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A MULTI-TRAIT MULTI-METHOD MATRIX EXTENSION FOR URBAN PUBLIC TRANSPORT ANALYSIS

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Abstract: *The paper introduces MTMM-TP, a multi trait-multi method model specifically designed as a structural addition to the public transport system. In its matrix form, this model connects socio-economic factors, user perceptions, and urban characteristics with transport supply variables such as mode types, service frequencies, and capacity levels. Based on a set of equations, the responses are described as a sum of trait, method, mode, spatial and temporal effects, and error, weighted by the respective loading matrices. Thus, MTMM-TP provides a tool to analyse user perceptions, enabling a precise evaluation of the level of service quality and safety. Through the implementation of the SEM model, it offers a scientific basis for the analysis and decision-making processes in public transport.*
Key words: *MTMM-TP, Multi Trait Multi Method, Public Transport, Reliability, Accessibility, Capacity, Passenger Perception, Service Evaluation.*

1. INTRODUCTION

Public transport is one of the most important infrastructures to ensure the efficient operation of cities in the world. The development of sustainable transport solutions with reduced carbon emissions and with increased accessibility of the urban services are key objectives of the European and international urban planning policies [15]. The evaluation of the level of passenger's satisfaction has become one of the tools that support the planning and monitoring of services. Recent papers point out that passenger's perception depends not only on the objective parameters (travel time, vehicle frequency, fare), but also on subjective parameters (comfort, safety, trust) [13], [14]. Still, the measurement of such perception faces challenges related to the data collection tools (online questionnaire or face-to-face interview), multimodal urban context, and spatial-temporal variations, which introduce systematic effects that might bias the model estimates.

The classical MTMM (Multi-Trait Multi-Method) model enables the assessment of convergent and discriminant validity; however, it has not been extended to accommodate a multimodal urban environment. In this study, the MTMM-TP model is introduced as a structural extension of the MTMM framework, allowing the incorporation of modal types as well as spatio-temporal effects, specifically adapted to the context of public transport.

This paper demonstrates how the MTMM-TP model can be used to identify sources of variation in passengers' perceptions, to estimate levels of satisfaction and trust among passengers, and to support planning and investment decision-making processes in the field of public transport services.

2. CURRENT RESEARCH PROGRESS REGARDING MULTITRAIT – MULTIMETHOD MODEL

2.1. The classical MTMM model

Campbell and Fiske proposed the multitrait–multimethod matrix to be used for the evaluation of the convergent and discriminant validity [1]. The core of the idea is that if two methods are used to measure the same trait, the correlation coefficients between them should be higher than the coefficients obtained for different traits. If this is not the case, discriminant validity has to be questioned.

2.2. Structural Extension (SEM)

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Jöreskog has introduced a structural extension of the MTMM model by using confirmatory factor analysis (CFA) that allows for the explicit modelling of the traits and the methods [2]. The broader SEM framework was detailed in [3] and used in applied work by [4], [5]. The general structure of the measurement equation is:

$$y = \Lambda\eta + \epsilon \quad (1)$$

where:

y vector of observed variables,
Λ matrix of loading coefficients,
η vector of latent variables (traits/methods),
ϵ measurement error.

Comprehensive treatments of CFA and SEM can be found in Brown [7] and Kline [8].

2.3 Recent Applications

In the past decade, MTMM has been used predominantly in psychology [7], [10], education [11] and marketing [12]. Extended SEM-based models have been refined to include hierarchical structures, residual method factors, and Bayesian approaches [9], [10]. However, the literature on the application of MTMM in public transport is virtually non-existent.

The multitrait-multimethod (MTMM) framework has witnessed a significant revival, primarily due to methodological innovations in structural equation modelling (SEM) and the increasing demand for robust measurement tools in complex social and behavioural sciences. While originally conceived as a conceptual matrix for detecting convergent and discriminant validity [1], contemporary research has expanded MTMM into a flexible analytical paradigm capable of addressing challenges associated with measurement error, method variance, and multidimensional constructs.

Psychology remains the field where MTMM has been most systematically applied. Recent works [7], [10] have emphasized the importance of controlling for method-specific variance in self-report data, particularly when assessing constructs such as personality, motivation and well-being. For example, in cross-cultural studies, researchers often face the problem of whether observed differences are attributable to genuine variations in traits or to differences in response styles (e.g., acquiescence, social desirability). MTMM-SEM models allow for a separation of these components, providing cleaner estimates of latent constructs. Moreover, residual method factors introduced in SEM-based MTMM models help capture systematic biases associated with instruments, which would otherwise confound trait estimation.

