Research Article

TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Transportation Research Record
1–17

DOI: 10.1177/03611981211041595
journals.sagepub.com/home/trr
SAGE

Effect of Robo-Taxi User Experience on User Acceptance: Field Test Data Analysis

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Abstract
With the advancement of self-driving technology, the commercialization of robot taxi (Robo-taxi) services is expected. However, there is some skepticism as to whether such taxi services will be successfully accepted by real customers because of perceived safety-related concerns; therefore, studies focused on user experience have become more crucial. Although many studies statistically analyze user experience data obtained by surveying individuals' perceptions of Robo-taxis or indirectly through simulators, there is a lack of research that statistically analyzes data obtained directly from actual Robo-taxi service experiences. Accordingly, based on the user experience data obtained by implementing a Robo-taxi service in the downtown of Seoul and Daejeon in South Korea, this study quantitatively analyzes the effect of user experience on user acceptance through structural equation modeling and path analysis. Balanced and highly valid insights were also obtained by re-analyzing meaningful relationships obtained through statistical models based on the results of in-depth interviews. The results revealed that the experience of the traveling stage had the greatest effect on user acceptance, and the cutting-edge nature of the service and apprehension of technology were emotions that had a significant effect on user acceptance. Based on these findings, guidelines are suggested for the design and marketing of future Robo-taxi services.

With the advent of the sharing economy and of "robot" or self-driving taxis (Robo-taxis), the automotive industry is facing new technological, social, and regulatory changes. The Robo-taxi is expected to alleviate traffic congestion and reduce the need for parking through an active car-sharing service, as well as lower carbon emissions through optimized operation by sharing connected road information (*1*). Furthermore, it will be a low-cost, affordable, and easily accessible option for people in the outskirts of cities or rural areas where advanced public transportation is not available (*2*). In this changing environment, auto makers, information technology firms, and shared service companies are quickly seizing the initiative in the Robo-taxi market through the establishment of various partnerships (*3–8*).

Even high-quality technology is not always necessarily accepted by consumers, however. Since self-driving is a technology directly related to safety, relieving the user's anxiety is a significant hurdle. As a result, various user-centered studies related to Robo-taxis have been conducted. Several studies have used a survey approach to analyze the relationship between the user and self-driving vehicle or Robo-taxi (*9–11*), while others have conducted experiments on the interaction between the taxi and the user in an indirect way using simulation and virtual reality (*12–16*). Recently, studies that test the interaction between the user and the Robo-taxi based on actual field tests have also been conducted to overcome the limitations of virtual experiments conducted through surveys and simulators (*17–22*). User response can be analyzed using quantitative statistical methods as well as qualitative interviews. For example, some studies analyze factors affecting the acceptance of self-driving technology through structural equation modeling (SEM) or path analysis based on customer surveys (*23–31*).

This study performs SEM and path analysis based on actual user experience data for the Robo-taxi service to analyze the factors affecting user acceptance. The differences between previous studies and this study are as follows. First, previous studies on SEM used survey data from people who had no experience with the Robo-taxi

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service. However, responses based on imagination about new technologies and services that they have never experienced before would differ greatly from reality. Specifically, for services directly related to safety, there are significant differences in user response before and after the experience (*22*). This study differs in that it collected survey data after participants had experienced an unmanned taxi service. Second, it compares the in-depth interview results and simultaneously analyzed videos to interpret the meaning of the statistical model analysis results. By performing quantitative and qualitative analyses in a balanced manner, more explainable and valid insights were obtained.

Three models were constructed and analyzed using the user experience data on the Robo-taxi obtained from previous studies (*21, 22*) performed by the authors. The first model was analyzed using path analysis to identify how the main evaluation factors for the quality of the Robo-taxi service by stage (i.e., call, pick-up, traveling, drop-off) affect user satisfaction with the Robo-taxi service. The second model was analyzed using SEM to identify how the Robo-taxi service experience affects user acceptance. The third model was analyzed with SEM to identify how positive and negative emotions toward the Robo-taxi service experience affect user acceptance.

The remainder of this paper is organized as follows. The second section reviews the related previous works. The third section introduces the hypotheses and theoretical background of this study. The fourth section presents the field test process for obtaining user experience data. The fifth section introduces three models for hypothesis testing and describes the analysis results. The sixth section analyzes the model results in detail and derives the implications. The final section summarizes the study and describes its limitations.

Related Works

The target research area is SEM studies using Robo-taxi field test data, and related works are introduced in this section. First, research on user-centered self-driving technology is classified into three categories of data collection methods: simple surveys, simulators, and field tests. The next sub-section introduces studies on SEM for self-driving experience. The third sub-section describes a research gap based on the limitations of previous studies.

User-Centered Self-Driving Technology Research

Survey-Based User Research. Hohenberger et al. (*9*) surveyed 1,603 people and found that those with high self-enhancement had low anxiety about self-driving vehicles. Hulse et al. (*10*) surveyed 1,000 people in the UK on road safety and user acceptance and found that self-driving vehicles would be more attractive to male and young participants. Tussyadiah et al. (*11*) surveyed 325 people on the influence of attitude and trust in technology on the intention to use self-driving taxis. They found that consumers could trust that the Robo-taxi would work as designed and that expectations of reliability, functionality, and usefulness contribute to their intention to use.

Simulator-Based User Research. Studies have used simulation and virtual reality to investigate the relationship between Robo-taxis and the user. Koo et al. (*12*) conducted experiments with 64 participants using a driving simulator equipped with automatic braking and presented an interaction model for the user to communicate with self-driving vehicles. The driving performance felt by drivers was improved when providing "reason" information as to why the vehicle behaved as it did rather than when providing the vehicle's "behavior" information. Koo et al. (*13*) conducted simulation experiments with 40 participants and showed that appropriate voice alerts alleviated driver anxiety. Cho et al. (*14*) tested 68 participants using a driving simulator with different automation levels and showed that the anxiety was highest for automation level 3 and dropped slightly for automation level 4. Jamson et al. (*15*) conducted experiments on 49 participants using a driverless car simulator and showed that drivers were willing to give up supervisory responsibilities. Griesche et al. (*16*) examined the relationship of preference between the driver's driving method and that of self-driving vehicles. The results revealed that most drivers liked a driving style similar to their own, and all participants did not like small safety margins and high acceleration driving styles.

Field Test-Based User Research. Recently, user studies through field tests have been conducted to overcome the limitations of surveys and simulators. Rothenbucher et al. (*17*) modified the driver's seat of a vehicle in such a way that pedestrians could not see the driver; thus, it was perceived as a fully autonomous vehicle. They investigated pedestrians' responses and experiences with self-driving vehicles on a university campus. Kim et al. (*18*) implemented a taxi service within a university campus using a real self-driving vehicle and tested passengers' responses and the validity of self-driving driving technology. Banks et al. (*19*) collected video data on user behavior through a field test of a partially automated self-driving vehicle and analyzed the relationship between self-driving function and user behavior. Zoellick et al. (*20*) tested user acceptance after experiencing a shared autonomous electric vehicle in Berlin. Kim et al. (*21*) tested user experience in Daejeon in Korea by implementing the Robo-taxi service. They suggested a solution that could compensate for the shortcomings of self-driving technology by introducing the concept of a virtual stop. Yoo et al. (*22*) analyzed the anxiety factors associated with Robo-taxis based on a field test. They designed and implemented a Robo-taxi human-machine interaction (HMI) that could relieve anxiety and tested the service in the downtown area of Seoul, Korea.

