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INSTITUTE OF ENGINEERING

PULCHOWK CAMPUS

THESIS NO: T03/78

Assessing Service Quality of Ride Hailing Bike Service within Kathmandu Valley

by

Ambika Chaudhary

A THESIS

SUBMITTED TO THE DEPARTMENT OF CIVIL ENGINEERING

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF SCIENCE IN TRANSPORTATION

ENGINEERING

DEPARTMENT OF CIVIL ENGINEERING

LALITPUR, NEPAL

JULY, 2024

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Head
Department of Civil Engineering
Pulchowk Campus, Institute of Engineering
Lalitpur, Kathmandu
Nepal

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DEPARTMENT OF CIVIL ENGINEERING

The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled **"Assessing Service Quality of Ride Hailing Bike Service within Kathmandu Valley"** submitted by Ambika Chaudhary in partial fulfillment of the requirements for the degree of Master in Transportation Engineering.

………………………………………….

Supervisor: Dr. Pradeep Kumar Shrestha
Assistant Professor
Department of Civil Engineering

…………………………………………

External Examiner: Rajesh Khadka
Assistant Professor
Nepal Engineering College

…………………………………………

Committee Chairperson: Anil Marsani
Coordinator: MSc in Transportation Engineering
Department of Civil Engineering

Date:………………………………..

ABSTRACT

Adopting a sustainable transportation approach necessitates a shift towards eco-friendly travel modes, such as ride-hailing bike services like Pathao and Indrive. These services which have introduced a potentially transformative change to Nepal's transportation landscape are prominent in Kathmandu valley, as evidenced by their daily ridership and public recognition. Being a relatively new concept, assessing its service quality is crucial for its continued viability. Evaluating perceived service quality involves a complex decision making process that considers various observed and unobserved factors. This study evaluates the service quality of Pathao and Indrive bike services using structure equation modeling to identify unobserved influencing factors. Six latent factors were identified through factor analysis. An empirical model was developed to understand the interactions among key variables affecting service quality. SPSS 22 and SPSS Amos 21 were used for model development. The study found that user safety is the most significant latent variable influencing service quality followed by service features and application efficiency. The heterogeneity among users regarding different service quality attributes were also analyzed. This study will provide valuable insights to improve these services, enhancing their effectiveness and usability and provide clarity to inform suitable policy decisions.

Key Words: Structural Equation Modeling, Factor Analysis, Latent Variables

ACKNOWLEDGEMENT

I would like to express my heartfelt gratitude to Department of Civil Engineering, Institute of Engineering, Pulchowk Campus for providing me the opportunity to carry out the thesis work. I would also like to convey my sincerest thanks to my research supervisor Dr. Pradeep Kumar Shrestha for his expertise, guidance and unwavering commitment that have been instrumental in shaping the outcomes achieved.

I also want to thank my external examiner Rajesh Khadka for his valuable insights in my study. Last but not the least, I would like to thank my family, colleagues and friends for their constant support in carrying out my research. Without their collective efforts, this endeavor would not have been possible.

Name: Ambika Chaudhary

Roll No. 078/MSTrE/003

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LIST OF ABBREVIATIONS

AE	Application Efficiency
AGFI	Adjusted Goodness of Fit Index
AIC	Alkaline Information Criteria
AMOS	Analysis of Moment Structures
AVE	Average Variance Extracted
BIC	Bayesian Information Criteria
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CMIN	Chi-square value
CR	Composite Reliability
DC	Driving Competency
EFA	Exploratory Factor Analysis
GFI	Goodness of Fit Index
GPS	Global Positioning System
IFI	Incremental Fit Index
KMO	Kaiser Meyer Olkin
MLE	Maximum Likelihood Estimation
MLM	Maximum Likelihood Method
MNL	Multinomial Logistic
MSV	Maximum Shared Variance
NFI	Normed Fit Index
OLS	Ordinary Least Squares
PCFI	Parsimonious Comparative Fit Index
PGFI	Parsimonious Goodness of Fit Index
PNFI	Parsimonious Normed Fit Index
RFI	Relative Fit index
RMSEA	Root Mean Square Error of Approximation
SA	Service Accessibility
SEM	Structural Equation Modeling
SPSS	Statistical Package for Social Sciences
SQ	Service Quality

SRMR	Standardized Root Mean Square Residual
TE	Trip Efficiency
TLI	Tucker-Lewis Index
TW	Trustworthiness
USAFT	User’s Safety

CHAPTER 1: INTRODUCTION

1.1 Background

Ride hailing bike service have been a revolutionary milestone in the transportation sector offering their services in non-traditional way where users can pick up and drop off bike for short term rentals especially by means of a website or app. Customers can book rides through the app by choosing their pickup and drop-off locations. The app displays the locations of both the rider and the user who requested the ride, along with the estimated fare. It also shows the rider's route to the pickup point. Ride booking and account management are managed via the ride-hailing app. Payments can be made manually or through online applications such as mobile banking or E-sewa. The user-friendly interface and ease of selecting destinations provide added convenience to customers (Ullah and Islam, 2015). Pathao a type of ride hailing application was founded in Bangladesh in 2015 by Hussain M Elius and Shifat Adnan. The objective of the company was to provide efficient transportation solutions with less time consuming trip to urban dwellers. Ride hailing bike services were introduced in Bangladesh and quickly became popular. Similarly, In-drive was launched in Estonia in 2013. In Nepal, ride-hailing bike services began with the creation of the Tootle app by Sixit Bhatta in 2017. Tootle aims to provide a safe and convenient travel option, connecting people around Kathmandu with bikers. Although there are numerous ride hailing applications like Pathao, Tootle, Sahara, In-driver, Taximandu that has been used in Nepal, Pathao and In-drive proved to be most used and popular ride hailing bike service applications among public. There are about 1,80,000 registered riders in Pathao out of which only 70,000 riders are active with 30,000 riders to be regularly active. As per operation manager of Pathao, a bike rider registered in Pathao can typically complete 25-30 trips per day on average. Starting as a small operation, the company has grown into one of the leading ride-hailing services in Nepal. Pathao launched in Kathmandu on September 25, 2018. Asheem Man Singh Basnyat is the present regional director of Pathao Nepal. Indrive, launched in 2022, offers similar services to Pathao and has quickly become the most popular ride-hailing service in Kathmandu. It is one of the fastest-growing tech startups, widely used by city residents. Indrive has created significant employment opportunities by allowing individuals with their own vehicles to become Pathao riders, empowering bike and car owners to sign up as drivers and offer transportation services. In addition to ride-hailing, Pathao provides food delivery, parcel, and e-commerce services. Pathao has achieved immense popularity, with 3.5 million downloads, 150,000 daily rides/deliveries, and impacting 5 million lives (Pathao official website). Service quality is a crucial factor in service planning and improvement, benefiting both the company and its users. Passengers' experiences in ride-sharing significantly influence their usage frequency (Sourav, 2021). However, like many businesses in Nepal, the ride-hailing sector lacks transparency, with limited public data. The growing number of Pathao bike users raises concerns about the quality of its service. Structural equation modeling is used in this study to assess the service quality of ride hailing Pathao and Indrive bike service. It is a multivariate statistical method used to examine complex relationships between variables. SEM involves two types of variables. Latent variables are the underlying concepts which cannot be directly measured and Observed variables are the measurable indicators of the latent variables. SEM is viewed as a two- step process: Measurement model assessment which evaluates how well the observed variables represent the latent constructs and Structural model analysis which focuses shift to the hypothesized casual relationships among the latent variables. In conclusion, SEM provides a powerful tool to explore intricate relationships. It goes beyond correlations, providing a framework to understand the underlying structure of complex phenomena.

1.2 Problem Statement

In recent years, the number of ride-hailing bike users in Kathmandu has seen significant growth (Hamal, 2019). This growth is positively impacting the country's revenue by creating employment opportunities for both riders and company employees (HRM, 2022). The rapid expansion of these services requires balancing the growth with public safety to create a safe, convenient and sustainable ride hailing ecosystem through responsible use. In Kathmandu, these services have encountered several challenges such as security measures, technical hiccups, features enhancement hindering their full potential. Due to limitations in service features, application efficiency, potential safety gaps, it can lead to user's dissatisfaction affecting the overall service.

Service quality is affected by the user’s preferences that gives out the most significant variables (Shahid, et.al, 2020). Understanding user perceptions focus groups that can reveal public concerns about safety and accessibility. Analyzing data can help identify areas for improvement in operational efficiency.

1.3 Research Objectives

The overall objective of the study is to assess the service quality of ride hailing bike service. The specific objectives of the research are as follows:

- To develop a service quality model by using structural equation modeling.
- To study heterogeneity among users with respect to their perceived service quality attributes.

1.4 Scope of Study

The models prepared through this research can be used in appraising various aspects of the service provided by ride hailing companies that can be used by the operators, decision makers and transport planners to make improvement and enhancement. The exploration of the relationships between service quality dimensions and interactions which influences overall user satisfaction helps in identification of areas for improvement. The prioritization can guide ride hailing service in focusing their efforts on aspects that will have the most significant repercussion on enhancing user experience. Based on findings, specific actionable strategies can be employed in each prioritized area. These strategies could confront tangible aspects like bike maintenance, app functionality, or intangible aspects like communication and customer service. By applying SEM, the study can go beyond simply measuring service quality. It can provide precious perspectives into the relationships between various service dimensions and ultimately guide these services developing targeted improvement strategies for their bike services. To maintain desired standards, policymakers can use this tool to monitor, evaluate, and implement service improvements. They can identify critical variables that significantly influence service acceptance. By prioritizing these variables and enhancing those that can greatly improve overall service quality, quick results can be achieved in attracting potential users.

1.5 Study Limitations

The limitations of the study are as follows:

- The study did not separately analyze Pathao and Indrive bike service.
- The study focuses on current user perceptions and may not consider future trends or potential changes in user expectations.

1.6 Organization of Report

The thesis report consists of five chapters as follows:

Chapter 1: Introduction

This chapter depicts about the ride hailing bike service and issues related to it.

Chapter 2: Literature Review

This chapter explores the available literature based on structural equation modeling approach in developing the relation between important variables which are essential for the performance of ride hailing services.

Chapter 3: Research Methodology

This chapter includes study area, data collection, extraction, and data analysis used in this study to accomplish the research objectives.

Chapter 4: Results and Discussions

This chapter consists of descriptive statistics on demographic characteristics of the people involved in questionnaire survey. It also includes the model interpretation of SEM .

Chapter 5: Conclusions & Recommendations

This chapter elaborates the outcomes of the thesis & recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Concept of Ride Hailing

Ride hailing is an opportunity to establish interaction between rider and passengers. The widespread adoption of ride hailing service has been fueled by the seamless connectivity provided by the internet, revolutionize the way people commute and travel (Mishra, 2021). The study presents detail features and the steps to use the service. It elaborates the risk and opportunities on adoption of ride hailing. The advancement of algorithms for dynamically pairing drivers and passengers in real time is the main concept of ride hailing (Agatz et al. 2012). Two groups exist in ride hailing ie. passengers and driver. Being time oriented transportation service, it mostly involves viable use of different modes of transportation usually car and bike. The drastic change in transportation industries by addressing the present demand of this generation like travel time reduction, traffic congestion, etc (Hair et al, 2006 and Hooper et al, 2008)

Hawlitscheck, et al. (2016) laid the groundwork for future research on customer behavior within the sharing economy. Hansen, et al. (2010) focused on community-driven resource kits as a promising technology to reduce transaction costs. Various entry times allowed for the comparison of traffic congestion before and after Uber's introduction in urban areas. Potential instruments' effects promote the adoption of pooled autonomous car usage (Dong, et al. 2018). Kiatkawsin and Han (2017) investigated the environmental benefits of ride-sharing through its potential to mitigate CO_2 emissions. Zhang et al. (2015) developed a simulation model to analyze the potential impact of shared autonomous vehicles on urban pricing demand. Ahmed and Burki (2017) compared ride sharing between business class faces and economic class faces. It also covers the comfort and security these company can offer for both classes. The difficulties that are faced while using the application are also discussed.

The features of both the driver and passenger based applications provide better understanding to the users. Koirala P.R (2020) studied financial, technical, psychological, usability, marketing aspect on the riders end. It suggested ride sharing companies to improve and achieve their goals.

2.2 Ride Hailing & its Essence in Nepal

Ride hailing has revolutionize urban transportation by offering convenient, eco-friendly mobility solutions for city dwellers. The sharing economy provides efficacious approach for the development of creative mobility models and realizes sustainable transport (Ekundayo, 2024). Real time monitoring of the route is made possible by wireless communication technology like GPS (Mora, 2024). Being an innovative transportation approach, it has being widely used in different parts of the world. Ullah and Ashraful (2017) conducted a case study on Pathao, exploring it as a technology-based solution to Dhaka's traffic congestion problem. The study emphasized challenges in starting online platform based transportation service and creation of business model within the country. It also presented the working mechanism of Pathao about how they raise funds and challenges of operating in Bangladesh. It further elaborated Pathao to be a constantly evolving future economy of Bangladesh.

Kathmandu is rapidly emerging as a burgeoning techno hub, attracting innovators and tech enthusiasts from around the world. With high techno growth rate, ride sharing application is mostly available in Kathmandu. The daily life of people is affected by these technology. Hamal (2019) deployed mobile ethnographic approach for studying Pathao & Tootle in Kathmandu. The study highlighted the emergence of online platform based ride sharing and local, global and social issues associated with them. It concluded that both the online platform to be emerged as response to poor mechanized transportation service penetrated by the economic blockade in the post earthquake period. Being a profit motive platform, it attracted many riders into ride sharing platform. The study further depicts the class distinction between the riders and customers. It also shade some light on the harassment by the male riders to female customers. The study finally concluded digitization to be a remedy to development problems solving everyday commute problem but at the same time it increases social risks.

2.3 Evolution of SEM Model

The evolution of SEM is made with substantive problems faced by individual disciplines. It has incorporated additional statistical modes to discover casual structures for specifying assumptions inferring casualty with non-experimental data (Matsuda, 2011).

SEM is beneficial as it can test the descriptive ability of different models allowing them to be compared. SEM directly incorporates unmeasured variables as well. It also provide fit indices indicating areas with poor model fit and this point to further observation that might describe the data (Mitchell, 2018)

Structural Equation Modeling (SEM) involves a set of equations based on the system's assumptions, using statistical observations for parameter determination. These equations include both observable and latent variables (Joreskog and Sorbom, 1993). SEM development stemmed from academic researchers' growing need for effective methods to understand latent phenomena's structure and interactions. Spearman (1904, 1927) laid the foundation for SEM with his factor model, which became a crucial part of SEM analysis. He published a paper on fitting by planes using orthogonal least squares, forming the basis for principal component analysis applied to correlation matrices by Hotelling (1933). Spearman's work revolutionized researchers' thinking by illuminating the measurement of latent variables within True Score Theory.

Thurston (1935) developed the centroid method for factoring a correlation matrix and defined a simple structure for factor analysis based on five principles, fostering interpretation and ensuring invariant loadings despite other items' inclusion. Factor analysis initially focused on various rotation methods, with rotated loadings' standard errors being diagonalized (Clarkson, 1980). The issue of factor rotation was resolved with the advent of confirmatory analysis.

The idea of SEM was actually initiated by Wrigh who used strategy based on path analysis with structural coefficients on the observed variables. Dissatisfied with the outcomes of partial correlation analysis, he introduced path analysis to incorporate a causal structure with structural coefficients into observed correlations. Path diagrams enabled the swift decomposition of relationships into various causal components, such as direct and indirect effects.

