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Determinants of customer's intention to use ride-hailing services in Kathmandu Valley

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Abstract

This study identifies the key factors influencing the adoption of ride-hailing services in Kathmandu Valley, guided by the Theory of Planned Behavior (TPB). The research examines how attitudes, subjective norms, and perceived behavioral control affect the intention to use ride-hailing services, and how these intentions translate into actual usage behavior. A quantitative method was adopted, with 389 respondents from Kathmandu Valley, using a structured questionnaire designed to capture TPB constructs. Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate the questionnaires and assess the hypothesized relationships. The findings indicate that both attitude and perceived behavioral control significantly impact the intention to use ride-hailing services. Furthermore, intention was found to be a strong predictor of actual usage behavior. However, subjective norms did not exhibit a significant effect on the intention to use ride-hailing services in this context. This study provides insights into the behavioral drivers of ride-hailing service adoption, offering valuable information for ride-sharing and hailing mobility services to boost their business and for government institutions to regulate accordingly. As ride-hailing is growing in Nepal, future investors and enterprises would benefit from adopting various strategies to attract customers, focusing on the key factors that influence service adoption. For future research, expanding the sample size and incorporating additional contextual factors would enhance the understanding of ride-hailing adoption across different regions.

Keywords: *ride-hailing services, Theory of Planned Behavior, intention, Kathmandu Valley, PLS-SEM*

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1. Introduction

Kathmandu Valley, which includes the districts of Bhaktapur, Lalitpur, and Kathmandu, is home to over 3 million people (Central Bureau of Statistics, 2021). Nearly 49% of this population falls within the youth category, defined in Nepal as individuals aged 16 to 40 (Nepal Government, Ministry of Youth and Sports, 2015). This age group plays a crucial role in adopting new technologies, particularly in the transportation sector (Dzisi et al., 2020). In recent years, ride-hailing services like InDrive and Pathao have become increasingly popular, providing flexible and cost-effective solutions to the Valley's persistent traffic congestion and limited public transport infrastructure (Kathmandu Post, 2024a).

Nepal’s ride-hailing market currently features 25 companies using GPS and mobile apps, but inDrive and Pathao dominate due to their efficiency and large user base (Kathmandu Post, 2024a; Statista, 2024). According to the 60th annual report of the Auditor General, inDrive facilitates around 29,300 rides daily and reports an annual turnover of Rs 2.11 billion (Kathmandu Post, 2023). Meanwhile, as of April 2024, Pathao has over 200,000 registered service providers, including 190,000 bike riders, 10,000 taxi drivers, and 5,000 food delivery personnel (Kathmandu Post, 2024b; MyRepublica, 2024). Furthermore, the ride-hailing market in Nepal is expected to generate substantial growth, with revenues projected to reach US$68.05 million by 2024, further expanding in the coming years and the number of users is forecasted to reach 7.01 million by 2029, with user penetration rising from 15.7% in 2024 to 21.3% in 2029. This increasing reliance on ride-hailing services among the youth reflects the growing importance of understanding the factors driving their adoption, including attitudes, social norms, and ease of use (Acheampong et al., 2020; Vanderschuren & Baufeldt, 2018).

The government has recognized ride-sharing as a formal service under the Industrial Enterprises Act 2020. However, regulatory challenges persist due to contradictions between the Motor Vehicle and Transport Management Act 1993, and federal governance. Despite these issues, the Bagmati State Vehicle and Transport Management Act 2022 allows private vehicles to operate under a regulated framework, reflecting the growing gig economy and demand for shared mobility in Kathmandu (Kathmandu Post, 2024a).

Technological advancements have been rapidly transforming urban transportation globally (Dia et al., 2021; Yigitcanlar et al., 2019). Ride-hailing platforms, which connect passengers to drivers via smartphone apps, are reshaping commuting patterns and offering convenience, particularly in cities with limited public transportation options and traffic congestion (Acheampong et al., 2020; Tirachini, 2020). The adoption of these services has been studied through the lens of the Theory of Planned Behavior (TPB), emphasizing key factors like attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). Globally, attitudes toward ride-hailing services are shaped by factors such as convenience, service quality, and safety (Tirachini, 2020; Lavieri & Bhat, 2019). Additionally, subjective norms, or social influence, have been found to significantly affect adoption decisions, particularly in younger populations (Tirachini & Del Río, 2019; Javid et al., 2022). Research also underscores the role of perceived behavioral control, with studies in countries like China and Vietnam revealing that factors like ease of app use and availability of vehicles influence adoption (Guo et al., 2019; Nguyen-Phuoc et al., 2022).

Although research on ride-hailing services is expanding, critical gaps remain in the literature, especially in the Nepalese context. Existing studies tend to focus on specific aspects, such as micro mobility (Shah et al., 2024) and gender differences in service usage (Mahato et al., 2024; Hamal & Huijsmans, 2022). For instance, Shah et al. (2024) highlighted how weather conditions influence e-moped preferences in Kathmandu, while Mahato et al. (2024) revealed that women rely more on two-wheelers for work travel. Despite these contributions, there is limited research on the broader factors affecting ride-hailing adoption in Nepal, such as attitudes, subjective norms, and perceived behavioral control. The TPB has been applied globally to technology adoption (Ajzen, 1991), but its application to ride-hailing in Nepal remains unexplored. Furthermore, while factors like safety, comfort, and availability are acknowledged (Singh, 2022; Singh & Sah, 2022; Kumar Yadav et al., 2024), research lacks a comprehensive understanding of how these factors, alongside TPB constructs, influence the adoption of ride-hailing services in Nepal.