SEM-Based Self-Driving Technology Research

In studies on self-driving vehicles and the Robo-taxi, Payre et al. (*23*) analyzed technology acceptability, attitudes, personality characteristics, and the intention to use self-driving vehicles with SEM. They surveyed 153 male drivers and observed a strong positive correlation between attitudes and the intention to use self-driving vehicles. Rödel et al. (*24*) surveyed 336 people and investigated the factors of user acceptance and user experiences, such as the ease of use for self-driving vehicles, attitudes toward system use, cognitive behavior control, and behavioral intention. Ro and Ha (*25*) surveyed 1,506 participants and showed that convenience, safety, ethics, holding a driver's license, and cost had a direct effect on the acceptance attitude toward self-driving vehicles, while convenience, safety, and financial cost had a direct effect on the intention to use self-driving vehicles. Bennett et al. (*26*) conducted a survey of 211 blind people, showing that hope for independence, concern over safety, and affordability affect the acceptance of autonomous vehicles. Rahimi et al. (*27*) presented an analysis of user acceptance for shared mobility and autonomous vehicles based on user characteristics (e.g., age, education, income, etc.). Zhu et al. (*28*) found that mass media and social media had different impacts on the acceptance of self-driving cars, based on a survey of 355 college students. Wu et al. (*29*) showed that green perceived usefulness, perceived ease of use, and environmental concerns have a positive relationship with the user acceptance of autonomous electric vehicles. Acheampong and Cugurullo (*30*) analyzed user acceptance of self-driving cars generally, self-driving car-sharing services, autonomous public transport services, and self-driving car ownership, respectively. Manfreda et al. (*31*) tested millennials for smart cities, and the results showed that the perceived benefits of autonomous vehicles affect their adoption, and perceived safety can reduce concerns about autonomous vehicles.

Research Gap

To the best of the authors' knowledge, no SEM research has been conducted based on actual user experience data obtained through Robo-taxi field testing. Robo-taxis manifest significant differences in real-life experience versus imagination. In particular, it is difficult to analyze the perception of the safety of Robo-taxis from imagination without experience. Therefore, the results of the SEM studies without field testing are of limited reliability. This study used actual user experience data obtained through field tests to propose user acceptance SEM and emotion SEM. In addition, the quantitative analysis results were complemented with qualitative analysis through in-depth interviews.

Hypotheses

Effect of User Experience on User Acceptance

User perception of new technology affects user acceptance (*32*). Users who do not have direct experience in a given area perceive new technology by judging it on an abstract basis but could judge based on more specific criteria after direct experience (*33*). Because users judge based on experience, user experience has been heavily covered in multiple studies on user acceptance (*34–37*).

This study defines the observed variables of user experience as the service quality of the Robo-taxi service by stage. The service quality evaluation values are used for a total of four stages: call, pick-up, traveling, and drop-off. The call stage is a process in which the participant enters a destination using a mobile phone app and finds a taxi. In the pick-up stage, when a taxi is dispatched through the app, the taxi's location is displayed on the app. The participant looks at the map, finds the location, recognizes the taxi, and boards. The traveling stage is a process in which the participant travels from the origin to the destination in a Robo-taxi. The drop-off stage is the process by which the taxi arrives near the destination, pulls over to the side of the road, and the occupants get off safely. The detailed evaluation method is described Tables 1 and 2. Overall satisfaction, intention to use, and willingness to pay (WTP) were also selected as the observed variables of user acceptance.

First, overall satisfaction refers to overall satisfaction after experiencing the Robo-taxi service. Satisfaction has been used as an important predictor variable of user behavioral intention (*38*), and studies related to public transportation services have mainly analyzed factors affecting satisfaction to increase user acceptance, for example, taxi service (*29*), subway service (*39*), and railway service (*40*).

Second, intention to use evaluates whether there is a plan to use Robo-taxis in the future and represents the meaning of user acceptance. Choi and Ji (*40*) argued that usefulness and trust were crucial factors for the intention to use self-driving vehicles, explaining the user adoption factors of self-driving vehicles. In addition, several studies have analyzed ways to increase the intention to use self-driving vehicles (*9, 25, 41*).

Lastly, WTP is a variable for the reasonable price of the Robo-taxi service. Price perception and price acceptance play a vital role in affecting the user's consumption and post-consumption process (*42–44*). Price is also a determinant of value perception (*45*).

Based on these, the following hypothesis is established:

H1a: The user experience of the Robo-taxi service will affect user acceptance.

Effect of User Emotion on User Acceptance

Studies on the acceptance of self-driving vehicles and user emotion have mainly covered specific emotions related to safety, such as anxiety and trust. Hohenberger et al. (*9*) showed that anxiety has a negative effect on the willingness to use self-driving vehicles. Choi and Ji (*40*) demonstrated that trust was a decisive factor in the intention to use self-driving vehicles. Similarly, Kaur and Rampersad (*41*) found that trust and performance expectations were decisive factors in the adoption of self-driving vehicles. Stanton and Young (*46*) considered the psychological variables related to driving automation, such as feedback, locus of control, mental workload, driver stress, situational awareness, and mental representation.

Extensive research on the relationship between user emotion and user acceptance has been conducted in other service industries (*47*). According to Ali et al. (*48*), customer satisfaction and price acceptance were affected when users felt sufficient positive emotions through service experience. Lee et al. (*49*) investigated the effect of customers' positive and negative emotions on satisfaction and brand loyalty. Grace and O'Cass (*50*) revealed that service experience, emotion, satisfaction, and brand attitude were related.

Most studies find positive emotions, such as trust, built up user acceptance, whereas negative emotions such as anxiety and stress negatively affect user acceptance. This study investigates which emotions greatly affect user acceptance among the detailed positive and negative emotions that the user feels through the experience of the Robo-taxi service. The 24 detailed emotions used as the observed variables are presented below in Table 3 and, based on these, the following hypotheses are established.

H2a: Positive emotions toward Robo-taxi technology will have a positive effect on user acceptance.
H2b: Negative emotions toward Robo-taxi technology will have a negative effect on user acceptance.

Data

This section presents the vehicle and service configuration used in the experiment, the experimental path, the survey design, and the participants. Data obtained from the Robo-taxi field test studies were also used (*21, 22*).

Robo-Taxi Vehicle and Service Configuration

It is difficult to provide the Robo-taxi service in a complex city center environment with current self-driving technology, and there are no laws and regulations in Korea allowing self-driving vehicles to drive on general roads. Therefore, the Robo-taxi service was implemented using the "Wizard of Oz" method, which is a way of getting participants to believe that they are using real services, but in reality, experimenters manually play the role of the automation system (*51, 52*), completely blocking the driver's seat of the vehicle with partitions. The driver boarded and drove during the experiment, and by installing cameras, microphones, and speakers, the situation of the vehicle and participants was controlled in real time from a remote control tower. It was explained to the participant that a safety guard is in the driving seat, who would control the Robo-taxi manually only in case of emergency. During the trip, participants were able to change the driving mode through the tablet's interface and voice recognition function (e.g., commands such as "turn on the radio" or "open the window"). When the remote control receiver recognized the participant's command, it delivered commands to the driver via a telephone connection, and the driver directly controlled the car to conduct the experiment as if the Robo-taxi worked. The voice communicated with the participant by machine voice using text-to-speech, and when driving, the handling was smoothed and sudden acceleration and sudden stops were avoided, making it feel more like a Robo-taxi. The survey confirmed that all participants believed that they were experiencing fully autonomous driving when using the service. Figure 1 shows the Robo-taxi service implementation and the test scenes. The details of the experiment are described by Yoo et al. (*22*).

