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Agent based modeling and simulation approach to identify and classify the key influential factors for satisfaction of public transport users

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ABSTRACT

The issue of mobility from disadvantaged areas to places of interest for work, health care, education, or entertainment poses specific challenges that cannot be approached under the same prism as that of well-resourced areas. In such areas, commuters are often captive of available transportation modes. However, very few studies have focused on identifying the key factors that influence the satisfaction of these commuters. In this paper, we introduce an agent based modeling and simulation approach, to identify and classify these factors. We show, for the case study of a township in South Africa, that speed and quality of the infrastructure are crucial factors, while waiting time and accessibility are to be improved; safety and travel time being to be watched. Then recommendations are provided to improve the service according to these factors.

KEYWORDS

Agent based modeling and simulation; Public transportation; Disadvantaged areas; Satisfaction.

1. Introduction

Although population diversity and social cohesion are key to sustainable urban development, cities often face segregation and inequality, which can weaken the social fabric and significantly affect the economic, social, and health outcomes of residents (Moro, Calacci, Dong, & Pentland, 2021). According to some scholars, access to mobility is differentiated according to social groups and in particular according to income levels (Olvera, Mignot, & Paulo, 2004). Regardless of a possible accumulation of social handicaps, poverty in economic resources has specific effects on daily mobility. Income or lack thereof influences household transportation decisions and the ways in which individuals travel. Low-income households are less likely to own cars and are more likely to travel by other modes than the automobile (Blumenberg & Pierce, 2012).

Low-income people in developing countries have been argued to often live in the peripheries, trading higher transport costs for cheaper, often illegal housing; contrary to the conventional theory of residential location based on a first-world perspective (Waldeck, Holloway, & Van Heerden, 2020).

Related to income, Carvalho and El-Geneidy (2024) stated that: (i) low-income populations have been found to experience low satisfaction levels with transit services, which can be attributed to the use of transit due to a lack of travel options and not due to preference; (ii) those who take transit out of choice show higher levels of satisfaction.

Satisfaction can be defined as a psychological state that reflects the evaluation of the relationship between customer expectations and service delivery. The key notion is that individuals evaluate choice alternatives by comparing experienced attributes against a set of reference points, defining their expectations. Commuters who perceive the good quality of a public transport service are more likely to have a higher degree of satisfaction and continue to use the service (Gao, Rasouli, Timmermans, & Wang, 2018).

Service quality in public transportation depends on various attributes including accessibility, comfort, fares, frequency of service, information, reliability, speed, safety within the vehicle, the time taken to cover the routes and the convenience and existence of any supporting infrastructure (Dell’Olio, Ibeas, & Cecin, 2011). Studies carried out during or after the COVID-19 pandemic show that occasional users report lower satisfaction levels compared to frequent users and tend to be more concerned with the safety and reliability of transit services (Hsieh, 2023). In Rifai and Hastuti (2023), importance of safety and security of commuters during the trip, as well as accessibility to transport modes, was highlighted. Ismael, Esztergár-Kiss, and Duleba (2023) focused on a comparative analysis of private vehicle and public transport users’ perceptions on service quality and showed the proximity, the frequency, and the service hour attributes are essential and were executed well during the pandemic. In contrast, cleanliness and temperature were not important forecasters of the public transport and private vehicle users’ satisfaction.

In disadvantaged areas, commuters often have no alternative, regardless of the quality of the available public transportation. They are effectively dependent on existing transit options. As a result, solutions that work in other contexts may prove ineffective if they fail to consider the unique sociological and economic characteristics of these areas. Therefore, it is essential to develop a model that specifically captures passenger satisfaction within this societal context. Such a model would enable the exploration of "what-if" scenarios, allowing for an assessment of the impact of service improvement or deterioration.

Various satisfaction models have been developed in the literature for the general context. They are based on Structural Equation Model (SEM), factor and regression analysis, logistic regression, etc. (see (van Lierop, Badami, & El-Geneidy, 2018) for a review). However, they are not designed for what-if type questions. Furthermore, these models do not explicitly consider consumers’ heterogeneity and the complex dynamics of social processes that shape the satisfaction and can therefore tackle only a limited set of theoretical issues (Appiah et al., 2021).

In this paper, we adopt an agent-based modeling and simulation (ABMS) approach. It can be used to model complex emergent phenomena such as satisfaction with an innovation or dissatisfaction with an altered service. In agent-based satisfaction models, the atomic model element is not the social system as a whole, but the individual consumer or agent. Consumers’ heterogeneity, their social interactions and their decision making processes can be modelled explicitly (Appiah et al., 2021). The use of ABMS

is still in its infancy for customer satisfaction; very few works have been carried out for transportation systems (Dugundji & Gulyás, 2012). However, it is worth noting that agent-based modeling can be applied to any aspect of a phenomenon (Bell & Mgbemena, 2018) and has found applications in various domains including economics (Farmer & Foley, 2009), ecology (Foramitti, 2023), healthcare (Murakami & Tanida, 2014), epidemiology (Perez & Dragicevic, 2009), and marketing (Torrens, 2023), to cite a few. By considering an ABMS approach, our aim is: (i) to identify the *key factors* of satisfaction, i.e. attributes for which an improvement or an alteration in the provided service could significantly increase or decrease the proportion of satisfied users; (ii) to classify these factors in order to inform decision and policy makers about priorities.

The paper is organized as followed. In Section 2, some related papers are reviewed and the paper’s contribution with regards to the existing literature is stated. Section 3 concerns the methodology. It contains a new result on a analytical way to identify the key influential factors influencing the perceived satisfaction of the commuters. In Section 4, the study area and the data collection process are described. And then results are presented and analyzed. Finally a discussion and policy implications are provided in Section 5 before concluding the paper.

2. Related works

2.1. Perceived satisfaction

Studies on public transport users satisfaction are based on questionnaires where some system attributes are evaluated. Based on descriptive and inferential statistics, and depending on the context of the study, different results have been reported in the literature. For example, several studies found attributes related to time (service frequency, speed, on-time performance) as the most important (Mouwen, 2015; Wan, Kamga, Hao, Sugiura, & Beaton, 2016) while other works argued that lower fares, followed by speed, would make significant contributions to enhance customer perceptions of public transport service quality (Redman, Friman, Gärling, & Hartig, 2013). Both time and fare levels are actually vital in influencing customer satisfaction with public transport.

