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Advancing sustainable urban mobility: An empirical travel time analysis of the 15-minute city model in Porto

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ABSTRACT

The Fifteen-Minute City (FMC) concept presents a transformative approach to urban planning, prioritizing accessibility to essential services within a 15-minute walk or cycling distance. This study evaluates the feasibility and practical implications of implementing the FMC model in Porto, Portugal, bridging theoretical concepts with real-world applications. Employing a Weibull hazard-based survival model, the research draws on data from over 11,000 trips to explore the relationship between travel times and urban mobility patterns. Results show that approximately 70% of trips in Porto are completed within 15 min, indicating partial alignment with FMC principles. However, significant barriers persist, including low active mobility (AM) adoption (less than 40% of trips) due to cultural preferences for motorized transport, inadequate infrastructure, and limited public awareness of AM benefits. By identifying temporal thresholds and examining influential variables shaping modal choices, the study provides actionable insights into the challenges and opportunities of FMC implementation. The findings highlight the need for targeted interventions to shift societal attitudes and reduce reliance on private vehicles, proposing strategies such as enhancing pedestrian pathways, expanding cycling networks, and promoting mixed-use zoning. These efforts aim to foster sustainable, health-conscious urban settings, reduce traffic congestion, and improve residents' quality of life. The study concludes by suggesting directions for future research to further explore the scalability and adaptability of the FMC model in diverse urban contexts, ultimately contributing to more accessible and sustainable urban environments.

1. Introduction

Urban mobility is a fundamental component in the design of contemporary cities, directly influencing residents' well-being, accessibility, and the overall sustainability of urban environments (Glaeser and Gottlieb, 2009; Mouratidis, 2021). With the rapid expansion of metropolitan areas and projections indicating that over 60 % of the global population will reside in central cities by 2030 (United Nations, 2020), it has become crucial to implement mobility solutions that foster quality of life and address the demands of modern urban centers (Washington et al., 2004; Gavsker, 2023). In Porto, Portugal, the increasing population density intensifies demand for housing, congestion in transportation systems, and strains public services, underscoring the need for sustainable and efficient transportation solutions.

In this context, the Fifteen-Minute City (FMC) concept has gained significant traction as a transformative model for urban planning, particularly for sustainable development. Designed to create communities where all residents have access to essential services within a maximum distance of 15 min walking or cycling, this concept aims to transform urban environments by reducing reliance on motorized transport (MT) while promoting active mobility (AM) (Moreno et al., 2021).

The adoption of the FMC framework offers distinct advantages over traditional sector-based planning models when applied to cities like Porto, where sustainability and urban livability are pressing concerns. Sector-based models, which organize urban functions into specialized zones, such as residential, commercial, and industrial areas, often reinforce spatial segregation and lengthen travel distances. This separation of functions increases dependency on private motorized vehicles (PMVs), generates higher environmental externalities, and reduces opportunities for localized community engagement. In contrast, the FMC approach emphasizes spatial integration, functional mix, and decentralized accessibility, promoting urban forms where essential services, employment, education, and leisure are available within short distances.

This shift from mobility-based to accessibility-based planning is particularly suited for Porto, a city characterized by its compact

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morphology, historical street patterns, and pre-existing mixed-use urban fabric, especially in its central and intermediate neighborhoods. These features position the FMC as an actionable planning model, comparable to successful applications seen in Barcelona, Paris, and Milan, where proximity-oriented strategies have led to demonstrable improvements in urban livability (Moreno et al., 2021; Pozoukidou and Chatziyiannaki, 2021).

In contrast to traditional approaches, this study introduces a novel integration of the FMC concept employing a parametric survival model with the Weibull hazard function to analyze mobility data, specifically examining event durations (Kiefer, 1988). This model facilitates the examination of temporal variability and travel time reliability across various modes of transport by incorporating sociodemographic variables, with a specific focus on trips lasting up to 15 min (Hu et al., 2019; Ahmed et al., 2023). These insights will enable us to estimate the probability of trip completion within the specified timeframe, thereby enhancing our understanding of travel time behaviors (Harsha and Mulangi, 2022). Ultimately, this research addresses key gaps in the FMC literature by operationalizing its principles through empirical data and statistical modeling, offering a structured examination of urban mobility data for evaluating proximity-oriented mobility in similar urban contexts.

Building on this foundation, our study aims to compare current travel patterns in Porto with the guidelines of the FMC model. While Bibri et al. (2020) and Thondoo et al. (2020) have provided valuable conceptual insights into the potential of the FMC framework to promote sustainable mobility, address environmental challenges, and enhance urban livability. This study extends their contributions by providing a detailed, empirically grounded analysis of its applicability in the context of Porto. This methodology allows us to quantify the impact of various socioeconomic and trip-related factors on travel time, providing a more nuanced understanding of the challenges and opportunities for FMC implementation in this specific urban context. By providing a theoretical and empirical foundation, the study contributes to the discourse on sustainable urban planning, enriching the dialogue and offering practical applications for addressing urban mobility challenges faced by 21st-century cities.

2. Literature review

In the field of urban mobility, the influence of spatial organization is widely recognized as a central determinant of mobility patterns. Crane (2000) argues that travel behavior is strongly shaped by how cities are spatially structured, specifically, the location of housing, employment, services, and leisure relative to one another. From this foundation emerges the concept of the FMC, popularized by Carlos Moreno in 2016, which advances the idea of reconfiguring urban form to foster polycentric, self-sufficient neighborhoods (Moreno et al., 2021).

The central premise of the FMC model is that residents should be able to access essential services, such as employment, education, healthcare, commerce, culture, and recreation, within a 15-minute walk or bike ride from their homes (Moreno et al., 2021; Pozoukidou and Angelidou, 2022). By minimizing travel times, this proximity-based approach aims to improve urban livability and promote AM, while reducing dependence on PMVs (Mueller et al., 2020; Moreno et al., 2021; Allam et al., 2024). In doing so, the FMC framework fosters the development of compact and interconnected urban environments that are aligned with broader sustainability goals, namely, reducing environmental impact, advancing social equity, and enhancing public health outcomes (Pozoukidou and Chatziyiannaki, 2021).

Evidence from real-world implementations, such as Barcelona's superblocks and Portland's complete neighborhoods, demonstrates that promoting proximity in urban design enhances both accessibility and social cohesion (Pozoukidou and Chatziyiannaki, 2021; Ferrer-ortiz et al., 2022). These case studies reinforce the notion that cities designed around the PMVs often produce longer, car-dependent trips that undermine the potential for short, sustainable journeys. Conversely, cities that prioritize walkability, mixed-use development, and neighborhood-level infrastructure create conditions more conducive to the adoption of FMC principles. Therefore, assessing the extent to which urban form supports the FMC framework necessitates analyzing travel duration in relation to sociodemographic and temporal variables.

Among the approaches suitable for this task, one that has gained traction in transportation research is the use of hazard-based duration models, particularly those using the Weibull distribution (Anastasopoulos et al., 2012). These models, originally developed in the medical and economic fields, have been recently adapted for transportation studies to investigate travel distances, duration, and waiting periods in urban settings (Anastasopoulos et al., 2012; Shi et al., 2016; He et al., 2020; Ahmed et al., 2023). By assuming specific time distributions, it can help in estimating how factors such as environmental variables, income, transport modes, and service proximity influence travel choices (Lee and Wang, 2003).

These insights are essential for identifying spatial or social inequalities that may compromise the FMC's promise of local accessibility and equity. Additionally, this framework provides an investigative approach to understanding and quantifying travel time distributions. Analyzing the factors that influence these distributions enables a detailed examination of event occurrence probabilities, thereby elucidating patterns in mode preferences (Schoenfelder et al., 2014). This is especially important for facilitating the transition to AM when MT proves inadequate (Crane, 2015; Lefebvre-Ropars et al., 2017).

Several empirical studies have demonstrated the utility of this approach. For instance, Anastasopoulos et al. (2012) explained how hazard-based models provide crucial insights into travel durations, which are essential for designing cities that promote AM and PT while limiting the use of PMV. Xu and Wang (2019) used hazard-based models to assess e-bike trip durations in Shaoxing, China, revealing that time-of-day and gender significantly influenced trip length. Parsa et al. (2020) applied similar models to examine in Tehran, Iran, how demographic and temporal factors can affect various dimensions of urban mobility, including trip lengths, frequency of use, and mode choice preference.

Furthermore, survival models in traffic congestion studies have shown that variables like road characteristics, traffic volume, as well as environmental and behavioral factors, can influence travel times and congestion levels (Moylan and Rashidi, 2017; Gore et al., 2023). In a more recent study, Gonçalves et al. (2024) explored how social activities and urban form shape travel duration, reinforcing the notion that thoughtfully designed urban spaces can shorten travel times and promote accessibility. This approach underscores the influence of urban design on travel behavior, demonstrating how thoughtfully structured environments can reduce travel time by optimizing routes and improving accessibility to daily necessities (Ding et al., 2017).