Robo-Taxi Service Path

The experiments were conducted in the downtown areas of Daejeon and Seoul, Korea. The travel distance was approximately 7 km, and the travel time was approximately 30 min. The details and path of the Daejeon experiment are described in Kim et al. (*21*) and the Seoul experiment can be found in Yoo et al. (*22*). The experimental path was a mixture of a quiet and wide road, a road with many vehicles and floating populations, and narrow alleys and steep hills for vehicles to pass. This path gave the participants experiences not only of comfortable situations but also uncomfortable ones. Beyond the unsafe scenarios, such as sudden pedestrians that actually occurred, unexpected scenarios were artificially set up during the experiment, such as putting obstacles on the road or sounding the accident occurrence alarm—

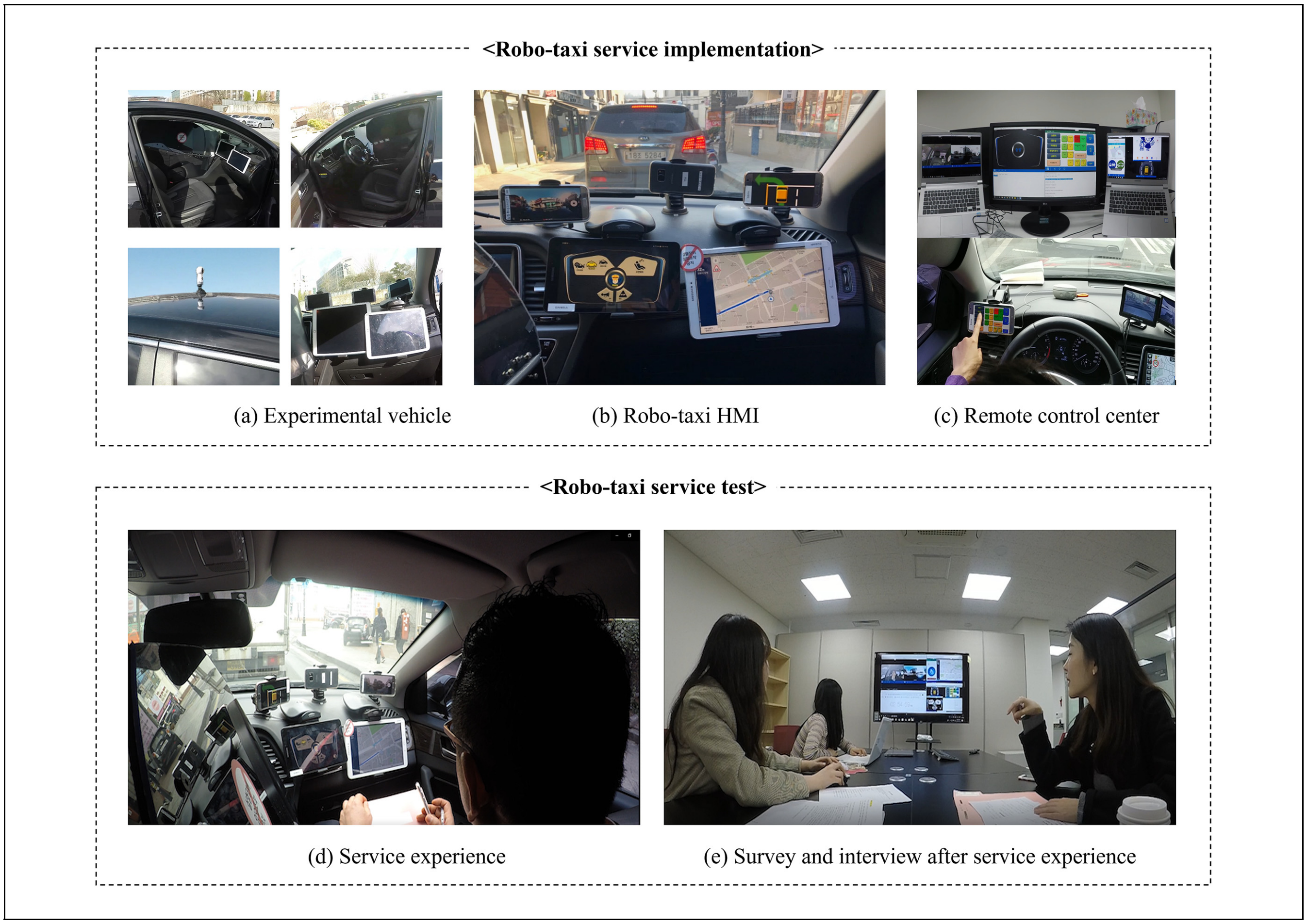

Figure 1. (*a*) From the upper left, front passenger seat, driver's seat, and the 360-degree camera attached in front of the passenger seat, the view seen when sitting in the passenger seat. (*b*) View from the passenger seat. There are three mobile phones used for 360-degree camera images, for recording the participant's images, and for directions. Of the two tablets, the left one is an app for communication with and operation of the Robo-taxi, and the right one is for navigation. (*c*) (top) Robo-taxi control center environment, (bottom). Photo of controlling voice guidance through the app from the driver's seat. (*d*) The participant experiencing Robo-taxi in the field. (*e*) Interview with the participant while watching a video of the experiment after participant had experienced the Robo-taxi service (*22*).

events which are likely to happen during Robo-taxi service.

Survey and Interview by Service Stage

The participants received pre-guidance during the experiment. The participants returned to the laboratory for the post-experiement survey and interview after experiencing the four stages of the Robo-taxi service (i.e., call, pick-up, traveling, drop-off). The survey questions are presented in Appendix A.

First, the participants performed a quantitative test on a seven-point Likert scale with the evaluation factors shown in Table 1 for each service stage. Appropriate evaluation factors for the Robo-taxi service were selected by referring to those used in evaluating transportation systems in previous studies (*39, 40, 53–55*). The first level is to evaluate the service quality for each stage, and the evaluation factors corresponding to the second level are detailed evaluation items that are likely to affect service quality. Table 2 presents the definitions of evaluation factors.

In addition, the overall satisfaction and intention to use the service were surveyed on a seven-point Likert scale. For the WTP question, there are seven options for how much participants were willing to pay relative to a manned taxi: less than 50%, 50–74%, 75–99%, 100%, 101–124%, 125–149%, and 150% or more.

In addition to the evaluation by service stage, after experiencing the entire service, a quantitative survey was conducted that used a seven-point Likert scale for detailed emotions felt by the participants throughout the Robo-taxi service. Emotions, which were derived through brainstorming and a semantic differential

Table 1. Perceptual Evaluation Factors by Stage

	Evaluation factor	
Stage	First level	Second level
Call	Service quality	Reliability, promptness, predictability, information, kindness, convenience
Pick-up	Service quality	Reliability, safety, predictability, information, accessibility, punctuality, kindness, communication, confirmation
Traveling	Service quality	Reliability, speed, ride comfort, safety, predictability, information, kindness, communication, pleasantness, convenience, comfort
Drop-off	Service quality	Reliability, safety, predictability, information, accessibility, punctuality, communication, kindness

Table 2. Definition of Quantitative Evaluation Factors (*21*)

Evaluation factor	Description
Service quality	Felt satisfaction at each stage as integrated evaluation covering all other evaluation factors below.
Reliability	Felt that the service was reliable.
Predictability	It was possible to predict what had to be done.
Information	Necessary information was received properly.
Kindness	Felt kindness in the service.
Safety	Felt it was safe.
Communication	Communication with the taxi was satisfactory.
Accessibility	The taxi came to the desired place.
Punctuality	The taxi arrived at the predicted time.
Convenience	It was convenient and easy to use.
Promptness	The service was carried out promptly.
Confirmation	It was easy to identify my taxi.
Speed	The speed was appropriate.
Ride comfort	The ride was smooth and comfortable.
Pleasantness	Felt pleasant in the taxi.
Comfort	Felt comfortable psychologically.

method, were divided into positive and negative emotions. Table 3 shows the 12 positive and 12 negative emotions used in the evaluation.

