Node-Place (NP) model's limitation in depicting the "Design" characteristics of transit stations. This update acknowledges that there is a need to understanding whether the Node and Place are functionally sustaining each other through a walkable area or not. To introduce this virtual third dimension, Vale overlaid actual walkable areas derived from OpenStreetMap (OSM)³ data onto a 700-meter radius around each station, calculating the proportion that is genuinely walkable. Notably, this approach points out a major limitation: Place dimension variables are still measured within the entire 700-meter radius, rather than the area that is practically accessible by foot. As a result, some activities considered may not be reachable via the pedestrian network.

While Vale's (2015) approach undoubtedly improved upon the original NP model, several limitations persist in realistically measuring the TODness of stations. Not only do Place indicators often measure areas that are not actually accessible on foot, but the third factor, the Ped-shed ratio, can also be misleading. For instance, if a station is near the sea, a 700-meter radius would include significant water areas that are inherently inaccessible, thus artificially lowering the ped-shed ratio and distorting the true walkability. Though Vale explicitly addresses such a scenario and cites it as a geographically restricted catchment area, it cannot distinguish between the cases where the potential catchment area is not in use because of the street configuration or the geographical restraints.

Aside from the details of Vale's work, it is important to note that Kang & Miwa (2025) classify this work as a Mixed NP model because of its mixed statistical methodology, where he calculated the node, place, and pedestrian ped-shed ratio and then ran a multivariate analysis to cluster them using the K-means method to group the stations and then plotted them on two dimensional Node and Place map. Because he mixed an objective machine algorithm (clustering) with a heuristic visual framework (the scatter

³ <https://www.openstreetmap.org/>

plot overlay), this was classified as a mixed NP model by Kang and Miwa (2025)'s work, while in another systematic review by Robillard et al. (2025), Vale (2015)'s work is grouped as an extended NP model.

In any case, Vale (2015) was not the first to use the mixed NP model and Reusser et al. (2008) and Zemp et al. (2011) preceded him (Kang & Miwa, 2025). Vale's example was chosen here because his work most clearly demonstrates the distinction between the extended NP model and the mixed NP model. While he conceptually introduced a third dimension (the pedestrian shed ratio) and used multivariate analysis to cluster the stations based on all three indices, he ultimately plotted the resulting clusters back onto a traditional two-dimensional Node-Place diagram. This heuristic methodological choice resulted in Kang & Miwa (2025) to classify Vale's approach as a mixed NP model.

The contrast becomes even clearer when comparing Vale's methodology with that of Lyu et al. (2016). Directly influenced by Vale's concept of walkability, Lyu et al. (2016) developed the Transit (Node) – Oriented (Morphological tie) – Development (Place) model, where the third 'Oriented' dimension was introduced to determine whether the Node and Place dimensions are functionally and morphologically connected. However, while the theoretical approach toward the TOD assessment is like Vale's, their constructional methodology is different. Even though Lyu et al. (2016) also used multivariate analysis (PCA) and hierarchical clustering to classify the stations, they fundamentally expanded the framework by plotting and evaluating the stations within a three-dimensional model, whereas Vale, as mentioned, relied on overlapping his clusters onto a 2D plot.

Following Lyu et al. (2016), many other scholars used the extended NP model idea, though the nature of the predefined dimensions is different. This variance across the methods, especially in the third dimension, implies shortcomings in the NP model's capacity to capture the reality of the transit network and catchment areas, especially the dimensions by which the stations' functions are assessed.

These differences between methods point up the need to consider the larger interconnections among different factors influencing train stations and their surroundings. Many efforts have been done, whether by introducing a third dimension like what Lyu et al. (2016) did, or other similar efforts to capture the contextual reality (Li et al., 2019; Rabiei et al., 2022), or using advanced statistical methods to improve the accuracy of the model (Reusser et al., 2008; Robillard et al., 2025), like improving clustering methods to group the similar stations, or using regression to test if the model corresponds to the real-world data (Cao et al., 2020; Jeffrey et al., 2019; Su et al., 2021b), or even using visual aids like radar charts or 3D cubes to make the data easier to understand (Su et al., 2021; Vale et al., 2018).

Why there are so many divergences in the methodologies? NP model scheme, rooted in the relationship of node and place is limited by its overly simplistic structure, qualitative ambiguity, and insufficient attention to contextual factors affecting station function (Kang & Miwa, 2025). Kang & Miwa contend that the Extended NP model, though it improved the prior model, still they suffer from the same problem, which is a subjective and heuristic approach in the analysis. The problem is that there is a flaw in the way the Node or Place is defined. As in an urban context, phenomena are varied and too interconnected to simply separate Node and Place and plot them on a diagram.

For example, Monajem and Nosratan (2015) used an indicator called passenger frequency which measures the number of daily station users, and attributed it to the Node dimension, meaning that it is inherently a transit feature. In contrast to them, Caset et al. (2019) considered passenger frequency a distinct characteristic, assigning it to their third dimension, called "people." Meanwhile, Zemp et al. (2011) and Renne (2009) considered another application of such a variable, and they used it for validating the clusters with it. These divergent approaches highlight the lack of consensus in indicator selection and classification. Moreover, as briefly mentioned,

this problem occurred during the classification of the accessibility indicators, as some scholars placed them under the node and others under the place.

As Kang & Miwa (2025) observe, the heuristic approach often relies on subjective rules of thumb, experience-based shortcuts, or expert judgment instead of a rigorous, data-driven methodology, and that is why the divergence occurs between different scholars and experts in defining the baseline for assessment of TODness of stations. The problem is, seeing the stations through the duality of Node and Place seems to be straightforward and logical, but it must be supported also by empirical, scientific methods as well. The main criticism of the heuristic approach is its high degree of subjectivity and qualitative ambiguity, as researchers depend heavily on their own judgment (Kang & Miwa, 2025).

Regarding the related dimensions, or more coherently, the situation and context in which stations function, Zemp et al. (2011) performed valuable research that is closely related and helpful in understanding the different dimensions related to the functions of stations. Although the article did not mention the word “TOD” or “TOD typologies” at all, the study is completely relevant to the discussion. When addressing the comparability of stations, they first theoretically distinguish between the context and system structures, where context refers to the external environment and urban morphology in which stations are located. They acknowledged that stations are in different contexts, such as some in populated areas surrounded by high-rise buildings and high-density, high-traffic zones, while others are in low-density areas or on industrial sites. On the other hand, the system structure concerns the stations with respect to transportation features, such as the number of platforms or, more precisely, the quality of transit provided by stations.

Zemp et al. (2011), continue by asserting that classification of the stations (typologies), helps to promote a station and its site to its optimal functions (here functions refer to what stations must do). Classification then should distinguish the relevant contexts in which the stations are operating. To obtain these functions, they conducted interview

with 28 experts and the results showed 5 main functions that stations have: “F1- link catchment area and transport network; F2- support transfer between modes of transport; F3- facilitate commercial use of real estate; F4- provide public space; F5- contribute to the identity of the surrounding area.” (Zemp et al., 2011, p. 673). Then, the Context Factors (CF) that exist within the catchment area of the station dictate the demand for these functions and the situational conditions under which they must operate. For instance, context factors like “Size” (CF3), and “Proximate Urban Density” (CF7) indicate that whether there is enough local demand for the station to require the function of F3 (facilitating commercial use) or not. There are 14 context factors related to those 5 functions (Zemp et al., 2011, Table 1). Furthermore, as the context factors are inherently abstract concepts used to relate the 5 functions of the stations with external conditions that shape the context of the stations and sites, Zemp et al. (2011) convert these context factors into assessable indicators.

It is important to note that although Zemp et al. (2011) relied on expert interviews to identify the five functions of train stations and the fourteen context factors that define their context, this approach does not conflict with the perspective of Kang & Miwa (2025) or their criticism of heuristic practices. It is because Kang & Miwa (2025) criticize the heuristic approach for subjectively allocating variables to predefined dimensions, not the heuristic approach for gathering initial variables. Zemp et al. (2011) adopted a systematic procedure to provide a solid basis for station comparison and effective classification. A particularly notable progress was their innovative strategy for identifying key dimensions, which deals with the limitations of predefined, heuristic dimensions such as Node and Place. Instead of deciding what the dimensions should be, they used Principal Component Analysis (PCA), which is a data-driven method to let the data reveal the underlying hidden structures that drove the stations.

Zemp et al. (2011) are influential for offering an alternative to the commonly used heuristic approach prevalent throughout the TOD typologies literature. Although the

Zemp et al. model is classified as a Mixed NP model alongside a large portion of the reviewed literature (Kang & Miwa, 2025, Figure 1), few studies have moved beyond rule-of-thumb methods and relied on exploratory or confirmatory approaches to detect relevant dimensions or factors, and the majority still depend on heuristic approaches. It is because, as mentioned before, Kang & Miwa (2025) classified all methodologies that used multivariate analysis but overlapped the results onto a 2D map as the Mixed NP model. Aggregating these heuristic approaches within the Mixed NP model with other groups means that almost all studies, except for a few (Niu et al., 2021; Rodríguez & Kang, 2020; Wang et al., 2021; Yang et al., 2024; Zemp et al., 2011), suffer from heuristic problems.

Considering using confirmatory or exploratory or similar approaches that solve the problem of heuristic approaches like Node-Place and the extended versions, we need to bear in mind that often these models lead to producing new factors that are made by variables that are inherently very different in nature, and consequently naming the new born factors and assessing the context of the stations based on them is challenging and making targeted policies production difficult (Caset et al., 2019). Zemp et al. (2011) who at first employed this method pointed out that, TOD policy requires political approval, which seek straightforward methods. Eventually there is a dilemma to choose: one path offers a straightforward but potentially subjective classification lacking scientific or statistical support, while the other provides data-driven results with mathematical rigor and a solid scientific foundation yet may be difficult to interpret and apply in practice. Because the broader application of these confirmatory and exploratory methods within TOD typologies has only gained momentum relatively recently, the practical applicability of this approach is still under development.

2.6.2.2. Indicators: Selection, Data Availability and Measurement Problems

This section aims to review the literature to address the question: *“Which indicators should be selected and applied to effectively measure stations and their surroundings?”*

Choosing meaningful, relevant indicators that accurately reflect critical aspects of stations, and their contexts is fundamental to producing reliable TOD typologies. Kang & Miwa (2025), in their systematic review of 65 TOD typology papers, identified 1,264 indicators (Indicators sometimes overlapped) used in the literature, underscoring the complexity of this task. They found significant inconsistency in both the use and interpretation of these indicators, as scholars often apply and define them differently. While much of this variation stems from the prevalent heuristic approaches used in the procedure, the essential question remains: which indicators genuinely capture the necessary information for strong TOD typology analysis?

The 5Ds framework (Density, Diversity, Design, Destination Accessibility, and Distance to Transit) (Ewing & Cervero, 2010) is one of the most popular benchmarks that scholars take as indicators to measure TODness. Generally, scholars often use variables that are coordinated with the nature of Node and Place dimensions. For example, variables like the number of platforms, train frequency, centrality and betweenness in the transit network, and the number of reachable stations within a set travel time are attributed to Node dimensions where it often assesses a station’s transit status within the network. Similarly, Place indicators describe the distribution of urban form and activities, including land use, population size and density, the presence of specific amenities, and closeness to those amenities, as mentioned, they are mostly in accordance with the 5Ds. Together, these indicators intend to characterize a station’s context in relation to the conceptual definitions of a TOD area (Bertolini, 1999; Lyu et al., 2016; Reusser et al., 2008).

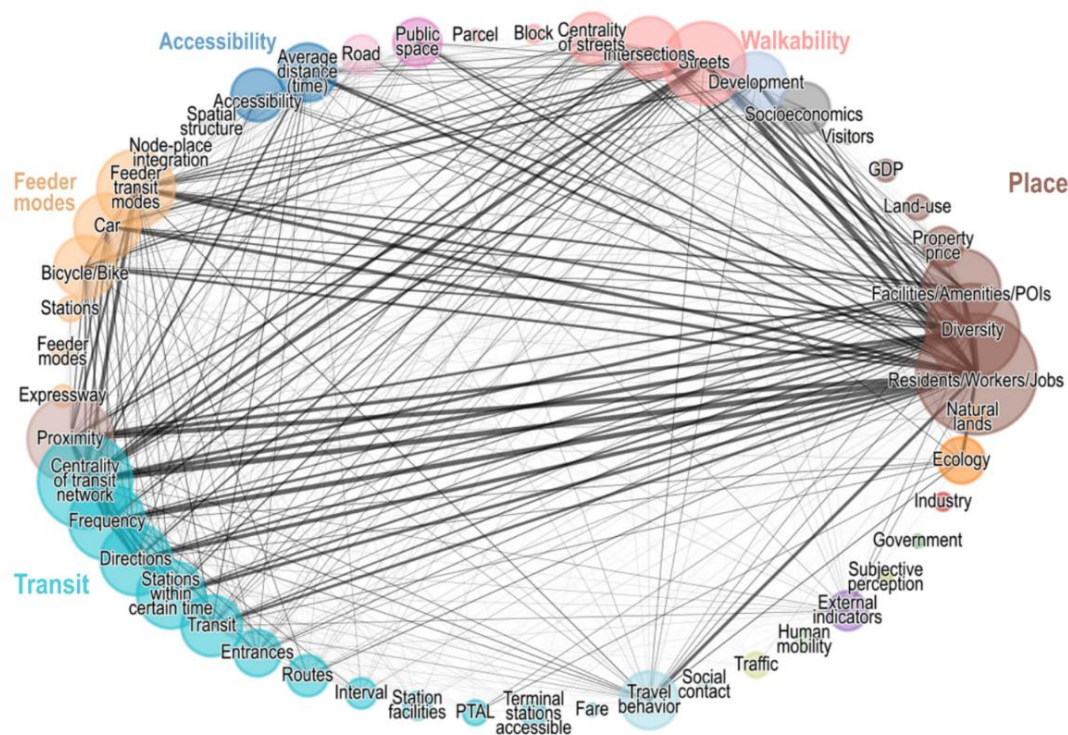


Figure 4 - Frequency and co-occurrence of indicators used in the literature.⁴

Kang & Miwa (2025), during their 65 papers reviewed, identified the frequency of the use of indicators in the literature. Accordingly, the size of each circle represents how often an indicator is used, and as it is detectable, the most frequently used indicators belong to common dimensions such as Node and Place, following them, Walkability indicators are the third prominent dimension that is commonly used. As the authors note and as visible in Figure 4, there are different associations of indicators to dimensions that as explained before, it derives from the divergence of interpretation of the indicators. Later, they summarize the trends into a table that shows the top 30 indicators and their attributed dimensions (Kang & Miwa, 2025, Table 1).

Ultimately, data availability is one of the most critical factors in selecting indicators (Monajem & Ekram Nosrati, 2015; Robillard et al., 2025). When moving from theory to practice, analyses are often limited by whether the desired indicators can be

⁴ Frequency and co-occurrence of indicators used in the literature. From “Systematic review and methodological comparison of TOD typologies based on the node-place model,” by H. Kang and T. Miwa, 2025, *Journal of Transport Geography*, 128, Article 104373 (<https://doi.org/10.1016/j.jtrangeo.2025.104373>). CC BY 4.0.

measured. For example, Zemp et al. (2011) identified 14 theoretical context factors but found that seven could not be quantified due to insufficient data, leaving only 10 measurable indicators. Challenges related to data scarcity and the difficulties of measurement and data collection are commonly highlighted in the literature, forcing the researchers to compromise on their model correctness (Lyu et al., 2016).

Moreover, data collection challenges are regularly amplified when a case study area goes beyond administrative boundaries. Many geospatial datasets produced by government agencies are managed and distributed by local governments through regional portals (such as Lombardia Geoportale⁵ or Piemonte Geoportale⁶). As a result, data availability and coverage typically conform to these administrative areas, and when it goes outside of these boundaries, other municipalities may not have collected comparable data or may use different time frames and formats. These differences further undermine data consistency and credibility (Robillard et al., 2025).

Another major challenge in this process is integrating diverse data types. Urban environments involve many interconnected phenomena, resulting in indicators that vary widely in nature and scale (Lyu et al., 2016). For instance, some indicators measure distance to points of interest (POIs), others count specific facilities, while some capture population density. Since these variables are measured on different scales, combining them can disproportionately emphasize those with larger numerical ranges.

To ensure that dataset preparation and classification are statistically rigorous, scholars employ a range of methods. Data standardization techniques that bring the data on to a common ground include Min-Max scaling (Lyu et al., 2016), Z-score standardization (Zemp et al., 2011), and vector normalization (Rabiei et al., 2022), this step is crucial to preventing overestimation on the variables that are inherently contain large values. Non-normal data distributions are addressed using transformations such as the log

⁵ <https://www.geoportale.regione.lombardia.it/>

⁶ <https://geoportale.igr.piemonte.it/cms/>

transformation (Liu et al., 2025; Zemp et al., 2011), and the Box-Cox transformation (Kang & Miwa, 2025), this step is usually used because the latent procedures, including factor extraction engines, require normally distributed data. Factor extraction that find the latent structure within the data, is performed usually by using Principal Component Analysis (PCA) (Zemp et al., 2011) and Exploratory Factor Analysis (Kang & Miwa, 2025), often with maximum likelihood (Kang & Miwa, 2025) or minimum residuals and an Oblimin rotation (Kang & Miwa, 2025). Finally, clustering step that build the groups, it includes partitional methods such as K-means (Vale, 2015) and K-medoids (Robillard et al., 2025), hierarchical clustering (often with Ward's method) (Kang & Miwa, 2025), and probabilistic models such as two-step clustering (Reusser et al., 2008) and Latent Class Cluster Modeling (LCCM). Furthermore, as Factors often contribute to explaining the data with different share of variance explanations, weighting score is assigned to them through methods like information entropy weighting (IEW) (Cao et al., 2020; Kang & Miwa, 2025), Criteria Importance Through Intercriteria Correlation (CRITIC) (Rabiei et al., 2022), Analytic Hierarchy Process (AHP) (Su et al., 2021a), Fuzzy AHP (Li et al., 2019), and Shapley Additive Explanations (SHAP) (Su et al., 2021a).

2.6.2.3. The Transit Station Catchment Area: Delineation Problems

The primary goal of this section is to search through the literature to answer the following question: *"How can the catchment area be delineated to reflect actual pedestrian accessibility rather than hypothetical boundaries?"* It is important to clarify that the discussion of catchment area here specifically concerns its delineation within TOD typologies. This focus though exhibits similarities, it differs from the previous section, where accessibility (Section 2.5) was discussed mainly in terms of comparability and compatibility between the quality of service provided by public transport, active transport, and private cars. In other words, this section focuses on comprehending

local accessibility, with stations as main points and, importantly, to define the extent within which the indicators of TOD typologies are measured.

Probably the best way to comprehend why it is important to carefully define the catchment area is through understanding that the indicators by which the typologies will eventually be produced can differ significantly according to the geographic extent by which they are measured. Therefore, it is essential to define the catchment area using a solid and logical approach that accurately reflects how far people are willing to walk between the station and its surrounding environment. Understanding this is important as it guides us to define the aforementioned extent of the study for each site.

As discussed earlier in Section 2.2, from its foundational stages, Peter Calthorpe, in his definition of TOD, delineated the catchment area by specifying a 2000 ft (600 meters) radius around transit hubs. This distance is presented as a logical approximate threshold / the maximum distance people are generally willing to walk to reach the station or nearby destinations, based on his conceptual design criteria for a TOD-friendly catchment area (Calthorpe, 1993). Accordingly, TOD typology models also used a similar delineation to assess and measure the relevant context indicators to proceed with producing TOD typologies. For instance: 500 meters Euclidean radius buffer (Vale et al., 2018), 600 meters Euclidean radius buffer (Dou et al., 2021), 700 meters Euclidean radius buffer (Monajem & Ekram Nosrati, 2015), 700 meters walkable buffer (Bertolini, 1999; Reusser et al., 2008; Zemp et al., 2011), and 800 meters walkable buffer (Kamruzzaman et al., 2014), and other thresholds. As these few examples indicate, there is no consensus threshold or approach to estimate the catchment area.

Jiang et al. (2012) define the catchment area as the area served by a transit station. However, complexities arise when considering what it means for an area to be "served" and how to precisely delineate its boundaries. As already mentioned, scholars in the literature use different delineation methods. Most approaches define

the catchment area as the region from which a station is accessible by foot, with the distance calculated based on the maximum distance people are willing to walk to reach the station (Jiang et al., 2012). Like section 2.5, we agree that socio-economic and demographic characteristics here are determinant. As Jiang et al. (2012) articulated, people decide how to travel by comparing the benefits of a method against the deficiencies of other choices, which can be assessed in terms of costs (in different forms, such as time). For instance, with respect to time as the cost, the journey is divided into two forms of cost: actual cost and perceived cost, where actual cost is the literal measurement of time, and perceived cost is shaped by comfort.

Empirical studies show that actual walk access distances vary between countries and cities, depending on a range of factors. These include the station's location (such as whether it is in the Central Business District, suburb, or downtown), quality of transit service (type, frequency, etc.), socio-economic characteristics (gender, age, occupation, etc.), trip features (length, purpose), transit system (rail, multi-mode, light-rail), and the built environment (Jiang et al., 2012, Table 1). Therefore, applying a universal fixed-size catchment area to all stations without considering these diverse factors, is both misleading and inaccurate. For example, a standard threshold, such as a 15-minute walk, does not accurately reflect the true catchment area in areas with steep terrain or other physical barriers (Coelho et al., 2025). Additionally, a longitudinal approach is needed to account for variables such as time of day, temperature, and perceived safety, all of which influence the perceived cost and feasibility of a trip.

Literature in this field continues to improve the methodology by which the catchment area is delineated. Away from the simple, fallacious Euclidean methods that use isochrones, newer methods use network-based areas that try to consider the areas that are actually walkable according to the street configuration. More recently, the network buffer method was further advanced by the Pedestrian-Effort Network Weighted Buffer (Coelho et al., 2025), which, on top of the street configuration, also incorporates walking speed and maximum acceptable walking distance based on topographical

features such as slope. For instance, while a person would walk 600 meters when the street is flat, he might give up walking half that distance if the slope is steep. This opinion is also supported by Coelho et al. (2025), as they applied this model to *Belo Horizonte, Brazil*, and found that it significantly reduced the calculated size of the catchment area compared to traditional network-based models. Despite all of these improvements, many other influential factors remain unresolved. Using a factor-specific impedance function, as suggested by Verma & Ukkusuri (2025), may be necessary to delineate catchment areas with greater accuracy, and yet multimodal accessibility needs to be addressed as well.

Lastly, a major methodological challenge occurs when measuring indicators within catchment areas for TOD typologies: the overlap of catchment areas between geographically proximate stations. When two stations are spatially close that their catchment areas intersect, there is a risk of double-counting indicators. This overlap can lead to misleading results, including assigning identical typologies to distinct stations and overestimating the availability of real-world facilities.

Scholars incorporate different solutions. For instance, Robillard et al. (2025) used different thresholds for different cities to avoid overlap, but the adjustments were applied to all stations within the same city (in their case, Rotterdam with 800 meters, rather than Montreal with 1200 meters). Other methods involve hierarchical catchment zones (Jun et al., 2015), and cropped catchments (Wang et al., 2021).

2.6.2.4. Spatiotemporal impact on TOD typologies: Cross-Sectional and Relativity Problems

This section reviews the literature to examine how scholars have acknowledged, addressed, and resolved the challenges that arise from variations in spatial extent and temporal changes, and how these factors influence the outcomes of TOD typology analyses. The research question for this section explicitly is: *How different spatial extents and variation in time can affect the results of TOD typologies?*

Probably, the fundamental question that we need to address is: on what basis should the spatial scope of the study be defined? Reading the prior articles, we observe that many studies use administrative boundaries of cities or regions as the framework for their analysis. For example, Robillard et al. (2025) used the administrative boundaries of Montreal, while for Rotterdam, they applied those of the South Holland province. Singh et al. (2017) also used the City Region of Arnhem and Nijmegen in the Netherlands. Other studies have defined their spatial scope more broadly or narrowly but still loyal to administrative borders, such as including all stations within an entire country (Niu et al., 2021; Reusser et al., 2008), a metropolitan area (Vale, 2015), or a single city (Kamruzzaman et al., 2014).

Kang & Miwa's (2025) study, explicitly provide an empirical data on why the geographical extent is important. They showed that TOD typology results can vary significantly depending on the context by conducting two separate analyses using the same methodology for two geographical extents with same core region in Japan, the Chukyo Metropolitan Area (CMA) and Nagoya City, each representing a different spatial extent. Their findings revealed that typology of the stations varies when the geographical extent differs. For instance, when the geographical extent is set to regional, the results indicated a clear distinction between inner cities stations and outer cities stations. On the other hand, the city-level analysis uncovered more nuanced intra-city patterns (Kang & Miwa, 2025, Figure 7,8). It is mainly because the methodology and clustering algorithms group the stations according to dataset's average and baseline, and changing the study area basically changes the baseline. Importantly, some stations were assigned to different typologies based on the scale of analysis. This is critically important as one of the main objectives of TOD typologies is to provide a reliable foundation for targeted policy interventions (Robillard et al., 2025). Therefore, accurate clustering is essential to generate actionable, trustworthy results which this is possible only through correct definition of the study area (Cascetta et al., 2013). The conclusion of the author of this thesis is: policy

recommendations must be tailored to the spatial extent of the analysis: broader studies should inform general policy directions, while studies at a finer scale can support more specific, detailed interventions.

Kang & Miwa (2025) proved that why the geographical extent is important, yet the central research question of this section remains unresolved. Though the TOD typology literature hasn't addressed this question specifically, it is logical to assume that the geographical context by which the stations are selected must demonstrate a functional spatial relationship within the area. Bertolini (1999) once articulated that how ambiguous urban boundaries are in contemporary cities. Individuals may live in one place, work in another, and spend their leisure time in a third space. Jonas et al. (2015) describe this phenomenon as "Regional Urbanization," referring to urban agglomerations that span multiple local jurisdictions. They emphasize that urban environments are shaped by continuous flows of capital, labor, and private-sector development, resulting in economic activities that transcend official municipal borders. Consequently, it is reasonable to conclude that the study area should be delineated according to economic functional regions or the network of interrelated economic dependencies within regional urbanization because accordingly the movement of people, goods and categorically, daily spatial relations are shaping. Notably, this functional area may exist independently of the transit network to which TOD principles are being applied. In fact, if the area is not served by the mentioned transit network, it highlights the transit system's shortcomings in providing proper service and accessibility, which as talked before, can deteriorate the whole TOD network efficiency.

