

Perceived risks and intention to use ride-hailing services: Insights from an emerging market



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Background: Ride-hailing services (RHS) offer accessible and affordable transport and are gaining traction in cities globally. However, there is limited research that addresses how perceived risks shape the intention to use RHS in emerging markets.

Objectives: This study examined the relationship between perceived risk dimensions and the intention to use RHS.

Method: Data from 179 respondents (users and non-users) were analysed using structural equation modelling.

Results: Uber and Bolt dominate the RHS landscape in Nairobi. Key risk factors include driver performance, service and/or application (App) performance, and privacy concerns significantly affect users' perceived risk. Lower perceived risks in these factors are positively associated with the intention to use RHS.

Conclusion: The findings highlight the need for policies that ensure service quality and user safety in technology-mediated transport. By applying perceived risk theory (PRT) and digital collaborative consumption (DCC), the study clarifies how risk perceptions influence RHS adoption in emerging urban contexts.

Contribution: This study contributes to RHS literature by integrating PRT and DCC frameworks, and identifying critical service-related risks influencing user behaviour in emerging economies.

Keywords: ride-hailing service; perceived risk; intention to use; emerging markets; urban mobility; app performance.

Introduction

Ride-hailing services (RHS) are a relatively recent mobility innovation where users request a ride using a mobile application (App) on the Internet. Ride-hailing services have been embraced in major cities across the world, albeit with some resistance from traditional taxi service providers in some places (Wang et al. 2019). The emergence of RHS has significantly increased the supply of taxi services, thus creating increased competition with traditional taxis, as well as among the various RHS providers. From a user perspective, the service has offered customers an alternative to traditional taxis and public transport. Therefore, RHS, such as Uber and Bolt, have bridged a mobility gap by providing an efficient and effective service, especially for short-distance urban trips.

The global ride-hailing market is currently valued at \$203.54 billion and is expected to grow to \$322.47bn by 2030 at a compound annual growth rate (CAGR) of 9.64% (Mordor Intelligence 2025a). The growth of RHS is fuelled by rapid urbanisation, growing tourism industries and rising traffic congestion in urban cities. The growth of the ride-hailing sector is impacting the car segment, as it is likely to drive the adoption of electric mobility, as well as providing convenient urban mobility for tourists. The adoption of electric cars is globally advocated as a clean form of transport with reduced emissions, especially in cities. There are several benefits for RHS users, such as a high quality and dignified transport service (Wang et al. 2019), increased social economic status (Soltani et al. 2021) and a relatively low cost of service (Furuhata et al. 2013). Ride-hailing services, while often examined as a standalone stream within platform-based urban mobility, are best conceptualised within the broader framework of digital collaborative consumption (DCC). Digital collaborative consumption refers to digitally mediated peer-to-peer systems that facilitate temporary access to goods or services, typically for a fee, without transferring ownership (Garrett, Straker & Wrigley 2017). In emerging

markets, the adoption of DCC models has been driven by rising smartphone penetration (World Bank 2023), worsening urban congestion (Rwakarehe 2022), and eroding confidence in conventional service delivery. Empirical studies in the African context (e.g., Berndt, Pretorius & Blaauw 2021; Shumba & Saruchera 2023, 2024) highlight that trust in platforms and perceptions of user safety are central to the viability of DCC initiatives. Motsi and Chipangura (2024) viewed platforms from the perspective of taxi entrepreneurs and found that perceived usefulness and perceived trust were critical to the adoption of such platforms. These findings are directly applicable to RHS, where users' (and drivers') uptake is shaped by perceived utility, affordability and risk. Situating RHS within the DCC paradigm thus enables a more comprehensive understanding of the structural and behavioural dynamics that underpin digitally mediated access to urban mobility in emerging city contexts.

Despite the benefits and growing significance of RHS in creating jobs, supplementing short-distance public transport and offering convenient mobility for tourists in unfamiliar cities, these services are increasingly exposed to various perceived risks that may negatively influence future use intentions. For instance, security risks, especially physical harm resulting from the business rivalry with the traditional metered taxis; personal privacy risks, which may result from sharing personal information; health risks, which might result in becoming infected with communicable diseases; and other risks, such as financial risks. Users are likely to use the RHS if the benefits outweigh the perceived risks, that is, sufficient value is created when using the service (Wang et al. 2019). Although there are studies that have investigated the RHS phenomenon, many have focused on the adoption of ride-hailing Apps in various cities across the globe and RHS regulations by transport agencies. Many others have studied the phenomenon from a ride-sharing perspective rather than an on-demand service. Specifically, Cheng et al. (2023) investigated the relationship between ride-sharing transactions and mutual trust, and established that order distance, time and the completion rate influence trust. Witt, Suzor and Wikström (2015) addressed the regulatory challenge of ride-sharing in the sharing economy. Hamal and Huijismans (2022) claimed that safety concerns in ride-sharing have resulted in some platforms having gender as part of their digital design, especially to link women clients to women drivers. Ride-hailing services are growing rapidly in emerging markets; however, it remains unclear which perceived risk dimensions, such as safety, privacy or App reliability, most influence users' intention to adopt or continue using these services. This gap is particularly evident in African urban contexts, where structural conditions and platform governance differ markedly from those in developed markets. Despite the relevance of perceived risk theory (PRT) and DCC frameworks, few studies have applied them to understand user behaviour in ride-hailing in African cities. This study addresses that gap by examining how specific risk perceptions shape user intentions in Nairobi. The specific objectives are:

- To analyse market dominance and user preferences among RHS.
- To determine the relationship between the perceived risks and the intention to use RHS.
- To determine the reasons for not using RHS among the non-users.

The study was underpinned by the collaborative consumption framework and the PRT. The collaborative consumption framework refers to the systems where individuals obtain and provide resources or services, often facilitated by digital platforms (Bosman & Rogers 2010). The concept originated with Felson and Spaeth, who defined collaborative consumption as a process in which one or several individuals use goods or services by engaging in shared activities with others (Felson & Spaeth 1978). The collaborative consumption framework makes assumptions that it can enhance resource optimisation, is a community-based exchange, prioritises access over ownership, and is technology-enabled sharing. These assumptions align well with RHS offered by Uber, Bolt, Lyft and other players in this sector. While Frenken and Schor (2019) question the relevance of the collaborative consumption framework in highly commercialised RHS, we argue that the current RHS still fall within the framework, especially from a socio-economic perspective, where it is likely to reduce car ownership, create new job opportunities and integrate with public transport systems. The behavioural intention to use RHS in the context of risks can be explained using the rarely used PRT. The PRT suggests that consumer behaviour can be influenced by perceptions of uncertainty and the consequences of their decisions (Mitchell 1992). Uncertainty and perceived negative consequences of RHS are likely barriers to the use or continued use of ride-sharing. The consequences related to perceived risk can comprise financial, social, performance, physical and time risks (Mitchell 1992). Thus, perceived risk in the RHS can be construed to be multidimensional and affected by contextual factors, such as demographics, social, economic, technological and institutional regulatory frameworks (Wei et al. 2018). The collaborative consumption framework and PRT together offer a comprehensive lens to understand RHS adoption in African cities. While collaborative consumption highlights access, shared value and socio-economic benefits, PRT explains how context-specific concerns influence users' trust and willingness to engage with these services.

Literature review

Ride-hailing services and intention to use

The emergence of RHS in African cities presents a significant mobility innovation that has transformed travel behaviour and created new economic opportunities for the youth, who are often unemployed. The penetration of RHS in the top five markets in African countries is estimated to range from 41% to 51%, with South Africa, Zambia and Kenya being the top three, in that order (Sagaci Research 2024). The market is

dominated by international players, including Uber and Bolt in most African countries. Uniquely, in South Africa, most of the RHS are concentrated in the suburbs, while the residents in the low-income areas rely on minibus taxis to meet their mobility needs.

From the launch of the Uber RHS application in 2009 and its first requested trip in 2010 (Uber 2025), the rise of mobility-on-demand services is one of the greatest innovations in the personal movement environment in the last decade. Uber had completed over 9.44 billion passenger trips by 2023 with about \$37.2bn in revenue (Iqbal 2025). Globally, RHS and service providers have grown considerably, with the estimated value of the industry being over \$203bn in 2025, with an estimated growth to \$322.47bn by 2030 (Mordor Intelligence 2025c). In Africa alone, it is estimated that there are over 60 RHS companies across 21 African countries (Kandil 2019). The strong growth of these services in developing countries is often associated with local transport services being of poor quality, unreliable and expensive (Kandil 2019; Nguyen-Phuoc et al. 2022a), and the lack of alternative forms of transport.

The relative lack of acceptable public transport services suggests that in developing African countries, car ownership is increasing at a rapid rate (Mordor Intelligence 2025a; 2025b). For example, Kenya indicates that vehicle ownership is on a growth path. Furthermore, RHS have gained popularity in developing countries, partly because they provide the benefits of private car usage without the requisite capital investment. The RHS are filling a gap left by inadequate public transport systems, while relying on the use of cars or buses. In Brazil, Cats et al. (2022) found that, although many RHS routes have a viable public transport alternative, 20% to 40% have no alternative. This suggests that RHS frequently complement the total transit system by providing transport in areas not serviced by public transport. This is reinforced by Jin, Kong and Sui (2019), who found that in New York, Uber complements public transport from midnight, and in places with insufficient public transport services. This implies that in cases where there are unreliable public transport services, there is a likelihood of a significant increase in RHS usage.