Safety is also an attribute of great interest. Prior to the emergence of the COVID-19 pandemic, assessments of safety on public transport did not account for the risk of disease spread and was restricted to crime and accidents. Post-COVID-19 pandemic studies point out that passengers’ feelings of safety enhanced their overall satisfaction with regard to public transport (Dong, Ma, Jia, & Tian, 2021; Zarabi, Waygood, & Schwanen, 2024). An extensive literature review on service quality during COVID-19 can be found in Ismael et al. (2023).

However, it has also been shown that satisfaction is a complex phenomenon that can emerge from contradictory combination of separate attributes (Sukhov, Lattman, Olsson, & Friman, 2021).

Actually, user’s perception towards service quality of public transport and therefore satisfaction is also influenced by socioeconomic factors such as age, gender, education, disability, and income. For instance, in developed countries, it was shown that the elderly and higher-educated male commuters with high income are more satisfied with their trips compared to their other counterparts (Lancée, Veenhoven, & Burger, 2017). Contrariwise, it was argued in (Carrel, Mishalani, Sengupta, & Walker, 2016) that gender is not significantly related to satisfaction, while other studies reported significant effects for gender. For example, (Higgins, Sweet, & Kanaroglou, 2018) found that men

were more likely to be very satisfied with their commutes compared to women.

Although not widely investigated in the transport field, culture (learned customs, values, and beliefs) also generates a bias in the perception of service quality. For example, (Nahiduzzaman et al., 2021) shows how socio-cultural stigma affects public transportation usage and satisfaction in Saudi-Arabia.

As stated by recent critical literature reviews (Kalaoane et al., 2024; Majumdar, Jayakumar, Sahu, & Potoglou, 2021), research on quality of service and satisfaction in transportation system is well researched in developed countries while very few studies have been carried out in developing countries. The travel behavior being different from developed to developing countries, results obtained in developed countries may not be directly transferred to developing countries and vice versa. Mobility challenges of the developing nations are significantly different than in wealthier nations (Cervero & Dai, 2014; Walters, 2013). For instance, in global south where people resort mainly to informal transportation modes, it was shown that availability of public transport is a major factor as compared to affordability in determining patronage of various public transport modes (Adom-Asamoah, Asibey, & Nyarko, 2021). The perception of low quality service is increased with lack of comfort, crowding, poor infrastructure, and reckless driving (Olowosegun, Moyo, & Gopinath, 2021). In South Africa, most studies have focused on customer satisfaction with a specific focus on bus service punctuality, reliability, availability, driving quality, safety, vehicle quality, contract compliance and revenue protection (Cele, Kibangou, & Musakwa, 2024, 2025; Chinomona, Mofokeng, & Poee, 2013; Mokonyama & Venter, 2018). These works don't really focus on customer satisfaction on ride hailing or minibus taxi, which are the main transportation modes for people living in disadvantaged areas. The work in (Radder & Han, 2011) concerns expectations of minibus taxi commuters not satisfaction.

2.2. Measuring satisfaction and identifying the most important explanatory variables

Satisfaction is typically measured as a function of selected explanatory variables, with the form of the model generally determined through empirical analysis. The first family of models includes linear regressions between satisfaction and explanatory variables (de Oña, de Oña, Forciniti, & Mazzulla, 2016; De Vos, Mokhtarian, Schwanen, Van Acker, & Witlox, 2016; Wan et al., 2016). The second family concerns nonlinear models like binary logistic regression and ordered logit (Cats, Abenoza, Liu, & Susilo, 2015; Mahmoud & Hine, 2016; Yang, Zhao, Wang, Liu, & Li, 2015). Identifying the most important variables, both in terms of inclusion in the model and their contribution to predictions, is crucial from both theoretical and practical perspectives. Since larger coefficients do not necessarily indicate greater predictive importance, standardized regression coefficients or changes in R-squared are often used to assess variable significance. For linear regression models, Braun and Oswald (2011) reviewed various techniques for determining relative importance, including the proportional contribution of each attribute to the model. However, regression weights become harder to interpret when predictor variables are correlated. To address such challenges, machine learning models, particularly Random Forest, have been used for feature selection (Ruiz, Yushimito, Aburto, & de la Cruz, 2024). Random Forest determines variable importance by constructing multiple decision trees and evaluating how much each feature reduces impurity (e.g., Gini impurity or entropy). Features that contribute more to splitting data and improving predictive accuracy receive higher importance scores.

This is quantified using measures such as Mean Decrease in Impurity (MDI) or Mean Decrease in Accuracy (MDA), the latter assessing the impact of permuted feature values on model performance. By ranking features based on their importance, Random Forest helps interpret the model and reduce dimensionality, especially in complex, high-dimensional datasets. However, statistical measures of relative importance alone cannot determine whether a variable is practically meaningful. Moreover, all these models are inherently static and do not capture the dynamic nature of satisfaction. A recent study addressed this issue but did not specifically focus on the key factors of satisfaction (Kibangou & Kalaoane, 2024).

2.3. Contribution

Understanding the practical importance of attributes in public transport satisfaction requires domain expertise. In this paper, we adopt the following definition:

Definition 2.1. An attribute is considered a key factor if its future improvement or deterioration leads to a significant change in the overall satisfaction rate.

While classical statistical analyses often define key factors based solely on their correlation or regression coefficients, our approach goes beyond static associations. Traditional models typically identify important attributes by evaluating their current contribution to satisfaction using predefined statistical thresholds (e.g., p-values, beta coefficients). However, these methods do not capture how future variations in an attribute might affect satisfaction, nor do they provide actionable guidelines on whether a factor should be prioritized for improvement or monitoring. The main contribution of this paper is methodological: we introduce an Agent-Based Modeling and Simulation (ABMS) approach to identify key factors influencing commuter satisfaction. Unlike traditional statistical methods, our approach enables a dynamic and context-sensitive assessment of factors impacting user experience. Beyond identification, we propose a classification framework to better interpret these key factors:

Definition 2.2. A key factor is categorized as

- crucial - if both future improvement and deterioration leads to a significant change in the overall satisfaction rate;
- to be improved - if only its improvement leads to a significant increase in the overall satisfaction rate;
- to be watched - if only its deterioration leads to a significant decrease in the overall satisfaction rate.
- neutral- if changes (positive or negative) do not significantly affect satisfaction.

This classification moves beyond conventional statistical approaches, as it provides a forward-looking perspective that helps decision-makers prioritize interventions based on potential future impacts, rather than just retrospective significance.