In Porto, however, the potential of survival analysis to examine the applicability of the FMC model remains underexplored. This gap presents an opportunity for research on how survival models could support the adaptation of the FMC concept to Porto's unique context. By applying this approach to assess travel time by different transport modes according to the purpose of trips for daily activities, we can determine Porto's alignment with this proximity-based framework. This analysis could serve as a prototype for similar cities, providing insights that could shape public policies and guide the development of sustainable urban mobility strategies, thereby fostering more resilient, accessible, and equitable communities for residents.

To contextualize this research within the broader academic landscape, Table 1 presents a comparative summary of key studies addressing short-distance travel behavior, accessibility, and the operationalization of the FMC model. The table contrasts the conceptual foundations, methodological approaches, and geographic focus of these works, highlighting their empirical and methodological contributions.

Table 1
Comparative Overview of Key Literature on Urban Mobility and the 15-Minute City.

Study (Author, Year)	Focus / Concept Explored	Key Methodology / Approach	Case Study City/ Region	Key Contribution
Moreno et al. (2021)	Introducing the "15-Minute City": Sustainability, Resilience and Place Identity in Future Post-Pandemic Cities	Conceptual framework, Review of principles	Global (Conceptual)	Defines the core principles of the 15-Minute City (accessibility to essential services within 15 mins by walk/bike).
Pozoukidou & Chatziyiannaki (2021)	15-Minute City: Decomposing the New Urban Planning Eutopia	Literature Review, Case Study Analysis (e.g., Melbourne's 20-min neighborhoods)	Various (e.g., Melbourne)	Reviews the theoretical underpinnings and practical applications of the FMC concept; discusses benefits and challenges.
Ferrer-ortiz et al. (2022)	Barcelona under the 15-Minute City Lens: Mapping Accessibility and Proximity Potential Based on Pedestrian Travel Times	Spatial Analysis, GIS-based accessibility mapping (pedestrian travel times)	Barcelona, Spain	Maps and evaluates accessibility to services based on pedestrian travel times within Barcelona's superblocks, assessing spatial alignment with FMC principles.
Wu et al. (2021)	Analysis and optimization of 15-minute community life circle based on supply and demand matching: A case study of Shanghai	Supply and demand matching analysis, Spatial analysis	Shanghai, China	Analyzes the spatial distribution of services and population to assess the feasibility of a 15-minute community life circle; proposes optimization strategies.
Anastasopoulos et al. (2012)	Analysis of urban travel times	Hazard-Based Duration Models (various distributions)	US Cities (General)	Demonstrates the efficacy of hazard-based models for analyzing urban travel durations and identifying influential factors.
Ahmed et al. (2023)	Analysis of urban travel time and travel distance: A fully parametric bivariate hazard-based duration modelling approach with correlated grouped random parameters	Bivariate Hazard-Based Duration Modelling (with correlated grouped random parameters)	US Cities (General)	Develops and applies advanced hazard-based models for simultaneously analyzing travel time and distance.
Mackett (2003)	Why do people use their cars for short trips?	Survey analysis, Qualitative insights	Several European Countries	Identifies reasons (convenience, carrying goods, time constraints) why people choose cars even for short distances, hindering active mobility adoption.
Ton et al. (2019)	Cycling or walking? Determinants of mode choice in the Netherlands	Discrete Choice Models, Survey analysis	Netherlands	Analyzes factors influencing the choice between cycling and walking for short trips, highlighting infrastructure and environmental influences.
Fonseca et al. (2022)	Perceived Walkability and Respective Urban Determinants: Insights from Bologna and Porto	Survey analysis, Walkability Index assessment	Bologna, Italy and Porto, Portugal	Compares perceived walkability and urban determinants in Bologna and Porto, highlighting infrastructural differences impacting walking as a transport mode.
Tran & Ovtracht (2018)	Promoting sustainable mobility by modelling bike sharing usage in Lyon	Statistical modeling (e.g., regression)	Lyon, France	Analyzes factors influencing bike-sharing usage, highlighting the role of integration with public transport.

3. Study area

According to the National Statistical Institute of Portugal (INE), the AMP comprises 17 municipalities and houses around 1.7 million residents, representing 17 % of the country's total population. Its demographic density stands at roughly 844 inhabitants per square kilometer. (INE, 2021). Furthermore, the AMP shows a slight predominance of females, who comprise 51.4 % of the population, compared to 48.6 % males. The region also features a highly mobile population, with 78.9 % of residents engaging in daily travel activities, resulting in over

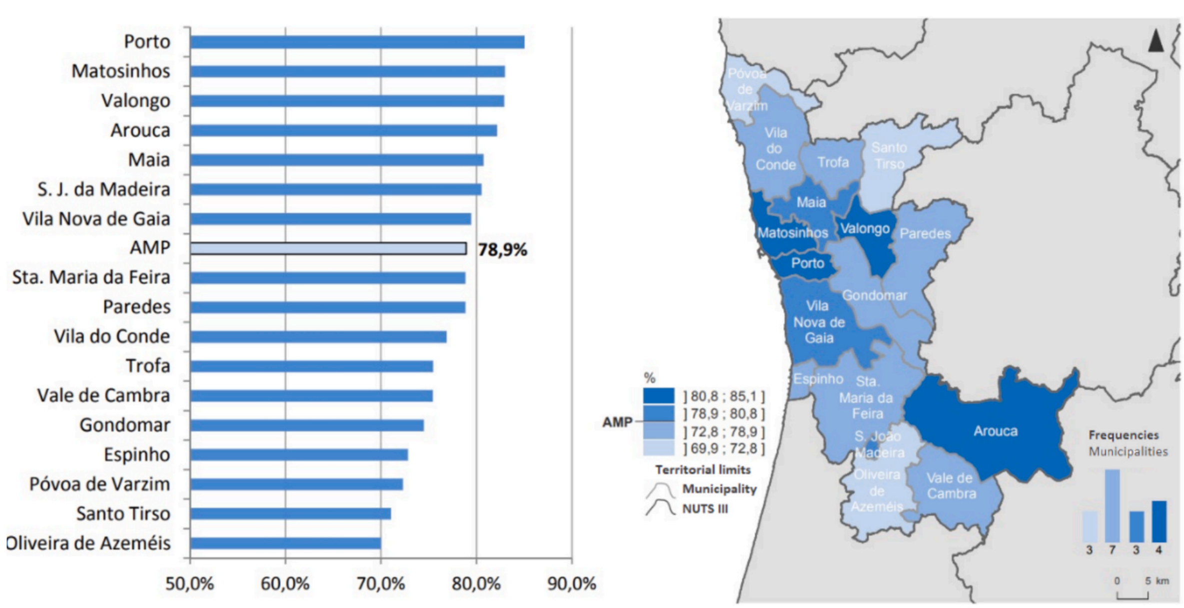

Fig. 1. Moving population in the AMP ().
Source: INE, 2018

3.4 million daily trips (INE, 2018).

To effectively address the objectives of this study, the city of Porto was strategically selected as the primary research site. As the principal urban center within the AMP, Porto experiences significant commuter flows from neighboring cities, standing out as the region with the highest recorded volume of trips, as illustrated in Fig. 1.

Consequently, for this study, only trips originating and terminating within the administrative boundaries of Porto were considered, ensuring a rigorous alignment with the FMC concept. The overall map of Porto is represented in Fig. 2.

Serving as the seat of the AMP, Porto exhibits the second-largest population within the region (approximately 231,900 inhabitants), surpassed only by Vila Nova de Gaia (approximately 304.000 inhabitants), as evidenced by INE (2021). Functions as a prominent attractor of trips for employment, educational, and recreational purposes, Porto maintains a leading position in terms of population density, as illustrated in Table 2.

Complementing, Porto presents a significant set of challenges in terms of urban mobility, further justifying its selection as the focal point of this analysis. The city contends with elevated levels of congestion on primary access routes, particularly during peak hours, considerable strain on the PT system, and structural challenges associated with intermodality between active and collective modes (Rocha et al., 2023).

The region is served by a PT system that includes a network of metro lines and buses. Porto's light rail system, the Metro do Porto, comprises six key lines (A, B, C, D, E, and F) that connect central areas to surrounding neighborhoods and municipalities. The metro operates at regular intervals, with departures approximately every 5 to 15 min during peak hours. Each metro line is capable of transporting up to 9000 passengers per hour, significantly contributing to a more sustainable urban environment by reducing CO2 emissions by 70,000 tons annually (Metro do Porto, 2025).

The bus network, primarily managed by private companies, plays a complementary role to the metro by extending coverage to areas not directly served by rail infrastructure. However, despite this intended synergy, significant gaps remain in the effective integration between modes. Issues such as inconsistent schedules, lack of physical infrastructure for seamless transfers, and limited coordination between services continue to hinder PT use in Porto (Shafiq et al., 2024). These shortcomings underscore the structural challenges in achieving a fully connected and efficient urban mobility system, reinforcing the city's relevance as a critical case study within the FMC framework.

