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Travel Mode Choice Responses to a Real-Time Information-Enabled Bus Service in Kigali, Rwanda: A Stated Preference Analysis

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Abstract

Public transport in rapidly growing sub-Saharan African cities faces long travel times, long waits, and overcrowding. This study examines how commuters in Kigali, Rwanda, respond to a hypothetical bus service equipped with a Real-Time Passenger Information System (RTPIS), termed iBus, using a stated preference survey and a multinomial logit (MNL) model with four alternatives: conventional bus, private car, motorcycle taxi (Moto), and iBus. An online sample of 306 respondents provided 1671 valid choices. In-vehicle travel time ($\beta = -0.0152$, $p < 0.001$), travel cost ($p = 0.029$), and iBus crowding significantly affected choices, whereas waiting time did not ($p = 0.210$). The value of in-vehicle time was approximately 5281 RWF/h (95% CI 1842–27,224). On the Kimironko–Nyabugogo corridor, replacing the conventional bus with an iBus that also offers shorter waiting and in-vehicle times and less crowding raised the simulated bus share from 8.6% to 29.5%; the information-related component alone raised it to 15.9%. A nested logit specification did not reject the MNL model. Because the sample is young and highly educated, the results apply mainly to digitally connected commuters. RTPIS appears most effective when combined with measures that increase bus speed and manage crowding.

Keywords: real-time passenger information system; stated preference; multinomial logit; travel mode choice; value of time; Kigali; sub-Saharan Africa; developing countries; intelligent transport systems

1. Introduction

Rapid urbanization in sub-Saharan Africa is straining transport infrastructure, particularly in secondary and capital cities experiencing fast population growth [1]. The issue of sustainable urban development focuses on the challenge of delivering sustainable mobility services in terms of reliability, safety, and affordability. In this regard, Intelligent Transport Systems (ITSs) and real-time Passenger Information Systems (RTPISs) have become a global trend that is revolutionizing service quality, reducing perceived waiting time, and attracting new ridership to modes of transportation [2]. RTPIS offers real-time data to passengers about the whereabouts of buses, expected arrival times, congestion, and service delays on digital displays at bus stops, via mobile apps, and short message service (SMS) services. Evidence from high-income countries shows ridership growing steadily following RTPIS implementation, alongside improved passenger satisfaction and reduced

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subjective waiting time. Nevertheless, their applicability to low-income urban settings with a fragile digital infrastructure, large disparities in smartphone penetration, and a diverse transport mode ecosystem has not been adequately examined. The capital city of Rwanda, Kigali, is a good case study in this sense. Being one of the fastest-growing cities in Africa and a government-planned smart city contender within the Rwanda Vision 2050 platform, Kigali encounters critical urban mobility issues: inadequate development of the formal bus system, overdependence on informal motorcycle taxis (Motos), high traffic congestion during rush hours, and a public transport share among commuters of roughly 70 percent [3]. The Rwanda Transport Development Agency (RTDA) has specifically employed RTPIS implementation as one of the prioritized interventions for enhancing the attractiveness of bus services. Although there is policy interest, little rigorous empirical evidence exists on commuter behavioral responses to RTPIS in Kigali, or in East African cities more broadly. The available body of research on stated preference studies conducted on RTPIS is mostly based in Europe, North America, or East Asia, and the results cannot be directly applied to the Kigali situation due to differences in income levels, travel attitudes, current mode availability, and baseline level of service quality. More importantly, while some studies have investigated travel time reduction in other African cities [4,5], this remains a key area for further empirical research in the context of Kigali.

This paper addresses these gaps by estimating a discrete choice model of commuter mode choice in Kigali, based on a stated preference survey that presents a hypothetical RTPIS-equipped bus alternative (iBus) alongside existing modes. The research has three objectives: (1) to identify and quantify the main determinants of transport mode choice among commuters in Kigali; (2) to estimate the Value of Travel Time (VTT) and Value of Waiting Time (VWT) in monetary terms, together with their uncertainty; and (3) to estimate changes in modal share when the conventional bus is replaced by an RTPIS-equipped improved bus service on a representative Kigali corridor, and to decompose this change into the contribution of the information-related component and of individual service attributes. Based on the conceptual framework in Section 3, we test the following hypotheses: H1: The relative disutility of waiting time compared with in-vehicle travel time among Kigali commuters differs from the pattern commonly reported in high-income countries, where waiting time is weighted more heavily than in-vehicle time [6,7]. H2: Crowding disutility differs between the RTPIS-equipped iBus and the conventional bus, potentially because passengers hold higher expectations of an information-rich service. H3: Replacing the conventional bus with an RTPIS-equipped improved bus service will increase the bus mode share on a representative corridor, and part of this increase can be attributed to the information-related component of the service.

The results contribute to the nascent literature on ITS adoption in developing cities and offer evidence-based guidance to transport planners and policymakers in sub-Saharan Africa. The rest of the paper is organized as follows. Section 2 discusses the literature on the effects of RTPIS and mode choice behavior. Section 3 presents a conceptual model linking RTPIS to behavioral mechanisms and modal shift. Section 4 describes the study area, survey design, and methodological framework, including the discrete choice model specification and parameter estimation approach. Section 5 summarizes and analyzes model results and the case study application. Section 6 discusses policy and sustainability implications, and Section 7 covers conclusions and limitations.

2. Literature Review

2.1. Real-Time Passenger Information Systems: Evidence on Impacts

The application of RTPIS to urban public transport has been widely researched in the Global North, and a consensus exists regarding its beneficial impact on the number of

passengers, their satisfaction with services, and their perception of service reliability [8]. Research by Ref. [9] revealed that subjective waiting time decreases by 20% when passengers are provided with real-time information, regardless of the real service changes. This psychological impact of RTPIS, namely the decrease in uncertainty, is a primary factor by which RTPIS enhances service quality perception [8].

These findings are supported by empirical evidence from North American and European cities. Ref. [10] discusses ridership, noting prior research that found a 2% rise attributed to the system. Ref. [11] explored the implementation of real-time crowding information in the Stockholm Metro and found that passengers' travel experience improved through reduced on-board crowding.

Studies of RTPIS in developing countries remain limited [12]. One study from India describes a prototype real-time passenger information system that uses Global Positioning System (GPS) and General Packet Radio Service (GPRS) to estimate arrival times and provide passengers with up-to-date bus information, highlighting the potential of such systems to make public transport more attractive. A broader African-focused review of ITS implementation issues offers valuable insight, concluding that implementation failures are frequent despite the sector's significant promise. These failures are often attributable to inadequate integration with existing informal transport networks and to a poor fit between information-delivery technologies and commuters' patterns of device ownership. The broader literature on African paratransit and mode choice further underscores this integration challenge. It documents how informal minibusses and paratransit systems dominate urban mobility across the continent, shaping the feasibility of interventions aimed at formal transport systems. Research from Nairobi demonstrates that mode choice in African cities is driven by a distinct set of income, infrastructure, and reliability constraints that differ from those in higher-income settings. Similarly, evidence from minibus reform efforts in South Africa shows that technology-led interventions succeed only when they are designed around the operating logic of existing informal services rather than imposed upon them. This insight extends to the digital domain: smartphone-based and data-driven transit innovations in African cities must account for the informal transit sector's patterns of device ownership and connectivity [13].

Taken together, this body of work indicates that, to our knowledge, no stated-preference-based RTPIS mode-choice study has been published for an East African city. This gap is the specific focus of the present paper.

2.2. RTPIS Technology Architecture and Components

An effective RTPIS combines three components of hardware and software: the on-bus unit, the central server unit, and the bus-stop display unit. The on-bus unit uses a GPS receiver connected to a GPRS communication unit to transmit the vehicle's coordinates, speed, and direction to the central server at set time intervals (typically 10–30 s) [14]. This positional data allows the system to calculate the bus's position relative to its scheduled stops and to feed an arrival-time prediction algorithm.

The central server maintains a real-time database of all bus positions, routes, and schedules [15]. Arrival-time prediction can range from simple historical-average models to more sophisticated Kalman-filtering and machine-learning approaches that estimate the arrival time (ETA) at every upstream stop on the route [15,16]. The server also functions as the operator's control module, allowing dispatchers to monitor fleet speed, flag timetable violations, and apply holding or stop-skipping interventions to restore headway regularity.

The bus-stop display unit shows waiting passengers the incoming buses' ETAs in real time, reducing uncertainty and allowing more informed travel decisions [17,18]. In contexts characterized by socio-economic inequalities, such as in many African cities, an RTPIS

deployment would need to support multiple information channels simultaneously [19]. This multi-channel approach is what allows the benefits of reduced waiting-time uncertainty to reach across both income levels and levels of technology access, addressing the equity concerns raised about selective ITS access in African cities [19].