In the field of education, MTMM approaches have been applied to large-scale assessment programs, including studies of student achievement and teacher evaluation [11]. Here, the challenge lies in the multi-informant and multi-context nature of data: student performance is often evaluated through test scores, teacher ratings and self-assessments. MTMM models facilitate the disentanglement of genuine ability factors from rater or method effects. This has been particularly useful in longitudinal educational research, where method variance can obscure developmental trajectories. Recent extensions have even integrated hierarchical structures, acknowledging that students are nested within classrooms and schools, thereby combining MTMM with multilevel SEM.

Marketing and organizational behaviour have also benefited from MTMM advancements [12]. Constructs such as customer satisfaction, organizational commitment and brand loyalty are often measured through self-reports, leading to the classic issue of common method bias. MTMM-SEM offers a principled way of quantifying and correcting for such biases, ensuring that correlations among constructs are not inflated by shared method variance. For example, in customer surveys, responses collected via online forms may differ systematically from those collected through in-person interviews; MTMM models allow these differences to be modelled explicitly.

Between 2015 and 2025, methodological developments have considerably extended the MTMM toolbox. One key innovation is the introduction of Bayesian MTMM models [9], [10]. Bayesian estimation provides more flexibility in handling small samples, complex hierarchical structures and prior information about trait-method relationships. Another refinement is the use of residual method factors, which allow researchers to capture non-shared method variance without requiring the unrealistic assumption that method effects are fully independent. Finally, the integration of MTMM into longitudinal SEM frameworks enables the study of trait stability and method consistency over time, offering insights into whether observed changes in constructs reflect real developmental processes or shifting measurement artifacts.

2.4. Gaps in transportation research.

Despite these advances [7], [9], [10], [11], [12], the application of the MTMM framework in transportation research remains largely unexplored. Most studies on public transport satisfaction rely on single-method approaches, typically cross-sectional surveys based on Likert-type scales. While such studies provide valuable descriptive insights, they are limited by their inability to disentangle substantive variation from method-related bias.

For instance, responses obtained via online questionnaires may systematically differ from those collected through on-board interviews, not necessarily because passengers experience transport services differently, but due to mode-of-response effects. Similarly, satisfaction ratings may vary across transport modes (e.g., bus, tram, trolleybus), reflecting both genuine service differences and method-specific perceptual biases.

Originally developed to assess convergent and discriminant validity [1], MTMM frameworks are particularly well suited to disentangle these effects; however, their adoption in urban mobility research has been minimal.

Introducing MTMM-based approaches into the study of public transport opens new avenues for addressing long-standing methodological challenges. First, they enable the evaluation of convergent validity across different data sources, as conceptualized in the original MTMM framework [1]. Second, they allow the modelling of discriminant validity among related constructs, such as comfort, safety, and trust, which are often correlated but theoretically distinct. Third, SEM-based MTMM models [2], [3], [7] provide a robust framework for integrating spatial and temporal dimensions of public transport experience, capturing how perceptions vary across neighbourhoods, routes, or time-of-day.

A concrete example could involve measuring passenger satisfaction with buses, trams, and trolleybuses using both online surveys and face-to-face interviews. Without MTMM, analysts might simply aggregate all responses, potentially conflating genuine service differences with methodological artifacts. With MTMM, however, one can explicitly model both trait variance and method variance within the SEM structure [2], [3], [8]. The result is a set of more valid and reliable estimates that can inform transport planning, resource allocation and policy interventions.

Looking ahead, MTMM approaches could be combined with other methodological innovations in transport research. For example, integrating MTMM with item response theory (IRT) could enhance the measurement of passenger perceptions across heterogeneous groups, ensuring comparability of responses across different demographic segments. Similarly, combining MTMM with geospatial modelling may allow for the analysis of how satisfaction varies across urban areas while controlling method effects. The increasing availability of big data sources presents both an opportunity and a challenge: while they enrich the measurement of transport experience, they also introduce additional layers of method variance. Bayesian SEM developments [9] provide additional flexibility in handling such complex data structures.

In conclusion, although the MTMM framework has undergone substantial development in psychology, education and marketing [7], [11], [12], its application within transportation science remains an underexplored area. Extending MTMM to the context of urban public transport not only addresses a notable gap in literature but also responds to pressing methodological challenges in the assessment of passenger satisfaction.

By disentangling trait, method and error components, as originally conceptualized in MTMM theory [1], the framework has the potential to yield more accurate and actionable insights, thereby supporting evidence-based policy-making for sustainable and equitable urban mobility [15].