The significant advancement in SEM software development coincided with the introduction of several commercial computer packages, including EQS (Bentler, 1985), LISREL (Joreskog, 1973), and (Steiger, 1989). Amos, developed by Arbuckle and Wothke in 1999, offered a distinct advantage over other software by providing a flexible interface for path diagrams instead of requiring syntax. Goldberger (1964) formalized an approach to estimating SEM models, while Bock and Bergman (1966) pioneered covariance structural analysis for estimating covariance elements of observed variables with multidimensional, normal distributions and latent characteristics.

2.4 Previous Study on Service Quality

Carman (1990) and Parasuraman et al. (1985) defined three characteristics of service: intangibility, heterogeneity, and inseparability. The perception of service quality results from comparing consumer expectations with their perception of actual service performance (Gronroos, 1988., Parasuraman et al. 1985).

Service quality consists of three dimensions: technical quality (what the consumer actually receives), functional quality (how the service is delivered), and image. Because services often lack tangible elements, the focus is on intangible elements (functional quality) (Parasuraman et al. 1985, 1988). A generic set of attributes and dimensions is used to analyze service quality across various service types (Parasuraman et al., 1988).

Different researchers have used different methods for evaluating service quality of different transportation services. SERVQUAL (Service Quality Model, Impact Score Technique, Customer Satisfaction Index, Structural Equation Modelling (SEM). The response to traveler’s needs is one of the prominent concern to accurately estimate transportation demand.

Customer satisfaction is defined differently across the literature: "the emotion customers feel when they encounter a service that meets or surpasses their expectations" (Kiran and Diljit, 2011), and "a customer's emotional state of pleasure or disappointment arising from comparing a product's perceived performance with their expectations" (Anglelora and Zekiri, 2011).

Zeithaml et al. (1993) proposed that customer satisfaction is influenced by the customer's assessment of service quality, product quality, and price relative to their expectations. Rust and Oliver (1994) define customer satisfaction as a customer's cognitive response to a service encounter, influenced by their perception of service quality. Satisfaction hinges on whether the service performance meets, exceeds, or falls short of expectations. When service performance exceeds expectations, customers tend to be highly satisfied and are likely to become repeat users.

Defining and measuring service quality poses challenges (Parasuraman et al. 1988, Brown and Swartz, 1989, Carman, 1990). Service quality serves as a critical tool in an organization's efforts to distinguish itself from competitors (Ladhari, 2008).

Several researchers have devised various approaches to measure service quality. Parasuraman et al. (1985) identified ten factors affecting service quality through focus group research: reliability, communication, access, tangibles, responsiveness, competence, courtesy, credibility, security, and customer knowledge and understanding. These dimensions were later consolidated into five categories tangibles, responsiveness, reliability, assurance, and empathy as part of the SERVQUAL model used for measuring service quality. The reliability dimension refers to the consistency and dependable with transportation services operate according to their schedules and commitments. It encompasses factors such as punctuality, frequency, consistency and ability to deliver goods or passenger safely and on time. A reliable transportation service is one that can be counted on to fulfill its obligations consistency and efficiently minimizing disruptions and delays for its users. The responsiveness dimension relates to the willingness to assist customers. The tangible dimension pertains to the physical facilities, equipment, and appearance of personnel. Conversely, the assurance dimension involves employees' knowledge, courtesy, and ability to instill trust and confidence. Various studies have explored the impact of service quality on customer satisfaction. The role of social media in updating customers has been crucial in enhancing service quality and satisfaction (Ramanathan et al., 2017). Service quality and customer satisfaction are fundamental aspects of any business, as they retain customers through effective service and satisfaction (Edward and Sahadev, 2011). Customer satisfaction is closely tied to high service quality, which enhances competitiveness in the marketplace. Service quality became a critical element in car industry's success through good customer contact (Lambert, 2010).

2.5 Effect of Demographic Factors on Service Quality

In recent years, there is rapid expansion of ride hailing services, understanding the determinants behind users intentions to opt for these services is crucial. Socio demographic factors play a significant role in predicting traveler's adoption behavior towards these services. Numerous investigations in developed countries have sought to invest the intricate correlation between the ride hailing usage and socio-economic characteristics. The socio-demographic characteristics have significant effect on ride hailing services like Pathao & Indrive. For instance, Dias et al. (2017) aimed to investigate the impact of socio-economic and demographic factors on the simultaneous use of ride sourcing and car sharing services, employing a bivariate ordered probit model. They found that educated young adults in densely populated areas are likely the main users of these services. Meanwhile, Henao & Marshall (2019) addressed equity concerns among ride sourcing users by examining the correlation between demand, waiting times, and demographic factors such as age, income, and education, integrating geographical considerations into their analysis. Clewlow, Reogina and Mishra (2017) studied the adoption of the ride hailing and car sharing platform in seven cities of U.S.A It analyzed the demographic factors of the users on adoption. It also showed the differences between the adaptors and non-adaptors of ride sharing.

Additionally, Gulibert et al. (2017) found a preference for a ride sourcing services among young people, while Alemi et al. (2018) identified a higher propensity for usage among highly educated individuals, older demographics, long distance travelers and frequent mobile app users. These findings underscore the need of coordinated policymaking and incentives to leverage the benefits of these services while mitigating negative impacts. Studies have indicated that land use mix and activity density patterns affect ride hailing frequency, with the former decreasing and latter increasing it (Alemi et al. 2019). Moreover, individuals who frequently use smartphone apps are more likely to consider ride-hailing services (Alemi et al. 2019). Factors such as income, waiting time, vehicle ownership, trip purpose, residential location, occupation, and prior experience with public transport are also significant predictors of ride-hailing behavior (Dawes, 2016; Javid et al., 2021; Sisiopiku et al., 2021). Gender has been identified as a moderating factor in the relationship between perceived utility, perceived risk, and the intention to use ride-hailing services (Goel and Haldar, 2020). Research conducted in Bangladesh has shown that income, gender, motorcycle ownership, social norms, and performance influence the frequency of motorcycle-based ride-hailing services. Bauer (2017) delved into the social and cultural factors influencing the adoption and acceptance of employees of Sodertalje, Sweden. The study provided insights to employees about ride sharing. A technology acceptance model was developed to find how users behave. It is concerned about the social practices for ride sharing.

Barbour et al (2019) identified factors influencing bike sourcing and assessed mode substitution effects, stressing the importance of age, income, trip types and vehicle ownership in ride hailing decisions.

The impact of socio demographic factors on ride sharing reveals varying patterns of usage and preferences among different age groups, income, brackets and geographical regions (Dias, 2017). The study concluded most of the customers to be young educated , high income groups. Shah & Hiremath A.d (2022) identified problems associated with ride sharing . It also present the risk associated with these applications ignoring the benefits and significance of it. The problems recognized were lack of door to door service, less reliable schedule, fixed route, reduction of environmental pollution and congestion, ride matching time and implement implement shortest path.

Furthermore, research such as that by Saboure et al. (2020) and Sabouri et al. (2020b) explored the correlation between ride sourcing services and vehicle ownership, as well as the influence of urban environments on ride sourcing demand. These studies highlighted the impact of socio-economic factors on transportation preferences and proposed implications for urban planning and policy formulation. In Ibadan, Nigeria, a study by Ojekalu et.al (2019) investigated how demographic characteristics affect customers' perceptions of service quality. The research discovered that both the gender and education level of occupants had a notable impact on how service quality was perceived, while the age of respondents didn't show significance. Specifically, women tended to rate property manager's service quality higher compared to men. Occupant's age, however did not have a significant effect on service perception.

2.6 SEM in analyzing people's perception

A study in Bangladesh examined Pathao bike service to evaluate perceived service quality (Shahid, et al. 2020). The study employed SEM methodology to assess overall service quality, incorporating nineteen variables and two latent variables: 'service feature' and 'system performance'. The latent variable 'service feature' was characterized by observed variables such as riding safety, riding comfort, cleanliness, driving skill, vehicle quality, female security, and driver's behavior. Similarly, 'system performance' was represented by observed variables including contact with drivers, destination display System, system upgradation, system availability, customer care service, trip completion, responsiveness, credibility of billing, and fare rates. Among these latent variables, system performance was found to have the highest influence with a regression coefficient of 1, followed by Service Feature. The study investigated the correlation between the quality of service provided by ride sharing bike services and various service related factors using SEM. These finding suggest that policies focusing on these aspects could contribute to the development of a safer, higher quality, and more reliable framework, complementing broader transportation sector initiatives.

The emergence of application-based ride sharing services has led to a reduction in traffic congestion and provided employment opportunities in Bangladesh (Sourav, Tabassum and Opu, 2021). The study evaluates the overall structured questionnaires formulated based on existing literatures and input from stakeholders. A total of 350 responses were gathered from car sharing users in Bangladesh through online survey. A SEM model was validated using SPSS Amos 26. The model was employed to examine the hypotheses related to the acceptance of ride sharing services. The result indicated a positive relationship between safety and security features of ride sharing services and user's judgement category, factors such as the driver's attitude, skill, traffic congestion and environmental impact significantly influence ride sharing service acceptance. Similarly, personal and account information significantly affect sharing attitudes under the safety and security category. These findings offered insights into user's attitudes and perceived risks, aiding policymakers and service providers in enhancing service quality to attract retain users. Measures such as improving driver's skills, attitudes towards users during congestion, and promoting the sue of environmentally friendly fuel can enhance the acceptability of ride sharing services.

Travel behavior results from a complex decision making process influenced by individual socio economic factors, mode and trip characteristics and other unseen variables (Shrestha, 2007). The study aimed to uncover these unseen factors impacting travel behavior. Through factor analysis, six latent variables, termed as travel factors, were identified. SEM was utilized to establish casual relationships between observed and unobserved variables. Upon analyzing the most significant factors influencing travel behavior, it was found that safety from theft, minimal waiting times, absence of delays, low daily travel costs, high average speed, and short travel durations predominantly explained perceptions of safety, comfort, reliability/accessibility, cost sensitivity, efficient service, and time savings, respectively. All influencing variables including gender, age, household size, education, occupation, car ownership, trip purpose, travel distance, and trip cost were statistically significant at a 5% significance level. The factor related to personal safety and comfort showed a positive association with gender, age, education, car ownership, and trip purpose, indicating that women prioritize safety and comfort more than men, and individuals place greater emphasis on these factors for shopping and business trips compared to other purposes. In contrast, a negative relationship with occupation suggested that students, unemployed individuals, and laborers were less concerned about safety and comfort during their travels. The negative correlation between reliability/accessibility and age suggested that younger individuals prioritize reliability and accessibility more. The results indicated that the model incorporating these travel factors performed better than the model without them. Continuing to apply these factors in various contexts could effectively assess their impact on travel demand modeling.

The advent of ride-hailing services has facilitated on-demand and flexible transportation options for passengers (Javid, Abdullah, and Ali, 2022). The study investigated travelers' behavioral intentions toward ride-hailing services in Lahore, utilizing the theoretical framework of the Theory of Planned Behavior (TPB). The reliability of TPB's latent variables was confirmed through Chronbach's alpha values. Significant correlations were observed between observed variables and their corresponding latent constructs. The findings highlight that attitudes, subjective norms, and perceived behavioral control were influential predictors of behavioral intentions, with perceived behavioral control and intentions strongly predicting actual traveler behavior. Difficulty in using ride hailing services negatively impacts travel behavior. Intentions serve as a mediator in the relationship between attitudes, norms, behavioral control, and behavior control, and behavior. Factors such as possessing a driving license, motorcycle ownership, age above 30, low income and current ridership positively influence behavior. Service quality attributes like attributes like affordability, driver attitude, coverage, regulations, comfort, and safety, especially for female riders were crucial. Ensuring the safety and security of female riders was crucial for fostering positive attitudes and social norms towards ride hailing services. However, the study had limitations, as it did not fully evaluate all dimensions of service quality. It only examined a limited number of attributes, and the sample included both users and non-users of ride-hailing services.

Bike sharing has emerged as a popular transportation option in numerous cities worldwide, appealing to users for its convenience, eco-friendliness, affordabilility, and suitability for short trips (Zhou and Zhang, 2018). This research assessed the key determinants influencing the perceived quality of service, satisfaction, and loyalty among bike sharing customers. The study established measurement variables by conducting a satisfaction survey among users of the OFO bike sharing service in Ningbo, China. They constructed a Service-Satisfaction-Loyalty model using SEM and performed statistical analysis. Perceived service quality was categorized into three dimensions: platform service quality, bicycle quality, and value perception. Results indicated that the SEM model successfully identified underlying variables influencing satisfaction and loyalty in bike sharing. The quality of the bike and platform significantly affected customer satisfaction, whereas perceived value did not emerge as a significant factor. The study reaffirmed that satisfaction played a pivotal role in fostering loyalty to bike sharing services. A structural equation model was constructed to explore how overall satisfaction correlates with various service quality attributes, such as safety, cleanliness, primary and additional services, information provision, and personnel interactions. The study focused on rail services in Northern Italy, covering 32 regional lines, 9 suburban lines connecting different towns around Milan, and 2 express lines linking Milan with Malpensa airport. The model provided valuable insights for transportation agencies and planners to understand the connections between service quality attributes and prioritize improvements. Key findings highlighted that factors like punctuality, regularity, service frequency, and cleanliness had the most significant positive impact on service quality. Therefore, SEM serves as a crucial tool for analyzing customer perceptions by developing models that capture complex relationships between variables.

2.7 Summary

The service generates positive economic and social outcomes while addressing environmental concerns, thereby promoting sustainability (Sakib, 2019). Additionally, ride-sharing enhances travel efficiency and capacity (Beria et al., 2017; Wang et al., 2019), making it a preferred option for high-quality trips within Dhaka city.

Since Pathao and Indrive commenced operations, there has been significant attention in the capital city of Kathmandu. This includes the creation of vlogs on youtube discussing these platforms (Biel et al. 2011), as well as regular media coverage comparing their services and digital applications. This media coverages often emphasizes the positive aspects of ride sharing platforms in Kathmandu Valley, such as their role in facilitating everyday commuting and providing a hassle free experience (Sapkota, 2017 Prasain, 2018 and Adhikari, 2018). However, recent news coverage has shed light on the challenges faced by these platforms. Despite claims of having mechanisms in place to prevent harassment of women, they have not been entirely successful in doing so (Gurung, 2019 and Nepali Telecom, 2019). This underscores the social concerns regarding class and gender dynamics within this emerging online economic practice.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design

The methodology was focused on assessing the service quality of ride hailing bike service based on customer's perception. The research employs selecting service quality variables, collecting and sorting data for various tests and utilizing structural equation models in the study.

The methodological framework adopted during the study is being summed up in the form of flow chart.