Table 2
Population and Population Density of cities within the AMP (source INE, 2022).

Municipality	Population (2021)	Area (km^2)	Population Density (inhabitants/km^2)
Porto	231,962	41.42	5600
São João da Madeira	22,162	7.94	2770
Matosinhos	172,669	62.42	2766
Vila Nova de Gaia	304,149	168.46	1805
Maia	134,959	82.99	1626
Espinho	31,027	21.06	1509
Valongo	94,795	75.12	1261
Gondomar	164,255	131.86	1245
Póvoa de Varzim	64,320	82.21	782
Santa Maria da Feira	136,720	213.45	640
Vila do Conde	80,921	149.03	543
Trofa	38,612	72.02	541
Paredes	84,414	156.76	536
Santo Tirso	67,785	136.60	496
Oliveira de Azeméis	66,212	161.10	411
Vale de Cambra	21,279	147.33	144
Arouca	21,154	329.11	64

4. Data acquisition and preparation

The data for this study were collected in 2017 through the Urban Mobility Survey (IMob), a comprehensive household survey (revealed-preference) conducted within the AMP by INE. The survey's primary objective was to gather detailed information on the travel patterns and transportation preferences of the region's residents. Specifically, the survey targeted households within the AMP to capture a representative sample of the population's mobility behaviors. The survey included

Fig. 2. City Map of Porto (.
Source: QGIS Software, based on data from INE's municipalities)

people between 6 and 84 years old who had made at least one trip during the survey's reference day, ensuring a comprehensive understanding of the mobility patterns of individuals within the AMP. The questionnaire covered a range of essential topics, including demographic information (age, gender, socioeconomic status, and family composition), travel habits (commonly used transportation modes, travel frequency, and trip motivations), and travel durations (time spent on each journey and distance covered).

After an extensive data selection process that incorporated participants from a wide range of sociodemographic and geographic backgrounds to ensure statistical representativeness, the survey gathered a substantial dataset comprising 18,169 valid responses. This dataset captured 80,314 individual trips within the AMP region, accounting for approximately 2.5 % of daily trips recorded by the (INE, 2018). The sample size was determined to ensure statistical representativeness and reliability, facilitating meaningful analyses of transportation behaviors within the AMP (Rocha et al., 2023).

A comprehensive data curation process was also conducted to ensure the inclusion of only relevant data exclusive to Porto in the analysis. This procedure encompassed critical steps such as data selection, cleansing, validation, and encoding. Notably, the curation process was deliberately confined to incorporate only those trip routes where both the origin and destination points were situated within the geographic boundaries of Porto's limits.

To ensure a focused and robust analysis of travel preferences among Porto residents, we intentionally excluded variables of minimal significance or influence, as guided by Bogner and Landrock (2016); Busenbark et al. (2022). In addition to statistical relevance, the selection process also prioritized variables conceptually aligned with the analytical goals of this study, particularly those most pertinent to the FMC framework. By concentrating on the most influential factors and reducing potential biases, we omitted observations constituting less than 1 % of the dataset, such as responses categorized as 'not apply,' 'prefer not to answer,' or 'do not know.' This method intended to eliminate non-representative data possibly arising from entry errors, incomplete responses, or outliers, thereby ensuring reliable conclusions. Additionally, this approach was implemented to address non-response bias, a known cause of potential distortion in comparing respondents and non-respondents, thus enhancing the accuracy and validity of our findings (Tourangeau and Plewes, 2013; Berete et al., 2019).

Following the data-cleaning process, a total of 11,360 individual trips were deemed suitable for analysis. This subset constituted the primary dataset, from which 11 variables were carefully selected to construct an integrated model. To enhance methodological transparency and ensure replicability, Appendix A provides a summary table detailing all candidate variables considered in this study. The table explains the rationale for each variable's inclusion or exclusion, drawing on criteria such as theoretical relevance to the FMC framework, empirical variance, and data completeness.

Building upon this variable selection process, the robustness and validity of the model were further reinforced through a detailed evaluation of the interrelationships among the selected variables. Recognizing that several explanatory variables comprise sets of dummy variables, correlation measures such as Cramer's V were appropriately utilized via IBM SPSS 29 to assess these interrelationships comprehensively. The analysis revealed that all variables exhibited Cramér's V values below

Table 3
Descriptive Statistics of the variables.

Variables		*N*	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*	
Travel time in minutes (Duration variable)		11,360	1	120	19.43	15.189	
Categorical variables (Category 1; 0 otherwise)							*Marginal Percentage*
Transport mode	Active transport	4428					39.0 %
	Public transport	1890					16.6 %
	Private vehicle	5042					44.4 %
Trip Purpose	Work purposes	1931					17.0 %
	Educational activities	1576					13.9 %
	Leisure activities	1209					10.6 %
	Personal errands	1815					16.0 %
	Return home	4829					42.5 %
Sex	Female	6103					53.7 %
	Male	5257					46.3 %
Age	<25	1284					11.3 %
	≥65	2795					24.6 %
	25–44	3065					27.0 %
	45–64	4216					37.1 %
Education Level	Higher education (Bachelor's, Master's, Doctor's, Higher Professional Technical Course)	5932					52.2 %
	No education (completed 1st, 2nd, or 3rd year	245					2.2 %
	Secondary education (12th year of complete schooling or post-secondary with non-higher technological specialization)	2156					19.0 %
	Basic education (1st cycle, 2nd cycle, or 3rd cycle completed)	3027					26.6 %
Condition towards employment	Others (Student, Retired, Mainly engaged in household chores)	4445					39.1 %
	Unemployed	820					7.2 %
	Employee	6095					53.7 %
Driving license	No	2663					23.4 %
	Yes	8697					76.6 %
Transport Ticket	No	8319					73.2 %
	Yes	3041					26.8 %
Per Capita Income	Above 2000 euros	1435					12.6 %
	From 1000 to less than 1500 euros	2339					20.6 %
	From 1500 to less than 2000 euros	837					7.4 %
	From 650 to less than 1000 euros	2654					23.4 %
	Up to 650 euros	4095					36.0 %
Vehicle Ownership	No	2098					18.5 %
	Yes	9262					81.5 %

0.10, indicating a negligible level of association and suggesting minimal risk of multicollinearity (Evans 1996; Kearney, 2017).

For a more detailed presentation of the included variables, additional information can be found in Table 3.

Fig. 3, generated with *IBM SPSS 29* software, presents a detailed breakdown of travel time distributions, illustrating the frequency of trip durations within the dataset. The horizontal axis shows trip durations in minutes, while the vertical axis indicates frequency counts. This visualization provides insight into typical durations, enabling the identification of patterns relevant to the study's objectives.

The distribution underscores that most trips within the city are under 20 min, highlighting the potential for implementing efficient mobility solutions aligned with the FMC framework. To fully leverage this potential, analyzing the transport modes and trip purposes is essential to determine which journeys are suitable for integration into this framework. This analysis includes evaluating whether AM contributes to these short trips or whether their brevity is attributed to the use of MT. As our research progresses, examining the distribution of travel times in Porto will enhance our understanding of why most trips are completed in under 20 min.

5. Methodology

Traditionally, trip durations have been represented as continuous variables using conventional modeling techniques; however, a different perspective emerges when we consider them as temporal measures extending until the trip's end (Anastasopoulos and Haddock, 2012). This alternative perspective not only facilitates the application of hazard-based modeling, a common technique in the analysis of temporal data, but also underscores the significance of the hazard-based approach in comprehending the complex dynamics of travel time. This approach centers on examining the conditional probability of a journey reaching its conclusion within a specific timeframe, represented as '*t*' (Collett, 1993).

Such models have the ability to provide an understanding of crucial aspects of trip duration. These insights include how the likelihood of a journey concluding within a short time frame evolves as the journey unfolds. This is essential in assessing whether the trip is more or less likely to exceed the specified time limit (Anastasopoulos and Haddock, 2012).