As an application, the second key contribution of this study is its focus on captive users in a disadvantaged area, a group often overlooked in public transport satisfaction studies. While few works in the literature have examined public transport user satisfaction in developing countries, they do not specifically address the experiences of captive users—those who have no alternative but to rely on public transport. By filling this gap, our study provides new insights into the specific needs and vulnerabilities of these users, informing targeted policy recommendations.

3. Agent based modeling and simulation approach

Agent-based models allow studying how system-level properties emerge from the adaptive behavior of individuals and conversely how systems affect those individuals (Bell & Mgbemena, 2018). Within this framework, a complex system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation, makes decisions and possibly executes actions on the basis of a set of rules. Repetitive competitive interactions between agents are a feature of agent-based modeling, which relies on the power of computers to explore dynamics out of the reach of pure mathematical methods (Axelrod, 1997; Bonabeau, 2002). At the simplest level, an agent-based model consists of a system of agents and the relationships between them. Even a simple agent-based model can exhibit complex behavior patterns and provide valuable information about the dynamics of the real-world system that it emulates (Bonabeau, 2002). Hereafter, we design an agent based model in order to identify and classify the key attributes affecting the commuters satisfaction. Given the current evaluation of the transportation system by the commuters, the agent-based model is designed here to answer the question *how would the satisfaction rate evolve among the commuters if a given attribute is upgraded or downgraded?* Then attributes will be classified according to their impact on the overall satisfaction. According to definition 2.2, the classification will be illustrated as in Fig. 1. This representation can be related to the Kano model (Kano, Seraku, Takahashi, & Tsuji, 1984) and the Importance-Performance Matrix (e.g., Ismael et al. (2023)), but differs in that the former link satisfaction to expectations and importance to performance, whereas our proposed model connects satisfaction to the effects of overall service improvement and degradation.

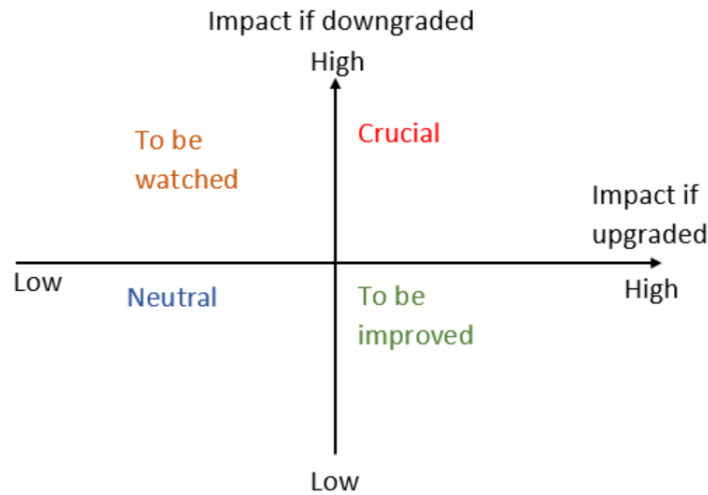


Figure 1. Classification of attributes

3.1. Model:

Commuters interact each others and with the service provider about improvement or deterioration of a given service. Interactions among commuters also influence customer perception on the service. In the proposed approach, commuters

are modelled as agents. They can take decisions and interact each other. Therefore, for I evaluated attributes, each agent a is characterized by a state vector $\mathbf{x}_a(t) = (x_{a1}(t), x_{a2}(t), \dots, x_{ak}(t), \dots, x_{aI}(t))^T \in \mathfrak{R}^I$ (its perception on the I evaluated attributes of the system) and a decision rule (a function allowing to decide about its overall satisfaction about the transportation system)

$$\sigma_a(t) = g(\mathbf{x}_a(t), \boldsymbol{\theta}_a) \quad (1)$$

where $\boldsymbol{\theta}_a$ allows customizing the decision rule of agent a . A Heaviside step function, a sigmoid or a hyperbolic tangent can be used as function $g(\cdot)$ for the decision rule. Considering, a binary decision (satisfied or dissatisfied), the satisfaction rate of a population of N agents can be computed as:

$$\rho(t) = \frac{100}{N} \sum_{a=1}^N \sigma_a(t). \quad (2)$$

We are interested with knowing $\rho_k(t+1)$, $k = 1, 2, \dots, I$, if the k th attribute of the transportation system is upgraded or downgraded. We assume that some agents form their own opinions of the service, while others are in addition influenced by their neighbors. For this purpose, we define two types of agents: leaders and followers grouped in two disjoint sets \mathcal{L} , the set of leaders, and \mathcal{F} , the set of followers, respectively. We also denote by \mathcal{N}_a the set of the neighbors of an agent a .

The perception of a leader ℓ is only based on the actions of the service provider and its own initial perception about the service:

$$\mathbf{x}_\ell(t+1) = \mathbf{x}_\ell(t) + \alpha_{\ell,k} \mathbf{e}_k, \quad \ell \in \mathcal{L} \quad (3)$$

where \mathbf{e}_k stands for the k th vector of the natural basis of \mathfrak{R}^I ; $\alpha_{\ell,k}$ being a random variable from a given distribution. If the service on the considered attribute has been upgraded then $0 \leq \alpha_{\ell,k} \leq \bar{A}$ while $\underline{A} \leq \alpha_{\ell,k} \leq 0$ if the service has been downgraded. \bar{A} and \underline{A} being some specified bounds. In other words, in case of service upgrade, a leader can maintain its evaluation on the service or increase it up to \bar{A} . In case of service downgrade, it can still maintain its evaluation or lower it up to \underline{A} .

For a follower f , it first updates its own perception then its final opinion is influenced by its neighbors as modelled with equations (4) and (5):

$$\mathbf{y}_f(t+1) = \mathbf{x}_f(t) + \alpha_{f,k} \mathbf{e}_k, \quad (4)$$

$$\mathbf{x}_f(t+1) = h_f(\mathbf{y}_i(t+1), \mathbf{x}_\ell(t+1)), \quad f \in \mathcal{F}, \quad i \in \mathcal{N}_f \cup \{f\}, \quad \ell \in \mathcal{L} \cap \mathcal{N}_f \quad (5)$$

where $h_f(\cdot)$ can be any opinion dynamic model (majority vote, local consensus, averaging, etc.) (Sîrbu, Loreto, Servedio, & Tria, 2017). Finally, each agent can take a decision $\sigma_a(t+1)$ according to (7) and then

$$\rho_k(t+1) = \frac{100}{N} \sum_{a=1}^N \sigma_a(t+1).$$

3.2. Emerging behavior by simulation:

Selection of leaders, followers, neighbors of followers and leaders perception of the service upgrade or downgrade are randomized. Monte Carlo simulations are carried out. For a given percentage p_L of leaders and size S_F of \mathcal{N}_f , M Monte Carlo runs are realized. We can compute the median value of the satisfaction rate increment $\Delta\rho_k = \rho_k(t+1) - \rho_k(t)$. Let us denote by $\Delta\rho_k(p_L, S_F)$ the median value of the satisfaction rate increment for a percentage p_L of leaders and a neighborhood size S_F and by τ a threshold characterizing the significance of the satisfaction rate increment. We can therefore compute the empirical probability $\mathbb{P}(\Delta\rho_k(p_L, S_F) \geq \tau)$ to be above the threshold τ ; the higher the probability, the more crucial the considered attribute. Repeating the process for each attribute, one can get a full characterization of the attributes not only telling how important they are but also classifying them in terms of importance of required actions from the decision maker.