2.3. Mode Choice Behavior and Stated Preference Methods

The choice of travel mode has been a focus of research in the transport field, and discrete choice models, especially the multinomial logit model, have traditionally served as the dominant analytical framework [20].

The MNL model is an operationalization of random utility theory, which assumes that individuals choose the mode of transport with maximum utility, and that utility is a function of observable characteristics and unobservable individual heterogeneity [21,22].

Recent meta-analysis of worldwide evidence suggests that the value of waiting time is around 1.5 to 1.75 times the value of in-vehicle time [7]. Nevertheless, this ratio is highly context-specific, depending on service frequency, climate, the built environment, and the availability of real-time information itself [6,23].

Orthogonal design techniques are typically employed to produce statistically efficient choice situations that are balanced across attribute levels and independent of each other, reducing the number of choice situations needed to estimate model parameters [24,25].

3. Conceptual and Theoretical Framework

3.1. RTPIS Behavior–Modal Shift Causal Pathway

The research is based on a three-stage causal model linking RTPIS implementation to quantifiable transport mode shift (Figure 1). The framework combines random utility theory, information-processing theory, and the psychology of uncertainty in travel behavior [3,20].

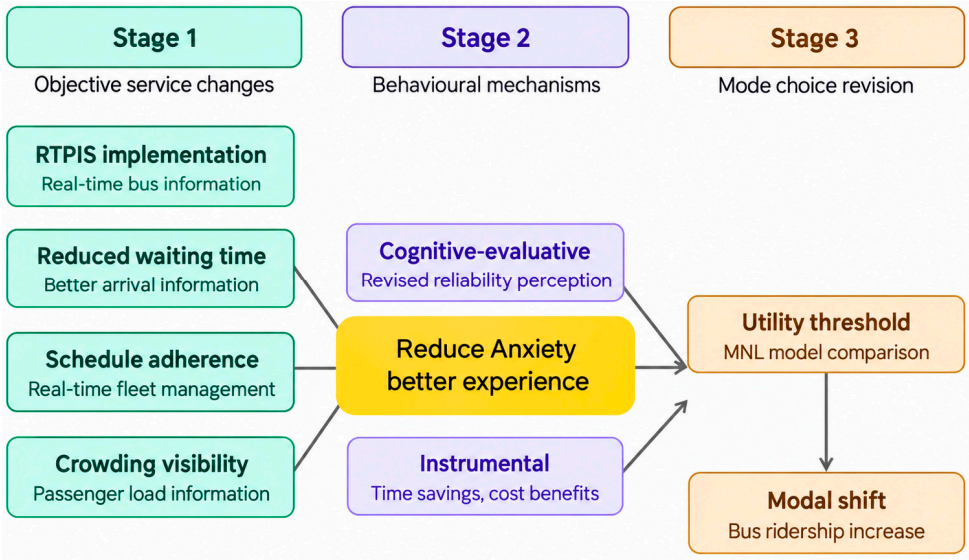


Figure 1. Conceptual framework.

In Figure 1, Stage 1 covers the service changes associated with an RTPIS-equipped bus service. RTPIS itself provides arrival and departure information, which allows passengers to time their arrival at stops and supports real-time fleet management that can improve headway regularity. Other changes considered in this study, notably shorter in-vehicle travel times and lower crowding, cannot be produced by passenger information alone and require complementary measures such as bus priority and additional capacity. The stated preference survey captures both components: the information-related component through

the labeled iBus alternative, and the service attributes through attribute levels that vary independently of the label.

Stage 2 involves the behavioral processes that convert objective service changes into a change in perceived utility, along three dimensions. The cognitive-evaluative dimension concerns passengers revising their mental model of service reliability: as RTPIS delivers accurate ETAs, perceived waiting-time uncertainty and waiting stress decrease [26]. The affective dimension concerns the quality of the travel experience itself: reduced anxiety about waiting [27] and better awareness of crowding can improve passengers' evaluations of the overall trip [28]. The instrumental dimension captures direct time-saving and cost effects: RTPIS can improve punctuality [29], and real-time information can facilitate adaptive route decisions [30] and travel-cost savings [31], while any fare premium for the iBus service must be weighed against these attribute improvements [29,30].

Stage 3 reflects the outcome of the utility-maximization process: when the utility of the RTPIS-equipped iBus (calculated using the MNL model) exceeds the utility of competing modes for a given commuter, a modal shift occurs. The framework estimates these relative weights from local SP data rather than transferring values from other contexts.

3.2. Random Utility Theory as the Modeling Foundation

Stage 3 of the framework is operationalized through random utility theory (RUT). Under RUT, every decision-maker chooses the alternative with maximum utility within the available choice set [19,32]. The full model specification, the decomposition of utility into deterministic and stochastic components (Equation (1)), the MNL probability formula (Equation (2)), and the IIA assumption are presented in Section 4.

$$U_in = V_in + \varepsilon_in \quad (1)$$

Assuming the stochastic components are IID Gumbel-distributed, the choice probability takes the generic MNL form:

$$P(i \mid C_n) = \exp(V_in) / \Sigma_j \in Cn \exp(V_jn) \quad (2)$$

The MNL model relies on the Independence of Irrelevant Alternatives (IIA) property, under which the relative probability of choosing one alternative over another is unaffected by the presence or characteristics of any other alternative [33]. Because the conventional Bus and the iBus are closely related alternatives, this assumption was tested against a nested logit specification (Section 4.5), and the results are reported in Section 5.1.

The deterministic utility component of each alternative is specified as a linear function of the corresponding attributes, with alternative-specific constants (ASCs) representing modal preference not captured by the measured attributes. Generic time and cost coefficients impose equal sensitivity across modes; ASCs account for the residual mode-specific intercepts [34].

4. Materials and Methods

4.1. Study Area: Kigali, Rwanda

Kigali, the capital and primate city of Rwanda, hosts approximately half of the country's urban population [35]. The city sits at an average altitude of around 1600 m, with a mountainous topography of ridges (1600 m) and valleys (1300 m) that constrains bus-route design and service frequency [36,37]. The location of the study area and the study corridor are shown in Figure 2.

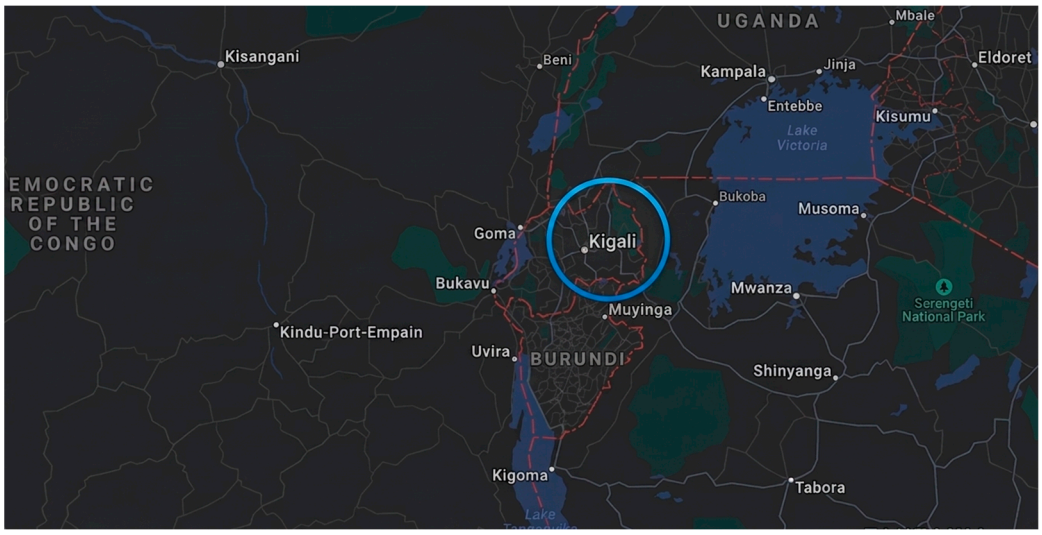


Figure 2. Location of the City of Kigali (blue circle) in East Africa. Red dashed lines indicate national borders, gray lines indicate roads, blue areas indicate lakes, and green areas indicate protected areas.

Kigali's public transport network is serviced by private companies [38] on a set of fixed bus routes. Network coverage is uneven, with developing peripheral areas underserved by formal services [39]. Motorcycle taxis (Motos), operated by registered riders, provide ubiquitous first- and last-mile services and compete directly with buses on many routes [40]. Both Rwanda Vision 2050 and the Kigali City Master Plan explicitly target a modal shift from private vehicles and Motos toward formal public transport, and RTPIS implementation is part of the National Transport Development Strategy's approach to making bus services more attractive.