3. PROPOSED METHODOLOGY: THE MTMM-TP MODEL

3.1 Definition and Innovation

The proposed Multitrait–Multimethod Transport Public (MTMM-TP) model extends the classical MTMM framework by embedding contextual factors that are essential for understanding user perceptions in complex urban environments. While the classical MTMM structure disentangles trait variance from method variance, it overlooks the spatial, temporal and modal heterogeneity that characterizes public transport systems. The MTMM-TP framework introduces three additional latent dimensions:

1. Mode of transport (θ) – distinguishing between buses, trams and trolleybuses. Each mode has unique operational characteristics (capacity, comfort, reliability), and these attributes systematically influence passenger perceptions.
2. Spatial effects (ζ) – capturing differences between central and peripheral urban zones. Transport services in central areas may exhibit higher frequency and better infrastructure, while peripheral zones often experience irregular service and lower accessibility.
3. Temporal effects (τ) – reflecting variation across time intervals (peak vs. off-peak hours) and days of the week (weekdays vs. weekends). Temporal heterogeneity is particularly relevant for public transport, where crowding, delays, and perceived safety can fluctuate significantly across time.

Formally, the observed response of individual i, for trait j, method k, mode t, spatial zone z and temporal moment m, is defined as:

$$y_{ijktzm} = \lambda_j \eta_j + \gamma_k \mu_k + \delta_t \theta_t + \alpha_z \zeta_z + \beta_m \tau_m + \epsilon_{ijktzm} \quad (2)$$

where:
y_{ijktzm} observed perception score,
$\lambda_j \eta_j$ trait component (e.g., comfort, safety, trust),
$\gamma_k \mu_k$ method component (survey type, response format),
$\delta_t \theta_t$ transport mode component,
$\alpha_z \zeta_z$ spatial component,
$\beta_m \tau_m$ temporal component,
ϵ_{ijktzm} residual error capturing random variance.

This formulation extends the confirmatory factor analytic (CFA) logic of the MTMM-SEM by systematically including contextual covariates as latent dimensions, rather than treating them as mere grouping variables or fixed effects.

3.2 Matrix Representation

The MTMM-TP model can be expressed compactly using a matrix notation that extends the traditional multitrait - multimethod framework. In its full form, the model can be written as:

$$Y = \Lambda_T T + \Lambda_M M + \Lambda_\Theta \Theta + \Lambda_Z Z + \Lambda_\tau \tau + E \quad (3)$$

where:
Y vector of observed responses,
Λ_T factor loading matrix for traits (e.g., comfort, safety, trust),
Λ_M factor loading matrix for methods (e.g., online survey, on-board interview),
Λ_Θ factor loading matrix for modes of transport (bus, tram, trolleybus),
Λ_Z factor loading matrix for spatial zones (central vs. peripheral),
Λ_τ factor loading matrix for temporal effects (time intervals and days of the week),
E residual error term.

This formula essentially extends the classic MTMM setup. It does this by conceptualizing context not simply as a nuisance variable to be ignored or collapsed, but rather as a collection of structured latent variables. Each loading matrix represents an association between the responses of respondents and a specific latent variable domain. In terms of how this matrix specification advances the literature, it:

- Offers a unified representation: Trait, method, and context effects all reside in a single structural equation, allowing for joint estimation.

- Allows flexible parameterization: Each block of loadings can be constrained, free, or constrained to be equal according to the needs of the study design, thus enabling testing of substantive hypotheses (for example, "Are certain modes associated with higher levels of comfort?")
- Permits straightforward application to the large class of confirmatory factor analytic models available in popular SEM packages (LISREL, Mplus, lavaan in R, and so on).
- Importantly, $\Lambda_\Theta, \Lambda_Z$ and Λ_τ have interpretations different than that of (T) and methods (M) are latent contextual variables in this formulation (even if we do not explicitly refer to them as "context" as is done in the classic MTMM literature, where the primary focus is trait and method).

For example:

- Λ_Θ could represent variation in latent satisfaction for a given trait due to the mode of transport. Λ_Z the zone or period Λ_τ
- If Λ_Θ for trams is substantially greater than Λ_Θ for buses in terms of comfort, then mode effects are clearly at work

The MTMM-TP model is thus a multilevel variation decomposition method that is both psychometrically robust and empirically relevant.

