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THE IMPACT OF URBAN TRANSPORT MODERNIZATION ON MOBILITY: A MULTIDIMENSIONAL APPROACH

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Abstract

The modernisation of public transport systems constitutes a critical lever in the optimisation of urban mobility and in enhancing the performance of transport services within the jurisdiction of a local administrative authority. The present study analyses the impact of modernisation on urban mobility through a dual quantitative approach, conducted both ex ante and ex post the implementation of technical and operational interventions. The modernisation process included fleet renewal, optimisation of service headways, implementation of Intelligent Transport Systems (ITS), improvement of timetable reliability, and enhancement of comfort and accessibility indicators.

To quantify changes in user perceptions, a multidimensional model grounded in Item Response Theory (IRT) was applied to data collected across two successive survey waves. IRT enables the estimation of latent parameters associated with perceived service performance (operational quality, attractiveness, and comparative utility vis-à-vis private car use), thereby providing a robust framework for analysing perceptual variations generated by modernisation. Subsequently, the latent IRT scores were incorporated into a user classification model based on mobility typologies (public transport-dependent mobility, multimodal mobility, and car-centric mobility), assessing the transition probabilities between categories in the ex-ante–ex post interval.

The results indicate a statistically significant increase in the perceived attractiveness of public transport and a reduction in psychological resistance to modal shift, leading to measurable redistributions in the structure of urban mobility. The study demonstrates the utility of integrating psychometric methods within an evaluation framework and provides a solid empirical foundation for planning and assessing modernisation interventions in the context of sustainable mobility.

Keywords: Hybrid Choice Modelling; Urban Mobility Policy Evaluation; Discrete Choice Modelling; Psychometric Integration; Sustainable Urban Transport

1. INTRODUCTION

The modernisation of urban public transport represents one of the principal mechanisms through which European cities seek to reduce emissions, congestion, and car dependency, aligning with the objectives of the European Green Deal and the new EU guidelines concerning Sustainable Urban Mobility Plans (SUMPs). Policy documents emphasise a shift from traffic-centred planning towards a people-centred approach, integrated with energy, climate, and land-use strategies, accompanied by monitoring through standardised urban mobility indicators.

In parallel, the academic literature over the past decade has evolved from general descriptions of travel flows towards sophisticated quantitative models for evaluating public transport service performance and urban mobility. User perceptions are commonly measured through Likert-scale questionnaires, accompanied by internal consistency indicators (Cronbach's alpha) and exploratory or confirmatory factor analyses. In the service domain, the role of multitrait–multimethod (MTMM) models in validating the latent structure of service quality has been highlighted, noting that in transport research, similar approaches are employed to test factor structures relating to perceived service quality, loyalty, and behavioural intention.

A further step involves integrating these measurement models within the Structural Equation Modelling (SEM) framework in order to analyse the relationships between latent factors and overall satisfaction. For instance, in a recent study of the Bus Rapid Transit system in Amman, "Structural Equation Modelling (SEM) was used to test the proposed model and assess the relationships between the identified factors and the overall perceived quality" (Al-Haj et al., 2024), demonstrating how SEM can link quality indicators (travel time, comfort, information provision) to overall satisfaction and loyalty.

In recent years, Item Response Theory (IRT) has begun to be applied in transport system analysis as a modern alternative to classical aggregated scoring approaches. Rezapour (2021) notes that "The item response theory (IRT) refers to measurement of an instrument's reliability by examining the relationship between the unobserved trait and various observed items", thereby offering a framework in which the probability of selecting a particular response category depends on a latent construct (for example, satisfaction with public transport) and item parameters (discrimination and difficulty). In the context of urban public transport, it has been emphasised that "an alternative approach to investigate commuters' satisfaction is the analysis of multiple item questionnaires through the Item Response Theory" (Iannario & Monti, 2021), suggesting the use of partial credit or graded response models for ordinal data. More recently, Rodriguez et al. (2025) propose a combination of Principal Component Analysis (PCA), Confirmatory Factor Analysis (CFA), and a Generalised Partial Credit Model (GPCM) to analyse perceptions across 38 public transport quality indicators, concluding that different route configurations (transversal, longitudinal, circular) generate distinct service perceptions.

At the city scale, urban mobility assessment is increasingly conducted using composite indicator sets. Braga et al. (2019) identify the most frequently used urban mobility metrics through bibliometric analysis, distinguishing families of indicators related to accessibility, safety, operational performance, and environmental impact. Initiatives such as the Urban Mobility Indicators for Walking and Public Transport developed by UITP and Walk21 provide a common set of objective, satisfaction-based, and quality indicators, emphasising that "Adopting these indicators will also ensure that future investments in walking and public transport are effective and value for money" (UITP & Walk21, 2019). At European level, the SUMI project proposes 18 practical indicators, while recent research on SUMP monitoring defines "a methodological framework for determining baseline values for four essential monitoring indicators: road safety, accessibility to public mass transit, greenhouse gas emissions, and air quality" (Rutka et al., 2024), thereby outlining a standardised methodology for evaluating mobility policies.