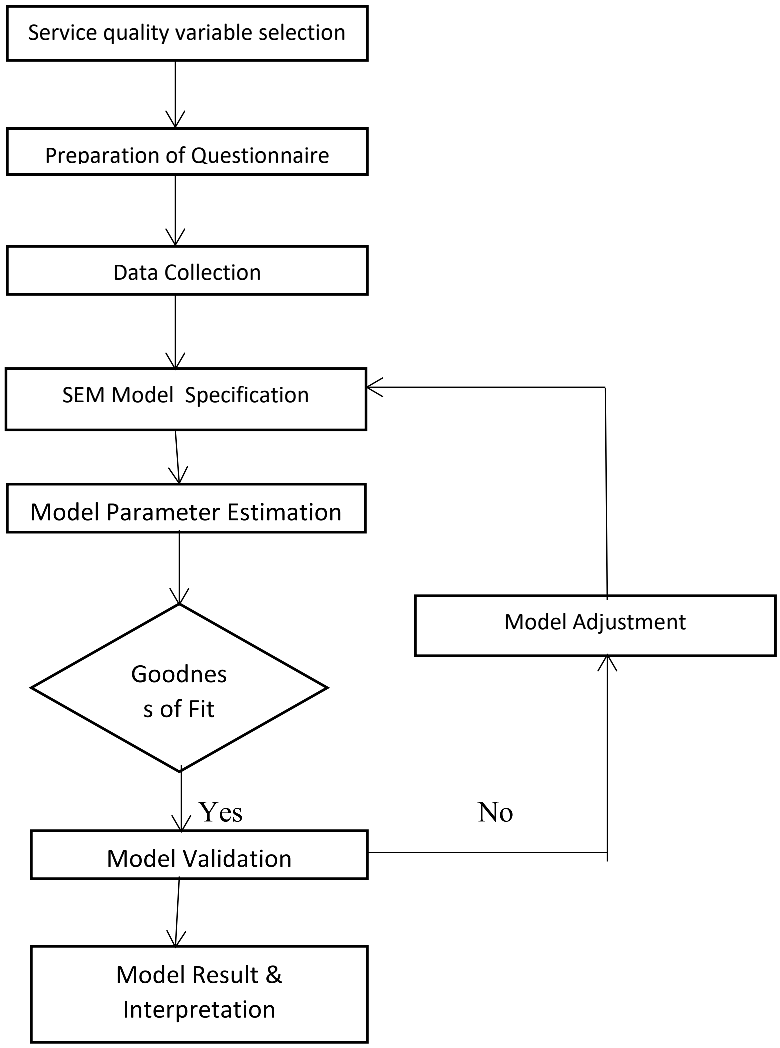

Figure 3.1 Framework of Research

3.2 Study Area

The Kathmandu Valley, nestled in the Himalayan mountains of Nepal, is a bowl-shaped valley consisting of three districts: Kathmandu, Lalitpur, and Bhaktapur. It stands as Nepal's most developed and largest urban agglomeration. In Kathmandu Valley, there is presence of large number of customers who use various means of transportation as their daily necessity. Pathao and Indrive quickly gained popularity as a convenient and efficient mode of transportation within the bustling urban landscape of Kathmandu. They are popular for their door to door service so it is difficult to get the exact location of the riders and customers. The users are scattered all over the valley. The data were collected at three major sites of the valley ie. Kalanki, Tribhuvan International Airport and Sundhara because the users are more concentrated in these areas. The prime location is Sundhara (site).

Figure 3.2 Study Location (Kathmandu) ***Source:Google***

3.3 Sample Size

The sample size requirement for SEM can vary based on several factors including the complexity of the model, the number of latent variables, observed variables, the desired level of statistical power and the quality of the data. There are several general guidelines to follow when working with SEM. It is recommended to have a sample size of at least 200 to 250 participants (Kline, 2015), although a larger sample size is preferable for complex models or those involving numerous latent variables. Levy and Lemeshow (2008) provided an empirical formula assuming a normal distribution of the population for determining the sample size:

$$no=\frac{Z^2pq}{e^2}\dots\dots\dots\dots(3.1)$$

where, no=Sample size for infinite population

Z= Statistical parameter corresponding to confidence level (Z is 1.96 for 95% confidence interval)

e=Desired margin of error (adopted as 5%)

p=Hypothesized true proportion for population (adopted as 0.5 to account for the worst case) and q=1-p

Inserting these values in equation 3.1, we get no=384.16. For the study we have collected 503 data for the accuracy of our model.

3.4 Data Collection

A pilot survey was conducted prior to the main questionnaire survey to identify any issues such as ambiguous or confusing questions. The pilot involved experts from Pathao's office as well as Pathao and Indrive riders. The data for the research was collected manually using a paper-based questionnaire, designed in accordance with the research objectives. The questionnaire was divided into three sections:

- The first section gathered demographic information such as gender, age, occupation, family income, household size, purpose of travel, and frequency of using the bike service.

- The second section collected passenger opinions on various service quality variables using a Likert scale ranging from 1 to 5.
- The third section assessed overall service quality, also on a scale from 1 to 5.

3.4.1 Selection of Variables

The variables were selected from questionnaire survey carried out manually after pilot survey of group of experts about service quality dimensions.

Table 3.1 Classification and Description of Socio-Demographic Variables

S.N	Variable name	Symbol	Description
1	Gender	GEN	Identity as male or female
2	Age	AGE	Length of time an individual has lived since birth
3	Occupation	OCU	Type of work or employment that an individual engages to earn livelihood.
4	Household size	HOUS	Number of members in a family
5	Monthly family income	MFI	Total earnings received by all members of a household within a month.
6	Vehicle Ownership	VO	Refers to possession or legal ownership of one or more vehicles in a family.
7	Driving ownership	DO	Refers to possession of a valid driver's license
8	Frequency	FREQ	Rate or pattern at which individuals or households utilize the bike service for transportation purposes.

Table 3.2 Classification and Description of Service Quality Variables

S. N.	Variable name	Symbol	Description
1	Managing Speed	MS	Reducing traffic speeds to a safe and appropriate level
2	Defensive Driving	DD	Avoiding dangerous situations in a road
3	Patience	PAT	Ability to stay calm and composed while facing challenges on the road
4	Driver's Skills	DS	Ability to operate a vehicle safely and efficiently in variety of conditions.
5	Driver's Behaviour	DB	The conduct and demeanour exhibited by the motorcycle rider during the trip arranged through the application.
6	Live Location Sharing	LLS	Transmitting real time to another person or group of people.
7	Real Time GPS Tracking	RGT	Allowing monitoring the location of a person, vehicle or asset with minimum delay
8	Driver's Rating and Reviews	DRR	Numerical scores often out of 5 stars that reflects a rider's overall experience with a driver.
9	System Availability	SA	Probability that a system is functional and ready to use when you need it.
10	Travel Time Saving	TTS	Reduction in the amount of time it takes to get from one place to another.
11	Less Waiting Time	LWT	Reduction of the amount of time someone has to spend idle before receiving service or continuing an activity.
12	Vehicle Condition	VC	The cosmetic appearance and the mechanical functionality of bike
13	Optimization of Routes	OOR	Most efficient way to travel between multiple stops.
14	Rate of Fare	RF	Cost of travel per unit of distance or time.
15	Safety from Threat	SFT	Measures and precautions taken to protect both the rider and the passenger from intentional harms, assault or robbery.
16	Safety from Accidents	SFA	Measures and precautions taken by both riders and passenger to minimize the risk of collisions, injuries
17	User's Security	US	Measures to ensure secure transactions, data privacy and safeguards against potential risks such as fraud.
18	Easy to Book Trip	EBT	Quickly assessing the app, specifying the desired pick-up and drop off locations, and promptly being matched with a nearby motorcycle rider for the trip
19	Easy to Cancel Trip	ECT	A straightforward process within the app for swiftly cancelling a booked motorcycle ride.
20	Easy to Pay	ETP	It involves seamlessly linking a payment method to the app, receiving transparent fare estimates upfront, and effortlessly executing payment upon reaching the destination, often through digital wallets, credit/debit cards, or cash.
21	Trip Completion	TC	Entailing the passenger reaching their intended destination safely and the driver confirming the completion of the trip within the app, indicating that the journey has been successfully fulfilled.
22	Customer Support	CSU	It includes channels such as in-app chat support, email support, phone support and assistance centers , through which users can seek help with various aspects of using the Pathao bike service.

3.5 Data Analysis

3.5.1 Reliability Analysis

A reliability test was conducted using IBM SPSS 22 software to measure the consistency of the data. The reliability of the data was assessed using Cronbach's Alpha test, which evaluates how closely related a set of items are as a group, aiming to determine if they measure the same underlying construct or concept. Cronbach's Alpha provides a numerical value between 0 and 1, with higher values indicating greater internal consistency.

3.5.2 Confirmatory Factor Analysis

Confirmatory factor analysis was conducted to reduce the number of observed variables by grouping them into smaller sets based on their interrelationships. This process reduced the original 35 variables to 22 based on their integrity. To evaluate the suitability of the data for factor analysis, KMO (Kaiser-Meyer-Olkin) and Bartlett's tests were performed. The KMO test assesses the adequacy of the data for factor analysis, producing a statistic between 0 and 1, where higher values indicate better suitability for extracting underlying factors. Bartlett's test evaluates whether the observed variables are appropriate for this type of analysis. A KMO value closer to 1 suggests that data is well suited for factor analysis because there is common variance among the variables. KMO values above 0.8 are considered excellent indicating strong suitability. Values between 0.7 and 0.8 are considered good, while values below 0.6 suggest that factor analysis is not suitable (Kaiser and Rice, 1974). Similarly, Bartlett's test examines whether the correlation matrix of the data significantly deviates from an identity matrix, indicating sufficient inter-correlation among the variables for factor analysis. This test calculates a chi-square statistic and compares it to a critical value. If the chi-square statistic is statistically significant (i.e., the p-value is less than the chosen significance level), it suggests significant correlation among the variables, making factor analysis appropriate. A significant result (low p-value) indicates that factor analysis is suitable because there is evidence of variable correlation (Bartlett and M.S, 1951).

3.5.3 Model formulation

The model was developed in SPSS Amos 21. Model formulation involved specifying a structural equation model using a graphical interface. Two types of model are involved in SEM.

- Measurement Model: It determines the relationship between the latent variables and indicators; analyzes according to composite reliability, convergent validity and discriminant validity.
- Structural Equation Model: It determines the relationship between the dependent and independent factors/variables; analyzes the multi-collinearity issue.

Both the models were used in SEM because combining both models allows for comprehensive analysis that covers both the measurement quality and the structural relationships.

3.5.4 Model fitting

Model fitness in SEM refers to the evaluation of how well a specified SEM model fits the observed data. It assesses the degree to which the model accurately represents the relationships between variables. It helps in determining whether the theoretical model aligns with the observed data. Various measures, including absolute, incremental, and parsimonious fit indices, are used to assess how well the proposed model aligns with the collected data. For instance, absolute fit indices indicate the strength of model's fit with the data and help identify the model that best fits the data (Mc Donald and Ho, 2002). The indices present in Table 3.3 are utilized to evaluate the fit of the measurement models to the data (Yuan, 2005)

Table 3.3 Index category and the level of acceptance

Statistic Measurement	Test Indices	Full Form	Test Standard
Absolute Fit Measurement	RMSEA	Root Mean Square Error of Approximation	≤0.08
	GFI	Goodness of Fit Index	≥0.9
	AGFI	Adjusted Goodness of Fit Index	≥0.9
	CMIN/df		≤3.84
Incremental Fit Measurement	NFI	Normed Fit Index	≥0.9
	RFI	Relative Fit Index	≥0.9
	IFI	Incremental Fit Index	≥0.9
	TLI	Tucker Lewis Index(TLI)	≥0.9
	CFI	Comparative Fit Index	≥0.9
Parsimonius Fit Measurement	PNFI	Parsimonius Normed Fit Index	≥0.5
	PCFI	Parsimonious Comparative Fit Index	≥0.5
	PGFI	Parsimonius Goodness of Fit Index	≥0.5

3.5.5 Model Validation

Model validation is a critical step to ensure that the proposed model accurately represents the relationships between variables in the dataset. It provides credibility and reliability of the model. For the validation of the model, convergent validity and discriminant validity is done. Hair et al. (2006) recommended that the average variance extracted (AVE) should be 0.5 or higher, while Byrne (2006) indicated that reliability should be 0.6 or greater. The validation of the measurement model was done by composite reliability, convergent validity and discriminant validity.

The composite validity is also known as convergent validity which assesses the extent to which different indicators (observed variables) of the same latent construct (unobserved variable) are related to each other. It confirms that the indicators chosen to measure a latent construct are indeed related and converge onto that construct. It was typically assessed by examining the factor loadings of the observed variables on their latent construct in a confirmatory factor analysis. High and statically significant factor loadings indicate good composite reliability. When composite reliability is established, it means that the observed variables are effectively measuring the same underlying construct, providing evidence for the reliability and consistency of the measurement. Discriminant validity evaluates the extent to which different latent constructs in the model are distinct from each other. Low correlation indicates good discriminant validity. SPSS Amos was used for the validation of the model.

CHAPTER 4: RESULT ANALYSIS AND INTERPRETATION

4.1 Measurement Model

The data was collected through questionnaire survey.. After discarding the questionnaires with incomplete information, 503 responses were taken for analysis purposes.

4.1.1 Sample Characteristics

Gender difference, Age disparity, Occupation, Household size, Monthy family income, Vehicle Ownership, Driving ownership, Frequency of using service are given below:

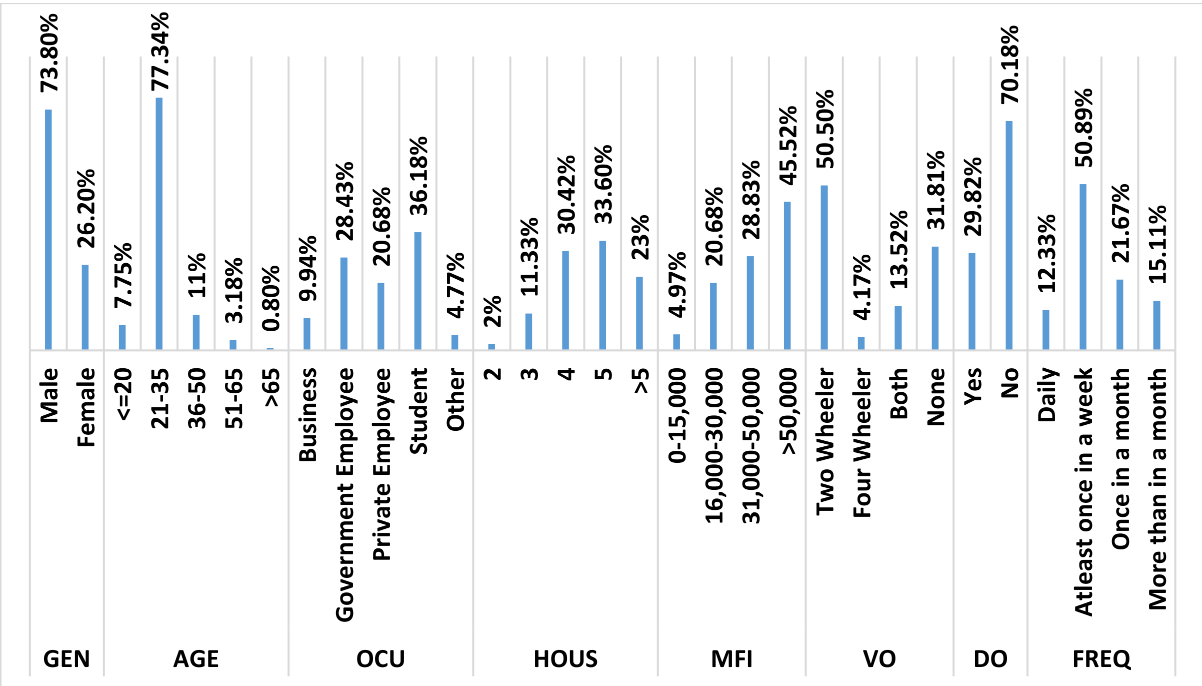

Figure 4.1 Socio-demographic characteristics of sample

The data showed a significance gender disparity in Pathao and Indrive bike service users. About 73.8% of users were male and rest were female. This shows that women concentration is less in these services.