The underlying concept of this approach is encapsulated in the cumulative distribution function *F(t)* (Hensher and Mannering, 1994).

$$F(t) = P(T < t) \tag{1}$$

This function reflects the likelihood (*P*) of a trip (random time variable *T*) being completed at or before a time *t*. It is a valuable tool in the analysis of duration data, and the correspondent probability density function *f(t)* is represented by Eq. (2) (Hensher and Mannering, 1994):

$$f(t) = \frac{dF(t)}{dt} \tag{2}$$

Conversely, the survivor function indicated as *S(t)*, represents the likelihood that a given duration goes beyond a designated time point *t*, and mathematically, it is formulated as follows:

$$S(t) = P(T > t) \tag{3}$$

Consequently, it is correlated to the cumulative distribution function:

$$S(t) = 1 - F(t) \tag{4}$$

By understanding the survivor function and the density of event durations up to a specific moment *t*, we can clarify the connection between when events fail and the survivor function. This connection is facilitated by the hazard function *h(t)*. The hazard function tells us about the inherent encapsulated risk rate when an event happens at a precise moment (Hensher and Mannering, 1994).

$$h(t) = f(t)/S(t) \tag{5}$$

Significantly, when *h(t)* increases within a specific timeframe, it suggests a higher likelihood of the event happening during that interval. On the contrary, a decrease in *h(t)* signifies a lower risk rate. Finally, if the hazard function is constant throughout the trip, the probability that

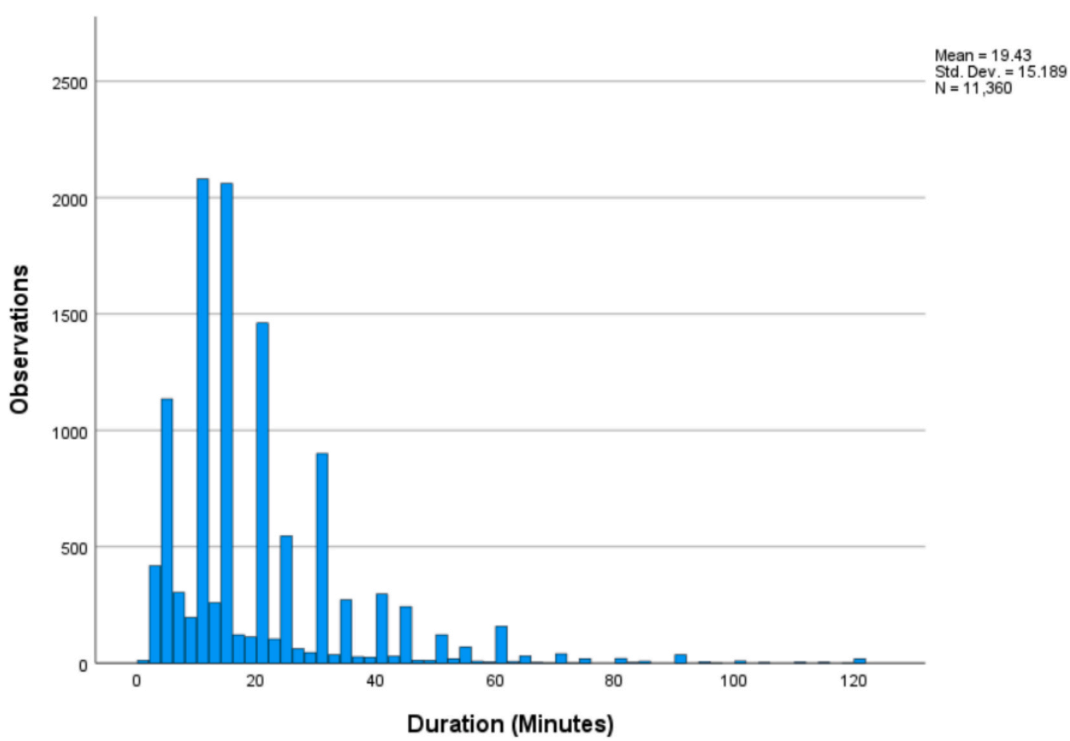

Fig. 3. Distribution of trip durations in minutes (.
Source: IBM SPSS 29)

a trip will end soon does not depend on how long the trip has lasted (Hensher and Mannering, 1994). This measure of risk is essential for understanding how the failure rate varies continuously over time and is represented by equation 6:

$$h(t) = \frac{f(t)}{S(t)} = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t | T \ge t)}{\Delta t} \tag{6}$$

The slope of the hazard function, which represents its rate of change over time, is essential in unveiling the connection between the event's duration and the probability of its ending. This concept, frequently denoted as duration dependence, highlights how the likelihood of the event concluding evolves as time progresses. Notably, a steeper slope in this context indicates a stronger influence of time on the event's probability ending, presenting perceptions of how time shapes the event's outcome.

Besides addressing the concept of duration dependence, hazard-based duration models also encompass the integration of covariates to assess their impact on probabilities (Washington et al., 2004). Nevertheless, for this study, the decision was made to employ the Proportional Hazards metric model within the Weibull distribution, assuming that hazard ratios between groups remain constant over time, where the explanatory factors exert a multiplicative influence on the baseline, as depicted by equation 7 (Washington et al., 2004):

$$h(t|X) = h_0(t)\exp(-\beta X) \tag{7}$$

This mathematical expression serves to quantify the relationship between the explanatory variables and the hazard function within a linear context. Considering the explanatory variables X , the hazard function at a given time t is represented as $h(t|X)$. The term $h_0(t)$ refers to the baseline hazard function. Furthermore, the $\exp(-\beta X)$ signifies the exponential of the scalar product between the explanatory variable vector X and the coefficient vector β.

This model, as represented in equation 8, is readily estimated through standard maximum likelihood methods.

$$LL = \sum_{i=1}^{I} \left[\beta X - \sum_{j \in R_i} \exp(\beta X_j) \right] \tag{8}$$

where R_i denotes the set of observations j with durations greater than or equal to i.

In a fully parametric setting, survival models are estimated by assuming an appropriate distribution of the duration variable (Washington et al., 2004). The distribution is often selected based on theoretical appeal and statistical evaluation since selecting a specific distribution has important implications relating to the shape of the underlying hazard function and the efficacy and potential biasedness of the estimated parameters (Taketomi et al., 2022).

Common distribution alternatives include Weibull, lognormal, exponential, gamma, log-logistic, and Gompertz distribution (Washington et al., 2004). The Weibull and log-logistic models are among the most employed parametric forms (Anastasopoulos et al., 2012; Ahmed et al., 2023). According to Haque and Washington (2015), the Weibull distribution should be selected because of its suitability for modeling data characterized by monotone hazard rates that increase or decrease exponentially with time or remain constant, depending on its scale parameter.

The Weibull distribution is utilized in the model to characterize the duration from the start to the completion of a trip. This distribution effectively captures the variability in trip durations. It is defined by two parameters: $\lambda > 0$, the scale parameter, and $P > 0$, the shape parameter. The latter, P, influences the hazard function's behavior over time, determining whether the likelihood of trip completion increases, remains constant, or decreases as time progresses. The Weibull distribution is described by the following density function (Washington et al., 2004):

$$f(t) = \lambda P(\lambda t)^{P-1} exp\,(-\lambda t)^{P} \tag{9}$$

This density function gives rise to the hazard and survival function (Washington et al., 2004).

$$h(t) = \lambda P(\lambda t)^{P-1} \tag{10}$$

$$S(t) = exp(-(\lambda t)^{P}) \tag{11}$$

When the Weibull parameter P exceeds one, the hazard progressively rises with trip duration; if P is less than one, the hazard decreases monotonically with the trip duration; and when P equals one, the hazard remains constant over time.

In constructing proportional hazard models, there is an underlying assumption of homogeneity in the survival function across different observations (Hensher and Mannering, 1994; Washington et al., 2004). This implies that all variations in durations are captured by the explanatory variable vector X. This is crucial as unobserved factors not included in X can impact the survival of travel time (Washington et al., 2004; Hensher and Mannering, 1994). However, this unobserved heterogeneity can lead to specification errors, causing inaccurate inferences about the risk function's shape and inconsistent parameter estimates (Heckman and Singer, 1984).

To address heterogeneity, various approaches have been developed, as noted by (Hensher and Mannering, 1994). In fully parametric models, addressing heterogeneity typically involves incorporating a term denoted as 'w'. This term accounts for unobserved effects across the population by following a distribution $g(w)$ which interacts with the resulting conditional survival function, $S(t|w)$ (Butler and Worrall, 1991). Consequently, the unconditional survival function can be represented as the integration of the conditional survival function and the heterogeneity distribution, resulting in equation 12 (Hensher and Mannering, 1994; Washington et al., 2004):

$$S(t) = \int S(t|w)g(w)dw \tag{12}$$

A widely accepted approach involves incorporating variability by assuming a distribution across the population, often favoring the gamma distribution for this purpose. In our application of a Weibull distribution incorporating gamma heterogeneity, we define the variable w to follow a gamma distribution. The gamma distribution is characterized by two parameters: a shape parameter k and a scale parameter θ. In this specific context, we set the scale parameter $\theta = 1/k$, ensuring equivalency to our assumption of a mean value of 1 and a variance of $1/k$. This configuration allows us to systematically incorporate variability into the hazard function, leading to equation 13, framed as follows (Hensher and Mannering, 1994; Washington et al., 2004):

$$h(t) = \lambda P(\lambda t) P^{P-1} [S(t)]^{\theta} \tag{13}$$

when θ, which represents the scale parameter and is defined as the variance $1/k$, equals zero, the Weibull model is applied, and no heterogeneity is present.