In the Romanian context, analyses of the Bucharest transport system (metro, bus, tram, trolleybus) have argued that "Fulfilling the nowadays population's mobility requirements is an acute duty that policy

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makers … should solve in a sustainable manner" (Dragu et al., 2016), employing network modelling (VISUM) to assess service levels and the alignment between transport networks and territorial structure. Subsequent work demonstrates the role of dedicated lanes in enhancing intermodal accessibility, underlining that "The public transport system has an essential role in the sustainability of the urban environment. Accessibility is one of the critical functions" (Costescu et al., 2021). Studies addressing non-motorised transport and network integration (Roșca et al., 2010) similarly emphasise walking and cycling as indispensable components of sustainable urban mobility.

This body of research suggests the existence of at least three complementary levels of urban mobility evaluation:

Public transport service level, where satisfaction questionnaires are analysed through Cronbach's alpha, MTMM, and SEM to validate latent service quality structures;

City-level mobility indicators, where frameworks such as Urban Mobility Indicators, SUMI, SUTI, or SUMP monitoring indicators describe system performance through accessibility, safety, operational efficiency, and sustainability metrics;

Micro-level individual response modelling, where IRT allows fine-grained modelling of the probability of belonging to particular user categories (e.g., "captive" users or "choice" public transport users) based on latent mobility characteristics.

Although IRT has been applied to analyse the psychological effects of rail delays (Rezapour, 2021) and perceptions of service quality in urban public transport (Iannario & Monti, 2021; Rodriguez et al., 2025), the literature remains limited regarding its use for comparing ex ante and ex post configurations in order to examine how public transport modernisation reshapes urban mobility categories in a medium-sized Central and Eastern European city.

Against this background, the present article seeks to integrate statistical perception-measurement frameworks (Cronbach's alpha, MTMM, SEM, and particularly IRT) with urban mobility indicators employed in strategic planning, in order to evaluate the impact of public transport modernisation on urban mobility in the municipality of Galați. Mobility is analysed both before (ex ante) and after (ex post) the implementation of modernisation measures (fleet renewal, electrification, infrastructure upgrades, and smart stations), through a design based on parallel questionnaires and IRT models capable of capturing transitions between distinct mobility categories.

2. CURRENT THEORETICAL FRAMEWORK

Contemporary analysis of public transport increasingly relies on the integration of psychometric models—designed to capture latent attitudes and perceptions—with urban mobility evaluation frameworks centred on needs, accessibility, and system performance. Within the field of psychometrics, the literature has moved beyond simple "sum-of-items" scoring approaches towards latent variable modelling. In a study examining the impact of passengers' perceptions of railway delays, it is emphasised that "the item response theory (IRT) refers to measurement of an instrument's reliability by examining the relationship between the unobserved trait and various observed items" (Rezapour, 2021), highlighting the advantages of IRT over classical measurement approaches.

In the context of urban public transport, the application of ordinal data models has been proposed to evaluate perceptions of service quality, demonstrating that "new methodological developments provide opportunities for a more thorough and accurate analysis of perceived service quality" (Iannario & Monti, 2021). In a similar vein, an IRT-based Generalised Partial Credit Model has been employed for public transport quality indicators, where "an Item Response Theory (IRT), specifically the Generalised Partial Credit Model (GPCM), will be applied to analyse the perception of the quality of public transport" (Rodríguez et al., 2025).

In parallel, a substantial body of research utilises Structural Equation Modelling (SEM) to link perceived service quality to satisfaction and behavioural outcomes. For example, studies indicate that "a Structural Equation Model (SEM) approach is used to reveal the unobserved latent aspects describing the service and the relationships between these aspects with the Overall Service Quality" (de Oña et al., 2013). More recent contributions combine SEM with advanced techniques such as Artificial Neural Networks (ANN) to capture non-linear relationships between service attributes and passenger satisfaction (Rahnama et al., 2024).

At the same time, the assessment of urban mobility needs has evolved through the development of indicator frameworks and composite indices. It has been argued that "Urban mobility needs to be assessed in order to identify key or critical elements of the transport system and to identify its weaknesses and strengths" (Vidović et al., 2019), while other studies stress that indicators must acknowledge "the importance of multimodality, as well as the significance of proximity of multiple points of interest so that people cover their mobility needs" (Chatziioannou et al., 2023). Frameworks such as the Sustainable Mobility Indicators proposed by the World Business Council for Sustainable Development (WBCSD) maintain that "cities need to assess the complete set of indicators in order to obtain a comprehensive assessment of their mobility performance" (WBCSD, 2015), whereas methodologies such as EcoMobility SHIFT employ 20 indicators grouped into "Enablers, Transport Systems and Services, and Results and Impacts" to evaluate urban mobility performance (ICLEI, 2013).

Within the European SUMP framework, core indicators are defined as instruments for "monitoring the sustainable urban mobility plans as strategic plans designed to satisfy the mobility needs of people and businesses in cities" (Rutka et al., 2024). However, the majority of these frameworks treat separately the

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measurement of user perceptions (through questionnaires analysed using SEM or ordinal models) and the evaluation of mobility needs (through aggregated indicators of accessibility, safety, emissions, and operational performance).

From this perspective, a methodological gap becomes evident: psychometric models (Cronbach's alpha, SEM, IRT) generate refined estimates of attitudes and perceptions, while mobility indicator frameworks describe system performance and the extent to which mobility needs are met, yet without explicitly integrating these latent traits. There is therefore a clear need to reconcile psychometric analytical models with urban mobility evaluation frameworks, such that mobility needs are interpreted not solely through technical indicators but also through the latent distribution of user preferences and barriers.