The majority of interviewees (77.34%) fell within the age range of 21-35 years. This suggested a strong user base among young professionals, students and young families. This age group might be more comfortable with technology and using mobile apps to hail rides. A significant portion (7.75%) were users 20 years old or younger. A smaller percentage of users fell into the 36-50 (11%) and 51-65 (3.18%) which suggest that ride hailing services are used by a wider range of adults, but with a declining frequency compared to the younger demographic. The data showed very few users (0.80%) were above 65 years old. This may be due to less familiarity or comfort with mobile applications or health limitations that might make bike sharing services impractical.

Most of the sampled individuals were students with sizable portion being government and private employees. About 9.94% of people were involved in business and other occupation make up about 4.77% of the passengers.

It appeared that the households with 4 and 5 members were the most frequent users of these services in Kathmandu followed by households with 3 people. Smaller households of 2 people and larger households with more than 5 people make up a smaller portion of ride hailing bike service users.

According to the information provided about their income, the majority reported income above Rs.50,000 ie (45.52%). About 20.68% of the reported income was between 16,000-30,000 and 28.83% is between 31000-50,000. It depicted that higher income people generally use these services.

Two wheeler (50.50%) was the most common category of vehicle ownership among users. Both (13.52%) of two wheeler and four wheeler ownership were less common among users. Four wheeler ownership was the least common category among users. A significant portion of users do not own any vehicles. This suggested that the service is viable alternative for people who cannot afford or do not have space for a personal vehicle.

The data suggested that a larger portion of responses (70.18%) do not have driving license. This suggest that ride hailing bike service is viable transportation option for people who do not have vehicle registered in their name.

About 12.33% of users use the service on daily basis. A significant portion of the users, 50.89%, use the service at least once in a week. This category likely includes those who use it several times a week but not necessarily every day. 21.67% of users use the service once a month. About 15.11% of users use the service even less frequently than once a month. Overall, the data suggests that ride hailing in Kathmandu valley is dominated by regular users (daily and at-least once a week) who make up over 63% of total users. There is also significant portion of occasional users (once a month).

Table 4.1 Preliminary Statistics of Research Data

S.N.	Variables	Symbol	Mean	Standard deviation	Numerical rating scale	Qualitative scale
1	Managing Speed	MS	3.292	0.872	1 to 5	Very Poor to Very Good
2	Defensive Driving	DD	3.278	0.809		
3	Patience	PAT	3.382	0.855		
4	Driver's Skill	DS	3.469	0.81		
5	Driver's Behaviour	DB	3.485	0.823		
6	Live Location Sharing	LLS	3.252	0.973		
7	Realtime GPS Tracking	RGT	3.352	0.948		
8	Driver's Rating Reviews	DRR	3.527	0.940		
9	Service Accessibility	SA	3.157	0.924		
10	Travel Time Saving	TTS	3.535	0.848		
11	Less Waiting Time	LWT	3.517	0.844		
12	Vehicle Condition	VC	3.239	0.848		
13	Optimization of Routes	OOR	3.467	0.738		
14	Rate of Fare	RF	3.507	3.469		
15	Safety from Theft	SFT	3.396	0.845		
16	Safety from Accidents	SFA	3.274	0.886		
17	User's Security	US	3.167	0.934		
18	Easy to Book Trip	EBT	3.503	0.910		
19	Easy to Cancel Trip	ECT	3.722	0.802		
20	Easy to Pay for the Trip	ETP	3.805	0.787		
21	Trip Completion	TC	3.008	1.097		
22	Customer Support	CSU	2.928	0.8314		

4.1.2 Reliability test

For SEM model, Chronbach's alpha test was done to check the consistency of the data. The result is shown in table4.2

Table 4.2 Reliability test

Cronbach's Alpha	Cronbach's Alpha based on standardized item	No. of items
0.933	0.935	35

The Cronbach's alpha value was determined to be 0.933, indicating that the items in the questionnaire or scale were highly internally consistent and likely measure the same underlying construct. It is considered as a very good level of reliability (Nunnally, J.C.1978).

4.1.3 Factor Analysis Results

Exploratory Factor Analysis was done to reduce the dimensionality of data. It takes a large amount of data and reduce it using small factor.

i. KMO and Bartlett's test

This was conducted to verify the suitability of the data for factor analysis. The KMO test helps identify variables that may not be appropriate for factor analysis. Bartlett's test of sphericity evaluates whether the data's correlation matrix significantly differs from an identity matrix (where variables are uncorrelated). Higher values from both the KMO and Bartlett's tests indicated that the data was suitable for factor analysis.

Table 4.3 KMO and Barlett's Test

<table>
<tr><td colspan="2">Test Statistic</td><td>Value</td></tr>
<tr><td colspan="2">Kaiser-Meyer-Olkin Measure of Sampling Adequacy</td><td>0.897</td></tr>
<tr><td rowspan="3">Bartlett's Test of Sphercity</td><td>Approx. Chi-square</td><td>4133.770</td></tr>
<tr><td>df</td><td>231</td></tr>
<tr><td>Sig.</td><td>0.000</td></tr>
</table>

The KMO value, which assesses the adequacy of the data for factor analysis, was 0.897, indicating that the data was well-suited for factor analysis. The test results showed a chi-square value of 4133.770 with 231 degrees of freedom (df) and a significance level of 0.000. A significant result ($p<0.05$) in Bartlett's test suggested that the correlation matrix among the variables was statistically significant, further supporting the suitability of the data for factor analysis or SEM.

ii. Undimensionality

The Communalities was taken as a baseline for rejecting the variables. Principal Component Analysis with Varimax rotation was applied. Communalities indicates the percentage of variance in the observed variable that is accounted for by the latent construct. It assesses the reliability or consistency of the measurement model. Undimensionality assessment aims to ensure that each item in the factors meet the minimum criterion for acceptable factor loadings (Awang, 2012). The process involves iteratively removing items with the lowest factor loadings until all remaining values exceed 0.5. Subsequently, the measurement model is re-tested until unidimensionality criteria are met. The table4 displays the factor loading results for each item. As depicted in the table, all factor loadings values exceed 0.5, indicating that all items meet the undimensionality.

Table 4.4 Communalities

Variables	Symbol	Initial	Extraction
Managing Speed	MS	1	0.745
Defensive Driving	DD	1	0.697
Patience	PAT	1	0.613
Driver's Skills	DS	1	0.615
Driver's Behaviour	DB	1	0.569
Live Location Sharing	LLS	1	0.694
Realtime GPS Tracking	RGT	1	0.681
Driver's Rating & Reviews	DRR	1	0.595
Service Accessibility	SA	1	0.588
Travel Time Saving	TTS	1	0.551
Less Waiting Time	LWT	1	0.667
Vehicle Condition	VC	1	0.590
Optimization of Routes	OOR	1	0.673
Rate of Fare	RF	1	0.641
Safety from Theft	SFT	1	0.666
Safety from Accidents	SFA	1	0.610
User's Security	US	1	0.607
Easy to Book Trip	EBT	1	0.620
Easy to Pay for the Trip	ECT	1	0.601
Easy to Cancel Trip	ETP	1	0.695
Trip Completion	TC	1	0.694
Customer Support	CSU	1	0.66

Among 35 observed variables, 13 variables were rejected having their communalities lower than 0.5 because the observed variables below 0.5 did not share a significant amount of variance with the underlying factor and could indicate that the factor model is a poor fit for the data.

iii. Rotated Component matrix

The rotated component matrix was obtained through Exploratory Factor Analysis. It is a crucial output that simplifies the factor structure. It aims to maximize the interpretability of the factors. By applying the rotation technique varimax, a more straightforward and clearer alignment of variables with factors are obtained.

Table 4.5 1 Rotated component matrix

Observed Variables	Symbol	Latent Factors					
		1	2	3	4	5	6
Managing Speed	MS	0.821					
Defensive Driving	DD	0.773					
Patience	PAT	0.719					
Driver's Skills	DS	0.692					
Driver's Behaviour	DB	0.683					
Live Location Sharing	LLS		0.781				
Realtime GPS Tracking	RGT		0.762				
Driver's Rating & Reviews	DRR		0.697				
Service Accessibility	SA		0.644				
Travel Time Saving	TTS			0.702			
Less Waiting Time	LWT			0.657			
Vehicle Condition	VC			0.645			
Optimization of Routes	OOR			0.609			
Rate of Fare	RF			0.593			
Safety from Theft	SFT				0.763		
Safety from Accidents	SFA				0.696		
User's Security	US				0.625		
Easy to Book Trip	ECT					0.796	
Easy to Pay for the Trip	EBT					0.7	
Easy to Cancel Trip	ETP					0.684	
Trip Completion	TC						0.793
Customer Support	CSU						0.759

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 8 iterations.

Rotation highlighted which observed variables have the strongest associations with specific factors. Cross loadings can occur when an observed variable loads significantly on multiple factors. Rotation aims to minimize these cross loadings ensuring that each variable primarily contributes to one factor, enhancing the distinctiveness of the factors. Six factors were extracted from EFA.

iv. Confirmatory Factor Analysis

Confirmatory factor analysis involved creating a measurement model, also known as the "measurement portion." It establishes how well the observed variables relate to the latent variable. It defines the relationships between the latent variables and any direct effects among them. The rotated component matrix with pattern matrix model builder gives a measurement model in Amos 21.

The CFA model is as follows.

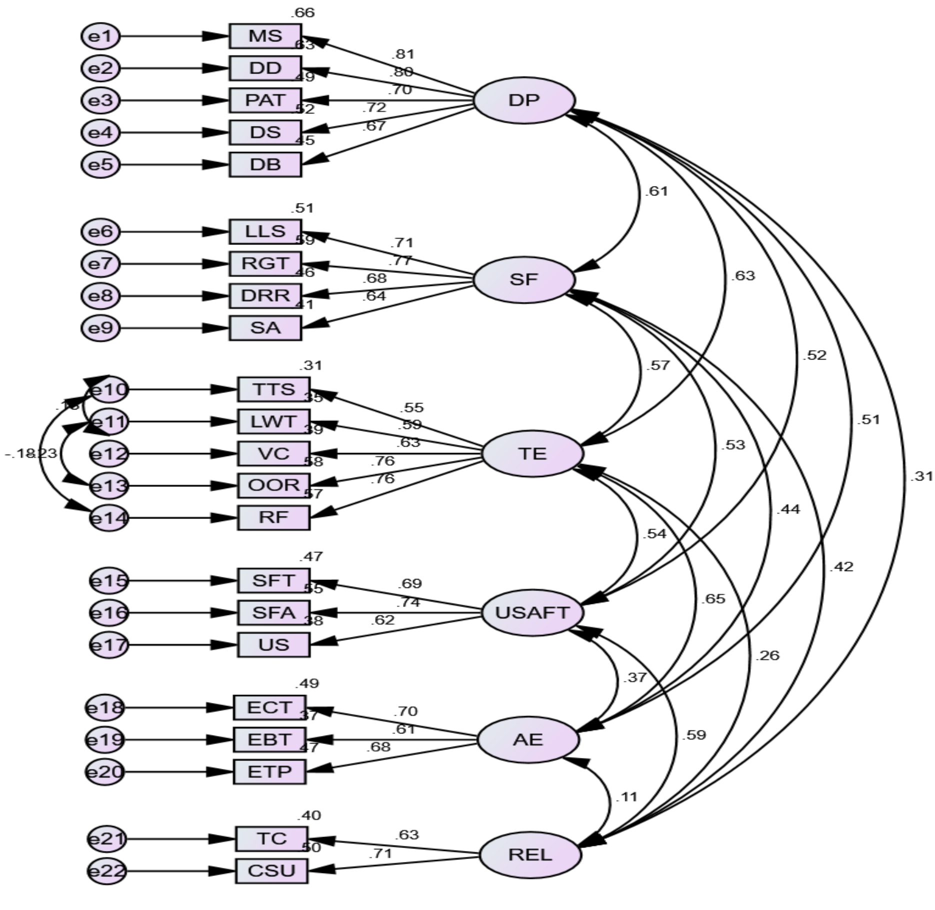

Figure 4.2 Measurement Model Showing Standardized Estimate

The measurement model included six latent variables named based on the descriptions of the observed variables. In this CFA, 22 observed variables were categorized under these six latent variables. "Driving Proficiency" encompassed observed variables such as Managing speed, Defensive driving, Patience, Driver's skill, and Driver's Behavior. "Service Feature" was assessed through Live Location Sharing, Real Time GPS Tracking, Driver's Rating and Reviews, and System Availability. "Trip Efficiency" was measured using variables like Travel Time Saving, Less Waiting Time, Vehicle Condition, Optimization of Routes, and Rate of Fare. "User Safety" included Safety from Theft and Safety from Accidents. "Application Efficiency" was gauged by variables such as Easy to book Trip, Easy to Cancel Trip, and Easy to Pay. "Reliability" was evaluated through Trip Completion and Customer Support.

Table 4.6 Measurement Model Result

		Estimate	S.E.	C.R.	P	St. R.W
DP	MS	1				0.81
	DD	0.912	0.048	18.961	***	0.796
	PAT	0.851	0.052	16.342	***	0.703
	DS	0.824	0.049	16.771	***	0.718
	DB	0.785	0.05	15.548	***	0.674
SF	LLS	1				0.714
	RGT	1.051	0.072	14.66	***	0.771
	DRR	0.917	0.069	13.258	***	0.678
	SA	0.85	0.068	12.59	***	0.64
TE	TTS	1				0.554
	LWT	1.067	0.101	10.575	***	0.593
	VC	1.136	0.113	10.032	***	0.627
	OOR	1.203	0.11	10.966	***	0.764
	RF	1.19	0.113	10.498	***	0.758
USAFT	SFT	1				0.689
	SFA	1.126	0.091	12.372	***	0.739
	US	0.987	0.089	11.079	***	0.615
AE	ECT	1				0.701
	EBT	0.981	0.093	10.533	***	0.606
	ETP	0.956	0.085	11.281	***	0.683
REL	TC	1				0.633
	CSU	1.059	0.136	7.788	***	0.709

Note:*$p<0.05$,**$p<0.01$,***$p<0.001$

Analyzing the connection between the latent variables and their observable indicators uncovers significant insights. Driving Proficiency was primarily associated with managing speed (0.81), while Service Feature was predominantly linked to real time GPS tracking (0.771). The relationship between Trip Efficiency and its indicators showed that optimization of routes was best explained this latent variable. The latent variable representing user safety was more effectively explained by factor safety from accidents. Application efficiency is primarily associated with easy to cancel trip. All the variables were significant with p value 0.000. Reliability was best explained by customer support (1.059).

Table 4.7 Correlation between latent variables

Latent Variable	DP	SF	TE	USAFT	AE	REL
	Estimates					
DP	1	0.613	0.63	0.524	0.51	0.312
SF		1	0.568	0.532	0.437	0.416
TE			1	0.541	0.648	0.258
USAFT				1	0.371	0.593
AE					1	0.115
REL						1

Table 4.8 Correlation between error terms

e10	<-->	e11	0.184
e11	<-->	e13	-0.23
e10	<-->	e14	-0.185

The correlation between two latent variables in a statistical model represents the degree of association or relationship between the underlying constructs that these variables represent. A positive correlation suggests that as one variable increases, the other variable tends to increase as well. From the correlation table, it was found that higher correlation exist between the latent variable Trip Efficiency and Application Efficiency (0.648). If application efficiency enhances, it increases trip efficiency of ride hailing bike services. The latent variable Driving Proficiency has higher correlation with Service Feature (0.613) which has higher association with trip efficiency. In the same way, user safety has higher association with reliability. A negative correlation exist between the error term which suggest that when one error term is larger than expected, the other tends to smaller than expected, and vice versa.