6. Model results

In alignment with the methodological framework outlined in the previous section, the model was estimated using *NLOGIT 5* software, facilitating the integration of covariates to assess their multiplicative impact on the baseline hazard function.

Table 4 presents the coefficients, standard errors, and significance levels for a range of socioeconomic and trip-related variables, offering a nuanced understanding of how these factors modulate the likelihood of trip completion within specified timeframes.

The variables "Gender," "Age Group," and "Transport Credentials" (specifically, "Transport ticket" and "driving license") were not included in the presented table as they did not demonstrate statistical significance

Table 4
Results of the survival model: Weibull distribution with Gamma Heterogeneity.

Dependent Variable				
Travel Time Variables		**Coefficient**	**Standard Error**	**Prob. (β) |z|>Z***
Constant		2.75412***	0.02299	0
Socioeconomic Variables				
Education Level	No education	−0.09061**	0.04618	0.0497
	Secondary education	0.04020**	0.01803	0.0258
	Basic education	0.02845	0.0187	0.1283
	Reference group: Higher education			
Monthly Income	From 650 to less than 1000 euros	−0.01388	0.01709	0.4166
	From 1000 to less than 1500 euros	−0.03354*	0.01922	0.081
	From 1500 to less than 2000 euros	−0.08174***	0.02852	0.0042
	Above 2000 euros	−0.01563	0.02311	0.4989
	Reference group: Up to 650 euros			
Trip-related Variables				
Vehicle Ownership	Do not own vehicles	0.03358*	0.01864	0.0716
Trip Purpose	Work purposes	0.00747	0.02034	0.7134
	Educational activities	−0.12154***	0.02103	0
	Leisure activities	−0.05786***	0.02061	0.005
	Personal errands	−0.10549***	0.01791	0
	Reference group: Return home			
Transport Mode	Active transport	−0.09724***	0.01496	0
	Public transport	0.65734***	0.0238	0
	Reference group: Private vehicle			
Parameters of underlying density at data means				
	Parameter	**Estimate**	**Std. Error**	
	Lambda	0.06041	0.00058	
	P	2.24446	0.033	
	Median	15.50956	0.14903	
	Log-likelihood function	−11871.22655		
	Estimation based on	N = 11,360		
	*Inf.Cr.*AIC	23792.5		
	AIC/N	2.094		

Note: ***, **, * are Significance at 1%, 5%, 10% level.

within the model, with p-values exceeding the threshold of 0.05. This indicates that these variables did not have a meaningful impact on the dependent variable, "Travel Time," within the context of this analysis. Consequently, they were excluded from the results to maintain clarity and focus on the factors that significantly influence urban mobility patterns.

The estimated coefficients for the independent variables indicate the relative impact of these variables on travel time rather than their impact on risk. Positive coefficients denote a proportional increase in duration, whereas negative coefficients represent a proportional decrease. The magnitude of these coefficients provides an understanding of how strongly these variables affect the outcome of travel time. In addition to the coefficients of the independent variables, Table 4 also includes the estimation of auxiliary parameters related to the underlying Weibull survival distribution. These parameters are lambda, P, median, and survival percentiles, contributing to a more comprehensive understanding of the survival distribution implicit in the model.

Firstly, we observed the estimated Lambda parameter (0.06041), representing the average event rate (in this case, travel time). Furthermore, the parameter P, with a value of 2.24446, suggests a non-constant risk distribution over travel time. The model also identifies several independent variables—education level, monthly income, vehicle ownership, trip purpose, and transport mode—that significantly affect travel time. The parameter β quantifies the effect of each of these variables on the hazard rate of completing a trip, indicating both the direction and magnitude of their influence. These variables and their respective effects elucidate travel dynamics by shaping commuting patterns and highlighting how specific activities can directly impact travel duration.

7. Discussion

Considering the identified socioeconomic and behavioral factors influencing travel dynamics, the analysis reveals that trips related to educational activities, leisure, and personal errands tend to be of shorter duration. PT users endure longer travel times compared to those using active AM, which benefits from shorter travel durations due to their direct routes and greater flexibility. These findings align with research from Shanghai, China, where FMC strategies have successfully promoted walking and cycling as efficient options for short-distance travel, resulting in quicker and more consistent travel times for AM users compared to MT users (Wu et al., 2021).

Unlike car-oriented planning, which separates land uses and promotes long-distance travel, the FMC framework is grounded in the principle of spatial proximity and proposes a more integrated strategy, particularly suited to medium-sized European cities with spatial constraints and polycentric structures. Importantly, one of its core objectives is to improve travel efficiency and accessibility, especially for lower-income groups who are more dependent on non-motorised and PT modes (Moreno et al., 2021; Allam et al., 2024). However, the relationship between income and travel time in the Porto context presents a complex picture. The model results indicate a negative correlation between income and travel time (coefficient = -0.08174), suggesting that individuals with higher incomes tend to experience shorter travel durations. This finding contrasts with the common expectation that higher income is associated with longer commutes, diverging from patterns observed in other urban contexts, such as Denmark, where higher wages correlate with increased travel times (Mulalic et al., 2014).

Porto's compact urban form and historical development have contributed to a concentration of high-income residents in areas near the city center or in well-serviced neighborhoods with efficient access to essential services and employment opportunities (Alves, 2016). This spatial arrangement enables these individuals to benefit more fully from AM, thus contributing to shorter travel times. However, the situation is notably different for lower-income groups, particularly those earning less than 1,000 euros per month. These populations are more likely to reside in peripheral or underserved areas, which results in longer commutes, despite the broader goals of the FMC.

In this context, the FMC presents a pragmatic alternative through its focus on small-scale, distributed service nodes and walkable catchment areas, which facilitate more targeted improvements in mobility and service provision. Embedding proximity into policymaking further promotes more equitable urban environments, where access to opportunities does not depend on PMV ownership or geographic location (Moreno et al., 2021; Allam et al., 2024). Such an approach holds particular significance for Porto's post-industrial districts and suburban neighborhoods, where lower-income residents continue to face extended travel times.

Individuals with higher education levels in Porto experience longer travel times. This trend reflects the employment patterns of highly educated individuals, who often work in specialized sectors such as research hubs and business parks, typically situated outside central city areas, thereby extending commuting durations. This finding aligns with Johnston (2019) research, which identifies a significant correlation between higher educational attainment and lengthened commute times. Similarly, Giménez-Nadal et al. (2022) found across multiple European cities, that highly educated workers often pursue specialized job roles, necessitating travel over greater distances due to the geographic dispersion of these opportunities.

PMV ownership correlates strongly with reduced travel times, reinforcing dependence on PMVs. Such factors are not unique to Porto; they mirror broader trends identified in different city contexts, where urban design and socioeconomic conditions shape transportation habits. A literature review conducted by Mackett (2003) highlights that car usage for short trips is prevalent in several European countries, including Denmark, Norway, and Britain. This preference is primarily driven by practical considerations such as the need to transport goods, strict time constraints, convenience, and shopping requirements (Neves and Brand, 2019). These components highlight the challenges in reducing PMV dependency for short distances, even in regions with well-developed PT and AM infrastructure.

Similar dynamics were observed by Pozoukidou and Chatziyiannaki (2021) in Melbourne, Australia, where the 20-minute city model has been implemented with a degree of success. Nevertheless, the city has not entirely reduced its reliance on PMVs. Rather, its urban development, historically shaped by car-centric policies, has resulted in low-density, zoned areas. These zones further reinforce PMV dependence by segregating essential urban functions, thereby exacerbating the challenge of promoting modal shift in urban settings.

These examples highlight a broader issue across multiple urban contexts: the persistent struggle to balance sustainable mobility with infrastructures historically designed around PMVs. This tension is especially evident when cities pursuing efforts to promote more efficient and inclusive transport systems clash with existing frameworks that continue to reinforce PMV dependence. In the case of Porto, understanding how these tensions materialize in everyday mobility requires an examination of actual travel patterns and their statistical representations. Fig. 4 presents the survival function *S(t),* which estimates the probability that a trip will exceed a given duration, offering insight into travel time patterns, highlighting the proportion of trips that are longer than a certain duration.

The curve starts at a probability close to 1 for very short trips and drops steeply within the first 30 min, indicating that most trips in Porto are relatively short. Notably, the curve approaches zero beyond 60 min, highlighting that very long trips are rare in this urban context. This function effectively visualizes the general distribution of trip durations, providing a probabilistic baseline for the study area. Such information is crucial for assessing the feasibility of FMC strategies within a car-oriented urban fabric.

In contrast, Fig. 5 shows the hazard function *h(t)*, which represents the instantaneous rate of completing a trip at a certain time, given that it has not yet ended.

The curve rises initially and peaks around 20 min, indicating that trips are most likely to conclude around this duration. After this point, the hazard rate declines, meaning that trips longer than 20 min become progressively less frequent and less likely to end in the immediate next time intervals.