3.3. Selection of a decision rule:

A crucial issue with an agent based model is related to the decision rule. What makes a commuter satisfied or dissatisfied? Logistic regression can be used to answer this question. We will evaluate it and then show its limitations to answer the what-if question. Precisely, what will be the satisfaction level if a service is upgraded or downgraded?

3.3.1. Logistic regression

Let p be the probability to be satisfied. The principle of logistic regression is to model $\ln\left(\frac{p}{1-p}\right)$ as a linear combination of scores given to attributes:

$$\ln\left(\frac{p}{1-p}\right) = w_0 + \sum_{l=1}^9 w_l x_l \quad (6)$$

the constant coefficient w_0 being called intercept. A maximum likelihood estimator (MLE) is generally used to estimate the parameters w_i . In this study, the Matlab classification learner App was used to estimate the model. We resorted to a k -fold cross-validation approach where the training set is split into k smaller sets. For each of the k “folds”: (i) a model is trained using $k - 1$ of the folds as training data; (ii) the resulting model is validated on the remaining part of the data (i.e., it is used as a test set to compute a performance measure such as accuracy). The performance measure reported by k -fold cross-validation is then the average of the values computed in the loop. In the considered binary classification scheme, being satisfied is the positive case while being dissatisfied is the negative case. From the definitions in Tab. 1, a confusion matrix can be built up for evaluating the performance of the classification method.

3.3.2. High score frequency based decision rule:

The principle here is to counts for the frequency of high scores. For an agent a , a score $x_{ak}(t)$ on the k th attribute is high if it exceeds a given threshold τ_a . Therefore the frequency of high score of this agent is given by $\frac{H(x_{ak}(t) - \tau_a)}{I}$ where $H(\cdot)$ stands for the Heaviside step function¹. This agent will be satisfied if the frequency of high score

¹ $H(x) = 1$ if $x \geq 0$ and $H(x) = 0$ if $x < 0$

Table 1. Notations.

Name	Definition
True positive rate (TPR)	$TPR = \frac{TP}{TP+FN}$
True negative rate (TNR)	$TNR = \frac{TN}{TN+FP}$
False positive rate (FPR)	$FPR = \frac{FP}{TN+FP}$
False negative rate (FNR)	$FNR = \frac{FN}{TP+FN}$
True Positive (TP)	Values that are actually positive and predicted positive.
False Positive (FP)	Values that are actually negative but predicted to positive.
False Negative (FN)	Values that are actually positive but predicted to negative.
True Negative (TN)	Values that are actually negative and predicted to negative.

exceeds a threshold $\tilde{\tau}_a$. The decision rule is then given by

$$\sigma_a(t) = H \left(\frac{\sum_{k=1}^I H(x_{ak}(t) - \tau_a)}{I} - \tilde{\tau}_a \right). \quad (7)$$

4. Case study

The study considers a township named KwaDabeka Ward 20. A disadvantaged area located 25 kilometers west of the Durban's Central Business District (CBD), in the KwaZulu Natal Province of South Africa (see Fig. 2). This township has a population

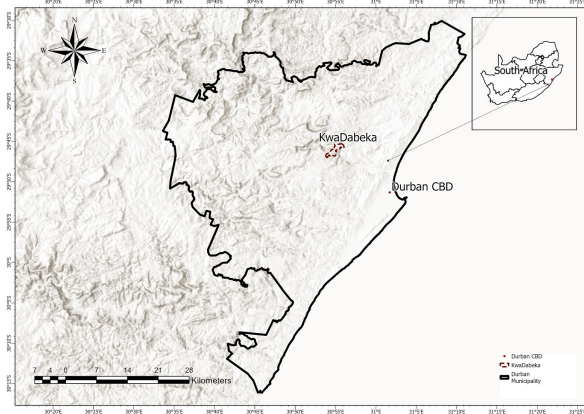


Figure 2. Study area

of 28,853 constituting 7,364 households. It is mostly inhabited by Blacks, unemployed, and low income earners with basic education. The average annual household is ZAR 30,000 (\approx US \$1,600) while nationwide it is ZAR 119,542 (\approx US 6,538). In addition, 20% of the population is unemployed. KwaDabeka was developed as a result of upgrading informal settlement that were located on public land (Deyi, Van Zyl, & Shepherd, 2014). Thus it has hostels, in-situ upgrades, informal settlements and suburban layouts. The area is mostly residential with little economic or industrial activity.

Given the socioeconomic background of the area, it is necessary to travel to Durban CBD and other places of interest for work, health, education, and entertainment. This can be done using minibus taxi, bus, and ride hailing services. However, the township

is dominated by the minibus taxi industry. This has proven to be one of the greatest challenges in public transportation in KwaDabeka. There are regulations in-place but the minibus taxi industry hardly adheres to these regulations. The public transport system in the area has been monopolized by the minibus taxi industry for decades. The minibus taxi operators halted the operations of municipal buses in the area and ceased the Go Durban integrated rapid public transport project.

Government has tried for many years to negotiate with the minibus taxi industry. To find a solution and a way forward but has proved to be unsuccessful. Also, the minibus taxi industry has halted the operations of ride hailing, on-demand services, such as Uber and Bolt. On-demand drivers operating under Uber and Bolt do so at their own risk. Instead, the minibus industry has introduced their own on-demand service company. However, the transport fees are doubled compared to Uber and Bolt.