4.1.4 Model Fitness

The result of the fitness index for the measurement model is shown in table 4.9.

Table 4.9 Fitness indexes for model

Statistic Measurement	Test Indices	Test Standard	Result	Model Fit Verification
Absolute Fit Measurement	RMSEA	≤0.08	0.052	Good Fit
	GFI	≥0.9	0.926	Good Fit
	AGFI	≥0.9	0.902	Good Fit
	CMIN/df	≤3.84	2.347	Good Fit
Incremental Fit Measurement	NFI	≥0.9	0.893	Close to Approx Fit
	RFI	≥0.9	0.871	Close to Approx Fit
	IFI	≥0.9	0.936	Good Fit
	TLI	≥0.9	0.922	Good Fit
	CFI	≥0.9	0.935	Good Fit
Parsimonius Fit Measurement	PNFI	≥0.5	0.739	Good Fit
	PCFI	≥0.5	0.773	Good Fit
	PGFI	≥0.5	0.699	Good Fit

The table revealed that the results for the fitness index for the measurement model are fulfilling for all index categories.

4.1.5 Model Validation

The validation of the model was given by the composite reliability, convergent validity and discriminant validity.

i. Composite Reliability (CR)

The reliability of the model was achieved based on specific criteria. It is considered achieved when Cronbach's Alpha value reaches at least 0.7. Additionally, the composite reliability value must be above 0.6. Both of these values should meet the minimum requirements to ensure reliability for a construct.

Table 4.10 Composite reliability of latent variables

	CR
DP	0.859
SF	0.795
TE	0.796
USAFT	0.723
AE	0.703
REL	0.622

From the table 4.10, we observe that the composite reliability for all the construct was above 0.6, which satisfy the composite reliability of the model.

ii. Convergent Validity

Convergent validity is attained when the Average Variance Extracted (AVE) exceeds 0.5. However, an AVE value above 0.4 is considered acceptable if the composite reliability is greater than 0.6, as suggested by Fornell and David (1981).

Table 4.11 Average variance extracted for every construct

Latent Construct	CR	AVE
Driving Proficiency	0.859	0.551
Service Features	0.795	0.493
Trip Efficiency	0.796	0.442
User's Safety	0.723	0.466
Application Efficiency	0.703	0.442
Reliability	0.622	0.452

iii. Discriminant Validity

Discriminant validity ensures that items within a construct are distinguishable from each other within the model. To fulfill this criterion, a discriminant validity test was conducted to verify if the items were distinct rather than redundant. Discriminant validity was confirmed when the bold values (representing the square root of Average Variance Extracted) were higher than the correlations with other constructs in their respective rows and columns.

Table 4.12 Square root of average variance extracted

	DP	SF	TE	USAFT	AE	REL
Driving Proficiency	**0.742**					
Service Features	0.613***	**0.702**				
Trip Efficiency	0.630***	0.568***	**0.665**			
User's Safety	0.524***	0.532***	0.541***	**0.683**		
Application Efficiency	0.510***	0.437***	0.648***	0.371***	**0.665**	
Reliability	0.312***	0.416***	0.258***	0.593***	0.115†	**0.672**

4.2 SEM Model

The SEM model for service quality was formulated after series of trial with measurement model and overall service quality variable. The service quality model consists of three exogeneous latent variable. The latent variable which have positive effect on overall service quality is only taken into consideration for our service quality model.

4.2.1 Model Result

The latent variable **User's Safety** was measured by observed variables user's security, safety from accidents and safety from threat. Similarly, the latent variable **Service Feature** was measured by observed variable live location sharing, real time GPS tracking, Driver's rating and reviews and system availability. Where as, the latent variable **Application Efficiency** was measured by observed variables easy to book trip, easy to cancel trip and easy to pay for the trip. The structural equation model is shown below:

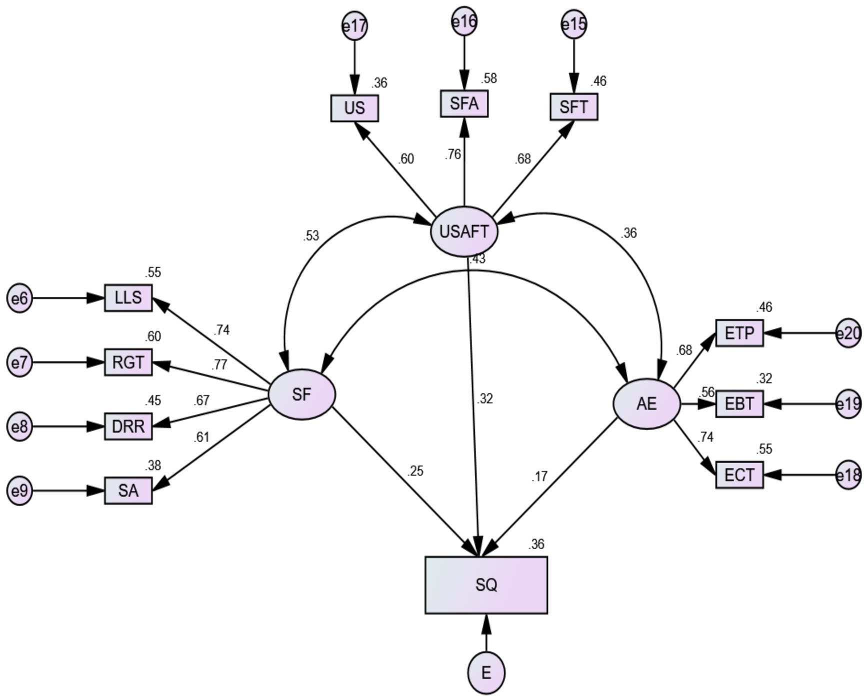

Figure 4.3 Structure Equation Model with Standardized Estimate

From the structure following equation can be written:

$Z=A+\alpha\eta+E$……………………4.1

$X=\lambda\eta+e$…………………………4.2

Where,

Z represents Overall Service Quality (SQ).

A represents a constant value (also known as an intercept or intercept term helps in model iidentification)

X represents the observed variable, η represents the latent variable influenced by observed variable α, λ represents coefficients of Z & X respectively.

E & e represent error terms in Z and X respectively.

i. Service Feature

From the model results, it can be seen that among the observed variable of "Service Feature", "Real Time GPS Tracking"(0.772) had the strongest positive influence which was followed by "Live Location Sharing"(0.74), Driver's Rating and Reviews (0.671) and System availability (0.614). One unit increased in standardized level of real-time GPS tracking is associated with 0.772 unit increase in the dependent variable ie. Service feature. This suggests that real time GPS tracking was the most important factor for users choosing Pathao or In-drive. User's also consider live location sharing but is slightly less critical than RGT. They also consider driver's rating and reviews when choosing a ride but it's less impactful than the tracking features and having a reliable and accessible system is moderately important for users. Overall the data suggests that users of Pathao and Indrive in Kathmandu prioritize features that enhance transparency, safety and convenience during their rides.

ii. User's Safety

The model suggested that all three observed variables safety from threat, safety from accident and user's security contribute positively to the latent variable user's safety. Among the, SFA (0.763) had the strongest positive standardized regression weight. Improvements in the perceived safety from accidents likely have the greatest impact on a user's overall perception of safety. Safety from threat (0.679) and user's security (0.599) have moderately positive relation with user's safety. Overall, the data implies that user's of Pathao and Indrive in Kathmandu consider these factors to be influencial in perception of ride hailing bike service.

iii. Application Efficiency

The standardized regression weight of easy to cancel trip (0.743) was the highest. The ease of cancelling a Pathao or Indrive bike ride allows user for last minute changes without penalty, which could be more important than the booking process itself. A user might book a bike initially but then find a readily available alternative, making a smooth cancellation process valuable. While “easy to cancel trip” has the strongest weight, the other variables “easy to book trip” (0.564) and easy to pay (0.679). A seamless booking and payment process still plays a major role in user experience.

iv. Overall Service Quality

The findings suggest that user safety was the most important factor influencing the perceived service quality of ride hailing bike service followed by service features and then application efficiency. User safety (0.322) had the strongest positive impact on service quality. Users likely value feeling safe and secure during their rides. Service Features (0.254) encompass various aspects of the ride itself which fosters overall service quality. Application efficiency (0.173) had the least impact but still contributed positively to service quality. A user friendly and efficient app experience likely contribute to a smoother overall ride experience. Overall, this analysis highlights that bike services should prioritize user safety and service features to enhance the perceived service quality of their bike sharing service. Additionally, maintaining an efficient and user friendly app experience was important as well. The results of the model is shown in table no15. Nearly every variable shows significance in a two-tailed test with a critical value of 1.96 for a 95% confidence interval. This outcome is determined from standardized regression weights.

Table 4.13 Model Results

Latent Variables	Observed Variables	Estimate	S.E.	C.R.	P	Std R.W
Service Feature	Live Location Sharing	1				0.74
	Real-time GPS Tracking	1.016	0.068	14.882	***	0.772
	Driver's Rating and Reviews	0.876	0.066	13.348	***	0.671
	Service Accessibility	0.788	0.064	12.29	***	0.614
User's Safety	Safety from threats	1				0.679
	Safety from Accidents	1.178	0.1	11.837	***	0.763
	User's Security	0.975	0.092	10.595	***	0.599
Application Efficiency	Easy to Cancel Trip	1				0.743
	Easy to Book Trip	0.861	0.089	9.645	***	0.564
	Easy to Pay for the Trip	0.896	0.086	10.442	***	0.679
Service Quality	Service Feature	0.271	0.062	4.367	***	0.254
	User's Safety	0.43	0.08	5.409	***	0.322
	Application Efficiency	0.223	0.068	3.26	0.001	0.173

4.2.2 Covariance

A positive covariances was found between the latent variables. A positive covariances indicate that when one variable increases the other tends to increase as well, and vice versa for a negative covariance.

Table 4.14 Covariance between latent variables

Variables			Estimate
SF	<-->	USAFT	0.218
USAFT	<-->	AE	0.121
SF	<-->	AE	0.184

A positive covariance of 0.218 implied a positive relationship. As ride hailing bike services implements more safety features, user safety likely improves (fewer accidents). The covariance of 0.121 between user safety and application efficiency is also positive but weaker. This suggests a potential connection between a safer user experience and a more efficient application. Perhaps a user feels more comfortable using the service efficiently (finding bikes quickly, reporting issues) when they perceive to be safe. Similarly, the positive covariance between service feature and application efficiency indicated that implementing better service feature also lead to a more efficient application. Features like GPS tracking or in app reporting of malfunctions contribute to a smoother user experience.

Table 4.15 Correlation

Variables			Estimate
SF	<-->	USAFT	0.529
USAFT	<-->	AE	0.356
SF	<-->	AE	0.428

A moderately strong positive correlation was found between service feature and user safety (0.529). This means that as service features of bike enhances, there is a corresponding increase in perceived or actual user safety. A weak to moderate correlation between user safety and application efficiency (0.356) suggests that when users feel safer riding, they may also perceive the application used for booking and managing rentals to be more efficient. Similarly, a moderate positive correlation of 0.428 found between the presence of service features and a user's perception of application efficiency. Bikes with well designed app with clear instructions and features might contribute to a smoother and safe riding experience.

4.2.4 Model Fitness

The model fitness was done with the help of three fitness measures ie. Absolute Fit Measurement, Incremental Fit Measurement and Parsimonius Fit Measurement.

Table 4.16 Model Fitness Results

Statistic Measurement	Test Indices	Test Standard	Result	Model Fit Verification
Absolute Fit Measurement	RMSEA	≤0.08	0.045	Good Fit
	GFI	≥0.9	0.973	Good Fit
	AGFI	≥0.9	0.955	Good Fit
	CMIN/df	≤3.84	2.024	Good Fit
Incremental Fit Measurement	NFI	≥0.9	0.950	Good Fit
	RFI	≥0.9	0.929	Good Fit
	IFI	≥0.9	0.974	Good Fit
	TLI	≥0.9	0.963	Good Fit
	CFI	≥0.9	0.974	Good Fit
Parsimonius Fit Measurement	PNFI	≥0.5	0.673	Good Fit
	PCFI	≥0.5	0.690	Good Fit
	PGFI	≥0.5	0.575	Good Fit

All the three fit measurement were acceptable from fitness measurement point of view. Thus, our model fits the data well.

4.2.5 Model Validation

The model validation process included assessing composite reliability, convergent validity, discriminant validity, and average variance estimation (Hu, L., Bentler, P.M, 1999). Analysis of the model validation table indicated that nearly all latent constructs exhibited significant composite reliability (>0.6). Although the average variance extracted (AVE) was below 0.5, Fornell and Laker (1981) suggested that AVE values less than 0.5 are acceptable when composite reliability exceeds 0.6. It's important that AVE exceeds the maximum shared variance (MSV), and that the square root of AVE is greater than the inter-construct correlations. In this study, MaxR(H) (Maximum Shared Variance) should ideally exceed 0.8, although this may vary by specific research context.

Regarding discriminant validity, the square root of AVE was compared with all inter-construct correlations. The diagonal values (0.638, 0.613, and 0.584) indicated that the square root of AVE was higher than the other inter-construct correlations, meeting the criteria for discriminant validity. These assessments ensure the reliability and validity of the model, affirming the composite reliability, convergent validity, and discriminant validity.

Table 4.17 Model Validation Results

	CR	AVE	MSV	MaxR(H)	SF	USAFT	AE
SF	0.759	0.407	0.28	0.807	0.638		
USAFT	0.691	0.376	0.28	0.745	0.529***	0.613	
AE	0.639	0.341	0.184	0.721	0.428***	0.356***	0.584

4.3 Heterogeneity Among Users

Users can indeed vary greatly in their preferences, behaviors, and needs. Factors such as demographics, cultural background, technological proficiency, and personal interests contribute to heterogeneity among users. It’s essential for services to consider this diversity to ensure inclusivity and effectiveness. Users may vary in age, gender, income level and occupation, each with different expectations and needs regarding service quality. People with varying levels of physical ability may have different experiences with the ride hailing bike services, leading to differences in their perceptions of service quality. Some users may be occasional users, while others may be frequent users leading to different perspectives on service quality based on their usage pattern. The heterogeneity among users for different socio-demographic factors are as follows:

a. Gender

Gender based safety concerns may affect the willingness of individuals, particularly women, to use ride hailing bike services. For male user group, the variable safety from accident (0.787) has higher regression weight which shows safety concerns are paramount that ensure protection from accidents followed by real time GPS tracking (0.776), easy to cancel trip (0.765), live location sharing (0.723), easy to pay (0.714), safety from threats (0.676), driver’s rating and reviews (0.667), system availability (0.644), user security (0.63) and easy to book trip (0.571). The challenging road conditions and traffic congestion in Kathmandu valley lead to numerous accidents. Thus, safety from accident is important factor for choosing bike service for male users in Kathmandu. Overall, the data suggested that male users in Kathmandu prioritize safety, convenience and transparency when using these services reflecting the unique challenges and preferences within local transportation landscape.