Ride-hailing services thus complement the total transport service offering in an area, but also often competes with public transport services (Jin et al. 2019), especially where public transport is perceived to be of inferior quality and crime rates are high. Ride-hailing services therefore become a viable alternative to public transport. Where public transport is considered unsafe, RHS are often perceived to be a safer alternative. There are, however, many service elements associated with RHS that are perceived as being of a higher quality than public transport, thus providing the RHS with a competitive advantage. Long waiting times and total trip times associated with public transport have driven the demand for RHS. For example, Etmnani-Ghasrodashti and Hamidi (2019) cite

reduced waiting times, less stress and cost-effectiveness as key benefits of RHS. Service elements, such as travel time, commuting distance, convenience, affordability and security, are important in RHS. Comfort and convenience, including an alternative to drunk driving, slow public transport and long walking or cycling distances (Etmnani-Ghasrodashti & Hamidi 2019) are central to the decision to use RHS. It is also a viable alternative when there is bad weather and is used as a mobility substitute for households that do not have access to private vehicles. Other reasons for using RHS include difficulty in finding parking or that the parking is expensive at the destination, reducing the stress of driving in traffic, providing a service to those who do not have a licence to drive or simply providing an alternative to getting lost while driving.

Ride-hailing service is, therefore, used in numerous ways. In some instances, it replaces the user's traditional method of commuting or supplements the public transport commute to access medical services, shopping, education, sports, recreation, parcel delivery and online food orders (Cats et al. 2022).

Despite the popularity of RHS, the sustainability of the model depends on the unique service attributes offered. Ride-hailing services are generally used to provide comfortable, convenient, safe and reliable transport alternatives, and their use and loyalty are dependent on users' perceptions of the service quality (Nguyen-Phuoc et al. 2022b). Typical modal choice features include comfort, on-time pick-ups and drop-offs (Man et al. 2019), vehicle standards or conditions (Ziyad et al. 2020) and drivers' professionalism and attitude (Nguyen et al. 2020). Other modal choice factors unique to RHS include that the application used should always work, be secure, easy to use, quoted rates should be accurate and customer payment and personal information should be safe and secure (Nguyen-Phuoc et al. 2022). A variety of payment options should be available, and payment disputes should be easily resolved (Spicer 2021). Price is also a key determinant of using RHS, such as a too high a cost would be a disincentive to use the services (Assegaff & Pranoto 2020). The ability to attract and retain customers is largely dependent on the perceived safety of the service. In Kenya, almost 65% of the respondents in Kamais's (2019) study believed that abductions, carjacking, sexual harassment, murders, robberies and burglaries were all potential risks associated with RHS. Concerns regarding safety from the drivers' conduct are, however, mitigable through the use of the driver rating system (Mao et al. 2021) and the use of female drivers. Users and non-users are periodically discouraged from using RHS because of the threat of attacks from traditional metered taxi services. The growth of RHS is significant in African cities; however, it is largely driven by the limited public transport. The intention to use the service depends on the quality of service perceived to be good enough to justify the higher cost of the RHS. It should not present a higher risk than the services the users are currently using.

The intention to use RHS can be influenced by personal innovativeness, environmental awareness and perceived usefulness, while perceived risk is negatively associated with users' intention (Nguyen-Phuoc et al. 2022a). This implies that the intention to use RHS can be influenced by personalised benefits, but can be discouraged if there are privacy concerns or associated risks. Higher physical risk reduces trust in drivers, which lowers trust in the RHS platform and increases the intention to discontinue use (Ma et al. 2019). Therefore, the intention to use RHS depends on a range of variables, such as perceived usefulness, perceived risk, perceived ease of use, attitudes and performance expectations; although their importance varies across different studies, indicating that the context in which they are investigated is significant. It is important for RHS providers and policymakers to assess the constructs underlying the intention to use RHS, and identify the factors most likely to affect behavioural intention within the specific market. The use of RHS can be inhibited by various factors, including risks associated with its use.

Perceived risks of ride-hailing services

Safety concerns consistently emerge as a significant barrier to ride-hailing adoption and continued use in African cities. In Nairobi, non-users cited safety as their primary deterrent, supported by reports of robbery, assault and harassment affecting both riders and drivers. In Johannesburg, violent clashes between metered taxi operators and ride-hailing drivers have heightened safety perceptions (Henama & Sifolo 2017), thus reducing the willingness to ride in certain areas. Similarly, in Lagos, users reported feeling unsafe during at least one trip, especially at night, and by female users (Akande et al. 2019).

Regulatory challenges in African cities have created uncertainty and operational challenges for the ride-hailing platforms, potentially undermining consumer confidence. Currently, there is ambiguity regarding licensing, taxation and operational requirements. These challenges have resulted in confrontations between metered taxis and ride-hailing operators in Johannesburg, as mentioned earlier (Mpfungu et al. 2020), as well as undermining ride-hailing investments in certain African countries, such as Nigeria.

Economic and technological factors present significant barriers to RHS adoption in African cities. The market is highly price-sensitive, with fare increases often leading to reduced usage. In many contexts, RHS remains largely accessible only to middle- and upper-income residents. Technological barriers, such as limited smartphone ownership, high data costs and poor network coverage, further restrict access, particularly among older users and those in low-income communities. In addition, trust issues between users and ride-hailing platforms are a recurring concern in cities. In Nairobi, inconsistencies in driver quality and vehicle condition undermine confidence, particularly among female users, with trust in platform vetting cited as a

key factor (Olayode et al. 2023). In Johannesburg, perceptions of inadequate driver screening and the mishandling of complaints reduce trust and regular use. In Lagos, trust concerns include both physical safety and digital privacy, with 37% of users expressing data security concerns (Akande et al. 2019).

Critical review of empirical literature

The literature review established that safety, regulatory and economic and technological concerns are likely barriers to using RHS. A further review of empirical literature on the adoption and use of RHS, particularly in emerging markets, investigated studies that cover a range of theoretical frameworks, including the technology acceptance model (TAM), theory of planned behaviour (TPB) and risk-based models. The focus in the literature is largely related to psychological, technological and socio-demographic aspects of RHS drivers, with increasing attention to perceived risk, service quality, trust and platform performance (see Table 1). While constructs, such as usefulness, ease of use and social norms, consistently influence intention to use RHS, the role of perceived service risks, such as driver behaviour, App reliability and privacy, remain underexplored, especially in the African context. Moreover, few studies apply a combined lens of PRT and DCC to explain user behaviour. Based on this review, the study proposes to test the following hypotheses:

H1: Perceived driver risk influences intention to use RHS.

H2: Perceived App performance risk influences intention to use RHS.

H3: Perceived privacy risk influences intention to use RHS.

Research methods and design

A quantitative research approach is applied to investigate the effect of risks on the benefits and intention to use RHS; thus, a positivist research philosophy formed the foundation of this study. A survey research design enabled the collection of a large number of responses, from which inferences could be drawn, and therefore, considered to be the most appropriate to investigate the research problem at hand.

Both users and non-users of RHS were considered to investigate the perceived risks of RHS. For this reason, Nairobi's 4 million people in the research area were the population. A sample size of 385 was determined using the Taherdoost (2017) sample size calculator to achieve a confidence level of 95% with a margin of error of 5%. To ensure robust results, this was rounded up to 400 targeted respondents (Taherdoost 2017). The number of valid responses was 179 (a response rate of 44.75%), but even though below 200, the sample size was considered sufficient for variance based structural equation modelling (VB-SEM) analysis, given the low complexity of the specified model (Gerbing & Anderson 1985). A convenience sampling technique was used to collect data from the highly populated areas of Nairobi, specifically the shopping centres along Thika Road, Westlands, Ngong Road and Mombasa Road.

TABLE 1: Summary of key studies on ride-hailing services adoption.

Number	Authors	Context	Theoretical framework	Research focus	Methodology	Key findings	Limitations
1	Inan et al. (2022)	Indonesia, focusing on technology anxiety and social influence	Technology acceptance model (TAM); UTAUT	Examines how anxiety and social influence impact the intention to use ride-hailing.	Quantitative; survey 251 respondents; SEM-PLS.	Social influence and technology anxiety significantly affect the intention to use; social influence is the strongest predictor.	Limited to a specific region; potential for broader demographic exploration. Perceived risk on RHS not examined.
2	Ma et al. (2019)	China, with a focus on DiDi Chuxing	Risk-to-trust unidirectional model	Relationship between risk perception and discontinuation intention.	Quantitative; 443 users; SEM.	Physical risk reduces trust in the driver; affects platform trust and discontinuation intention.	Focused on discontinuation rather than adoption.
3	Irawan et al. (2023)	Indonesia; motorcycle-based RHS	Theory of Planned Behaviour (TPB)	Explores texting while driving, intentions of drivers.	Survey; 497 drivers; regression analysis.	Attitudes and risk perception influence texting intentions; the risk of an accident reduces intention.	Focuses on drivers rather than users.
4	Gumilar et al. (2019)	Indonesia, Jabodetabek region	TAM with added variables (personal innovativeness, perceived risk)	Examines factors influencing actual RHS use.	Quantitative; 100 respondents; SmartPLS.	Ease of use and usefulness affect intention; perceived risk impacts intention but not usefulness.	Small sample; generalisability limited.
5	Arora, Singh and Gupta (2022)	India (Punjab, Chandigarh)	TAM + Fuzzy AHP	Factors influencing ride-hailing adoption.	Fuzzy AHP; survey of 251 respondents.	Perceived usefulness is most influential; risk is least influential.	Limited geographical scope; only 8 factors from TAM were studied. The relationship between perceived service risk and intention to use RHS was not addressed.
6	Hasan et al. (2022)	United Kingdom	TPB	Attitudes towards autonomous vehicles in RHS.	Survey; Spearman's rank test.	Positive attitudes, but safety risk remains.	Focused on young adults (18–24 years), only UK context. Correlation between perceived risk and intention to use was not measured. The study examined AVs and not RHS.
7	Auditanto et al. (2019)	Indonesia	TAM and Gig economy literature	Factors influencing PGE use.	PLS-SEM; 318 respondents.	Hedonic motivation, trust and platform quality are the key drivers.	Does not isolate RHS; combines gig sectors.
8	Zaigham, Chin and Dasan (2022)	Malaysia	Extended TAM	Determinants of RHS use among drivers.	Survey ($n = 495$); SEM.	Trust, regulation and ease of use are important. Perceived risk only matters if trust is low. This finding conflicts with prior studies.	Driver perspective only; excludes users.
9	Goel and Haldar (2020)	India (New Delhi)	TAM	Factors influencing shared RHS.	SEM; 355 respondents.	Trust, ease of use and risk affect intention; gender moderates the effect.	Focused only on shared RHS; single city. Did not specifically focus on the dimensions of perceived risk.
10	Elnadi and Gheith (2022)	Egypt	TAM and IDT	Investigates the factors influencing consumers' continued intention to reuse ride-hailing services.	SEM; 379 respondents.	Attitudes significantly drive continued use of ride-hailing apps in Egypt, shaped by perceived usefulness, ease of use, enjoyment, social influence, risk, compatibility, interactivity and innovativeness. Gender and age moderate some effects.	Focuses on continued use only; limited to Egypt; excludes non-digital users.
11	Nguyen-Phuoc et al. (2022b)	Vietnam	Extended TPB	Examines how psychological factors affect passengers' intention to use OSR services.	Survey of 520 ride-hailing users; SEM.	Psychological factors significantly influence intention to use OSR. Perceived risk reduces intention directly.	Context-specific (Vietnam); limited generalisability; reliance on self-reported data.