The European Union and the Organization for Economic Cooperation and Development (OECD) have jointly developed a new definition and interpretation of cities and their Functional Urban Areas (FUAs) (Lewis Dijkstra et al., 2019). FUAs consider the functional and economic reach of cities, which differs from traditional definitions based solely on density and population size. In addition to the core city,

FUAs also include surrounding areas that are economically and functionally connected to the city. Specifically, FUAs are defined as part of a city's labor market and commuting zones. They explicitly articulated that commuting flows capture both travels for going to work, and access to education, health, culture and sports or shops. The OECD defines a city's commuting zone as the contiguous area surrounding the city where at least 15% of the employed population works within the city itself (Lewis Dijkstra et al., 2019). Based on the given foundation on how FUAs are defined, they could be better alternative comparing to administrative boundaries. This claim aligns with Cheng & Bertolini (2013), as in their research in Amsterdam, they realized that need to go beyond their administrative borders, because the actual spatial extent was significantly larger due to job competition from residents outside those boundaries (Cheng & Bertolini, 2013).

Proving that spatial context influences the results of the typologies, it is also correct with respect to the time variable. Time significantly shapes both variable measurements and accessibility, affecting how stations are classified. Since traditional methodologies often derive typologies from clustering based on dimension scores calculated from variables at each station, any temporal fluctuation, such as daily or seasonal changes, can alter these classifications meaning that we would have different typologies for the same station at different times. This is especially true for variables linked to human mobility (which typically define the Node dimension) and human activities (which shape the Place dimension), both of which are inherently time sensitive.

For instance, Zemp et al. (2011) warn that some stations experience heavy crowding at certain times of year due to tourism or leisure activities. As a result, measuring transit-related indicators using a cross-sectional approach may result in an overestimation of the transit system's performance relative to its performance during other periods. Moreover, Robillard et al. (2025) also acknowledged a limitation in their TOD typology as their model failed to fully account for harsh winters, during which

bicycle infrastructure is unavailable for part of the year. More comprehensively, Shin et al. (2022) concluded the topic by criticizing traditional models for relying on static features, which overlook human mobility patterns. They argue that a single station can function as a different type of TOD at different times of day, like how a station can be a commuter hub in the morning and a leisure-hub at night. Interestingly, they developed a “activity-based dynamic TOD typology” that explains variation in single station’s typology by understanding how passengers interact with station, hour-by-hour. They design their analysis using smart-card data that captures all public transportation trips by passengers, in the form of a trip chain of origin, transfer, and destination areas. It was possible because in Seoul, South Korea (their case study), smart cards handle multimodal information for buses and subways: the system charges differently based on the distance traveled, and it provides a discount for multimodal public transportation trips. To address the challenge of identifying trip purposes, the researchers employed a Hidden Markov Model (HMM). An HMM is an AI and Machine Learning-based mathematical tool that attributes a purpose to each trip using the principle: “What you do next depends on what you are doing right now.” For example, if someone is currently working, it is unlikely their next activity will also be work. Instead, it is more probable they will engage in leisure or return home. To improve the accuracy of activity prediction, the model uses clues such as the start time and duration of each activity using a Gaussian distribution and finally the model generates “emission probabilities” that characterize the likelihood of various activities following one another (Shin et al., 2022).

They ultimately identified six types of activity. Rather than relying on static land-use patterns, they assigned these activities to spatial units and used clustering algorithms to classify stations into three primary functional categories: residential, business, and mixed. By analyzing the continuous temporal patterns of activity start times and durations, they identified micro-dynamics that proved a single station can fluctuate between different typologies by change in time (Shin et al., 2022). While further

research is needed to determine how this model can enhance TOD typology methodologies, it nonetheless represents a significant shift from static planning approaches to a more dynamic, human-centered model. This approach helps planners better understand how passengers actively interact with spaces, providing a more accurate picture of a station's true functional role within the urban network.

Lastly, it is important to recognize that TOD typologies (in dominant methodology in the literature) are inherently relative, not absolute. It means that a high TOD score for a dimension like Node does not necessarily mean that the cluster has a good absolute quality of service. For example, transit services might be inadequate across the entire system, yet some stations may still score higher relative to others. This relativity stems from the use of clustering algorithms, which group stations based on normalized and standardized values, making typology results comparative rather than definitive. Therefore, typologies are potentially useful for distinguishing between stations from each other rather than for concluding whether a typology is determinately TOD-friendly (Kang & Miwa, 2025). Some scholars, such as Hale (2014), argue that to genuinely claim success in TOD, at least half of all trips should be made by sustainable modes of travel. Hale proposes this proportion as a necessary benchmark for assessing the success of TOD in a given area (Hale, 2014). Building on Hale's (2014) suggestion, it is important to remind the findings of Kamruzzaman et al. (2013) and Schwanen and Mokhtarian (2004; 2005) which discuss residential self-selection. They argue that increases in public transit (PT) ridership attributed to TOD may be overstated if the overall number of PT-oriented residents has not actually increased. Therefore, while benchmarks remain essential, they should reflect the city's overall transit behavior rather than just TOD-specific areas.

2.6.2.5. Typologies Results: Validation

It remains necessary to verify whether the resulting clusters truly formed distinct clusters or not. These typologies or clusters must demonstrate similarities in their

context. Therefore, one should be able to observe clear patterns of distinction between groups within their specific contexts. With this regard, this section aims to review the literature to answer this question: *“How to validate the typologies to understand if they are really distinct?”*

There are different approaches for typology validation: statistical validation (Jeffrey et al., 2019; Robillard et al., 2025; Zhao et al., 2024), validation through observing functional differences between the clusters (Kamruzzaman et al., 2014; Rodríguez & Kang, 2020; Zemp et al., 2011), and validation through spatial pattern (Jeffrey et al., 2019; Robillard et al., 2025).

Statistical validation refers to methods for testing whether the produced clusters are not arbitrary mathematical anomalies or subjective groupings. It is mostly done by comparing the dimensions and variable values of the clusters. Among the methods, Analysis of Variance (ANOVA) tests whether the means of variables differ significantly across clusters. Moreover, Post-Hoc Tests, commonly the Tukey Honestly Significant Difference (HSD), are used for pairwise comparisons, as ANOVA does not tell you which specific clusters differ (Zhao et al., 2024).

When clusters are conceptually and statistically distinct, these differences should be observable in their functional outcome in the real world. For example, Zemp et al. (2011) used passenger frequency to find a meaningful distinction between the clusters, while Rodríguez & Kang (2020) used annual average passenger boardings to confirm the meaningfulness of their cluster distinctions.

Also, it is possible to use Geographic Information System (GIS) to overlay the clusters with satellite imagery and other spatial data to find a distinct pattern in urban structure within the clusters. It is logical and expectable, as different clusters imply different contexts that sometimes these are decipherable through urban form. These urban structures are sometimes distinguishable by different clear spatial patterns, such as differences between urban, rural, and suburban stations. Many scholars

employ this method to visually demonstrate the contextual distinctions among clusters (Jeffrey et al., 2019; Zemp et al., 2011; Zhao et al., 2024).

2.6.2.6. Typologies Results: Formulating Targeted Policy Packages

As previously discussed, TOD typologies have been used to support and facilitate the decision-making process. Therefore, a strong and accurate assessment of both macro and micro TOD perspectives of the situation is needed to provide useful insights for the decision makers. Another reason that makes the TOD typology studies necessary for implementing any TOD policy is that stations and their surroundings are inherently context-dependent, consequently a one-size-fits-all approach is incorrect. Instead, tailored interventions are necessary to address specific local characteristics and regional dynamics. However, implementing national or regional strategies poses the challenge of scale, analyzing thousands of stations and their contexts individually is often impractical. Typologies address this challenge by descriptively grouping stations that share similar characteristics at various levels. By identifying these similarities, typologies simplify the policy-making process, enabling planners to design targeted, group-specific interventions that are both efficient and contextually more appropriate. Eventually, the aim of this section is to answer this question: *“How do scholars build targeted policies out of the TOD typologies?”*

In the literature, Zhao et al. (2024) provided a useful example of how they conducted a typology analysis of 133 transit hubs in Austin using a Node-Place-People Model and how they translated the results into an actionable list of targeted policies. Their model identified five station clusters. They built the profile of each cluster according to the scores on the dimensions they had, and finally, according to their characteristics, they developed the targeted policies.

To guide policy formulation, they put 5 clusters into four main categories: Downtown and Urban Stations, Vulnerable Stations, Rural Stations, and Suburban Stations.

Reviewing them can help us to better demonstrate how the policies could be drastically different for different clusters. In their work, for Downtown and Urban Stations, the authors recommended improvements to last-mile connectivity, such as expanding shared micromobility and paratransit services, and enhancements to pedestrian infrastructure, including better sidewalk design and increased tree canopy. These policy recommendations are simply because the stations were characterized by high node and place values and medium vulnerability, largely due to a higher proportion of elderly residents and households without cars.

The next cluster, Vulnerable Stations, is distinguished by moderate place indices, low node indices, and very high vulnerability were found to serve populations that included more minorities, foreign-born individuals, low-income households, and people without private vehicles. These stations also exhibited the largest disparity between employment and population. Accordingly, the proposed policies focused on improving transit services, promoting land-use diversity, and advancing affordable housing initiatives.

For Rural Stations, the recommendations centered on strategic resource concentration, such as focusing development on primary sub-centers, and gradual planning, reflecting the current low reliance on public transit. The authors also suggested on-demand transportation options to better serve dispersed vulnerable populations. In the case of Suburban Stations, targeted policies mostly included proactive displacement monitoring as gentrification is mostly expected to happen, incentives for developers to pursue economically feasible projects near stations, and tax exemptions designed to promote affordable housing (Zhao et al., 2024).

The above targeted policies, which Zhao et al. (2024) provided using the results of TOD typologies, clearly demonstrate how, based on the characteristics of the clusters, the different policies would be needed to pursue. It is also worth mentioning that, often in articles in this field, scholars use the clustering results and scores on different dimensions to build a qualitative profile of the clusters. This is mostly because it is

easier to understand how the clusters are different from each other and, respectively, develop the policies (Rodríguez & Kang, 2020). The next step after the descriptive qualitative diagnosis of the scores in different dimensions, as Higgins and Kanaroglou (2016) explain, is the policy-making stage, which is inherently normative, moving beyond what actually is, to bridge toward where it should go by considering the aspirational vision of what the region can achieve (Rodríguez & Kang, 2020). Consequently, the targeted policy provides a normative roadmap of policies and plans designed to bridge the gap between the current stations' conditions and their optimal transit-oriented future.

One question may arise: why TOD typologies ultimately abandon strict numeric targets in favor of qualitative, descriptive policy roadmaps? And why is it necessary? The answer can be concisely stated as, we need to do this because of urban planning theory, political reality, and stakeholder negotiations. As noted by Caset et al. (2019), over-reliance on quantification makes them less compatible with end-users, who are policy makers and stakeholders, and eventually makes the targets essentially extremely difficult to apply. Urban planning processes are not completely rational, financial, and mechanical processes (Thomas et al., 2018), instead they involve political powers, real plans, and real people, and that is why the policies need to be descriptive rather than rigid numbers (Ibraeva et al., 2020).

3. Methodology

The methodological framework considered in this study is presented in Figure 5. This method is conceptualized into 4 distinct steps. The preliminary step is to prepare the data. The key point is that the data structure must be consistent with the method used to construct the typology. Phase 1 continues with standardization and factorability testing to ensure that the data are suitable for subsequent phases.

Phase 2 is the iterative factor-definition step, using a Minimum Residuals statistical core that is appropriate for the multivariate nature of the urban data. A Scree Plot is used for factor retention to determine the number of factors to retain for the underlying construct of the data. To correlate the new dimensions (Factors), an oblique (Oblimin) rotation is applied, and iterative refinement ensures the suitability of the indicators' loadings and cross-loadings; this requires trial and error to refine the data.

By reaching the dimensions, we use a linear multiple regression to calculate the stations' score on each dimension. Eventually, hierarchical clustering (Ward's method) is used to build the clusters. This method of clustering is particularly suitable when the total sample size is small. Ultimately, dendrogram analysis can help us to determine the final number of station typologies through inspection.

Finally, by determining the total number of clusters we need to validate the results, and this is the phase 4. The validation process includes overlaying the clustering results on the map and use GIS tools to find the potential patterns in relationships within and among the clusters. As discussed in the literature review, it is expected to find a degree of connection between the stations of a cluster through the urban structure.

In this methodology Python 3.12.7 was used, with the help of Gemini (Google, 2025), to perform some of the measurements and data processing.

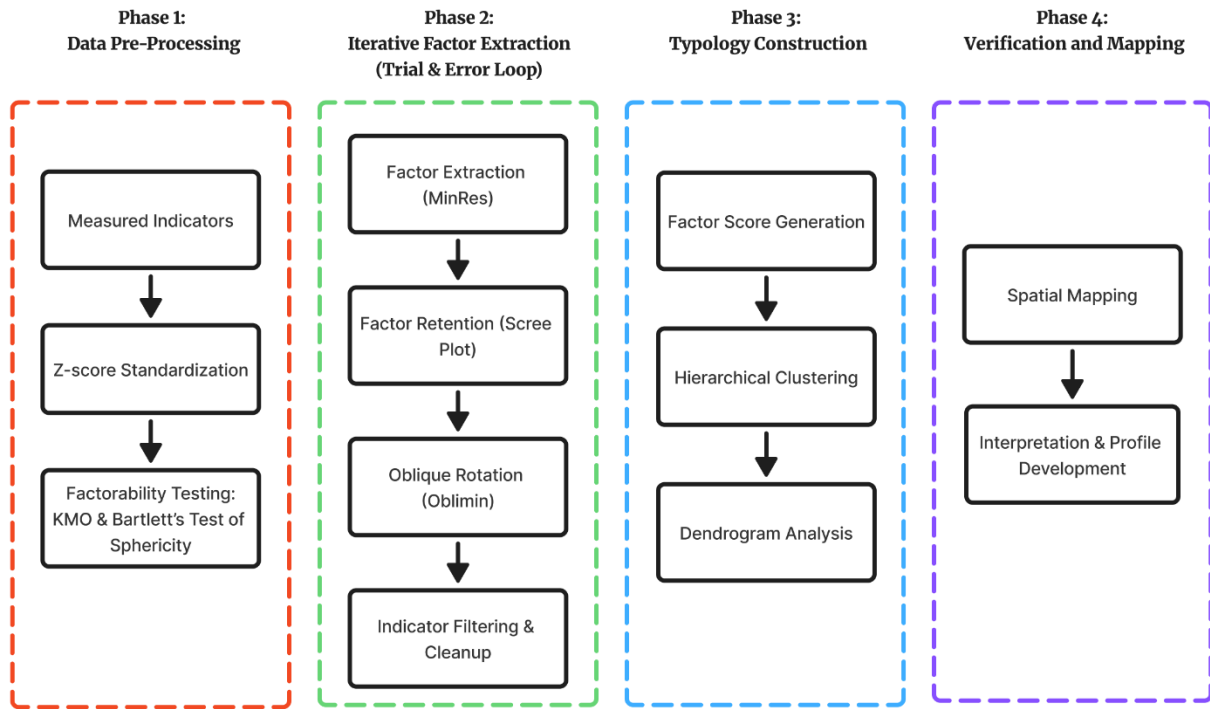


Figure 5 - The outline of the methodology

As Figure 5 illustrates, a Mixed NP using an EFA model has been used to perform the analysis. EFA is a multi-step statistical process that identifies the underlying relationships among measured indicators (variables). In EFA, we do not assume predefined dimensions (factors) shaped by combinations of indicators (variables), as other TOD typology methods, such as the NP model or the Extended NP model, do (e.g., Node, Place, and Walkability dimensions). Instead, in EFA, we let the data itself reveal the hidden patterns among the variables. The number of dimensions (factors) and the magnitude of each indicator (variable) in shaping those dimensions are unknown and depend on the data itself.

EFA is a variable-reduction technique. There are also other similar techniques, such as Principal Component Analysis (PCA), that reduce the number of variables. However, they are mathematically and conceptually different from each other. PCA primarily aims to reduce the number of variables in the model and break it into the most

important components that make up the data. On the other hand, EFA focuses on finding the hidden relationships between the samples.

The mathematical core of EFA is a linear equation in which a standardized indicator (variable) is expressed as a linear combination of factors and factor loadings. As discussed earlier, factors represent the underlying dimensions, and factor loadings indicate the magnitude of the correlation between indicators and factors. Each indicator is also accompanied by a unique factor or error, as shown in Eq (3).

$$x_i = \lambda_{i1}F_1 + \lambda_{i2}F_2 + \dots + \lambda_{im}F_m + e_i \text{ for } i = 1, \dots, p, \text{ where } m \leq p \quad (3)$$

x_i is the standardized value of the measured indicator.

λ_{im} is the factor loading or weight. It indicates the extent to which the variable contributes to the factors.

F_m is the factor or the latent dimension that was constructed within the data.

e_i is residual or error. This reports the variance for that specific indicator (variable) only.

As noted in Equation 3, we standardize the variables to avoid skewing the results due to different units of measurement. For instance, if x_1 denotes population density and x_2 denotes the number of bicycle racks, standardization places them on the same scale. λ_{im} also, the correlation coefficient between the variable and the factors. Higher values of λ_{im} means that the variable is a strong representative of that factor. F_m is the latent dimension or unobserved entities constructed from the data (Mulaik, 2009).

The correlation matrix (R) or covariance structure shows the latent structure among the observed variables. In matrix notation, this relationship is defined as:

$$R = \Lambda\Lambda^T + \Psi \quad (4)$$

Where Λ is the factor loading matrix, Λ^T is the transposed factor loading matrix and Ψ is the unique variance matrix (A diagonal matrix containing the variance of each

variable). Also, the variance of each indicator equals the sum of commonality and specificity, as shown in Eq. 3 (Ewing & Park, 2020).

$$Var(\chi_i) = C_i + \Psi_i = \lambda_{i1}^2 + \lambda_{i2}^2 + \dots \lambda_{im}^2 + \psi^i \quad (5)$$

Here, as shown by m , the total number of factors should be determined by a criterion. This contribution is calculated as the sum of the eigenvalues of the matrix R . Most studies retain all factors with eigenvalues greater than 1.0 (Kaiser, 1960), as in Kang & Miwa (2025). However, there is a consensus in the literature that this method is not standard, and it may cause the result to be overestimated (Costello & Osborne, 2005).

An alternative to this method is the Scree test. We can examine the eigenvalue plot and identify the point where the trend changes markedly. This method can be refined through trial and error by running the analysis multiple times and setting the number of factors above and below the Scree test's suggestion to find the one that looks the cleanest, meaning that loadings are above 0.32, there are few or no cross-loadings, and no factors have fewer than three items (Costello & Osborne, 2005).

3.1.1. Phase 1: Data Preparation - Sample size & variable ratio, data consistency, and distribution check

The first step in performing EFA is to prepare the dataset. Several requirements must be met before performing the analysis, including data preparation, such as checking the sample size and variable ratio, measurement scale, missing data, distribution checks, and linearity (Tabachnick & Fidell, 2019).

The sample size and variable ratio: in our case, the sample size is the number of train stations, and the number of variables is the number of indicators measured. A general rule of thumb is to follow the 10:1 rule: for each variable, we need 10 samples. A survey on published studies found that 62.9% of researchers used a ratio of 10:1 or less (Costello & Osborne, 2005). Also, research in TOD areas and social sciences indicated

that with strong data (with high communalities), we can also have a 5:1 ratio of variables and sample size (Costello & Osborne, 2005; Kang & Miwa, 2025).

NO.	ABBR.	INDICATOR'S NAME	INDICATOR'S DESCRIPTION
1	N1	Railway lines	Number of Train Lines operating in the stations
2	N2	Transit frequency	Frequency of trains departing the station
3	N3	Bus Lines	Number of lines of buses within the station area
4	N5	Bus stops	Number of bus stops within the station area
5	N7	Number of Platforms	Total number of platforms in each station
6	N8	Stations within 30-min travel	Number of accessible stations within 30-min travel on the railway network
7	N9	Metro stops	Number of metro stops within the catchment area
8	N10	Transit betweenness centrality	The betweenness degree of the station within the transport network
9	N11	Transit closeness centrality	The closeness degree of the station within the transport network
10	P1	Number of Bicycle parking	Number of bicycle parking racks
11	P2	Lengths of the bike lanes	Total length of bike paths in meters within the catchment area
12	P4	Number of residents	Total number of people living within the catchment area
13	P5	Proportion of educational, health, and cultural areas	Ratio of educational, health, and cultural areas to the total catchment area
14	P6	Proportion of recreational area	Ratio of recreational area to total catchment area
15	P7	Proportion of industrial area	Ratio of industrial area to total catchment area
16	P8	Proportion of residential area	Ratio of residential area to total catchment area
17	P10	Population density	Density of population with respect to the catchment area
18	P11	Proportion of public offices and service facilities	Ratio of public offices and service facilities to the total catchment area
19	P12	Land use entropy (H)	Degree of entropy
20	S2	Shortest distance to the bus stations	Shortest distance to the bus stations
21	S3	Shortest route distance from train station to educational facilities (m)	Calculate the shortest walking route distance from the train station to the educational facilities
22	S4	Shortest route distance from train station to cultural facilities (m)	Calculate the shortest walking route distance from the train station to the cultural facilities
23	S5	Shortest route distance from train station to leisure facilities (m)	Calculate the shortest walking route distance from the train station to the leisure facilities
24	S6	Shortest route distance from train station to workplaces (m)	Calculate the shortest walking route distance from the train station to the workplaces
25	W1	Intersection density	The number of intersections divided by the area of the catchment area
26	W2	Street Line Density	Sum of the length of the lines in km divided by the area in km ²
27	TCI1	Demographic consonance index	Proposed based on Kamruzzaman's article

Table 1 - The initial list of measured indicators

More importantly, EFA does not support NULL (Watkins, 2018). This limitation is problematic, as in urban planning or transport studies, we may need to measure variables such as the average distance to specific points of interest. The problem arises when the POI doesn't exist in the area, and we cannot put 0 because the model treats it as a distance value rather than as non-existent, which is not correct.

Finally, the distribution of the data is crucial for the method we use and for the results of the Extraction phase, in which we identify the underlying latent structure. Among the various extraction methods, Maximum Likelihood (ML) is among the most widely used and requires a relatively normally distributed dataset. However, in the social sciences or urban planning studies, we rarely encounter datasets that are normally distributed (Costello & Osborne, 2005). Table 1 shows the indicators:

3.1.2. Data Acquisition and Preparation Challenges

Before explaining and justifying the selection and processing of the aforementioned indicators, it is important to clarify two key prerequisites for this study. As discussed, train transit-hubs serve as the primary unit of analysis. Therefore, it is essential to identify all train stations with rail lines that provide access through various routes and offer service according to different train line schedules (such as regional, suburban, etc.).

Collecting the exact number of stations though seems to be easy, it was challenging due to need for cleaning the freight train stations from passenger stations, and the fact that the infrastructure manager companies like Rete Ferroviaria Italiana (RFI), Ferrovienord, and FER often only provide information about their own stations and railways. Hence, understanding if the list of the train stations is complete needed verification. Even, the data provided in Lombardy Geoportale does not contain all the

stations⁷. Eventually, the full list of the stations in Lombardy region was extracted using Wikipedia⁸ and they were geocoded using google Cloud service. The results again double checked with General Transit Feed Specification (GTFS) obtained from Lombardy Geoportale⁹, corresponding to October 2025. Eventually, the total number of 313 stations identified across the region.

Moreover, as discussed in the literature review (2.6.2.4), the Functional Urban Areas boundary of Milan, defined by the OECD, was selected as the study area. By overlaying all train stations onto this boundary, a total of 131 train stations were identified within the study area. This process established both the geographical extent, and the total number of train stations used for measuring the indicators in this study.

The catchment area of the stations was delineated using ArcGIS Pro's network analysis tool. Road network data were sourced from OpenStreetMap, and the data were also checked with satellite imagery to see if they are accurate for the stations or not. Line features that were labeled in the attribute table as "motorways," "motorway_links", "trunk", and "trunk_ways" were intentionally excluded from the database to ensure that only truly walkable areas are integrated. The walking distance limit was set to 800 meters, centered around the train stations. The network dataset was configured for high precision, with a trim distance of 10 meters and a search tolerance of 5 meters. These settings ensured that the catchment areas accurately followed the road network, particularly in locations where railways or other barriers forced people to take longer routes to station entrances. Overlaps between catchment areas of closely situated stations were split to avoid double-counting. Finally, a visual inspection of all station catchment areas was conducted to confirm that no anomalies were present, such as catchment zones extending into inaccessible areas, including those blocked by railway infrastructure or rivers.

⁷ <https://www.geoportale.regione.lombardia.it/>

⁸ https://en.wikipedia.org/wiki/List_of_railway_stations_in_Lombardy

⁹ https://www.dati.lombardia.it/Mobilit-e-trasporti/Orario-Ferroviano-Regionale-Gtfs/3z4k-mxz9/about_data

Table 1 contains the indicators that were used in this procedure. Their selection was conducted through conducting a literature review and selecting the indicators that were used by scholars frequently, well-justified, and in accordance with TOD principles. The data collection procedure is generally challenging as many different issues happen, including differences in data acquisition methods and reporting periods. This problem is specifically challenging when dealing with time-sensitive variables such as transit schedules, population figures, and bicycle parking counts. These issues are further aggravated when similar datasets are collected in varying formats or at different time intervals, as it potentially leads to discrepancies between the data. For instance, it raises doubts and questions when a district provides spatial data on bicycle parking in 2025, and another district's spatial data goes back to 2015. To summarize, the main problems encountered during data acquisition include temporal and spatial incompatibility, technical data errors and ghost entities, data fragmentation and incomplete official portals, and algorithmic or tool failures. The following section details the measurement, adjustment, and processing of each indicator, along with their respective purposes.

The number of Train Lines (**N1**) that serve a station primarily tries to capture the degree of accessibility of the station. The logic for selecting this indicator is that, while railways provide the physical infrastructure for access, the actual degree of accessibility depends on the number of lines that serve the station. The assumption is that a greater number of rail lines equates to access to more stations. This indicator is commonly used in literature (Bertolini, 1999; Cao et al., 2020; Zhao et al., 2024).

Transit Frequency (**N2**) is another indicator that is widely used in the literature of TOD typology methodologies (Bertolini, 1999; Lyu et al., 2016; Robillard et al., 2025; Vale, 2015; Zhao et al., 2024). This indicator has also been used not only for train transit systems, but also for bus and light rail transit systems. The aim of this indicator is to measure the total number of trains that serve the station within 24 hours. This number

reflects service reliability have implications for both accessibility and quality of the transit service. It is also commonly categorized as a Node indicator.

In order to calculate this indicator, the General Transit Feed Specification (GTFS) datasets from both the regional operator (Trenord) and the national operator (Trenitalia) were collected. Later, the datasets were checked to see that only the train schedules were included. Also, as we need to calculate the indicator based on a daily frequency, a typical working day (Wednesday, November 12, 2025) was selected for indicator measurement.

Bus Lines (**N3**) & Bus Stops (**N5**) have a similar goal to the number of train lines that serve a train station (**N1**), indicating how many distinct bus lines pass through the catchment area. A greater number of bus lines suggests higher network accessibility and enhanced transit service. Since train stations serve as the unit of measurement in TOD typology, variables related to bus and bicycle services are typically categorized under the Place dimension and labeled as complementary one-last-mile services. However, as previously discussed, the literature does not offer unanimous agreement on these classifications. Nonetheless, this indicator is frequently used in various analyses (Gan et al., 2021; Wu et al., 2024; Zhao et al., 2024).