3.3 Conceptual Innovation

The conceptual novelty of the MTMM-TP approach is its ability to discriminate the distortions due to methods from the heterogeneity produced by the transport environment. The latent variable methods have usually attributed the systematic variance to the instrument method or to the residual error variance. However, in transport contexts, in which the operating conditions are characterized by a high level of variability of an operational, spatial and temporal nature [16][17], this attribution appears inadequate, because the travel experience emerges from a process that is characterized by the continuous interaction of the characteristics of the vehicles, the quality of the infrastructures, the congestion of the passengers, the punctuality and accessibility [18]. Therefore, the evaluations regarding the comfort, punctuality, reliability and trust are not only the result of the latent psychological predisposition but also are conditioned by the context in which the transportation takes place [18].

The MTMM-TP method, extending the concept of multimodal-multimodal measurement, introduces latent dimensions for the context of the transport mode (θ), the context of the geographic location (ζ) and the context of time (τ). In this way, observed variance can be decomposed into behavioural and operational components.

One of the most significant sources of heterogeneity is modal. The different transport modes have different characteristics and are therefore perceived differently. In the case of public transport in urban area, trams are often evaluated as more comfortable and reliable than buses due to the smoother driving quality, higher vehicle capacity or the less crowd [19]. In this respect, the introduction of the mode factor (θ) can discriminate between systematic modal heterogeneity and latent satisfaction. Without this factor, the differences could contribute to the growth of the variance of the latent trait and it is likely, if the data allows this, to absorb the variation as residual error variance.

Similarly, there is spatial heterogeneity. The services provided in the urban central area have, usually, greater frequency, better interconnection with other transport modes and shorter distances than in the urban peripheral area [20]. The user of the central area will therefore tend to perceive a high reliability or punctuality and a greater safety of public transport than that of the user of the peripheral area. It does not follow, however, that the latter has lower latent expectations than the former regarding satisfaction and quality of service.

Therefore, the use of the location factor allows discriminating infrastructural differences from the latent psychological trait and, therefore, improves the interpretative ability of the indicators of perceived quality.

On the other hand, there is a temporal variability. The congestion conditions during the rush hour may lead to a reduction in the perceived service comfort and reliability while, conversely, in the evening hours, the problem of service safety may emerge [21]. In these cases, the use of traditional methods based on SEM or MTMM may lead to confounding variance of temporal variation as residual error, which should not be the case. Here, the introduction of the time factor (τ) makes it possible to reduce the variability due to different operating conditions and to improve the stability of the evaluation of the latent constructs.

The introduction of modal, spatial and temporal dimensions thus give rise to MTMM-TP which, unlike traditional MTMM, is a model capable of interpreting latent perceptions in the context in which transport occurs [22]. The framework makes it possible to relate the measurement of behaviours to transport engineering, since the latent perceptions are evaluated in relation to the environment in which they are experienced [22]. Thus, the evaluation of service quality (satisfaction, trust, and perceived service reliability) refers not only to an isolated psychological entity, but to an evaluation that originates from a process of interaction between the user and the service offered. The interpretation of the variance as described above improves the discriminant validity of the models between latent variables and reduces the likelihood of attributing to the trait the variation due to method [23]. At the same time, MTMM-TP also allows for better comparison between different modalities, spatial zones and different periods of time, and thus enables the improvement of ex ante and ex post evaluations on the introduction of interventions for the modernization of the urban public transport system. In this way, the MTMM-TP approach contributes to the passage from a static evaluation of service satisfaction to a dynamic and contextual analysis of behaviour in the urban transport environment [24].

3.4 Analytical Implications

The proposed formulation has several methodological implications. First, construct validity should be substantially improved, such that the trait effects for satisfaction and trust are more accurately reflective of the true effects in passengers by controlling for modal, temporal, and spatial effects. Second, there is likely a substantial reduction in the proportion of variation that is unattributable, which is a consequence of explicitly modelling the contextual dimension. This will lead to an improvement in the error terms and in the explanatory power of the model. Finally, the MTMM-TP model will allow for comparison of the magnitude of the effect of satisfaction and trust across modes, zones, and time periods. For example, you can use this framework to examine if trust in public transit holds consistent levels across different vehicles, such as buses versus trams, or if it shifts in a predictable way depending on whether the neighbourhood is central or outlying.

Regarding policy impact: breaking down variance into trait-specific, methodological and contextual components creates a solid foundation for developing data-driven solutions. So, if the spatial component (ζ) accounts for more variance in satisfaction planners might decide it makes more sense to pour resources into building new infrastructure in outlying areas instead of modernizing their vehicles.