The data revealed interesting insights into the priorities of female users of ride hailing bike service in Kathmandu. Real time GPS Tracking (0.778) was the most crucial factor, highlighting the importance of feeling safe during the ride. Live location sharing (0.776) also scored high indicating a strong desire for continuous tracking and the ability to share location with others for added security. Driver's rating and reviews (0.669) shows that past user experiences and drivers play a significant role, suggesting women prioritize a good driver reputation. Safety from threat (0.673) and safety from accident (0.722) underlined the concern for physical wellbeing during the trip. Overall, the data suggest that for female users in Kathmandu, safety and security were paramount. They prioritize features that enhance their sense of security during the ride such as real time tracking, driver reputation and overall safety measures. Convenience factors like ease of booking cancellation and payment are also valued to a lesser extent.

Table 4.18 Standardized regression weight of responses having different gender

Latent Variables	Observed Variables	Standardized Regression Weight	
		Male	Female
Service Feature	Live Location Sharing	0.723	0.776
	Real-time GPS Tracking	0.776	0.778
	Driver's Rating and Reviews	0.667	0.669
	Service Accessibility	0.644	0.546
User's Safety	Safety from Threats	0.676	0.673
	Safety from Accidents	0.787	0.722
	User's Security	0.63	0.493
Application Efficiency	Easy to Cancel Trip	0.765	0.621
	Easy to Book Trip	0.571	0.564
	Easy to Pay for the Trip	0.714	0.547

b. Age

The age of user can affect ride hailing bike service usage in Kathmandu in several ways. Young users might find it easier to navigate the city on a bike compared to older users who may have physical limitations. For the age group <=20, the observed variable easy to cancel trip (0.878) has highest standardized regression weight and the variable real time GPS tracking has least regression weight (0.542). Younger users, especially those under 20, prioritize convenience and flexibility.

The users from age group (21-35 and 36-50) years of age were highest in number. The study revealed that the variable 'real time GPS tracking' has the highest standardized regression weight while the variable 'easy to book trip' has the least weight among the observed variables. Users in the age group (21-35 and 36-60) years of age may be more likely to use these bike services for longer distances or unfamiliar areas. Real time GPS tracking becomes essential for providing them with accurate navigation assistance, ensuring they reach their destinations efficiently. Users aged (21-35) years of age are often more accustomed to digital platforms and may not prioritize the ease of booking as highly as older or younger age groups.

The findings also indicate that the users of age group between 51-65 years of old gave more preference to 'live location sharing' which has the highest standardized regression weight of 1.46, while 'system availability' has the least weight of 0.171 among the observed variables. Older users, especially those aged 51-65, may prioritize safety and security during their travels. Live location sharing provides them reassurance that someone knows their whereabouts, which can be particularly important while travelling in unfamiliar areas. They may become more cautious about their movements, particularly in urban environments.

Table 4.19 Standardized regression weight of responses having different age groups

Latent Variable	Observed Variable	Age(yrs)			
		<20	21-35	36-50	51-65
		Standardized Regression Weight			
Service Feature	Live Location Sharing	0.716	0.72	0.837	1.46
	Real-time GPS Tracking	0.542	0.789	0.883	0.51
	Driver's Rating and Reviews	0.583	0.687	0.712	0.263
	Service Accessibility	0.601	0.607	0.785	0.171
User Safety	Safety from Threats	0.836	0.672	0.495	0.777
	Safety from Accidents	0.876	0.722	0.798	0.992
	User's Security	0.56	0.595	0.776	0.745
Application Efficiency	Easy to Cancel Trip	0.878	0.731	0.45	0.699
	Easy to Book Trip	0.605	0.532	0.317	0.399
	Easy to Pay for the Trip	0.668	0.659	0.895	1.237

c. Occupation

Occupation can significantly affect the usage of these bike services. The study suggest that for students, users involved in business 'easy to cancel trip' has highest regression weight 0.891 & 0.852 respectively. Similarly for students and private employee, the preference to easy to book trip is lowest which suggest that both students and individuals with private jobs are likely to be tech-savy, they may not perceive the process of booking a trip as challenging or time consuming, leading to a lower emphasis on the ease of booking. The government employee gave more preference to 'real time GPS tracking' and least preference to 'easy to pay for the trip'. For people involved in other occupation, highest preference is given to 'safety from accidents' and least preference to 'safety from threats'.

Table 4.20 Standardized regression weight of responses having different occupation

Latent Variable	Observed Variable	Occupation				
		Standardized Regression Weight				
		Student	Business	Govt. Employee	Private Employee	Other
Service Feature	Live Location Sharing	0.736	0.72	0.742	0.796	0.791
	Real-time GPS Tracking	0.746	0.764	0.87	0.707	0.802
	Driver's Rating and Reviews	0.552	0.842	0.728	0.59	0.745
	Service Accessibility	0.477	0.616	0.688	0.63	0.832
User Safety	Safety from Threats	0.703	0.637	0.768	0.64	0.325
	Safety from Accidents	0.781	0.79	0.791	0.674	1.114
	User's Security	0.464	0.549	0.753	0.56	0.549
Application Efficiency	Easy to Cancel Trip	0.891	0.852	0.659	0.737	1.326
	Easy to Book Trip	0.402	0.673	0.667	0.475	0.559
	Easy to Pay for the Trip	0.614	0.51	0.648	0.712	0.339

d. Household size

The impact of household size on ride hailing bike service is complex. While smaller households might find it more convenient, larger households can still benefit for specific trips. The findings suggest that household size having three members, safety from accidents (0.868) become critical with highest standardized regression weight where as easy to pay is least critical indicate that availability of multiple payment options, familiarity with existing payment options, familiarity with existing payment methods or the perception overshadow payment convenience. For household size having four and five members easy to book for the trip is less important whereas real time GPS tracking and easy to cancel trip is important. In the same way, For household size greater than 5, the fear of accidents could be a significant deterrent, leading to a stronger influence on their perception of overall service quality.

Table 4.21 Standardized regression weight of responses having different household size.

Latent Variable	Observed Variable	Household Size			
		Standardized Regression Weight			
		3	4	5	>5
Service Feature	LLS	0.803	0.747	0.691	0.728
	RGT	0.869	0.819	0.781	0.685
	DRR	0.831	0.647	0.607	0.719
	SA	0.811	0.547	0.574	0.693
User Safety	SFT	0.547	0.697	0.709	0.682
	SFA	0.868	0.66	0.757	0.828
	US	0.506	0.528	0.609	0.686
Application Efficiency	ECT	0.62	0.733	0.812	0.704
	EBT	0.813	0.503	0.559	0.549
	ETP	0.375	0.631	0.768	0.675

e. Family Income

Family income could potentially affect various service quality variables of Pathao and Indrive bike service. If these bike service offers different tiers of service with varying price points and features, this can cater to customers with different income levels. From the table, we conclude that for low income users (Rs 0-15,000), ease of cancelling a trip might be a major concern. As these services are expensive compared to public vehicle service, the easy of cancelling trip might be useful to explore alternative options. The standardized regression weight of user security is least which shows that basic transportation for this income groups might be the primary concern, overshadowing security measures. For income groups Rs (16,000-50,000), users prioritize real time GPS tracking that enhance their sense of safety. RGT allows user to share their location during the trip, potentially deterring theft and offering peace of mind to themselves. Users with higher income greater than Rs.50,000, there is a higher weight for live location sharing and least weight for easy to book for the trip.

Table 4.22 Standardized regression weight of responses of different income level

Latent Variable	Observed Variable	Family Income(Rs) Standardized Regression Weight			
		0-15,000	16,000-30,000	31,000-50,000	>50,000
Service Feature	Live Location Sharing	0.68	0.686	0.79	0.779
	Real-time GPS Tracking	0.567	0.823	0.852	0.715
	Driver’s Rating and Reviews	0.465	0.761	0.789	0.531
	Service Accessibility	0.694	0.613	0.703	0.536
User Safety	Safety from Threats	0.78	0.619	0.676	0.732
	Safety from Accidents	0.955	0.756	0.651	0.775
	User’s Security	0.421	0.616	0.753	0.519
Application Efficiency	Easy to Cancel Trip	1.003	0.761	0.703	0.68
	Easy to Book Trip	0.602	0.627	0.579	0.496
	Easy to Pay for the Trip	0.787	0.516	0.696	0.757

f. Vehicle Ownership

Vehicle ownership influences user behavior of choosing these services. Findings suggest that for family having two wheeler or no vehicle in their family, safety is a paramount concern. Real time GPS tracking (0.764) allows them to monitor the user's location, providing a sense of security and potentially reducing anxiety. If a family can track the bike's location and ensure the user's safety, they might be more comfortable letting family members use these service instead of relying on a personal vehicle. System availability and generic security measures might be less important for this specific user group. For families with two wheelers, ‘drivier's rating and reviews’ has the highest weight and ‘system availability’ has the least weight. Families with cars might prioritize safety and reliability when using a bike service for their members. Driver rating and reviews provide a sense of security, especially if they concern responsible riding behavior, bike conditions and safety measures. Families with four wheelers likely have alternative options. While system availability is important, it might not be deal breaker if a bike isn't readily available as they can resort to their car. Also the data suggests that "easy to cancel trip" has a higher standardized regression weight than "easy to book trip" for families owning both four wheelers and two wheelers in Kathmandu valley.

Table 4.23 Standardized regression weight of responses of different vehicle ownership

Latent Variable	Observed Variable	Vehicle Ownership – Standardized Regression Weight: Two Wheeler	Four-wheeler	Both	None
Service Feature	Live Location Sharing	0.706	0.313	0.806	0.745
	Real-time GPS Tracking	0.764	0.394	0.791	0.808
	Driver's Rating and Reviews	0.545	1.273	0.743	0.801
	Service Accessibility	0.626	0.203	0.696	0.597
User Safety	Safety from Threats	0.66	0.85	0.804	0.652
	Safety from Accidents	0.743	0.58	0.848	0.773
	User's Security	0.46	0.899	0.537	0.793
Application Efficiency	Easy to Cancel Trip	0.665	1.249	1.002	0.787
	Easy to Book Trip	0.568	0.537	0.288	0.606
	Easy to Pay for the Trip	0.689	0.335	0.76	0.614

g. Driving Ownership

People with driving ownership are less likely to use the services in comparison to people with no driving ownership. For the users having driving ownership, real time GPS tracking (0.839) is significant followed by other variables. Similarly, for the people having no driving license 'safety from accidents' has high regression weights. Users without driving license might feel vulnerable in Kathmandu traffic and value measures that enhance safety. Also users with driving license prioritize convenience and efficiency. Real time tracking allows them to see the nearest available bike and plan their journey accordingly.

Table 4.24 Standardized regression weight of responses having different driving ownership

Latent Variable	Observed Variable	Driving Ownership	
		Standardized Regression Weight	
		Yes	No
Service Feature	Live Location Sharing	0.75	0.727
	Real-time GPS Tracking	0.839	0.745
	Driver’s Rating and Reviews	0.56	0.726
	Service Accessibility	0.671	0.595
User Safety	Safety from Threats	0.731	0.649
	Safety from Accidents	0.684	0.791
	User’s Security	0.662	0.579
Application Efficiency	Easy to Cancel Trip	0.797	0.732
	Easy to Book Trip	0.486	0.594
	Easy to Pay for the Trip	0.718	0.655

h. Frequency

People using the services more often are more likely to perceive the service accurately in comparison to those using rarely. A high regression weight for ‘safety from accident’ (0.885) observed variable measuring user safety in SEM focusing on daily and at least once a week users of Pathao and Indrive users in Kathmandu likely reflects several key reasons. Kathmandu's traffic can be chaotic, with a mix of vehicles, pedestrians. This can make daily and frequent users of Pathao or Indrive bikes more acutely aware of potential safety hazards. No dedicated bike lanes and uneven road surfaces can heighten safety concerns for regular users. For the users who use these services once in a month, a high weight of real-time GPS tracking suggests it's a significant factor in service quality perception for infrequent users in Kathmandu. For those, who use these services very rarely that is ‘more than in a month’. For non-frequent users or who use this services more than in a month safety might be a primary concern that needs to be addressed before they even consider using ride hailing bike service.

Table 4.25 Standardized estimate of responses having different frequency of using the service

Latent Variable	Observed Variable	Frequency Standardized Regression Weight Daily	Atleast once in a week	Once in a month	More than in a month
Service Feature	Live Location Sharing	0.722	0.757	0.692	0.851
	Real-time GPS Tracking	0.884	0.748	0.781	0.791
	Driver's Rating and Reviews	0.878	0.616	0.658	0.569
	Service Accessibility	0.76	0.599	0.658	0.411
User Safety	Safety from Threats	0.611	0.676	0.715	0.911
	Safety from Accidents	0.885	0.814	0.669	0.606
	User's Security	0.793	0.514	0.672	0.517
Application Efficiency	Easy to Cancel Trip	0.661	0.775	0.581	0.877
	Easy to Book Trip	0.775	0.628	0.226	0.503
	Easy to Pay for the Trip	0.551	0.651	0.752	0.812

Table 4.26 1 Heterogeneity Among Users with their Variable of Importance

Socio-Demographic Factors		Variable of Importance
Gender	Male	Safety from Accident
	Female	Real Time GPS Tracking
Age	<20	Safety from Accident
	21-35	Real Time GPS Tracking
	36-50	Easy to Pay for the Trip
	51-65	Safety from Accident
Household size	3	Real Time GPS Tracking
	4	Real Time GPS Tracking
	5	Easy to Cancel Trip
	>5	Safety from Accident
Family Income	0-15,000	Easy to Cancel Trip
	16,000-30,000	Real Time GPS Tracking
	31,000-50,000	Real Time GPS Tracking
	>50,000	Live Location Sharing
Vehicle Ownership	Two Wheeler	Real Time GPS Tracking
	Four Wheeler	Driver's Rating & Reviews
	Both	Easy to Cancel Trip
	None	Real Time GPS Tracking
Driving Ownership	Yes	Real Time GPS Tracking
	No	Safety from Accident
Frequency	Daily	Real Time GPS Tracking
	Atleast once in a month	Safety from Accident
	Once in a month	Real Time GPS Tracking
	More than in a month	Safety from Threat

CHAPTER 5: CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study investigation showed that among six latent variables extracted through factor analysis three latent variables ‘service feature’, ‘user safety’ and ‘application efficiency’ positively influence service quality of ride hailing bike service in Kathmandu valley. All these latent variable are important aspects of Pathao and In-drive bike service. Ten specific service aspects (observed variables) contribute to three broader categories (latent variables): The factors that most influence these categories are ‘real time GPS tracking’ for ‘service feature’, ‘safety from accident’ for ‘user safety’ and ‘easy of cancelling trip’ for ‘application efficiency’. These findings highlight the importance of real time GPS tracking, safety from accident, and a user friendly application. Real time GPS tracking allows In-drive and Pathao to monitor bike locations potentially deter theft. Additionally, if a user has an accident, their location can be readily identified for assistance. This ensures there are bikes available in area with high ridership. It provides valuable data regarding preference of users that can significantly improve the user experience and efficiency. Customers may choose a service perceived as safer even it comes with a slight price difference. Focusing on safety from accidents is not just about fulfilling a moral obligation; it’s a strategic decision that can significantly enhance Indrive and Pathao’s service quality, brand image, and overall success in Kathmandu’s ride hailing bike service. Easy to cancel trip is also important in determining service quality of these service. Users might exploit the cancellation system to manipulate pricing or gain an unfair advantage.