Participants

A total of 71 participants were recruited online for the field test; 43 and 28 people participated in the experiments in Daejeon and Seoul, respectively. By gender, 45% were men and 55% were women. By age, 8% were in their teens, 65% in their twenties, 14% in their thirties, 7% in their forties, and 6% in their fifties. The participants' frequency of using taxis was: 42% used taxis less than once a week, 28% used taxis once a week, 24% used taxis two or three times a week, 4% used taxis four to six times a week, and 2% used taxis every day. The participants were paid 20,000 Korean won per hour to participate in the experiment. The entire experiment and interview took approximately three hours for each participant. The

Table 3. Emotion Evaluation Index (*21*)

Type	Emotions
Positive	Convenient, comfortable, familiar, safe, reliable, excellent, simple, sophisticated, ingenious, trendy, efficient, new
Negative	Nervous, uncomfortable, afraid, unpleasant, annoying, disappointing, stuffy, tiresome, complicated, dull, strange, frustrating

reliability of the responses was checked by asking what percentage of Robo-taxi driving was completed during driving without the intervention of safety personnel. As a result, 74% responded that the Robo-taxi seemed to have been running fully autonomously without the intervention of safety personnel, and the rest replied that it seemed to have been running partially autonomously with some intervention by safety personnel.

Models and Results

Path analysis and SEM were performed using SPSS Amos 23 (*56*) based on experience data from 71 users collected through the field test. The significance of the hypotheses defined above was analyzed. The following sub-sections describe each of the three models. Model A finds the important factors of each stage that affect overall satisfaction by using path analysis. Model B is a model that examines the relationship between user experience and user acceptance using SEM. Model C analyzes potential emotions that significantly influence user acceptance using SEM.

Model A: Path Analysis for Overall Satisfaction and Service Quality in Each Stage

Path analysis was performed to identify crucial evaluation factors by boarding stage that significantly affected overall satisfaction, which was a crucial factor for user acceptance.

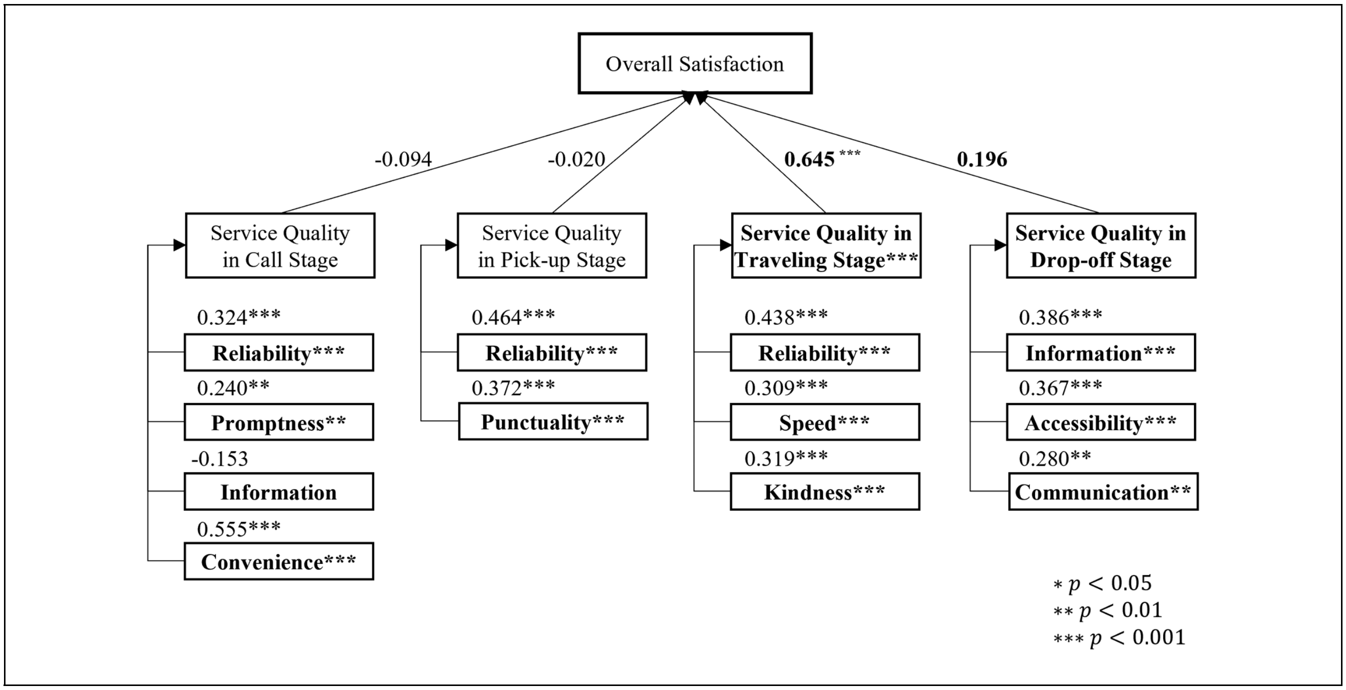

Figure 2. Path analysis model of overall satisfaction and service quality by service stage (Model A).

Figure 2 shows the results of path analysis. Path analysis is a multiple regression statistical analysis that examines the relationships between independent variables. By specifying the relationship between independent variables with arrows, we can analyze whether the independent variable affects the dependent variable (*57*). The evaluation factors in bold indicate significant or less significant, but still influential, factors. When looking at multicollinearity between sub-variables and service qualities of each stage, all of the R2 values were less than 0.9, and variance inflation factors were less than 10; thus, no multicollinearity was found. The results showed that service quality in the traveling stage was significant ($p < 0.001$), and service quality in the drop-off stage was significant ($p < 0.1$). The estimates of service quality in the traveling and the drop-off stages were 0.643 and 0.196, respectively. That is, the effect of service quality on the traveling stage was the highest. Figure 2 presents the path analysis results, which were significant at $p < 0.1$. The reason for the relaxation of the threshold is that the p-value was slightly high, but it was judged to be a sufficiently meaningful factor when looking at the interview results together.

As to service quality in the traveling stage, reliability and speed were significant, and the effect was in the order of reliability and speed. As to service quality in the drop-off stage, accessibility and information were significant. Of these, accessibility had the highest effect. Kindness in the traveling stage and communication in the drop-off stage did not satisfy $p < 0.05$, with a narrow margin, but they were judged as important factors because of having a large estimate.

The calculation results of the effect of the crucial factors on overall satisfaction with service quality in the traveling stage showed that reliability was 0.283 ($= 0.438 \times 0.645$), kindness was 0.206 ($= 0.319 \times 0.645$), and speed was 0.199 ($= 0.309 \times 0.645$). In the drop-off stage, information was 0.076 ($= 0.386 \times 0.196$), accessibility was 0.072 ($= 0.367 \times 0.196$), and communication was 0.055 ($= 0.280 \times 0.196$). Therefore, the factors that have the largest effect on overall satisfaction are: reliability, speed, kindness, accessibility, information, and communication. That service quality in the traveling stage was significant was also true in Model B, below. However, path analysis revealed that reliability, speed, and kindness, which are the second level evaluation factors, are crucial.