4.1. Data

The data collection process was achieved in three stages: questionnaire design, respondent recruitment, and survey implementation. The questionnaire, designed after reviewing the past studies, covered several aspects of the transport users and their satisfaction. Precisely, 9 attributes of the transportation system were evaluated (see Tab. 2) with a score between 1 and 10, where 10 represents the highest level of satisfaction (see the questionnaire in Fig. A1). Data was collected over a period of two months (30

Table 2. Evaluated attributes.

Name	Definition
Politeness	Friendly attitude towards commuters (e.g. greetings, respect,...).
Safety	Crime level or violence at stations or during transit.
Travel time	Time during transit from origin to destination.
Waiting time	Time spent before departure.
Speed	Driving in high speed.
Driving style	Compliance to road traffic regulation, following the demarcated route.
Affordability	Level of fares.
Accessibility	Space and time coverage.
Quality of Infrastructure	State of roads and shelters (bus stops, taxi ranks,...).

September to 2 December 2022). Participants provided written informed consent. The study did not include minors but only adults aged 18-65 years. Two rounds of data collection, 120 respondents each making a total of 240 respondents, were achieved. The sample size was found to be adequate (> 194) for a population of 19,042 at a 95% confidence level, 7% margin error, and worst-case percentage of 50% (Sudman, 1976). The sample was randomly selected from a population that uniquely used public transportation to access places of employment, and other services such as health care and shopping centres. A clear target was to equally distribute the sample between males and females. The socio-demographic information of the respondents is given in Tab. 3. Pen-and-Pencil Interview (PAPI)/Face to face interview was used for the sur-

Table 3. Demographics information

Total number of respondents: 240		
Gender	Male	50%
	Female	50%
Age	Under 25	22%
	26-33	28%
	34-41	29%
	Above 41	21%

vey purpose. The researcher explained the purpose of the study and the definitions of the considered attributes to each respondent. Then she asked how satisfied they were with a given attribute; satisfaction being ranked from 1 to 10, with 1 being the lowest value. Finally an overall score were asked as an evaluation of the whole transportation system. Evaluation was carried out for different transportation modes. The researcher made sure the questions were really understood by using the local language if necessary. The ethical clearance numbered UJ-FEBE-FEPC-00290 was obtained from the Faculty of Engineering and the Built Environment, Ethics committee at University of Johannesburg.

4.2. Results

In this section, we will consider two scenarios: service upgrade and service downgrade. We evaluate the effect of upgrade and downgrade on each attribute separately, since we want to identify the attribute having significant effects on commuters satisfaction. We first study the decision rule issue before tackling identification and classification of key factors. For this purpose, we first consider a random forest approach before applying the proposed ABMS approach.

4.2.1. Decision rule:

Using Matlab and its classification learner App, we selected a logistic regression model that gives very good results. Precisely, the model with the following parameters was obtained (see Tab. 4):

Table 4. Parameters of the Logistic regression model

	Estimate	SE	tStat	p-value
Intercept	-16.725	3.426	-4.881	1.0×10^{-6}
Travel Time	0.786	0.213	3.687	2.3×10^{-4}
Speed	0.882	0.221	3.996	6.5×10^{-5}
Affordability	0.351	0.149	2.363	1.8×10^{-2}
Accessibility	0.303	0.153	1.976	4.8×10^{-2}
Quality of Infrastructure	0.369	0.171	2.154	3.1×10^{-2}

As it can be seen in Table 5, good classification results are obtained with the learned logistic regression model.

Table 5. Classification results of the learned logistic regression model

TPR	TNR	FPR	FNR
91.2%	91.3%	8.8%	8.7%

Given this model, any change in the other parameters (politeness, safety, waiting time, driving style) would not change the probability to be satisfied. For instant, consider an agent a with state vector $\mathbf{x}_a = (10, 7, 6, 8, 1, 7, 1, 1, 5)^T$. Applying the obtained logistic model it gets a probability $p = 1.79 \times 10^{-4}$ to be satisfied; this agent is classified as dissatisfied. This is because its satisfaction for speed, affordability and accessibility are very low (equal to 1). Assume now that the service, according to quality of infrastructure, is upgraded and this agent increases his opinion on quality of infrastructure by one unit (from 5 to 6). From the learned model, the probability of satisfaction p increases only to $p = 2.6 \times 10^{-4}$. If quality of infrastructure is something

that matters more than travel time or speed, this upgrade would make the agent become satisfied. The logistic regression model doesn't allow to capture the evolution in satisfaction changes of the agents. A new model is to be learned. It is worth noting that an agent a with scores $\mathbf{x}_a = (2, 7, 3, 5, 3, 3, 3, 3, 4, 4)^T$ has less probability to be satisfied than b whose attribute scores are $\mathbf{x}_b = (1, 7, 8, 4, 4, 8, 8, 9, 10, 10)^T$. Obviously different models could be adopted, by weighting the scores according to the importance given by the respondent to each attribute. Since this information is not available and cannot be inferred from the available data, we restrict our study to a high score frequency based decision rule (see Eq. 7). To validate this model, we compare the histogram of satisfied-dissatisfied in Fig. 3. By considering the same thresholds $\tau_i = \tau$ and $\tilde{\tau}_i = \tilde{\tau}$ for all the agents, through trial and error, we found that $\tau = 6$ and $\tilde{\tau} = 0.56$ allows getting the best match between the histogram from collected data and the one from the model. The absolute error being 1.22%. The model overestimate of 1.22% the proportion of dissatisfied people, which is not significant. The model can therefore give a good macroscopic view of satisfaction, which is what we want to characterize. In addition, it is well adapted to answer what-if question.

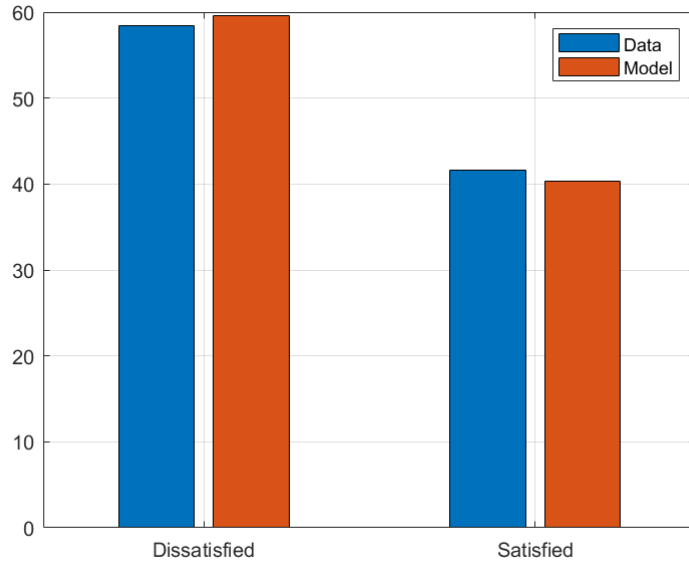


Figure 3. Satisfied-Dissatisfied histogram

4.2.2. Identification and classification of key factors

4.2.2.1. Random forest approach. Using Matlab, we carried out an analysis using random forest, based on the following steps: (i) randomly separate data in training and validation sets (2/3 for training 1/3 for validation); (ii) train the model; (iii) validate the model; (iv) if the validation accuracy is above 90% the importance score of each feature is computed. This process was repeated 500 times. Fig. 4 presents the statistical distribution of the computed importance score. One can note that speed, travel time, accessibility have a median importance score higher than 0.5. According to this approach, they constitute the key factors. Politeness and affordability are the least important.