This matrix specification has several implications for measurement and applied transport research. A key methodological advantage of the proposed specification lies in its ability to isolate passenger perceptions from artefactual environmental effects. In conventional survey-based approaches, observed changes in satisfaction scores are often attributed solely to passengers; however, such variations may also arise from contextual factors, including mode of travel, residential location, or time of day.

Within the MTMM-TP framework, this limitation is explicitly addressed:

- Λ_T ensures the consistency of the latent variables such as comfort, safety and trust.
- Λ_M accounts for method effects, ensuring that differences between online surveys and face-to-face interviews are not confounded with trait-related variation.
- Λ_Θ, Λ_Z and Λ_τ capture contextual heterogeneity and identify systematic effects that may inform targeted policy interventions.

This hierarchical decomposition of variance enhances construct validity and reduces the risk of drawing erroneous inferences regarding passenger perceptions.

3.5. Compatibility with SEM Estimation Methods

The MTMM-TP framework is completely compatible with standard SEM estimation methods. Two main estimation approaches are particularly relevant.

Maximum Likelihood (ML) estimation is appropriate for large-scale surveys with a sufficient number of observations across all contextual categories. Provided that the assumption of multivariate normality is reasonably satisfied, ML yields efficient and consistent parameter estimates, making it suitable for city-wide standardized surveys.

Bayesian estimation offers several advantages within the MTMM-TP framework. In particular, it can accommodate small or unbalanced samples (e.g., when the number of trolleybus users is substantially lower than that of bus users). Moreover, prior information regarding expected contextual effects (e.g., crowding during peak periods) can be explicitly incorporated into the estimation process through the specification of prior distributions.

Posterior distributions are more informative regarding parameter uncertainty and hence are more useful in policy-relevant research.

Both mentioned estimation methods make it possible to extend the model to hierarchical or longitudinal settings, which would provide for future work directions, such as Bayesian hierarchical MTMM-TP to model neighbourhoods nested in districts within a city, or different waves of surveys conducted over multiple years.

3.6 Relation to Classical MTMM

While the classical MTMM's main advantages remain in the MTMM-TP model (i.e. the test of the convergent and discriminant validity is the basic test still), it expands the MTMM matrix beyond the traits and methods by building an additional layer. To summarize:

- Traits (η) still stand for the constructs of interest (comfort, safety, and trust).
- Methods (μ) stand for the measurement procedure (types of surveys, scales used for the response).
- Contextual factors (θ, ζ, τ) represent the specific context of the urban transport environment.

Visually, we can imagine this as a three-dimensional version of the MTMM matrix, instead of a two-dimensional matrix crossing traits with methods, MTMM-TP introduces other dimensions, those representing mode, space and time.

3.7 Practical Application

Consider the case of analysing passenger satisfaction in a moderately sized European city. The urban transport system comprises three modes (bus, tram and trolleybus), two spatial zones (city centre and suburbs) and three time periods (peak, off-peak and evening). Data are assumed to be collected using both online surveys and face-to-face interviews.

Within this setting, three latent passenger traits are specified, namely comfort (η_1), safety (η_2), and trust (η_3), which are incorporated into a structural equation modeling (SEM) framework. Each observed response $y_i$is assumed to be jointly determined by latent traits, method effects, as well as mode, spatial zone and temporal context.

For an individual i, the corresponding SEM specification can be expressed as follows:

$$y_{ijktzm} = \lambda_j \eta_j + \gamma_k \mu_k + \delta_t \theta_t + \alpha_z \zeta_z + \beta_m \tau_m + \epsilon_{ijktzm} \qquad (4)$$

where:
$j \in \{1,2,3\}$ (comfort, safety, trust),
$k \in \{1,2\}$ (online, interview),
$t \in \{1,2,3\}$ (bus, tram, trolleybus),
$z \in \{1,2\}$ (central, peripheral),
$m \in \{1,2,3\}$ (peak, off-peak, evening).
So, for example the same trait (e.g., safety) can be measured across different methods, modes, zones and time intervals.

$$y_{i,\text{safety,interview,tram,peripheral,evening}} = \lambda_2 \eta_2 + \gamma_2 \mu_{\text{interview}} + \delta_2 \theta_{\text{tram}} + \alpha_2 \zeta_{\text{peripheral}} + \beta_3 \tau_{\text{evening}} + \epsilon_i \qquad (5)$$

A classical MTMM framework enables the assessment of whether satisfaction with "comfort" is consistent across online and face-to-face modes (convergent validity) and whether it is empirically distinguishable from satisfaction with other constructs such as "safety" (discriminant validity).