4.2. Survey Design: Orthogonal Stated Preference Approach

The stated preference survey examined commuter mode-choice behavior across four alternatives: conventional public bus (Bus), private car (Car), motorcycle taxi (Moto), and hypothetical RTPIS-equipped bus (iBus). The iBus alternative was introduced to respondents as a bus service with a real-time passenger information system that provides departure and arrival times through mobile phones, displays at stops, and screens inside the bus. Drawing on the literature review and expert interviews with RTDA officials, four mode-choice attributes were selected: in-vehicle travel time (TT), waiting time (WT), travel cost (CT), and bus crowding (CD). Crowding was modeled at three levels: Level 1 (free seats), Level 2 (standing, not congested), and Level 3 (crowded, standing only). Attribute levels were set using field information from bus operators, motorcycle taxi riders, and car owners in the Kigali network, consistent with established stated-preference design guidance that attribute levels be calibrated against locally realistic ranges to preserve respondent engagement and choice-task realism [23,26] (Table 1).

An orthogonal main-effects design was generated with the Orthoplan procedure in SPSS Statistics 27 (IBM Corp., Armonk, NY, USA), yielding 64 candidate scenarios. To avoid dominant alternatives, the candidates were ranked by a utility-balance criterion. For each candidate scenario, the utilities of the four alternatives were computed with prior coefficient values taken from a stated preference study of commuter mode choice [41], namely −0.1138 per minute for bus, iBus, and Moto time; −0.0959 per minute for car time; −0.0022 per RWF for bus, iBus, and Moto cost; −0.00085 per RWF for car cost (converted from the original currency); and −1.301 (Level 2) and −2.088 (Level 3) for crowding. The average absolute difference between the utilities of all pairs of alternatives was then calculated, and candidates with smaller differences were treated as better balanced. The

final 18 scenarios were selected from the ranked candidates so that every attribute level was represented in the questionnaire: eight were taken from the 18 best-balanced candidates and ten from lower-ranked candidates. In seven of the selected scenarios, one attribute level was changed; in six cases, to present the iBus at crowding Level 3, which did not occur in the orthogonal design. The final set of scenarios is therefore not strictly orthogonal. The 18 scenarios were divided into three blocks of six, and each respondent was randomly assigned to one block. An example choice task is shown in Figure A1.

Table 1. Alternatives and defined attribute levels in the stated preference survey.

Alternative	Attribute	Levels
Bus	Waiting time (min)	15, 25, 45
	In-vehicle travel time (min)	30, 45, 60, 75
	Cost (RWF)	300, 400, 500, 650
	Crowding	Levels 2, 3
Car	Waiting time	None
	In-vehicle travel time (min)	15, 25, 35, 45
	Cost (RWF)	1500; 2500; 3000; 3500
	Crowding	None
Moto	Waiting time	None
	In-vehicle travel time (min)	15, 25, 35, 45
	Cost (RWF)	500, 800, 1200, 1800
	Crowding	None
iBus	Waiting time (min)	2, 5, 10
	In-vehicle travel time (min)	20, 30, 45, 60
	Cost (RWF)	350, 450, 550, 700
	Crowding	Levels 1, 2, 3

The questionnaire was administered electronically via Google Forms (Google LLC, Mountain View, CA, USA), in both English and Kinyarwanda. At the start of the questionnaire, respondents were asked whether they had access to a private car that they could use for commuting; respondents with car access received a four-alternative version (Bus, Car, Moto, iBus), and the others received a three-alternative version (Bus, Moto, iBus).

4.3. Sample Characteristics

The survey was administered online through Google Forms, in English and Kinyarwanda. The target geographical area was the City of Kigali, Rwanda, which comprises the Gasabo, Kicukiro, and Nyarugenge districts, and the target population was commuters traveling within, into, or out of the city. Apart from the question on car access, which determined the version of the questionnaire, no screening questions were used; respondents self-selected as Kigali commuters, and the choice tasks asked them to consider a commute from home to a new workplace. The questionnaire link was distributed online and could be forwarded freely by recipients. The sample therefore combines convenience sampling and, where recipients forwarded the link, snowball (referral-based) sampling, an approach widely used when no sampling frame is available, but one that does not yield a probability sample [42]. Online, non-probability samples of this kind are common in stated preference studies of mode choice, including studies in African cities [43,44], and they typically over-represent younger and more educated respondents [45]. Because the link was distributed openly, the number of people who received the invitation is unknown, and a response rate cannot be calculated. Respondents were randomly assigned to one of three blocks of choice tasks, but this randomization concerns the allocation of choice tasks

and does not make the sample a random sample of Kigali commuters. A total of 309 people responded, of whom 306 provided at least one valid choice.

Of the 1854 intended choice observations (309 × 6), 1671 were valid and used in the analysis. The 183 missing observations correspond to respondents who did not complete their full block: 57 respondents answered between one and five of their six choice tasks, and three respondents recorded no valid choice. Incomplete responses were retained for the tasks that were answered. The distribution of respondents and valid choices across blocks is shown in Table A1. The sample was balanced by gender (male: 50.5%, female: 49.5%) but skewed towards young (74.7% aged 20 to 30, none over 50) and highly educated respondents (82.3% with a bachelor's degree and 12.5% with a master's degree or above; Table 2). While the youth skew is broadly consistent with Rwanda's population structure, in which about 65% of residents are under 30 years, and the median age is 20 years [46], the education skew is not representative of Kigali's commuting population (Figure 3), and online administration is likely to have under-sampled older, less formally educated, and less digitally connected commuters [47].

Table 2. Descriptive statistics of valid survey respondents.

Characteristic	Category	Percentage (%)
Age	<20	2.9
	20–30	74.7
	30–40	21.4
	40–50	1.0
	>50	0.0
Education	Basic level	0.3
	Secondary level	4.9
	Bachelor's level	82.3
	Master's and above	12.5
Gender	Male	50.5
	Female	49.5
Commute time	<30 min	46.3
	30–60 min	45.6
	>60 min	8.1
Work time flexibility	Flexible	43.4
	Fixed	56.6
Marital status	Not married	82.4
	Married	17.6

Of the 306 respondents with valid choices, 154 (50.3%) reported access to a private car that they could use for commuting and therefore answered the four-alternative version described in Section 4.2. Income was not collected. The car-access share is therefore much higher than would be expected for Kigali's commuting population, and the absence of income data means that cost sensitivity cannot be related to ability to pay. Both limitations reinforce that the results describe a young, highly educated, and relatively car-accessible segment of commuters.

Two aspects of the sample should be distinguished. In terms of statistical precision, the 1671 valid choices from 306 respondents are sufficient to estimate the in-vehicle time, cost, and iBus crowding coefficients at the 5% level; a post hoc calculation following Rose and Bliemer [48] indicates minimum sample sizes of approximately 65 and 250 respondents for the in-vehicle time and cost coefficients, respectively, but approximately 750 respondents for the waiting-time coefficient. In terms of composition, the sample is a non-probability online sample and is not representative of Kigali's commuting population (Figure 3). Post-stratification weighting was not applied because the sample contains very few respondents

with basic ($n = 1$) or secondary ($n = 15$) education, which would lead to extreme and unstable weights. The estimated coefficients and simulated mode shares should therefore be interpreted as describing young, university-educated, digitally connected commuters rather than the city as a whole.

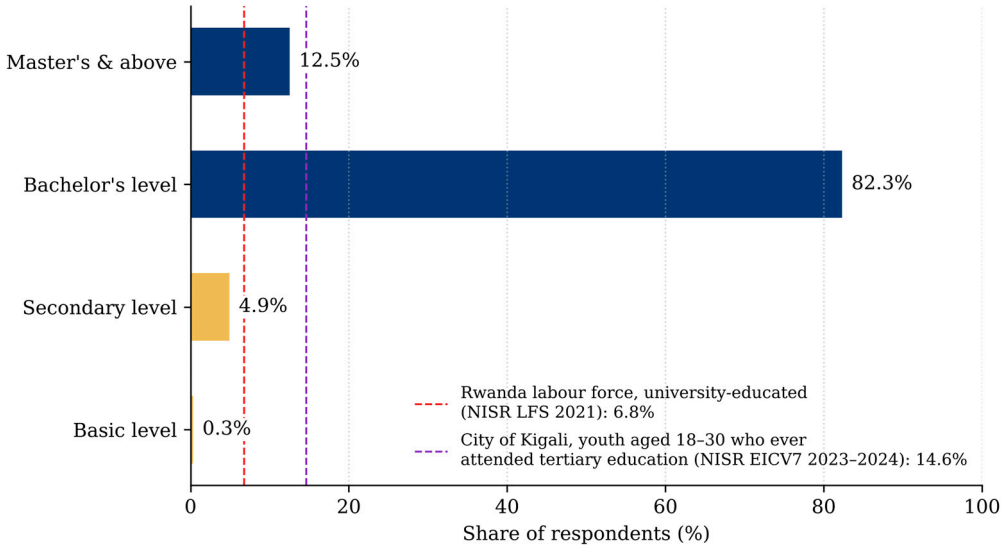


Figure 3. Sample educational attainment vs. independent population benchmarks. The comparison quantifies the sample's education skew relative to the general Kigali commuting population, motivating the scoped-generalizability language used throughout Sections 4.3 and 7.2.