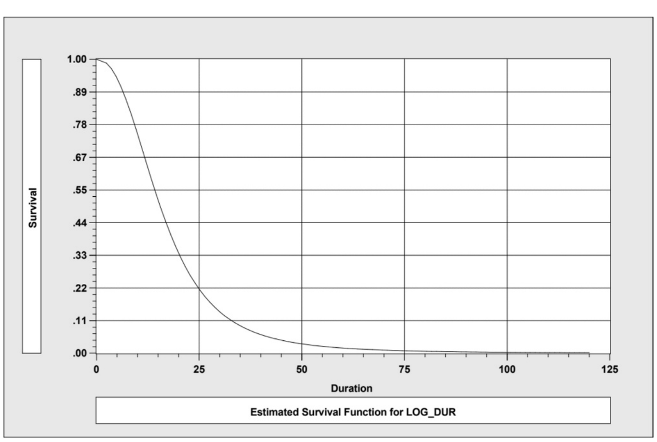

Fig. 4. Survival function S(t) (.
Source: NLOGIT 5)

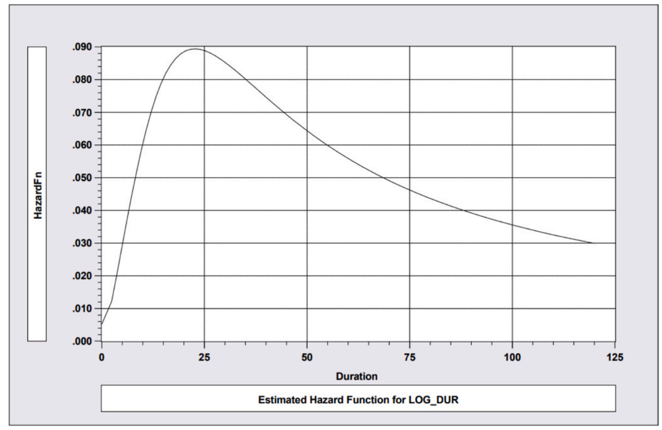

Fig. 5. Hazard function h(t) (.
Source: NLOGIT 5)

7.1. Analysis of transport mode impacts on travel time

To emphasize the findings from the survival model, we further examined daily travel time patterns within Porto's urban area, analyzing the effects of three primary transport modes to identify which one most closely aligns with the FMC model (the reference category was assumed for other variables). This approach is fundamental to understanding where sustainable transport options play a key role in enabling rapid access to daily activities within a short travel time (Bocca, 2021; Pozoukidou and Chatziyiannaki, 2021; Ferrer-ortiz et al., 2022).

Fig. 6 illustrates the probability of a journey concluding over time, estimated using equation 10. A vertical line marks the 15-minute threshold, highlighting the distribution of short trips and the potential adoption of sustainable modes, such as AM.

The travel time analysis in Porto highlights significant obstacles in achieving the FMC objectives. While AM accounts for 39 % of total trips, 65 % of these trips conclude within 15 min. Meanwhile, MT remains dominant for most journeys, constituting 61 % of daily trips. This dependency is particularly evident in short trips, where nearly 20 % of PT and 60 % of PMV journeys are completed in less than 15 min. Such patterns align with the findings of Ton et al. (2019), who observed that the comfort and accessibility of PMVs for shorter trips enable them to compete directly with AM, even in densely urban settings. This underscores a strong cultural and infrastructural reliance on MT in Porto, contrasting with the FMC objectives on sustainable, non-motorized

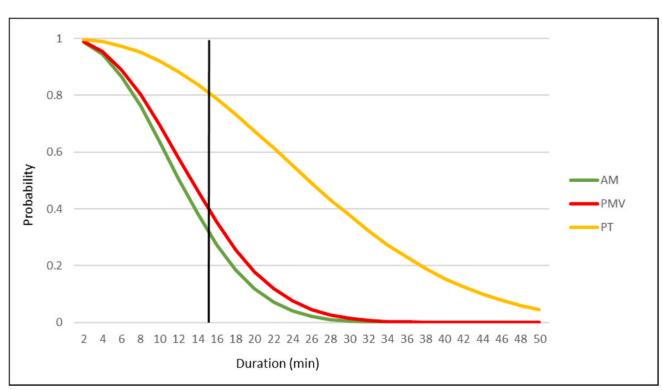

Fig. 6. Travel Time per Transport Mode (.
Source: Excel)

options (Pozoukidou and Angelidou, 2022). Such dominance of PMVs reinforces a cycle of MT dependency (Soza-Parra and Cats, 2024), perpetuating challenges such as urban congestion, air pollution, and emissions—issues that FMC frameworks aim to address (Moreno et al., 2021).

Infrastructure limitations further amplify the challenges in Porto. The limited number of dedicated bus lanes and the lack of priority for cyclists perpetuates reliance on PMVs, which occupy road space, creating a less welcoming environment for AM (Rocha et al., 2023). This situation underscores the importance of infrastructure adaptations, as evidenced by Thondoo et al. (2020) and Wu et al. (2021). Such adaptations, including exclusive bus lanes and expanded cycling networks, are instrumental in fostering the use of AM by reducing travel times and increasing reliability (Mueller et al., 2020).

Moreover, the overlap between buses and PMV routes in Porto exacerbates traffic congestion, leading to prolonged PT travel times. This congestion diminishes the attractiveness of PT even for short trips, as evidenced by the fact that only 16.6 % of daily trips are made using PT, and of these, merely 20 % are completed within 15 min. This limited usage is further compounded by inconsistent schedules and indirect routes, which deter potential users from seeking efficient travel options. Furthermore, Porto's metro network remains inaccessible to numerous neighborhoods, with the most accessible areas predominantly located in the central part of Porto (Shafiq et al., 2024).

Cultural factors and social norms in Porto significantly contribute to perceiving PMV as more convenient and prestigious, discouraging residents from adopting AM even for short trips (Rocha, et al., 2023). This finding is consistent with studies in Western Europe, the US, and China, where factors such as autonomy (82 %), emotional connection (38 %), and the status symbol effect (59 %) further entrench PMV dependence despite efforts to promote AM (Soza-Parra and Cats, 2024).

7.2. Analysis of trip purpose impacts on travel time

To further understand travel time efficiency within Porto, a secondary analysis was conducted, focusing on three essential trip categories that significantly impacted the model: personal errands, educational activities, and leisure. This analysis explicitly emphasizes AM as these are key to the FMC model. By concentrating on AM, we aim to assess the accessibility of these services and activities within 15 min, providing a picture of the city's design to support the FMC concept.

Fig. 7 presents the survival probabilities for each trip purpose, estimated by equation 10, depicting how travel times are distributed across different activities (the reference category was assumed for other variables).

The data reveals that approximately 70 % of trips in Porto are completed within a fifteen-minute timeframe, with trips for personal errands and educational activities showing a slightly higher likelihood of being concluded within shorter durations compared to leisure activities. This distribution suggests that Porto's services are relatively well-positioned, aligning partially with the principles of the FMC. However, significant barriers remain in fostering the widespread adoption of AM.

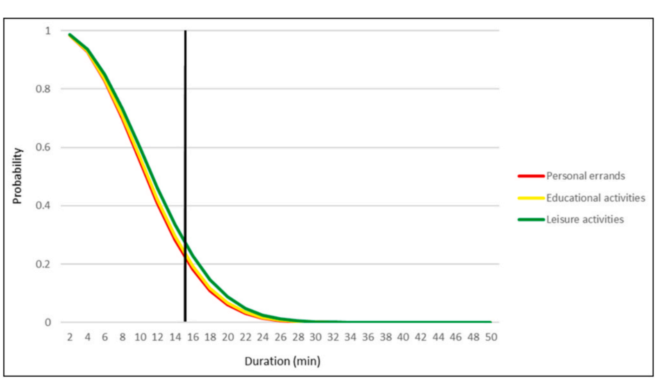

Fig. 7. Travel Time per Trip Purpose (.
Source: Excel)

Currently, 39 % of trips in Porto utilize AM, with walking accounting for 98 % and cycling a mere 2 %. This disparity arises largely from Porto's challenging topography, characterized by hilly and narrow streets that impede cycling infrastructure development. Additionally, the absence of a cohesive urban planning strategy focused on AM, compounded by metropolitan growth primarily shaped by private actors without long-term mobility planning, has resulted in fragmented infrastructures that deter AM adoption, mostly cycling (Serra et al., 2017).

Insights from similar-sized cities, such as Bologna in Italy and Lyon in France, offer valuable lessons for improving AM. Bologna's emphasis on pedestrian infrastructure has successfully encouraged AM. Fonseca et al. (2022) highlighted that well-maintained sidewalks, street connectivity, and proximity to services significantly improved AM as a main transport mode in Bologna. Furthermore, the city of Lyon illustrates the advantages of integrating PT systems with AM to reduce reliance on private vehicles (Tran and Ovtracht, 2018). Its extensive bike-sharing program, connected with several PT networks, has effectively increased sustainable transportation options.