Note: Please see the full reference list of the article, Mageto, J. & Luke, R., 2025, 'Perceived risks and intention to use ride-hailing services: Insights from an emerging market', *Journal of Transport and Supply Chain Management* 19(0), a1173. <https://doi.org/10.4102/jtscm.v19i0.1173>, for more information.

CAGR, Compound annual growth rate; UTAUT, Unified theory of acceptance and use of technology; PLS-SEM, Partial least squares structural equation modelling; IDT, Innovation diffusion theory; OSR, on-demand shared ride.

Quantitative primary data were collected from users and non-users of RHS using a structured questionnaire. The questionnaire had two sections: Section A collected demographic data, and Section B, the data related to perceived risks, benefits and intention to use RHS. The items in Section B were drawn from the studies of Venkatesh et al. (2003), Wang et al. (2019), Nguyen-Phuoc et al. (2022a, 2022b) which were modified to meet this study's requirements.

The questionnaire was developed by academic users of RHS and piloted among 20 users and five non-users. A few items were ambiguous and were revised accordingly. Data were collected directly from the respondents either by sharing the survey link or their answering the electronic Google Form.

The collected data were exported from Google Forms to MS Excel, coded and cleaned. Demographic data were

analysed using descriptive statistics to profile the respondents. Items related to perceived risk and intention to continue using RHS were subjected to exploratory factor analysis (EFA) to develop the scales of the extracted constructs. The effect of perceived risks on benefits and intention to use RHS was investigated using partial least squares structural equation modelling (PLS-SEM). The predictor latent variables were generally related to the dimensions of perceived risk of using RHS, while the outcome latent variable was intention or willingness to use (WTU) RHS. All the indicators were modelled as reflective, as the latent construct manifests through the indicators. Partial least squares structural equation modelling was chosen for its predictive power and ability to maximise explainable variance and theory development even with small samples (Dash & Paul 2021).

Reliability of the scales was tested using Cronbach's alpha to ensure internal consistency. Validity was tested using the discriminant validity test from the confirmatory factor analysis result.

Ethical considerations

Ethical clearance was obtained on 05 March 2021 according to the ethical codes of the CBE Research Ethics Committee at the University of Johannesburg (Reference number: 2021-TSCM007). All participants were between 18 years and 65 years of age and provided written informed consent after being fully briefed about the study's objectives, their right to withdraw at any stage and the potential use of anonymised data in future academic publications.

Results

Descriptive statistics

The frequency distribution of the demographics is presented in Table 2. About 21% of the respondents were unemployed. The majority of those employed earned below \$1000.00 per month, implying that RHS caters to relatively low-income users and therefore, cannot charge the higher rates, often prevalent in developed countries. Most of the respondents do not own cars and have at least an undergraduate degree. The most popular mode of transport is the *matatu* [generally known as a minibus taxi], and private cars are second.

The average age of the respondents was 32 years, with about 70% below the age of 35 years or generally within the youth category. This finding aligns with the 2019 population census (KNBS 2019). Uber and Bolt were found to be the most popular RHS in Nairobi, where 86% of the respondents had used both. Among the local RHS providers in Nairobi, Little was the most popular as 41.3% of the respondents had used it. On the other hand, only 22.3% and 10.1% of the respondents had experienced PewinCabs and Mondoride RHS, respectively. The results reveal that young users of RHS usually ride with friends or strangers, while older users ride

TABLE 2: Demographic information.

Variable	Frequency	%	Cumulative %
Gender			
Male	81	45.3	45.3
Female	98	54.7	100.0
Employment			
Full time	87	48.6	48.6
Part time	54	30.2	78.8
Unemployed	38	21.2	100.0
Car ownership			
Yes	45	25.1	25.1
No	134	74.9	100.0
Education level			
Certificate	19	10.6	10.6
Diploma	42	23.5	34.1
Bachelor's degree	91	50.8	84.9
Master's degree	22	12.3	97.2
Doctorate degree	5	2.8	100.0
Monthly salary			
Below 50k	83	46.4	46.4
50k – 100k	53	29.6	76.0
101k – 200k	27	15.1	91.1
201k – 300k	8	4.5	95.5
301k – 400k	4	2.2	97.8
401k – 500k	4	2.2	100.0
Common mode			
Bodaboda	7	3.9	3.9
Taxi	3	1.7	5.6
Car	56	31.3	36.9
Walk or bicycle	4	2.2	39.1
<i>Matatu</i> [Minibus taxi]	109	60.9	100.0
RHS use			
Yes	161	89.9	89.9
No	18	10.1	100.0

RHS, ride-hailing service.

either alone or with family. This might imply that the younger users would be splitting fares, given the relatively low-income levels in Nairobi, as well as many of the developing countries.

The general perceived risk of the RHS was examined, as well as the expected risk during a reported outbreak of a communicable disease, such as the coronavirus disease 2019 (COVID-19) pandemic. The results showed that most respondents consider RHS to be of a low to moderate risk, with only about 15% rating them as a high to very high risk. The findings support the general acceptance of the RHS in Nairobi and other cities in Kenya. In addition, the respondents considered the service to be safe even during the COVID-19 pandemic. This implies that the strict measures of wearing a mask during rides with Uber and Bolt were well received by users and might have reduced the perceived risk.

The risk levels of RHS were examined based on age, gender, car ownership and user versus non-user (Figure 1). The respondents between the ages of 24 years and 26 years perceived the RHS as being of high risk, while the majority of those in the 30–40 age group considered the risk to be moderate to low, as illustrated in Figure 1a. Both female and

male users perceived RHS to be of moderate to low risk, with female users considering it to be slightly riskier than their male counterparts (Figure 1b). Although respondents who owned cars and those who did not rated the risk level as moderate to low, none of those with cars perceived the risk as very high (Figure 1c). Some non-users of RHS consider these to be of high risk (Figure 1d), which might be the reason for not using these.

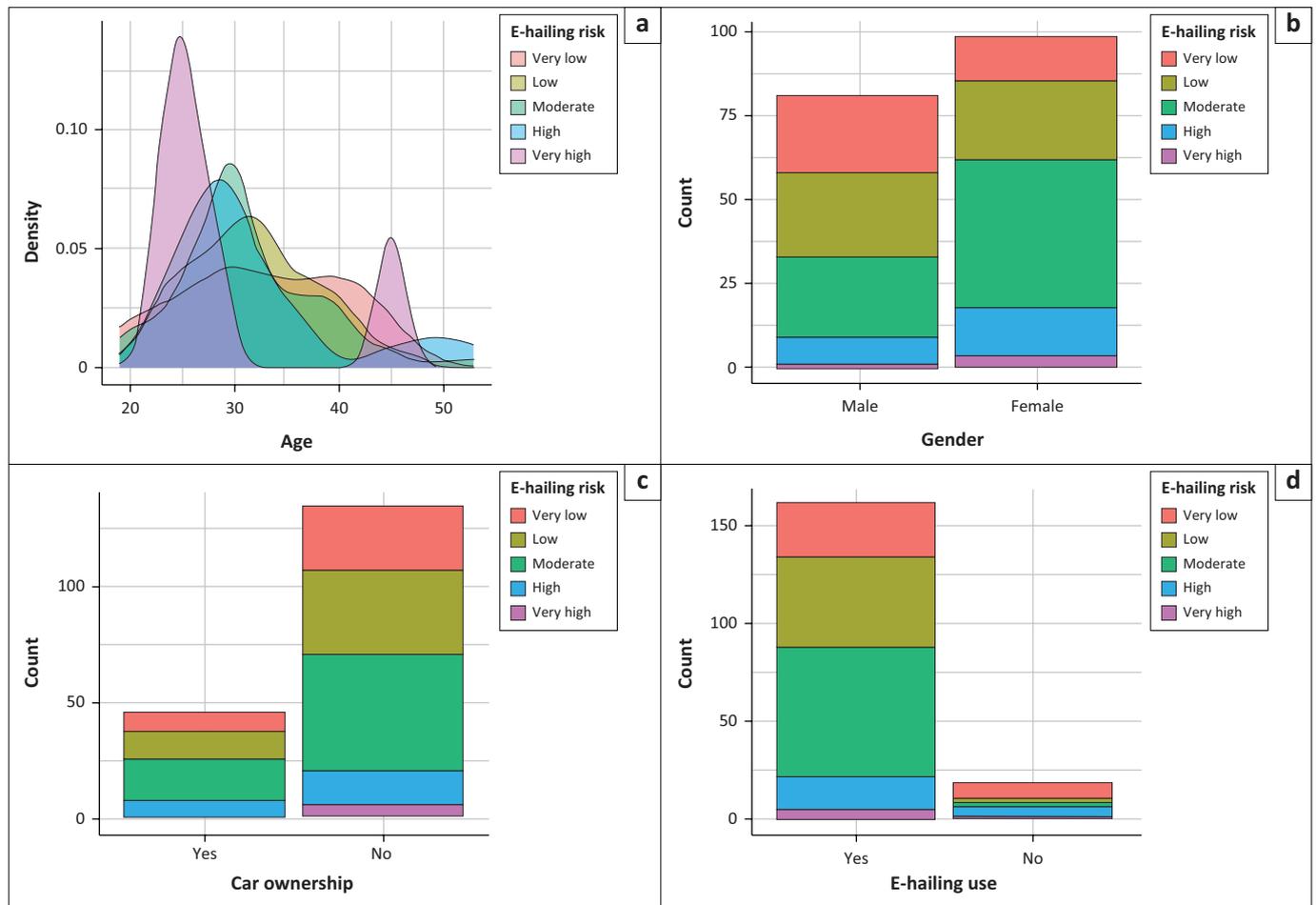
The level of the perceived risk of RHS was examined against the frequency of each of the services. Uber and Bolt, which are used regularly, are perceived to have a moderate to low risk, compared to when used less regularly (Appendix 1: Table 2-A1). This implies that regular users, who have higher levels of familiarity with the service, perceive it to be low risk, while less regular users do not seem to have built up a level of trust as yet.