The education skew mainly affects external validity. When a sample is stratified on exogenous characteristics such as education, maximum likelihood estimates of the choice-model parameters remain consistent for the population from which the sample was drawn, provided that preferences do not differ systematically across the sampling strata once the observed attributes are controlled for Ref. [49]. Because preferences for time, cost, and crowding may plausibly vary with education and income, which could not be tested here, the estimates should be regarded as valid for the sampled segment of young, university-educated, online-active commuters. This segment is relevant for RTPIS planning because it is likely to include early users of smartphone-based information, but the results should not be transferred to older, less formally educated, or lower-income commuters without further data.

4.4. Discrete Choice Modeling Framework

Discrete choice models based on random utility theory are among the most widely used tools for analyzing commuter mode-choice behavior and have also been applied to route choice, destination choice, and vehicle-ownership decisions [50,51]. The most common specification uses a linear, fixed-coefficient utility function over the observed attributes [52].

A discrete choice model is characterized by four elements: the decision-maker, the range of available alternatives, the attributes describing those alternatives, and the decision rule [47]. Here, the decision-maker is an individual Kigali commuter. The choice set contains four alternatives: Bus, Car, Moto, and iBus. All four alternatives were offered to respondents with car access; respondents without car access were offered three (Bus, Moto, iBus), reflecting realistic mode availability for each group.

Attributes are the characteristics commuters weigh when choosing a mode [53]. Some are generic across alternatives, such as in-vehicle travel time (TT) and travel cost (CT), while others are alternative-specific: waiting time (WT) applies only to Bus and iBus (Car and Moto involve no queuing), and crowding (CD) applies only to the two bus modes.

Crowding was operationalized on three ordinal levels: Level 1 (seats available), Level 2 (standing room available, not full), and Level 3 (fully crowded, standing only). The iBus was presented at all three levels, with Level 1 as the reference category, whereas the conventional bus was presented only at Levels 2 and 3, reflecting current conditions on Kigali buses. Attribute levels were set from field interviews with bus operators, motorcycle taxi riders, car owners, and RTDA officials, so the values presented to respondents were realistic for the Kigali network.

4.5. Multinomial Logit Model Specification

A multinomial logit (MNL) model was used as the primary modeling approach. The MNL model assumes decision-makers select the alternative offering the highest utility, and that the unobserved utility components are independently and identically distributed as Type I extreme value [54]. Under these assumptions, the probability that individual n chooses alternative i from choice set C_n is given by Equation (2) above, where V_in is the systematic utility component of alternative i.

The deterministic utility functions for the four alternatives are given in Equations (3)–(6):

$$U(\text{Bus}) = \text{ASC_BUS} + \beta\text{_TT}\cdot\text{TT_BUS} + \beta\text{_WT}\cdot\text{WT_BUS} + \beta\text{_CT}\cdot\text{CT_BUS} + \beta\text{_C3,Bus}\cdot\text{CD3_BUS} \quad (3)$$

$$U(\text{Car}) = \text{ASC_CAR} + \beta\text{_TT}\cdot\text{TT_CAR} + \beta\text{_CT}\cdot\text{CT_CAR} \quad (4)$$

$$U(\text{Moto}) = \text{ASC_MOTO} + \beta\text{_TT}\cdot\text{TT_MOTO} + \beta\text{_CT}\cdot\text{CT_MOTO} \quad (5)$$

$$U(\text{iBus}) = \beta\text{_TT}\cdot\text{TT_IBUS} + \beta\text{_WT}\cdot\text{WT_IBUS} + \beta\text{_CT}\cdot\text{CT_IBUS} + \beta\text{_C2,iBus}\cdot\text{CD2_IBUS} + \beta\text{_C3,iBus}\cdot\text{CD3_IBUS} \quad (6)$$

where TT, WT, and CT denote in-vehicle travel time, waiting time, and travel cost, respectively, and CD2 and CD3 are indicator variables for crowding Levels 2 and 3.

The alternative-specific constants (ASCs) capture systematic differences in mode attractiveness not explained by the observed attributes. The ASC for iBus was normalized to zero for identification. Because the conventional bus was never presented at crowding Level 1, its Level 2 effect cannot be separated from its constant; ASC_BUS therefore represents the conventional bus at crowding Level 2, and β_C3,Bus measures the change from Level 2 to Level 3. Time and cost coefficients were specified as generic across modes. With all attributes held equal, the difference between the iBus and Bus constants represents the non-attribute (information-related) components of the iBus, which is used in Section 5.3 to isolate the effect of the information component.

Because the conventional Bus and iBus are closely related alternatives, they may share unobserved characteristics, which would violate the IIA property of the MNL model [55]. To test this, a nested logit (NL) model was estimated in which Bus and iBus share a nest, with the same utility specification. The likelihood-ratio test of the NL model against the MNL model and a Wald test of the nesting parameter are reported in Section 5.1.

4.6. Model Estimation Approach

Because the iBus does not yet exist in Kigali, revealed preference data could not be collected, so a stated preference (SP) survey was used instead, presenting respondents with hypothetical choice situations. SP methods are well established for evaluating policy interventions involving new transport options [56].

Because each respondent completed up to six choice tasks, the observations are not independent. Inference is therefore based on robust (sandwich) standard errors clustered at the respondent level, computed from the respondent-level sums of the analytical scores; conventional standard errors are also reported in Table 3 for comparison.

Table 3. Multinomial logit model estimation results (1671 choices; 306 respondents).

Parameter	Estimate	Std. Error	Robust Std. Error (Clustered)	Robust *p*-Value	Interpretation
ASC_BUS	−1.499	0.222	0.218	<0.001	Conventional bus at crowding level 2, relative to iBus at level 1
ASC_CAR	−0.285	0.221	0.250	0.255	Not significant
ASC_MOTO	−0.373	0.126	0.167	0.025	Dispreference for Moto relative to iBus
β_TT (per min)	−0.01520	0.00285	0.00358	<0.001	In-vehicle time
β_WT (per min)	−0.00741	0.00804	0.00591	0.210	Waiting time; not significant
β_CT (per RWF)	−0.000173	0.0000875	0.0000794	0.029	Travel cost
β_C3, Bus	+0.077	0.196	0.149	0.604	Bus crowding level 3 vs. level 2; not significant
β_C2, iBus	−0.470	0.132	0.131	<0.001	iBus crowding level 2 vs. level 1
β_C3, iBus	−0.718	0.144	0.134	<0.001	iBus crowding level 3 vs. level 1

Note: ASC_IBUS = 0 (reference). LL(0) = −2075.71; LL(constants only) = −1872.54; LL(β) = −1846.64; ρ^2 = 0.110; adjusted ρ^2 = 0.106; LR test against the constants-only model = 51.8 (6 df, p < 0.001).

The 18 scenarios were categorized into three blocks of six, with respondents randomly assigned to one block, giving each respondent six choice tasks. Each scenario was shown graphically, with the attributes of all available modes displayed together to enable direct comparison. The survey was conducted online via Google Forms, in both English and Kinyarwanda.

4.7. Parameter Estimation and Value of Time Derivation

Maximum likelihood estimation (MLE) was used to estimate model parameters by maximizing the likelihood of the observed choices across respondents and choice occasions:

$$LL(\beta) = \Sigma_n \Sigma_t \ln P(i_nt \mid C_nt) \quad (7)$$

where n denotes the respondent and t the choice occasion.

The model was initially estimated using PandasBiogeme and was re-estimated for this study with PandasBiogeme (version 3.2.14) [57], which reproduced the original estimates. Respondent-clustered standard errors, Wald tests, the nested logit model, and the simulations reported below were computed in Python (version 3.13) using NumPy (version 2.5.3) and SciPy (version 1.18.1) by maximum likelihood with analytical gradients, and reproduce the Biogeme estimates for all identified parameters. Model performance is reported using ρ^2 relative to the equal-probability model, adjusted ρ^2, and a likelihood-ratio test of the full model against the constants-only model.

The values of in-vehicle travel time (VTT) and waiting time (VWT) were derived from the ratio of the relevant time coefficient to the travel-cost coefficient (Equations (8) and (9)):

$$VTT = \beta_TT/\beta_CT \quad (8)$$

$$VWT = \beta_WT/\beta_CT \quad (9)$$

Because travel time and waiting time were measured in minutes and travel cost in RWF, this ratio is naturally expressed in RWF per minute; it was multiplied by 60 to express VTT and VWT in RWF per hour, the units reported throughout the remainder of this paper (Sections 5.2, 6.2 and 7.1).