Model B: SEM for User Experience and User Acceptance

Model B, as shown in Figure 3, assumes that user experience is related to user acceptance. The service quality of each stage of the Robo-taxi service explains the user experience. The data collected through the quantitative survey conducted after the experiment, that is, overall satisfaction with the service, intention to use Robo-taxi, and WTP, explained the potential variable of user acceptance. In the initial model, demographic factors such as

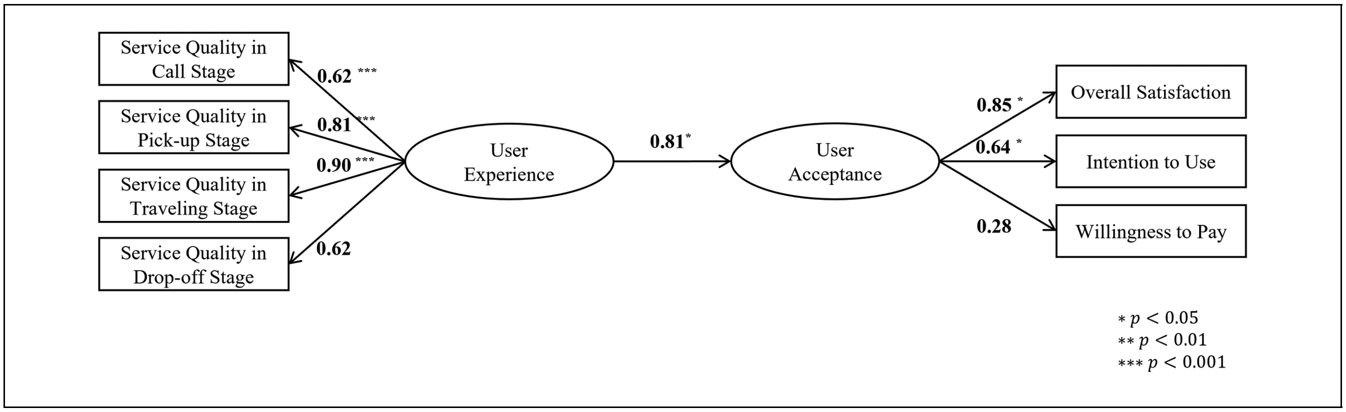

Figure 3. Structural equation modeling for the relationship between user experience, user acceptance, and demographic (Model B).

gender, age, and usage frequency were added to the model, but all of these observed variables were insignificant and thus were excluded. The initial demographic model is presented in Appendix B1.

Model B can be represented as the following equations:

$$\mathbf{X} = \boldsymbol{\lambda}_x \xi + \boldsymbol{\delta}$$
$$\mathbf{Y} = \boldsymbol{\lambda}_y \eta + \boldsymbol{\varepsilon}$$
$$\eta = \Gamma \xi + \zeta \quad (1)$$

where $\mathbf{X}$ is the observed exogenous variables indicating service quality. X_1 is service quality in call stage, X_2 is service quality in pick-up stage, X_3 is service quality in traveling stage, and X_4 is service quality in drop-off stage. ξ is the latent exogenous variable indicating user experience. $\boldsymbol{\lambda}_x$ is the path from user experience ξ to service quality $\mathbf{X}$. $\boldsymbol{\delta}$ is the errors of service quality $\mathbf{X}$. $\mathbf{Y}$ is the observed endogenous variables. Y_1 is overall satisfaction, Y_2 is intention to user, and Y_3 is WTP. η is the latent endogenous variable indicating user acceptance. $\boldsymbol{\lambda}_y$ is the path from user acceptance η to $\mathbf{Y}$. $\boldsymbol{\varepsilon}$ is the errors of $\mathbf{Y}$. Γ is the path from user experience ξ to user acceptance η. ζ is the error of user acceptance η.

The results of the goodness of fit test of the model showed that the normed-fit index (NFI) = 0.84, the goodness of fit (GFI) = 0.85, root mean square residual (RMR) = 0.09, and root mean square error of approximation (RMSEA) = 0.13. RMSEA deviated slightly from the threshold criterion, yet showed an acceptable fit. NFI is judged to be appropriate at 0.8 to 0.9 or higher (*58*), and GFI is judged to be appropriate at 0.8 to 0.9 (*59*). RMR is judged to be appropriate at 0.08, or lower (*60*), and RMSEA is judged to be appropriate at lower than 0.08 (*61*). In Figure 3, the numbers above the arrows indicate the standardized regression weights for each relationship.

User experience was significant ($p < 0.05$) for user acceptance and had a positive correlation with a magnitude of 0.81. Service quality in the call, pick-up, traveling, and drop-off stages were all $p < 0.001$, which significantly explained the potential variable of user experience. Intention to use was $p < 0.05$, and overall satisfaction was $p < 0.05$, which significantly explained the potential variable. Of the observed variables of user experience, service quality in the traveling stage was the highest (0.90) when examining the estimate in standardized regression weights. For the rest, the regression coefficient was high in the order of service quality in the pick-up stage with 0.81, in the call stage with 0.62, and in the drop-off stage with 0.62. This indicates that the most important factor in the user experience is the service quality in the traveling stage. Of the observed variables of user acceptance, intention to use was 0.64, WTP was 0.28, and overall satisfaction was 0.85.

In conclusion, in the case of hypothesis H1a, user experience was positively correlated with user acceptance; thus, the hypothesis was accepted.

Model C: SEM for Positive and Negative Emotions and User Acceptance

A total of 24 emotions were evaluated and exploratory factor analysis was used to select typical emotions. To determine the number of factors, a scree plot of the 24 emotion factors was drawn. As shown in Figure 4, the component numbers between two and four indicate the elbow. The SEM was tested by reducing the factors from four to two in sequence. When the factor was reduced to four in the SEM, the p-value of one latent variable was not significant. When the factor was reduced to two in the SEM, the total cumulative explanatory amount of principal component analysis (PCA) was insufficient. (Results of factors two and four PCA and the model are presented in Appendix B5–6.) For this reason, the

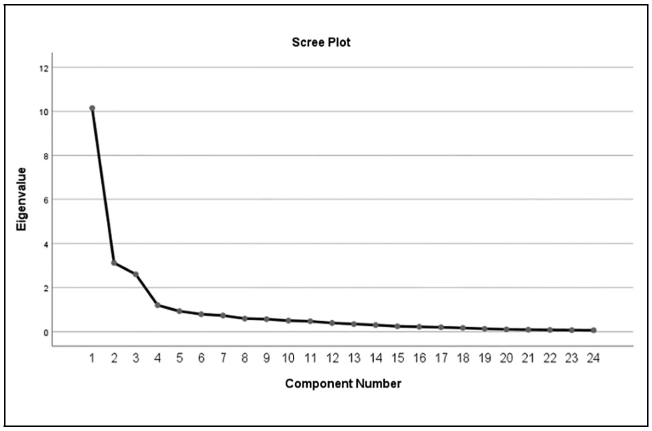

Figure 4. Scree plot of 24 emotional factors.

components were fixed to three and PCA was performed using varimax factor rotation. The varimax factor is one of the methods used to rotate a factor in factor analysis. The varimax factor stands for "Variance is maximized" which maximizes the variance of factors so that factors can be interpreted (*62*). The results are shown in Table 4.

The Kaiser–Meyer–Olkin measure (KMO) represents the degree to which correlations between variables are explained by other variables. KMO >0.7 is judged to be good; the result in this study is good at 0.848. Bartlett's test of sphericity determines whether the use of factor analysis is appropriate if the p-value is less than 0.05. In this case, the p-value was appropriately set to 0.000. The total cumulative explanatory amount of PCA was 66.11%, indicating that the explanatory power was sufficient for the factors to be divided into three components. The top three factors were selected from the results of the factor analysis. New, ingenious, and trendy were selected as the final factors for positive emotions, while unpleasant, disappointing, annoying, uncomfortable, afraid, and nervous were selected as negative emotions. Positive emotions were represented as a potential variable called "cutting-edge." Unpleasant, disappointing, and annoying emotions were represented as a potential variable called "bothersome." Uncomfortable, nervous, and afraid emotions were represented as a potential variable called "apprehensive." Various ways to add demographic data to the model were also tested, but the results were not significant.