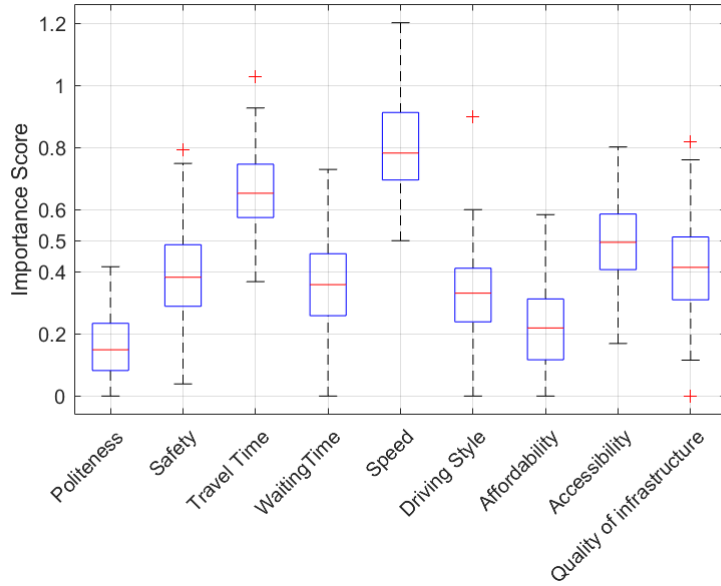


Figure 4. Importance score distribution using Random Forest.

4.2.2.2. Proposed agent based modeling and simulation approach. To run the ABMS approach described in Section 3, the number of agents is set equal to the number of respondents to the survey. The state $x_a(t)$ of each agent at instant t is set equal to the scores given by the corresponding respondent to each evaluated attribute. To compute $x_a(t+1)$, according to (3) or (4)-(5), the score increment $\alpha_{a,k}$ is randomly chosen as an integer in the set $[0; 4]$ (case of service upgrade) or $[-4; 0]$ (case of service downgrade) following a uniform distribution. According to the threshold $\tau_a = 6$ found in the previous section, the limits $\underline{A} = -4$ and $\bar{A} = 4$ are chosen so that a leader who initially has a very bad opinion on the service (score equal to 1) cannot move to satisfaction. Similarly a leader with a very high score (10) cannot transit to dissatisfaction. For followers (Equation (5)), $h_f(\cdot)$ corresponds to averaging its score and those of its neighbors. Leaders and followers are chosen at random, as is the neighborhood of each follower. Different values of S_F (the number of neighbors connected to a given follower) are evaluated, going from 1 to 10. The percentage of leaders is selected from 50% to 99%. For each set of parameters (p_L, S_F) , 500 Monte Carlo runs were considered.

From data (see Fig. 3), the gap between dissatisfaction and satisfaction rate is equal to 15.85%. We will consider as significant, a change for which the gap is reduced or increased of at least 50%. This corresponds to approximately increasing or decreasing the satisfaction rate of 4%.

In a service upgrade scenario, the service provider upgrades a given attribute of the transportation system. Then the agents increase or not their score on this attribute. Using the proposed agent based method, we got the results depicted in Fig. 5. It can be seen that the probability to get an overall satisfaction rate increment higher than 4% is equal to 1 for *waiting time*, *speed*, *accessibility*, and *quality of infrastructure*. Otherwise, it is zero.

In a service downgrade scenario, the service provider does not maintain some attributes leading to a service downgrade. Then the agents decrease or not their score on

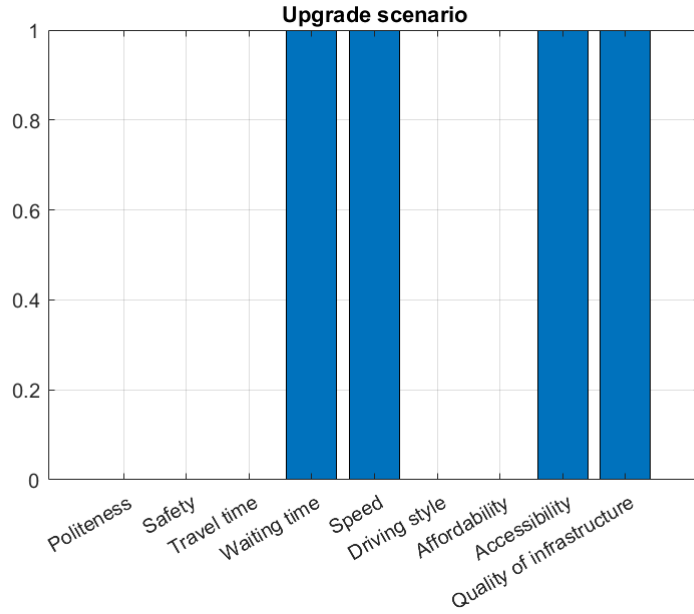


Figure 5. Probability for the increment of the overall satisfaction rate to be higher than $\tau = 4\%$

the considered attribute. The results depicted in Fig. 6 show that the probability to have a decrease in the overall satisfaction rate higher than 4% is equal to 1 for *safety*, *speed*, and *quality of infrastructure*, 0.43 for *travel time*, 0.16 for *driving style*, 0.14 for *accessibility* while it is zero for the remaining attributes.