Because VTT and VWT are ratios involving an imprecisely estimated cost coefficient, their 95% confidence intervals were computed with the Krinsky–Robb method [58], using

100,000 draws from a multivariate normal distribution with the estimated coefficients and the respondent-clustered covariance matrix. The same draws were used to compute 95% intervals for the simulated mode shares in Section 5.3. Hypotheses H1 and H2 were tested with Wald tests on linear combinations of coefficients.

5. Results

5.1. Model Estimation Results and Diagnostics

The estimated MNL coefficients are presented in Table 3, with conventional standard errors and robust standard errors clustered at the respondent level to account for the six repeated choices per respondent. The attributes are jointly significant: the likelihood-ratio statistic against the constants-only model is 51.8 (6 degrees of freedom, $p < 0.001$). The ρ^2 relative to the equal-probability model is 0.110 (adjusted $\rho^2 = 0.106$), indicating that the observed attributes explain a modest part of the variation in stated choices. All time, cost, and iBus crowding coefficients have the expected negative signs. The coefficients and their 95% confidence intervals are shown in Figure 4.

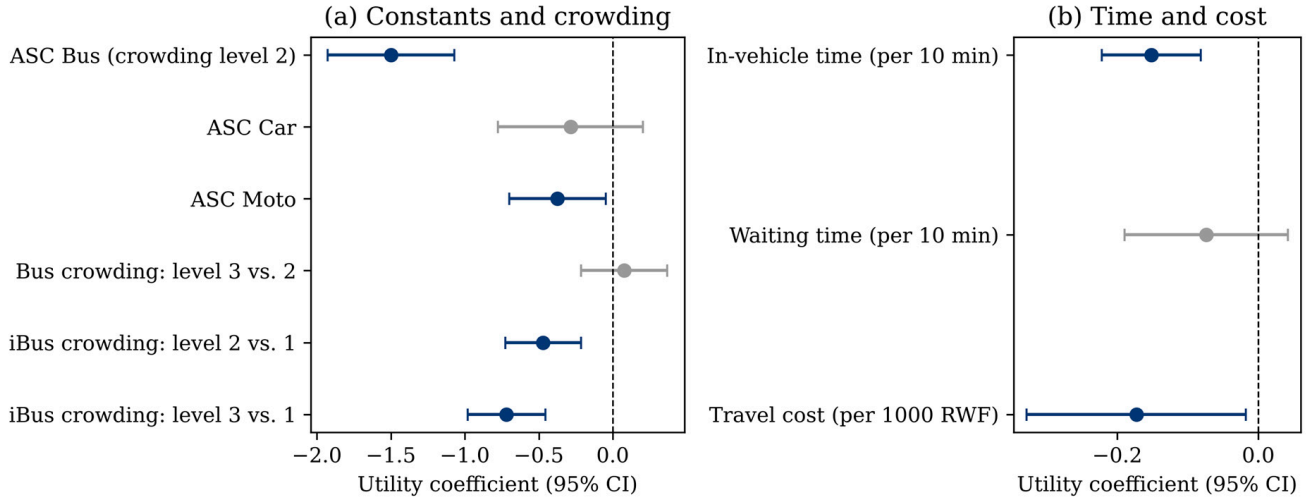


Figure 4. MNL coefficients with 95% confidence intervals based on respondent-clustered standard errors: (**a**) alternative-specific constants and crowding coefficients; (**b**) time and cost coefficients, with time coefficients shown per 10 min and the cost coefficient per 1000 RWF. Navy markers denote coefficients significant at $p < 0.05$; gray markers are not significant. The dashed line marks zero.

In-vehicle travel time is strongly significant ($\beta_TT = -0.0152$, $p < 0.001$), whereas the waiting-time coefficient is negative but not statistically significant ($\beta_WT = -0.0074$, $p = 0.210$). Travel cost is significant at the 5% level ($\beta_CT = -0.000173$, $p = 0.029$). A Wald test does not reject equality of the waiting-time and in-vehicle-time coefficients ($p = 0.138$), but rejects a waiting-time multiplier of 1.5 ($p = 0.008$), so H1 is only partly supported (Section 6.1).

Because the conventional bus was presented only at crowding levels 2 and 3, its crowding effect relative to level 1 cannot be identified separately from ASC_BUS; ASC_BUS therefore refers to the conventional bus at crowding level 2, and β_C3,Bus measures the change from level 2 to level 3. For the iBus, both crowding levels reduce utility relative to level 1 ($\beta_C2,iBus = -0.470$ and $\beta_C3,iBus = -0.718$, both $p < 0.001$), and moving from level 2 to level 3 reduces utility by a further 0.248 ($p = 0.009$). For the conventional bus, the corresponding change is small and not significant ($+0.077$, $p = 0.604$). A Wald test of equal level-2-to-level-3 effects for the two alternatives gives a difference of -0.325 ($p = 0.058$ with respondent-clustered standard errors; $p = 0.184$ with conventional standard errors).

H2 is therefore not supported at the 5% level, although the direction of the difference is consistent with it.

The nested logit model grouping Bus and iBus did not improve on the MNL model. The estimated nesting parameter was 1.49, not significantly different from 1 ($p = 0.72$ with respondent-clustered standard errors), and the likelihood-ratio test against the MNL model was not significant (LR = 0.81, 1 df, $p = 0.37$). The time and cost coefficients were similar in both models ($\beta_TT = -0.0162$ in the NL model). Using the NL coefficients in the corridor case study gives a bus share of 4.4% in the baseline and 26.8% with the full iBus package, compared with 8.6% and 29.5% in the MNL model. The MNL model is therefore retained, while recognizing that neither model accounts for random taste heterogeneity.

5.2. Values of Travel Time and Waiting Time

The estimated values of travel time and waiting time are presented in Table 4. Because travel time and waiting time were measured in minutes and travel cost in Rwandan Francs, the coefficient ratios initially yield monetary values in RWF per minute; these were multiplied by 60 to express them on an hourly basis (Section 4.7).

Table 4. Estimated values of travel time and waiting time.

Measure	Point Estimate (RWF/h)	USD/h	95% Interval (RWF/h)
In-vehicle travel time (VTT)	5281	5.37	1842 to 27,224
Waiting time (VWT)	2573	2.62	−2718 to 15,467
Ratio VWT/VTT	0.49	n/a	−0.36 to 1.18

Note: Values are ratios of the time coefficient to the cost coefficient, multiplied by 60. Intervals are Krinsky–Robb percentile intervals (100,000 draws, respondent-clustered covariance). Exchange rate: 1 USD = 983 RWF.

The estimated value of in-vehicle travel time (VTT) is approximately 5281 RWF/h (USD 5.37/h), and the estimated value of waiting time (VWT) is approximately 2573 RWF/h (USD 2.62/h). Because both values are ratios to an imprecisely estimated cost coefficient, their uncertainty was assessed with the Krinsky–Robb method using 100,000 draws from the estimated parameter distribution with respondent-clustered covariance. The 95% interval for VTT is 1842 to 27,224 RWF/h, and the interval for VWT (−2718 to 15,467 RWF/h) includes zero. The point estimate of the VWT/VTT ratio is 0.49, but its 95% interval (−0.36 to 1.18) includes one (Figure 5). The results therefore do not establish that respondents value waiting time less than in-vehicle time, and the VWT estimate should not be used for appraisal. The VTT estimate is more robust in sign but remains uncertain in magnitude.

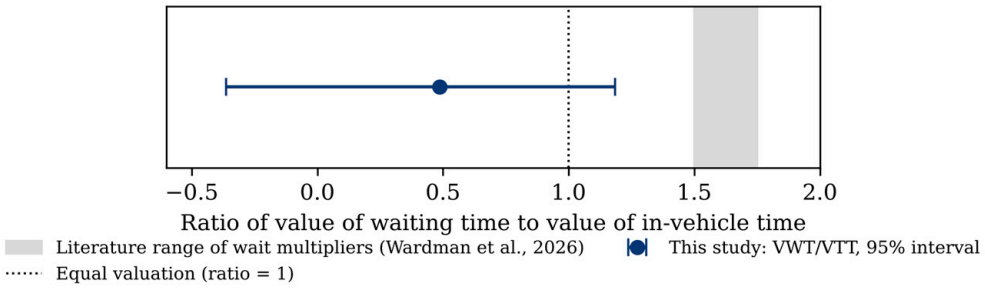


Figure 5. Estimated VWT/VTT ratio with its 95% Krinsky–Robb interval compared with the range of waiting-time multipliers reported in the literature [7]. The interval includes one, so the data does not establish that waiting time is valued less than in-vehicle time.