Expanding on these observations, further studies highlight additional barriers to AM adoption. Mackett (2003) observed that hilly terrain critically discourages the utilization of AM, resonating with Porto's issues. Basil and Nyachieo (2023) identified safety as a critical obstacle to cycling uptake, highlighting perceptions of danger as a significant deterrent. Similarly, Thuany et al. (2020) underscored that insufficient cycling infrastructure and steep street conditions discourage cycling. Ton et al. (2019) emphasized the importance of infrastructure continuity and aesthetics for AM adoption, suggesting that mixed land use in high-density areas can positively influence uptake.

However, as Lu and Diab (2025) explained, the effectiveness of policies can vary significantly depending on the local context, indicating the importance of understanding specific conditions before implementing these strategies.

8. Policy implications

The results of this study have several important insights to guide public policy toward more sustainable, inclusive, and proximity-oriented urban mobility systems in Porto. The empirical findings, particularly concerning travel time disparities and mode choice, point to several areas where urban mobility strategies can be enhanced. Based on the observed challenges and opportunities, we outline five key policy recommendations:

- *Promote AM:* Since a significant share of trips in Porto already fall within the 15-minute threshold, investment in pedestrian- and cyclist-friendly infrastructure should be prioritized. Expanding safe sidewalks, protected bike lanes, and bike-sharing systems will further reinforce AM as viable and efficient travel options (Wu et al., 2021; Basil and Nyachieo, 2023; Teixeira et al., 2024). Additionally, awareness campaigns can be used to educate residents on the health, environmental, and social benefits of AM (Banister, 2008; Pozoukidou and Chatziyiannaki, 2021).
- *Address Spatial and Income-Based Accessibility Inequities:* The observed longer travel times among lower-income residents underscore the need for PT-targeted investments in peripheral neighborhoods. Expanding service coverage and frequency, alongside offering subsidized fares, can bridge the accessibility gap and reinforce the inclusive spirit of the FMC (Shafiq et al., 2024). Infrastructural improvements such as dedicated bus lanes and pre-signal priority can also reduce delays and promote efficiency (Kampitakis et al., 2023; Papadakis et al., 2024; Bennaya and Kilani, 2024). Enhancing user experience through real-time information systems through mobility

apps is another measure that can support PT attractiveness (Soza-Parra and Cats, 2024).

- *Foster Neighborhood-Level Planning Through Mixed Land Use:* To effectively implement the FMC framework, local planning should foster polycentric development that ensures the collocation of housing, employment, services, and leisure opportunities to minimize the need for long-distance travel, thereby enhancing neighborhood-level proximity and accessibility (Moreno et al., 2021). Mixed-use zoning and transit-oriented development can minimize travel distances and enable more residents to meet their daily needs locally (Banister, 2008; Ton et al., 2019; Moreno et al., 2021; Allam et al., 2024).
- *Reduce PMV Dependency via Disincentives and Multimodal Integration:* High PMV usage undermines the sustainability goals of the FMC. Implementing congestion pricing, establishing low-emission zones, and enforcing stricter parking policies in central areas are proven strategies to discourage PMV usage (Rotaris et al., 2010; Bernardo et al., 2021). Simultaneously, these disincentives must be coupled with the expansion of multimodal solutions, such as shared PT systems, micro-mobility options, and integration of different transport modes, to support the behavioral shift (Papadakis et al., 2024).
- *Encourage Sustainable E-Mobility Options to Overcome Topographical Barriers:* Porto's hilly terrain can discourage traditional forms of AM. Integrating electric mobility options, such as e-bikes and e-scooters, can make sustainable travel more feasible for a broader demographic. Policy measures could include installing charging stations, offering tax incentives for e-mobility purchases, and supporting shared e-mobility programs (Newman et al., 2017; Neves and Brand, 2019; Pozoukidou and Chatziyiannaki, 2021; Pozoukidou and Angelidou, 2022).

By translating empirical insights into actionable strategies, these policy pathways provide a roadmap for aligning Porto's urban and transport policies with the FMC's vision of local accessibility, environmental sustainability, and transport equity. Furthermore, these recommendations may serve as a reference for other compact European cities seeking to operationalize the FMC paradigm.

9. Conclusions

This study analyzed urban mobility in Porto through the lens of the FMC concept, revealing key challenges and opportunities in advancing toward a more accessible and sustainable urban environment. Utilizing a Weibull hazard-based survival model, we assessed how socioeconomic and trip-related factors influence travel time, offering valuable insights into the structural and behavioral dimensions of urban mobility in the city. While Porto demonstrates partial alignment with FMC principles, substantial challenges remain in fully achieving a more connected, inclusive, and sustainable city. The key conclusions are as follows:

- *Income-related disparities in travel time remain a major barrier to equitable mobility:* Lower-income residents tend to reside in peripheral areas with less access to efficient transport, resulting in longer travel durations and undermining the FMC's goal of universal accessibility.
- *Porto's compact morphology facilitates short trips, but not for all:* Although 70 % of trips fall within 15 min, this benefit is not evenly distributed, particularly for those lacking access to active or efficient PT modes.
- *AM offers the shortest travel durations:* AM emerged as the most efficient mode, reinforcing the importance of promoting AM as a key pillar of FMC-based mobility systems.
- *Highly educated individuals experience longer commutes:* The spatial distribution of specialized jobs contributes to longer travel times, highlighting the need for decentralizing economic opportunities within the city.
- *Reducing PMV reliance is crucial for sustainability:* With over 60 % of trips being made by PMVs, Porto must implement stronger disincentives and infrastructure alternatives to realize the full benefits of proximity-based urban planning.

Despite the insights derived regarding travel durations in Porto, it is important to acknowledge certain limitations inherent to the study's scope and methodological framework. Specifically, the analysis focused exclusively on quantitative dimensions of travel time, excluding qualitative aspects such as perceived safety, user satisfaction, and accessibility. Furthermore, it lacked consideration of land-use characteristics at trip origins and destinations, factors that could influence travel duration and mode choice.

The modeling approach also treated individual trips as independent events, consequently overlooking the complexities of trip chaining, which may limit a comprehensive understanding of travel behavior. These analytical boundaries are further shaped by the nature of the available mobility data. While the dataset offers a robust and representative overview of daily travel patterns in Porto, it captures a specific segment of urban mobility, based on self-reported travel behavior, which may not fully encompass the complexity of all travel dynamics in the city. Importantly, the findings reflect the specific geographic, social, and infrastructural characteristics of Porto, a medium-sized European city with a dense historical core. As such, direct extrapolation to cities with different urban morphologies, mobility cultures, or institutional frameworks may be limited.

Considering these limitations, future research should incorporate qualitative assessments of mobility experiences, alongside spatially disaggregated analyses across different neighborhoods. Such an approach could help identify areas that lack FMC-supportive infrastructure. Additionally, extending the analysis to include post-pandemic behavioral shifts would offer further insights into the adaptability and resilience of FMC strategies in evolving urban contexts. Beyond these, future studies should also expand their scope to enhance external validity. This includes conducting multi-city comparisons, utilizing real-time mobility data, and adopting longitudinal perspectives. These combined efforts would contribute to a more comprehensive understanding of travel time models within the FMC paradigm.

10. Data availability statement

Interested parties wishing to access the data are kindly requested to contact the National Statistical Institute of Portugal (INE).

CRediT authorship contribution statement

Hudyeron Rocha: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Sara Ferreira:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. . Variable selection and Justification for inclusion in the model analysis.