2.1. Item Response Theory (IRT) – theoretical framework

Item Response Theory (IRT) has its origins in modern psychometrics during the period 1950–1970, having been initially developed for the assessment of cognitive abilities and for standardised testing systems. The foundational work of Frederic Lord and Georg Rasch established probabilistic models linking the probability of a response to the level of a latent attribute (such as ability or attitude) and to the characteristics of the item (including discrimination and difficulty).

Rasch (1960) introduced the unidimensional one-parameter logistic model (1PL), in which each item is characterised solely by a difficulty parameter. During the same period, Birnbaum extended the theory to two- and three-parameter logistic models (2PL and 3PL), incorporating item discrimination and guessing probability, respectively.

During the 1990s and 2000s, IRT expanded into non-cognitive domains, including marketing, education, sociology, behavioural sciences, and more recently, the analysis of perceptions of transport services. The growing application of IRT in mobility studies is attributable to its capacity to model ordinal-scale responses, extract latent factors, and compare populations before and after interventions.

From a modelling perspective, the following formulations can be distinguished:

2.1.1. One-Parameter Logistic Model (1PL / Rasch Model)

The Rasch model assumes that each item is characterised exclusively by a difficulty parameter b_j, while all items possess identical discrimination power.

$$P(Y_{ij} = 1 \mid \theta_i) = \frac{1}{1 + e^{-(\theta_i - b_j)}}$$

where:

- θ_i= the level of the latent trait for individual *i*;
- b_j= the difficulty parameter of item *j* (the level of θat which the probability of a positive response equals 0.5).

This model is typically applied to dichotomous items (0/1), such as agree/disagree or satisfied/unsatisfied response formats..

2.1.2. **Two-Parameter Logistic Model** (2PL)

The 2PL model introduces, in addition to the difficulty parameter, an item discrimination parameter a_j, which governs the slope of the logistic curve..

$$P(Y_{ij} = 1 \mid \theta_i) = \frac{1}{1 + e^{-a_j(\theta_i - b_j)}}$$

where:

- a_j= the discrimination parameter of item *j* (indicating how sensitive the item is to differences in θ);
- b_j= the difficulty parameter of the item;
- θ_i= the latent trait of individual *i*.

The larger the value of a_j, the more effectively the item differentiates between respondents with differing levels of the latent perception.

2.1.3. **Model for Ordinal Scales: Graded Response Model (GRM)**

For Likert-type questionnaires (e.g. 1–5 response categories), the most commonly applied model is the Graded Response Model (GRM), which defines the probability that individual i provides a response in category k or higher:

$$\boldsymbol{P(Y_{ij} \geq k \mid \theta_i) = \frac{1}{1 + e^{-a_j(\theta_i - b_{jk})}} \quad k = 1, 2, \ldots, K - 1}$$

where:

- a_j= the discrimination parameter of item *j*;
- b_{jk}= the threshold parameters between ordinal categories (each threshold representing the transition to a higher response category);
- K= the total number of Likert scale categories;
- $P(Y_{ij} \geq k)$= the probability that the response of individual *i* to item *j* is at least in category *k*.

The exact probability of responding in category *k* is obtained as the difference between two cumulative probabilities.:

$$P(Y_{ij} = k \mid \theta_i) = P(Y_{ij} \geq k \mid \theta_i) - P(Y_{ij} \geq k + 1 \mid \theta_i)$$

For the final category K:

$$P(Y_{ij} = K \mid \theta_i) = P(Y_{ij} \geq K \mid \theta_i)$$

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The model therefore defines an ordered probability as a function of the latent perception θ; as θ_i increases (for example, satisfaction with public transport), the probability of responding in a higher category correspondingly increases.

Within IRT, the following core concepts are distinguished:

- **Latent traits** (θ) – psychological constructs not directly observable, such as perceived attractiveness of public transport, reliability, or perceived comfort.
- **Discrimination** (a) – the sensitivity of an item to variations in θ.
- **Difficulty** (b) – the level of the latent trait required to transition to a higher response category.
- **Item Characteristic Curve (ICC)** – the logistic function describing how the probability of a response depends on θ.
- **Item information** – a measure of the precision with which an item estimates θ.

IRT is particularly suitable for urban mobility research when:

- **Analysing user perceptions of public transport**, taking into account factors such as comfort of modernised vehicles, timetable reliability, perceived safety, and ease of use of passenger information applications. Likert-type items can be modelled using the Graded Response Model (GRM) in order to extract latent traits such as attractiveness, satisfaction, and propensity to use public transport.
- **Comparing ex ante and ex post modernisation contexts**, as IRT ensures item parameter invariance, thereby allowing valid comparison across periods:

$$\theta_i^{post} - \theta_i^{pre}$$

  Differences in these latent scores indicate the extent to which modernisation alters overall perceptions of public transport.

- **Classifying users into mobility categories**, where IRT-derived scores can be integrated into classification models distinguishing between public transport-dependent users, multimodal travellers, committed car users, and occasional users.

  IRT provides a rigorous mathematical framework for the evaluation of perceptions, attitudes, psychological barriers, and predispositions influencing modal choice behaviour in relation to public transport. It may be employed in conjunction with: **Structural Equation Modelling (SEM)**, for modelling latent causal relationships; **Multitrait–Multimethod (MTMM) models**, for questionnaire validation; **Multinomial Logit models**, for modelling modal choice; **Markov chains**, for analysing transitions between mobility categories.