Model C can be represented as the following equations:

$$\mathbf{X} = \boldsymbol{\lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta}$$

$$\mathbf{Y} = \boldsymbol{\lambda}_y \eta + \boldsymbol{\varepsilon}$$

$$\eta = \boldsymbol{\Gamma}\boldsymbol{\xi} + \zeta \tag{2}$$

Table 4. Results of Principal Component Analysis of 24 Emotional Factors

Factor	Component 1	2	3
New	0.885	–	–
Ingenious	0.876	–	–
Trendy	0.845	–	–
Excellent	0.798	–	–
Sophisticated	0.711	–	–
Efficient	0.697	–	–
Simple	0.673	–	–
Familiar	0.632	–	–
Convenient	0.594	–	–
Reliable	0.582	–	–
Unpleasant	–	0.815	–
Disappointing	–	0.790	–
Annoying	–	0.789	–
Strange	–	0.772	–
Tiresome	–	0.756	–
Complicated	–	0.663	–
Dull	–	0.619	–
Frustrating	–	0.485	–
Stuffy	–	0.414	–
Uncomfortable	–	–	0.886
Nervous	–	–	0.844
Afraid	–	–	0.843
Safe	–	–	–0.767
Comfortable	–	–	–0.579

where $\mathbf{X}$ is the observed exogenous variables indicating emotions. X_1 indicates new, X_2 ingenious, X_3 trendy, X_4 unpleasant, X_5 disappointing, X_6 annoying, X_7 uncomfortable, X_8 afraid, and X_9 nervous emotions. $\boldsymbol{\xi}$ is the latent exogenous variables. ξ_1 represents cutting-edge, ξ_2 bothersome, and ξ_3 apprehensive emotions. $\boldsymbol{\lambda}_x$ is the path from $\boldsymbol{\xi}$ to emotion $\mathbf{X}$. $\boldsymbol{\delta}$ is the errors of $\mathbf{X}$. $\mathbf{Y}$ is the observed endogenous variables. Y_1 is overall satisfaction, Y_2 is intention to use, and Y_3 is WTP. η is the latent endogenous variable indicating user acceptance. $\boldsymbol{\lambda}_y$ is the path from user acceptance η to $\mathbf{Y}$. $\boldsymbol{\varepsilon}$ is the errors of $\mathbf{Y}$. $\boldsymbol{\Gamma}$ is the path from $\boldsymbol{\xi}$ to user acceptance η. ζ is the error of user acceptance η.

The model in Figure 5 is based on the assumption that the emotional factors representing cutting-edge, bothersome, and apprehensive are related to user acceptance. The results of the goodness of fit test showed that NFI = 0.91, GFI = 0.90, RMR = 0.10, and RMSEA = 0.04, thus showing acceptable fitness. The RMR deviated slightly from the threshold criterion, yet showed an acceptable fit. The threshold is described above in Appendix B7. In Figure 5, the numbers above the arrows indicate the standardized regression weight of each relationship, which was rounded to the third decimal place.

The cutting-edge factor was significant ($p < 0.01$) for user acceptance and had a positive correlation with the

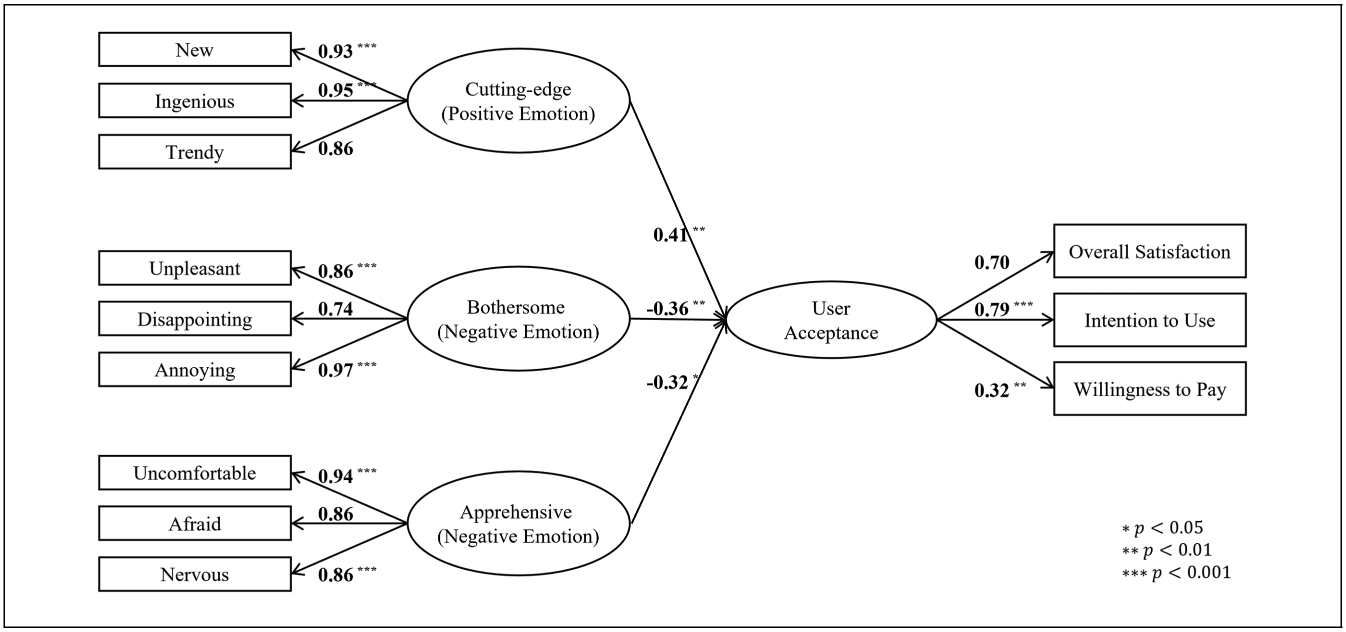

Figure 5. Structural equation modeling showing the relationship between positive and negative emotions and user acceptance (Model C).

estimate of 0.41. The bothersome factor was significant ($p < 0.01$) for user acceptance and had a negative correlation with the estimate of −0.36. Apprehensive was significant ($p < 0.05$) for user acceptance and has a negative correlation with the estimate of −0.32. Of the observed variables of cutting-edge, both new and ingenious were significant with $p < 0.001$, and both factors have a similar regression coefficient of 0.93 and 0.95, respectively. Of the observed variables of bothersome, both unpleasant and annoying were significant with $p < 0.001$, and had a regression coefficient of 0.86 and 0.97, respectively. Of the observed variables of apprehensive, both uncomfortable and nervous were significant with $p < 0.001$, and had a regression coefficient of 0.94 and 0.86, respectively. Of the observed variables of user acceptance, intention to use, and WTP were significant ($p < 0.001$ and $p < 0.01$, respectively). Intention to use had a significant effect of 0.79, and overall satisfaction was 0.70, yet the effect of WTP was relatively small at 0.32.

In conclusion, in the case of hypothesis H2a, cutting-edge, which is a typical positive emotion for the Robo-taxi, was positively correlated with user acceptance; thus, the hypothesis was accepted. In the case of hypothesis H2b, bothersome and apprehensive, which is a typical negative emotion toward the Robo-taxi, was negatively correlated with user acceptance; thus, the hypothesis was also accepted.

Discussion

This section discusses the quantitative results derived from the previous section and analyzes the qualitative results of the post-field test interviews to derive meaningful insights.

User Experience and User Acceptance

First, the results of model B showed that positive experience with the Robo-taxi service affected the improvement of user acceptance. This indicates that there is a need for a strategy that enables as many customers as possible to experience the service in advance at the beginning of the Robo-taxi service launch. Since user acceptance is high for those who have positive user experiences at the beginning of the service, they are highly likely to continue using the service. Therefore, it seems that various early marketing strategies, such as free trials, are critical. The additional field test results also support these results. Positive responses to questions about using Robo-taxis increased after the field test compared with before the field test. The interview results on intention to use Robo-taxis before and after the field test are as follows. Before the field test, 39% of the participants responded that they would use Robo-taxi as soon as it was commercialized, and 61% responded that they would use it when it was considered safe enough after its commercialization. After the field test, 96% of the participants responded that they would use Robo-taxi as soon as it was commercialized, while 4% responded that they had no intention to use it or would only use it when it became safe after its commercialization. Interestingly, these 4% had experienced more than one traffic accident and when asked after how many years it would be safe for Robo-taxis, they all answered "after 2050." A previous study, Rödel et al. (*24*), also found that prior experience of self-driving vehicles had a positive effect on user acceptance and experience.