5.3. Case Study: Kimironko Bus Park to Nyabugogo Taxi Park

The Kimironko–Nyabugogo corridor (11.9 km) was selected as an illustrative case study because it connects major residential and trip-attraction zones in Kigali [59,60]. Table 5 shows the attributes used for each mode. The Bus, Car, and Moto values are based on operator-reported data, field observation, and cost estimation, whereas the iBus row is an assumed service scenario. Car travel costs were computed from vehicle depreciation, fuel, and parking. Depreciation was calculated assuming a vehicle cost of 5,000,000 RWF over a 10-year lifespan and 730 trips per year, giving 500,000 RWF/year ÷ 730 trips ≈ 685 RWF/trip. Fuel cost was calculated as 11.9 km × 1100 RWF/L ÷ 16 km/L ≈ 818 RWF. Parking was assumed at 100 RWF/trip, based on typical informal parking rates observed in central Kigali; this figure is an estimate rather than a directly sourced rate. Total car travel cost is therefore 1603 RWF/trip. Mode shares are computed with the MNL formula in Equation (2) and the coefficients in Table 3, and all three existing modes are assumed to be available, so the shares refer to commuters with car access within the sampled segment.

Table 5. Mode attributes and utility components on the Kimironko–Nyabugogo corridor.

Mode	WT (Min)	TT (Min)	Cost (RWF)	Crowding	ASC and Crowding Terms	Time and Cost Terms	Utility V
Bus (current)	15	75	370	Level 3	−1.499 + 0.077	−1.140 − 0.111 − 0.064	−2.737
Car	0	35	1603	None	−0.285	−0.532 − 0.277	−1.094
Moto	0	30	1200	None	−0.373	−0.456 − 0.207	−1.037
iBus (assumed scenario)	2	45	424	Level 2	0 − 0.470	−0.684 − 0.015 − 0.073	−1.243

Note: Time and cost terms are β_TT × TT, β_WT × WT, and β_CT × Cost. Shares are $P_i = \exp(V_i)/\Sigma_j \exp(V_j)$. Baseline: Bus 8.6%, Car 44.4%, Moto 47.0%. With the iBus replacing the bus: iBus 29.5%, Car 34.2%, Moto 36.3%.

The iBus row of Table 5 is an assumed service scenario, not a consequence of RTPIS alone. The 2 min waiting time assumes that passengers use real-time information to time their arrival at the stop, which has been associated with actual waiting-time reductions of about 2 min [61], combined with higher frequency and improved headway regularity through real-time fleet management [18]; it should be regarded as optimistic. The reduction in in-vehicle time from 75 to 45 min (from about 9.5 to 16 km/h over 11.9 km) assumes bus priority measures, mainly dedicated bus lanes, signal priority, and faster boarding. This is consistent with the Kigali bus restructuring study, which reports peak commercial speeds of 11 to 16 km/h and estimates that BRT-level speeds of 18 to 20 km/h would reduce peak travel times on a comparable 13 km route by 10% to 40% [62]. The improvement from crowding level 3 to level 2 assumes additional capacity on the corridor. The iBus fare was assumed to be 424 RWF, approximately 14.6% above the conventional bus fare of 370 RWF used in the baseline scenario; this value is an illustrative scenario assumption for the hypothetical iBus service, not an observed or modeled fare. To show which elements drive the predicted shift, Table 6 reports scenarios in which one attributes changes at a time, as well as a cumulative decomposition.

In the baseline, the utilities in Table 5 give simulated shares of 8.6% for the conventional bus (95% interval 5.6% to 12.8%), 44.4% for Car, and 47.0% for Moto, reflecting the weak competitive position of the current bus service on this corridor. When the conventional bus is replaced by the full iBus package, the iBus share rises to 29.5% (24.5% to 34.7%), while the Car and Moto shares fall to 34.2% and 36.3%, respectively (Figure 6). These shares describe the sampled segment of commuters and are not city-wide forecasts.

Table 6. Simulated bus share on the Kimironko–Nyabugogo corridor under alternative scenarios (MNL; 95% intervals from 100,000 Krinsky–Robb draws using respondent-clustered covariance).

Scenario	Bus/iBus Share (%)	95% Interval (%)	Car (%)	Moto (%)
S0. Baseline: conventional bus (WT 15, TT 75, 370 RWF, crowding 3)	8.6	5.6–12.8	44.4	47.0
One attribute at a time (conventional bus)				
S1a. Waiting time only: 15 to 2 min	9.4	6.2–13.7	44.0	46.6
S1b. Crowding only: level 3 to 2 (a)	8.0	5.5–11.4	44.7	47.3
S1c. In-vehicle time only: 75 to 45 min	12.9	9.1–17.9	42.3	44.8
S1d. Fare only: 370 to 424 RWF	8.5	5.6–12.7	44.4	47.0
S1e. All attributes improved, no information (b)	13.0	8.8–18.6	42.2	44.7
Cumulative decomposition (iBus)				
S2. Information only: iBus label, bus attributes unchanged	15.9	10.9–22.6	40.8	43.2
S3. S2 + waiting time 2 min	17.3	12.5–23.3	40.2	42.5
S4. S3 + crowding level 2	21.1	16.0–27.2	38.3	40.6
S5. S4 + fare 424 RWF	21.0	15.8–27.0	38.4	40.6
S6. Full iBus package: S5 + in-vehicle time 45 min	29.5	24.5–34.7	34.2	36.3
Sensitivity of the full package				
S6a. Waiting time 7 min instead of 2 min	28.7	23.8–34.0	34.6	36.6
S6b. Waiting time unchanged (15 min), in-vehicle time 55 min	24.6	19.2–30.8	36.6	38.8

(a) The conventional-bus crowding coefficient (level 3 relative to level 2) is small, positive, and not statistically significant ($p = 0.604$), so this scenario should be read as no measurable effect. (b) Conventional bus with WT 2 min, TT 45 min, 424 RWF, and crowding level 2. The contribution of each step in the cumulative decomposition depends on the order in which attributes are added.

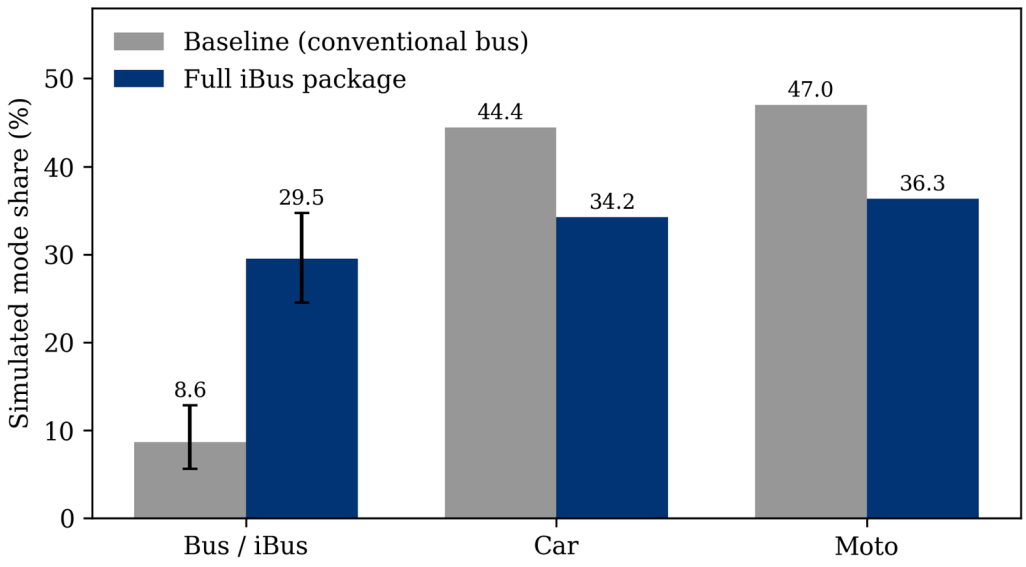


Figure 6. Simulated mode shares on the Kimironko–Nyabugogo corridor in the baseline and with the full iBus package. Error bars show 95% Krinsky–Robb intervals for the bus/iBus share.

Table 6 and Figure 7 show that no single attribute explains the predicted shift. Changing only the waiting time, crowding level, or fare of the conventional bus has little effect on its share, whereas reducing only the in-vehicle time from 75 to 45 min raises it to

12.9%. Offering the iBus label with all current bus attributes unchanged, which isolates the information-related component, raises the share to 15.9%. Improving all attributes without the information component raises it to 13.0%. The full package raises it to 29.5%. Because the information-related component is identified from the difference between the iBus and Bus constants, it may also capture perceptions of novelty or modernity and hypothetical bias, and the information-only scenario combines the iBus label with waiting and in-vehicle times outside the ranges presented for the iBus in the experiment; it should therefore be read as an upper bound on the effect of information alone. The results are robust to a less optimistic waiting-time assumption (28.7% with a 7 min wait) and, with an unchanged waiting time and an in-vehicle time of 55 min, the share is 24.6%. Using the nested logit coefficients gives 4.4% in the baseline and 26.8% with the full package. These results support H3, with the qualification that the increase reflects a package of improvements in which the information-related component accounts for only part of the shift.