To prepare the data, GTFS was used to collect the needed information for measuring these two indicators, but the coverage was substantially incomplete for areas farther from the Metropolitan city of Milan. Ultimately, the OSM dataset was used, as it provided information on a significant number of bus stops. Despite this, some catchment areas still appeared to lack bus station data. To address these gaps, the Google API was used and supplemented by manual checks using Google Maps. Eventually, the total unique bus lines and the number of bus stops within each catchment area were counted and noted.

Number of Platforms (**N7**) is another commonly used indicator that reflects the regional network accessibility and directionality of a transit service. A higher number

of platforms suggests greater regional access, as it enables more trains to serve the station, an aspect categorized under the Node dimension (Zemp et al., 2011). This indicator also has implications for the station's capacity, which relates to the Place dimension (Su et al., 2021). The primary sources for collecting the data were OSM. The subsequent verification was conducted by satellite imagery.

The number of stations that are reachable within a 30-min travel (**N8**) is also a popular indicator that provides insights on accessibility (Kang & Miwa, 2025), though some scholars used 20-min threshold (Lyu et al., 2016), and 45-min travel (Bertolini, 1999) threshold as well, we needed to consider a number that could represent an average amount of time that passenger tend to spend on PT for daily mobility. Data for this indicator were derived from GTFS and processed using Python. Also, unlike the frequency indicator that we proposed using the data on a specific day, here we do not consider a date, but we consider the broader schedule table to see how many stations are reachable within the threshold.

The Number of Metro Stops (**N9**) is also commonly used in the literature. This indicator refers to other means of transit services that exist within the catchment area, which has implications for both the Node and Place dimensions. Metro stop locations were collected using the Google API, and the data was checked to remove anomalies, including duplications. Rabiei et al. (2022) and Song and Deguchi (2013) used such Transit Betweenness Centrality (**N10**) illustrates which stations act as bridges within the transit network. Stations with higher betweenness centrality are assumed to have greater control over passenger flows and thus possess greater potential accessibility. This indicator is in accordance with Space Syntax theory (Bill Hillier, 1998) which is inherently different from standard engineering approaches that treat cities simply as metric graphs with impedances and capacities. Instead, Space Syntax views the network as a topological configuration, a permeable space defined by available trip schedules. The indicator is calculated using GTFS data and measures how often a

specific station acts as a node on the shortest path on a trip between every other two stations. It is calculated using the standard Betweenness Centrality formula (Eq. 6):

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (6)$$

Where $C_B(v)$ is the Betweenness centrality of station v , and σ_{st} is the total number of shortest paths from station s to station t , finally $\sigma_{st}(v)$ is the number of those shortest paths that pass-through station v .

Transit Closeness Centrality (**N11**), unlike N10, considers time and distance to see how accessible the stations are. It takes into account actual travel times, as derived from the GTFS database, providing a strong approximation of regional accessibility. Cao et al. (2020), Rabiei et al. (2022), Kang & Miwa (2025), Liu et al. (2025), and some other scholars used such indicator in their analysis.

The Number of Bicycle Parking spaces (**P1**) and the Total Length of Bike Lanes (**P2**) are used to understand whether the AT is supported by the catchment or not. Data for both indicators were collected from OSM. However, it should be acknowledged that data accuracy may decline for stations located farther from the city center or in less prominent areas. Within the literature, such indicators are often classified under the Place/Design dimension by scholars and reflect the quality of multimodality in TOD areas. Both are also commonly used in the literature (Bertolini, 1999; Wu et al., 2024).

Number of Residents (**P4**) shows the number of people who live within the catchment area. It is a key indicator frequently used in the literature. It directly reflects TOD principles such as Density, as introduced by Cervero, and is consistently applied in most research studies (Lyu et al., 2016; Reusser et al., 2008; Vale, 2015; Zemp et al., 2011). Data for this indicator were obtained from Istituto Nazionale di Statistica (ISTAT)¹⁰, which provided 2021 demographic data at the census block level for all of Italy. However, a major challenge arose because the boundaries of the catchment areas did not align with those of the census blocks, which in some cases could significantly

¹⁰ Istat.it

impact the results. As no finer-scale demographic data were available, an approximation method was developed to estimate population within TOD areas. This approach distributed census block population into individual buildings based on their volume, calculated using land-use data (DUSAF 7.0)¹¹, building footprints (OSM), and building heights from Geo-Topographic Database (DBGT)¹². As the finer-grade data enabled this, only the population attributed to the buildings that intersect with the catchment area counted.

The proportions of educational, health, cultural, recreational, industrial, public offices & services, and residential areas (**P5, P6, P7, P8, P11**) are intended to reveal the diversity characteristics within each catchment area. Although P7 is labeled as "industrial," it also includes commercial activities. These are popular indicators that scholars often use, usually, they are classified under the Place dimension. They were directly adopted from the analyses of Su et al. (2021, 2022) due to the availability of comprehensive land-use data, which enabled accurate measurement. Alternative approaches, such as using the Google API or OSM, were not feasible for such an extensive area, as extracting geospatial locations and descriptive activity data proved impractical.

Finally, we can develop another indicator based on the other indicators related to land use to measure the degree of diversity. It is called Land-use Entropy (**P12**). This variable ranges from 0 to 1 and quantifies the degree of land-use mix within the catchment area. Widely used in the literature, this indicator reflects a core principle of TOD. It is computed using P5, P6, P7, P8, and P11 according to the Shannon entropy formula (Eq. 7):

$$H = \sum (p_i \times \ln(p_i))$$

¹¹https://www.geoportale.regione.lombardia.it/metadati?p_p_id=detailSheetMetadata_WAR_gptmetadataportlet&p_p_lifecycle=0&p_p_state=normal&p_p_mode=view&_detailSheetMetadata_WAR_gptmetadataportlet_identifier=r_lombar%3A7cd05e9f-b693-4d7e-a8de-71b40b45f54e&_jsfBridgeRedirect=true

¹² <https://www.geoportale.regione.lombardia.it/stato-database-topografici>

Population Density (**P10**) was included as an indicator because, unlike the total number of residents, population density might vary considerably according to the size of each station's catchment area, which is determined by the extent of walkable streets. As such, this indicator delivers a more accurate reflection of actual population concentration than P4. However, this does not diminish the value of P4, since many other urban variables are also influenced by the absolute population count. This indicator also is constantly used in the TOD typologies literature (Reusser et al., 2008; Yi et al., 2024).

The next group of indicators, the shortest route distance from train stations to bus stops, educational, cultural, leisure, and workplace destinations (**S2, S3, S4, S5, S6**), aims to provide insights into functionality based on being accessible of key destinations within each catchment area. Unlike land-use indicators, which focus on the presence of various functions, these indicators assess the proximity of important destinations to transit hubs. According to TOD principles, it is desirable for major strategic destinations to be located near stations. Although comprehensive land-use data were available, they could not be used directly to calculate these indicators. Bus stop locations, which we had already collected and processed for the N5 indicator, while data for the remaining destinations were gathered using both the Google Maps API and OSM. All datasets were carefully reviewed to eliminate irrelevant entries. For example, driving schools, dance studios, and yoga centers were excluded from the educational facilities category.

The indicators originally borrowed from Su et al. (2021), however after reviewing its application it is deduced that the application of such indicator is flawed, as the original indicators tend to calculate the average route distance to diverse destinations, which such approach fallaciously award a single destination when it is close to the transit-hubs over a station with several destination within the catchment area while the average distance is higher than the previous case, so it conveys the first has a better

situation while it is not correct. Hence, the indicators had changed into the shortest route to various destinations, and the insight does not imply accessibility, but rather functionality.

Intersection Density (**W1**) and Street Line Density Measure (**W2**) were included after the initial attempt to use a different metric for walkable streets (S1) proved unsuccessful and was excluded from the study. Both indicators aim to give insights into the walkability of catchment areas. Higher intersection density is often deciphered as a convenient environment for pedestrians, as it typically means smaller blocks and consequently, a stronger connected street grid. Moreover, street line concentration measures the total length of the accessible streets, showing the availability of walkable streets within the area. The use of both indicators is heavily supported by the literature (Kamruzzaman et al., 2014; Singh et al., 2017; Zhao et al., 2024).

Lastly, the Demographic Consonance Index (**TCI1**) is a novel indicator, introduced here for the first time. Adapted from Kamruzzaman et al. (2013), who pointed out the importance of individual characteristics in TOD areas, TCI1 intends to assess how closely the socio-economic and demographic profiles of TOD residents match TOD-friendly attributes. This index was constructed using available data on age, family size, and employment status, with different weightings assigned to each variable. The formula for TCI1 is provided below (Eq. 8):

$$TCI1 = \frac{\left(\frac{NO. people with suitable age}{Total Pop}\right) + 1.5 \times \left(\frac{NO. suitable families}{Total families}\right) + 0.5 \times \left(\frac{NO. employees}{Total working age pop}\right)}{3}$$

ALIAS	NULLS	MEAN	MEDIAN	STD.	RANGE	CV	SKEW	KURT
N1	0	2.72	2.00	2.61	15.00	0.9599	2.4178	9.8396
N2	0	138.98	83.00	127.23	824.00	0.9154	2.2124	9.4113
N3	0	3.97	3.00	4.10	18.00	1.0321	1.6162	5.2475
N5	0	10.51	6.00	11.21	51.00	1.0665	1.3199	3.9071
N7	0	3.29	2.00	3.08	23.00	0.9353	4.0201	23.8500
N8	2	17.4341	14	10.1656	60	0.5830	1.8972	7.0726
N9	112	0.3206	0	0.8881	5	2.7700	3.0323	12.0941
P4	0	7,172.61	6,006.00	6,205.10	31,172.00	0.8651	1.5277	5.7476
P10	0	0.01	0.00	0.00	0.02	0.7892	1.3276	4.5859
TCI1	0	0.34	0.34	0.06	0.46	0.1675	-2.7693	20.6997
P1	0	9.70	2.00	19.48	106.00	2.0081	3.2490	13.8188
P2	0	2,226.65	1,858.00	1,802.33	8,656.00	0.8094	0.9097	3.6112
P5	0	0.01	0.00	0.01	0.10	2.0450	3.5596	19.5128
P6	0	0.07	0.06	0.05	0.39	0.7361	2.0961	10.8614
P7	0	0.14	0.12	0.11	0.69	0.7551	1.8878	9.1642
P8	0	0.45	0.46	0.17	0.71	0.3871	-0.7154	2.8655
P11	0	0.04	0.03	0.04	0.28	1.0932	2.2882	11.0899
P12	0	0.56	0.58	0.13	0.83	0.2366	-1.1481	5.9615
S2	17	482.03	507.14	147.35	825.61	0.3057	-0.5689	3.5520
S3	17	621.45	642.83	110.66	527.87	0.1781	-0.3219	2.6818
S4	33	608.67	616.34	128.80	608.61	0.2116	-0.0548	2.5604
S5	14	3,753.39	2,632.76	3,366.62	16,709.20	0.8970	1.7495	6.4507
S6	0	632.56	633.84	86.39	471.97	0.1366	-0.2439	3.3632
N10	0	0.01	0.00	0.02	0.24	3.3728	7.6902	72.7604
N11	0	0.03	0.03	0.01	0.04	0.2392	-0.9224	5.9644
W1	0	0.00	0.00	0.00	0.00	0.3986	0.0964	2.6754
W2	0	1.26	1.26	0.35	1.90	0.2781	0.2651	3.4461

Table 2 - Statistics related to the distribution of the dataset

As shown in Table 2, which was produced by ArcGIS Pro's Data Engineering tool (Esri, 2024), there are some critical points to pay attention by checking the statistics. First, indicators S2, S3, S4, and S5 have NULL values and are therefore unsuitable for use in the EFA model (Watkins, 2018). The reason why we cannot handle NULL values by replacing them with 0 or another constant value is that it produces fallacious meaning, so we have no choice but to remove them. This reduces the total number of indicators from 27 to 23. This already leads to a ratio of 131:23 (5.7:1), which can be acceptable depending on data communalities (Kang & Miwa, 2025). On the other hand, although the indicator N9 (Number of metro stations) contains 112 NULL values, we can substitute them with 0 just because it simply means that there is no metro station

within the catchment area, while for S2, S3, S4, and S5 putting 0 instead of NULL means the average distance is 0.

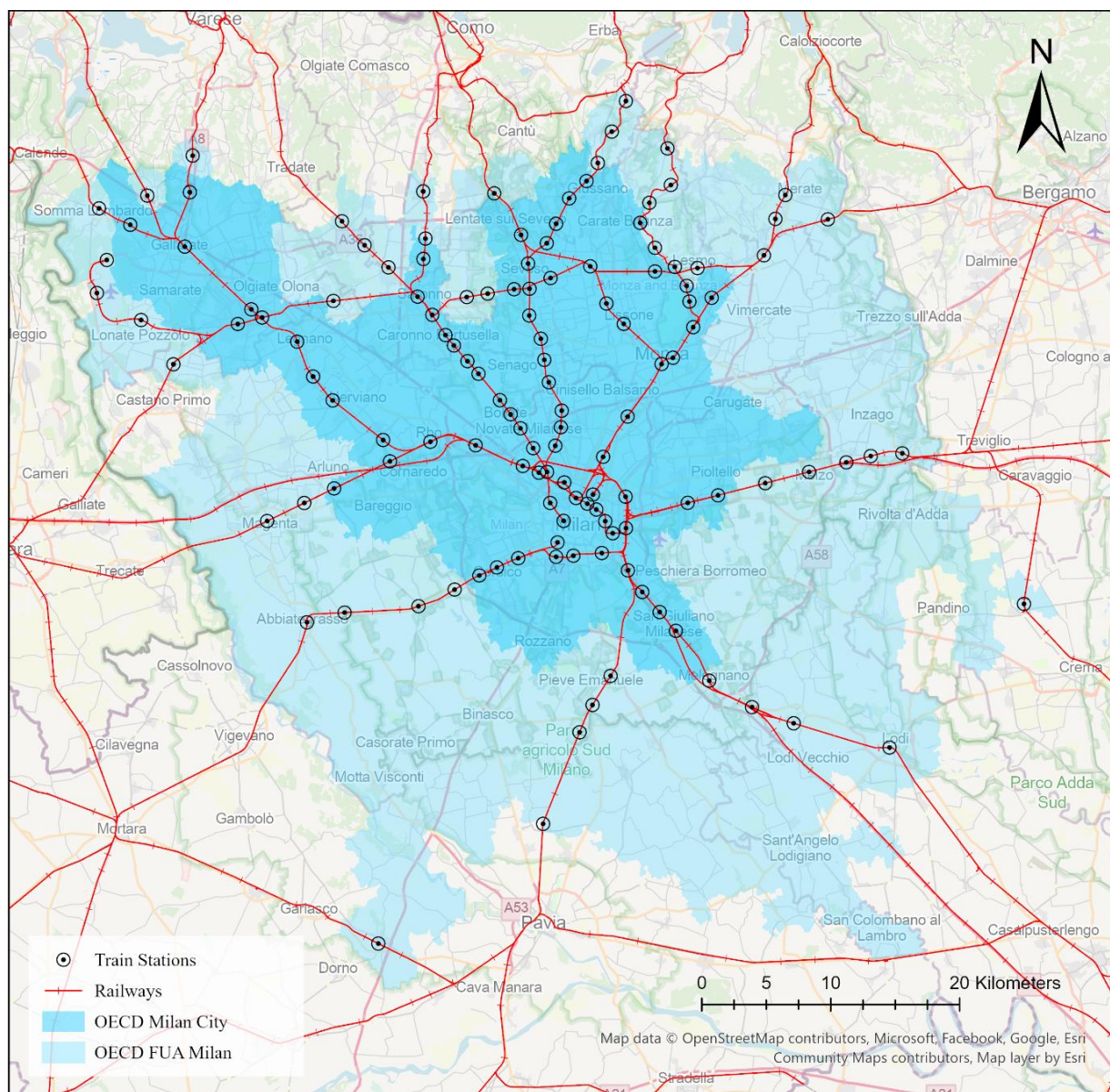
We can also fix the problem of the N8 (number of stations reachable within 30 minutes). N8 shows 2 NULL values, there are two train stations within the FUA of Milan for which, according to GTFS data, no trains depart or arrive. These two stations, Ceriano Laghetto Groane¹³ and Cesano Maderno Groane¹⁴, are both served by the S9 Metropolitan City of Milan suburban railway but have no scheduled trains departing from or arriving at them. These two ghost stations, though existing, have no function, so we exclude them from the samples. This changes the total number of stations from 131 to 129.

N10 (Transit Betweenness Centrality) shows high skewness (7.69) and kurtosis (72.76), indicating that most stations do not serve as “bridges” in the train network. However, stations such as Milano Garibaldi (0.2365) and Saronno (0.07991) serve as gateways for the entire FUA. This is further supported by indicator N7 (Number of Platforms), which exhibits high skewness (4.02), indicating that most stations have 2-track stops, whereas Milano Garibaldi has 20 platforms.

Other indicators related to the ‘Place’ dimension also exhibit high skewness. As the data is already validated, we are sure that it is not an anomaly though a reality within the system. Some station areas within the Milan metropolitan area display higher concentrations of services and greater diversity of activities. Indicators such as P1 (Bike Parking), P5 (Industrial volume), and P11 (Commercial volume) are located near Metropolitan City of Milan. Milano Porta Garibaldi station’s area has the highest value for P1 (106). Milano Affori has the highest value for P5 (0.09), and Milano Bovisa Politecnico has the highest value for P11 (0.28), all conforming to the pattern of higher development and facility concentration.

¹³ 9.1001911°E 45.6272472°N

¹⁴ 9.1264964°E 45.6303436°N



Map 1 - Map of Milan FUA with Metro stations and rail lines

Moreover, because the data measure different indicators, their scales differ. The scale similarity within the data is crucial for factor extraction and clustering, as variables with naturally larger numerical ranges can disproportionately dominate the factor extraction results. Also, as discussed, the EFA formula (equation 1) assumes that the variables are standardized. Thus, we need a standardization method to bring all data to a common scale. EFA is based on the Correlation Matrix to identify shared variance (communalities) among variables and to extract factors.

As discussed earlier, both data standardization and distribution matter when defining the method of factor extraction. As we agreed, we will discard ML because it requires transforming data into a normal distribution, and some transformation techniques, like Cox-Box, used for EFA (as in Kang & Miwa, 2025), cannot be applied because the Cox-Box transformation requires the dataset to be positive (Box & Cox, 1964), given the fact that many variables we measured contains 0 values, this method is not suitable.

Given these considerations, and as suggested by Costello & Osborne (2005), we should use an extraction method appropriate for non-normal data. Among the available methods, Principal Axis Factoring (PAF) and Minimum Residuals (MinRes) are both applicable when the data is messy (Costello & Osborne, 2005). PAF explains as much as possible, while MinRes minimizes the error (residuals) in the correlations. Both can handle non-normal data, MinRes is specifically robust when the normality is rejected. PAF estimates communalities, whereas MinRes ignores the diagonal elements to find the best off-diagonal fit (Costello & Osborne, 2005). Consequently, because our data are highly non-normal and we wish to avoid multivariate normality issues, MinRes is used for factor extraction.

Returning to the problem of scale heterogeneity, we used the Z-score method to standardize the data, then employed a Scree plot to determine the number of factors and the MinRes correlation matrix. We observe the Z-score structure in Eq. 9. Z-score centers all of the variables around 0, and by dividing it by the standard deviation, we can make sure that the variance of each indicator is 1 (Ewing & Park, 2020).

$$Z = \frac{x - \mu}{\sigma} \quad (9)$$

Where: x is the raw value of the indicator.

μ is the mean of that indicator across all of 129 stations.

σ is the standard deviation, which measures the amount of variation or dispersion in the dataset.



Figure 6 - Z-score transformation of the values

As shown in the figure above, after applying the Z-score, the data are centered at 0, and each variable's mean is close to 0. This is confirmed by a validity check. Now that we have the standardized data, we can proceed with factor extraction, but in order to make sure that the dataset is suitable for factor extraction, we validate the data by using the Kaiser-Meyer-Olkin (KMO) test, which measures sampling adequacy (Hair, Black, Babin, & Anderson, 2010) and a Bartlett's test of sphericity that checks if the variables are truly related or if they are just a collection of random numbers (Tabachnick & Fidell, 2019).

KMO compares the magnitude of the observed correlation coefficient to the partial correlation coefficient. If the variables share common factors, the partial correlations would be very small. The KMO formula is given in Eq. 10 (Hair, Black, Babin, & Anderson, 2010). The KMO test yields a score of 0.818, which is considered excellent,

meaning that the sample size is large enough and indicators are related. This is encouraging, because we already discussed how the 5:1 ratio needs high communalities within the data to compensate for the small sample size.

$$KMO = \frac{\sum \sum_{i \neq j} r_{ij}^2}{\sum \sum_{i \neq j} r_{ij}^2 + \sum \sum_{i \neq j} a_{ij}^2} \quad (10)$$

Where r_{ij} is the standard correlation coefficient between variables i and variable j .

a_{ij} is the partial correlation coefficient between variable i and variable j .

In continuous data, Bartlett's test of sphericity assesses whether the correlation matrix differs significantly from an identity matrix (I), which is diagonal with all entries equal to 1. If the indicators are completely unrelated, the determinant absolute value cap R , end absolute value would be 1, and $\ln(1)$ would be 0, resulting in a test statistic (χ^2) of 0. The test statistic is calculated using Eq. 11 (Tabachnick & Fidell, 2019). The Bartlett's test statistic for our dataset is approximately 0, which provides strong evidence that the correlations among the indicators are not due to random chance.

$$\chi^2 = -\left((n-1) - \frac{2p+5}{6}\right) \cdot \ln|R| \quad (11)$$

Where n is the sample size (in our case, 129).

p is the number of indicators (in our case, 23).

$|R|$ is the determinant of the correlation matrix.

$\ln$ is the natural logarithm.

3.2. Phase 2: Iterative Factor Extraction (trial & error loop)

The next step in the methodology is iterative factor extraction, in which we identify the total number of factors and refine them through trial and error. This step begins with a factor extraction method, as discussed previously, the minimum residuals method, which indicates the potential number of factors based on the eigenvalues. We

then use a scree plot to inspect the trend in the eigenvalues, a method that helps us move beyond the traditional criterion of eigenvalues above 1, which has been used in many studies. Instead, we examine the trend to identify the “elbow” point in the data. This elbow point marks the start of the number of factors. Using this number, we perform an Oblimin rotation to examine the extent to which each indicator loads onto the new dimensions. It is useful to check the number of loadings and cross-loadings within the factors. Based on the results of this matrix, we refine the indicators and rerun the model to eventually finalize the total number of dimensions.

The logic of Minimum Residuals is to find a factor loading matrix Λ that minimizes the difference between the observed correlation matrix (R) and the reproduced correlation matrix ($\Lambda\Lambda^T$). Hence, MinRes focuses on the off-diagonal elements, ignoring the diagonal (communality) during extraction. The function to be minimized is the sum of the squared residuals (SR), Eq 7. Consequently, we run MinRes on all 23 indicators, yielding a series of eigenvalues that indicate the proportion of variance explained by each potential factor.

$$SR = \sum_{i < j} (r_{ij} - r^{\wedge}_{ij})^2 \quad (12)$$

Where r_{ij} is the observed correlation between indicator i and indicator j . $r^{\wedge}_{ij}$ is the reproduced correlation, the row i of the loading matrix times the column j of the transposed loading matrix ($i < j$) (Ewing & Park, 2020).

$$\text{Transposed loading matrix} = \sum_{k=1}^m \lambda_{ik} \lambda_{jk} \quad (13)$$

The result eigenvalues are as follows. We can use these eigenvalues and a scree plot in descending order:

[8.72448848, 2.76089946, 1.95398228, 1.39435489, 1.2878882, 1.12794708, 0.89018449, 0.76312811, 0.70100284, 0.59784263, 0.52529922, 0.47505341, 0.43686807, 0.33378958, 0.21216433, 0.18209722, 0.17264026, 0.14566315, 0.11921454, 0.07407796, 0.06359754, 0.03633566, 0.02148062]

The scree plot, developed by Raymond B. Cattell (1966), is an alternative to the Kaiser Criterion (i.e., retaining eigenvalues above 1) in which eigenvalues are plotted on a

graph. As confirmed by other studies, Kaiser Criterion often causes over factoring (Costello & Osborne, 2005). A scree plot plots eigenvalues on the Y-axis and factor numbers on the X-axis, and we can inspect the trend to identify the elbow point, where a vertical drop turns into a horizontal plateau. The scree plot is heuristic, meaning that the elbow point is not necessarily the best number of factors, and often researchers evaluate the neighboring models as well (Costello & Osborne, 2005).

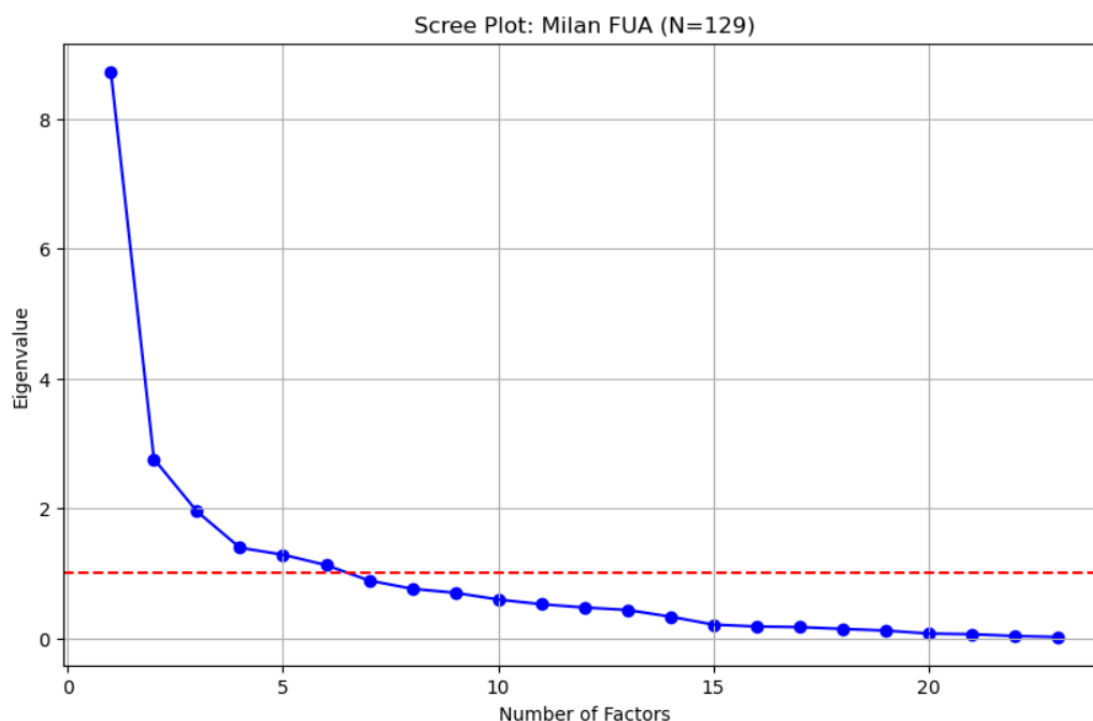


Figure 7 - Scree Plot result

In Figure 7, there is a sharp drop after the first factor. Although according to the Kaiser criterion, there are 6 factors to keep (eigenvalues > 1), the trend in the scree plot mostly emphasizes the dominant effect of factor one, followed by factors two and three, which are also relatively important because factors 4 or 5 are located at the end of the elbow. Given that, from a heuristic perspective, the number of factors is 4 or 5.