Some non-users indicated that they did not understand how it works, considered RHS expensive or preferred a private car or public transport. The majority (63%) of the respondents indicated that they would use public transport if RHS were not available. About 34% would use a metered taxi and 29% would use a private car. While the results indicated that other users would walk or use a motor bike, 6% of the respondents

seemed captive to RHS as they indicated they would not travel in the absence of RHS.

The respondents indicated that they used RHS for a variety of reasons, including being quicker than public transport, comfortable and safe, and dependent on weather conditions; but it is important to note that users find it to be a preferred mode rather than public transport as a mobility solution, as reflected in Figure 2. This reinforces the perspective that RHS frequently replaces public transport in developing countries, rather than replacing car ownership, which may stimulate private vehicle ownership.

The main purpose of travelling using the RHS was examined. The results indicated that the primary reason for use is social trips (35% of respondents), suggesting that the services supplement the public transport sector. However, about 25% of respondents do use RHS to commute to work, implying that some commuters prefer RHS rather than public transport. Ride-hailing services is also used for shopping by 17% of the respondents, parcel delivery (9%), ordering food (8%) and commuting to school (3%). Other travel reasons include attending sports, running errands and visiting the hospital, but all on a limited basis.



Note: E-hailing risk refers to ride-hailing service risk.

FIGURE 1: Ride-hailing service risk levels based on: (a) age, (b) gender, (c) car ownership and (d) use.

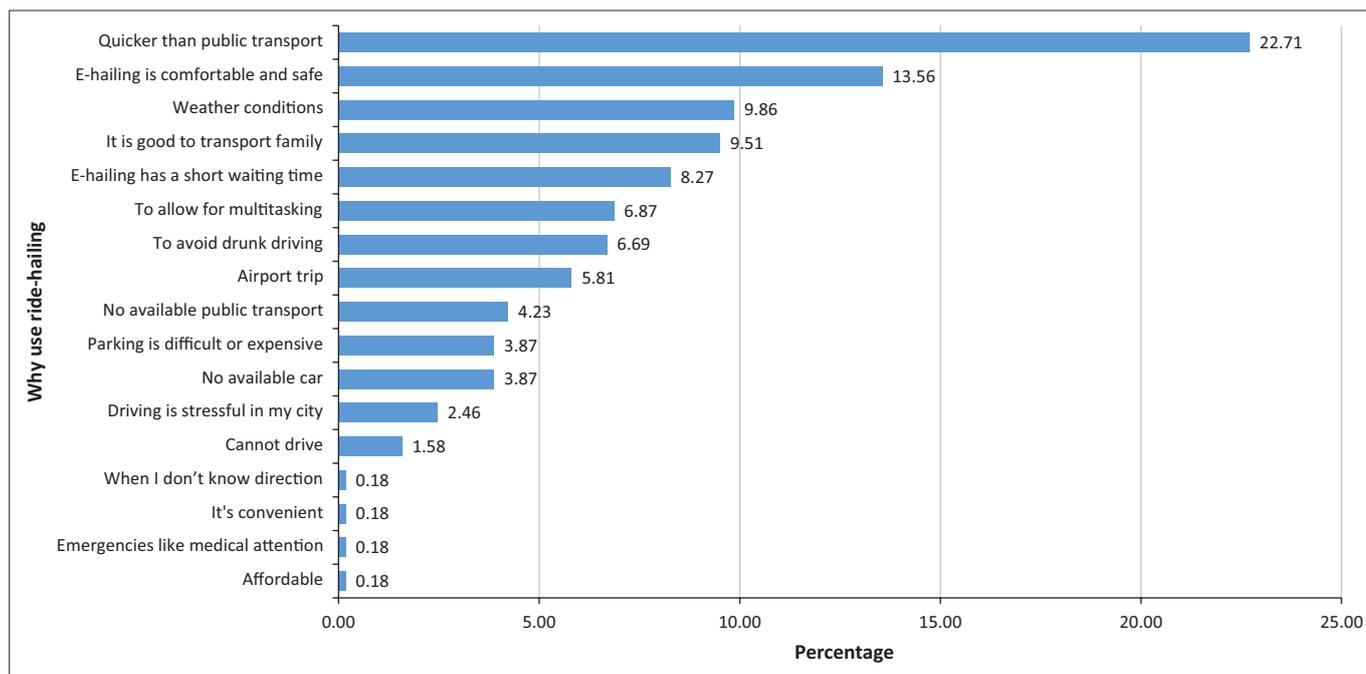


FIGURE 2: Reasons for using ride-hailing services.

Factor analysis of the perceived risk of ride-hailing service

Respondents were asked to rate their perceived risks associated with using RHS. The risks were grouped into four categories, namely financial risk (FNR), safety risk (SFR), privacy risk (PVR) and driver performance risk (DPR).

The 18 items of perceived risk of using a RHS were subjected to principal component analysis (PCA) using Statistical Package for the Social Sciences (SPSS) Version 28 (IBM Corp. 2021). The initial correlation matrix revealed that there were sufficient coefficients of 0.3 and above. The Kaiser-Meyer-Olkin value was 0.854, which is above the threshold value of 0.6 (Kaiser 1974), and Bartlett's test of Sphericity had statistical significance ($p < 0.05$), supporting the factorability of the correlation matrix. The KMO and Bartlett's results implied that the data were suitable for factor analysis based on the sampling adequacy and significant correlations among the factors. The PCA revealed three components with eigenvalues exceeding 1, explaining a total of 68.26% of the variance. The final PCA results were retained after removing the four indicators (FNR1, SFR1, SFR2 and SFR3) because of cross-loading. However, this did not affect the theoretical grounding of the study, given that each of the latent constructs had more than three indicators with a high reliability (Table 3). Thus, a three-factor solution was retained. A varimax rotation was performed, revealing a simple structure with indicators loading substantially on three components. Components 1, 2 and 3 were interpreted as 'Service/App performance risk (SAPR)', 'Driver performance risk (DPR)' and 'Privacy risk (PVR)', respectively. The result implied that RHS users were concerned that the service be delivered to expectation, the

application is available when required, the driver is professional, and whether personal data are protected from misuse or opportunistic third parties. The extracted components and the associated scale reliability are illustrated in Table 3.

The SAPR as perceived by users is hypothesised to affect the WTU RHS. The risk is expected to be low when the App performs as expected and the service is acceptable regarding on-time pick-ups, on-time drop-offs and accurate pricing. Therefore, low perceived SAPR positively affects the WTU RHS. Privacy risk is related to the unlawful sharing of personal information, such as credit card details and phone numbers. When RHS users perceive the PVR to be low, they are likely to use the service in future. For this reason, low PVR positively influences the WTU RHS. Driver performance risk refers to the service provided by the driver regarding driving behaviour, roadworthiness of the car, following the fastest route and safety. When DPR is low, the users are more likely to use RHS in the future. In addition, the moderating effects of gender, age, salary and car ownership demographics were tested.

Relationship between perceived risk of ride-hailing services and willingness to use

The relationship between the perceived risk factors of RHS and the WTU the services was investigated, and the correlations between the factors were tested. The relationships between each of the perceived risk constructs (SAPR, DPR, and PVR) and WTU were tested using correlation analysis. All the relationships were positive and significant, although PVR had a weak correlation (DPR-SAPR = 0.707, PVR-SAPR = 0.455, PVR-DPR = 0.416, WTU-SAPR = 0.612, WTU-DPR = 0.569 and WTU-PVR = 0.269).

TABLE 3: Extracted components and scale reliability.