Second, in both Models A and B, the effect of the traveling stage experience was the highest. The interview results also showed that the travel stage was the most crucial. After the field test, of the answers to the question "What was good about the Robo-taxi compared with general taxis?" the differentiation of the traveling stage between them was good and accounted for 97%. In particular, approximately 50% were about the convenience provided by unmanned services during travel. Participants were satisfied with the service in that they did not have to talk to the driver, the environment was private, and there was no body or cigarette odor inside the vehicle. Some responses are quoted below.

> *"I loved being able to do whatever I wished with nobody around me." (p. 05)*
>
> *"I didn't have to talk to the taxi driver and there was no burden." (p. 63)*
>
> *"I felt comfortable without emotional discomfort in the absence of the driver." (p. 68)*

Approximately 30% of the reasons why the Robo-taxi was good were that artificial intelligence (AI) was driving, driving was safe, and riding quality was good.

> *"I felt safe because it followed the traffic rules. It was good to be quiet." (p. 08)*
>
> *"It was good to keep the appropriate distance from the car in front. I thought it was safe, and it seemed to follow the rules well." (p. 53)*

There were other views about freedom of action, such as the possibility of consuming food, reclining and sleeping, and answering calls. This indicates that focusing on the development and improvement of the service for the traveling stage can greatly contribute to the improvement of technology acceptance.

Third, in Model B, of the variables representing user acceptance, WTP showed relatively low significance. Additionally, the Pearson correlation coefficient between the demographic variables (i.e., age, gender, and usage frequency) and WTP was not significant. Of the participants who responded positively to the intention to use, some indicated that they were willing to pay more because Robo-taxi was a new technology, whereas others felt that the fare should be lowered because there was no driver. Therefore, there are different views on WTP. Several previous studies argued that it was possible to reduce the transportation cost because there was no need for a driver; accordingly, the participants expected there would be a price advantage to the Robo-taxi (*44, 45, 63*). Some responses are quoted below.

> *"The fare initially seems to be similar to manned taxis. However, if a person drives directly, labor charges apply because it is a service job; thus, Robo-taxi seems to have a different pricing policy because it simply uses machines." (p. 44)*
> *"I will use it more frequently when the fare is lowered and commercialized." (p. 45)*
>
> *"Just like expressway buses offering luxury or premium amenities according to the class, if the Robo-taxi had such features, I would use it." (p. 69)*

Cutting-Edge and User Acceptance

In Model C, the cutting-edge factor, which represents positive emotions, affects user acceptance. The cutting-edge factor can be explained by emotions such as new, ingenious, and trendy. With an increase in the newness (freshness) users feel when they experience Robo-taxis, user acceptance can increase. Therefore, the differentiation between Robo-taxi and traditional taxi services should be maximized.

The interview results revealed that the participants thought highly of the cutting-edge nature of the new technology itself. Although they felt that Robo-taxis were not perfect, they expected Robo-taxis to make them more comfortable in the future. Some responses are quoted below.

> *"I felt it was more convenient. It was good to automatically check if the seat belt was fastened." (p. 11)*
>
> *"I thought it was convenient and I would do more activities if unmanned taxis were commercialized." (p. 50)*
>
> *"Above all, I liked it because I didn't have to tell the driver about my destination, there was no refusal of passengers, and it was good to display the navigation paths on the big screen." (p. 69)*

Service Apprehension and User Acceptance

Model C, dealing with the negative emotions, confirmed that apprehension toward new technology affected user acceptance. "Apprehensive" was defined as emotions such as uncomfortable, afraid, and nervous. To increase user acceptance, service apprehension needs to be addressed first. The interview results revealed that there was some apprehension toward using Robo-taxi since it was a new technology that the participants had never experienced before. In the early traveling stage, they felt uncomfortable about whether it worked well or was safe without a driver, but generally, in the later traveling stage, they responded that they felt relatively less uncomfortable, afraid, and nervous. Some responses are quoted below.

> *"I had doubt on how reliable this technology could be. I wondered if Robo-taxis could deal with unexpected situations." (p. 47)*

"I was terrified. I felt more uncomfortable because I was scared at the beginning." (p. 65)

"I felt uncomfortable at the beginning, but I was okay from the middle of the service. If passengers are provided with a preliminary explanation/coping method for some specific situations before boarding an unmanned taxi, it will likely reduce discomfort." (p. 67)

Bothersome and User Acceptance

In Model C (negative emotions), bothersome as an observation variable affected user acceptance. "Bothersome" was defined as unpleasant, disappointing, and annoying. To increase user acceptance, Robo-taxis need to increase their "human-free advantage" which makes the Robo-taxi better than regular taxis. Participants mentioned many advantages of not having a regular taxi driver. Participants did not prefer unfriendly taxi drivers, unwanted small talk with taxi drivers, taxi driver's body odor, or the smell of cigarettes. Thus, participants felt less of the "bothersome" negative emotions toward Robo-taxis than for regular taxis. Some responses are quoted below.

"There was no need to talk to the taxi driver and there was no burden..."(p. 63)

"There was no burden or discomfort about the driver's attitude. For example, the smell of cigarettes from the body, unkind words, and actions." (p. 49)

"It was comfortable because I didn't have to care about the driver." (p. 70)

Service Apprehension and Level of Autonomy

After the field test, the participant was asked the following question: "How much do you think the driverless robot taxi drove without the help of the safety guard while driving? Please tell me as a percentage. Why do you think so?" It was found that there was an inverse correlation between participant's apprehension and the level of autonomy. That is, apprehensiveness decreased when participants believed that the Robo-taxi was operated with full automation, and apprehensiveness tended to increase when the participant had doubts about the autonomous driving technology. The correlation results are presented in Table 5.

Table 5. Pearson Correlation Coefficient of Apprehension with the Level of Autonomy

	Pearson correlation	*p*-value
Nervous	−0.322	0.095
Uncomfortable	−0.380	0.046*
Afraid	−0.366	0.056

Note: $*p < 0.05$.

Below are some responses in which the participants answered why they believed that the Robo-taxi drove itself.

"The accelerator pedal, brake, steering wheel, etc. did not sound, so I thought it was autonomous driving. It was nice to go slowly and keep the signals well." (p. 47)

"At first I thought the driver was driving, but when I saw the rearview mirror covered, I thought the driver wasn't driving." (p. 68)

Reliability, Speed, and Kindness While Traveling

Model B showed that traveling-stage experience had a significant effect on acceptance of the technology. Reliability, speed, and kindness had a significant effect on the traveling-stage experience in Model A. In previous research, reliability was regarded as the most crucial factor for perceptions of Robo-taxis (*11*). In addition, as with the studies that demonstrated that the majority of experiment participants preferred the driving style of Robo-taxi to be similar to their driving style (*15*), it is expected that user acceptance can be increased if the optimization of the user-customized speed increases satisfaction with regard to the speed factor. In particular, reliability and speed were found to be related. Many users seemed to be very uncomfortable because they did not trust the new technology, and some users evaluated satisfaction according to speed. They felt differently even at the same speed, and some felt uncomfortable at high speeds, and vice versa. Some responses are quoted below.

"I felt a little discomfort as this was my first time experiencing an unmanned taxi. I felt that the speed of the taxi was not completely consistent, and I noticed a bit of a sudden jerk when it changed lanes." (p. 13)

"The speed was reasonable, and it was comfortable and good like a normal taxi." (p. 55)

"The speed was a little slow compared to a normal car, and I felt a little discomfort about self-driving cars." (p. 7)
"It drove slowly in crowded alleys, so I felt safe." (p. 62)

In the interview results related to kindness, some participants felt that the voice from the systemized machine was kind in the absence of a driver, whereas there were opposing views that, since it was an efficient system that aimed to get to the destination from a departure point, they did not feel any kindness. Since kindness turned out to be crucial in the traveling stage, which was the most important stage in the Robo-taxi service, the way that a Robo-taxi could engage the user emotionally should also be considered. Some responses are quoted below.