In contrast, the MTMM-TP specification extends this framework by allowing the identification of factors that jointly and simultaneously drive differences in observed ratings. In this context, variation in comfort, safety and punctuality can be decomposed according to multiple sources of systematic influence, including transport mode, neighbourhood, time of day or combinations thereof.

For instance, comfort may be influenced by transport mode (θ), with, on average, higher perceived comfort associated with tram use relative to bus use. Perceptions of safety may be more strongly determined by spatial context (ζ), with central areas typically evaluated as safer than peripheral zones. Punctuality, in turn, may be affected by temporal conditions (τ), with lower perceived punctuality during peak hours compared to off-peak periods. These effects may operate independently or jointly within a unified specification.

In block matrix notation the model can be expressed as follows:

$$Y = \Lambda_T T + \Lambda_M M + \Lambda_\Theta \Theta + \Lambda_Z Z + \Lambda_\tau \tau + E \quad (6)$$

meaning A stacked vector of all measured items. For example, with 3 traits × 2 methods × 3 modes × 2 zones × 3 times = 108 observed responses per individual

$$Y = \begin{bmatrix} y_{1,\text{comfort, online, bus, central, peak}} \\ y_{2,\text{comfort, online, bus, central, off-peak}} \\ . \\ . \\ . \\ y_{108,\text{trust, interview, trolleybus, peripheral, evening}} \end{bmatrix} \quad (7)$$

4. PRACTICAL APPLICATION OF THE MTMM-TP MODEL

4.1 Study Context

Consider, for instance, a mid-sized city in Europe with 250,000 residents, served by an urban public transit network of 110 buses, 15 trolleybuses, and 10 trams. Services run every day from 05:00 am to 11:00 pm. It includes the city centre and the surrounding districts. As far as the temporal factor is concerned, a typical workday is divided into three-time segments: peak hours (7 to 9 a.m., 4 to 6 p.m.), off-peak hours (9 a.m. to 4 p.m.) and evening time (6 to 11 p.m.).

In this model, the following passenger latent variables are assumed: comfort (η_1), safety (η_2), and punctuality (η_3). The questionnaire was distributed among citizens through the internet; on board surveys were also realized to obtain the needed data.

4.2 Sample Design

The sample includes 1,200 respondents, a number thought to be sufficient to obtain statistically representative results but still manageable and not excessive. With a city like the one described, with 250,000 inhabitants, the sample can be roughly obtained with the following classic formula for finite populations:

$$n = \frac{N \cdot z^2 \cdot p(1-p)}{e^2(N-1) + z^2 \cdot p(1-p)} \quad (8)$$

where:
N=250,000 (population size),
z=1.96 (confidence level 95%),
p=0. 5 (maximum variability assumption),
e= 0.03 (margin of error 3%).
Substituting values:

$$n \approx 1{,}067$$

4.3 Simulated Data Illustration

To illustrate, average Likert-scale responses were computed across relevant subgroups, yielding the following mean ratings based on a sample of 1,200 respondents (table 1).

Table 1

Mean rating Likert responses by means of transport

Trait / Mode	Bus	Tram	Trolley
Comfort	3.2	3.8	3.5
Safety	3.0	3.6	3.3
Punctuality	2.8	3.4	3.2

Breaking further by zones and time intervals, results suggest:

- Central zone scores are generally higher (+0.3 points on average),
- Peak hours reduce punctuality perceptions (-0.4 points on average),

- Evening hours reduce safety perceptions (-0.5 points on average).

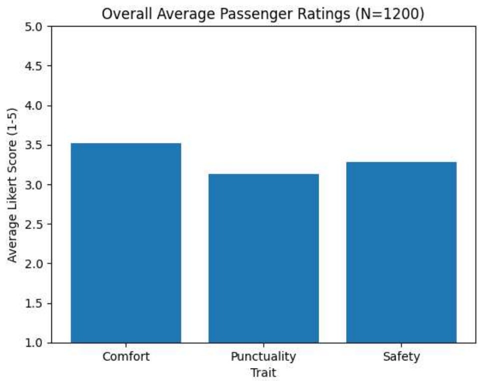

Fig. 1 Passenger ratings - overview

For instance, the expected comfort rating for **bus users in peripheral areas during peak hours** becomes:

$$\widehat{y_{comfort}} = \lambda_{comfort}(3.2) + \alpha_{peripheral}(-0.3) + \beta_{peak}(-0.2) \approx 2.7 \quad (9)$$

while for tram users in central areas during off-peak hours:

$$\widehat{y_{comfort}} = \lambda_{comfort}(3.8) + \alpha_{central}(+0.3) + \beta_{offpeak}(+0.1) \approx 4.2 \quad (10)$$