This study aims to investigate the factors influencing the adoption of ride-hailing services in Kathmandu Valley, focusing on the application of the TPB framework. By examining how attitudes, subjective norms, and perceived behavioral control impact users' intentions and actual use of these services, this research provides insights that are valuable for both policymakers and service providers. The study’s findings will help to identify strategies for promoting the sustainable uptake of ride-hailing services in urban areas facing similar challenges. The structure of this paper is as follows: Section 2 provides a literature review of ride-hailing adoption and the TPB framework in transportation studies, Section 3 outlines the methodology used for data collection and analysis, Section 4 presents the key findings and discussion, and Section 5 concludes with recommendations for enhancing ride-hailing services in Kathmandu Valley.

2. Literature Review

2.1 Hypotheses Development

Attitude toward ride-hailing services. Attitude significantly influences an individual's decision to adopt new technologies, including ride-hailing services. Ajzen (1991) defines attitude as an individual's overall evaluation of a behavior, which directly impacts their intention to engage in that behavior. In the context of ride-hailing services, factors like convenience, affordability, and service quality have been shown to shape positive attitudes (Tirachini, 2020). Similarly, Acheampong et al. (2020) found that perceived time savings and flexibility drive favorable attitudes, particularly in developing regions. Lavieri and Bhat (2019) also highlight that service availability and perceived safety play a critical role in fostering positive attitudes. Furthermore, studies in emerging markets like Pakistan and Vietnam confirm the significance of attitude in predicting ride-hailing intentions (Sajid et al., 2022; Giang et al., 2017). Although these studies provide robust evidence of attitude's importance, there is an ongoing theoretical debate about whether these factors operate uniformly across different cultural and infrastructural contexts. In Kathmandu Valley, where challenges such as congested urban areas and variable service quality may influence consumer expectations, the impact of attitude might differ from that observed in other emerging markets. These findings suggest attitudes towards ride-hailing services influence intention to adopt the services in Kathmandu Valley. Therefore, it could be hypothesized as:

H1: Attitude significantly impacts the intention to use ride-hailing services in Kathmandu Valley.

Subjective norms. Subjective norms, defined as the perceived social pressure to engage in or refrain from a behavior, are another key determinant in behavioral decision-making (Ajzen, 1991). Social influence, which can originate from family, friends, or peers, has been shown to affect ride-hailing adoption. In Santiago de Chile, subjective norms were especially influential among younger users (Tirachini & Del Río, 2019), while Javid et al. (2022) found social pressure significantly impacted ride-hailing adoption in Lahore, Pakistan. Similar effects were observed in studies on carsharing in China, where subjective norms were found to be directly associated with intention (Zhang & Li, 2020). Giang et al. (2017) and Akbari et al. (2021) further emphasize the critical role of subjective norms in predicting behavioral intention, reinforcing their importance across different cultural contexts. However, in Kathmandu Valley, where individual decision-making is increasingly valued alongside traditional communal influences, the effect of subjective norms may not be as pronounced as in other regions. Consequently, it could be hypothesized as:

H2: Subjective norms significantly impact the intention to use ride-hailing services in Kathmandu Valley.

Perceived behavioral control. Perceived behavioral control, which reflects the ease or difficulty individuals feel in performing a behavior, is a significant factor in adopting ride-hailing services (Ajzen, 1991). Factors such as the ease of accessing the app and finding available vehicles often shape this sense of control. Studies indicate that a higher perception of control increases the likelihood of using ride-hailing services (Guo et al., 2019), a relationship observed in diverse contexts, including China, where travel time and income significantly influenced control perceptions (Tang et al., 2020). Further evidence highlights perceived behavioral control's importance in technology adoption (Javid et al., 2022; Kaplan et al., 2015). For instance, Zhang and Li (2020) found that greater perceived control positively impacts car-sharing intentions among Chinese students. In Vietnam, Nguyen-Phuoc et al. (2022) emphasized that perceived control, alongside factors like risk and price sensitivity, plays an essential role in shaping ride-hailing behavior. The discussion in the literature also centers on whether perceived behavioral control is more influenced by technological ease or by broader socio-economic conditions. Given the variable infrastructure and digital penetration in Kathmandu Valley, local consumers' perceptions of control may be particularly sensitive to contextual factors such as network reliability and road conditions. Based on these, the following hypothesis is proposed as:

H3: Perceived behavioral control significantly impacts the intention to use ride-hailing services in Kathmandu Valley.

Intention to use ride-hailing services. The intention to perform a behavior is often the most direct predictor of actual behavior (Ajzen, 1991). Research consistently shows a strong link between behavioral intentions and actual ride-hailing use. For instance, Hall et al. (2018)

found that users with strong intentions to adopt Uber were more likely to do so, particularly in areas with limited public transport options. In emerging markets, this relationship remains robust, with studies demonstrating that intention strongly predicts ridesharing use (Akbari et al., 2021; Sajid et al., 2022). In Kathmandu Valley, where public transportation may not always meet demand and where ride-hailing services represent a relatively new option, the strength of the intention-behavior link may be influenced by immediate urban challenges and consumer experiences. Thus, it is expected that behavioral intention will significantly predict ride-hailing service use in Kathmandu Valley. Therefore, it could be hypothesized as:

H4: Intention significantly impacts the actual use of ride-hailing services in Kathmandu Valley.