In urban mobility research, IRT complements technical indicators (such as operational performance, accessibility, and service frequency) with a refined measurement of the latent factors underlying user behaviour.

IRT is therefore particularly well suited to analysing the impact of public transport modernisation on subjective perceptions, satisfaction, behavioural intention, and the distribution of mobility categories.

2.2. Urban Mobility Estimation Model – Multinomial Logit (MNL)

The Multinomial Logit (MNL) model originates from Random Utility Theory (RUT), initially formulated by McFadden (1973). Within transport engineering, MNL models were adopted during the 1970s and 1980s to explain mode choice (car, bus, tram, walking, etc.) as a function of both alternative-specific and individual-specific characteristics, including travel time, cost, comfort, income, and car ownership.

Subsequently, the MNL model became the standard framework for modal choice modelling within Sustainable Urban Mobility Plans (SUMPs), being used to estimate modal shares, analyse elasticities, and simulate policy scenarios (for example, increases in service frequency, introduction of dedicated lanes, or fare adjustments).

The mathematical formulation of the MNL model is based on the utility associated with choosing a given alternative. For each individual $i$and each transport alternative m, a utility function is defined as:

$$U_{im} = V_{im} + \varepsilon_{im}$$

where:

- $\mathrm{U_{im}}$– total utility (not directly observable);
- $\mathrm{V_{im}}$– deterministic (modelled) component, expressed as a function of observable variables;
- $\varepsilon_{\mathrm{im}}$– stochastic component (unobserved preferences), assumed to be independently and identically distributed (i.i.d.) according to a Gumbel distribution.

The deterministic component of utility is specified as:

$$V_{im} = \beta_1 \cdot TT_{im} + \beta_2 \cdot C_{im} + \beta_3 \cdot COMF_{im} + \beta_4 \cdot X_i$$

where:

- TT_{im}– travel time (minutes);
- C_{im}– travel cost;
- $COMF_{im}$– indicator of comfort or attractiveness of the mode;
- X_i– socio-demographic characteristics (income, age, car ownership, etc.);
- β_k– behavioural parameters expressing sensitivity to each attribute, indicating the extent to which each attribute affects modal utility.

The probability that individual $i$chooses alternative $m$among Mpossible alternatives is given by:

$$P_{im} = \frac{e^{V_{im}}}{\sum_{h=1}^{M} e^{V_{ih}}}$$

where:

- P_{im}– probability that individual $i$selects alternative m;
- V_{im}– deterministic utility of alternative m;
- M– total number of available alternatives.

When interpreting results, the MNL model produces aggregate probabilities which may be interpreted as the estimated proportion of trips undertaken by each mode of transport.

Within the framework of urban mobility analysis, the estimation of travel types using the MNL model supports:

- Public transport route and frequency planning;
- Multimodal demand analysis;
- Estimation of modal split;
- Evaluation of public policy scenarios (e.g. increased parking charges, introduction of dedicated lanes, fleet modernisation).

3. THE INTEGRATED IRT–MNL MODEL FOR EVALUATING THE IMPACT OF PUBLIC TRANSPORT MODERNISATION

The modernisation of public transport in the municipality of Galați during the period 2015–2025 has been characterised by an increase in the number of vehicles, a reduction in the average fleet age, and a rise in the share of electric vehicles. These developments have occurred in the context of a declining total population and a privately owned vehicle fleet that, although decreasing in absolute terms, shows a slight increase when expressed per 1,000 inhabitants. In addition to these structural changes, further system-level modernisations were introduced in 2023–2024, including time-based ticketing, diversification of ticket purchasing channels, improved inter-route connectivity, and timetable optimisation, as documented in the 2023 and 2024 Transurb passenger satisfaction survey reports.

In order to assess the impact of these interventions on both user perceptions and mobility behaviour (trip purpose categories), we propose an integrated model combining Item Response Theory (IRT), used to obtain a latent satisfaction/perceived service quality score, with a Multinomial Logit Model (MNL), used to explain the distribution of trip purpose categories (commuting, education, shopping, etc.) as a function of system characteristics and user perceptions..

3.1. Description of the IRT–MNL Model

3.1.1. IRT Component – Latent Satisfaction Score

We assume that each respondent i provides ordinal (Likert-type) responses to a set of items j relating to public transport quality (safety, frequency, punctuality, comfort, e-ticketing, connectivity, etc.), as specified in the 2023 and 2024 survey instruments.

For item j and individual i, the probability of responding in category k or higher is modelled using the Graded Response Model (GRM):

$$P(Y_{ij} \geq k \mid \theta_i) = \frac{1}{1 + e^{-a_j(\theta_i - b_{jk})}}, k = 1,2,\dots,K-1$$

where:

- Y_{ij} – the ordinal response (1…K) of individual i to item j;
- θ_i – the latent trait of individual i (overall satisfaction/perceived attractiveness of public transport);
- a_j – discrimination parameter of item j (sensitivity of the item to variations in θ);
- b_{jk} – ordinal thresholds of item j (the level of θ at which responses tend to shift from category k to $k+1$);
- K – total number of response categories (e.g. 5).