Given the trial-and-error nature of this methodology, it is crucial to examine the correlation matrix of the indicators and factors to assess the extent to which each variable contributes to the factor loadings and to identify cross-loadings that indicate noise.

This is the exact moment in this phase when we need to iterate the results to find the cleanest possible scenario. The criteria that can satisfy our requirements are as follows: First, the primary loading threshold is 0.32, meaning that variables of a factor should have at least 0.32 loadings on the indicator. Second, the cross-loadings of a variable for different factors should be less than 0.32, and lastly, each factor should be composed of at least 3 variables (Costello & Osborne, 2005).

To understand the relationships among the variables and factors, and to verify the requirements we derived, we need to calculate the Pattern Matrix. This is the pattern matrix used to assess the loading of a variable on different factors and to identify cross-loadings. To do so, we need an Oblique Rotation. Oblique rotation transforms the initial factor axes to align with the actual clusters of variables, even if the axes are no longer orthogonal.

As explained before, during the MinRes extraction phase, we identify eigenvalues to determine the variance each factor captures. This leads to an unrotated factor matrix λ_{ik} where the factors are orthogonal. Mathematically, the observed variables x_i are modeled as a linear combination of these underlying factors, F , and unique errors. In this state, most of the factors load on the first factor, making it impossible to distinguish among the factors. To address this, we apply a transformation matrix to rotate the axes so that the variances are more distinguishable.

Direct Oblimin is an oblique rotation (like the main component axes in PCA, but with orthogonal rotation); it seeks to minimize the simplicity criterion function (f). It uses a parameter, γ which controls the degree of allowed correlation. The function is as follows:

$$f(L) = \sum_{p < q} \left(\sum_{j=1}^k \lambda_{jp}^2 \lambda_{jq}^2 - \frac{\gamma}{p} \sum_{j=1}^k \lambda_{jp}^2 \sum_{j=1}^k \lambda_{jq}^2 \right) \quad (14)$$

Where λ_{ik} represents factor loadings. This function will tilt the axes toward the data clusters and make them correlated. We must represent their relationship in a factor correlation matrix (Φ):

$$\Phi = T'T \quad (15)$$

Once the rotation was complete, the relationship among the variables was decomposed into two matrices: the structure matrix and the pattern matrix. The structure matrix (S) represents the correlation between variables and factors. However, because the factors now overlap, we need a pattern matrix (P) to see the unique contribution of each factor (Ewing & Park, 2020).

$$S = P\Phi \quad (16)$$

Simply, we can construct the pattern matrix with respect to Eq. 11 in Eq. 17:

$$P = S\Phi^{-1} \quad (17)$$

Based on the Scree plot, we initially ran the analysis using five factors. The resulting tables for Total Variance Explained, Factor Correlation Matrix, Communalities, and the Pattern Matrix are presented in continue.

3.2.1. First Iteration

Metric	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
SS Loadings	4.552	3.036	2.502	1.708	0.986
Proportion Var	0.198	0.132	0.109	0.074	0.043
Cumulative Var	0.198	0.330	0.439	0.513	0.556

Table 3 - Total Variance Explained ($\sum Var(\chi_i)$)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1.000	0.170	0.096	0.485	0.309
Factor 2	0.170	1.000	0.068	0.414	0.190
Factor 3	0.096	0.068	1.000	0.236	0.095
Factor 4	0.485	0.414	0.236	1.000	0.258
Factor 5	0.309	0.190	0.095	0.258	1.000

Table 4 - Factor Correlation Matrix

Indicator	Communality	Indicator	Communality
N1	0.985	P5	0.203
N2	0.805	P6	0.439
N3	0.63	P7	0.284
N5	0.757	P8	0.892
N7	0.523	P11	0.314
N8	0.797	P12	1.027
N9	0.498	S6	0.133
P4	0.623	N10	0.721
P10	0.611	N11	0.312
TCI1	0.258	W1	0.774
P1	0.446	W2	0.641
P2	0.111		

Table 5 - Communalities Table

Indicator	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
N1	0.99	-0.012	-0.014	-0.063	-0.009
N8	0.886	0.063	0.026	0.077	-0.029
N2	0.88	0.124	-0.029	0.036	-0.109
N10	0.776	-0.248	0.066	0.021	0.228
N7	0.713	0.024	-0.047	-0.048	0.097
N11	0.508	0.156	0.102	0.136	-0.028
P1	0.455	0.18	0.097	0.019	0.443
P11	0.4	0.161	0.106	0.339	0.043

N9	0.295	0.429	-0.078	-0.115	0.455
N3	0.203	0.756	-0.084	-0.095	0.009
P7	0.17	0.037	-0.106	-0.036	-0.492
W2	0.141	0.283	0.733	-0.037	-0.039
TCI1	0.129	0.265	0.214	0.346	0.077
W1	0.124	0.079	0.866	0.026	-0.05
P5	0.048	-0.191	0.131	0.235	0.304
P10	0.033	0.718	0.282	0.086	0.081
P12	0.026	-0.034	-0.021	1.011	-0.039
P2	0.012	0.123	0.096	0.202	0.213
P4	0.005	0.717	0.311	0.059	0.091
N5	-0.035	0.865	-0.028	0.083	-0.024
S6	-0.066	0.267	-0.131	-0.121	0.16
P8	-0.165	-0.1	0.92	-0.04	0.084
P6	-0.166	0.21	-0.195	0.512	0.257

Table 6 - Pattern Matrix

According to Tables 3-6, there are several important points that need attention. As shown in Table 3, the SS loadings for Factor 5 are less than 1. This is inconsistent with the expected value derived from the Scree plot (Figure 7). Factor 5 has an eigenvalue above 1, yet Table 3 does not reflect this. The primary reason is that the initial eigenvalues (which use perfect communalities) and the extraction eigenvalues (which use estimated communalities) are not identical.

As explained by Matsunaga (2010), while both PCA and EFA are based on correlation matrices, PCA assumes a value of 1 on the diagonal, whereas EFA uses methods such as MinRes or PAF that rely on reliability estimates or communalities in those diagonals (Matsunaga, 2010). This explains how the discrepancy happens.

Moreover, Table 3 shows that Factor 1 accounts for nearly 20% of the variance in the data. Factors 2 and 3 also account for a sufficient proportion of the variance in the data. On the other hand, Factors 4 and 5 explain about 7% and 4% of the total variance. This means that Factors 4 and 5 have an insufficient role. Finally, the model explains 56%

of the variance in the data. While this number is not outstanding or excellent, it is considered acceptable in urban planning studies (Hair, Black, Babin, & Anderson, 2010).

We should consider that our dataset is based on urban dynamics, and urban dynamics are interconnected. So, it is crucial to consider the correlations among the factors shown in Table 4. This helps clarify the relationships among the factors. The most important points in this table are the relationships between factors 1 and 4 (0.485), factors 2 and 4 (0.414), and factors 1 and 5 (0.309). Because the correlation is not very high (>0.8), we conclude that the factors are interconnected but not identical. Later, using this table and Table 4 (the pattern matrix), we can interpret the data's message.

Table 5, which presents the communalities factor (h^2), shows the proportion of the measured variable's total variance that is accounted for by the extracted factor. The scale ranges from 0 to 1, with 1 indicating that the variable is fully explained by the model. When a variable has a low score, it suggests that its presence does not influence the model and may represent an outlier or noise within the data. N1 (0.985) and N8 (0.797) have the highest communalities, both of which are related to the rail network's structure. P8 (0.892) and P12 (1.027), by contrast, are associated with station-area characteristics. Notably, P12 exceeds 1.0, a condition known as a Heywood case, which can occur when a variable is highly correlated with the factors and the sample size is small.

In contrast, P2 (0.111), S6 (0.133), P5 (0.203), and TCI1 (0.258) have low shared variance with the remaining factors. These variables are unreliable for the model because most of its information is just noise or unique error.

Finally, Table 6 is intended to clarify the meaning and definition of each factor. The pattern matrix in Table 6 shows which variables contribute to each factor and to what extent. As observed, Factor 1 is primarily composed of indicators related to the train network's structure: N1 (0.998), N8 (0.886), N2 (0.88), N10 (0.776), N7 (0.713), N11

(0.508), P1 (0.445), and P11 (0.4). This factor is the most robust, displaying strong correlations with node variables and 2 place variables. Factor 1 is therefore purely related to transport supply and centrality.

Factor 2 is interestingly composed of both indicators that are commonly classified under Node and Place. Indicators N5 (0.865), N3 (0.756), P10 (0.718), P4 (0.717), and N9 (0.429) imply bus connectivity and population density.

Factor 3, comprising P8 (0.92), W1 (0.866), and W2 (0.723), is mostly shaped by W variables having implications for design characteristics. It reveals a pattern in which several indicators align, most of which are related to intersection density, street length, and residential land use.

Remembering the criteria that we set using Costello (2005), for our analysis, each factor must have at least three contributing indicators, each with a loading above 0.32 and cross-loadings with other factors below 0.32. Given these requirements, let's scrutinize Table 6 once again. N9 (Number of metro stops) exhibits high cross-loading with factors 2 and 5 (0.429 and 0.455, respectively). Indicators P2, S6, and P11 have very low loadings on the factors.

In conclusion, as mentioned earlier, phase 2 requires a trial-and-error approach. Our observations indicate that Factor 5 accounts for minimal variance in the data, suggesting that, in the next round, we will rerun the model with only four factors. Additionally, indicators P2, P6, and S6 do not contribute sufficiently to the model, so we will test the model without them and assess how the results differ this time. We will also retain P11 to observe whether its loading changes. Table 5 also indicates a potential problem, as nearly 10 variables exhibit low communality. As noted by Costello (2005) and McNeish (2016), in models with a small number of samples, the sample-to-variable ratio can be 5:1 when the model has high communalities. This implies that we may lose more variables during the next iterations (McNeish, 2016).

Moreover, we do not simply neglect the P12 Heywood case problem (communalities greater than 1) and the N9 problem (high cross-loadings between factors). In particular, the Heywood problem with P12 is a critical issue that requires attention. For now, in iteration 2, we will keep them as the first option to assess the results. If it isn't resolved, we will change the dataset configuration again.

3.2.2. Second Iteration

As concluded in the first round, three indicators were removed, reducing the total to 20. With 129 samples, the ratio of samples to indicators is now 6.45:1, which, according to Costello (2005), is more appropriate for our model. Since we have already decided to use four factors, the Scree plot is no longer necessary. Instead, we examine the dataset using KMO and Bartlett's test of sphericity, and then analyze the Total Variance Explained by the factors to assess their strength. The methodology remains the same as what we did in iteration 1: we use the standardized dataset with 20 indicators and 129 samples, perform a MinRes extraction with four factors, apply Oblimin rotation, and then verify the results using the thresholds established by Costello et al. (2005). The result is as follows:

NO.	Metric	Value
0	KMO Overall	0.829713812
1	Bartlett Chi-Square	2433.892881
2	Bartlett p-value	0

Table 7 - KMO & Bartlett's test result (Iteration 2)

	Factor 1	Factor 2	Factor 3	Factor 4
SS Loadings	4.831282	3.155115	2.369682	1.410055
Proportion Var	0.241564	0.157756	0.118484	0.070503
Cumulative Var	0.241564	0.39932	0.517804	0.588307

Table 8 - Total Variance Explained (iteration 2)

Indicator	Communality	Indicator	Communality
N1	0.987309	P1	0.420514
N2	0.708806	P5	0.156093
N3	0.628489	P7	0.050943
N5	0.781006	P8	0.922044
N7	0.565096	P11	0.334647
N8	0.77432	P12	1.021959
N9	0.386505	N10	0.812305
P4	0.674861	N11	0.285278
P10	0.6645	W1	0.702411
TCI1	0.298446	W2	0.590604

Table 9 - Communalities (Iteration 2)

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1	0.169261	0.132563	0.509789
Factor 2	0.169261	1	0.088829	0.447056
Factor 3	0.132563	0.088829	1	0.244163
Factor 4	0.509789	0.447056	0.244163	1

Table 10 - Factor Correlation (Iteration 2)

Indicator	Factor 1	Factor 2	Factor 3	Factor 4
N1	0.990706	-0.02138	-0.03269	-0.06546
N2	0.827171	0.134209	-0.08074	0.007974
N3	0.204639	0.75223	-0.11534	-0.08636
N5	-0.04948	0.877825	-0.0742	0.049756
N7	0.749562	0.022282	-0.0447	-0.02754
N8	0.876716	0.058679	0.000653	0.047381
N9	0.448414	0.427007	-0.00787	-0.05507
P4	0.01174	0.775732	0.261701	0.066904
P10	0.035061	0.775165	0.231564	0.093641
TCI1	0.127059	0.300862	0.181957	0.398341
P1	0.595648	0.206329	0.145922	0.043035
P5	0.16956	-0.19771	0.208895	0.211227
P7	-0.01887	0.04018	-0.20751	-0.07689
P8	-0.12303	-0.09286	0.947524	-0.02195
P11	0.395343	0.183462	0.076385	0.372637

P12	-0.02298	-0.01208	-0.05688	1.008984
N10	0.858429	-0.24943	0.102586	0.051624
N11	0.498547	0.172633	0.067684	0.04843
W1	0.115558	0.099424	0.824118	0.00094
W2	0.132355	0.30526	0.690557	-0.05508

Table 11 - Pattern Matrix (Iteration 2)

The results of the second iteration remain unsatisfactory, and several serious issues still need to be addressed. However, there are also positive aspects. First, the four-factor model appears more robust, as the fourth factor has an eigenvalue of 1.4, indicating it is sufficiently strong. Nevertheless, the gap between the third and fourth factors is considerable. Additionally, the results indicate that the model accounts for approximately 58% of the total variance, an improvement over the 5-factor model. Moreover, as Table 7 illustrates, we obtain an excellent KMO value, indicating factorability, and a very good Bartlett's test of sphericity. This implies that the dataset is suitable for conducting the analysis.

The most significant issue that we should deal with, is the P12 variable. As shown in Table 9, P12 has a communality value of 1.02, indicating a persistent Heywood case. Removing three variables with low loadings and high cross-loadings during the first iteration did not resolve this issue. According to Kolenikov and Bollen (2008), the recurrence of a Heywood case may signal structural misspecification. If the underlying structure of the train stations differs from the variables used to uncover it, the Heywood case will likely persist. Another possible explanation is that a set of variables with excessive kurtosis can increase parameter estimate variability, thereby increasing the frequency of Heywood cases (Kolenikov & Bollen, 2008).

A warning regarding the Moore-Penrose pseudoinverse also occurred during the second iteration, necessitating its use for factor score estimation. This warning usually appears when a correlation matrix is singular or near singular. This conforms with the Heywood Case problem.

We can observe that a series of new variables that previously had acceptable loadings are problematic: TCI1 (0.2987), P5 (0.1560), P7 (0.0709), and N11 (0.2852). Additionally, Table 11 reveals cross-loadings for indicator N9 (0.4484 for Factor 1 and 0.4270 for Factor 2) and P11 (0.3953 for Factor 1 and 0.3726 for Factor 4). Notably, P7 does not load significantly on any factor, suggesting it acts as noise within the data.

Based on the results from the second iteration, considering the current sample size, variable ratio, and Costello's (2005) criteria for strong data, we conclude that the data are not yet robust. For the third iteration, variables P5, P7, N9, P11, and P12 will be removed from the model. We will not delete TCI1, as its loading was only slightly below the threshold, and the results from iteration 3 may show increased loading for TCI1. Additionally, a three-factor model can be analyzed to further assess the results.

3.2.3. Third Iteration

Metric	Value
KMO Overall	0.820259
Bartlett Chi-Square	2085.105
Bartlett p-value	0

Table 12 - Factorability assessment (Third iteration)

	Factor 1	Factor 2	Factor 3
Factor 1	1	0.155355	0.439015
Factor 2	0.155355	1	0.36618
Factor 3	0.439015	0.36618	1

Table 13 - Factor Correlation (Third iteration)

	Factor 1	Factor 2	Factor 3
SS Loadings	4.704411	2.599973	3.170897
Proportion Var	0.294026	0.162498	0.198181
Cumulative Var	0.294026	0.456524	0.654705

Table 14 – Total Variance Explained (Third iteration)

Indicator	Communality	Indicator	Communality
N1	0.903122	TCI1	0.259788
N2	0.729899	P1	0.495687
N3	0.627417	P7	0.429342
N5	0.864029	P8	0.919551
N7	0.670186	N10	0.942637
N8	0.768376	N11	0.364092
P4	0.639287	W1	0.649776
P10	0.6295	W2	0.582591

Table 15 - Communalities (Third iteration)

Indicator	Factor 1	Factor 2	Factor 3
N1	0.948114	-0.06057	0.023081
N10	0.922544	0.111752	-0.281178
N11	0.528756	-0.006872	0.290624
N2	0.829642	-0.103311	0.175839
N3	0.227926	-0.100791	0.75187
N5	-0.034605	-0.051555	0.927456
N7	0.816912	-0.049954	-0.018601
N8	0.863527	-0.04227	0.144602
P1	0.651925	0.233184	0.127693
P10	0.102379	0.316259	0.720416
P4	0.076169	0.34164	0.718866
P7	-0.137957	-0.532171	0.356517
P8	-0.132339	0.947954	-0.058489
TCI1	0.145874	0.254874	0.416591
W1	0.084335	0.775809	0.201949
W2	0.118805	0.660471	0.363668

Table 16 - Pattern Matrix (Third iteration)

The good news about iteration 3 is that we no longer have the Heywood case, as none of the communalities exceed 1. However, we received a warning that the inverse of the variance-covariance matrix was calculated using the Moore-Penrose generalized inverse because its determinant was at or very close to zero. Which implies a singularity problem, mostly due to the variables N1 and N10, which are almost identical. This is highly prone to repeat the Heywood case in iteration 4 if we do not address this issue.

Moreover, as in previous iterations, the factorability tests with KMO and Bartlett's sphericity test provided acceptable results. Iteration 3 also provides a total variance explained of 65%, which is 6% higher than in iteration 2. In the Communalities table, we can see that only the variable TCI1 has a low communality. Comparing its loading to factor 3 (0.41), we can conclude that it may retrieve its influence on the model in iteration 4. Unfortunately, there is higher-than-standard cross-loading for variable P7.

For iteration 4, we primarily aim to address the Moore-Penrose warning by reducing the tendency toward singularity caused by variables with identical values. Also, the variable P7 must be deleted from the model because of cross-loading.

3.2.4. Fourth Iteration

Metric	Value
KMO Overall	0.832276
Bartlett Chi-Square	1705.455
Bartlett p-value	0

Table 17 - Factorability assessment (Fourth Iteration)

	Factor 1	Factor 2	Factor 3
SS Loadings	3.552876	2.960744	2.35564
Proportion Var	0.253777	0.211482	0.16826
Cumulative Var	0.253777	0.465259	0.633519

Table 18 - Total Variance Explained (Fourth Iteration)

	Factor 1	Factor 2	Factor 3
Factor 1	1	0.50078	0.51303
Factor 2	0.50078	1	0.221917
Factor 3	0.51303	0.221917	1

Table 19 - Factor Correlation (Fourth Iteration)

Indicator	Communality	Indicator	Communality
N5	0.88579879	P10	0.684787537
W1	0.847566197	W2	0.631483211
N8	0.839886032	N3	0.56347543
P8	0.78511003	N7	0.559993937
N10	0.762407826	P1	0.401092984
N2	0.693483287	N11	0.327791654
P4	0.690234281	TCI1	0.196149026

Table 20 - Communalities (Fourth Iteration)

Indicator	Factor 1	Factor 2	Factor 3
N5	-0.051272	0.933259	-0.11044
P10	0.047858	0.799526	0.207979
P4	0.017863	0.795712	0.23824
N3	0.218474	0.708975	-0.114449
TCI1	0.162819	0.372733	0.17524
W2	0.125131	0.220919	0.753008
N11	0.542009	0.175267	0.057435
P1	0.589974	0.165074	0.160543
N2	0.820773	0.121701	-0.070743
N8	0.914477	0.058282	-0.014846
W1	0.098975	0.018418	0.915113
N7	0.747496	-0.011792	-0.033241
P8	-0.16744	-0.051425	0.868579
N10	0.842245	-0.218385	0.073065

Table 21 - Pattern Matrix (Fourth Iteration)

Finally, iteration 4 revealed acceptable results within the data. As expected, the Factorability tests (KMO and Bartlett's test) are suitable. The total variance explained by iteration 4 is slightly lower than that of iteration 3, but it is still acceptable. More importantly, the warnings regarding the Heywood case and the singularity have disappeared, as we removed the N1 variable. Among all the remaining variables, TCI1, though contribute to the loading of factor 2 in an acceptable range, it has a low total of communalities. As it provided the acceptable threshold, we kept it. All the remaining variables are in accordance with the rules regarding loadings and cross-loadings.

Iteration 4 gave us 3 final factors (dimensions) that the data inherently are suggesting it as they construct the hidden structure between the stations. Factor 1 consists of N8 (Number of stations within 30 min travel, 0.91), N10 (Transit betweenness centrality, 0.84), N2 (Railway frequency, 0.82), N7 (Number of platforms, 0.74), P1 (Number of bicycle parking, 0.58), N11 (Transit, closeness centrality, 0.54) explains 0.25 total variance within the data. The sum of squared loading of factor 1 is 3.55, which is the highest among the 3 factors, referring it has the most exploratory power within the data, especially for the clustering phase.

Factor 2, with a total of 2.11% of the variance explained, is the second most important factor. Its eigenvalue is slightly lower than factor 1 with 2.96, implying that it is also a powerful factor in explaining the data. The main components of factor 2 are N5 (Number of bus stops, 0.93), P10 (Population density, 0.79), P4 (Total population, 0.79), N3 (Bus directions, 0.7), and TCI1 (Demographic consonance, 0.37), making this factor multidisciplinary. Though the configuration of the initial variables used in this analysis is not the best set, given limited data availability, this factor is valuable because it underscores the importance of context shaped by the transit network.

Finally, the third factor has a 2.35 SS loading, though lower than the other 2, it is still very influential. Factor 3 explains 0.16 of the total variances of the data. Referring to the result of the scree plot, though there is a difference in the value of the eigenvalues

between the MinRes result and Scree Plot estimation, the trend of the elbow in shaping the number of factors is almost congruent with our result, as the elbow almost shaped in the third factor within the scree plot. Factor 3 consists of W1 (Intersection density, 0.91), P8 (Proportion of residential area, 0.86), and W2 (Street line density, 0.75). Factor 3 refers to walkability and residential patterns in the data. Given all the components of the factors, we can define and interpret the new dimensions qualitatively.

3.2.5. Factor 1 – Multimodal Regional Accessibility

Factor 1, as illustrated in Table 18, is mostly shaped by the variables that show the station's status within the transit network structure. This factor is heavily influenced by the indicators that distinguish the station's regional accessibility. We can observe that variables that are expected to be in accordance with each other, like N8 and N10, are in this factor. When a station is ideally situated, it can also reach more stations within 30 minutes. Though this is also closely related to the distance between the stations, as the N8 is produced using GTFS data that accounts for actual schedules.

Moreover, two other main components of this factor (N2 and N7) are correlated. As N7 measured the number of platforms at each train station and N2 measured the frequency or service intensity, we can conclude that all these criteria are related to the station's status within the network system. Naturally, a well-connected station, at the intersection of the rail lines, will receive more frequent visits from different locations. This is congruent with expectations within TOD and Transport studies as well.

More interestingly, we observed that, alongside the Node indicators in this factor, a Place variable also shapes this dimension. P1, which measures the number of bicycle parking spaces within the catchment area, shows a similar pattern to the network data. This can be justified by the multimodality of the transport. It shows us that when there

is a strong transit supply, it is also equipped with bicycle storage. It also implies the convergence of the node and place development.

3.2.6. Factor 2 – Local Intensity and Service Hub

The second factor has an eigenvalue slightly lower than Factor 1, with an SS loading of 2.96 and explaining 21.1% of the variance. While Factor 1 describes the model from a regional connectivity perspective, Factor 2 is more context-specific and relates closely to local development patterns. It is a combination of node and place indicators. Although the number of bus directions and bus stops were classified as "N" indicators, their categorization under the node dimension is debated (Kang & Miwa, 2025), as some literature places them within the place index. Regardless, the alignment of bus lines and stops with population indices reflects the degree of development in the catchment area. This approach exemplifies the mixed NP model, as Factor 2 combines different dimensions through various indicators.

3.2.7. Factor 3 - Urban Fabric and Walkable Design

Factor 3 also exhibits a substantive SS loading of 2.356, the lowest among the factors, yet it still explains 16.8% of the total variance. This factor comprises two indicators reflecting the area's walkability and one indicator representing demographic consonance. Interestingly, these two categories of indicators can be heuristically justified. A higher value for intersection or road length density suggests a greater concentration of development and a larger catchment area. In other words, a well-developed street network can maximize the walkable area within acceptable walking distances or times.

Dimensions	Indicator	ABBR.	Fac. 1	Fac. 2	Fac. 3
Factor 1 Multimodal Regional Accessibility	Stations within 30-min travel	N8	0.914	0.058	−0.015
	Transit betweenness centrality	N10	0.842	−0.218	0.073
	Transit frequency	N2	0.821	0.122	−0.071
	Number of Platforms	N7	0.747	−0.012	−0.033
	Transit closeness centrality	N11	0.542	0.175	0.057
	Number of Bicycle parking	P1	0.590	0.165	0.161
Factor 2 Local Intensity and Service Hub	Bus stops	N5	−0.051	0.933	−0.110
	Population density	P10	0.048	0.800	0.208
	Number of residents	P4	0.018	0.796	0.238
	Bus Lines	N3	0.218	0.709	−0.114
	Demographic consonance index	TCI11	0.163	0.373	0.175
Factor 3 Urban Fabric and Walkable Design	Intersection density	W1	0.099	0.018	0.915
	Street Line Density	W2	0.125	0.221	0.753
	Proportion of residential area	P8	−0.167	−0.051	0.869

Table 22 – The final result of Factor Extraction Iterations

3.3. Phase 3: Typology Construction

3.3.1. Factor Score Generation

Now that we have the total number of factors (dimensions), we can proceed to the Factor Score Generation. Factor Score Generation uses the result of iteration 4 and produces a series of scores for each factor for all the stations, using it we can proceed with the clustering phase. It is important to note that during this process, we use only the Z-score-standardized values of the stations, not the raw measured values.