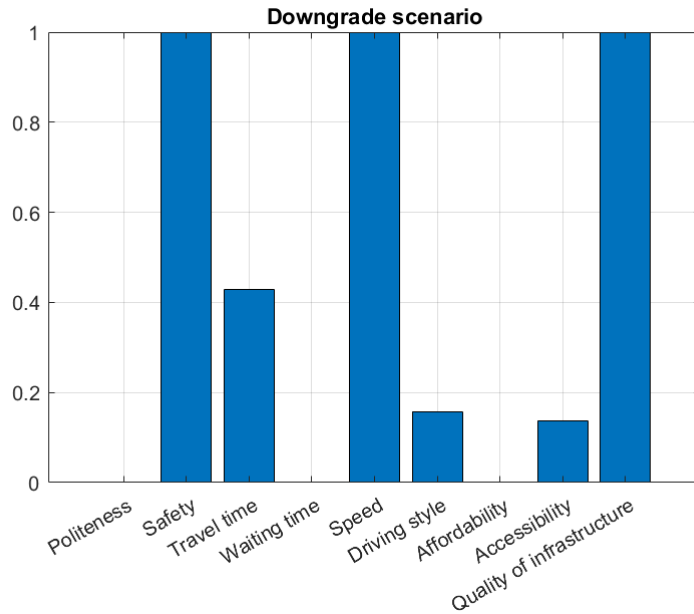


Figure 6. Probability for the decrement of satisfaction rate to be above $\tau = 4\%$

From the two scenarios considered, we can see that there is no symmetry on the impact (positive and negative) of the attributes considered. Fig. 7 shows the classification

of the evaluated attributes. The impact is evaluated with the probability computed above. Such a representation allows one to see the relative importance of each factor and in which axis. We set the threshold at 0.5 for the impact if the attribute is upgraded and to 0.4 in the downgrade axis.

Similarly to the Random Forest approach, *politeness* and *affordability* are the least important factors. They are neutral. *Speed*, *travel time*, and *accessibility* are important factors. In contrast to Random Forest, our ABMS approach allows specifying in which sense they are important. The ABMS approach also highlights the importance of *safety*, *waiting time*, and *quality of infrastructure*. This is because Random Forest doesn't take into account dynamics as it is the case in ABMS. As a summary: *speed* and *quality of infrastructure* are the two crucial attributes to be focused on while *safety* and *travel time* need at least to be maintained; if they are downgraded the satisfaction rate will decrease. Note that an improvement on *waiting time* and *accessibility* would be beneficial to the overall satisfaction. Finally, *politeness*, *driving style*, and *affordability* are neutral.

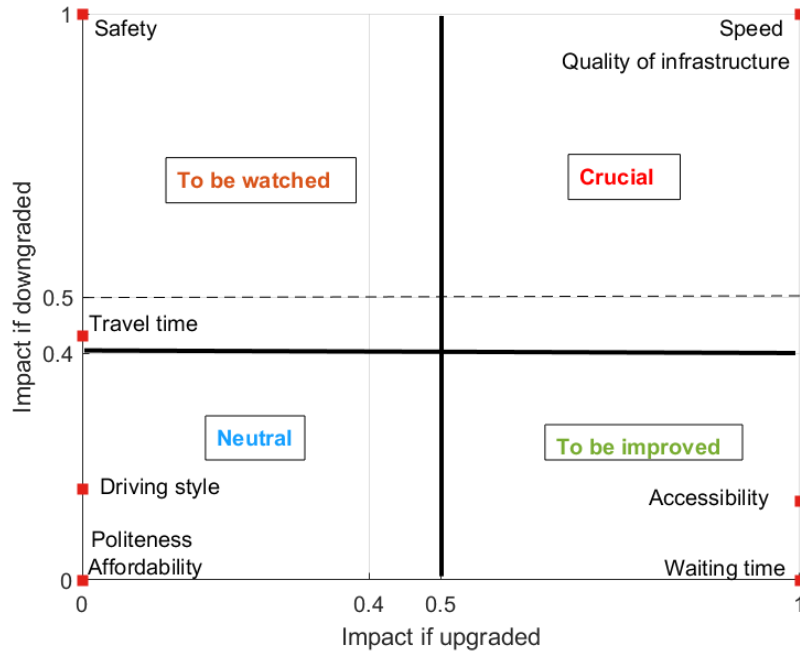


Figure 7. Classification of the evaluated attributes

5. Discussion

In this section, we discuss the challenges related to the different classes of attributes according to Fig. 7.

5.1. Crucial attributes

5.1.1. Speed:

Recent works, Cele et al. (2024, 2025), have shown that aggressive driving and speeding are the main factors characterizing minibus taxi drivers. In addition, it was also stated that speeding occurs more in uncontrolled areas, i.e. areas with less visibility of law enforcement, as it is the case in KwaDabeka. Minibus taxi drivers are more likely to speed during rush hours in contrast to off-peak hours. Their objective is to increase trips frequency with maximum load so that their profit is increased. To remedy this, it would be necessary to: (i) have more visibility of metro police, speed cameras, and community safety officers; (ii) engage with the South African National Taxi Council (SANTACO) to develop programs and training sessions in the importance of driving within the speed limit; (iii) have in place more regulations for ride hailing services.

5.1.2. Quality of infrastructure:

The municipality has not provided proper stops or bus stops, bus shelters, and dustbins at stops or bus stops. At the minibus taxi ranks, bus ranks, or stations, the public uses the public toilets (which unfortunately do not have water and have an unpleasant smell very often). Once commuters are in the minibus taxi or bus or waiting at the ranks and stations they normally do not dispose their litter in the provided dustbins (which are usually full and spilling) and causes litter at the ranks and stations. It is the municipality responsibility to ensure that each area has proper stops, bus stops, stations, shelters, dustbins at stops, bus stops or stations. The municipality must ensure that stops are constructed, shelters and dustbins are provided. The preservation and cleanliness of infrastructure does not only depend on the municipality but also on the public, drivers and commuters. The community needs to be taught on the importance of sustaining the provided facilities to enable a healthy and livable environment that everybody can thrive.

5.2. Attributes to be watched

5.2.1. Safety

Even though the safety measures in place are insufficient to safeguard commuters from criminal violence or violence at stations or during transit, it seems that commuters can live with the situation, but would be unable to tolerate a worsening of the situation. It is worth noting that there is no metro police nor South African Police Service (SAPS) visibility in ward 20 unless a road-block is underway and there is limited visibility. It is therefore important to have specialized policing to protect commuters. Increasing metro police and SAPS visibility in the ward, minibus taxi ranks, bus ranks and stations would go with appointing and equipping community safety officers in the fight against crime and violence. The community must be made aware of the importance to work with the police in the fight against crime and violence. Such increased police visibility would be corruption free. For this purpose, it is necessary to create a system that protects whistle blowers to enable corrupt officials to be subjected to the law.