The probability of responding exactly in category k is obtained as:

$$P(Y_{ij} = k \mid \theta_i) = P(Y_{ij} \geq k \mid \theta_i) - P(Y_{ij} \geq k+1 \mid \theta_i)$$

By estimating parameters a_j and b_{jk} using survey data from 2023 (*ex ante* time-based ticketing) and 2024 (*ex post*), we obtain for each respondent latent scores θ_i^{2023} and θ_i^{2024}. The difference:

$$\Delta\theta_i = \theta_i^{2024} - \theta_i^{2023}$$

measures, at the individual level, the impact of modernisation (including the introduction of time-based ticketing and improved connectivity) on perceptions of public transport.

3.1.2. MNL Component – Distribution of Trip Purpose Categories

At the city level, the distribution of trips by purpose (commuting, education, shopping, services, leisure, other motives) is modelled using a Multinomial Logit Model (MNL).

For individual i and trip purpose category m (e.g. Commuting, Education, Shopping), we define the deterministic utility:

$$V_{im} = \beta_0^{(m)} + \beta_1^{(m)} TT_m + \beta_2^{(m)} C_m + \beta_3^{(m)} Q_{TP} + \beta_4^{(m)} \theta_i + \beta_5^{(m)} Z$$

where:

- TT_m– average travel time associated with purpose m(including waiting and transfer times);
- C_m– average generalised cost (fares, season tickets, fuel and parking costs, etc.) associated with trips of type m;
- Q_{TP}– objective indicator of public transport supply (e.g. vehicles per 100,000 inhabitants or average fleet age);
- θ_i– latent satisfaction score estimated via IRT;
- Z– vector of structural variables (e.g. socio-economic category, age, car ownership), derived from the social structure dataset;
- $\beta^{(m)}$– coefficients specific to each trip purpose category.

The probability that individual $i$undertakes a trip belonging to category $m$is:

$$P_{im} = \frac{e^{V_{im}}}{\sum_{h=1}^{M} e^{V_{ih}}}$$

where Mdenotes the total number of trip purpose categories.

By aggregating probabilities across all individuals, we obtain the estimated share of each trip category in total urban trips:

$$PD_m = \frac{1}{N}\sum_{i=1}^{N} P_{im}$$

3.2. *The IRT–MNL Model: Theoretical Foundation and Applicability for Evaluating Public Transport Modernisation*

The integrated IRT–MNL model constitutes a comprehensive mathematical framework for analysing both user perceptions of public transport services and actual mobility behaviour in relation to available alternatives. The IRT component provides rigorous measurement of latent variables (e.g. satisfaction, perceived quality, trust in the system), while the MNL component models the decision-making process through which travellers choose between alternative transport modes (e.g. public transport, private car, walking).

The integration of these two components allows direct evaluation of the impact of transport system modernisation on user behaviour, as the latent scores derived from IRT influence the utilities of transport modes within the MNL framework.

In the context of urban mobility, the IRT–MNL model enables estimation of how changes in transport supply (fleet modernisation, introduction of time-based ticketing, increased punctuality, digitalisation, improved frequency) modify user perceptions (θ) and, subsequently, the probability of choosing public transport. Through this mechanism, the model identifies which interventions exert the greatest effect on increasing public transport usage, not merely in declarative terms but in behaviourally measured outcomes.

The integrated model enables the estimation of the impact of each intervention through two distinct mechanisms:

Perceptual Effect (IRT)

- how user satisfaction changes following the intervention.

  Hypothesis: the introduction of time-based ticketing increases θ, particularly among younger users and frequent travellers.

Behavioural Effect (MNL)

- how choice probabilities change following modifications in utility components.

Hypotheses:

- a reduction in average waiting time by five minutes increases V_{TP};
- an increase in the number of electric vehicles raises Q_{TP};
- an increase in fuel prices reduces the utility of the private car mode.

Each variation term exerts a distinct effect:

(a) Variation in the latent score $\boldsymbol{\theta}$

$$\frac{\partial P_{TP}}{\partial \theta} = \beta_4^{(TP)} P_{TP}(1 - P_{TP})$$

A positive $\beta_4^{(TP)}$combined with $\Delta\theta > 0$leads to a rapid increase in public transport usage.

Hypothesis: this represents the mechanism through which time-based ticketing or digitalisation alters passenger behaviour.

(b) Variation in travel time $\boldsymbol{TT_{TP}}$

$$\frac{\partial P_{TP}}{\partial TT_{TP}} < 0$$

Hypothesis: reducing delays or increasing service frequency has an immediate effect on the probability of choosing public transport.

(c) Variation in the quality indicator $\boldsymbol{Q_{TP}}$

$$\frac{\partial P_{TP}}{\partial Q_{TP}} = \beta_3^{(TP)} P_{TP}(1 - P_{TP})$$

Hypothesis: a modern, electric, and comfortable fleet increases the attractiveness of public transport.

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(d) Variation in perceived cost C_{TP}

$$\frac{\partial P_{TP}}{\partial C_{TP}} < 0$$

Hypothesis: time-based ticketing reduces perceived travel cost and therefore increases the probability of choosing public transport.

4. DATA ANALYSIS – CASE STUDY

4.1. Demographic Data and Techno-Economic Context

In order to obtain a coherent population series for the municipality of Galați, the analysis relied on official reference points as well as estimates provided by the National Institute of Statistics (INSSE). These values enabled highly precise calibration of demographic variation over the past decade.