Variable Name	Status in Model Analysis	Justification
Travel time in minutes (Duration variable)	Included in Final Model (Table 4)	Core Dependent Variable: This is the central variable of interest, representing the duration of trips. The study's primary objective is to analyze the factors influencing this duration using a hazard-based survival model.
Transport mode	Included in Final Model (Table 4)	Key Explanatory Variable: Essential for understanding how different modes (Active Mobility, Public Transport, Private Vehicle) relate to travel time and align with the 15-Minute City concept. Directly relevant to the study's focus.
Trip Purpose	Included in Final Model (Table 4)	Key Explanatory Variable: Included to analyze how the reason for travel (e.g., work, education, leisure) influences trip duration and the feasibility of completing essential activities within a 15-minute radius. Statistically significant.
Education Level	Included in Final Model (Table 4)	Socioeconomic Explanatory Variable: A standard demographic factor known to influence travel behavior and access to opportunities, thus impacting travel time. Included to capture socioeconomic disparities in mobility. Statistically significant.
Condition towards employment	Included in Initial Model Construction (Table 3), Excluded from Final Presentation (Table 4)	Socioeconomic Explanatory Variable: Initially included in the model building process (as listed in Table 3), as employment status can affect travel patterns and schedules. Excluded from the final presented results (Table 4) as it did not demonstrate statistical significance in the model run.
Driving license	Included in Initial Model Construction (Table 3), Excluded from Final Presentation (Table 4)	Access Explanatory Variable: Initially included as a key indicator of access to private vehicle usage, which strongly influences mode choice and potentially travel time. Excluded from the final presented results (Table 4) as it did not demonstrate statistical significance in the model run.
Transport Ticket (Possession of a transport pass)	Included in Initial Model Construction (Table 3), Excluded from Final Presentation (Table 4)	Access Explanatory Variable: Initially included to reflect accessibility and propensity to use public transportation. Excluded from the final presented results (Table 4) as it did not demonstrate statistical significance in the model run.
Per Capita Income (Monthly income)	Included in Final Model (Table 4)	Socioeconomic Explanatory Variable: A crucial socioeconomic indicator influencing travel decisions, mode choice, and the ability to live closer to services, thus impacting travel time. Statistically significant.
Vehicle Ownership (Vehicle Ownership/Availability Type)	Included in Final Model (Table 4)	Access Explanatory Variable: A direct determinant of private vehicle availability, which is a major factor in mode choice and dependence, significantly impacting travel time. Statistically significant.
Sex	Included in Initial Model Construction (Table 3), Excluded from Final Presentation (Table 4)	Demographic Variable: Initially included as a standard demographic factor potentially influencing travel habits. Excluded from the final presented results (Table 4) as it did not demonstrate statistical significance in the model run.
Age	Included in Initial Model Construction (Table 3), Excluded from Final Presentation (Table 4)	Demographic Variable: Initially included as a standard demographic factor potentially influencing travel mode choice and preferences across life stages. Excluded from the final presented results (Table 4) as it did not demonstrate statistical significance in the model run.
Accommodation address	Not Included in Model Analysis	Personal identification information was systematically excluded during data cleaning to ensure participant privacy and anonymity, in compliance with European data protection regulations.
Reason for the nonexistence of trip	Not Included in Model Analysis	Outside Model Scope: This variable pertains to individuals who did not make a trip. The study's model analyzes the duration of completed trips, making this variable irrelevant to the analytical scope.
Cell phone	Not Included in Model Analysis	Personal identification information was systematically excluded during data cleaning to ensure participant privacy and anonymity, in compliance with European data protection regulations.
Place of origin of the first trip	Not Included in Model Analysis (Used for Data Selection)	Spatial Detail Excluded from Model: While origin location was used to filter the dataset to include only trips starting within Porto's boundaries, detailed spatial coordinates were not included as explanatory variables in the model itself. The model focuses on broader socioeconomic and behavioral factors, acknowledging the lack of fine-grained spatial analysis as a limitation.
Email	Not Included in Model Analysis	Personal identification information was systematically excluded during data cleaning to ensure participant privacy and anonymity, in compliance with European data protection regulations.
Place of travel destination	Not Included in Model Analysis (Used for Data Selection)	Spatial Detail Excluded from Model: While destination location was used to filter the dataset to include only trips ending within Porto's boundaries, detailed spatial coordinates were not included as explanatory variables in the model itself. The model focuses on broader socioeconomic and behavioral factors, acknowledging the lack of fine-grained spatial analysis as a limitation (page 34).
Quantity of vehicles	Not Included in Model Analysis	Specific Vehicle Detail Excluded: The model uses the broader "Vehicle Ownership" variable, which captures the primary influence of having access to a private vehicle. The exact number of vehicles owned was deemed a less critical factor for this specific model's focus on trip duration.
Travel start time	Not Included in Model Analysis	Temporal Detail Excluded: While start time can influence congestion, this specific model focuses on the duration itself and the influence of socioeconomic/behavioral factors, not time-of-day effects on traffic flow.
Vehicle registration year	Not Included in Model Analysis	Specific Vehicle Detail Excluded: Specific details about the vehicle itself (like registration year) were not considered relevant explanatory variables for the duration of a trip in this model.
Which car is used for travel	Not Included in Model Analysis	Specific Vehicle Detail Excluded: Specific details about which particular car was used were not included as explanatory variables, as the model focuses on the mode of transport (private vehicle) rather than specific vehicle characteristics.
Type of fuel	Not Included in Model Analysis	Specific Vehicle Detail Excluded: Specific details about the vehicle's fuel type were not considered relevant explanatory variables for trip duration in this model.

(*continued on next page*)

(*continued*)

Variable Name	Status in Model Analysis	Justification
No. of vehicle seats	Not Included in Model Analysis	Specific Vehicle Detail Excluded: Specific details about the vehicle's seating capacity were not considered relevant explanatory variables for trip duration in this model.
What is the river crossing	Not Included in Model Analysis	Spatial Detail Excluded: Specific route details like river crossings were not included as explanatory variables, as the model is not spatially disaggregated and focuses on broader factors.
Parking at home	Not Included in Model Analysis	Parking Detail Excluded: Parking availability or details at home were not included as explanatory variables, as the model focuses on the trip duration itself rather than factors influencing trip start or end convenience related to parking.
No. of consecutive buses from the same operator	Not Included in Model Analysis	Specific PT Detail Excluded: Specific details about public transport service usage patterns (like consecutive buses) were not included as explanatory variables; the model uses a general public transport mode variable.
Relationship with the respondent	Not Included in Model Analysis	Personal identification information was systematically excluded during data cleaning to ensure participant privacy and anonymity, in compliance with European data protection regulations.
Public transport operator	Not Included in Model Analysis	Specific PT Detail Excluded: Specific details about the public transport operator were not included; the model uses a general public transport mode variable, focusing on the mode itself rather than service provider specifics.
Entrance station	Not Included in Model Analysis	Spatial Detail Excluded: Specific public transport station details were not included as explanatory variables, as the model is not spatially disaggregated.
Exit station	Not Included in Model Analysis	Spatial Detail Excluded: Specific public transport station details were not included as explanatory variables, as the model is not spatially disaggregated.
Used transport title	Not Included in Model Analysis (Covered by Other Variable)	Redundant Variable: This variable is essentially captured by "Possession of a transport pass" (Transport Ticket), which was included in the initial model construction.
Location data	Not Included in Model Analysis (Used for Data Selection)	Spatial Detail Excluded from Model: Location data was used to filter the dataset to include only trips within Porto's boundaries, but detailed location coordinates were not used as explanatory variables in the model itself, consistent with the model's non-spatial focus.
Driving frequency	Not Included in Model Analysis	Not Included in Model: This variable was not included as an explanatory variable in the model analysis presented.
Waiting time	Not Included in Model Analysis	Not Included in Model: This variable was not included as an explanatory variable in the model analysis presented.
Fuel expenses	Not Included in Model Analysis	Cost Detail Excluded: Cost-related variables (fuel, parking, tolls, PT expenses) were not included as explanatory variables, as the model focuses on time and behavioral/socioeconomic factors, not the economic cost of travel.
Transport pass type	Not Included in Model Analysis	Not Included in Model: Specific details about the type of transport pass were not included as explanatory variables; the model uses the broader Possession of a transport pass variable.
Parking expenses	Not Included in Model Analysis	Cost Detail Excluded: Cost-related variables were not included as explanatory variables.
Type of workplace	Not Included in Model Analysis (Covered by Other Variable)	Destination Detail Excluded: Specific details about the type of workplace were not included; the model uses the broader "Trip Purpose" variable ("Work purposes"), which captures the reason for travel.
Toll expenses	Not Included in Model Analysis	Cost Detail Excluded: Cost-related variables were not included as explanatory variables.
Location of the workplace	Not Included in Model Analysis (Covered by Other Variable / Spatial Detail Excluded)	Spatial Detail Excluded: Specific location details of the workplace were not included; the model uses the broader "Trip Purpose" variable and is not spatially disaggregated.
Public transport expenses	Not Included in Model Analysis	Cost Detail Excluded: Cost-related variables were not included as explanatory variables.
Parking at work	Not Included in Model Analysis	Parking Detail Excluded: Parking availability or details at work were not included as explanatory variables, as the model focuses on trip duration rather than factors influencing destination convenience.
Location of the study site	Not Included in Model Analysis (Covered by Other Variable / Spatial Detail Excluded)	Spatial Detail Excluded: Specific location details of the study site were not included; the model uses the broader "Trip Purpose" variable ("Educational activities") and is not spatially disaggregated.
Evaluation of the use of individual transport	Not Included in Model Analysis	Subjective Variable Excluded: Subjective perception or evaluation variables were not included in the model, which focuses on observed travel time and objective socioeconomic/behavioral characteristics. This aligns with the study's stated limitations.
Parking at the study site	Not Included in Model Analysis	Parking Detail Excluded: Parking availability or details at the study site were not included as explanatory variables.
Evaluation of the use of public transport	Not Included in Model Analysis	Subjective Variable Excluded: Subjective perception or evaluation variables were not included in the model, which focuses on observed travel time and objective socioeconomic/behavioral characteristics. This aligns with the study's stated limitations.

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