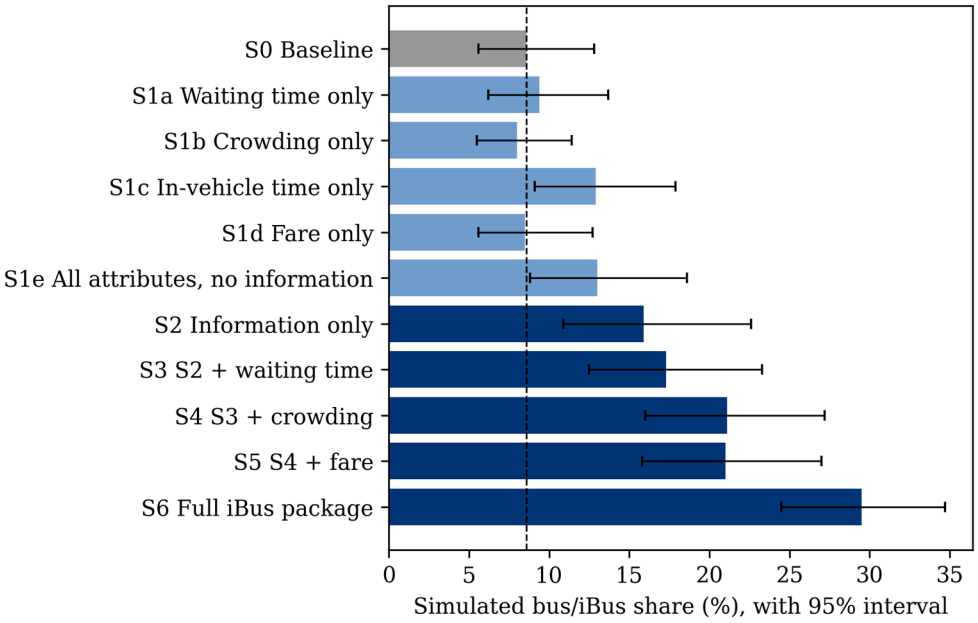


Figure 7. Simulated bus/iBus share on the Kimironko–Nyabugogo corridor under the scenarios in Table 6. Error bars show 95% Krinsky–Robb intervals; the dashed line marks the baseline share.

6. Discussion

6.1. Theoretical Contributions and Contextual Comparison

This research contributes evidence on how commuters in a sub-Saharan African city respond to an RTPIS-equipped bus service. In relation to the first objective, in-vehicle travel time, travel cost, and iBus crowding were the attributes that significantly shaped the stated mode choices of the sampled commuters, whereas the effects of waiting time and conventional-bus crowding could not be distinguished from zero.

First, the results do not reproduce the waiting-time premium that is typical in the literature, where waiting time is commonly valued at about 1.5 to 1.75 times in-vehicle time [7]. The point estimate of the VWT/VTT ratio is 0.49, but its 95% interval (−0.36 to 1.18) is wide, and a Wald test does not reject equality of the two-time coefficients ($p = 0.138$). The data are less consistent with a multiplier of 1.5 ($p = 0.008$ with respondent-clustered standard errors). H1 is therefore only partly supported: the Kigali sample shows no evidence of a waiting-time premium, but the analysis cannot establish that waiting time is valued less than in-vehicle time.

Several explanations are plausible. Waiting-time multipliers tend to be lower in stated preference than in revealed preference studies; reviews summarized by Fan et al. report an average ratio of about 1.4 for stated preference designs, compared with about 2.3 for revealed preference designs [63]. In addition, when crowding is modeled explicitly, waiting may be weighted much closer to in-vehicle time: a recent revealed preference study in Santiago, Chile, found that the value of waiting time was almost identical to the value of uncrowded in-vehicle time once crowding and preference heterogeneity were accounted for, whereas a model without crowding implied a multiplier of 1.72 [64]. Because the present model includes separate crowding terms for both bus alternatives, part of the discomfort usually attributed to waiting may be captured by these terms. Evidence from sub-Saharan Africa also indicates that the waiting-time effect can be weak for parts of the market: in a stated and revealed preference study of public transport users in Soweto, South Africa, waiting time was not significant for the largest latent class [65]. Real-time information can also reduce both perceived and actual waiting time [9,61], and its availability may lower the valuation of waiting [23]; because the iBus alternative explicitly offered such information, part of the waiting-time variation in the experiment occurred in an informed context. Finally, preference heterogeneity may attenuate the average effect estimated by a fixed-coefficient MNL model, and the experimental design offered waiting times of 15 to 45 min for the conventional bus and 2 to 10 min for the iBus, so within-alternative variation was limited; future designs should use overlapping and wider waiting-time ranges. A post hoc calculation following Rose and Bliemer [48] indicates that, at the present point estimate, roughly 750 respondents would have been needed to estimate the waiting-time coefficient at the 5% significance level.

Second, crowding on the iBus reduced its utility significantly, and the difference between crowding levels 2 and 3 was larger for the iBus than for the conventional bus, although this difference was significant only at the 10% level. One possible interpretation is that passengers who are offered a higher-quality, information-rich service expect better on-board conditions and are therefore more sensitive to crowding on that service. This interpretation is consistent with the direction of the estimates but was not tested directly and confirming it would require a design that presents both bus alternatives at all crowding levels.

Third, the simulated increase in the bus share on the corridor, from 8.6% to 29.5%, reflects a package of improvements rather than the effect of real-time information alone. The decomposition in Table 6 shows that the information-related component raises the share to 15.9%, that the reduction in in-vehicle time is the largest single attribute effect, and that changes in waiting time, crowding, or fare alone have small effects. Because the information-related component is estimated from the difference between the iBus and Bus constants, it may also capture perceptions of novelty or modernity and hypothetical bias, and should be read as an upper bound on the value of information itself.

6.2. Policy Implications

6.2.1. Implications Supported by the Choice Model

Three implications follow directly from the estimates, within the limits of the sample. First, in-vehicle travel time has the most robust effect on stated choices, and in the corridor scenarios the reduction in in-vehicle time is the largest single attribute contribution to the predicted shift. Measures that increase bus speed are therefore likely to be an important complement to RTPIS, consistent with evidence from India [66]. Second, the information-related component of the iBus has a positive effect on its own, which suggests that respondents value the provision of real-time information as part of the bus service. Third, crowding significantly reduces the attractiveness of the iBus, so the benefits of improved service may be eroded if additional demand is not matched by capacity. The

VTT estimate (5281 RWF/h, 95% CI 1842–27,224) indicates the order of magnitude of willingness to pay for in-vehicle time savings and can be compared with values reported for less-developed countries [55]; for example, a 10 min saving corresponds to about 880 RWF per trip (95% CI 307–4537), but this wide interval means that the value should be used in appraisal only with sensitivity analysis.

6.2.2. Measures That Require Further Operational and Cost Analysis

The study does not estimate the costs or the operational performance of specific measures. Dedicated bus lanes, signal priority, and BRT are candidate measures for reducing in-vehicle time, as illustrated by the bus rapid transit system in Dar es Salaam [67], and earlier planning work for Kigali has identified them as options [67], but their relative cost-effectiveness on specific corridors requires dedicated engineering and benefit–cost analysis. Similarly, the choice among information channels (stop displays, SMS, mobile applications) and the use of real-time load information for crowding management should be evaluated against deployment costs, coverage across user groups, and accuracy requirements. These questions are beyond the scope of the present choice model.

6.3. Possible Sustainability, Safety, and Equity Implications

The implications discussed in this section are not estimated by the choice model. They are illustrative and indicate where a shift from cars and Motos to an improved bus service could matter, assuming that the simulated corridor shares were realized. A shift away from Motos could reduce exposure to a mode whose vehicles were the most frequently involved in road traffic accidents in Rwanda between 2016 and 2020, and whose users were the largest group of accident victims [68], whose economic cost can be substantial when valued with the value of a statistical life [69]; and a shift away from cars and Motos could reduce fuel use and emissions per passenger-kilometer [70,71]. The size of these effects would depend on bus occupancy, fleet technology, and induced demand, none of which were modeled here. Similarly, because income was not collected, the study cannot show how the benefits of an improved bus service would be distributed across income groups, which matters for the livelihoods of lower-income urban residents [46]. Quantifying these implications would require network-level demand modeling, emissions and safety models, and a cost–benefit analysis using local deployment costs.