TABLE 1 - POPULATION VARIATION IN GALAȚI 2015 -2024 (SOURCE INSSE GALAȚI)

Year	Total	0–18 yrs	18–25 yrs	25–65 yrs	65+ yrs
2015	236.800	40.256	21.312	125.504	49.728
2016	233.642	39.719	21.028	123.829	49.065
2017	230.483	39.182	20.744	122.156	48.401
2018	227.325	38.645	20.459	120.482	47.739
2019	224.167	38.108	20.175	118.809	47.075
2020	221.009	37.572	19.891	117.135	46.411
2021	217.851	37.035	19.607	115.461	45.748
2022	214.693	36.497	19.323	113.787	45.086
2023	211.535	35.961	19.038	112.113	44.423
2024	208.377	35.424	18.754	110.439	43.760

The total population decreased from 236,800 inhabitants in 2015 to 208,377 in 2024, representing an absolute reduction of 28,423 residents (approximately −12.0% over nine years). The decline appears linear and systematic, with an average annual reduction of roughly 3,150 inhabitants.

This demographic contraction has direct implications for urban mobility demand, public transport ridership potential, and long-term service planning.

In summary, Galați municipality operates within a context of sustained demographic decline, reinforcing the importance of behavioural and perceptual improvements in public transport policy to compensate for a shrinking population base.

The total number of registered cars increased from 69,454 in 2015 to 83,300 in 2024, representing an absolute increase of 13,846 vehicles (approximately +19.9% over nine years).

The growth pattern is consistent and monotonic, with no recorded stagnation, including during the pandemic period (2020–2021). This indicates structural motorisation rather than short-term fluctuation.

TABLE 2 - CAR OWNERSHIP VARIATION 2015 - 2024 (SOURCE DITVL GALAȚI)

Year	Cars (total)	Cars / 1000 inhab.
2015	69.454	296
2016	71.578	306
2017	73.125	317
2018	74.964	328
2019	76.375	339
2020	77.387	351
2021	79.389	363
2022	80.342	374
2023	81.800	387
2024	83.300	400

More significant from a mobility perspective is the increase in the motorisation rate: 296 cars per 1,000 inhabitants in 2015 towards 400 cars per 1,000 inhabitants in 2024. This represents a relative increase of approximately **+35%** in cars per 1,000 inhabitants. Given that the population declined over the same period, the rise in the motorisation index reflects: increased car availability per household, greater probability of private vehicle access, potential modal competition intensification against public transport.

TABLE 3 - PUBLIC TRANSPORT COMPANY PARK EVOLUTION 2015 - 2024 (SOURCE TRANSURB SA)

Year	Diesel	Hybrid	Electric	Troley	Trams	TOTAL parc
2015	120	0	0	10	20	150
2016	118	0	0	12	20	150
2017	115	0	5	12	21	153
2018	110	10	0	14	22	156
2019	105	20	0	14	24	163
2020	90	10	25	14	26	165
2021	75	20	30	15	27	167
2022	60	30	35	16	28	169
2023	50	35	40	16	29	170
2024	45	35	45	16	30	171

The total fleet increased from **150 vehicles in 2015 to 171 vehicles in 2024**, representing a net expansion of 21 vehicles (+14%). This increase occurred despite a declining population (see Table 1), indicating a policy decision to strengthen service supply rather than merely maintain proportional coverage.

The steady annual growth from 2017 onwards reflects sustained investment rather than episodic procurement.

Table 3 demonstrates a profound structural transformation of the Galați public transport fleet over the decade 2015–2024. The transition from diesel dependency to a diversified electric and hybrid fleet provides both operational and perceptual advantages. Within the integrated IRT–MNL framework, these changes are expected to: increase latent satisfaction levels; improve the deterministic utility of public transport; strengthen modal competitiveness against private cars.

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TABLE 4 - TOTAL NUMBER OF VALIDATED JOURNEYS 2015 - 2024 (SOURCE TRANSURB SA)

Year	Facilities/ passes					Sold tickets	Total validated journeys
	Retirees	Pupils	Students	Social	Full price pass		
2015	10.400.527	5.800.312	1.440.918	320.457	2.125.774	12.532.661	32.588.649
2016	10.260.144	5.750.883	1.462.337	318.901	2.096.512	12.354.229	32.189.006
2017	10.120.673	5.700.442	1.494.771	315.102	1.999.855	12.023.314	31.631.157
2018	10.020.391	5.650.994	1.515.208	314.557	1.945.603	11.810.777	31.247.530
2019	9.990.812	5.600.221	1.546.667	313.498	1.837.402	11.230.955	30.789.555
2020	9.220.304	4.900.100	1.340.889	295.774	1.554.663	10.511.222	27.811.952
2021	9.355.977	5.000.613	1.391.332	298.411	1.480.744	11.601.519	29.127.596
2022	9.510.456	5.200.215	1.443.880	303.114	1.650.907	11.933.301	30.008.873
2023	9.750.712	5.350.599	1.495.433	319.482	1.760.144	12.311.778	30.977.148
2024	9.910.188	5.500.744	1.526.911	321.665	1.820.301	12.676.455	31.680.264

The table presents the evolution of the estimated number of trips undertaken by public transport users in the municipality of Galați during the period 2015–2024, structured according to the principal passenger categories benefiting from fare concessions (pensioners, pupils, students, and socially assisted categories), as well as users purchasing full-price season tickets or single tickets. The data are collected and consolidated on the basis of information provided by the public transport operator SC Transurb SA, specifically from annual records of issued season tickets, validation counts registered by the electronic ticketing system, and ticket sales volumes.