"I didn't have to worry about the driver's mood, a chat with the driver, and uncomfortable things." (p. 61)

"I didn't have to unwillingly talk to the driver, and it was good that all communication was done by machine." (p. 56)
"I believe that kindness is such a thing that if there was a driver, the driver could have a humorous chat with me or could greet me, but I was not able to share the emotion of kindness with an unmanned taxi. I just got in the car, but I am not sure if there is any element of kindness." (p. 69)

Accessibility, Information, and Communication While Dropping Off

In Model A, in the drop-off stage, particular attention should be paid to accessibility, information, and communication to increase overall satisfaction. In the case of a manned taxi, the driver drops the passenger off flexibly by identifying traffic situations at their discretion. However, a Robo-taxi drops passengers off only at the designated safe stop. Therefore, there is a need to develop an HMI for flexible dropping off with regard to accessibility. Passengers have an approximate destination, but they should be able to ask the Robo-taxi specifically where exactly around the destination they should alight. In the same context, Robo-taxis should be able to offer passengers a safe place to be dropped off so that they can choose where to be dropped. The interview results also revealed that the Robo-taxi service was inconvenient with regard to the accessibility of where to get out and not being able to specify this through information and direct communication. Some responses are quoted below.

"I could not get out at the right place when I arrived. Voice recognition made it difficult for me to specifically control it." (p. 26)

"I felt uncomfortable when it stopped because of a car in front." (p. 12)

"It went smoothly. Before getting out, I asked about AI voice recognition for the expected time to be dropped off. I was satisfied with the information provided." (p. 68)

"I was a little confused when to get out." (p. 23)

"In general, when I ask a taxi driver to be dropped off at a desired place, the driver drops me off. However, it seemed impossible for an unmanned taxi to drop me off flexibly. From the first call, it is necessary to determine the arrival place specifically. It would be inconvenient if the drop-off place was set in advance." (p. 10)

"When I wanted to get off near my destination, I couldn't convey my message to the Robo-taxi." (p. 37)

Heterogeneity

To examine the heterogeneity of the Robo-taxi service, a *t*-test was used to analyze the relationship between demographics (e.g., gender and age) and user acceptance (i.e., overall satisfaction, intention to use, and WTP). Overall satisfaction was significantly different depending on gender (i.e., p-value = 0.004), where males had higher overall satisfaction than females (i.e., male: 5.75, female: 4.98, on average). This gender difference was also observed in previous studies (*10*). However, there was no significant relationship between gender and intention to use and WTP. In addition, no significant relationship was found between age and user acceptance. A more detailed analysis of gender and age differences is presented in Appendix B2.

Distribution and Correlation of the Responses

Looking at the distribution of service quality in each stage, the average service quality of the pick-up stage was rated the highest. This is because the process was similar to that of using a regular taxi, according to the interview results. A detailed analysis is presented in Appendix B3.

In addition, as a result of the correlation analysis of each stage factor, predictability was directly correlated with reliability at all stages. Among them, communication between Robo-taxi and traveler was important to finding a Robo-taxi in the pick-up stage, and sufficient information about Robo-taxis was important in the traveling stage. In the drop-off stage, communication was important for the Robo-taxi to drop off passengers safely near the destination. Information and communication are also correlated with kindness; consequently, Robo-taxis should pay attention to information and communication in each stage to give passengers a perception of kindness and reliability. The detailed analysis results are presented in Appendix B4.

Conclusion

Unlike previous user experience studies on self-driving vehicles which mainly depended on surveys and simulators, this study was based on a survey and in-depth interview data obtained after participants experienced a Robo-taxi service operating in an actual city center. Based on the collected quantitative data, SEMs were built and a path analysis model and analyzed them by comparing them with the in-depth interview results, which were qualitative data. Furthermore, by analyzing the relationship between user experience and user acceptance, this paper suggests ways to further improve the Robo-taxi service.

First, for the results of Model A, path analysis was performed for the relationship between the 34 evaluation factors by service stage and overall satisfaction. Service quality in the traveling and drop-off stages was found to have a significant effect on overall satisfaction. Reliability, speed, and kindness were found to be crucial factors in the traveling stage, and accessibility, information, and communication were found to be crucial factors in the drop-off stage. Second, the results of Model B, which showed the relationship between user experience and user acceptance, proved that user experience had a significant effect on user acceptance. Service quality in the traveling stage had the largest effect on user experience, and overall satisfaction had the largest effect on user acceptance, whereas WTP had a relatively low effect. Third, Model C, which analyzed 24 emotional factors and the relationship between these factors and user acceptance, showed that cutting-edge was selected as the typical emotion that had a positive relationship with user acceptance, whereas bothersome and apprehensive were selected as typical emotions that had a negative relationship. New, ingenious, and trendy relate to cutting-edge; and unpleasant, disappointing, and annoying relate to bothersome and uncomfortable, afraid, and nervous relate to apprehensive.

Based on the results, some suggestions can be offered for design and marketing of a Robo-taxi service. Since the initial service experience turned out to be crucial, there is a need for a strategy to provide as many customers as possible with service experience in the early stage of the Robo-taxi launch. Moreover, since cutting-edge has a significant effect on user acceptance, the differentiation between Robo-taxi and conventional taxi services should be maximized. Apprehension, a negative emotion, also affects user acceptance; thus, the issue of low reliability should be addressed more than anything else. Since reliability, speed, and kindness were found to be crucial in the traveling stage, it is necessary to provide an optimized speed service for an individual user and for in-vehicle AI to approach the user emotionally. In the drop-off stage, because accessibility, information, and communication are crucial, there is a need to develop an HMI for flexible drop-off (e.g., virtual stop [*21*]).

This study makes the following contributions. First, it conducts an SEM analysis based on survey data on the Robo-taxi user experience. The findings of previous studies were mainly based on data from simple surveys or simulator testing, and there was a lack of SEM study cases based on real user experience. Second, the quantitative SEM and qualitative interview results were analyzed simultaneously. By identifying crucial relationships between the factors based on the SEM results and deriving the basis for them from the interview results, the reliability of the model analysis results was improved and a balanced analysis was performed. Third, through the analysis results, guidelines are suggested for the design and marketing of future Robo-taxi services.

The limitations of this study and future research directions are as follows. First, owing to the physical limitations of the Robo-taxi field test, it was difficult to secure a statistically sufficient amount of user experience data. In future research, the authors will continue to increase the number of participants with diverse backgrounds. Participants' social status and income level will be collected and analyzed in detail. Second, Robo-taxi service data will be collected considering various environments. For example, night service situations, when the demand for Robo-taxis is high, and service environments for the socially disadvantaged, such as the disabled and the elderly, will be taken into account. Third, only the correlation between user experience and user acceptance was examined in this study. To confirm causality, further research is needed to sufficiently increase the amount of experimental data. In addition, the authors plan to capture the effect of unobserved heterogeneity from unobserved factors (e.g., income and travel mode choice). Fourth, the authors plan to test unsafe driving scenarios separately, and analyze how these negative experiences affect user acceptance.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Lee, S. Yoo, S. Kim, E. Kim, N. Kang; data collection: S. Lee, S. Yoo; analysis and interpretation of results: S. Lee; draft manuscript preparation: S. Lee, N. Kang. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by National Research Foundation of Korea (NRF) grants funded by the Korean government [grant numbers 2017R1C1B2005266 and 2018R1A5A7025409].

Supplemental Material

Supplemental material for this article is available online.

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