Construct	Code	Indicator	Loadings	Reliability
Service and application performance risk	PFR1	Pick-ups are always on time	0.577	0.888
	PFR2	The e-hailing application always works	0.649	-
	PFR3	Drop-offs are on-time	0.687	-
	PFR7	I usually check the driver rating before confirming trip	0.641	-
	SFR3	I feel safer when the driver is female	0.512	-
	FNR1	The price the application shows is usually accurate	0.638	-
Privacy risk	SFR5	I am concerned about attacks from metered taxi drivers	0.573	-
	PVR1	It would be a risk to disclose my personal information	0.845	0.851
	PVR2	It would be a risk to share my credit card information	0.792	-
	PVR3	It would be a risk to share my telephone information	0.823	-
Customer service	CS1	Overall, I am satisfied with the service of e-hailing services	0.939	0.954
	CS2	The e-hailing service provider performs better compared to other service providers	0.962	-
	CS3	In general, I am happy with the e-hailing service experience	0.961	-
Willingness to use	WTU1	I intend to use e-hailing services if accessible to me	0.778	0.860
	WTU2	I predict I would use an e-hailing service if accessible	0.779	-
	WTU3	I intend to use e-hailing services if possible	0.815	-
	WTU4	I intend to use e-hailing services, if necessary, in life or work	0.690	-
Driver performance risk	PFR4	The car is always of the expected standard	0.816	0.889
	PFR5	Driver drives as expected	0.634	-
	PFR6	Driver takes the best, fastest, or most direct route	0.710	-
	SFR1	E-hailing is safe	0.650	-
	SFR2	Drivers are professional	0.683	-
	SFR4	The car is safe to ride in	0.573	-

The effect of perceived risk on the willingness or intention to use RHS was investigated using PLS-SEM. The PLS-SEM was developed in SmartPLS 4 (Ringle, Wende & Becker 2022). Structural equation modelling has gained acceptance among researchers as a technique for investigating customer attitudes and behaviours regarding the use of specific modes of transport or any other service. Ringle et al. (2022) argued that SEM helps to accurately test multiple hypotheses to examine complex relationships, especially where moderation and mediation variables are involved. In addition, PLS-SEM is a dynamic technique that helps researchers answer a variety of research questions because it can handle non-normal data, work with a wide range of sample sizes and has high predictive capabilities (Hair et al. 2022). The current study aimed to develop a prediction model to test the effect of perceived risk on the intention to use RHS. The model was specified to test the relationship between the perceived risk factors and intention to use, with gender, age, salary and car ownership as moderating variables. The demographics selected as moderators have been identified in prior studies affecting customer perceptions of various services; however, their moderating effect on intention to use RHS from a risk perspective is unknown. Previous studies argued that women commuters feel unsafe when using public taxis on their own, especially during off-peak hours (Sham et al. 2019). Older customers are likely to perceive risks differently from younger customers. Ride-hailing services customers who earn higher incomes or own cars are likely to choose an alternative mode of transport if they perceive the service as risky.

A successful PLS-SEM analysis process requires that the right research questions are formulated, the measurement

and structural models are correctly specified, and the model output or results are evaluated correctly (Hair et al. 2022). The current model was specified with only reflective indicators and allowed for the analysis of the moderating effect. The PLS-SEM model evaluation was performed in two stages, starting with the evaluation of the measurement model, followed by the structural model.

Andersson, Cuervo-Cazurra and Nielsen's (2014) approach was followed to analyse and present the results of the PLS-SEM with moderators. It was important to test the direct relationship without the moderators, as well as the direct relationship between the moderators and the overall outcome variable, the WTU as advised by Memon et al. (2019). The direct effect of the independent variables (PVR, DPR and SAPR) on the dependent variable (WTU) was tested, and the path coefficients are provided in Table 4.

A statistically significant positive association was established between DPR and WTU, as well as between SAPR and WTU. The effect of PVR on WTU was negative and negligible. The direct effect of the moderating variables (age, salary and car ownership) on WTU was positive, though not significant ($p > 0.05$). The moderating effect was also evaluated separately for each of the moderators; gender and car ownership slightly weaken the influence of PVR and DPR on WTU. However, age and monthly salary did not affect the relationships between the dependent and independent variables. The combined effect of all the moderators weakened the relationships between SAPR, PVR, DPR and WTU, implying that the moderating effect had little or no effect. The insignificant effect of the selected moderating variables

TABLE 4: Path coefficients.

Path	Path coefficients
PVR -> WTU	-0.003
DPR -> WTU	0.192**
SAPR -> WTU	0.556**
Age -> WTU	0.134
Car_ownership -> WTU	0.198
Monthly_salary -> WTU	0.057
Gender -> WTU	-0.079

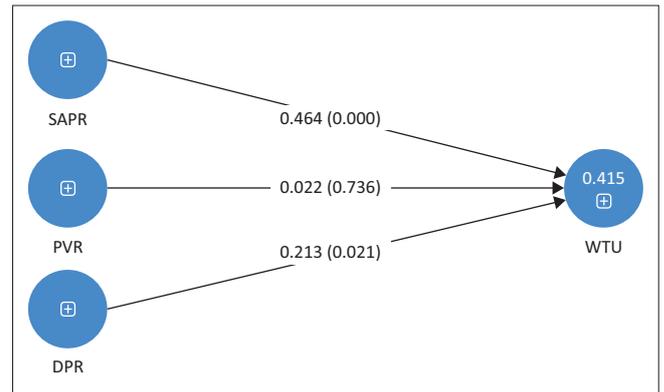
PVR, privacy risk; WTU, willingness to use; DPR, driver performance risk; SAPR, service and/or application performance risk.

** , Statistically significant at 95% confidence level.

implies that the users of RHS in emerging cities might have the same perceptions regarding the risks associated with using the service. Consequently, the PLS-SEM analysis was run with bootstrapping, and the results are presented in Figure 3.

Evaluation of the measurement model involved the examination of: (1) indicator reliability and internal consistency using the Cronbach's alpha and composite reliability measures, with acceptable values over 0.70 but below 0.95 (Ringle et al. 2022) and (2) convergent validity and discriminant validity using average variance extracted (AVE) (acceptable values are above 0.50) and hetero-trait mono-trait (HTMT) (the acceptable values are below 0.90), respectively (Hair et al. 2022). The measurement model results revealed that Cronbach's alpha values (ranged between 0.843 and 0.888), composite reliability (ρ_a) (ranged between 0.854 and 0.895), composite reliability (ρ_c) (ranged between 0.895 and 0.923) and the AVE (ranged between 0.681 and 0.768), indicating a high internal consistency and lack of convergent validity issues. The discriminant validity of the model was tested using the HTMT (ranged between 0.338 and 0.818), and all values were below 0.90 as expected, and statistically significant, ruling out discriminant validity problems from the model (Appendix 1: Table 1-A1).

Partial least squares structural equation modelling models are usually grounded on predictive accuracy with proper causality explanations, making it uncommon to test model fitness (Sarstedt, Ringle & Hair 2021). Nevertheless, model fitness was evaluated using the standard root mean square residual (SRMR) (acceptable measures should be below 0.10) and R -squared. The predictive relevance of the structural model was evaluated using the R -squared value. The model $R^2 = 0.415$ reveals a moderate strength prediction capability. All the predictor variables have a positive relationship with the outcome variable, WTU, and are statistically significant ($p < 0.05$) except with PVR. The R^2 value obtained was statistically significant and implies that 58.5% of the variance in the WTU RHS was not related to perceived risks. This might imply that the benefits of using RHS outweigh the risks and therefore, drive the intention to use or to continue using the service. The SRMR value was 0.066, where the low value revealed a higher model fit.



PVR, privacy risk; WTU, willingness to use; DPR, driver performance risk; SAPR, Service/App performance risk.

FIGURE 3: Structural model: Path coefficients and p -values.

Discussion

The findings revealed that the top three RHS providers related to usage were Uber, Bolt and Little, in that order, with the top two sharing close to 90% of the market between them. Previous studies have confirmed Uber's dominance in many cities across the globe, including emerging cities, such as Nairobi, Johannesburg and Lagos in Africa, as well as in Europe, the United States, Asia and South America. Little is a Nairobi-based service provider with a presence in all the major cities in Kenya. Bolt is popular in Eastern Europe, Asia and Africa and is a major competitor to Uber in these markets. A large majority of the randomly sampled respondents had used an RHS. The adoption of RHS may be related to the fact that it offers users a modal alternative to complete trips or portions of trips by private car without owning one (Ahmed & Hyland 2022). In addition, RHS is attractive to users in many cities across the world as it complements public transport and at the same time acts as a substitute for travellers who do not have access to a private car (Ahmed & Hyland 2022). This implies that many RHS users in African cities, especially where car ownership is low, use RHS in combination with other modes to complete trips. To attract users who are cost sensitive, most of the RHS, including Uber, Bolt and Little, have developed products that range from Comfort, which is the premium offering; UberX, which is medium; Uber ChapChap in Kenya, and UberBoda, which target price-sensitive customers. Bolt and Little have similar product ranges. Many of the trips were for social, work, shopping, and parcel delivery purposes. Parcel delivery is a later product introduced to meet market needs, especially during pandemics or social disruptions, as well as in response to the growth in e-commerce. The use of RHS to deliver parcels is a new product addition provided by Uber, Bolt and Little in Nairobi, as well as other cities globally where the on-demand taxis operate.

There are a multitude of benefits to using RHS, including shorter travel times rather than public transport, comfort and safety, the ability to transport more people, such as the whole family, allowing for multitasking, avoiding drunk driving, and airport trips. It is important to observe that some of the

respondents consider RHS safer than public transport, often providing poor service quality, especially in emerging African cities, such as Nairobi, Johannesburg and Lagos (Salon & Aligula 2012). Previous studies identified benefits of RHS, such as short travel times in China, filling the gap because of low coverage of public transport, and high parking costs when using a private car (Tang et al. 2021).

Though most of the respondents used RHS, there is a significant number that do not. The major reason for not using it was a preference for public transport and cost. Commuters might find RHS costly given the long commuting distances (an average of 18 km, taking about an hour) in Nairobi (Salon & Gulyani 2019). Some of the commuters revealed that they do not understand how the technology works, while some were captive to the private car, given the convenience it offers, albeit at a higher cost. It was surprising that the risks associated with RHS did not hinder the sampled respondents from using it. This confirms the earlier finding that the risks associated with RHS were regarded as low to moderate. The management of the RHS in emerging cities is informed by potential users who need related information to be converted into users.

Perceived risk of using RHS was measured using three latent variables, that is, SAPR, PVR and DPR. The three constructs were modelled as predictors of the WTU RHS in an emerging city context. The relationship between the perceived risk measures and WTU was tested directly and through gender, age, salary and car ownership (whether an RHS user owns a car or not). The WTU RHS is positively influenced by SAPR, which includes high service quality, such as timeliness, usability of the RHS App and an accurate pricing model, which are important to customers. When there is a variation between the estimated cost at the origin and the final trip cost shown by the RHS App, users are likely to perceive this as a risk. Previous studies have highlighted that unpredictable prices charged per trip or variation of trip cost because a driver used a longer route, is a risk to users and might influence the intention to use the service (Cramer & Krueger 2016). Therefore, a combination of excellent service from the operators regarding timeliness and assurance of safety, as well as the RHS App regarding availability of service when needed, is likely to encourage users to continue using the service.