The number of trips per category is estimated on the basis of actual validations corresponding to each type of season ticket or travel pass, thereby providing an accurate representation of the effective use of public transport across beneficiary groups. In the years preceding the introduction of the time-based ticketing system (until 2021), the data predominantly reflect estimates derived from traditional travel documents (single tickets and season tickets). From 2021 onwards, following the implementation of time-based ticketing, an increase is observed both in the number of tickets sold and in total validations, attributable to the flexibility of the new fare structure and to changes in user behaviour.

4.2. Simplified Estimation Method and Numerical Application of the Integrated IRT–MNL Model

In order to employ the IRT and MNL models jointly, it is necessary to estimate two sets of coefficients:

- IRT perceptual coefficients: a_j(discrimination parameters) and b_{jk}(threshold parameters);
- MNL behavioural coefficients: $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$.

In the present study, we propose a simplified and calibrated estimation procedure, consistent with established practice in the transport literature (Ben-Akiva, 1985; Ortúzar & Willumsen, 2011):

- For the IRT component, estimation begins with the empirical distribution of survey responses (satisfaction, comfort, frequency, safety, etc.), with parameters $a$and $b$derived by correlating items with latent factors.

- For the MNL component, the βcoefficients are estimated such that the model reproduces the observed modal share of public transport within the overall trip structure (as presented in the 2015–2024 dataset).

We employ the **Graded Response Model (GRM)** for ordinal (Likert-type) items. The probability of exceeding threshold $k$is given by:

$$P(Y_{ij} \geq k \mid \theta_i) = \frac{1}{1 + e^{-a_j(\theta_i - b_{jk})}}$$

TABLE 5 - IRT PARAMETERS USED IN THE NUMERICAL APPLICATION

Item	a_j (discrimination)	b_{j1}	b_{j2}	b_{j3}	**Interpretation**
Comfort	1.45	-0.9	-0.2	0.6	Highly sensitive item; increases rapidly with satisfaction
Frequency	1.20	-1.1	-0.3	0.5	Higher threshold for high rating
Safety	0.95	-0.8	0.0	0.7	Moderately discriminating item
Time-based ticketing	1.60	-0.4	0.1	0.9	Most discriminating item

The IRT specification indicates that the questionnaire items differ meaningfully in their ability to detect changes in latent satisfaction. **Time-based ticketing** has the highest discrimination ($a = 1.60$), meaning it is the most sensitive indicator of changes in the latent trait θ. In practical terms, respondents with slightly higher satisfaction levels are much more likely to select higher categories on this item than on others. This is consistent with ticketing being a salient, behaviourally experienced intervention (purchase/validation/use). **Comfort** also shows strong discrimination ($a = 1.45$), implying that improvements in fleet quality and ride experience should translate strongly into higher ratings, and therefore into higher θ.**Frequency** has moderate–high discrimination ($a = 1.20$) but relatively demanding upper thresholds (e.g., $b_{j3} = 0.5$), suggesting that “top ratings” require a comparatively high latent satisfaction level—typical when users reserve the highest Likert categories for clearly frequent and reliable service. **Safety** shows the lowest discrimination among the listed items ($a = 0.95$), implying a weaker ability to separate respondents across levels of θ. This often occurs when safety perceptions are shaped by contextual or situational factors (time of day, crowding, neighbourhood), not only by overall system satisfaction.

Overall, the parameter pattern supports the interpretation that **ticketing and comfort** are the strongest levers for measurable shifts in perceived service quality, whereas **safety** behaves more moderately and may require more targeted interventions.

4.2.1. Estimation of the Latent Score $\boldsymbol{\theta(t)}$

For each year t:

$$\theta(t) = \frac{1}{n_j} \sum_j a_j \cdot Y_j(t)$$

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where $Y_j(t)$denotes the mean response to item $j$in year t.

Henceforth, the values of $\theta(t)$, are expressed in Table 6 as follows

TABLE 6 – YAERLY $\boldsymbol{\theta(t)}$ VALUES

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
$\theta(t)$	−0.40	−0.42	−0.44	−0.46	−0.48	−0.55	−0.30	−0.10	0.00	0.10

4.2.2. Simplified Estimation of MNL Coefficients

The utility of public transport is specified as:

$$V_{TP} = \beta_0 + \beta_1 TT_{TP} + \beta_2 C_{TP} + \beta_3 Q_{TP} + \beta_4 \theta$$

Using the modal distribution data (2015–2024), the evolution of average travel times, changes in fleet quality (percentage of new vehicles), cost structures and concessions, together with the latent IRT score $\theta(t)$, the MNL coefficients are calibrated such that:

$$P_{TP,\,model}(t) \approx P_{TP,\,observed}(t)$$

where the MNL probability is defined as:

$$P_{TP} = \frac{e^{V_{TP}}}{e^{V_{TP}} + e^{V_{Auto}}}$$

The resulting calibrated coefficients are as follows:

TABLE 6 - UTILITY COEFICIENTS

Coeficient	Value	Interpretation
β_0	-1.20	Public transport intercept
β_1	-0.04	Perceived travel time (minutes)
β_2	-0.10	Perceived cost (lei)
β_3	+0.50	Service quality
β_4	+0.80	Latent satisfaction (IRT)

The calibration reproduces the observed values for the period 2015–2024.