These considerations are relevant to transport project appraisal under Rwanda's Vision 2050 framework. A multi-channel information system combining stop displays, SMS services, and smartphone applications could help extend information benefits to commuters with different levels of technology access [19], but whether this would improve affordability or reduce mobility poverty for lower-income commuters cannot be assessed with the present data.

6.4. Generalizability and Transferability

Although based on Kigali-specific data, the methodological framework, SP survey design, MNL modeling, corridor case-study analysis, and multi-channel RTPIS architecture specification are potentially transferable to other East and Central African cities such as Dar es Salaam, Addis Ababa, and Kampala, where motorcycle taxis coexist with underdeveloped formal bus networks, a premise supported by the general literature on the transferability of model structures in developing cities [72]. The methodological framework transfers; the specific parameter values do not [73]. The non-significance of the waiting-time coefficient in the Kigali sample needs to be replicated before being treated as a regional pattern. Researchers applying this framework elsewhere should include crowding attributes in SP

designs where bus overcrowding is common and should use technology-specific attribute coefficients when introducing new technology alternatives.

7. Conclusions

7.1. Summary of Findings

This paper examined how commuters in Kigali, Rwanda, respond to a hypothetical RTPIS-equipped bus service, using a stated preference survey and multinomial logit modeling.

With respect to the first objective, the model identifies in-vehicle travel time, travel cost, and crowding on the iBus as statistically significant determinants of mode choice among the sampled commuters, together with substantial alternative-specific preferences. In-vehicle travel time has the most robust effect ($\beta_TT = -0.0152$, $p < 0.001$ with respondent-clustered standard errors). Travel cost is significant at the 5% level ($\beta_CT = -0.000173$, $p = 0.029$), although it is estimated with limited precision. Waiting time has the expected negative sign but is not statistically significant ($\beta_WT = -0.0074$, $p = 0.210$), and crowding on the conventional bus does not differ significantly between the two crowding levels presented for that alternative ($p = 0.604$). The first objective is therefore achieved for in-vehicle time, cost, and iBus crowding, whereas the evidence for waiting time and conventional-bus crowding remains inconclusive.

With respect to the second objective, the estimated VTT is approximately 5281 RWF/h (95% CI 1842–27,224), and the estimated VWT is 2573 RWF/h with an interval that includes zero. The data do not show the waiting-time premium typical of high-income settings, but they also do not establish that waiting time is valued less than in-vehicle time. Crowding reduced the attractiveness of the iBus, and the difference between crowding levels was larger for the iBus than for the conventional bus, although this difference was significant only at the 10% level. A nested logit specification did not reject the MNL model.

On the Kimironko–Nyabugogo corridor, replacing the conventional bus with the full iBus package (real-time information, 2 min waiting time, 45 min in-vehicle time, a fare of 424 RWF, and crowding level 2) raised the simulated bus share among the sampled commuters from 8.6% to 29.5%. The information-related component alone, with all other bus attributes unchanged, raised it to 15.9%, while improving the service attributes without information raised it to 13.0%. The predicted shift is therefore the result of a service package in which real-time information is an important but not the sole component, and the largest single attribute effect comes from in-vehicle travel time. These shares describe the sampled segment of commuters and are not city-wide forecasts.

7.2. Limitations and Future Research

The most important limitation is the sample. It is a non-probability online sample that over-represents young (74.7% aged 20 to 30), university-educated (about 95%), and car-accessible (50.3%) commuters, and it contains no income data. The coefficients, values of time, and simulated mode shares therefore describe this segment and should not be interpreted as city-wide forecasts. Methodological evidence indicates what such a sample can support. Internet-based stated preference surveys generally do not produce substantially different welfare estimates from other survey modes, with sample representation being the main concern [74], and hypothetical bias in choice experiments tends to affect total willingness to pay more than marginal rates of substitution such as values of time [75]. In contrast, inferences from non-probability samples to population-level quantities, such as mode shares, depend on modeling assumptions and are generally less accurate than those from probability samples [42]. Future work should use probability-based or intercept

sampling at bus stops and Moto stages, include income and car ownership, and test for preference heterogeneity across socio-economic groups.

Second, the experimental design had several limitations. The conventional bus was presented only at crowding Levels 2 and 3, so its crowding effect relative to seated conditions could not be estimated, and the waiting-time ranges for the two bus alternatives did not overlap, which limited the precision of the waiting-time coefficient. The utility-balance selection relied on prior coefficient values, and an efficient design based on the present estimates would improve precision in future surveys.

Third, the information-related component is identified from the difference between the iBus and Bus constants and may include perceptions other than the value of information, as well as hypothetical bias. Revealed preference data collected after RTPIS deployment would be needed to validate the stated preference results.

Fourth, the model has modest explanatory power, does not account for random taste heterogeneity, and treats repeated choices only through cluster-robust standard errors. Mixed logit or latent class models [76], estimated with a larger sample that includes income, would allow heterogeneity in responses to RTPIS to be examined. The nested logit test did not indicate correlation between Bus and iBus, but this test has limited power with the present sample.

Finally, the corridor analysis assumes specific service improvements whose costs and feasibility were not assessed, and it does not capture network-wide effects such as route rebalancing, induced demand, and congestion. City-scale network modeling and a benefit–cost analysis using RTDA's procurement and operating costs are recommended as follow-up work.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Figure A1 shows an example of the choice tasks presented to respondents, and Table A1 reports the distribution of respondents and valid choices across the three blocks of the experimental design.

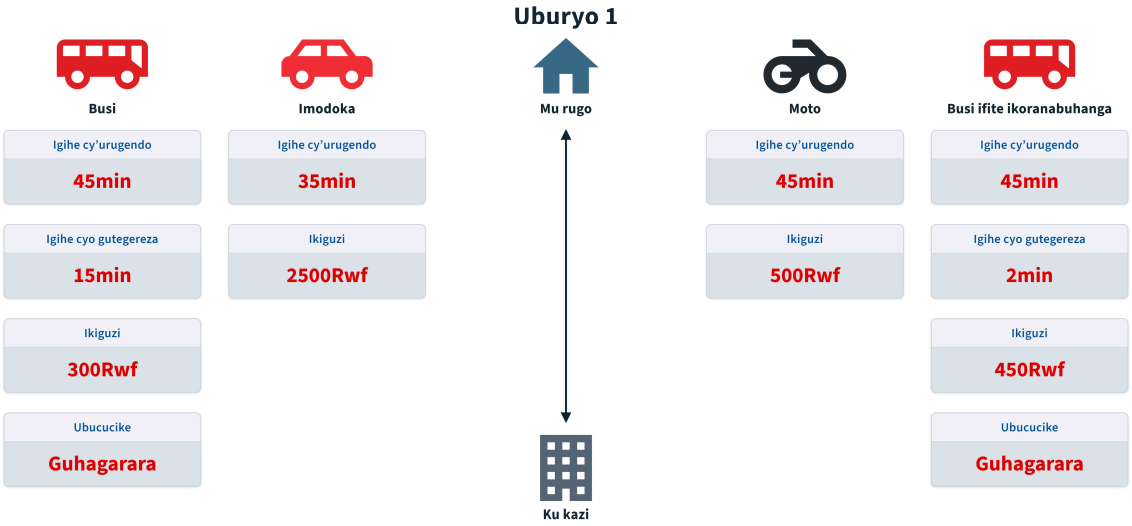


Figure A1. Example choice task (Block 1, task 1) as presented to respondents. Labels translated from Kinyarwanda: Uburyo 1 = Option 1; Busi = conventional bus; Imodoka = private car; Moto = motorcycle taxi; Busi ifite ikoranabuhanga = bus with real-time information (iBus); Mu rugo = home; Ku kazi = work; Igihe cy'urugendo = in-vehicle travel time; Igihe cyo gutegereza = waiting time; Ikiguzi = cost; Ubucucike = crowding; Guhagarara = standing. Photographs shown to respondents beside the crowding level have been omitted. The double-headed arrow represents the commute between home (Mu rugo) and the workplace (Ku kazi).

Table A1. Distribution of respondents and valid choices across blocks.

Block	Respondents Surveyed	Respondents with ≥1 Valid Choice	Completed All 6 Tasks	Valid Choices	Valid Responses per Task (Range)	Car-Access Version (Respondents)
1	102	102	89	573	93–97	53
2	104	103	79	549	87–95	58
3	103	101	81	549	87–99	43
Total	309	306	249	1671	87–99	154

Note: Three respondents (one in Block 2 and two in Block 3) provided no valid choice. Car-access respondents answered the four-alternative version (Bus, Car, Moto, iBus); the remaining respondents answered the three-alternative version (Bus, Moto, iBus). Valid responses per task gives = the minimum and maximum number of valid responses across the six choice tasks in each block; for the total, the range is across all 18 tasks.

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