Privacy risk includes the sharing of personal information, including telephone numbers and credit card information. While we argue that PVR can influence the WTU RHS, we are cognisant that this might be context-specific, especially based on the mode of payment, as well as whether the App shares personal and location data with third parties. Some of the emerging cities make use of mobile money, such as *Mpesa*, which has a low online risk compared to a credit card; thus, the risk related to bank cards might be low. Nevertheless, RHS users are likely to use the service if they perceive that their privacy is protected from possible cyberattacks. The finding supports studies that have emphasised the

importance of App-based vendors and service providers protecting the personal information of their customers, as users' perceived risks, benefits and trust highly influence their intention to use a service (Cheng et al. 2023). We find that protection of personal information by the RHS vendors is positively associated with a WTU the service, though many other factors, such as accessibility to a car, level of education and need for an airport transfer, might predict future intention to use RHS (Alemi et al. 2018).

The drivers of on-demand taxis are generally perceived as the face of the App service they are using; thus RHS is dependent on excellent drivers. Users perceive higher risks if the driver is unprofessional, deviates from the official route shown by the App, or the car is not of the expected safety, cleanliness or comfort standard. The performance of the driver being professional throughout the trip and presenting a car of acceptable standard is likely to positively influence the WTU the service. The importance of drivers in RHS is also emphasised by Henama and Sifolo (2017), who argue that driver professionalism can be an important determinant of a user's WTU the service. Many of the RHS providers have recognised the centrality of the driver to the provision of the service and thus, allow users to rate a driver at the end of the trip to help promote professionalism.

The demographics, such as age, gender, car ownership and monthly salary of RHS users did not alter the relationship between perceived risks and the WTU the service. This might imply that the sample was generally drawn from the same age group and, although salary and car ownership were varied, they did not have any unique influence on the willingness to continue using RHS. The finding is different from previous studies in the US, which had established that millennials are more likely to use RHS compared to older age groups (Alemi et al. 2018). Thus, the factors that influence the future WTU RHS might be context-specific and differ between developed and emerging cities in Africa. The finding that the WTU RHS is influenced by SAPR and driver performance in this study supports the PRT, which identifies most of these factors as the consequences likely to affect consumer behaviour. However, the intention to use RHS was not moderated by contextual factors, such as demographics, as argued by Wei et al. (2018), thus implying a lack of heterogeneity in the contextual factors of this study.

Conclusion

The two global players, Uber and Bolt, are the dominant RHS providers in many emerging cities. In addition, there are local RHS providers, such as Little in Nairobi, targeting niche markets, such as corporate role players. The typical RHS users in Nairobi are mostly millennials and a few older adults. In emerging cities, where public transport is inadequate, RHS offers an alternative mode for users to complete their trips efficiently. The users of RHS travel for social, work and shopping reasons. Users choose RHS because of benefits, such as shorter travel times, comfort, safety, being able to multitask and avoiding drunk driving.

In addition, the RHS offer shorter waiting times and greater convenience compared to public transport. Service and App performance risk, PVR and DPR were identified as measures of perceived risk of RHS in emerging markets. Where the RHS service quality is exceptional, related to timeliness, availability of the App when needed, and accurate pricing to avoid disputes, the perceived risk is low and is likely to encourage future intentions to use the RHS. Similarly, excellent drivers, defined as being professional, following official routes provided by the App and driving a car of acceptable standards, reduce the perceived risk and encourage usage of RHS. Therefore, risks associated with SAPR, as well as driver performance, affect the WTU RHS in emerging cities. Surprisingly, non-users of RHS did not identify risk as one of the reasons hindering current or future use of the service. Non-users found the RHS expensive compared to public transport, while others were captive to private cars, citing convenience. Managers of RHS operators are encouraged to continually improve the App in terms of its usability, accuracy and assurance of the safety of users. The App should also provide all the relevant information about the trip, for instance, delays, to reduce the likely risks from a user perspective. The car owners or drivers who are service providers should endeavour to present vehicles in good condition for the safety of the RHS users, thus reducing perceived risk. On the other hand, government agencies in emerging cities are encouraged to improve accessibility to affordable data bundles or the internet in public spaces to promote mobility. In addition, the government should develop policies that protect RHS users regarding risks related to service quality, use of personal information, safety, driver professionalism and App performance.

Therefore, the study contributes to the literature on PRT by identifying the key service risks, that is, driver performance, service and/or application performance, and privacy, that influence the intention to use RHS in emerging markets. It highlights the critical role of risk mitigation strategies for increasing the adoption of RHS and offers actionable insights for policymakers and service providers to enhance service quality, App reliability and user safety. By focusing on an emerging economy context, the research expands the understanding of how technological, operational and safety risks uniquely manifest and affect technology-based transport services in developing cities, addressing a gap in existing global research on RHS. The study confirms the assumptions of the collaborative consumption framework by identifying that affordability of price and mobile data improves access to RHS while reducing risk factors, such as the above-mentioned service risks, that influence the use of the RHS platforms.

This study has several limitations. Firstly, it is based on a single-city, single-country sample of 179 respondents in Nairobi, which constrains the generalisability of the findings to other emerging market contexts. Urban structure, digital access and transport conditions vary widely across developing cities, and the Nairobi case may not fully

represent broader trends. Secondly, the cross-sectional design limits the ability to observe how perceptions of risk and intention to use RHS evolve in response to platform changes, regulation or shifting user expectations. Thirdly, while the study distinguishes between users and non-users, it does not explore behavioural dynamics in-depth, such as changes in modal choice or usage frequency.

Future studies should adopt longitudinal research designs to track shifts in user perceptions and behaviours over time. Comparative studies across multiple cities (starting with Nairobi, Johannesburg and Lagos) would reveal how local context shapes risk perception and adoption patterns. Experimental or quasi-experimental designs, such as testing the effects of App modifications or driver training interventions, could offer stronger causal insights. Integrating behavioural data (e.g., trip frequency, platform usage logs etc.) with survey responses would improve explanatory power.

Further research should also examine whether RHS in emerging markets functions as a substitute for private car use or as a complement to public transport, and whether its availability inadvertently promotes car ownership. Understanding these dynamics is essential for evaluating the long-term sustainability impacts of RHS and for guiding transport policy in rapidly urbanising cities.

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Authors' contributions

J.M. conceptualised the study, collected data, analysed and presented the results, and wrote the discussion. R.L. wrote the literature review, reviewed the discussion and wrote the conclusion.

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Data availability

Derived data supporting the findings of this study are available from the corresponding author, J.M., on reasonable request.