Table 2

Mean rating comparison by zone

Trait	Zone	mean	std
comfort	central	3.4	0.85
comfort	peripheral	2.9	0.84
punctuality	central	3.3	0.85
punctuality	peripheral	3.0	0.85
safety	central	3.8	0.85
safety	peripheral	2.8	0.84

Table 2 indicates that, across all variables, systematic differences are observed between the two zones, with higher scores consistently recorded in the central area. In particular, the variable Safety exhibits the most pronounced disparity, with an approximately one-point difference on a five-point Likert scale. This finding is of particular relevance from a public transport management perspective, as it suggests substantial spatial heterogeneity in perceived safety conditions.

More specifically, the observed pattern may reflect differences in the provision and effectiveness of safety-related measures (e.g., lighting, surveillance systems, and police presence), which are likely to be more developed and reliable in central areas. Alternatively, lower safety perceptions in peripheral zones may be associated with higher exposure to crime or with infrastructural deficiencies. A further plausible explanation relates to differences in the type of transport vehicles predominantly operating across zones.

The Comfort variable also shows a notable, albeit smaller, difference between central and peripheral areas. This pattern may be attributed to variations in vehicle modernity, differences in maintenance levels, and disparities in service frequency, all of which may contribute to more favourable comfort perceptions in the central zone.

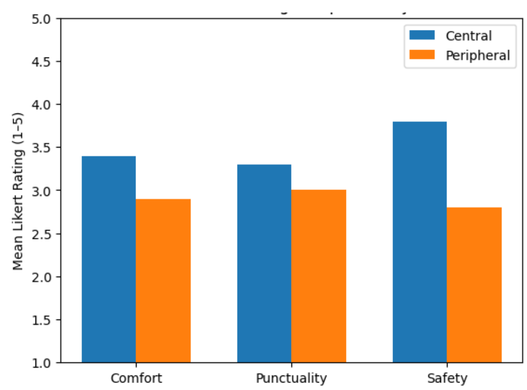

Fig. 2 Mean rating comparison by zone

Finally, on the punctuality issue, there is a smaller difference, but the perception is worse for periphery users, due to traffic, or to a worse service frequency of public transport. For this area, service should be increased to increase punctuality, and the public may perceive the improvement.

Finally, the standard deviation values reported in Table 2 are highly similar across all variables, ranging approximately from 0.84 to 0.85. This limited dispersion indicates the absence of substantial differences in variability between constructs. Accordingly, the results suggest that the observed spatial differences are not driven by heterogeneity of responses within zones, but rather by systematic differences in mean ratings. In other words, variability remains stable across zones, whereas average evaluations are consistently lower in the peripheral area.

Turning to the results by attribute presented in Table 3, pronounced differences are observed across temporal periods (peak, off-peak, and evening). The Comfort variable displays substantial variation over time: the lowest average score is recorded during peak hours (2.5), the highest during off-peak periods (4.0), while evening hours occupy an intermediate position (3.5). The resulting peak-to-off-peak difference of 1.5 Likert points represents a substantial operational disparity with clear practical implications.

Overall, these patterns suggest that comfort is strongly demand-sensitive, likely reflecting conditions such as overcrowding, limited seating availability, and increased noise and stress levels during peak periods. Consequently, perceived comfort appears to be closely linked to system load conditions.

A similar temporal pattern is observed for Punctuality, which deteriorates during peak hours and reaches its highest levels in the evening (4.0).

Table 3

Mean rating comparison by time

Trait	Time	mean	std
comfort	evening	3.5	0.84
comfort	offpeak	4.0	0.84
comfort	peak	2.5	0.84
punctuality	evening	4.0	0.84
punctuality	offpeak	3.8	0.84
punctuality	peak	3.0	0.85
safety	evening	2.8	0.84
safety	offpeak	3.5	0.85
safety	peak	3.8	0.85

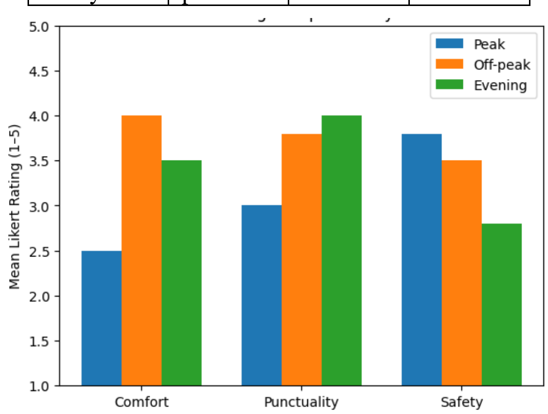

Fig. 3 Mean rating comparison by time

The 1.0 Likert point peak-to-evening gap suggests either intense peak hour traffic conditions or perhaps a rush hour effect whereby the schedule is compressed, or signals and other interruptions cause delays. In contrast, safety scores higher in the peak (3.8) than in the evening (2.8).