5.2.2. Travel time

Travel time has direct impact on daily productivity. Many commuters rely on minibus taxis for work, education, and essential activities, often facing long and unpredictable travel durations due to congestion, inefficient routing, and frequent stops. Since minibus taxis operate without fixed schedules in many regions, reducing travel time enhances reliability and convenience. Additionally, shorter travel times can lower costs associated with delays, such as lost income opportunities.

5.3. Attributes to be improved

5.3.1. Waiting time:

During the day most of the minibus taxis park at the various minibus taxi ranks until the afternoon when the transportation demand increases. Commuters are likely to arrive at the minibus taxi rank and wait for the minibus taxi to fill up. In the late afternoon there are long queues at the minibus taxi rank and commuters can wait in the queue for more than an hour to get a minibus taxi. To address the long waiting time of commuters in queues in minibus taxi ranks, the minibus taxi operators can improve their operations planning, increase the supply of minibus taxis because in the late afternoon the demand is high for minibus taxis. Information to commuters can also help to manage the waiting time. The high penetration rate of smartphones can help to inform commuters about waiting time or next departure time.

5.3.2. Accessibility:

The availability of the minibus taxi largely depends on operating hours. Commuters cannot access these modes of public transport 24 hours a day. The first miles is a big issue. Most commuters walk a distance to access the minibus taxi. Most of the commuter residences are located further away from the stop or bus stop and requires commuters to walk a distance to access minibus taxi or bus. Instead of minibus taxis operating along the main road they should operate within the area to address the issue of commuters walking long distances to access a minibus taxi. Also, the municipality should repair the streets within the ward as some of the road surfaces are damaged (potholes) and most of the streets are too narrow, partially allowing one vehicle to pass at a time. Most of the streets need to be widened to allow vehicles to move within the ward without being limited.

5.4. Neutral attributes

The neutral attributes identified by the study are *politeness*, *affordability*, and *driving style*.

Tab. 6 reports results on evaluation of drivers politeness for the three main transportation modes in KwaDabeka. Drivers have a friendly attitude towards commuters,

Table 6. Evaluation of drivers politeness

	Very polite or polite	Neither	Very impolite or impolite
Minibus Taxi	62%	15%	23%
Bus	60%	20%	20%
Ride hailing	82%	15%	3%

this has been engrained in the Zulu nation as part of their culture. Therefore, it is ex-

pected of the driver to be polite because generally Zulu people are polite (Mtshelwane, Nel, & Brink, 2016).

Concerning *affordability*, the analysis does not point it out as a key influential factor to customer satisfaction as it was also observed in a different context by (Adom-Asamoah et al., 2021), although minibus taxi and bus fares are high (see fares evaluation in Tab. 7). This proves that commuters have been captured and bullied, to accept

Table 7. Evaluation of transportation fares

	Affordable	Neither	Expensive
Minibus Taxi	20%	2%	78%
Bus	27%	0%	73%
Ride hailing	44%	10%	46%

the current situation in the public transport industry in the area. These captive users likely fear to speak out and challenge the public transport operators in the area.

Driving style is defined by Zhang et al. (2023) as how drivers decide to drive; the way they choose to handle themselves when they are driving. In Cele et al. (2024, 2025) it has been shown that, in addition to speeding, aggressive driving is also a component of driving style. For minibus taxis, in uncontrolled area it is considered as not as bad as in controlled area. However, it is to be watched. Regular training of these drivers needs to be made systematic.

6. Conclusion

In this paper, we present a novel approach for identifying and categorizing the key factors that shape overall commuter satisfaction in public transportation systems. The proposed method, based on Agent-Based Modeling and Simulation, offers valuable insights into capturing complex phenomena, particularly social interactions within communities. By integrating these interactions, the approach allows us to analyze how perceived satisfaction shifts as services are upgraded or downgraded. This involves understanding the network of interactions and how individual agents incorporate their neighbors' opinions. However, it is important to note that each attribute was evaluated separately, ignoring potential cascading effects where changes in one attribute can influence others. This limitation presents a clear direction for future research.

Another significant contribution of this paper lies in applying the proposed method to assess the satisfaction of captive users from disadvantaged areas, addressing a gap in the existing literature. The case study, set in a South African township, revealed that speed and infrastructure quality are the most critical factors influencing commuter satisfaction. Any positive or negative changes in these attributes would substantially alter the balance between satisfied and dissatisfied users. Safety also emerged as a key concern, with any decline likely to significantly increase dissatisfaction. On the other hand, improvements in accessibility and waiting times are necessary to boost overall satisfaction. Finally, affordability was found to be a neutral factor, despite commuters perceiving fares as expensive. This finding reinforces the notion that commuters are effectively captive to informal public transport operators, as noted in other African studies on service quality (Chinomona et al., 2013; Mokonyama & Venter, 2018). As such, it is crucial for policymakers to demonstrate strong political commitment to improving public transportation, particularly for low-income earners who remain reliant on, yet dissatisfied with, minibus taxis. While the current categorization framework provides a conceptual classification of key factors into crucial, to be improved, to be

watched, and neutral, the thresholds that define the boundaries between these categories need further formalization. Currently, the interpretation of factors that lie near the boundaries of these defined zones remains unclear. The lack of a precise, mathematically robust criterion to distinguish between categories leads to potential ambiguities when classifying factors that are on the borderline.

Disclosure statement

The authors report there are no competing interests to declare.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, A.K., upon reasonable request.

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Appendix A. Appendix: Description of Questionnaire Elements.

Two questionnaires were used for this study. In the first questionnaire, evaluation of different attributes were carried out through a Likert scale. For instance: Question: *How do you rate fare for this mode?* Answer options: *Affordable, Expensive, Very Expensive, Neither.*

In the second questionnaire, attributes had to be rated between 1 to 10, 10 being the highest score, as depicted in Fig. A1.

Questionnaire N°:
Age: Under 18 18-25 26-33 34-41 42-49 50-57 58-65 Above 65
Gender: Male Female Other
Education: None Primary Matriculated Certificate Diploma Degree Postgraduate
Rate from 1 to 10 your level of satisfaction (10 being the highest score)

	Overall score	Politeness	Safety	Travel-time	Waiting time	Speed	Driving style	Affordability	Accessibility to the stop (Bus stop/station, taxi rank/stop, train station or pick-up place)	Quality of infrastructure (Bus stop/station, taxi rank/stop, train station or pick-up place)
Taxi										
Bus										
Uber										
Metrorail										

Figure A1. Questionnaire