To generate the score, we first need to calculate the Factor Score Coefficients (W). The crucial step here is to acknowledge that, because the data and factors are interconnected, we used Oblimin rotation (Hair, Black, Babin, & Anderson, 2010). If we simply use the factor loadings in Table 18, we may double-count some variables, leading to incorrect results. To solve this issue, it is common in statistics to use multiple regression.

The regression in this step (Eq. 18) accounts for 3 components: Variable Correlations, Factor Correlations (Equation 10), and Unique error.

$$W = R^{-1}\Lambda \quad (18)$$

Where Λ is loading matrix from table 17, R^{-1} is correlation matrix and W is Factor Score Coefficient. Following this, we can generate the factor scores using Equation 19. We multiply the standardized values of each station by the coefficient of each factor and sum them.

$$F_{pm} = \sum_{q=1}^n Z_{pq}W_{qm}$$

By the end of this step, we have reconstructed the stations with new dimensions. Instead of 14 variables, we would have 3 values for each dimension. The result of the scores of each station can be found in Table 26.

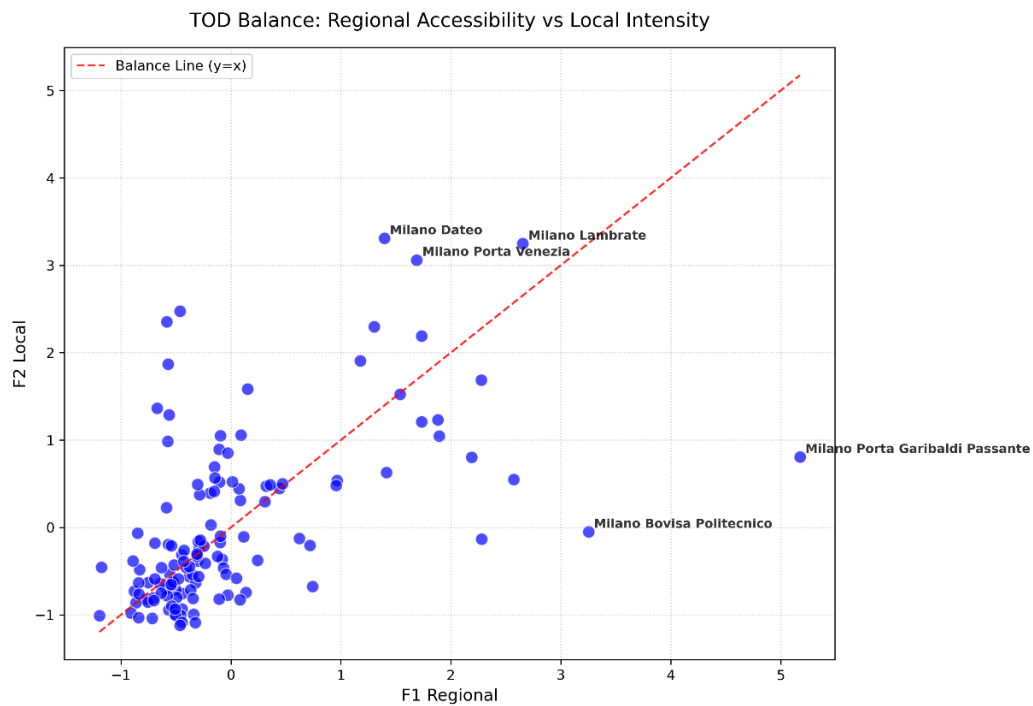


Figure 8 - Factor Score Scatter Plot (F1 - F2)

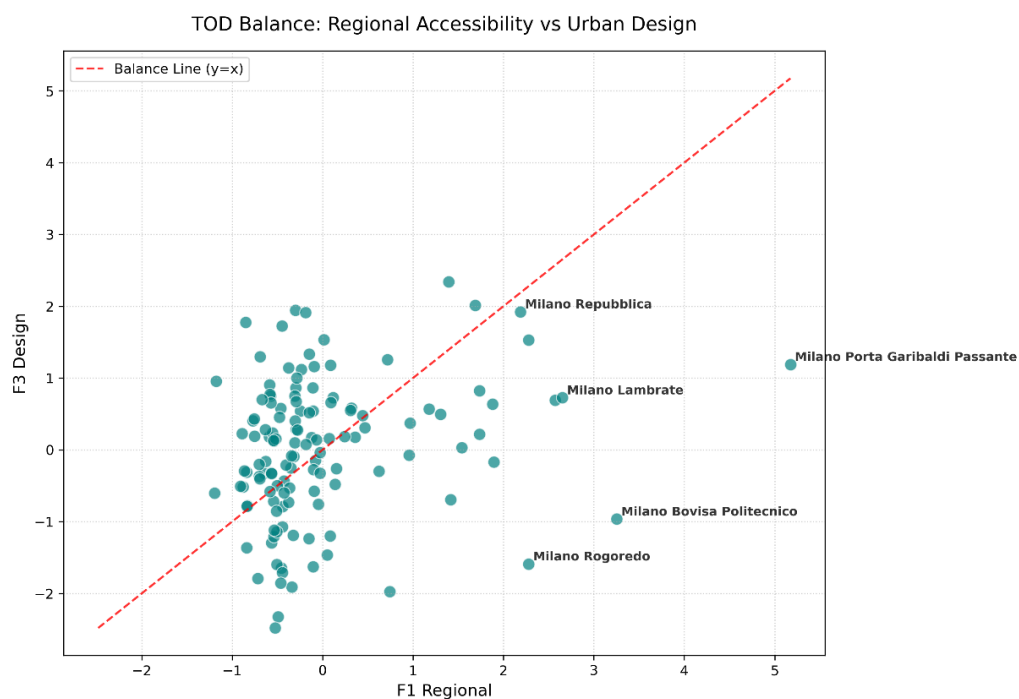


Figure 9 - Factor Score Scatter Plot (F1 - F3)

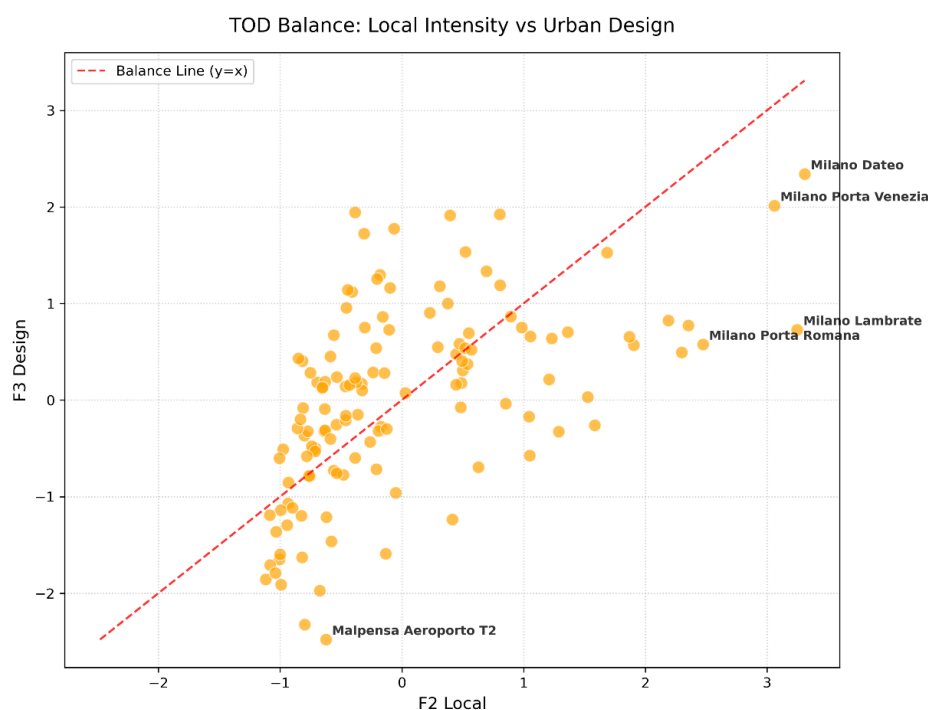


Figure 10 - Factor Score Scatter Plot (F2 - F3)

All the Factor Score Scatter Plots (Figures 9 - 11) include a diagonal line ($y = x$) to illustrate the heuristic Node-Place balance as described by Bertolini (1996). This is only put to facilitate visual comparison within the data, and not for the interpretation of the data.

3.3.2. Hierarchical Clustering (Ward's method)

Next step in Phase 3 is to cluster the factors (dimensions) scores of each station. The aim of this section is to provide the short definition of the Hierarchical Clustering (Ward's method) and providing the results, the discussion of different methods of clustering used in academia and their differences is discussed in literature review part.

Hierarchical Clustering Analysis, unlike methods such as K-means, does not require a predefined number of clusters to classify the stations. It is a bottom-up approach that attempts to merge the first two similar stations into a cluster, continuing until all stations belong to a group (Ewing & Park, 2020). It is also very useful when the sample size is small (Kang & Miwa, 2025). Hierarchical clustering analysis uses Euclidean

distance (Equation 20) to determine similarity by measuring the straight-line distance between samples in a 3D space of our 3 dimensions.

Meanwhile, there is a specific methodology in Hierarchical Clustering Analysis called Ward's Linkage, or the Ward's Minimum Variance Method, which is a criterion for deciding which cluster should be merged at each step. In Ward's method, instead of looking at the closest or furthest points in two clusters, it merges clusters based on the Total Within-Cluster Sum of Squares (ESS) (Ward & Jr., 1963).

$$D(i, j) = \sqrt{(F_{1i} - F_{1j})^2 + (F_{2i} - F_{2j})^2 + (F_{3i} - F_{3j})^2} \quad (20)$$

In Eq. 20, which is in accordant to our model, we have 3 factors (F1, F2, F3) generated from the Factor Score Generation step for each station. The algorithm in Eq. 15 starts with 129 clusters, groups all stations, and then merges the closest pairs (Ewing & Park, 2020). In continue, as explained the Ward's linkage strategy used to determine which clusters should merge at each other, Ward's method is based on an Analysis of Variance (ANOVA) approach (Ward & Jr., 1963). The goal is to minimize the increase in the error sum of squares (ESS) (Equation 21).

$$ESS = \sum_{i=1}^n \|x_i - \bar{x}\|^2 \quad (21)$$

Where ESS is the total within-cluster sum of squares (ESS). x_i is the factor score vector (F1, F2, F3) for station i and, $\bar{x}$ is the mean of the cluster. When considering merging two clusters into a single cluster, the algorithm calculates the potential increase in the variance (d_{AB}), and it decides based on which merging produces the minimum increase in the variance (Equations 22 & 23).

$$d(A, B) = ESS_{A \cup B} - (ESS_A + ESS_B) \quad (22)$$

$$d(A, B) = \frac{n_A n_B}{n_A + n_B} \|\bar{x}_A - \bar{x}_B\|^2 \quad (23)$$

Where n_A and n_B are the number of stations in clusters A and B. and $\bar{x}_A$ and $\bar{x}_B$ are the centroids of clusters A and B (Ward & Jr., 1963). The result of Hierarchical Clustering Analysis with Ward's method can be found in the Agglomerative Schedule (Table 27).

The Agglomerative Schedule (Table 27) is a logbook of the clustering process for the stations. It shows all the steps to group the 129 stations. It has 128 stages. In columns A and B, the numbers from 0 to 128 represent the stations, and numbers above 128 represent clusters that formed in earlier steps. For instance, in stage 128, cluster 254 merged into cluster 255. The Fourth column, which is called “Distance Coefficient,” shows the Ward’s distance or increase in total within-cluster variance. As explained, it tries to merge the groups that, when formed, have a total within-cluster variance that increases minimally (Ward & Jr., 1963). Consequently, we observe that when cluster 30 and cluster 115 (or station 30 and station 115) merge, the variance increases by 0.010864, which is proportionately low. As the steps increase, the variance increases, and we can observe that the difference in the distance coefficient between stages 127 and 128 is very large.

This sudden jump in the distance coefficient serves as the stopping rule in merging the clusters. This method, called the Elbow method, investigates the trend of increases and triggers when the difference is sharp. Although the elbow method and Ewing and Park (2020) may suggest a small number of clusters (like 2 or 3), Kang & Miwa (2025) suggest that for metropolitan areas, a higher number of clusters is necessary to capture a nuanced station profile. In our study, to decide about the final number of clusters we use a Dendrogram.

3.3.3. Indicating the total number of typologies with Dendrogram

A dendrogram is a tree-like figure that illustrates how clusters are shaped. It is a valuable tool for visually assessing how clusters are formed and connected, though we need to define the mathematical rule by which we form the groups, and in this case, we use Ward’s method, which joins the groups based on the minimum increase in total within-cluster variance. When looking into the dendrogram, we can see that groups are formed by different lengths on the horizontal line. Longer lines mean that the stations are grouped by a higher increase in total within-cluster variance. Unlike

flat clustering methods such as K-means, which require specifying the number of clusters in advance, this method is useful because it lets the clusters shape based on their relationship rather than the subjective decision of the analyst.

To obtain the number of clusters, we can use a horizontal cut-off. The number of intersections with the vertical lines indicates the number of clusters. As indicated in Figure 11, the total number of clusters is determined by considering the height of the vertical line between the clusters. As a higher height indicates a larger difference between the two clusters, or an increase in within-cluster variance, we can set the number of clusters accordingly. The criteria by which we decide about the number of clusters should take into consideration that it must not be very strict because it leads to large number of groups which is in contradiction with the aim of TOD typologies methodology, and it shouldn't be very lenient because then we will have few groups that cannot effectively explain the differences between the stations.

Figure 11 illustrates the clustering of the stations. As the horizontal axis indicates an increase in variance, the optimal number of clusters was between 6 and 7. The 7 clusters were eventually chosen because the variance difference between the green and red clusters is substantial and cannot be neglected. The efficacy of this cluster arrangement can later be validated through spatial analysis and cross-checking across different stations within a group. The key point here is that, though we are putting several stations into the same cluster, as the increasing variance indicates, some stations within the same cluster might have fundamental differences and still share important similarities. For instance, we can observe from Fig. 8 that the two terminal stations of the Malpensa Airport, at first are grouped together correctly, and then later with a substantial increase in variance they merged with 5 other stations, and we know that in our model we only have two terminal stations, meaning that the others could be industrial stations or even normal areas like low development residential catchment area. In continue, we can check the descriptive statistics of the clusters in Table 23.

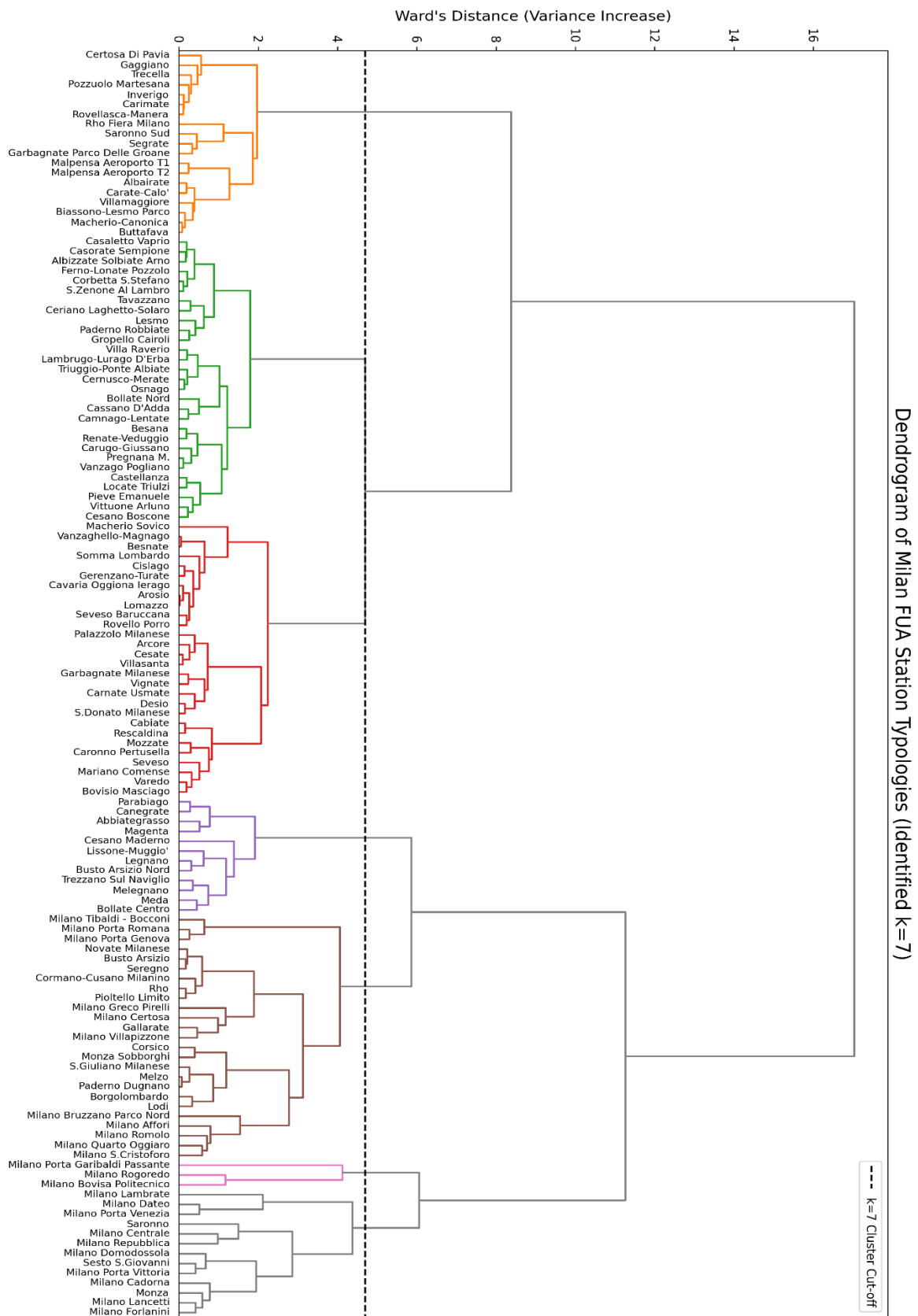


Figure 11 - Dendrogram of the stations' clusters

Cluster	F1 (mean)	F1 (Std)	F2 (mean)	F2 (Std)	F3 (mean)	F3 (Std)	Count
1	-0.364	0.352	-0.899	0.171	-1.577	0.409	19
2	-0.546	0.289	-0.647	0.214	-0.465	0.225	29
3	-0.394	0.312	-0.430	0.225	0.371	0.356	28
4	-0.231	0.411	0.107	0.356	1.419	0.352	12
5	0.072	0.541	0.877	0.638	0.223	0.534	25
6	3.568	1.474	0.207	0.520	-0.454	1.458	3
7	1.849	0.463	1.851	0.923	0.910	0.793	13

Table 23 - Descriptive Statistics of the clusters (High, above average, below average, low)

Milan FUA Station Typologies: Factor Space Analysis

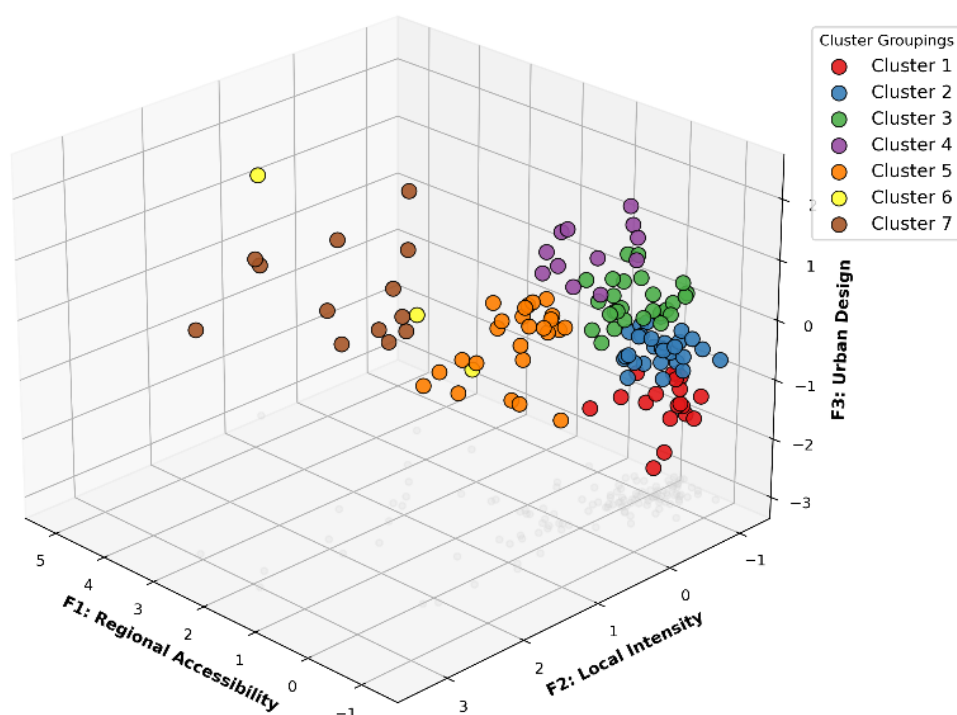


Figure 12 - 3-dimensional plot of stations' factor scores

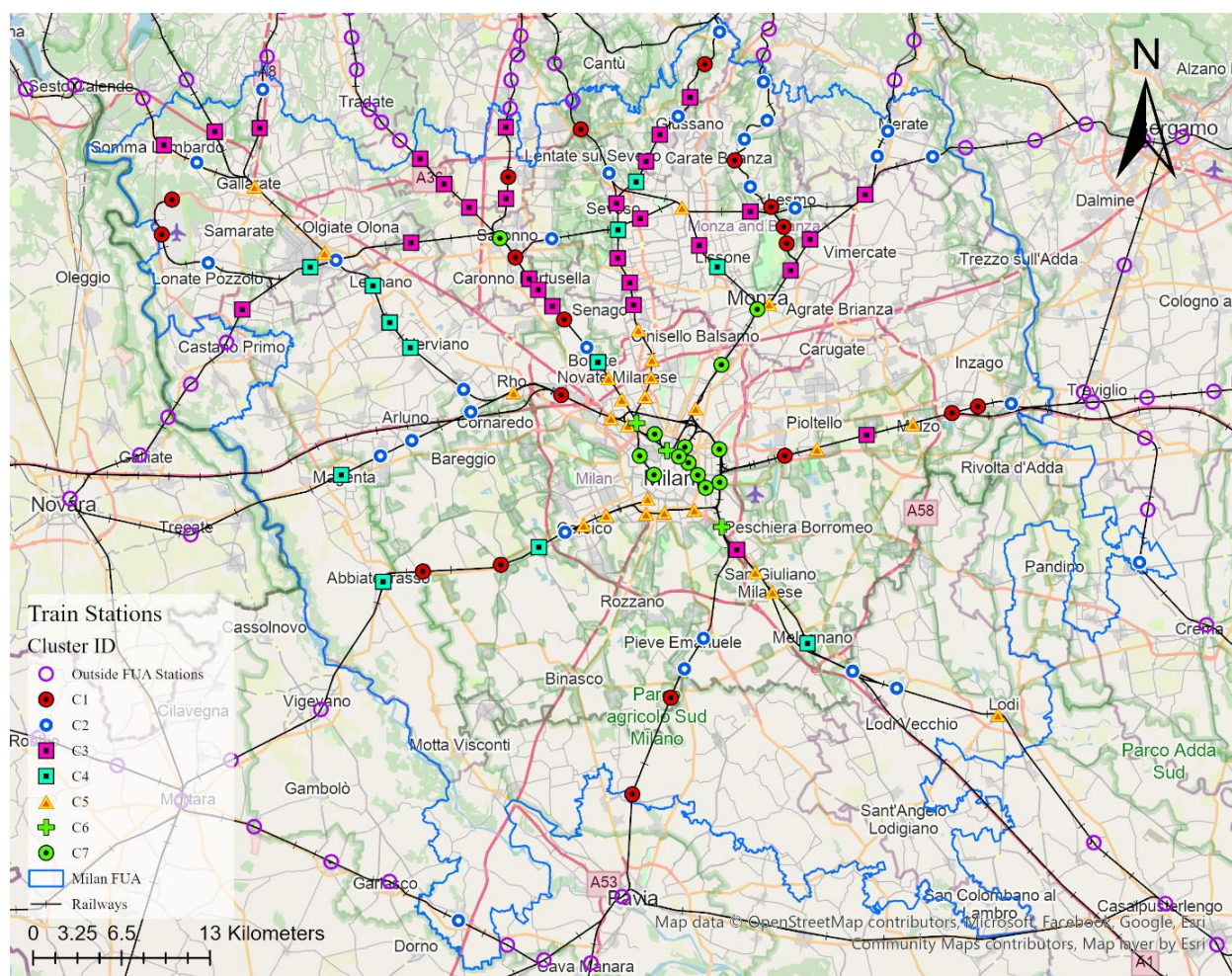
4. Results and Validation

4.1. Phase 4: Verification and Mapping

The final step of the analysis contains validation and interpretations of the findings. Table 23 presents the configuration of the clusters, with average values for each dimension, alongside Table 22, which shows the loadings of each factor. We can validate and interpret the results and cross-check the interpretation with satellite imagery and maps. Also, the final list of the stations with their cluster ID can be found in the appendix.

The TOD typologies are beneficial for planning future development in line with the essential requisites of TOD. Though we will discuss on the results later in the next chapter, we can observe here how the study distinguished between the different types of transit-hub types. Before looking into the clustering results, one could suggest that all the train stations in Milan are likely to have high transit status. Our results even distinguish between the same stations and show how some stations act as gateways and major hubs within Milan and some stations are underdeveloped.

It is also crucial to note that the numbers in Table 23 should be interpreted relatively within the dataset. For instance, when a cluster has higher values across all dimension scores, it doesn't necessarily mean it is more TOD compatible in absolute definition, it means it is more TOD compatible than other clusters, this argument is already presented in literature review (Section 2.6.2.5).



Map 2 - Clustered Stations¹⁵

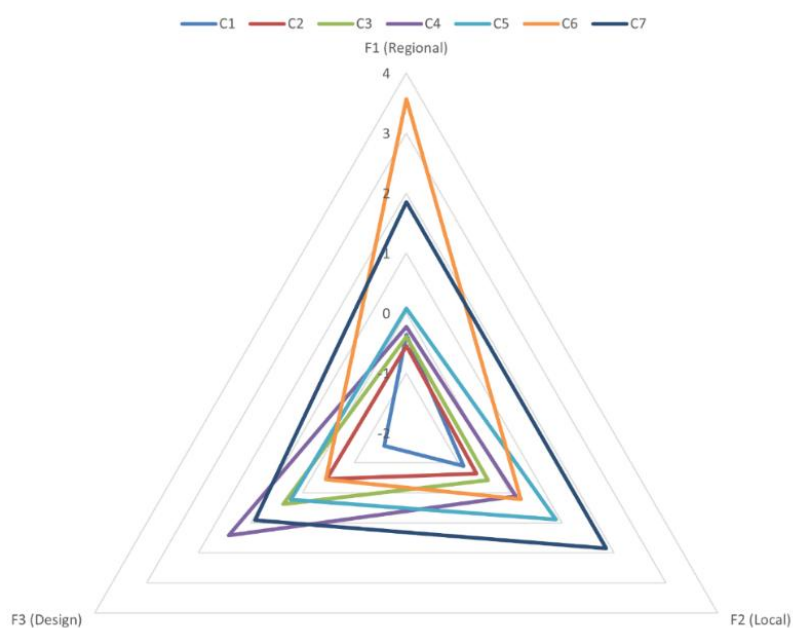


Figure 13 - Radar Chart of the clusters

¹⁵ *Note.* Clustered Stations in Milan FUA. Author's calculations. Base map © OpenStreetMap contributors.