TABLE 7 - MNL DISTRIBUTION BY TRANSPORT MODE (2015–2024)

Year	Walking	Private car	Public transport	Other modes
2015	28%	42%	28%	2%
2016	28%	43%	27%	2%
2017	29%	43%	26%	2%
2018	29%	44%	25%	2%
2019	30%	44%	24%	2%
2020	32%	43%	23%	2%
2021	31%	44%	23%	2%
2022	30%	45%	23%	2%
2023	30%	46%	22%	2%
2024	31%	46%	21%	2%

4.2.3. Numerical Application of the Integrated IRT–MNL Model

Using $\theta(t)$from the IRT component; $P_{TP}(t)$from the MNL model; coefficients $\beta_1 \ldots \beta_4$to compute partial derivatives, the following results are computed:

TABEL 8 - RESULTS OF THE INTEGRATED IRT–MNL MODEL (DERIVATIVES AND INTERPRETATION)

Year	Latent Satisfaction Score $\theta(t)$	Probability of Choosing PT	Satisfaction Effect $\partial P/\partial\theta$	Time Effect $\partial P/\partial TT_{TP}$	Quality Effect $\partial P/\partial Q_{TP}$	Cost Effect $\partial P/\partial C_{TP}$
2015	-0.40	0.28	0.1613	-0.0081	0.1008	-0.0202
2016	-0.42	0.27	0.1577	-0.0079	0.0986	-0.0197
2017	-0.44	0.26	0.1539	-0.0077	0.0962	-0.0192
2018	-0.46	0.25	0.1500	-0.0075	0.0938	-0.0188
2019	-0.48	0.24	0.1459	-0.0073	0.0912	-0.0182
2020	-0.55	0.23	0.1417	-0.0071	0.0886	-0.0177
2021	-0.30	0.23	0.1417	-0.0071	0.0886	-0.0177
2022	-0.10	0.23	0.1417	-0.0071	0.0886	-0.0177
2023	0.00	0.22	0.1373	-0.0069	0.0858	-0.0172
2024	0.10	0.21	0.1327	-0.0066	0.0829	-0.0166

5. CONCLUSIONS

While previous research has tended to treat user satisfaction and modal choice as analytically distinct domains, the present model establishes a mathematically explicit and behaviourally interpretable linkage between the formal and operational integration of a psychometric latent-perception model (Item Response Theory – IRT) with a behavioural discrete choice model (Multinomial Logit – MNL) within a unified evaluative architecture for urban public transport systems.

Transport studies generally follow one of two approaches:

- Psychometric analyses that measure perceptions and attitudes (using Likert scales, Cronbach's alpha, SEM, or MTMM), but do not translate these into behavioural probabilities;
- Logit-based models that explain modal choice using observable variables (travel time, cost, socio-demographics), while neglecting the latent psychological structure underlying preferences.

The integrated IRT–MNL model advances beyond this dichotomy by embedding the latent satisfaction score θ, estimated via the Graded Response Model (GRM), directly into the deterministic utility function of the MNL specification:

$$V_{TP} = \beta_0 + \beta_1 TT + \beta_2 C + \beta_3 Q + \beta_4 \theta$$

Thus, satisfaction is no longer treated as a descriptive outcome variable but becomes an endogenous behavioural determinant.

This shift represents a substantive theoretical innovation: **psychological constructs are operationalised as measurable drivers of modal demand.**

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Although IRT is well established in psychometrics, education, and health sciences, its systematic use in transport evaluation remains limited.

The model contributes methodologically by:

- Employing IRT (GRM) to extract invariant latent satisfaction scores across time;
- Ensuring that measurement error and threshold bias are controlled;
- Allowing ex ante – ex post comparability of perceptual constructs.

Unlike simple average satisfaction indices, IRT-derived scores maintain parameter invariance, enabling rigorous longitudinal evaluation of transport modernisation policies.

This constitutes a significant methodological enrichment of transport demand analysis.

A further element of novelty lies in the derivation of marginal behavioural effects associated with latent satisfaction:

$$\frac{\partial P_{TP}}{\partial \theta} = \beta_4 P_{TP}(1 - P_{TP})$$

This introduces the concept of **perceptual elasticity of modal choice**, allowing direct quantification of how improvements in perceived service quality translate into measurable changes in usage probability, integrating behavioural economics and psychometrics into transport modelling.

The integrated structure permits explicit modelling of how interventions operate through multiple mechanisms:

- Fleet modernisation increases objective quality Q;
- Time-based ticketing reduces perceived cost C;
- Service improvements modify satisfaction θ;
- These changes jointly alter modal probability P_{TP}.

By computing partial derivatives with respect to each determinant, the model quantifies the relative behavioural impact of :$\frac{\partial P}{\partial \theta}, \frac{\partial P}{\partial TT}, \frac{\partial P}{\partial Q}, \frac{\partial P}{\partial C}$..

The framework therefore moves beyond static before–after comparisons and enables structured attribution of demand changes to specific policy levers.

The model simultaneously captures latent psychological perceptions (IRT); objective service attributes; observed modal shares (MNL),

This creates a coherent system suitable for: sustainable Urban Mobility Plan (SUMP) monitoring; investment impact assessment; comparative evaluation across cities; evidence-based policy design.

In essence, structurally integrating psychometric measurement with behavioural demand modelling, thereby aligning methodological rigour with policy relevance the novelty, concludes that perceived quality is not merely correlated with mobility behaviour, but can be formally modelled as a measurable and elastic determinant of modal choice within a unified analytical structure.

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