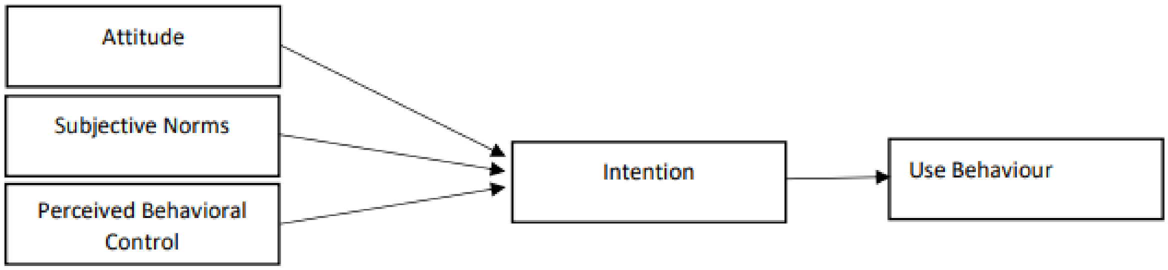
Actual use behavior. Actual use behavior, such as adopting ride-hailing services, is influenced by attitudes, subjective norms, perceived behavioral control, and behavioral intentions (Ajzen, 1991). Prior research has shown that strong behavioral intentions reliably predict actual usage (Dias et al., 2021). For example, Lavieri and Bhat (2019) found that stronger intentions led to more frequent engagement with ride-hailing services. Similarly, Akbari et al. (2021) confirmed the positive effect of behavioral intention on actual use among Iranian consumers, reinforcing the predictive power of intention.

2.2 Conceptual Framework

Based on the Theory of Planned Behavior (Ajzen, 1991) and insights from the literature, this study proposes a model that examines the factors influencing ride-hailing service adoption in Kathmandu Valley. The literature has consistently highlighted the role of attitude, subjective norms, and perceived behavioral control in shaping intention, which subsequently predicts use behavior (Wang et al., 2016; Javid et al., 2022). While attitude and perceived behavioral control have been found to significantly influence intention in various studies (Acheampong et al., 2020; Guo et al., 2019), the role of subjective norms remains more context-dependent, with some studies suggesting a diminished influence in regions where social conformity is less pronounced (Yuen et al., 2020). By integrating these constructs, the proposed model provides a comprehensive approach to understanding the behavioral drivers of ride-hailing service adoption in Kathmandu Valley. The conceptual framework is illustrated in figure 1.

Figure 1

Proposed model



3. Methodology

3.1 Research Design

This study utilized a quantitative causal-comparative survey design to examine the factors influencing the adoption of ride-hailing services in Kathmandu Valley. This design is appropriate for investigating cause-and-effect relationships between independent and dependent variables without experimental manipulation (Creswell, 2014). Quantitative methods are chosen to objectively measure the influence of various determinants on user behavior, a core focus in technology adoption research (Babbie, 2020).

3.2 Population and Sampling

The target population comprised individuals aged 16 to 40 residing in Kathmandu Valley, who own smartphones and are familiar with ride-hailing applications. This age group, defined as “youth” by Nepal’s Ministry of Youth and Sports (2015), is well-suited for studying ride-hailing adoption, as research from emerging markets indicates that youth in similar age ranges lead the adoption of digital transportation services (Acheampong et al., 2020; Sajid et al., 2022; Giang et al., 2017). A total of 400 questionnaires were distributed using a convenience sampling method, a non-probability technique appropriate for descriptive and correlational research focused on exploring relationships and impacts where a complete population list is impractical (Etikan et al., 2016). Of the 400 distributed questionnaires, 389 valid responses were returned, providing sufficient data for research activities suggested by Krejcie and Morgan (1970). Convenience sampling was utilized due to time and resource constraints, which is common in initial studies of consumer behavior (Cochran, 1977).

3.3 Data Collection

Data were collected through an online self-administered survey via Google Forms, selected for its broad reach and accessibility (Venkatesh et al., 2003), considering the high smartphone penetration in Kathmandu Valley. The survey contained 31 items measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to capture user perceptions of ride-hailing services. These items assessed constructs such as attitudes, subjective norms, perceived behavioral control, and behavioral intentions, drawn from validated technology adoption models (Ajzen, 1991).

3.4 Instrument Validation and Reliability

To assess reliability and validity, individual tests were conducted on the survey items rather than using exploratory or confirmatory factor analysis, given the study's focus on pre-established constructs. Items with factor loadings below 0.70 were removed to enhance the measurement model's reliability and validity (Hair et al., 1998). Cronbach's alpha was calculated to measure internal consistency for all constructs, which included Attitude (ATT), Subjective Norms (SN), Perceived Behavioral Control (PB), Behavioral Intention (INT), and Use Behavior (UB), all of which exceeded the recommended threshold of 0.70 (Nunnally & Bernstein, 1994). Additionally, composite reliability (CR) and average variance extracted (AVE) were assessed to confirm convergent validity, and discriminant validity was examined using the HTMT ratio and Fornell-Larcker criterion (Hair et al., 2019).

3.5 Data Analysis

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), a robust method for testing complex relationships between latent variables (Hair et al., 2011). PLS-SEM was chosen due to its suitability for predictive research and its ability to handle small-to-moderate sample sizes effectively (Chin, 1998). The model's reliability and validity were evaluated through factor loadings, Cronbach's alpha, composite reliability, and AVE. Discriminant validity was assessed using the HTMT ratio, Fornell-Larcker criterion, and cross-loadings. Multicollinearity was tested using the Variance Inflation Factor (VIF), with all VIF values below 5, indicating no issues with collinearity (Hair et al., 2010).