The heterogeneity among group concludes that people of different age, gender, income, occupation have different perception of service quality. The variables of importance differ for different group of people. Our study shows that real time GPS tracking is the most influencing variable in case of service quality perception among different group of people. Although only ten observed variables and three latent variables influences service quality positive that does not mean other factors are of less important.

5.2 Recommendations

The study can provide critical insights into the service quality of these bike services, helping to enhance customer satisfaction and inform better service management and policy decisions. It can help in identifying areas where Pathao and Indrive excel can help establish benchmarks for other transport services. Insights into customer preferences and pain points can drive innovations tailored to the local context. Successful implementation of app based services can encourage the adoption of similar technologies in other transport modes. Recommendations for enhancing user safety can lead to stricter safety regulations and standards for ride hailing services. The study could be expanded by examining moderating variables such as user demographics (age, income) or trip purpose (work commute, leisure). These factors could influence how service quality dimensions relate to overall satisfaction, and could be explored further through the development of a travel factor model using a graphical interface. The external factors like weather conditions, traffic congestions might moderate the relationships between observed and latent variables. This can provide insights into user behavior under different circumstances. Spatial analysis can be done by integrating geographical data into the model to examine how service quality perceptions vary across different areas of Kathmandu valley.

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APPENDIX A: QUESTIONNAIRE

(Sample Filled Questionnaire Form)

Thesis

Sample Questionnaire Form

त्रिभुवन विश्वविद्यालय

ईन्जिनियरिङ संस्थान

पुलचोक क्याम्पस

Assessing Service Quality of Ride Hailing Bike Service within Kathmandu Valley

Namaste Sir, Madam

My name is Ambika Chaudhary. I am a student of IOE Pulchowk Campus Studying in Master's Programme "Msc in Transportation Engineering". I am conducting an academic research study as a part of my master studies. The main aim of my research is to assess the service quality of Pathao and Indrive bike service within Kathmandu Valley. I shall be thankful for your contribution in the treasury of knowledge through responding to the questionnaire. The information provided will be strictly kept confidential and used for academic purpose only.

Thank you for your co-operation.

Ambika Chaudhary
078mstre003
IOE Pulchowk Campus
Tribhuwan University

Note: Fill the form only if you are a user of Pathao or Indrive bike service.

Please put tick mark on any one option of each questionnaire:

A. General Information :

i.	Gender: (A) Male ☑ (B) Female ☐
ii.	Age(yrs): (A) <=20 ☐ (B) 21-35 ☑ (C) 36-50 ☐ (D) 51-65 ☐ (E) >65 ☐
iii.	Occupation: (A) Student ☑ (B) Business ☐ (C) Government Employee ☐ (D) Private Employee ☐ (E) Other ☐
iv.	Household size (Number of members in a family) (A) 2 ☐ (B) 3 ☐ (C) 4 ☑ (D) 5 ☐ (E) >5 ☐
v.	Monthly Family Income (Rs): (A) 0-15,000 ☐ (B) 16,000-30,000 ☐ (C) 31,000-50,000 ☑ (D) >50,000 ☐
vi.	Vehicle ownership: Vehicles in family (A) Two wheeler ☐ (B) Four wheeler ☐ (C) Both ☐ (D) None ☑
vii.	Driving ownership: Vehicle registered in your name (A) Yes ☐ (B) No ☑
vi.	How often do you use Pathao or Indrive bike service? (A) Daily ☐ (B) Atleast once in a week ☑ (C) Once in a month ☐ (D) More than in a month ☐

A.1 Please kindly evaluate the given Pathao Bike/Indrive Service Features by using Five Point Likert Scale.

Very Poor=1 Poor=2 Average=3 Good=4 Very Good=5

S.No.	Service Features	(1)	(2)	(3)	(4)	(5)
1	Easy to book trip.	☐	☑	☐	☐	☐
2	Easy to cancel trip.	☐	☐	☑	☐	☐
3	Easy to pay for the trip.	☐	☐	☑	☐	☐
4	Riding comfort.	☐	☐	☐	☑	☐
5	Paying fare online.	☐	☐	☐	☑	☐
6	Paying fare manually by cash.	☐	☐	☑	☐	☐
7	Brand Reputation: Public Perception of Brand.	☐	☐	☐	☑	☐
8	Less waiting time.	☐	☐	☑	☐	☐
9	Travel time saving.	☐	☐	☐	☑	☐
10	Vehicle condition.	☐	☐	☑	☐	☐
11	Communication: Conversation with driver during booking as well as during ride.	☐	☐	☑	☐	☐
12	Optimization of routes. Finding most efficient route.	☐	☐	☑	☐	☐
13	Rate of fare.	☐	☐	☐	☑	☐

14	Driver's skill: Ability to operate vehicle safely and efficiently.	☐	☐	☑	☐	☐
15	Driver's behavior: Behaviour of riders towards customer.	☐	☐	☑	☐	☐
16	Defensive Driving: Ability to anticipate and avoid dangerous situations	☐	☐	☐	☐	☑
17	Managing speed: Ability to drive at a safe speed.	☐	☐	☐	☑	☐
18	Patience: Ability to stay calm and avoid getting angry or frustrated	☐	☐	☑	☐	☐
19	Knowledge of shortcuts	☐	☐	☑	☐	☐
20	Knowledge of traffic rules and regulation	☐	☐	☑	☐	☐
21	Condition of mirror and brakes.	☐	☐	☐	☑	☐
22	System availability	☐	☐	☐	☑	☐
23	Real time GPS Tracking: Tracking the real time location of rider and customer.	☐	☐	☐	☑	☐
24	Live location sharing: Sharing the live location with friends and family	☐	☐	☑	☐	☐
25	Driver's rating and reviews.	☐	☐	☑	☐	☐
26	24/7 customer support.	☐	☐	☑	☐	☐
27	Reaching destination as per expected time.	☐	☐	☑	☐	☐
28	Trip Completion.	☐	☐	☑	☐	☐
29	User's security: User's security from being their information leaked.	☐	☐	☐	☑	☐
30	Safety from accidents during riding	☐	☐	☑	☐	☐
31	Safety from threat. Feeling secure and protected from potential dangers.	☐	☐	☐	☑	☐
32	System upgradation. Updated features.	☐	☐	☑	☐	☐
33	Insurance coverage: Financial protection in case of accidents.	☐	☐	☑	☐	☐
34	Convenience: Easy to access	☐	☐	☑	☐	☐
35	Night time travelling.	☐	☐	☑	☐	☐

B. Thinking about all aspects of the service, please select a rating from 1 to 5.

Very Poor=1 Poor=2 Average=3 Good=4 Very Good=5

(A) 1 ☐ (B) 2 ☐ (C) 3 ☑ (D) 4 ☐ (E) 5 ☐

APPENDIX B: MODEL RESULTS

Estimates (G - Default model)

Scalar Estimates (G - Default model)

Maximum Likelihood Estimates

Residual Covariances (G - Default model)

	SQ	ETP	EBT	ECT	US	SFA	SFT	SA	DRR	RGT	LLS
SQ	.000										
ETP	.024	.000									
EBT	-.063	-.015	.000								
ECT	.009	-.007	.023	.000							
US	.037	.028	-.037	-.014	.000						
SFA	.003	.009	.017	-.061	-.020	.000					
SFT	-.029	.090	.005	-.001	-.001	.013	.000				
SA	.000	.014	-.037	-.039	.025	.017	-.053	.000			
DRR	.016	.062	.026	-.006	.052	-.012	.008	.027	.000		
RGT	-.027	.021	.016	-.017	.025	.002	-.027	.008	-.016	.000	
LLS	.019	.012	.001	-.030	.008	.006	-.016	-.024	-.014	.018	.000

Standardized Residual Covariances (G - Default model)

	SQ	ETP	EBT	ECT	US	SFA	SFT	SA	DRR	RGT	LLS
SQ	.000										
ETP	.869	.000									
EBT	-1.980	-.438	.000								
ECT	.315	-.209	.657	.000							
US	1.119	.842	-.96	-.421	.000						

	SQ	ETP	EBT	ECT	US	SFA	SFT	SA	DRR	RGT	LLS
			6								
SFA	.095	.278	.472	-1.879	-.482	.000					
SFT	-.957	2.983	.133	-.044	-.018	.357	.000				
SA	.001	.435	-.965	-1.167	.635	.448	-1.492	.000			
DRR	.486	1.844	.672	-.182	1.293	-.309	.218	.656	.000		
RGT	-.771	.606	.415	-.489	.621	.052	-.730	.178	-.354	.000	
LLS	.546	.341	.029	-.835	.180	.142	-.421	-.540	-.302	.371	.000

Modification Indices (G - Default model)

Covariances: (G - Default model)

			M.I.	Par Change
e20	<-->	USAFT	4.679	.038
e19	<-->	E	10.820	-.075
e16	<-->	e19	5.700	.059
e16	<-->	e18	6.248	-.050
e15	<-->	AE	5.108	.046
e15	<-->	e20	12.309	.071
e9	<-->	e15	4.741	-.052

Variances: (G - Default model)

	M.I.	Par Change

Regression Weights: (G - Default model)

			M.I.	Par Change
SQ	<---	EBT	6.492	-.080
ETP	<---	USAFT	5.954	.142
ETP	<---	SFT	14.148	.130
ETP	<---	DRR	4.590	.067

			M.I.	Par Change
EBT	<---	SQ	6.882	-.122
ECT	<---	SFA	6.998	-.087
SFA	<---	ECT	5.016	-.087
SFT	<---	ETP	10.029	.124
SFT	<---	SA	4.805	-.073

Modification Indices (G - Default model)

Covariances: (G - Default model)

			M.I.	Par Change
e20	<-->	USAFT	4.679	.038
e19	<-->	E	10.820	-.075
e16	<-->	e19	5.700	.059
e16	<-->	e18	6.248	-.050
e15	<-->	AE	5.108	.046
e15	<-->	e20	12.309	.071
e9	<-->	e15	4.741	-.052

Variances: (G - Default model)

	M.I.	Par Change

Regression Weights: (G - Default model)

			M.I.	Par Change
SQ	<---	EBT	6.492	-.080
ETP	<---	USAFT	5.954	.142
ETP	<---	SFT	14.148	.130
ETP	<---	DRR	4.590	.067
EBT	<---	SQ	6.882	-.122
ECT	<---	SFA	6.998	-.087
SFA	<---	ECT	5.016	-.087
SFT	<---	ETP	10.029	.124
SFT	<---	SA	4.805	-.073

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	27	78.922	39	.000	2.024
Saturated model	66	.000	0		
Independence model	11	1565.053	55	.000	28.456

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.026	.973	.955	.575
Saturated model	.000	1.000		
Independence model	.226	.507	.409	.423

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.950	.929	.974	.963	.974
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.709	.673	.690
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	39.922	18.362	69.254
Saturated model	.000	.000	.000
Independence model	1510.053	1384.701	1642.781

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.157	.080	.037	.138
Saturated model	.000	.000	.000	.000
Independence model	3.118	3.008	2.758	3.272

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.045	.031	.059	.694
Independence model	.234	.224	.244	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	132.922	134.244	246.877	273.877
Saturated model	132.000	135.233	410.559	476.559
Independence model	1587.053	1587.592	1633.480	1644.480

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.265	.222	.323	.267
Saturated model	.263	.263	.263	.269
Independence model	3.161	2.912	3.426	3.163

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	348	398
Independence model	24	27

APPENDIX C. SOCIO DEMOGRAPHIC OUTPUT

Gender (Male)						
Variables			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.053	0.084	12.54	***
DRR	<---	SF	0.898	0.08	11.194	***
SA	<---	SF	0.816	0.075	10.852	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.178	0.11	10.668	***
US	<---	USAFT	1.008	0.104	9.683	***
ECT	<---	AE	1			
EBT	<---	AE	0.813	0.093	8.735	***
ETP	<---	AE	0.918	0.096	9.597	***
SQ	<---	SF	0.269	0.073	3.704	***
SQ	<---	USAFT	0.446	0.092	4.831	***
SQ	<---	AE	0.222	0.072	3.099	0.002

Gender (Female)							
			Estimate	S.E.	C.R.	P	Estimate
LLS	<---	SF	1				0.776
RGT	<---	SF	0.975	0.12	8.115	***	0.778
DRR	<---	SF	0.835	0.117	7.124	***	0.669
SA	<---	SF	0.753	0.13	5.801	***	0.546
SFT	<---	USAFT	1				0.673
SFA	<---	USAFT	1.247	0.239	5.216	***	0.722
US	<---	USAFT	0.85	0.195	4.354	***	0.493
ECT	<---	AE	1				0.621
EBT	<---	AE	1.205	0.283	4.255	***	0.564
ETP	<---	AE	0.876	0.209	4.188	***	0.547
SQ	<---	SF	0.229	0.143	1.607	0.108	0.235
SQ	<---	USAFT	0.391	0.156	2.509	0.012	0.301
SQ	<---	AE	0.267	0.247	1.078	0.281	0.165

Age(21-35)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.076	0.083	12.94	***
DRR	<---	SF	0.919	0.078	11.753	***
SA	<---	SF	0.792	0.075	10.523	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.131	0.115	9.854	***
US	<---	USAFT	0.992	0.111	8.97	***
ECT	<---	AE	1			
EBT	<---	AE	0.835	0.106	7.905	***
ETP	<---	AE	0.877	0.1	8.762	***
SQ	<---	SF	0.17	0.073	2.329	0.02
SQ	<---	USAFT	0.526	0.095	5.51	***
SQ	<---	AE	0.324	0.085	3.836	***

Age(<=20)						
		Estimate	S.E.	C.R.	P	Label
LLS	<---	SF	1			
RGT	<---	SF	0.727	0.261	2.783	0.005
DRR	<---	SF	0.879	0.297	2.956	0.003
SA	<---	SF	0.806	0.266	3.028	0.002
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.144	0.223	5.129	***
US	<---	USAFT	0.731	0.211	3.466	***
ECT	<---	AE	1			
EBT	<---	AE	0.844	0.254	3.327	***
ETP	<---	AE	0.743	0.207	3.583	***
SQ	<---	SF	0.426	0.287	1.485	0.138
SQ	<---	USAFT	0.057	0.271	0.21	0.833
SQ	<---	AE	0.454	0.222	2.045	0.041

Age(36-50)						
		Estimate	S.E.	C.R.	P	Label
LLS	<---	SF	1			
RGT	<---	SF	1.057	0.133	7.972	***
DRR	<---	SF	0.791	0.135	5.865	***
SA	<---	SF	0.99	0.147	6.727	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.536	0.462	3.326	***
US	<---	USAFT	1.582	0.478	3.309	***
ECT	<---	AE	1			
EBT	<---	AE	0.719	0.384	1.872	0.061
ETP	<---	AE	2	0.769	2.602	0.009
SQ	<---	SF	0.694	0.139	4.987	***
SQ	<---	USAFT	0.164	0.275	0.596	0.551
SQ	<---	AE	-0.378	0.344	-1.1	0.272

Age(51-65)						
		Estimate	Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.329	0.223	1.476	0.14
DRR	<---	SF	0.18	0.163	1.107	0.268
SA	<---	SF	0.109	0.114	0.95	0.342
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.693	0.396	4.277	***
US	<---	USAFT	1.063	0.325	3.273	0.001
ECT	<---	AE	1			
EBT	<---	AE	0.655	0.299	2.194	0.028
ETP	<---	AE	2.031	0.63	3.224	0.001
SQ	<---	SF	0.103	0.1	1.034	0.301
SQ	<---	USAFT	0.604	0.29	2.078	0.038
SQ	<---	AE	-0.484	0.21	-2.306	0.021