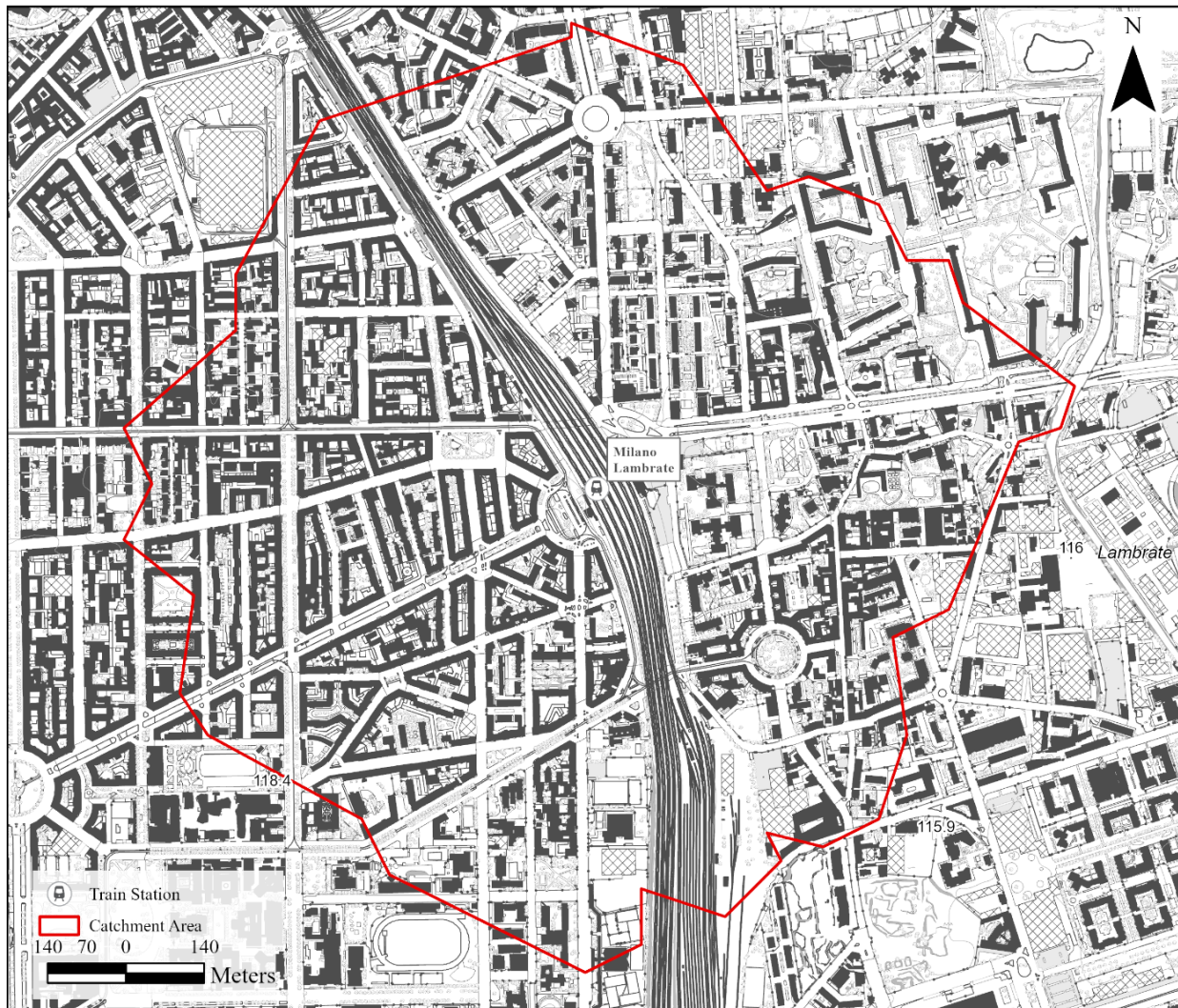
4.1.1. Cluster 7 – Case of Urban Stations

The stations within cluster 7, as illustrated in Map 2, are mostly located in the inner parts of Milan. C7 contains 13 stations, of which only 3 (Saronno, Monza, and Sesto S. Giovanni) are located farther from Milan. At first glance, scores for C7 reveal strong urbanization, with F1 (1.84) the second-highest, F2 (1.85) the highest, and F3 (0.91) the second highest among the other clusters. C7 stations display strong transit characteristics, within rail networks, bus services, and even active mobility (with high bicycle parking and high intersection density that promotes active mobility). A strong transit position is accompanied by high population density and residential land-use dominance within the catchment area. Hence, the F2 standard deviation score is the highest among the dimensions, indicating that these stations differ most on this dimension. It can be deciphered that residential blocks dominate these stations' catchment areas, the blocks are well connected (We can see that poorly connected blocks are less common), the urban morphology is often more historical with gridded permeable streets, and hence their highest difference within this cluster is whether the urban density is high or very high.

Also, we can summarize the explanations of this cluster by comparing it with C5, the C7 stations are C5 but with better transit access, without high-density isolated residential islands with less brownfield, industrial or production big lots in adjacency. The discussion on big lots here and on C5 explicitly is brought up because of its impact on mobility not diversity. In any case, to better understand how this cluster is shaped we need to check the dendrogram in Figure 11.

The dendrogram shows us that Milano Dateo and Milano Porta Venezia merged with a very low increase in within-cluster variance. These two stations are located near each other in the historical parts of Milan. Their dimensions scores are almost identical. Milano Lambarte then joined this cluster with a relatively substantial increase in

within-cluster variance. In fact, whether by checking the satellite imagery or the scores between these stations, the difference between them is distinguishable. Milano Lambrate, though, has a similar score on F2, referring to a similar pattern of concentration of population density and bus services, it has clear differences regarding urban morphology.



Map 3 - Milano Lambrate Station's catchment area, like spider network¹⁶

¹⁶ Note. Urban morphology in the Milano Lambarte catchment area. Created using ArcGIS Pro. Data from *Database Geo-Topografico (DBGT)* (Regione Lombardia, 2023). CC-BY 4.0.

The differences in urban morphology are evident: the first two stations feature a more gridded street pattern and smaller lot sizes than Lambrate. Lambrate, on the other hand, has a semi-spider network grid in which the train station is located at a convergence point, resulting in the largest catchment area among all stations, sharing the first rank with Milano Cadorna. While gridded blocks generally provide substantial catchment areas as well, the proximity of Milano Dateo and Milano Porta Venezia reduces their individual catchment sizes. This is due to our initial decision to define catchment areas as unique based on spatial adjacency (2.6.2.3), so when stations are close together, their catchment areas become more compact.

Map 3 illustrates the street configuration around Milano Lambrate. Although this research does not focus specifically on how urban morphology affects catchment size, the map makes it clear that a spider network with a station at its convergence point creates larger catchment areas and generally supports good walkability. Considering that the size of the catchment area implies that the design characteristics of the station's surroundings are probably suitable, we can observe that Lambrate's F3 score is not the highest. Lambrate's F3 score is significantly lower than those of the other two stations, even though its catchment area is larger. This can be explained as F3 is calculated based on intersection density, which benefits gridded street networks. Lambrate's catchment is larger, but it has fewer intersections compared to a gridded layout, which negatively affects its F3 score. Additionally, a substantial share of Lambrate's area is devoted to transport infrastructure, rather than residential land use. In contrast, for the other two stations, most transport infrastructure is underground, allowing for more residential areas at the surface. These factors together ultimately result in a lower F3 score for Lambrate and a higher score for the other two, while all of them have similar scores on F2.



Map 4 - Milano Repubblica Station's catchment area¹⁷

Probably, if you check Map 2, one important question may arise. Why did Milano Repubblica station not merge with Milano Porta Venezia and Milano Deseo at first, instead of Milano Lambrate? As these 3 stations share important characteristics, such as underground transport infrastructure and a gridded catchment area, Milano Repubblica is closer to the other two, instead it is grouped with Milano Centrale station at first. The reason why Milano Repubblica shares more similarities with Milano Centrale, compared to Milano Deseo and Milano Porta Venezia, can be explained by its substantial score on F1.

To conclude, the stations in this cluster exhibit high average scores across all three

¹⁷ Note. Data: DBGIT (Regione Lombardia, 2023). CC-BY 4.0.

dimensions, making them accessible, dense, and rich in population, services, and urban morphology. A higher F3 score suggests that the space is being used to its full potential, offering more opportunities for diverse activities and enabling more people to walk to the stations. Therefore, in this cluster, stations primarily require improvement in the quality of urban space, implementing soft interventions to stimulate more ridership. Soft interventions, such as regulations and incentives discussed in the literature review, as well as TOD-friendly street design features like bicycle-friendly streets and pedestrian areas, are the most important improvements needed for this category. Later, we will discuss development suggestions for each category thoroughly.



Map 5 - Milano Domodossola Station's catchment area¹⁸

¹⁸ Note. Data: DBG T (Regione Lombardia, 2023). CC-BY 4.0.

4.1.2. Cluster 6 – Case of Unsustained Node

Cluster 6, with only 3 stations, shares different characteristics among all clusters. C7 is composed of main transit stations within the network, as you can reach 63 stations within 30 minutes from Milano Garibaldi, 50 from Milano Bovisa Politecnico, and 45 from Milano Rogoredo. Their importance within the transit network is the key distinctive characteristic that distinguishes them from other stations. As Table 23 indicates, their F1 score is by far the highest, while F2 is near the mean, and F3 is even below the average. However, when we examine the dendrogram in Fig. 9, we see that the within-variance of the cluster increases exponentially as we combine the Milano Bovisa Politecnico and Milano Rogoredo cluster with Milano Garibaldi. The increase in the within-cluster variance is so substantial that, in fact, if we had set the horizontal cut-off line a bit more strictly, we could have separated these stations into different groups. Though this decision would also create two more clusters, making the total number of clusters 10. Hence, we do not officially form two distinct clusters, we do provide insights more specifically for each of them.

Station	F1	F2	F3
Milano Porta Garibaldi	5.17	0.80	1.18
Milano Bovisa Politecnico	3.25	-0.05	-0.96
Milano Rogoredo	2.27	-0.13	-1.59

Table 24 - Dimension scores for the stations of C6



Map 6 - Milano Porta Garibaldi Passante's catchment area.¹⁹

The regional accessibility of C7 stations is so high, and the difference between the F1 score and the other factors is so deep that we can assert, in these environments, that the local context is masked by the stations. With such a high score in regional accessibility, it is expected to detect the presence of extensive commercial activity alongside a high number of commuters using the streets, whether by bus, walking, bicycle, or taxi. These stations, especially Milano Porta Garibaldi, are gateways to the entire Metropolitan area. Their high score on F1 implies a high score on betweenness, people are not necessarily coming to visit those stations' catchment area but to access the whole city. As described by Bertolini (1999), a high score on the Node dimension

¹⁹ Note. Data: DBGIT (Regione Lombardia, 2023). CC-BY 4.0.

(like our F1 factor) and a low score on the Place dimension (Similar to our F2 and F3 dimensions) indicate a state of stress (Bertolini, 1999).

Paying attention to Table 23 and Table 24, it is decipherable that C7 is the most imbalanced cluster among all clusters. The imbalance is most visible at Milano Rogoredo, followed by Milano Bovisa Politecnico, while Milano Porta Garibaldi is comparatively less affected. From a planning perspective, both Milano Bovisa Politecnico and Milano Rogoredo are node-oriented, with fragmented land around the stations that fails to activate the catchment area from both points of view of active mobility and public vitality. In contrast, Milano Porta Garibaldi benefits from greater diversity and intensity of activities, achieving a strong score on F3, which shows a good mix of residential areas, dense intersections, and walkable spaces. The lower F2 score is logical, as much of the catchment area is occupied by commercial activities, serving the large volume of commuters passing through.

Conversely, both Milano Bovisa Politecnico and Milano Rogoredo exemplify cases of extreme Transit-Adjacent Development. This is evident from Table 24 (Development with low permeability) and satellite imagery. Despite high transit scores, the very low walkability (F3) and moderate local score (F2) indicate that nearby projects lead to failure to maximize the accessibility of the catchment area with the station.

The fragmentation resulted from the presence of other obstacles, like highways or brownfields near the station areas, which are also drastically influential. In fact, we can see that in Milano Rogoredo the catchment area is divided into 4 isolated parts, and for Milano Bovisa Politecnico it is 3 isolated areas. While for Milano Porta Garibaldi, we cannot observe this pattern.



Map 7 - Milano Bovisa Politecnico Station's catchment area.²⁰

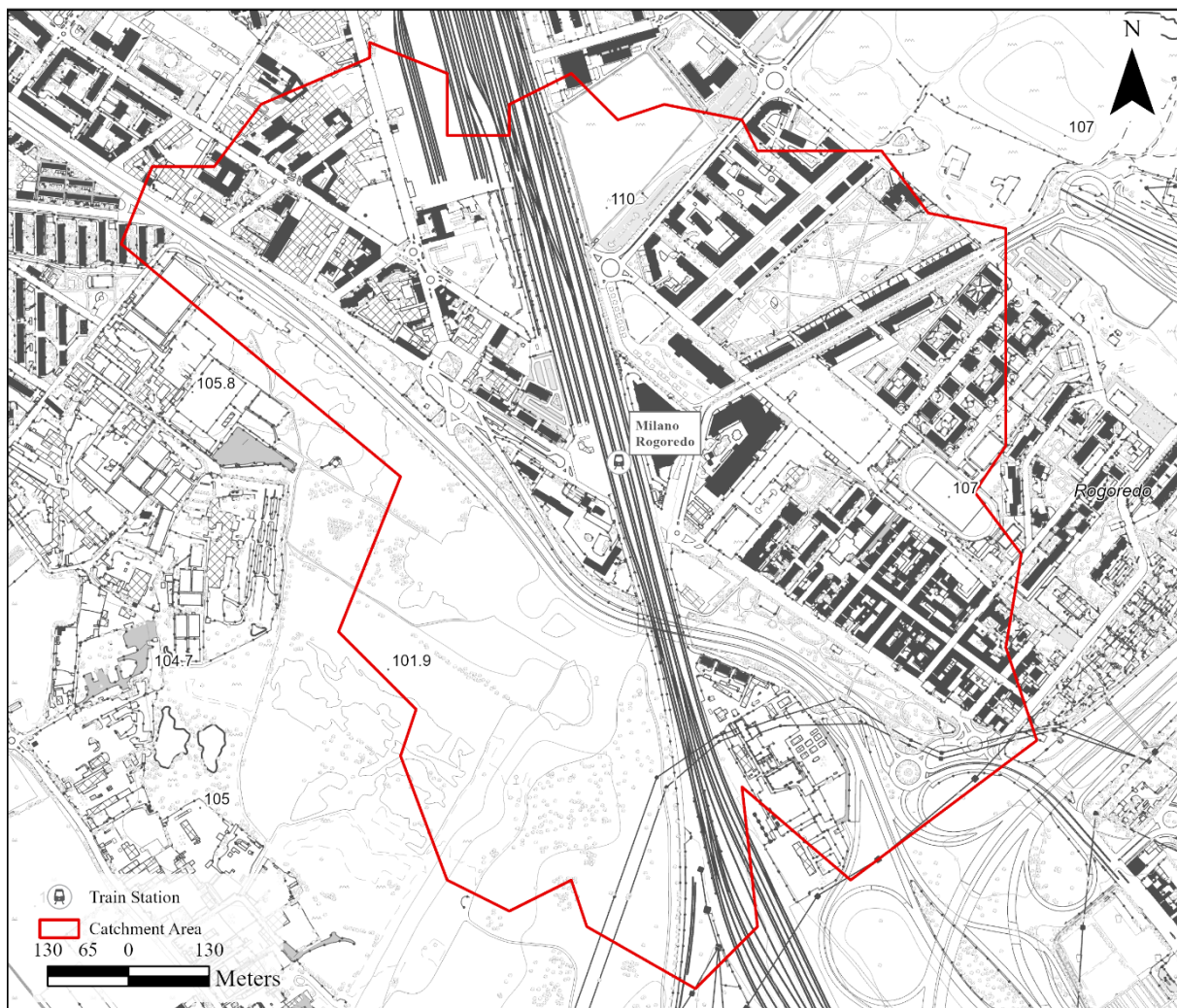
As the map illustrates, because of the presence of barriers like highways and rail infrastructure, the accessibility within the area is seriously degraded. It is important to note that in the case of Milano Bovisa Politecnico, the presence of Milano Villapizzone also affected the catchment area's size of the stations.

The same pattern of physical barriers can be spotted by checking the map. The presence of highways, bridges, and railways divided the space into fragmented pieces. The spatial pattern visible by Urban Morphology in the Map and the Map validate the result of the dimensions' scores. To wrap up the typology of this cluster, we can conclude that the first two stations are the case of extreme TAD, with very low

²⁰ Note. Data: DBG T (Regione Lombardia, 2023). CC-BY 4.0.

walkability and urban functionality.

Conversely, the case of Milano Porta Garibaldi is not an extreme TAD with very low walkability and urban functionality. This station is grouped with the other two solely because of their high importance to the transit network, as the F1 is the primary determinant of the clusters across all dimensions. With 1.18 in F3, Porta Garibaldi shows rich connectivity within the catchment area. The policy packaging suitable for this station would be like the C7 stations, where soft interventions and improving urban quality toward TOD should be the priority.



Map 8 - Rogoredo Station's catchment area. It shows fragmentation because of the physical barriers in the area.²¹

²¹ Note. Data: DBG (Regione Lombardia, 2023). CC-BY 4.0.

4.1.3. Cluster 5 – Case of Unsustained Place (Suburb Stations)

Map 2 illustrates the spatial distribution of C5 stations in the suburban areas. This cluster makes up nearly one-fifth of all stations, including 25 in total: 18 located in the suburbs of Milan and 7 in other areas surrounding Milan. To better understand how these suburban stations are grouped with both regional and some inner Milan stations, we can refer to the dendrogram in Figure 11. Notably, there is a significant increase in variance when the clusters containing Milano Tibaldi – Bocconi, Milano Porta Romana, and Milano Porta Genova are merged with the rest of cluster C5. These three stations, as their names suggest, are situated close to the city center and are first grouped together, with a small increase in their total within-variance, which explains that they share similar attributes across the analyzed dimensions. However, when they are subsequently clustered with the other C5 stations, there is a substantial jump in within-cluster variance. This suggests that these three stations are more like each other than to the remaining stations in the cluster. This assertion can also be validated by their spatial location.

In addition to the spatial location, we can also trace the difference through the dimension scores. These 3 stations, although located closer to the city center, have relatively lower F1 scores than other stations in the same cluster. On the other hand, their score for the other two dimensions is substantially higher, especially for F2, as the whole-cluster mean for F2 (including these 3 stations) is 0.87, whereas the mean score for only those 3 stations is 2.23. The high value in F2 implies a high population density and bus services. This difference is also high for F3, as the whole C5 score for F3 is 0.233, but these 3 stations have a mean score of 0.66. The conclusion is clear: the density of these 3 stations is higher for both population and street configuration, and they are grouped with other stations within C5, with a high increase in within-cluster variance. In fact, if we draw the cut-off line in the dendrogram a little more strictly, we could separate these 3 stations from the others. These stations are high-intensity outliers of C5. They are grouped with others, as can be seen in Figure 8. It is clear that

the proportion of data explained is primarily by the F1 factor, which gives it greater weight compared to the other two factors. Therefore, these three stations' lower scores on F1 are counterbalanced by their higher scores on the other two dimensions.

Moving away from these three stations and focusing on the rest of the stations within C5, we can see that this cluster has scores for all dimensions merely above 0.0. Meaning that compared to other stations, these stations are moderate. C5 stations have F2 as the dominant dimension, meaning that in those catchment areas the population density (P4 and P10) and the bus transport services (N3 and N5) are quite higher than most of the TOD areas, except for the C7.

As previously mentioned, but worth emphasizing further, one of the key implications of C5 emerges when examining the difference between the F2 and F3 scores. While F2 records the highest score among the three dimensions, F3 (Intersection density, Street line density, and proportion of residential areas) remains low. This suggests that although resident and bus service intensity is high, the connectivity is low. In other words, this points to several assumptions like discontinuous pattern of high-rise urban development: there are areas with a high concentration of residents (through high-rise buildings in gated big lots), but the street layout results in smaller catchment areas due to street configuration. This abstract reasoning is also validated by checking the satellite imagery of those catchment areas, like within the catchment area of Milano S. Cristoforo²², Milano Affori²³ (Fig. 10), Milano Quarto Oggiaro²⁴, Milano Bruzzano Parco Nord²⁵, and other stations in this cluster that show characteristics like Milan suburbs. It is important to clarify that, the suburb as its qualitative definition, not being proximate or necessarily on the periphery of Milan. Interestingly, in Figure 11 we can observe that in dendrogram, the mentioned stations are grouped together first within the C5 with low increase in variance-within.

²² 9.1302204°E 45.4427534°N

²³ 9.1667697°E 45.5204330°N

²⁴ 9.1448776°E 45.5193024°N

²⁵ 9.1725566°E 45.5331745°N

This pattern of development, which we can observe partially within the stations of cluster 5, interestingly displays Transit-Adjacent development (TAD) rather than Transit-oriented Development. These sites, as frontiers of Milan's urban expansion, seem to attract developers who invest near transit stations because of regional accessibility. They are building detached islands of density (Check Milano S. Cristoforo, parts of Corsico, parts of Borgolombardo). However, this is not the only case in C5.

As mentioned for C5, the high-rise development with large blocks is only one of the explanations for why stations in C5 are clustered together, and not necessarily all stations in this cluster are high-rise settlements. In fact, in comparison between the scores of F2 and F3, we should bear in mind that F3 has 3 main components, and one of them is the proportion of residential areas. So, when we have a higher score on F2 and a lower score on F3, the catchment area includes a substantial non-residential area, with a residential fabric that arises from a high concentration of residents and bus services. Cross-checking with satellite imagery and land-use maps corroborates this assertion.

Consequently, we can conclude that the stations within this category find themselves within catchment areas that residential usage are the dominant land-use of the catchment area, hence its proportion is lower than stations within C7 (located in city center) and other land-uses presence like industrial, commercial, production (agriculture) and even transport infrastructure is substantial (not dominant) and influential because they often come up with big lots that deteriorate the walkability of the catchment area as well. Figure 15 is an example of this case.



Figure 14 - Satellite view of the Milano Affori station area showing high-rise residential blocks. Map data ©2025 Google.



Figure 15 – Satellite view of the Lodi station area showing dominant residential areas with substantial non-residential lots within the catchment areas. Map data ©2025 Google.



Figure 16 - Satellite view of the Corsico station area showing high-rise residential blocks. Map data ©2025 Google.



Map 6 - Corsico's catchment area.²⁶

²⁶ Note. Data: DBG (Regione Lombardia, 2023). CC-BY 4.0.

4.1.4. Cluster 4 – Case of Compact Low-rise and Spread Development

The low score on F1 (transit status), the medium score on F2 (intensity of residential and bus services), and the very high score on F3 (Design) imply a unique situation in C4. As the numbers indicate, the C4 has the highest F3 value. It means we should expect dominant residential urban areas with small lots spread throughout the catchment area. This assertion can be validated by cross-checking the urban morphology maps of this cluster.

As shown by Map 7, the Canergate station's catchment area, together with the other 11 stations within C4, all share a similar pattern of development within the catchment area. This cluster mostly contains urban morphology, with highly dense urban areas, which affirms our initial assumption on the urban structure within this cluster. A relatively medium score on F2, accompanied by a high score on F3, also implies a horizontal population density.

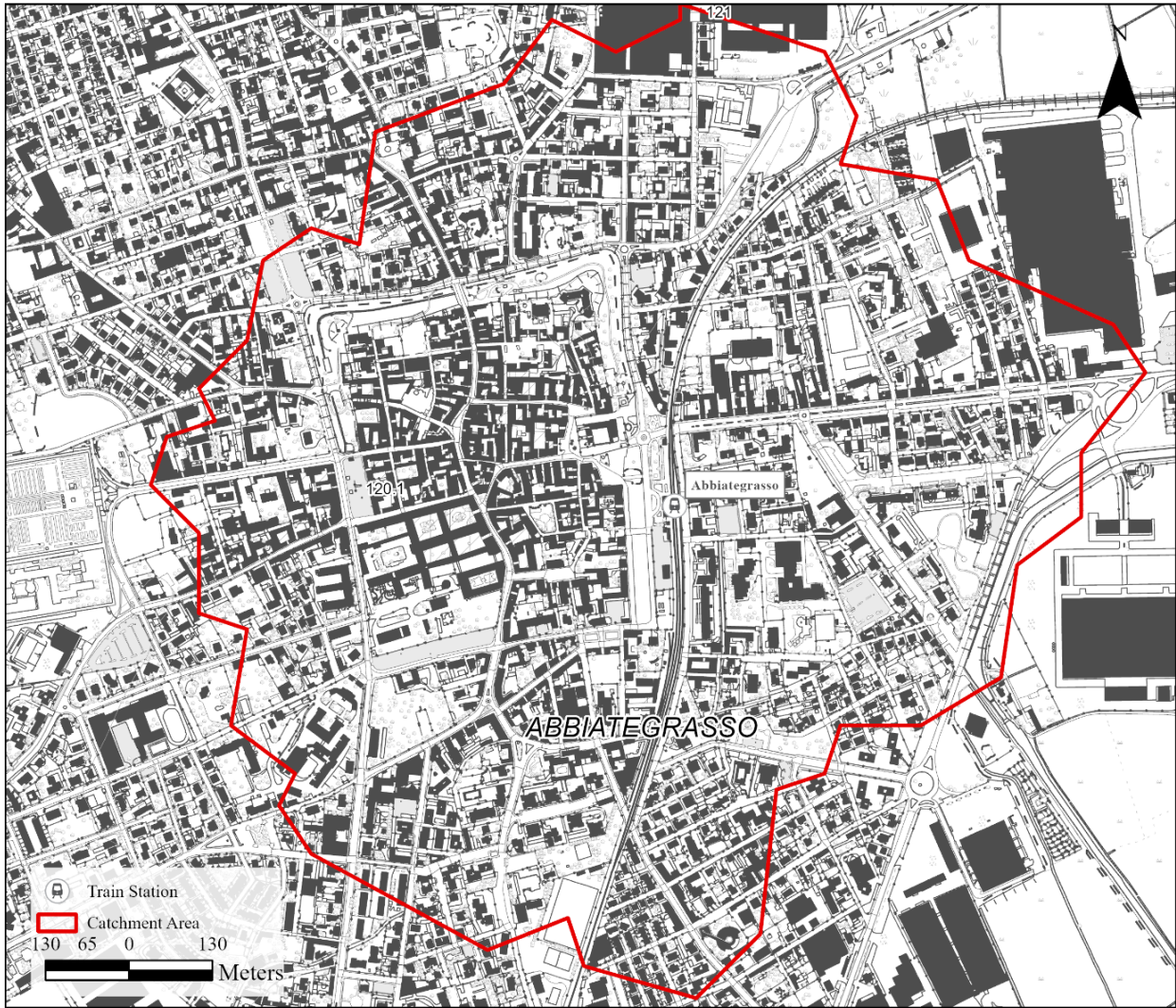
The high F3 score, indicating a high density of intersections and street lines, indicates high permeability within the catchment area. Making the station accessible by walking and expanding the catchment areas to their full potential within walking distance. In contrast to Milano Lambrate station, where we argued that because the catchment size is too big the F3 is proportionately lower, here we can see that we have big catchment areas while we have high score on F3, the reasoning here is simply implies on the fact that the urban morphology of this cluster contains presence of horizontal low-rise settlement when we can observe that majority of residential buildings are villas or single detached houses, while in Lambrate case, we have bigger condominiums next together, formed bigger blocks, leading to lower number of intersections.