Path analysis was conducted to test the hypotheses, and bootstrap resampling (with 5000 subsamples) was used to estimate the precision of the path coefficients and test their significance (Preacher & Hayes, 2008). The Goodness of Fit (GoF) index was used to assess model fit, ensuring an adequate level of explanatory power (Tenenhaus et al., 2005; Wetzels et al., 2009).

3.6. Research Ethics

This study was conducted in accordance with recognized ethical standards for research with human subjects approved by research committee of Central Department of Management, Tribhuvan University. Informed consent was obtained from all participants, confidentiality was maintained, and participation was entirely voluntary.

4. Findings and Discussion

4.1 Initial Data Analysis

In the first step of data analysis, several items were removed due to factor loadings below the accepted threshold of 0.70 (Hair et al., 1998). Specifically, items such as ATT1 (0.651), PB5 (0.696), INT2 (0.52), UB2 (0.45), UB5 (0.556), and UB9 (0.344) were excluded to improve the model's overall validity and reliability (Hair et al., 2010). Following this refinement, the model's reliability and validity were re-evaluated. This re-evaluation met the criterion of Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) – 0.70 for Cronbach's alpha, 0.80 for CR, and 0.50 for AVE (Nunnally & Bernstein, 1994; Fornell & Larcker, 1981), hereby confirming strong internal consistency and convergent validity. However, discriminant validity concerns arose during Heterotrait-Monotrait (HTMT) ratio testing, with values for Attitude (ATT) and Perceived Behavioral Control (PB) at 0.982, and Use Behavior (UB) and Intention (INT) at 0.936, indicating overlap between constructs (Henseler et al., 2015). To resolve these issues, a cross-loading analysis was performed, resulting in the removal of UB3 in the first step due to higher loadings on other constructs than on its own. After removing UB3, cross-loading was performed again, and items UB4, ATT5, INT5, and PB3 were removed because they had less than a 0.1 difference between their loadings on their own construct and other constructs (Hair et al., 2017). These removals helped refine construct distinctiveness, ensuring the final model captured clear and separate theoretical dimensions. Similarly, collinearity was found in two items, SN2 (VIF = 9.275) and SN4 (VIF = 6.058). This was addressed by first removing SN2, which had a VIF of 9.275, indicating severe multicollinearity (Hair et al., 2010). After removing SN2, the collinearity for SN4 dropped to a VIF below 5, resolving the issue without further modifications.

After these refinements, the initial 31-item pool was reduced to 17 high-quality items. The final set met all key reliability, validity, and collinearity criteria, ensuring that the survey instrument was both statistically robust and theoretically sound. These retained items had factor loadings above 0.70, confirmed discriminant validity, and addressed multicollinearity concerns, making them strong indicators for the final analysis. Table 1 provides a summary of retained and removed items.

Table 1

Final selection and deletion of survey items for Pathao/Indrive study

Questionnaire Items	Decision
ATT1: I like to use the Pathao/Indrive service because I can save my time.	Dropped
ATT2: I believe that the availability of Pathao/Indrive service provides a flexible travel option.	
ATT3: I like to use the Pathao/Indrive service because it saves more time than other public transportation.	
ATT4: I feel safe when traveling with Pathao/Indrive because the real-time information system increases the safety of female riders.	
ATT5: I like to use the Pathao/Indrive service because it helps me reach places I don't know of and takes me there easily.	Dropped
SN1: I use the Pathao/Indrive service as my friends/colleagues have recommended it to me.	
SN2: I use Pathao/Indrive service as it has become a social norm in the city.	Dropped
SN3: I need to use the Pathao/Indrive service because I have to share rides with my friends.	
SN4: I use the Pathao/Indrive service because my family and friends consider it safe and secure.	
SN5: I use the Pathao/Indrive service because it is positively accepted by society.	
PB1: Proper regulations are my major concern in the use of Pathao/Indrive service.	
PB2: The driver's skills and attitudes are crucial for the successful use of Pathao/Indrive services.	
PB3: Ensuring female safety is an important consideration when recommending the Pathao/Indrive service to others.	Dropped
PB4: I choose to use the Pathao/Indrive service as my preferred travel option.	
PB5: The price of a Pathao/Indrive service is important to me and I can afford it when I decide to use.	Dropped
INT1: I would prefer/continue to use Pathao/Indrive services because I am satisfied with the level of service.	
INT2: I would prefer to use Pathao/Indrive services due to their lower cost compared to others that provide similar levels of service.	Dropped

Questionnaire Items	Decision
INT3: I consider Pathao/Indrive services to offer a better comfort level.	
INT4: I intend to use Pathao/Indrive services only when they have an effective system for handling complaints and follow-ups.	Dropped
INT5: I believe that female riders will continue to use Pathao/Indrive services as long as operators ensure their safety and security.	Dropped
INT6: I would continue using Pathao/Indrive services as long as the drivers are well-trained and comply with traffic regulations.	
UB1: Security and safety concerns influence my use of Pathao/Indrive services.	
UB2: The affordability of Pathao/Indrive services is important in my decision to use them.	Dropped
UB3: The comfort and convenience of Pathao/Indrive services affect my usage.	Dropped
UB4: The compliance of Pathao/Indrive drivers with traffic rules and regulations is significant in my decision to use these services.	Dropped
UB5: I find the complaint management system of Pathao/Indrive effective in addressing my concerns.	Dropped
UB6: The real-time tracking feature of Pathao/Indrive influences my decision to use the service.	
UB7: I use Pathao/Indrive services more frequently if my friends or colleagues share positive experiences about their rides.	Dropped
UB8: The ease of booking a ride through the Pathao/Indrive app affects my usage of the service.	
UB9: The availability of promotions and discounts on Pathao/Indrive services encourages me to use them.	Dropped
UB10: The ability to share my ride details with family and friends impacts my decision to use Pathao/Indrive services.	