Occupation(Student)						
	Estimate		C.R.	P	Label	
LLS	<---	SF	1			
RGT	<---	SF	0.892	0.119	7.493	***
DRR	<---	SF	0.675	0.109	6.207	***
SA	<---	SF	0.54	0.099	5.451	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.137	0.184	6.166	***
US	<---	USAFT	0.792	0.156	5.068	***
ECT	<---	AE	1			
EBT	<---	AE	0.519	0.112	4.629	***
ETP	<---	AE	0.656	0.104	6.316	***
SQ	<---	SF	0.201	0.083	2.419	0.016
SQ	<---	USAFT	0.291	0.108	2.699	0.007
SQ	<---	AE	0.45	0.094	4.783	***

Occupation(Business)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.159	0.237	4.891	***
DRR	<---	SF	1.33	0.253	5.246	***
SA	<---	SF	0.776	0.194	3.991	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.271	0.326	3.896	***
US	<---	USAFT	0.785	0.252	3.121	0.002
ECT	<---	AE	1			
EBT	<---	AE	0.817	0.214	3.823	***
ETP	<---	AE	0.557	0.179	3.113	0.002
SQ	<---	SF	-0.102	0.28	-0.363	0.717
SQ	<---	USAFT	0.935	0.365	2.56	0.01
SQ	<---	AE	0.232	0.173	1.343	0.179

Occupation(Government Employee)							
			Estimate	S.E.	C.R.	P	Label
LLS	<---	SF	1				
RGT	<---	SF	1.215	0.125	9.695	***	
DRR	<---	SF	1.023	0.123	8.307	***	
SA	<---	SF	0.95	0.121	7.836	***	
SFT	<---	USAFT	1				
SFA	<---	USAFT	1.028	0.118	8.729	***	
US	<---	USAFT	0.929	0.111	8.395	***	
ECT	<---	AE	1				
EBT	<---	AE	1.147	0.217	5.275	***	
ETP	<---	AE	1.026	0.196	5.237	***	
SQ	<---	SF	0.346	0.12	2.879	0.004	
SQ	<---	USAFT	0.563	0.115	4.905	***	
SQ	<---	AE	0.046	0.147	0.317	0.752	

Occupation(Private Employee)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.945	0.147	6.446	***
DRR	<---	SF	0.717	0.131	5.458	***
SA	<---	SF	0.899	0.155	5.817	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.323	0.302	4.375	***
US	<---	USAFT	1.158	0.287	4.041	***
ECT	<---	AE	1			
EBT	<---	AE	0.845	0.22	3.845	***
ETP	<---	AE	0.935	0.197	4.742	***
SQ	<---	SF	0.324	0.146	2.219	0.027
SQ	<---	USAFT	0.078	0.246	0.319	0.75
SQ	<---	AE	0.133	0.206	0.644	0.52

Occupation(Other)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.115	0.271	4.117	***
DRR	<---	SF	0.848	0.225	3.773	***
SA	<---	SF	1.152	0.268	4.292	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	3.639	2.427	1.499	0.134
US	<---	USAFT	1.84	1.096	1.678	0.093
ECT	<---	AE	1			
EBT	<---	AE	0.382	0.254	1.503	0.133
ETP	<---	AE	0.247	0.207	1.193	0.233
SQ	<---	SF	0.546	0.24	2.275	0.023
SQ	<---	USAFT	0.106	0.465	0.229	0.819
SQ	<---	AE	0.106	0.109	0.972	0.331

Household Size(3)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.937	0.129	7.257	***
DRR	<---	SF	0.866	0.126	6.873	***
SA	<---	SF	0.81	0.121	6.67	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.619	0.495	3.267	0.001
US	<---	USAFT	0.935	0.324	2.885	0.004
ECT	<---	AE	1			
EBT	<---	AE	1.421	0.612	2.319	0.02
ETP	<---	AE	0.516	0.233	2.219	0.026
SQ	<---	SF	0.186	0.125	1.482	0.138
SQ	<---	USAFT	0.478	0.263	1.815	0.07
SQ	<---	AE	0.035	0.188	0.185	0.853

Householdsize (4)						
		Estimate	S.E.	C.R.	P	Label
LLS	<---	SF	1			
RGT	<---	SF	1.056	0.121	8.724	***
DRR	<---	SF	0.85	0.117	7.27	***
SA	<---	SF	0.72	0.117	6.169	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.007	0.204	4.938	***
US	<---	USAFT	0.902	0.196	4.607	***
ECT	<---	AE	1			
EBT	<---	AE	0.751	0.168	4.482	***
ETP	<---	AE	0.814	0.165	4.923	***
SQ	<---	SF	0.525	0.122	4.304	***
SQ	<---	USAFT	0.22	0.15	1.471	0.141
SQ	<---	AE	0.006	0.142	0.043	0.966

Householdsize (5)						
			Estimate	S.E.	C.R.	P	Label
LLS	<---	SF	1				
RGT	<---	SF	1.181	0.153	7.734	***	
DRR	<---	SF	0.855	0.13	6.564	***	
SA	<---	SF	0.826	0.132	6.262	***	
SFT	<---	USAFT	1				
SFA	<---	USAFT	1.07	0.144	7.425	***	
US	<---	USAFT	0.902	0.139	6.51	***	
ECT	<---	AE	1				
EBT	<---	AE	0.865	0.134	6.447	***	
ETP	<---	AE	1	0.126	7.917	***	
SQ	<---	SF	0.185	0.116	1.594	0.111	
SQ	<---	USAFT	0.517	0.128	4.024	***	
SQ	<---	AE	0.218	0.111	1.971	0.049	

Householdsize (>5)						
		Estimate	S.E.	C.R.	P	Label
LLS	<---	SF	1			
RGT	<---	SF	0.909	0.142	6.388	***
DRR	<---	SF	0.984	0.148	6.655	***
SA	<---	SF	0.895	0.139	6.454	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.36	0.202	6.74	***
US	<---	USAFT	1.122	0.184	6.107	***
ECT	<---	AE	1			
EBT	<---	AE	0.897	0.207	4.338	***
ETP	<---	AE	1.022	0.216	4.74	***
SQ	<---	SF	0.131	0.132	0.996	0.319
SQ	<---	USAFT	0.506	0.16	3.164	0.002
SQ	<---	AE	0.367	0.155	2.364	0.018

Monthly Family Income(0-15,000)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.859	0.371	2.315	0.021
DRR	<---	SF	0.609	0.314	1.943	0.052
SA	<---	SF	0.849	0.313	2.714	0.007
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.256	0.303	4.141	***
US	<---	USAFT	0.551	0.269	2.05	0.04
ECT	<---	AE	1			
EBT	<---	AE	0.661	0.193	3.43	***
ETP	<---	AE	0.827	0.16	5.161	***
SQ	<---	SF	0.573	0.527	1.086	0.277
SQ	<---	USAFT	-0.234	0.421	-0.556	0.578
SQ	<---	AE	0.777	0.198	3.936	***

Monthly Family Income(16,000-30,000)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.072	0.158	6.789	***
DRR	<---	SF	0.931	0.143	6.494	***
SA	<---	SF	0.753	0.139	5.417	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.311	0.255	5.142	***
US	<---	USAFT	1.095	0.235	4.661	***
ECT	<---	AE	1			
EBT	<---	AE	0.894	0.233	3.839	***
ETP	<---	AE	0.621	0.171	3.634	***
SQ	<---	SF	-0.006	0.144	-0.042	0.967
SQ	<---	USAFT	0.787	0.244	3.226	0.001
SQ	<---	AE	0.11	0.116	0.946	0.344

Monthly Family Income (31,000-50,000)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.104	0.105	10.511	***
DRR	<---	SF	1.09	0.112	9.754	***
SA	<---	SF	0.899	0.105	8.541	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	0.975	0.163	5.995	***
US	<---	USAFT	1.119	0.177	6.337	***
ECT	<---	AE	1			
EBT	<---	AE	0.944	0.179	5.278	***
ETP	<---	AE	0.947	0.165	5.744	***
SQ	<---	SF	0.182	0.099	1.833	0.067
SQ	<---	USAFT	0.528	0.131	4.039	***
SQ	<---	AE	0.451	0.15	3.001	0.003

Monthly Family Income (>50,000)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.904	0.096	9.38	***
DRR	<---	SF	0.659	0.092	7.177	***
SA	<---	SF	0.682	0.094	7.243	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.13	0.127	8.884	***
US	<---	USAFT	0.848	0.126	6.726	***
ECT	<---	AE	1			
EBT	<---	AE	0.868	0.147	5.908	***
ETP	<---	AE	1.15	0.162	7.12	***
SQ	<---	SF	0.456	0.09	5.064	***
SQ	<---	USAFT	0.371	0.119	3.123	0.002
SQ	<---	AE	-0.069	0.13	-0.531	0.595

Vehicle Ownership (Two Wheeler)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.015	0.107	9.506	***
DRR	<---	SF	0.738	0.1	7.395	***
SA	<---	SF	0.86	0.103	8.344	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.199	0.156	7.686	***
US	<---	USAFT	0.797	0.137	5.823	***
ECT	<---	AE	1			
EBT	<---	AE	0.945	0.144	6.541	***
ETP	<---	AE	1.072	0.152	7.043	***
SQ	<---	SF	0.23	0.092	2.516	0.012
SQ	<---	USAFT	0.397	0.132	3.01	0.003
SQ	<---	AE	0.251	0.129	1.943	0.052

Vehicle Ownership (Four wheeler)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.225	0.729	1.681	0.093
DRR	<---	SF	3.43	2.377	1.443	0.149
SA	<---	SF	0.609	0.518	1.175	0.24
SFT	<---	USAFT	1			
SFA	<---	USAFT	0.715	0.253	2.825	0.005
US	<---	USAFT	1.163	0.222	5.231	***

ECT	<---	AE	1			
EBT	<---	AE	0.453	0.373	1.214	0.225
ETP	<---	AE	0.24	0.238	1.01	0.313
SQ	<---	SF	-0.202	0.303	-0.666	0.505
SQ	<---	USAFT	0.668	0.214	3.128	0.002
SQ	<---	AE	-0.054	0.08	-0.671	0.502

Vehicle Ownership (Both)						
			Estimate	S.E	C.R	P
LLS	<---	SF	0.806			
RGT	<---	SF	0.791	0.134	6.828	***
DRR	<---	SF	0.743	0.137	6.344	***
SA	<---	SF	0.696	0.138	5.869	***
SFT	<---	USAFT	0.804			
SFA	<---	USAFT	0.848	0.182	5.591	***
US	<---	USAFT	0.537	0.183	4.128	***
ECT	<---	AE	1.002			
EBT	<---	AE	0.288	0.16	2.311	0.021
ETP	<---	AE	0.76	0.122	5.374	***
SQ	<---	SF	0.639	0.138	4.815	***
SQ	<---	USAFT	0.149	0.14	1.34	0.18
SQ	<---	AE	0.1	0.109	0.987	0.323

Vehicle Ownership (None)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.124	0.12	9.339	***
DRR	<---	SF	1.086	0.117	9.281	***
SA	<---	SF	0.744	0.106	7.017	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.225	0.166	7.397	***
US	<---	USAFT	1.267	0.17	7.457	***
ECT	<---	AE	1			
EBT	<---	AE	0.829	0.146	5.69	***
ETP	<---	AE	0.74	0.129	5.726	***
SQ	<---	SF	0.159	0.107	1.482	0.138
SQ	<---	USAFT	0.588	0.142	4.138	***
SQ	<---	AE	0.301	0.109	2.76	0.006

Driving Ownership (Yes)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.131	0.125	9.051	***
DRR	<---	SF	0.687	0.108	6.351	***
SA	<---	SF	0.896	0.118	7.615	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.015	0.148	6.883	***
US	<---	USAFT	0.989	0.147	6.723	***
ECT	<---	AE	1			
EBT	<---	AE	0.733	0.143	5.142	***
ETP	<---	AE	0.961	0.139	6.898	***
SQ	<---	SF	0.277	0.093	2.982	0.003
SQ	<---	USAFT	0.453	0.142	3.179	0.001
SQ	<---	AE	0.196	0.139	1.413	0.158

Driving Ownership (No)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.98	0.082	11.94	***
DRR	<---	SF	0.983	0.084	11.72	***
SA	<---	SF	0.759	0.077	9.847	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.259	0.132	9.504	***
US	<---	USAFT	0.994	0.117	8.461	***
ECT	<---	AE	1			
EBT	<---	AE	0.904	0.112	8.101	***
ETP	<---	AE	0.853	0.102	8.384	***
SQ	<---	SF	0.253	0.081	3.112	0.002
SQ	<---	USAFT	0.447	0.103	4.322	***
SQ	<---	AE	0.229	0.082	2.794	0.005

Frequency (Daily)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.346	0.205	6.576	***
DRR	<---	SF	1.32	0.202	6.543	***
SA	<---	SF	1.03	0.181	5.703	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.405	0.293	4.795	***

US	<---	USAFT	1.285	0.274	4.685	***
ECT	<---	AE	1			
EBT	<---	AE	1.386	0.361	3.84	***
ETP	<---	AE	0.959	0.285	3.362	***
SQ	<---	SF	0.229	0.16	1.43	0.153
SQ	<---	USAFT	0.618	0.193	3.199	0.001
SQ	<---	AE	0.286	0.229	1.247	0.212

Frequency (Atleast once in a week)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.907	0.088	10.332	***
DRR	<---	SF	0.749	0.085	8.778	***
SA	<---	SF	0.741	0.087	8.549	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	1.293	0.159	8.138	***
US	<---	USAFT	0.872	0.129	6.745	***
ECT	<---	AE	1			
EBT	<---	AE	0.932	0.126	7.397	***
ETP	<---	AE	0.776	0.104	7.487	***
SQ	<---	SF	0.373	0.093	4.012	***
SQ	<---	USAFT	0.286	0.116	2.455	0.014
SQ	<---	AE	0.086	0.088	0.983	0.325

Frequency (Once in a month)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	1.107	0.172	6.421	***
DRR	<---	SF	0.958	0.167	5.736	***
SA	<---	SF	0.921	0.161	5.734	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	0.961	0.17	5.65	***
US	<---	USAFT	1.063	0.188	5.67	***
ECT	<---	AE	1			
EBT	<---	AE	0.457	0.232	1.966	0.049
ETP	<---	AE	1.314	0.282	4.66	***
SQ	<---	SF	0.173	0.125	1.387	0.165
SQ	<---	USAFT	0.376	0.215	1.751	0.08
SQ	<---	AE	0.835	0.308	2.714	0.007

Frequency (More than in a month)						
			Estimate	S.E.	C.R.	P
LLS	<---	SF	1			
RGT	<---	SF	0.955	0.145	6.607	***
DRR	<---	SF	0.642	0.134	4.799	***
SA	<---	SF	0.454	0.134	3.38	***
SFT	<---	USAFT	1			
SFA	<---	USAFT	0.719	0.161	4.468	***
US	<---	USAFT	0.65	0.165	3.941	***
ECT	<---	AE	1			
EBT	<---	AE	0.547	0.128	4.287	***
ETP	<---	AE	0.878	0.125	7.035	***
SQ	<---	SF	0.244	0.1	2.45	0.014
SQ	<---	USAFT	0.199	0.121	1.641	0.101
SQ	<---	AE	0.336	0.12	2.793	0.005