The high peak-to-evening gap of 1.0 Likert point is almost certainly due to greater passenger density in peak periods, which provides a sense of security during travel. Passengers may feel more vulnerable at night when travelling in dimly lit stations and/or buses with only a few other passengers. Overall, these results indicate a clear contextual influence on the evaluated attributes.

The observed differences in mean scores do not appear to be solely driven by latent trait variation; accordingly, the incorporation of contextual latent factors within the MTMM framework is warranted. Failure to account for the MTMM-based decomposition of variance may lead to an over-attribution of observed differences between modes, locations, or temporal conditions (e.g., peak versus off-peak) to service quality alone, rather than to underlying contextual heterogeneity.

4.4 Methodological Implications

The MTMM-TP model provides a powerful new tool to explore these issues and to inform policy:

- variance decomposition - the MTMM-TP model breaks down the observed variance into the components: true latent trait variance (η) measurement error (μ) and contextual effects (θ, ζ, τ).
- policy recommendations - the MTMM-TP model is able to highlight in what contexts problems with each attribute are likely to occur. In this example, the problems with punctuality occur most severely with peripheral bus service in peak hours. This is a useful finding that may guide policy in such as establishing bus priority lanes in peak hours, introducing additional buses, or adjusting the timetables to account for delays during peak periods.
- statistical power - with 1200 observations, there should be sufficient statistical power to enable a range of subgroup analyses, e.g.

tram services in a district centre vs peripheral service in peak vs off-peak.

5. FUTURE EXTENSIONS

The MTMM-TP model can provide a useful foundation for future research:

- Multi-level extensions - spatial zones can themselves be hierarchical (e.g. neighbourhoods within districts) and the temporal dimension could be explored in different ways (e.g. at hourly, daily or seasonal levels).
- Dynamic MTMM-TP - it is possible to incorporate longitudinal data in the MTMM framework to explore the evolution of the trait and contextual effects over time (e.g. before and after a major investment in transport infrastructure) [9].
- Integration with IRT and Bayesian estimation - IRT is widely applied to estimate latent traits. It could be applied within the MTMM framework to estimate the latent dimensions of perceived quality of service. In addition, the model could also be estimated within a Bayesian framework, thus allowing one to explore the sensitivity of the model to misspecification and to the incorporation of prior information. It should also allow the model to be estimated on smaller samples and/or with more missing data [11].

In sum, the MTMM-TP model is a notable development in public transport service quality research that represents a significant methodological contribution. By explicitly considering the modal, spatial and temporal components of public transport within a latent variable model, the MTMM-TP model allows for a more nuanced understanding of latent traits in public transport research. Moreover, by allowing for the analysis of contextual and latent effects, the MTMM-TP model provides a more robust means of evaluating passenger satisfaction with public transport in ways that may yield more actionable results to the public transport operator. In this way, the MTMM-TP model represents an important advancement in the field of latent variable modelling.

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O extensie a matricii multi-trait-multi-metodă pentru analiza transportului public urban

Abstract: Lucrarea prezintă cadrul de evaluare MTMM-TP, un model multi-trăsături-multi-metodă conceput special ca o completare structurală a sistemului de transport public. În forma sa matricială, acest model conectează factorii socio-economici, evaluarea percepțiilor utilizatorilor și caracteristicile urbane cu variabilele ofertei de transport, cum ar fi modurile de transport, frecvența serviciilor și capacitățile de transport. Pe baza unui set de ecuații, răspunsurile sunt descrise ca un cumul de trăsături, metode de evaluare, moduri de transport, efecte spațiale, temporale și erori, ponderate de matricele de încărcare respective. Astfel, cadrul MTMM-TP oferă un instrument pentru analiza percepțiilor utilizatorilor, permițând o evaluare precisă a nivelului de calitate și siguranță a serviciilor. Prin implementarea modelului SEM, acesta oferă o bază științifică pentru procesele de analiză și luare a deciziilor în transportul public.

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