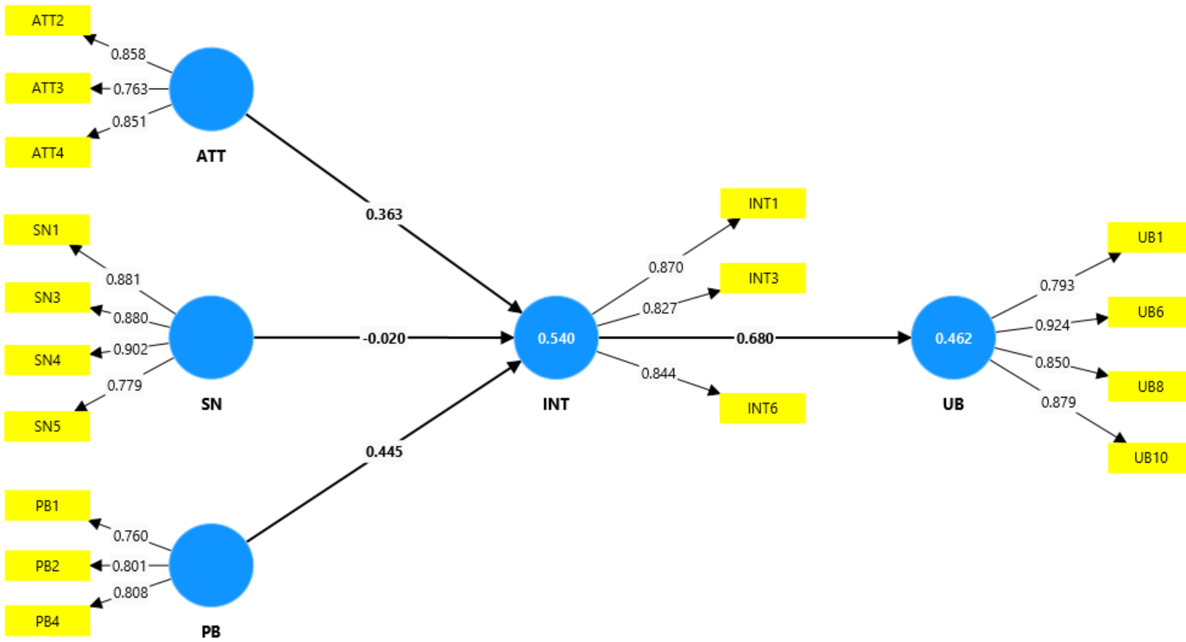
4.2 Final Data Analysis

4.2.1 Measurement model analysis

After refining the model by removing items with high cross-loadings and multicollinearity, all retained items demonstrated acceptable factor loadings above the 0.70 threshold suggested by Hair et al. (1998), indicating reliability and validity. For ATT, items ATT2 (0.858), ATT3 (0.763), and ATT4 (0.851) met this standard. INT was adequately measured by items INT1 (0.870), INT3 (0.827), and INT6 (0.844). PB included items PB1 (0.776), PB2 (0.801), and PB4 (0.808), while SN retained SN1 (0.881), SN3 (0.880), SN4 (0.902), and SN5 (0.779). Lastly, UB was effectively captured by UB1 (0.793), UB10 (0.879), UB6 (0.924), and UB8 (0.850).

Figure 2

Final measurement model



4.2.2 Construct reliability and validity assessment

Ensuring construct reliability and validity is crucial for credible research findings (Cronbach & Meehl, 1955; Fornell & Larcker, 1981; Hair et al., 2010). This assessment includes examining Cronbach's alpha, composite reliability (rho_a and rho_c), and the average variance extracted (AVE) for each construct.

Table 2

Reliability and validity

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	R Square
ATT	0.779	0.84	0.864	0.681	
PB	0.703	0.715	0.833	0.624	
SN	0.894	0.96	0.92	0.743	
INT	0.804	0.81	0.884	0.718	0.540
UB	0.884	0.89	0.921	0.745	0.462

All constructs demonstrated solid reliability, with Cronbach’s alpha values exceeding the recommended threshold of 0.70, confirming internal consistency (Hair et al., 2010).

Similarly, composite reliability values also exceed 0.70, the widely accepted threshold, supporting the reliability of the measurements (Hair et al., 2010). For convergent validity, the AVE for each construct surpassed the required threshold of 0.50, indicating that a significant portion of the variance is explained by the underlying constructs (Fornell & Larcker, 1981).

In terms of explained variance, the R^2 values for INT and UB were 0.540 and 0.462, respectively, meaning that 54% of the variance in intention and 46.2% of the variance in use behavior were accounted for by the model (Henseler et al., Hair et al., 2017). These results confirm that the constructs in the model demonstrate acceptable levels of reliability, validity, and predictive power.

4.2.3 Discriminant validity assessment

Discriminant validity ensures that constructs in a model are distinct and measure unique concepts. This assessment uses various criteria, including the Heterotrait-Monotrait (HTMT) ratio, the Fornell-Larcker criterion, and cross-loadings.