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References

- Ahmed, T. & Hyland, M., 2022, 'Exploring the role of ride-hailing in trip chains', *Transportation* 50(3), 959–1002. <https://doi.org/10.1007/s11116-022-10269-w>
- Akande, A., Cabral, P., Gomes, P. & Casteleyn, S., 2019, 'The Lisbon ranking for smart sustainable cities in Europe', *Sustainable Cities and Society* 44, 475–487. <https://doi.org/10.1016/j.scs.2018.10.009>
- Alemi, F., Circella, G., Handy, S. & Mokhtarian, P., 2018, 'What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California', *Travel Behaviour and Society* 13, 88–104. <https://doi.org/10.1016/j.tbs.2018.06.002>
- Andersson, U., Cuervo-Cazurra, A. & Nielsen, B.B., 2014, 'From the editors: Explaining interaction effects within and across levels of analysis', *Journal of International Business Studies* 45, 1063–1071. <https://doi.org/10.1057/jibs.2014.50>
- Arora, M., Singh, H. & Gupta, S., 2022, 'What drives e-hailing apps adoption? An analysis of behavioral factors through fuzzy AHP', *Journal of Science and Technology Policy Management* 13(2), 382–404. <https://doi.org/10.1108/JSTPM-12-2020-0177>
- Assegaff, S.B. & Pranoto, S.O., 2020, 'Price determines customer loyalty in ride-hailing services', *American Journal of Humanities and Social Sciences Research (AJHSSR)* 4(3), 453–463.
- Auditiano, A., Sucahyo, Y.G., Gandhi, A. & Ruldeviyani, Y., 2019, 'Discovering the influencing factors of physical gig economy usage: Quantitative approach on clients' perception', in *2019 International conference on advanced computer science and information systems (ICACSIS)*, IEEE, Nusa Dua, Bali, Indonesia, October 12–13, 2019, pp. 357–362.
- Berndt, A., Pretorius, A. & Blaauw, D., 2021, 'The intention of South Africans to engage in collaborative consumption: The case of Uber', *Acta Commercii* 21(1), 1–11. <https://doi.org/10.4102/ac.v21i1.961>
- Bosman, R. & Rogers, R., 2010, *What's mine is yours. The rise of collaborative consumption*, viewed 18 May 2025, from https://tantor-marketing-assets.s3.amazonaws.com/sellsheets/1920_MinelsYours.pdf.
- Cats, O., Kucharski, R., Danda, S.R. & Yap, M., 2022, 'Beyond the dichotomy: How ride-hailing competes with and complements public transport', *PLoS One* 17(1), e0262496. <https://doi.org/10.1371/journal.pone.0262496>
- Cheng, X., Fu, S., Sun, J., Zuo, M. & Meng, X., 2023, 'Trust in online ride-sharing transactions: Impacts of heterogeneous order features', *Journal of Management Information Systems* 40(1), 183–207. <https://doi.org/10.1080/07421222.2023.2172779>
- Cramer, J. & Krueger, A.B., 2016, 'Disruptive change in the taxi business: The case of Uber', *American Economic Review* 106(5), 177–182. <https://doi.org/10.1257/aer.p20161002>
- Dash, G. & Paul, J., 2021, 'CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting', *Technological Forecasting and Social Change* 173, 121092. <https://doi.org/10.1016/j.techfore.2021.121092>
- Elnadi, M. & Gheith, M.H., 2022, 'What makes consumers reuse ride-hailing services? An investigation of Egyptian consumers' attitudes towards ride-hailing apps', *Travel Behaviour and Society* 29, 78–94.
- Etminani-Ghasrodashti, R. & Hamidi, S., 2019, 'Individuals' demand for ride-hailing services: Investigating the combined effects of attitudinal factors, land use, and travel attributes on demand for app-based taxis in Tehran, Iran', *Sustainability* 11(20), 5755. <https://doi.org/10.3390/su11205755>
- Felson, M. & Spaeth, J.L., 1978, 'Community structure and collaborative consumption: A routine activity approach', *American Behavioral Scientist* 21(4), 614–624. <https://doi.org/10.1177/000276427802100411>
- Frenken, K. & Schor, J., 2019, 'Putting the sharing economy into perspective', in O. Mont (ed.), *A research agenda for sustainable consumption governance*, pp. 121–135, Edward Elgar Publishing, Massachusetts, USA
- Furuhata, M., Dessouky, M., Ordóñez, F., Brunet, M.E., Wang, X. & Koenig, S., 2013, 'Ridesharing: The state-of-the-art and future directions', *Transportation Research Part B: Methodological* 57, 28–46. <https://doi.org/10.1016/j.trb.2013.08.012>
- Garrett, A., Straker, K. & Wrigley, C., 2017, 'Digital channels for building collaborative consumption communities', *Journal of Research in Interactive Marketing* 11(2), 160–184. <https://doi.org/10.1108/JRIM-08-2016-0086>
- Gerbing, D.W. & Anderson, J.C., 1985, 'The effects of sampling error and model characteristics on parameter estimation for maximum likelihood confirmatory factor analysis', *Multivariate Behavioral Research* 20(3), 255–271. https://doi.org/10.1207/s15327906mbr2003_2
- Goel, P. & Haldar, P., 2020, 'Does India need a shared ride-hailing now more than ever? Understanding commuter's intentions to share ridesailing now than ever? Understanding commuters' intention to share rides', *Asian Journal of Business and Accounting* 13(2), 277–305.
- Gumilar, A., Dionisius, W.D., Oliver, I., Gunawan, J. & Sfenrianto, S., 2019, 'Factors affecting the actual use of ride-hailing services (GOJEK/GRAB) in Indonesia (Jabodetabek-Region)', in *13th International Quality Conference (IQC), Quality Festival 2019*, ISSN 2620-2832, 30 May – 1 June 2019, Proceedings on Engineering Sciences, Jakarta.
- Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P. & Ray, S., 2022, *A primer on partial least squares structural equation modeling (PLS-SEM)*, 3rd edn., Sage, London, UK.
- Hamal, P. & Huijsmans, R., 2022, 'Making markets gendered: Kathmandu's ride-sharing platforms through a gender lens', *Gender, Place & Culture* 29(5), 670–692. <https://doi.org/10.1080/0966369X.2021.1931046>
- Hasan, O., McColl, J., Pfefferkorn, T., Hamadneh, S., Alshurideh, M. & Al Kurdi, B., 2022, 'Consumer attitudes towards the use of autonomous vehicles: Evidence from United Kingdom taxi services', *International Journal of Data and Network Science* 6(2), 537–550.
- Henama, U.S. & Sifolo, S.P.P., 2017, 'Uber: The South Africa experience', *African Journal of Hospitality, Tourism and Leisure* 6(2), 1–10. viewed 25 January 2025, from <https://www.ajhtl.com>.
- IBM Corp., 2021, *IBM SPSS statistics for windows*, version 28.0, computer software, IBM Corp., Armonk, NY.
- Inan, D.I., Hidayanto, A.N., Juita, R., Andiyani, K., Hariyana, N., Tiffany, P. et al., 2022, 'Technology anxiety and social influence towards intention to use of ride-hailing service in Indonesia', *Case Studies on Transport Policy* 10(3), 1591–1601. <https://doi.org/10.1016/j.cstp.2022.05.017>
- Iqbal, M., 2025, *Uber revenue and usage statistics (2025)*, Business of Apps, viewed 04 February 2025, from <https://www.businessofapps.com/data/uber-statistics/>.
- Irawan, M.Z., Dharmowijoyo, D.B.E., Waluyo, T.A. & Widiastuti, N.O., 2023, 'Responding to customers while driving: Predictors of intention to text among motorcycle-based ride-hailing drivers', *Transportation Research Interdisciplinary Perspectives* 21, 100869.
- Jin, S.T., Kong, H. & Sui, D.Z., 2019, 'Uber, public transit, and urban transportation equity: A case study in New York City', *The Professional Geographer* 71(2), 315–330. <https://doi.org/10.1080/00330124.2018.1531038>
- Kamais, C.E., 2019, 'Emerging security risks of e-hail transport services: Focus on Uber Taxi in Nairobi, Kenya', *International Journal of Security, Privacy and Trust Management* 8(3), 1–18. <https://doi.org/10.5121/ijspmt.2019.8301>
- Kandil, M., 2019, *Ride-hailing apps are making the developing world's traffic problems worse*, World Economic Forum, viewed 04 February 2025, from <https://www.weforum.org/stories/2019/08/ride-hailing-apps-developing-world-traffic-problems/>.
- KNBS, 2019, *2019 Kenya population and housing census: Volume II I*, Kenya National Bureau of Statistics, viewed from <https://www.knbs.or.ke/?wpdmp=2019-kenya-population-and-housing-census-volume-ii-distribution-of-population-by-administrative-units>.
- Ma, L., Zhang, X., Ding, X. & Wang, G., 2019, 'Risk perception and intention to discontinue use of ride-hailing services in China: Taking the example of DiDi Chuxing', *Transportation Research Part F: Traffic Psychology and Behaviour* 66, 459–470. <https://doi.org/10.1016/j.trf.2019.09.021>
- Man, C.K., Ahmad, R., Kiong, T.P. & Rashid, T.A., 2019, 'Evaluation of service quality dimensions towards customer's satisfaction of ride-hailing services in Kuala Lumpur, Malaysia', *International Journal of Recent Technology and Engineering* 7(55), 102–109.
- Mao, H., Deng, X., Jiang, H., Shi, L., Li, H., Tuo, L. et al., 2021, 'Driving safety assessment for ride-hailing drivers', *Accident Analysis & Prevention* 149, 105574. <https://doi.org/10.1016/j.aap.2020.105574>
- Memon, M.A., Cheah, J.H., Ramayah, T., Ting, H., Chuah, F. & Cham, T.H., 2019, 'Moderation analysis: Issues and guidelines', *Journal of Applied Structural Equation Modeling* 3(1), i–xi. [https://doi.org/10.47263/JASEM.3\(1\)01](https://doi.org/10.47263/JASEM.3(1)01)
- Mitchell, V., 1992, 'Understanding consumers' behaviour: Can perceived risk theory help?', *Management Decision* 30(3), 26–31. <https://doi.org/10.1108/00251749210013050>
- Mordor Intelligence, 2025a, *Ride hailing industry – Companies, market share & size*, viewed 18 May 2025, from <https://www.mordorintelligence.com/industry-reports/ride-hailing-market>.
- Mordor Intelligence, 2025b, *Africa automotive market size & share analysis – Growth trends & forecasts (2025 – 2030)*, viewed 16 March 2025, from <https://www.mordorintelligence.com/industry-reports/africa-automotive-industry-outlook>.
- Mordor Intelligence, 2025c, *Ride hailing industry size & share analysis – Growth trends & forecasts (2025 – 2030)*, viewed 16 March 2025, from <https://www.mordorintelligence.com/industry-reports/ride-hailing-market>.
- Motsi, L. & Chipangura, B., 2024, 'Factors influencing taxi entrepreneurs to adopt intelligent transport management systems', *Journal of Transport and Supply Chain Management* 18, 1–9. <https://doi.org/10.4102/jtscm.v18i0.1042>
- Mpofu, T., Tsiobolane, P., Heeks, R. & Van Belle, J.-P., 2020, 'Risks and risk-mitigation strategies of gig economy workers in the global south: The case of ride-hailing in Cape Town', in J.M. Bass & P.J. Wall (eds.), *Information and communication technologies for development*, pp. 26–38, Springer International Publishing (IFIP Advances in Information and Communication Technology), Cham.
- Nguyen, T., Zhang, J., Zhou, L., Meng, M. & He, Y., 2020, 'A data-driven optimization of large-scale dry port location using the hybrid approach of data mining and complex network theory', *Transportation Research Part E: Logistics and Transportation Review* 134, 101816. <https://doi.org/10.1016/j.tre.2019.11.010>
- Nguyen-Phuoc, D.Q., Su, D.N., Nguyen, M.H., Vo, N.S. & Oviedo-Trespalacios, O., 2022a, 'Factors influencing intention to use on-demand shared ride-hailing services in Vietnam: Risk, cost or sustainability?', *Journal of Transport Geography* 99, 103302. <https://doi.org/10.1016/j.jtrangeo.2022.103302>
- Nguyen-Phuoc, D.Q., Oviedo-Trespalacios, O., Nguyen, M.H., Dinh, M.T.T. & Su, D.N., 2022b, 'Intentions to use ride-sourcing services in Vietnam: What happens after three months without COVID-19 infections?', *Cities* 126, 103691. <https://doi.org/10.1016/j.cities.2022.103691>
- Olayode, I.O., Severino, A., Alex, F.J., Macioszek, E. & Tartibu, L.K., 2023, 'Systematic review on the evaluation of the effects of ride-hailing services on public road transportation', *Transportation Research Interdisciplinary Perspectives* 22, 100943. <https://doi.org/10.1016/j.trip.2023.100943>