Map 7 – Urban Morphology of the catchment area of the Canegrate Train Station. It shows high-density, low-rise development.²⁷

It is worth noting that all 12 stations in this cluster are located a substantial distance from Milan city center. Their distribution also differs from that of clusters 7, 6, and 5, where many stations are situated near one another, allowing one to observe a pattern, whereas this pattern is not traceable in this cluster. This is largely due to the dominant morphology of these stations, characterized by horizontal, low-rise development and predominantly single-use land use.

²⁷ Note. Data: DBG T (Regione Lombardia, 2023). CC-BY 4.0.



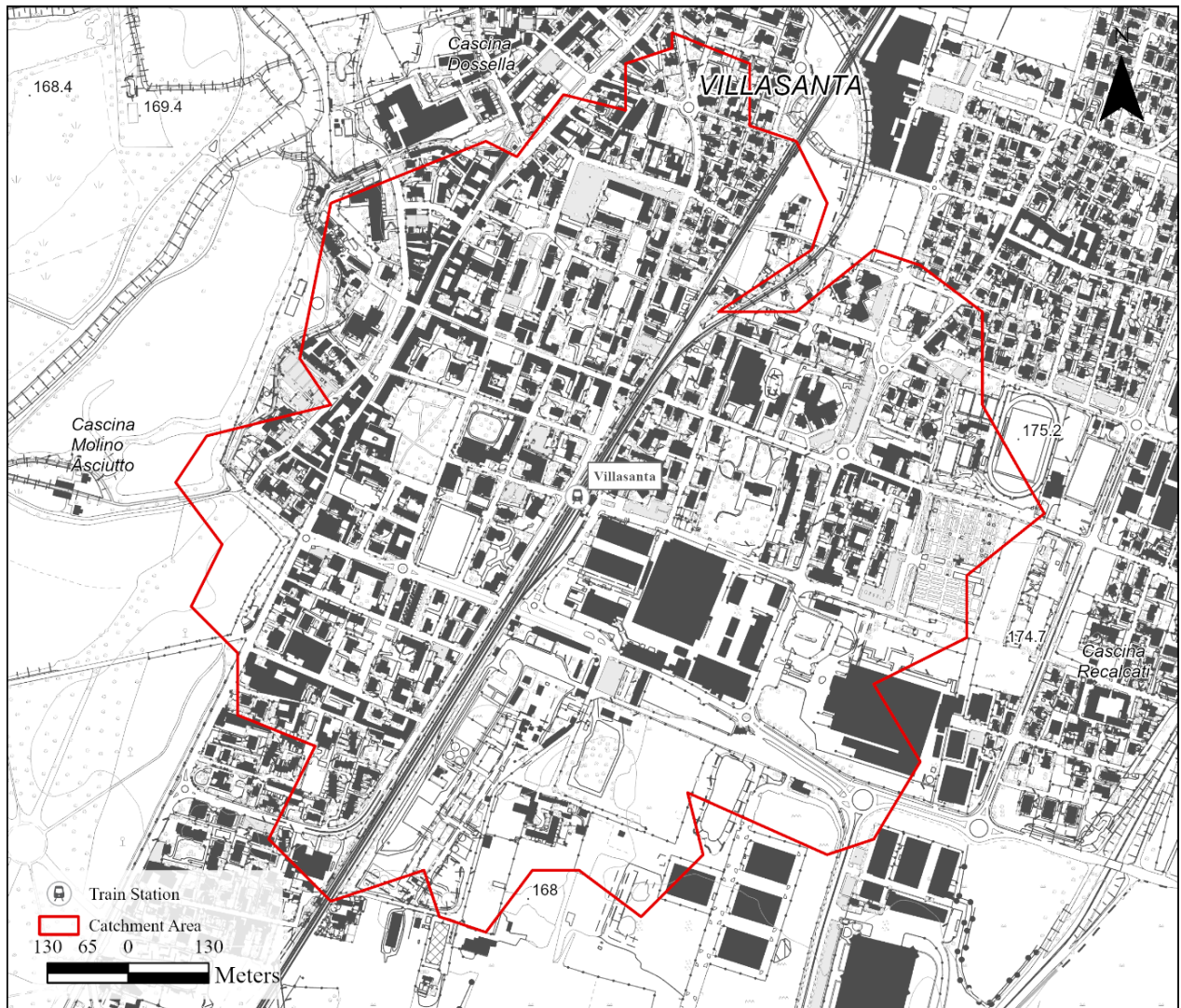
Map 8 - Urban Morphology of the catchment area of the Abbiategrasso Train Station. It shows high-density, low-rise development

To wrap up the C4 profile, we must emphasize the problematic condition within this cluster: the low F1 score. We can observe within this category of stations a high level of development, a transit-oriented catchment area, and poor-quality transit services. Though we will discuss this more fully in the policy packaging section later, any intervention for this cluster must address improvements in transit accessibility, accompanied by soft interventions and enhanced design quality in the catchment area to stimulate and facilitate active mobility. Catchment areas already have the needed environment for being walkable-friendly, and it can be further improved by implementing strategies like pedestrian-only corridors toward the station and bicycle parking.

4.1.5. Cluster 3 – Case of Low rise, Low density and Car-centric Development

C3 is the less developed, lower-density version of C4. The C3 and C2 clusters have the highest number of stations, and together they account for almost half of the dataset. C3 stations, interestingly, are mostly spread in the northern part of the rail network, except for two cases. The C3 cluster has relatively low scores for F1 and F2, indicating that transit betweenness and transit services are lower than at most stations. The residential density and bus services are also relatively low. However, the intersection density, street line density, and proportion of residential area are above the average. All these lead us to conclude that C3 stations are the catchment areas in which the urban fabric consists of a smaller cluster of houses in small lots next to each other, surrounded or accompanied by a considerable number of non-residential land uses, which are often industrial activities or agricultural lands.

Stations within this cluster often have more space and greater long-term development potential. The relatively higher score on F3 should be understood in relation to the catchment size. Due to the presence of non-residential parcels, the streets are less extensive throughout the catchment area. As a result, the density of intersections is higher compared to clusters with smaller catchment areas. The conclusion here is that this cluster features low-rise, spread development with small parcels similar to the C4 cluster. The C3 illustrates the potential to become an urban structure to C4 in the future if planning does not coordinate it to another course.



Map 9 - Villasanta's Catchment Area.²⁸

Map 10 clearly illustrates the presence of agricultural lands and industrial zones within the catchment area of Desio. The residential fabric is characterized by low density, small parcels, and narrow passages between them.

²⁸ Note. Data: DBG (Regione Lombardia, 2023). CC-BY 4.0.



Map 10 – Desio's Catchment Area.²⁹

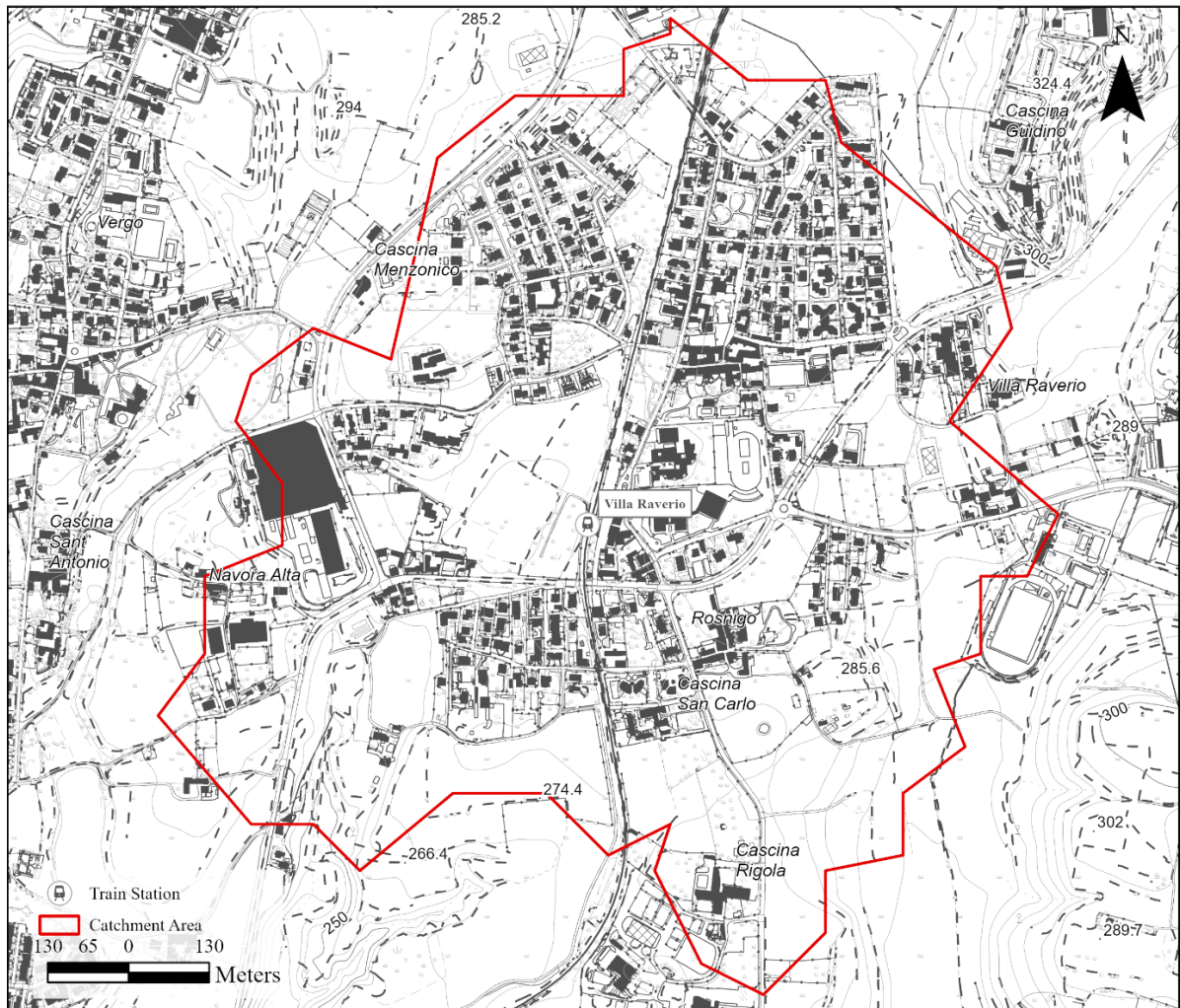
4.1.6. Cluster 2 – Case of Dispersed Car-centric Development

The C2 cluster, which contains 29 stations, is a case of a dispersed settlement with very low transit services and a low number of residents. Indicated by the score of F1 (-0.54), this cluster has the lowest transit services. Even though the amount of residential presence is higher than at the C1 stations, we can observe that the train service here cannot fulfill mobility needs. Sparse resident density and low bus availability (according to F2) result in double-high negative scores for the first two dimensions.

²⁹ Note. Data: DBGT (Regione Lombardia, 2023). CC-BY 4.0.

Compared with the other clusters, C2 has the least urban fundamentals to thrive as a TOD case.

As shown in Map 2, these stations are usually placed at the farthest distances, near the borders of the FUA, compared to other groups. Most of these stations are approachable only by a single train line, with relatively low train frequency. Bus service is weak or sometimes unavailable, making these stations effectively car-dependent.



Map 11 – Urban morphology of the catchment area of the Villa Raverio Train Station. It shows low-rise sparse settlement.³⁰

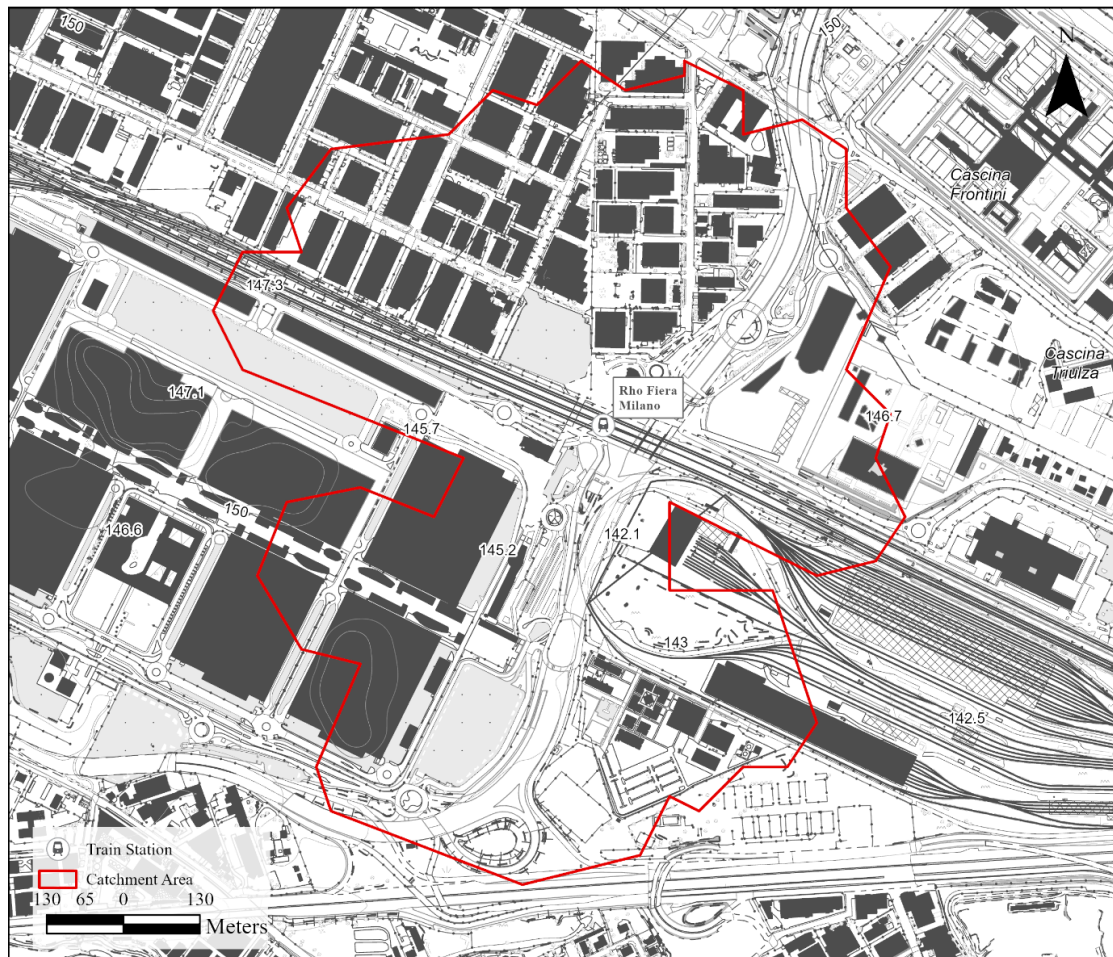
For example, Map 11 shows the settlement around the Villa Raverio station, and the map illustrates that the F2 score in this cluster is too low. Also, it is worth noting that, compared with other clusters, this cluster has more unbuilt space available near the

³⁰ Note. Data: DBGT (Regione Lombardia, 2023). CC-BY 4.0.

station. It is not necessarily usable, but there are agricultural lands that are easier to transform. That explains why, even when we have a low F2 score, the F3 score is relatively high: the catchment area is limited by a lack of available streets to move around.

4.1.7. Cluster 1 – Case of Non-residential Stations

C1, which includes 19 stations, has the lowest scores on F2 and F3, indicating the presence of non-residential station areas. Within this category, we can identify strategic industrial sites and two terminal train stations (Terminal 1 and Terminal 2) near Malpensa Airport. According to the dendrogram in Figure 8, these two terminal stations are the first to be grouped together, which is logical and a strong point for how the classification groups stations with similar profiles.

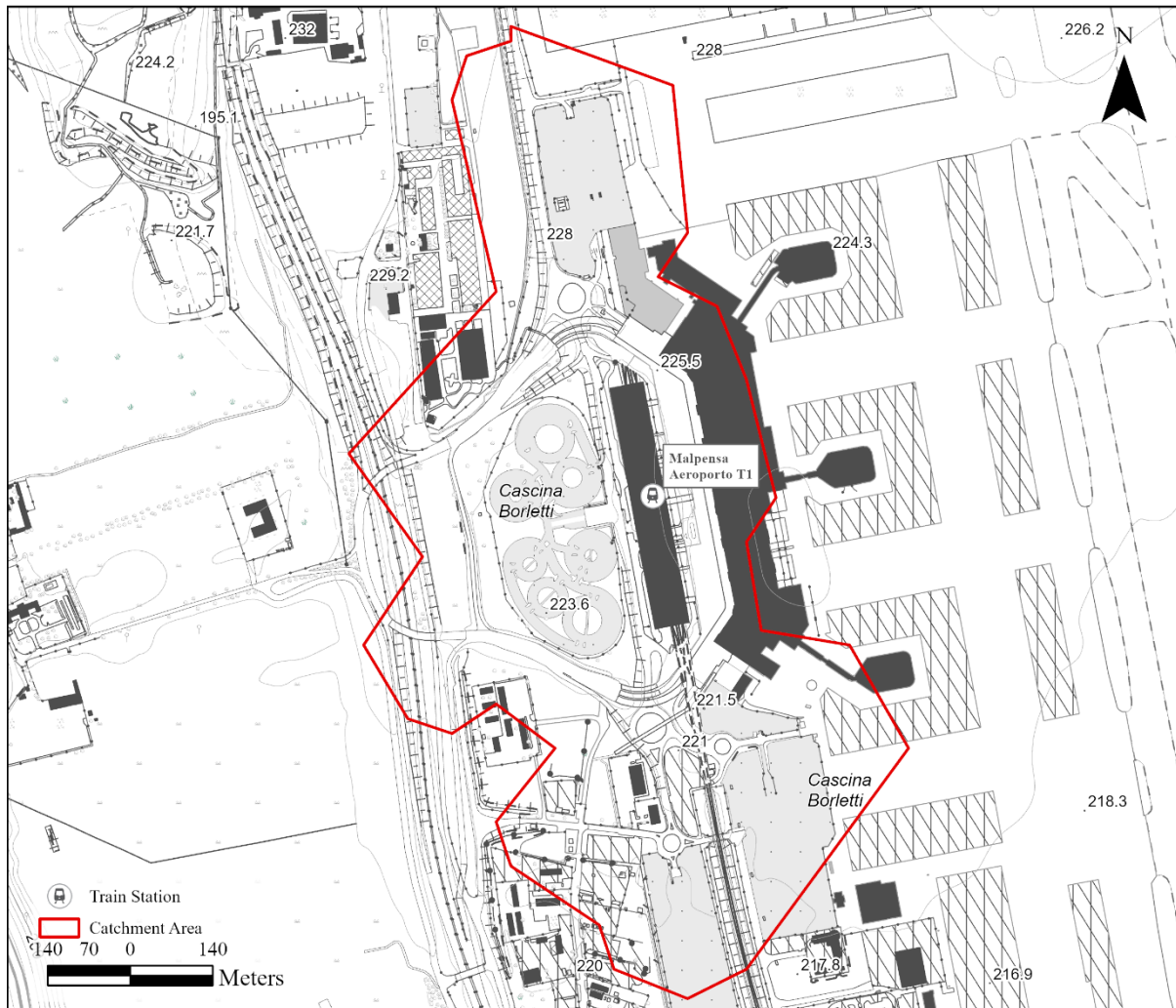


Map 12 - Urban morphology of the catchment area of the Rho Fiera Milano Train Station. It shows low-rise sparse settlement.³¹

³¹ Note. Data: DBGT (Regione Lombardia, 2023). CC-BY 4.0.

As Table 23 illustrates, the stations in this cluster have relatively higher train service compared to clusters 2 and 3. Their score on F2 is the lowest, indicating that the area is almost entirely industrial or commercial (non-residential), yet train service is still present. This suggests that these stations primarily function as destination nodes.

Map 12 clearly illustrates the station's catchment area in the Rho Fiera Milano district. The catchment area is very small due to a lack of walkable streets, as motorized highways are considered unwalkable. As a result, pedestrian traffic is effectively confined to providing access solely to industrial sites. This fully aligns with the expected morphology of this cluster, as it has the lowest scores on F2 and F3, the factors most strongly associated with residential presence.



Map 13 - Malpensa Aeroporto T1's Catchment Area³²

³² Note. Data: DBG T (Regione Lombardia, 2023). CC-BY 4.0.

4.2. Conclusion on the Clustering Results

There is substantial evidence supporting the accuracy of the clustering results. For example, some stations, such as the two Malpensa Airport stations, were merged with minimal increase in total within-cluster variance. Similarly, stations with comparable urban morphology, such as those in the inner parts of Milan, were grouped together. Furthermore, most C5 stations are suburban stations surrounding Milan. Also, the stations that are mostly used for non-residential uses (industrial, commercial, airports) are clearly distinguished and grouped together. These findings demonstrate that the method produced meaningful, unbiased results, as it is entirely data-driven and avoids heuristic approaches that could introduce the author's subjective judgments.

Moreover, the derived factors allow us to anticipate the characteristics of each cluster. As previously explained, even without consulting satellite imagery or other maps, we can expect to find a highly developed, low-rise area when a cluster has a very high score on F3 (intersection density, street density) and a relatively low score on F2 (attributes primarily related to residential population) as it implies on small-size residential parcels like in C4. Similarly, when the score on F2 is higher than on F3, we can expect to see high-rise developments with multi-story buildings, often including blocks that are poorly connected or large lots within the catchment area, as observed in the C5 cluster. All these findings underscore the reliability of our results in revealing the underlying dynamics of transit hubs, forming a solid foundation for proposing targeted policies.

We also need to articulate the model's limitations. As noted in Section 4.1, some stations do not fit accurately within their assigned clusters. The most prominent example is Milano Porta Garibaldi, whose urban morphology differs significantly from its other two cluster mates, Milano Bovisa and Rogoredo. This is primarily because F1 has the highest weight, compared to other factors, which explains a greater share of the data variance relative to the other two factors, as well as the distinctly

higher F1 scores of these three stations. As previously discussed, the dendrogram in Figure 12 clearly shows a substantial increase in within-cluster variance when Milano Porta Garibaldi is merged with the other two stations. Besides this case, the case of three stations in the inner part of Milan in C5 also highlights a probable discrepancy within the data, doubled with Figure 12, showing an increase in total within-cluster variance as they merged with other stations in cluster 5. Milano Tibaldi – Bocconi, Milano Porta Romana, and Milano Porta Genova feature distinct urban morphologies compared to other stations in C5. They have relatively higher scores on F2 and lower scores on F1, which counterbalance each other and explain why these stations are grouped together in this cluster.

Since TOD typology results often guide targeted policies for all stations within a cluster, recognizing differences in the outcomes is critical. No statistical method can fully reflect the complicated realities of urban stations. As G. Box (1987) aptly noted, “Essentially, all models are wrong, but some are useful.” Such differences indicate that certain aspects of station reality remain partially or completely unaddressed. Capturing all characteristics of stations and their contexts, like the way everything goes, is impossible, given data limitations. Moreover, heuristic approaches introduce the risk of subjectively selecting which factors to measure, as previously discussed. This raises an ongoing question: how to deal with the stations that do not consistently align with the results? Scholars often recommend adjusting models and conducting multiple iterations to find an optimal solution (Robillard et al., 2025), but achieving this is extremely challenging. Conversely, blindly applying cluster-based policies to such stations can also be problematic. Settling this dilemma likely requires further research and study.

Eventually, this is the final clusters:

Urban Stations: This cluster features highly accessible transit hubs, complemented by other urban services like buses and bicycle parking. The local urban areas in this cluster are densely populated, and a high F3 score represents a considerable presence

of residential zones with large lots. Most of these stations are situated in the inner areas of Milan, with some benefiting from underground rail infrastructure that allows for more effective use of the catchment area. It is also recommended to consider the station Milano Porta Garibaldi part of this group, instead of its origin, which is cluster 6.

Unsustained Nodes: This cluster consists of only 2 stations (with Milano Garibaldi classified under C7). These 2 stations, though highly accessible and play a key role in providing regional accessibility like transit gateways, their catchment area remains largely inefficient. The diversity, density, and street configuration in those areas are poor.

Unsustained Place: Stations in this cluster are mostly located in suburban areas, the transit status is moderate and lower compared to local Place characteristics. The neighborhoods are mostly dense with lower design quality in accordance with TOD. This can be explained by the presence of poorly connected large blocks, or significant industrial, commercial, agricultural, or transit infrastructure, all of which restrict movement and reduce catchment size.

Compact Low-rise and Spread Development: These stations are characterized by urban sprawl, featuring low-density, low-rise, and relatively compact development, as indicated by their high F3 scores. The high proportion of residential land use suggests a predominance of single-use zoning, which is supported by satellite imagery and maps. Public transport services, both train and bus, are limited, making greater reliance on cars inevitable and consistent with this development pattern.

Low-rise, Low-density and Car-centric Development (C3) and Dispersed Car-centric Development (C2): These clusters reflect a less-developed, lower-transit-service version of C4, suggesting it may follow a similar developmental trajectory unless interventions are made. The very low score on F1 indicates that the area cannot be sustained by public transport alone. Their relatively lower score indicates that also

they do not perform a feeder role compared to C4. Most of these stations are located at the farthest distance of Milan.

Non-residential Stations: Though this cluster is named non-residential stations, there are a few stations that are residential, they can be put under C2, implying a discrepancy within the results that are expected partially. The majority of these stations serve industrial or special destinations like airports or trade fair and exhibition organizer headquarters.

4.3. Cluster Based Policy Packaging

As discussed previously in the Literature Review section, the primary purpose of conducting a TOD typology analysis is to provide scientific, data-driven results in which stations are clustered into distinct groups based on their similarities and differences in morphological, functional, and socio-economic characteristics. TOD typologies are a tool used to measure the presence of the TOD concept in the current station environment. This measurement of current station conditions can then be used to coordinate future TOD planning, providing actionable policy packages to support decision-making processes.