Table 3

The Heterotrait-Monotrait (HTMT) criterion

	ATT	INT	PB	SN	UB
ATT					
INT	0.764				
PB	0.893	0.883			
SN	0.356	0.282	0.497		
UB	0.754	0.805	0.781	0.407	

The HTMT ratio provides a robust measure of discriminant validity. According to Henseler et al. (2015), an HTMT value below 0.85 generally indicates adequate discriminant validity. In this study, most HTMT values are below this threshold. For instance, the HTMT value between ATT and INT is 0.764, and between PB and INT is 0.883, which is just on the threshold. The highest HTMT value is 0.893 between ATT and PB, slightly above the recommended threshold, indicating a potential issue with discriminant validity between these two constructs. All other HTMT values are well below 0.85, indicating adequate discriminant validity for those pairs of constructs.

Table 4

The Fornell-Larcker criterion

	ATT	INT	PB	SN	UB
ATT	0.825				
INT	0.661	0.847			
PB	0.685	0.686	0.79		
SN	0.351	0.267	0.358	0.862	
UB	0.649	0.68	0.615	0.377	0.863

The Fornell-Larcker criterion compares the square root of the AVE of each construct with the correlations between the constructs. A construct should have a higher square root of AVE than its correlations with other constructs to establish discriminant validity (Fornell & Larcker, 1981). The results show that the square root of AVE for each construct (values on the diagonal) is higher than the correlations with other constructs (values below the diagonal). For example, the square root of AVE for ATT (0.825) is higher than its correlations with INT (0.661) and PB (0.685). This pattern is consistent across all constructs, indicating adequate discriminant validity according to the Fornell-Larcker criterion.

Table 5

Cross loading

	ATT	INT	PB	SN	UB
ATT2	*0.858*	0.501	0.601	0.342	0.462
ATT3	*0.763*	0.345	0.471	0.111	0.455
ATT4	*0.851*	0.69	0.598	0.348	0.641
INT1	0.507	*0.87*	0.549	0.206	0.541
INT3	0.457	*0.827*	0.547	0.139	0.631
INT6	0.69	*0.844*	0.637	0.317	0.558
PB1	0.486	0.411	*0.76*	0.449	0.52
PB2	0.498	0.588	*0.801*	0.205	0.377
PB4	0.627	0.593	*0.808*	0.247	0.574
SN1	0.419	0.295	0.33	*0.881*	0.383
SN3	0.243	0.246	0.257	*0.88*	0.275
SN4	0.255	0.182	0.348	*0.902*	0.346
SN5	0.199	0.066	0.361	*0.779*	0.259
UB1	0.666	0.565	0.517	0.326	*0.793*
UB10	0.514	0.553	0.494	0.425	*0.879*
UB6	0.546	0.646	0.627	0.411	*0.924*
UB8	0.517	0.575	0.471	0.133	*0.85*

Cross-loadings are used to ensure that each indicator loads more strongly on its associated construct than on any other construct. According to Chin (1998), the loading of each item on its respective construct should be higher than its loadings on other constructs, and the difference between these loadings should exceed 0.1 (Hair et al., 2017). Based on these criteria, all values in table 5 meet the required thresholds. This confirms that each item loads appropriately on its corresponding construct, thus supporting discriminant validity.

4.2.4 Model fit

Table 6

Goodness of fitness analysis

Metric	**Value**
Average of AVE	0.7022
Average of R-square	0.501
Avg AVE * Avg R-square	0.3518
Square Root of Multiplication Value (GoF)	0.5931

To calculate the Goodness of Fitness (GoF) value, the AVE and the average of R-square are first determined. These averages are then multiplied, and the square root of this multiplication provides the GoF value. For this model, the average of AVE is 0.7022 and the average of R-square is 0.501. The product of these averages is 0.3518, and the square root of this product gives a GoF value of 0.5931. According to Tenenhaus et al. (2005) and Wetzels et al. (2009), the cut-off values for assessing the GoF are: GoFsmall = 0.1, GoFmedium = 0.25, and GoFlarge = 0.36. A GoF value of 0.5931 indicates that the model has a very good global fit, surpassing the threshold for a large GoF value, thereby confirming the model fit in representing the constructs of interest (Hoffmann & Birnbrich, 2012).

4.2.5 Collinearity statistics

The Variance Inflation Factor (VIF) analysis for the outer model revealed that all constructs demonstrated acceptable levels of multi-collinearity, with values well below the threshold of 5 set by Hair et al. (2017). For ATT, the VIF values ranged from 1.372 to 2.237, confirming that multi-collinearity is not an issue. The INT construct showed VIF values between 1.603 and 2.065, further indicating the absence of multi-collinearity concerns. Similarly, PB had VIF values ranging from 1.336 to 1.448, ensuring reliable estimates. Although SN had a higher VIF for SN4 (4.144), this value remained below the critical threshold, indicating moderate but manageable multi-collinearity. Lastly, the UB construct had acceptable VIF values, with UB6 showing the highest at 3.78, which is still within the limits (Hair et al., 2017).

Table 7

Outer model

Variable	VIF
ATT2	2.237
ATT3	1.967
ATT4	1.372
INT1	2.065
INT3	1.765
INT6	1.603
PB1	1.448
PB2	1.336
PB4	1.356
SN1	1.971
SN3	2.6
SN4	4.144
SN5	2.598
UB1	1.775
UB10	2.743
UB6	3.78
UB8	2.483

Table 8

Inner model

Relationship	VIF
ATT -> INT	1.929
INT -> UB	1
PB -> INT	1.939
SN -> INT	1.176

In the inner model, all relationships exhibited low multi-collinearity, with VIF values as follows: ATT -> INT (1.929), INT -> UB (1.0), PB -> INT (1.939), and SN -> INT (1.176), confirming stable and reliable regression estimates (Hair et al., 2017).