- Ringle, C.M., Wende, S. & Becker, J.-M., 2022, *SmartPLS 4*, SmartPLS, Boenningstedt.
- Rwakarehe, E.E., 2022, 'Review of strategies for curbing traffic congestion in sub-Saharan Africa cities: Technical and policy perspectives', *Tanzania Journal of Engineering and Technology* 40(2), 24–32. <https://doi.org/10.52339/tjet.v40i2.730>
- Salon, D. & Aligula, E.M., 2012, 'Urban travel in Nairobi, Kenya: Analysis, insights, and opportunities', *Journal of Transport Geography* 22, 65–76. <https://doi.org/10.1016/j.jtrangeo.2011.11.019>
- Salon, D. & Gulyani, S., 2019, 'Commuting in Urban Kenya: Unpacking travel demand in large and small Kenyan Cities', *Sustainability* 11(14), 3823. <https://doi.org/10.3390/su11143823>
- Sarstedt, M., Ringle, C.M. & Hair, J.F., 2021, 'Partial least squares structural equation modeling', in C. Homburg, M. Klarmann & A. Vomberg (eds.), *Handbook of market research*, pp. 587–632, Springer International Publishing, Switzerland.
- Sham, R., Wahab, S.N., Anuar, M.M., Tong, W.H. & Yap, J.T., 2019, 'Safety indicator for taxi users in urban area', *International Journal of Supply Chain Management*, viewed 30 January 2025, from <http://excelingtech.co.uk/>.
- Shumba, T. & Saruchera, F., 2023, 'Determinants of digital collaborative consumption in the South African food delivery industry', *African Journal of Business and Economic Research* 18(4), 415–436. <https://doi.org/10.31920/1750-4562/2023/v18n4a20>
- Shumba, T. & Saruchera, F., 2024, 'Validating a theoretical model for digital collaborative consumption in emerging markets: Insights for contemporary managers', *Journal of Contemporary Management* 21(1), 354–383. <https://doi.org/10.35683/jcman1050.255>
- Soltani, A., Allan, A., Khalaj, F., Pojani, D. & Mehdizadeh, M., 2021, 'Ridesharing in Adelaide: Segmentation of users', *Journal of Transport Geography* 92, 103030. <https://doi.org/10.1016/j.jtrangeo.2021.103030>
- Spicer, A., 2021, *Ride-share risks: When your ride goes wrong*, Consumer NZ, viewed 16 March 2025, from <https://www.consumer.org.nz/articles/ride-share-risks-when-your-ride-goes-wrong>.
- Taherdoost, H., 2017, *Determining sample size: How to calculate survey sample size*, viewed 15 October 2024, from <https://ssrn.com/abstract=3224205>; <http://www.ahooraltd.com>; <http://www.hamta.org>.
- Tang, Y., Guo, P., Tang, C.S. & Wang, Y., 2021, 'Gender-related operational issues arising from on-demand ride-hailing platforms: Safety concerns and system configuration', *Production and Operations Management* 30(10), 3481–3496. <https://doi.org/10.1111/poms.13444>
- Uber, 2025, 'The history of Uber – Uber's timeline', *Uber Newsroom*, viewed 04 February 2025, from <https://www.uber.com/el-GR/newsroom/history/>.
- Venkatesh, V., Morris, M.G., Davis, G.B. & Davis, F.D., 2003, 'User acceptance of information technology: Toward a unified view', *MIS Quarterly* 27(3), 425. <https://doi.org/10.2307/30036540>
- Wang, Y., Gu, J., Wang, S. & Wang, J., 2019, 'Understanding consumers' willingness to use ride-sharing services: The roles of perceived value and perceived risk', *Transportation Research Part C: Emerging Technologies* 105, 504–519. <https://doi.org/10.1016/j.trc.2019.05.044>
- Wei, Y., Wang, C., Zhu, S., Xue, H. & Chen, F., 2018, 'Online purchase intention of fruits: Antecedents in an integrated model based on technology acceptance model and perceived risk theory', *Frontiers in Psychology* 9, 1521. <https://doi.org/10.3389/fpsyg.2018.01521>
- Witt, A., Suzor, N. & Wikström, P., 2015, 'Regulating ride-sharing in the peer economy', *Communication Research and Practice* 1(2), 174–190. <https://doi.org/10.1080/22041451.2015.1048041>
- World Bank, 2023, *Mobile cellular subscriptions (per 100 people) – Sub-Saharan Africa*, World Bank Open Data, viewed 15 June 2025, from <https://data.worldbank.org>.
- Zaigham, M., Chin, C.P.Y. & Dasan, J., 2022, 'Disentangling determinants of ride-hailing services among Malaysian drivers', *Information* 13(12), 584. <https://doi.org/10.3390/info13120584>
- Ziyad, A., Rehman, Z.U., Batool, Z. & Khan, A.H., 2020, 'Influence of service excellence on consumer satisfaction of ridesharing industry', *International Journal for Traffic and Transport Engineering* 10(4), 468–481. [https://doi.org/10.7708/ijtte.2020.10\(4\).06](https://doi.org/10.7708/ijtte.2020.10(4).06)

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Appendix 1

TABLE 1-A1: Discriminant validity.

Discriminant validity	Heterotrait-monotrait ratio (HTMT)		SAPR	DPR	PVR	WTU	Age	Gender	Monthly salary	Car ownership	SAPR	DPR	PVR	WTU	Age x SAPR	Gender x SAPR	Age x PVR	Gender x PVR	Age x PVR	Monthly salary x DPR	Car ownership x DPR	Gender x DPR	Age x DPR	
	Age	Gender																						
Age	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Car ownership	0.413	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Gender	0.041	0.068	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Monthly salary	0.342	0.344	0.072	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
PVR	0.041	0.046	0.052	0.069	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
WTU	0.131	0.028	0.082	0.080	0.317	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DPR	0.140	0.070	0.060	0.035	0.491	0.666	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SAPR	0.114	0.082	0.066	0.090	0.514	0.686	0.838	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Monthly salary x SAPR	0.007	0.089	0.136	0.017	0.111	0.133	0.053	0.034	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Car ownership x SAPR	0.102	0.019	0.113	0.115	0.334	0.549	0.676	0.920	0.256	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Gender x SAPR	0.004	0.040	0.037	0.050	0.359	0.541	0.582	0.743	0.008	0.592	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Age x SAPR	0.028	0.030	0.097	0.007	0.065	0.038	0.054	0.078	0.391	0.318	0.063	-	-	-	-	-	-	-	-	-	-	-	-	-
Monthly salary x PVR	0.123	0.002	0.059	0.028	0.078	0.119	0.097	0.100	0.572	0.046	0.017	0.126	-	-	-	-	-	-	-	-	-	-	-	-
Car ownership x PVR	0.019	0.012	0.065	0.059	0.934	0.227	0.357	0.325	0.046	0.341	0.241	0.070	0.111	-	-	-	-	-	-	-	-	-	-	-
Gender x PVR	0.037	0.012	0.022	0.007	0.806	0.271	0.260	0.322	0.016	0.221	0.428	0.009	0.072	0.672	-	-	-	-	-	-	-	-	-	-
Age x PVR	0.043	0.020	0.047	0.142	0.070	0.034	0.057	0.071	0.146	0.080	0.015	0.510	0.209	0.240	0.077	-	-	-	-	-	-	-	-	-
Monthly salary x DPR	0.128	0.029	0.111	0.007	0.105	0.082	0.043	0.033	0.699	0.137	0.016	0.088	0.663	0.006	0.020	0.100	-	-	-	-	-	-	-	-
Car ownership x DPR	0.102	0.019	0.123	0.004	0.359	0.525	0.934	0.671	0.134	0.730	0.478	0.146	0.004	0.383	0.187	0.153	0.163	-	-	-	-	-	-	-
Gender x DPR	0.020	0.082	0.018	0.065	0.270	0.544	0.801	0.536	0.016	0.449	0.731	0.072	0.021	0.191	0.326	0.066	0.046	0.567	-	-	-	-	-	-
Age x DPR	0.039	0.029	0.124	0.150	0.043	0.057	0.091	0.063	0.091	0.165	0.090	0.671	0.093	0.154	0.070	0.585	0.172	0.268	0.079	-	-	-	-	-

PVR, privacy risk; WTU, willingness to use; DPR, driver performance risk; SAPR, service and/or application performance risk.

TABLE 2-A1: Ride-hailing service and risk level.

E-hailing use	E-hailing risk				
	Very low (%)	Low (%)	Moderate (%)	High (%)	Very high (%)
Uber use frequency					
Not at all	3.9	2.8	5.0	1.1	1.1
Rarely	5.6	7.8	12.3	5.0	1.1
Sometimes (1–3 times per month)	4.5	9.5	10.6	4.5	0.6
Regularly (1–3 times per week)	6.1	6.7	10.1	1.7	0.0
Frequently (4 or more rides per week)	0.0	0.0	0.0	0.0	0.0
Bolt use frequency					
Not at all	3.4	4.5	5.0	1.1	1.1
Rarely	5.0	5.0	8.9	3.4	1.1
Sometimes (1–3 times per month)	5.0	8.9	15.1	5.6	0.6
Regularly (1–3 times per week)	6.7	8.4	8.9	2.2	0.0
Frequently (4 or more rides per week)	0.0	0.0	0.0	0.0	0.0
Little use frequency					
Not at all	12.3	16.2	22.3	5.6	2.2
Rarely	2.8	7.3	9.5	2.8	0.6
Sometimes (1–3 times per month)	1.7	3.4	3.4	3.9	0.0
Regularly (1–3 times per week)	3.4	0.0	2.8	0.0	0.0
Frequently (4 or more rides per week)	0.0	0.0	0.0	0.0	0.0
Mondoride use frequency					
Not at all	17.9	25.1	35.8	8.9	2.2
Rarely	0.6	1.7	1.7	1.7	0.6
Sometimes (1–3 times per month)	0.6	0.0	0.0	1.7	0.0
Regularly (1–3 times per week)	1.1	0.0	0.6	0.0	0.0
Frequently (4 or more rides per week)	0.0	0.0	0.0	0.0	0.0
PewinCabs use frequency					
Not at all	14.0	22.9	30.2	7.8	2.8
Rarely	2.2	3.9	6.1	2.8	0.0
Sometimes (1–3 times per month)	2.8	0.0	1.1	1.7	0.0
Regularly (1–3 times per week)	1.1	0.0	0.6	0.0	0.0
Frequently (4 or more rides per week)	0.0	0.0	0.0	0.0	0.0