Hence, one of the benefits of TOD typologies is to prevent providing a one-fits-all resolution that maybe prescribed for all stations, as discussed before, station areas are deeply context dependent (Su et al., 2021) and even adjacent stations within a neighborhood show profound differences between themselves (Map 2).

Since we have translated the results of the EFA and the scores of our 3 dimensions into TOD typologies profiles and validated them by cross-checking with satellite imagery and measured indicators, we have built a more profound understanding of the characteristics of distinct clusters. We can move forward and use this data to provide insights useful for policymakers and decision-makers.

We can now summarize the results and cluster profiles into actionable general policies that we could implement to improve the overall TODness of the station areas, tailored to their circumstances.

It is important to reassert that this study adopts a regional perspective. As outlined in the literature review, formulating detailed action plans for individual stations, such as allocating specific services or defining activities, falls outside the scope of this analysis. Micro-scale planning needs targeted assessments, guided by the accessibility criteria established earlier. Therefore, this study concentrates on outlining policy frameworks instead of specifying detailed interventions for particular stations. For example, as shown in Table 23, C5 stations are prime candidates for selective densification. In the long term, for C4 and C3 categories, preventing urban sprawl should continue to be a priority. This can be addressed by implementing zoning measures around stations to stimulate diverse, transit-oriented development. For C7 stations with already rich urban structures, improving the efficiency of urban design to promote AT is the top priority.

More importantly, as discussed in the literature review, these proposals alone cannot produce significant changes in individuals' transport mode choice without complementary interventions, both soft and hard. For example, South Korea's case (Jun et al., 2015) demonstrates how innovative solutions, such as offering additional discounts when combining several public transit trips together, can boost overall ridership. These incentives are especially effective when combined with shared e-bike services and supported by transit-oriented development (TOD) infrastructure which supports their use.

C. NO.	Profile	General Policy (Focus)	Intervention Suggestions
1	Non-residential Stations	-	- Not Suitable for TOD adjustments
2	Dispersed Urban Fabric with Low-Quality Transit Services	Plan zoning for long-term, potential TOD development	- Plan zoning for long-term, potential TOD development
3	Low rise, Low density and Car-centric Development	Create sub-city centers and enforce anti-sprawl boundaries. Focus zoning on gradual densification (Priority 3) near stations for future densification plans	- Zoning rules for densification and diversification near the transit hubs and curbing urban sprawl - Create sub-city centers for daily needs, allocate services based on strategic train access to other areas - Expand station parking and boost transit frequency and accessibility to enhance reliability - Develop demand-responsive transport (DRT) to reduce car dependence
4	Compact Low-rise and Spread Development	Create sub-city centers and enforce anti-sprawl boundaries. Focus zoning on gradual densification (Priority 2) near stations.	- Zoning rules for densification and diversification near the transit hubs and curbing urban sprawl - Create sub-city centers for daily needs, allocate services based on strategic train access to other areas - Expand station parking and boost transit frequency and accessibility to enhance reliability - Develop demand-responsive transport (DRT) to reduce car dependence - Add bicycle parking and incentivize e-bike sharing
5	Unsustained Place	Fix poorly connected blocks problems to improve AT, concentrate population growth by turning vacant industrial lots into dense, diverse TOD-style areas (Priority 1).	- Stitching the large blocks and gated communities to improve permeability and AT - Ground floor retrofitting: tax credits to convert ground floor residential units in superblocks into community services facilities - Developing brownfield or vacant industrial areas with mixed use land-uses for absorbing the population according to individuals TOD consonance characteristics - Strengthening one-last-mile service (Bicycle parking, shared E-bike) - Strategic bike lanes planning to connect the farther areas to the station - Improving the Train transit service - Diversification of activities near the transit-hubs
6	Unsustained Nodes	Strategic "Grid Repair" to host the bulk of new regional population for strategic needs	- Developing Specialized, Unique Activities that Serve a Broader Regional Population - Grid repair, land-bridges or underpasses
7	Urban Stations	Enhancing efficiency in already dense, high-value catchments	- Strengthening the one-last-mile infrastructure (Bicycle parking, shared E-bikes, separate bicycle paths, etc.) - Support paratransit services near stations (DRT) - Improving urban design according to TOD to support AT (Pedestrian Buffers), Restrictive Parking Management

Table 25 - Targeted Policies Proposal

5. Conclusion

This thesis employed a diagnostic regional approach to land use and transportation, to support the development of targeted policies that inform the policymaking process through quantitative TOD typology analysis for the Metropolitan City of Milan (Italy) case study. In doing so, it investigated whether Transit-Oriented Development (TOD) can function as an effective alternative to car-dominated transportation at the regional scale. The literature shows that what distinguishes TOD from the other solutions is its regional perspective, that is supposed to build a comprehensive system intended for enhancing sustainable accessibility, rather than merely upgrading individual transit hubs. Although TOD alone may not entirely alter urban mobility pattern, because of the persistent influence of entrenched behaviors and personal preferences, it remains important for advancing more sustainable mobility patterns. Yet, complementary interventions are needed to facilitate the TOD's success.

To go from theory to practice, as every urban area has a unique structure and that conditions may vary considerably even within the same city, it is essential to thoroughly understand the status quo and propose the appropriate adjustments to those conditions to propel TOD. Only with this understanding might policymakers effectively guide neighborhoods toward greater transit-oriented urbanization, where transit needs are met mainly via public transportation. In this respect, this thesis reviewed conventional TOD typology models, by which the scholars try to capture the cities' complicated dynamics.

The research found that many established methods rely on subjective and heuristic approaches, which hinder the development of scientific, data-driven clusters of transit hubs necessary for formulating effective, context-specific policies. These flawed frameworks frequently oversimplify the complex, multidimensional dynamics of transit hubs by forcing them fit into the limited Node and Place model, despite

evidence that their underlying structures are far more subtle and cannot be captured by simple predefined dual dimensions.

Moreover, the research addressed additional methodological shortcomings, including inconsistencies in indicator allocation within heuristic approaches, oversimplification, and errors in delineating the regional study area and the local catchment areas of transit hubs, and the influence of spatiotemporal dynamics on TOD systems, limitations of cross-sectional approaches in capturing dynamic changes, and issues related to putting forward the targeted policies according to clusters that are inherently relative, making them comparative rather than absolute.

To avoid the shortcomings of classic models, a multivariate analysis was conducted for the Milan functional urban areas case study. This approach resulted three latent factors: 1 – Multimodal Regional Accessibility, 2 - Local Intensity and Service, and 3 – Urban Fabric and Walkable Design, which jointly explained 62% of the variance in the data, a result that is considered acceptable given the study's contextual nature. Later, a hierarchical clustering using Ward's method was applied to form clusters, which eventually by using a dendrogram, 7 clusters were identified, and they were compared against the satellite imagery and maps to verify their accuracy. Finally targeted policies were developed to address the clusters according to their condition.

However, it remains to be assessed whether the method can truly overcome the shortcomings of standard models. As discussed, the multivariate analysis using EFA conducted in this analysis successfully addressed some of the limitations of heuristic approaches in standard models, particularly in dimension and indicator selection. The mathematical exactness of this approach shows that the resulting dimensions are not subjective, but instead derived from hidden structures within the data itself. Respectively, the interpretation of such dimensions as discussed in the literature review can be challenging because the indicators composing each factor are often attributed to different heuristic dimensions by various scholars. For instance, in our study, Factor 3 comprises two indicators related to design features and one indicator

referring to the proportion of residential area, which scholars often put under the place dimension rather than the design dimension. Therefore, the factor emerges inherently from the data, even though the dimension's name is chosen subjectively. It is important to emphasize that subjective naming of data-based factors serves mainly to facilitate interpretation. However, it is not always possible to assign a clear or appropriate title to each factor, as some may consist of diverse variables that are difficult to interpret collectively. Moreover, the mathematical process also presented multiple challenges. Restrictions in the ratio of sample size to measured variables required discarding several variables. The Heywood Case issue arose due to potentially identical measured variables. Additionally, the recurrent nature of the analysis made it computationally heavy.

Furthermore, this study offers a new perspective on the delineation of the study area, considering both micro and macro scales. It is evident that varying the extent of analysis can yield different results. Therefore, the delineation of the study area must be well-justified. From a macro perspective, it is proposed to define the spatial extent based on the agglomeration of urban areas that sustain daily activities through mutual relationships, essentially, according to their daily economic interactions, which propel the mobility between these areas. This approach is indeed one of the original contributions this thesis makes to the TOD literature, as almost all sources rely on administrative borders at different scales to conduct their work.

In this study, the borders were successfully delineated using the OECD's Functional Urban Areas. This enabled the identification of 129 functional transit hubs on the train network. The catchment areas of these stations were subsequently determined using walkable zones derived from network analysis. Although this approach is more precise than methods based on Euclidean distance from stations, it still does not provide a fully accurate approximation of catchment areas because it does not account for factors such as topography, safety, individual characteristics, and planned local importance, all which influence catchment area boundaries.

Moreover, in the field of TOD typology methodology, there is a huge need to develop a sophisticated Factor-specific impedance function that can also address multimodal potential accessibility. Though in this study an attempt was made to compensate for the lack of such a tool in the model by using a range of indicators that all illustrate the transit status and access to other locations, yet those estimations of accessibility are not reliable enough. For instance, a station with access to 10 other stations of low strategic importance (such as those in the C2 cluster) within a 30-minute travel time may score higher on accessibility than a station with access to only 5 stations, even if those 5 are in the more strategically significant C7 cluster. A sophisticated model of potential accessibility should not only distinguish between mere access to locations but also account for the quality of available opportunities as well.

It is also believed that this potential accessibility tool should be used when planning the location of essential services, such as schools or hospitals, in TOD areas, especially when these services are intended to serve beyond the immediate local catchment. Employing advanced multimodal accessibility analysis enables a more accurate assessment of suitability for siting public services.

Ultimately, if TOD typologies are to serve as effective strategic tools for urban planning, it is essential for future research to move beyond cross-sectional models and develop longitudinal approaches that account for the dynamic nature of urban environments.

6. Appendix

Station's name	Latitude	Longitude	F1	F2	F3
Abbiategrosso	45.39758018	8.920642026	-0.849050802	-0.065101715	1.774641638
Albairate	45.40438487	8.957944915	-0.340088297	-0.993664278	-1.910345004
Albizzate Solbiate Arno	45.7235359	8.806217579	-0.70029743	-0.832832439	-0.200159907
Arcore	45.6239254	9.323242827	-0.308416153	-0.327455145	0.100028895
Arosio	45.71834982	9.2102492	-0.539487407	-0.655833698	0.122850866
Besana	45.70283447	9.282999439	-0.319702975	-0.633832088	-0.093012393
Besnate	45.69547886	8.761103278	-0.754986537	-0.851897642	0.433091839
Biassono-Lesmo Parco	45.63228879	9.298360144	-0.444836584	-1.084732804	-1.707505152
Bollate Centro	45.54289478	9.122883367	0.086242398	0.310375197	1.178077863
Bollate Nord	45.55275374	9.11232052	-0.045272822	-0.536628234	-0.757464887
Borgolombardo	45.40445839	9.270458975	-0.108314121	0.892619415	0.864101145
Bovisio Masciago	45.61185612	9.141582089	-0.308919804	-0.304412815	0.751418901
Busto Arsizio	45.61621578	8.864948064	0.441053801	0.44605525	0.475004552
Busto Arsizio Nord	45.60595479	8.851537813	0.014374347	0.521645621	1.535470657
Buttafava	45.62136108	9.301136692	-0.505770973	-1.001752082	-1.596278154
Cabiate	45.67593257	9.168592784	-0.233886799	-0.410284532	1.119923877
Camnago-Lentate	45.66822631	9.133591203	0.137477623	-0.742430375	-0.479192433
Canegrate	45.56931041	8.926548747	-0.446849532	-0.31025951	1.723765877
Carate-Calo'	45.67643041	9.252297204	-0.461481239	-1.119375049	-1.855710071
Carimate	45.69727592	9.106927074	-0.504962514	-0.996784167	-1.138012145
Carnate Usmate	45.6534141	9.375455945	0.24298762	-0.377355062	0.185121739
Caronno Pertusella	45.59828374	9.058235022	-0.293762063	-0.561359917	0.673109128
Carugo-Giussano	45.70576014	9.198977204	-0.630749158	-0.460616395	-0.162183126
Casalezzo Vaprio	45.40871366	9.631786343	-0.864306455	-0.86009276	-0.291574947
Casorate Sempione	45.6750626	8.744185	-0.702885941	-0.802402414	-0.368825478
Cassano D'Adda	45.51451834	9.512102593	-0.029690399	-0.773356333	-0.324343147
Castellanza	45.61051779	8.875738192	-0.426686358	-0.262414306	-0.433811341
Cavaria Oggiona Ierago	45.69794717	8.803499935	-0.591339288	-0.698365659	0.182495767
Ceriano Laghetto-Solaro	45.62482272	9.079438443	-0.837177119	-0.761927856	-0.78357312
Cernusco-Merate	45.69544348	9.397077095	-0.502507381	-0.712129106	-0.499137068
Certosa Di Pavia	45.25671821	9.154425851	-0.839761681	-1.033034077	-1.365085085
Cesano Boscone	45.43032533	9.091656616	-0.428485281	-0.386022932	-0.598422865
Cesano Maderno	45.63060539	9.141955462	0.717920739	-0.20513232	1.256688342
Cesate	45.5909805	9.066598448	-0.291817054	-0.235825809	0.285625912
Cislago	45.66103967	8.977698908	-0.55521532	-0.534320695	0.237784369
Corbetta S.Stefano	45.48096402	8.917894256	-0.645022926	-0.640743359	-0.323223622
Cormano-Cusano Milanino	45.54538161	9.173727275	0.073445471	0.444442153	0.15941005
Corsico	45.43594039	9.109094292	-0.575460559	0.985295731	0.752631763
Desio	45.62015194	9.21850376	-0.121928945	-0.329240857	0.171330892
Ferno-Lonate Pozzolo	45.60857493	8.75524767	-0.840136916	-0.632189657	-0.31172924
Gaggiano	45.40885323	9.031243871	-0.537287876	-0.621198774	-1.21021976
Gallarate	45.6599118	8.7986579	0.965783304	0.53710356	0.37273025
Garbagnate Milanese	45.5800815	9.080053876	-0.07996441	-0.362990651	-0.149211175
Garbagnate Parco Delle Groane	45.57123664	9.091064792	-0.105781653	-0.820187896	-1.628889988
Gerenzano-Turate	45.64560843	9.001497648	-0.517075691	-0.43061687	0.154943576
Gropello Cairoli	45.17314146	8.991467452	-0.909282122	-0.977182553	-0.508772296
Inverigo	45.74024336	9.224323635	-0.443427405	-0.934844356	-1.071795591
Lambrugo-Lurago D'Erba	45.7615723	9.238447519	-0.508877493	-0.931668229	-0.853215072
Legnano	45.59367547	8.910671502	-0.147961805	0.693887925	1.334798829

Lesmo	45.64472675	9.30927962	-1.195421763	-1.00805759	-0.601168971
Lissone-Muggio'	45.6058912	9.235628753	-0.189076959	0.39477785	1.912037714
Locate Triulzi	45.35994104	9.221579292	-0.566943125	-0.194024438	-0.319591911
Lodi	45.30903348	9.49760104	0.092331255	1.056217632	0.659573081
Lomazzo	45.69868655	9.036109363	-0.54339684	-0.653084803	0.132607482
Macherio Sovico	45.64248082	9.266904757	-1.17577599	-0.455985136	0.956816213
Macherio-Canonica	45.64559052	9.286719081	-0.455428338	-1.005593143	-1.647859511
Magenta	45.4683235	8.881070172	-0.690420992	-0.179108713	1.298009619
Malpensa Aeroporto T1	45.62732071	8.711201412	-0.492975851	-0.798662998	-2.32387793
Malpensa Aeroporto T2	45.65043462	8.720875638	-0.526225025	-0.622950219	-2.480449361
Mariano Comense	45.69368041	9.181608365	-0.245366727	-0.212727886	0.539604228
Meda	45.66240928	9.15921636	-0.094010489	-0.098466953	1.162318218
Melegnano	45.35636542	9.319292846	-0.284856508	0.376436957	1.000160949
Melzo	45.50192627	9.419295462	-0.102908194	0.518938499	0.539315373
Milano Affori	45.52087289	9.167266892	0.151049525	1.583047391	-0.260094312
Milano Bovisa Politecnico	45.50258778	9.15908422	3.252203389	-0.051087488	-0.960968471
Milano Bruzzano Parco Nord	45.53376658	9.172827253	-0.152008233	0.414078827	-1.23492891
Milano Cadorna	45.46835628	9.175396695	1.881202025	1.230084319	0.637189895
Milano Centrale	45.48667389	9.204560961	2.276976326	1.686496706	1.528056238
Milano Certosa	45.50676651	9.134955827	0.621682366	-0.124878169	-0.297591769
Milano Dateo	45.46807649	9.216684912	1.395062882	3.308168178	2.340414521
Milano Domodossola	45.48089969	9.162085169	1.733880545	2.190065182	0.825237921
Milano Forlanini	45.46316569	9.237280226	1.538904586	1.52521392	0.031442461
Milano Greco Pirelli	45.51302011	9.214759103	1.414774125	0.62894688	-0.695116672
Milano Lambrate	45.4851178	9.236957772	2.652798915	3.247429578	0.729024191
Milano Lancetti	45.4952583	9.176159478	1.734740548	1.210007232	0.216173501
Milano Porta Garibaldi	45.48430428	9.187680662	5.173846367	0.805385331	1.18973582
Passante					
Milano Porta Genova	45.4533488	9.169310246	-0.582527452	2.353381279	0.774050879
Milano Porta Romana	45.44583731	9.213257426	-0.46357345	2.473676235	0.576216999
Milano Porta Venezia	45.47620449	9.207919976	1.689089794	3.059900765	2.013082665
Milano Porta Vittoria	45.45961659	9.22412071	1.304491418	2.297567251	0.493340151
Milano Quarto Oggiaro	45.5192095	9.14527826	-0.028066347	0.853739924	-0.038161062
Milano Repubblica	45.48032825	9.198918032	2.189111484	0.804184779	1.923748892
Milano Rogoredo	45.43364176	9.239063706	2.277926785	-0.132683996	-1.591241494
Milano Romolo	45.44325373	9.167852427	-0.563350525	1.288155223	-0.327623504
Milano S.Cristoforo	45.44234849	9.130289433	-0.094144996	1.049890195	-0.574123908
Milano Tibaldi - Bocconi	45.4439889	9.184986597	-0.570465325	1.868160236	0.654135022
Milano Villapizzzone	45.50205771	9.150918425	0.955271578	0.482278561	-0.074842022
Monza	45.57775061	9.273156682	1.895156004	1.045740413	-0.169765574
Monza Sobborghi	45.58211206	9.284465569	-0.670780939	1.363080496	0.702468237
Mozzate	45.67783148	8.955185474	-0.478992972	-0.588294992	0.452525901
Novate Milanese	45.53307923	9.13272445	0.307816301	0.294365298	0.548414502
Osnago	45.67881786	9.387075645	-0.581219936	-0.78168479	-0.579998013
Paderno Dugnano	45.56524167	9.160979861	-0.147334821	0.569526435	0.519987186
Paderno Robbiate	45.67834165	9.439360057	-0.878341896	-0.728986842	-0.51745817
Palazzolo Milanese	45.58088291	9.156520139	-0.18358801	0.028586955	0.074723608
Parabiago	45.55265992	8.945994108	-0.301673947	-0.384239067	1.942846232
Pieve Emanuele	45.33970219	9.203612182	-0.542468742	-0.20914017	-0.714545897
Pioltello Limite	45.48584492	9.328835015	0.46683044	0.498914441	0.307733275
Pozzuolo Martesana	45.5084759	9.456324348	-0.564443279	-0.943098923	-1.294650521
Pregnana M.	45.51008961	9.00299074	-0.352355996	-0.537710211	-0.253414906
Renate-Veduggio	45.72842025	9.279760731	-0.344864117	-0.81207088	-0.082284723
Rescaldina	45.62215762	8.946661944	-0.377012274	-0.446189929	1.140643082
Rho	45.5237647	9.0431599	0.357990421	0.489602062	0.178031627
Rho Fiera Milano	45.52123627	9.088156856	0.743295207	-0.67465433	-1.974711237
Rovellasca-Manera	45.66573174	9.038336869	-0.536920418	-0.900623733	-1.115159752

Rovello Porro	45.6514376	9.036261985	-0.634004409	-0.752227604	0.28180752
S.Donato Milanese	45.4185375	9.253209356	-0.068818176	-0.463583258	0.140923324
S.Giuliano Milanese	45.39130042	9.286460479	-0.302428778	0.493111768	0.402958877
S.Zenone Al Lambro	45.33777667	9.361574126	-0.692953491	-0.586539396	-0.403369174
Saronno	45.6251346	9.030524424	2.57311627	0.549273207	0.693355583
Saronno Sud	45.61242096	9.045051027	0.083630133	-0.825668852	-1.199689576
Segrate	45.48071362	9.298671151	0.050068263	-0.579228375	-1.464287633
Seregno	45.64616014	9.202453479	0.319470252	0.473461169	0.583608567
Sesto S.Giovanni	45.54111776	9.239228988	1.175858621	1.905506937	0.568425817
Seveso	45.64816285	9.140535581	0.11522505	-0.105790984	0.726366618
Seveso Baruccana	45.63803979	9.162920242	-0.752696082	-0.630626746	0.191165665
Somma Lombardo	45.68645734	8.713063648	-0.889949805	-0.384800357	0.226803234
Tavazzano	45.32635816	9.402802412	-0.831126423	-0.481019083	-0.774853027
Trecella	45.51274229	9.480715442	-0.323995902	-1.086972039	-1.191621668
Trezzano Sul Naviglio	45.42045771	9.067110017	-0.584881077	0.227843348	0.905350605
Triuggio-Ponte Albiate	45.65899324	9.266957875	-0.365179684	-0.713623081	-0.529086475
Vanzaghella-Magnago	45.57769333	8.787574494	-0.770358976	-0.819089673	0.402934358
Vanzago Pogliano	45.52498761	8.996170259	-0.404860331	-0.46037873	-0.210452234
Varedo	45.5956374	9.153096948	-0.296138739	-0.158095968	0.862682703
Vignate	45.49421455	9.375757288	-0.099559635	-0.171627605	-0.275266425
Villa Raverio	45.69043649	9.261540735	-0.440593345	-0.755287847	-0.788089301
Villamaggiore	45.32060754	9.190720584	-0.714736214	-1.040224428	-1.79225094
Villasanta	45.60340938	9.304805879	-0.277737891	-0.144886994	0.27853619
Vittuone Arluno	45.4911578	8.9474813	-0.377211459	-0.560494476	-0.729343356

Table 26 - Stations' Factor Scores

Stage	Cluster A	Cluster B	Distance Coefficient	Total Samples
1	30	115	0.010864	2
2	1	40	0.04714	2
3	56	81	0.070046	2
4	111	117	0.072179	2
5	28	87	0.092295	2
6	7	129	0.099444	3
7	27	32	0.102872	2
8	96	116	0.103877	2
9	16	24	0.107976	2
10	4	136	0.11077	3
11	13	113	0.13256	2
12	21	85	0.1381	2
13	119	132	0.142123	3
14	11	67	0.147625	2
15	14	59	0.149008	2
16	38	42	0.165313	2
17	44	60	0.169574	2
18	23	127	0.171408	2
19	8	123	0.180325	2
20	0	120	0.183097	2
21	50	105	0.18426	2
22	17	114	0.192589	2

23	12	33	0.193378	2
24	98	146	0.194355	3
25	2	118	0.200035	2
26	19	137	0.207509	3
27	70	139	0.207958	3
28	66	144	0.209661	3
29	3	91	0.224075	2
30	25	47	0.229956	2
31	5	20	0.229986	2
32	53	54	0.237687	2
33	22	138	0.243497	4
34	15	101	0.250268	2
35	134	150	0.254506	5
36	72	131	0.258463	3
37	63	78	0.260306	2
38	29	133	0.26457	3
39	6	10	0.27303	2
40	51	112	0.281109	2
41	84	121	0.289297	2
42	122	161	0.302909	5
43	83	135	0.305324	3
44	41	73	0.310306	2
45	69	149	0.31652	3
46	88	100	0.329931	2
47	106	124	0.330824	2
48	128	141	0.347955	4
49	36	57	0.347971	2
50	64	157	0.349894	3
51	140	163	0.355473	7
52	152	154	0.384664	6
53	148	176	0.386873	6
54	65	142	0.392755	3
55	62	99	0.392841	2
56	77	166	0.393913	4
57	125	162	0.404538	3
58	45	145	0.40718	3
59	35	92	0.414527	2
60	39	75	0.419399	2
61	93	175	0.445173	3
62	31	37	0.447092	2
63	61	110	0.45104	2
64	147	171	0.458731	5
65	46	170	0.464758	6
66	153	155	0.471537	5
67	80	158	0.497075	3
68	58	107	0.505208	2
69	89	179	0.508365	8
70	95	173	0.509799	4
71	9	26	0.515111	2
72	151	178	0.535215	5
73	126	193	0.552218	7

74	90	97	0.574541	2
75	156	186	0.577951	6
76	71	187	0.584833	3
77	18	172	0.619413	3
78	168	185	0.623448	5
79	94	165	0.632578	3
80	159	182	0.637736	5
81	130	197	0.641533	10
82	104	188	0.671543	3
83	43	202	0.698413	3
84	184	208	0.717345	9
85	177	190	0.73691	4
86	169	198	0.748017	6
87	167	199	0.768488	4
88	34	204	0.774187	4
89	82	211	0.790306	4
90	143	214	0.827626	8
91	164	174	0.857495	5
92	180	206	0.88316	11
93	86	108	0.970962	2
94	79	191	0.977676	3
95	194	195	1.017863	8
96	192	200	1.070679	10
97	109	189	1.121766	4
98	49	68	1.163236	2
99	74	222	1.171185	4
100	205	213	1.181136	7
101	183	219	1.189952	7
102	223	224	1.211772	18
103	103	209	1.224201	11
104	160	181	1.264066	8
105	48	228	1.385256	8
106	52	221	1.490554	3
107	76	217	1.54	5
108	220	230	1.794062	29
109	225	232	1.854833	12
110	203	227	1.88829	10
111	215	233	1.909581	12
112	210	216	1.943862	7
113	201	237	1.965291	19
114	212	218	2.068157	17
115	55	196	2.108279	3
116	231	242	2.232623	28
117	229	235	2.766092	12
118	234	240	2.856583	10
119	238	245	3.127857	22
120	207	247	4.05048	25
121	102	226	4.113019	3
122	243	246	4.374534	13
123	236	244	4.685197	57
124	239	248	5.857468	37

125	249	250	6.053188	16
126	241	251	8.372629	76
127	252	253	11.2533	53
128	254	255	17.03044	129

Table 27 - The Agglomerative Schedule

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