4.2.6 Predictive relevance (Q^2predict)

The predictive relevance of the model was assessed using Q^2predict, with values greater than zero indicating that the model has predictive relevance (Hair et al., 2017). The Q^2predict values for the items in this study were positive, with INT1 (0.325), INT3 (0.296), INT6 (0.501), UB1 (0.34), UB10 (0.28), UB6 (0.373), and UB8 (0.274). These results suggest that the model has good predictive relevance for all constructs.

Table 9

Q2 summary

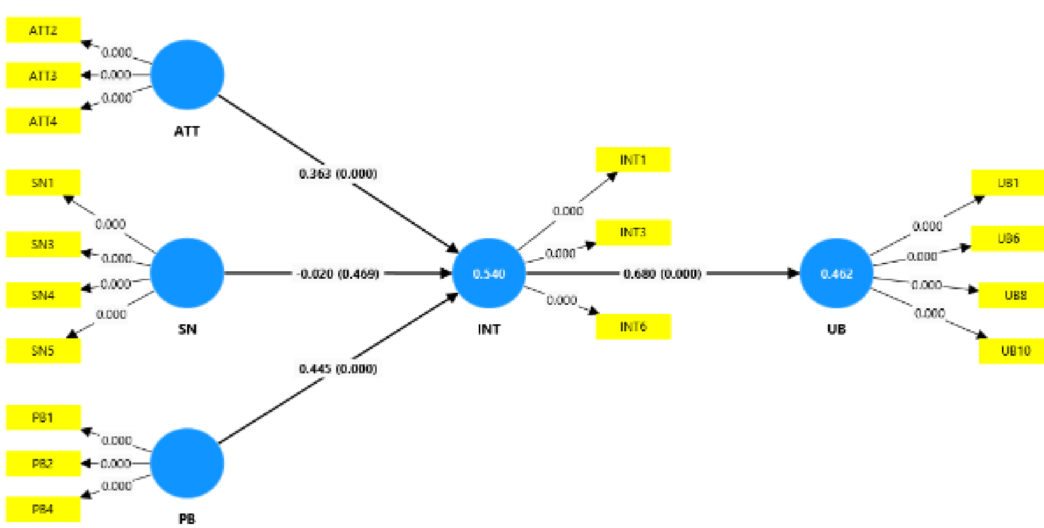
Items	Q^2predict
INT1	0.325
INT3	0.296
INT6	0.501
UB1	0.34
UB10	0.28
UB6	0.373
UB8	0.274

INT6 demonstrated the highest predictive relevance (Q^2predict = 0.501) within the Intention (INT) construct, while UB6 showed a strong value (Q^2predict = 0.373) within the Use Behavior (UB) construct. The consistent positive Q^2predict values across all items confirm the model's robustness in predicting future data points, reinforcing its practical applicability.

4.3.1 Structural model path analysis

Figure 3

Bootstrap analysis results



The bootstrap results provide insights into the significance and stability of the path coefficients in the structural model. The table shows the original sample (O), sample mean (M), standard deviation (STDEV), T statistics (|O/STDEV|), and P values for each path.

Table 10

Path coefficient table

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATT -> INT	0.363	0.365	0.046	7.876	0
INT -> UB	0.68	0.68	0.033	20.881	0
PB -> INT	0.445	0.442	0.052	8.595	0
SN -> INT	-0.02	-0.015	0.027	0.725	0.469

The path from ATT to INT shows a significant positive influence, with a coefficient of 0.363, T statistic of 7.876, and P value of 0.000, indicating a strong and statistically robust relationship. Similarly, the path from INT to UB is highly significant, with a coefficient of 0.680, T statistic of 20.881, and P value of 0.000, confirming that intention strongly predicts use behavior. PB also significantly affects INT, with a coefficient of 0.445, T statistic of 8.595, and P value of 0.000, suggesting that individuals' perceived control over using the service strongly influences their intention. However, the path from SN to INT is not significant, with a coefficient of -0.020, T statistic of 0.725, and P value of 0.469, indicating that subjective norms do not impact intention in this model.

4.3.2 Hypotheses testing

The hypothesis testing results provide a detailed understanding of the relationships between the constructs in the model.

Table 11

Hypothesis testing results

Hypothesis	Path Value	P Value	Result
ATT -> INT (H1)	0.363	0.000	Accept
INT -> UB (H4)	0.680	0.000	Accept
PB -> INT (H3)	0.445	0.000	Accept
SN -> INT (H2)	-0.020	0.469	Reject

H1: Attitude (ATT) → Intention (INT)

The results indicate a significant positive relationship and impact between ATT and INT ($\beta = 0.363$, $p < 0.001$), suggesting that a one-unit increase in attitude, keeping other variables constant, leads to a 36.3% increase in the intention to use ride-hailing services. This aligns with Ajzen's (1991) TPB and previous findings in the contexts of carsharing and ride-hailing services (Haldar & Goel, 2019; Javid et al., 2022; Sajid et al., 2022), where positive attitudes drive adoption intentions. These findings also reflect the role of convenience, affordability, and service quality in shaping user attitudes (Acheampong et al., 2020; Nguyen-Phuoc et al., 2022).

H2: Subjective Norms (SN) → Intention (INT)

Subjective Norms were not found to have a significant effect on Intention ($\beta = -0.020$, $p = 0.469$), which contrasts with some prior studies (Ajzen, 1991; Haldar & Goel, 2019). This suggests that in Kathmandu Valley, social pressures may not strongly influence ride-hailing adoption decisions. Cultural differences or the novelty of ride-hailing services in the region may explain this, as supported by similar findings in other emerging markets (Giang et al., 2017; Zhang & Li, 2020, Chau & Hu, 2002, Yu et al., 2018), where individual attitudes and perceptions play a more dominant role than social norms (Yuen et al., 2020).

H3: Perceived Behavioral Control (PB) → Intention (INT)

A significant positive effect was found for PB on INT ($\beta = 0.445$, $p < 0.001$), indicating that a one-unit increase in perceived control, holding other factors constant, results in a 44.5% increase in the intention to adopt ride-hailing services. This aligns with TPB and other transport-related studies (Ajzen, 1991; Guo et al., 2019; Zhang & Li, 2020), where perceived ease of use and availability strongly influence intention. Similar results have been observed in regions with infrastructural challenges, further highlighting the importance of control (Nguyen-Phuoc et al., 2022; Tang et al., 2020).

H4: Intention (INT) → Use Behavior (UB)

A strong and significant relationship between INT and UB ($\beta = 0.680$, $p < 0.001$) confirms that a one-unit increase in intention, with other factors constant, leads to a 68% increase in the likelihood of actual ride-hailing use. This is consistent with the TPB (Ajzen,

1991) and reflects findings in ride-hailing and other transportation services (Wang et al., 2016; Javid et al., 2022; Akbari et al., 2021), demonstrating that intention reliably translates into use in regions like Kathmandu Valley, where alternatives are limited.

4.3. Discussion

The study confirms that attitude strongly influences intention to use ride-hailing services in Kathmandu Valley (H1). Factors like convenience, affordability, and service quality shape positive attitudes, as highlighted by Acheampong et al. (2020), Nguyen-Phuoc et al. (2022), Sajid et al. (2022), and Javid et al. (2022). This finding aligns with Ajzen's (1991) TPB framework, emphasizing the role of positive evaluations in forming behavioral intentions in emerging markets. Interestingly, subjective norms (H2) did not have a significant impact on intention in this study. This contrasts with findings from Pakistan and China, where social pressure plays a stronger role (Javid et al., 2022; Ajzen, 1991; Zhang & Li, 2020). However, it aligns with the findings of Chau and Hu (2002) and Yu et al. (2018) based on TPB. One possible explanation for this difference is cultural variation. In countries like Pakistan and China, individuals may adhere more strictly to social expectations, whereas in the Kathmandu Valley, people might prioritize personal choices over societal influence. Research by Giang et al. (2017) and Yuen et al. (2020) supports this perspective, indicating that in some cultures, personal preferences outweigh social norms. Additionally, Tirachini and Del Río (2019) found that subjective norms can vary based on factors such as age and education, which might also explain the results of this study. These findings suggest that cultural and educational backgrounds shape how individuals perceive and adopt new technologies.

Perceived behavioral control (H3) positively affects intention, affirming that users feel more inclined to adopt ride-hailing when they perceive the service as accessible and easy to use. This result supports findings from Guo et al. (2019), Tang et al. (2020), and Zhang and Li (2020), indicating that perceived control plays a crucial role in regions with infrastructure challenges, as users prioritize accessibility (Nguyen-Phuoc et al., 2022).

The strong link between intention and use behavior (H4) validates that intention is the primary driver of actual use, consistent with TPB (Ajzen, 1991). Studies by Wang et al. (2016), Akbari et al. (2021), and Hall et al. (2018) similarly confirm that, especially where transportation alternatives are scarce, strong behavioral intentions reliably translate into usage.

5. Conclusion

This study examined the factors driving the adoption of ride-hailing services in Kathmandu Valley through the lens of TPB. Findings show that attitude and behavioral control significantly shape users' intentions to use these services, while social pressures, or subjective norms, have minimal effect. This pattern supports the relevance of TPB across diverse regions for technology adoption in transportation. Additionally, the strong link between intention and actual service use offers practical insights for both service providers and policymakers. To increase adoption, service providers should focus on making ride-hailing more affordable and reliable. They can introduce loyalty programs, offer discounts for frequent users, and insurance policies for any kind of accidents. Improving app features—such as multiple payment options, and quick customer support and offline mode—can also enhance user experience. Additionally, training drivers in customer service and safety protocols can build trust and improve ride quality. For policymakers, ensuring safety and trust is key. They should enforce strict background checks for drivers, require in-app safety features like an SOS button, and promote transparent pricing to prevent overcharging. Creating designated pick-up and drop-off zones in busy areas can also reduce traffic congestion and improve service efficiency.

These findings open up new areas for research, especially on how culture shapes social influence in ride-hailing. Future studies could use interviews or focus groups to get deeper insights into why people choose (or avoid) ride-hailing. Long-term studies could also track how adoption changes over time. Looking into factors like income, education, and gender could help understand how different groups interact with these services. However, this study has some limitations. The use of convenience sampling means the findings might not fully apply to everyone in Kathmandu Valley. Also, since the study only looks at one point in time (cross-sectional design), it does not capture how behaviors change over time. Future research could use random sampling and longer studies to make the findings more widely applicable. Additionally, combining TPB with models like Technology Acceptance Model or Unified Theory of Acceptance and Use of Technology could provide a fuller picture of what drives ride-hailing use in cities.

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This study was conducted in accordance with the ethical guidelines set by the Central Department of Management, Tribhuvan University. The conduct of this study has been approved and given relative clearance(s) by the research committee of Central Department of Management, Tribhuvan University.

Declaration

The author declares the use of Artificial Intelligence (AI) in writing this paper. In particular, the author used site.ai and Quillbot to find relevant literature and refine ideas. The author takes full responsibility in ensuring proper review and editing of contents generated using AI.

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