A Psychological Approach to Demand Forecasting: A Measure of Potential User in Bus Service

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Abstract: A recent trend in transport demand modeling with a focus on potential users emphasizes the understanding on the human decision-making process. Among various theories studying the process, loyalty-based theory has the closest relationship with the concept of potential users. However, conventional loyalty frameworks are insufficient for demand modeling. To address the issue, the present study proposed a psychological demand model based on a loyalty framework considering both service-quality-related and non-service-quality-related factors. The proposed model is able to quantify potential users and to measure maximum values of bus patronage respect to different service scenarios. Based on the proposed model, an increase of 18.05% on the group of car drivers could be expected to be at the highest priority for pushing up bus patronage in term of improving service quality. In contrast, a little increase was found on the group of non-car drivers with only 3.81% even an ideal service was provided.

Keywords: Psychological Demand Modeling, Bus Service, Latent Variables

1. INTRODUCTION

There is a need of a significant shift from car to public transport due to potential benefits including congestion reduction, improvement of efficiency of road-based transport operations and environmental gains (Balcombe *et al.*, 2004). Staying as a key reference for transport planners and managers in term of making transport planning and strategies, potential user measurement contributes to the possibility of making the shift possible.

Potential user has been studied through demand models. First researchers follow a random utility theory in which travelers select alternatives based on utility assessment. A general trend of studies within the approach is to use quantitative variables to represent alternatives. Then individuals choose the best available alternative. In order to have a better description of the human decision-making process, researchers had improvements such as including a wide range of factors, releasing assumptions, focusing on a better estimation procedures. However, the key point for demand studies is about changing behavior rather than picking up available choices (Diana, 2010). In particular, a focus of studies is to understand how people change their behaviors. Furthermore, people sometimes make decisions in situations where information of alternatives is incomplete. As such, the discrete choice approach is not enough to present human decision-making process.

To address the weakness of discrete choice approach, recent researchers suggested a psychological approach. The key feature of the suggested approach is to understand how people process their behaviors by considering users' psychological progresses and perceptions. There was evidence that attitudinal factors have a significant role toward mode-choice behavior (Kuppam *et al.*, 1999). Moreover, there is a need that transport profession should embrace disciplines such as sociology and psychology (Lyons, 2004). Up-to-date, there are evidences showing that factors such as attitudes and personal characteristics influence individual's choices (e.g., Galdames *et al*., 2011).

Under the view of the psychological approach, researchers strengthened a suggestion that a focus on the basis of the decision-making process will bring an improvement on understanding of the choice process as well as the forecasting process (e.g., Galdames *et al*., 2011). For demand model, there is a notion of conceptual change from mode choice to modal diversion (e.g., Hensher, 2001). Diana (2010) insists a theoretically possibility and practically potential for studying modal diversion with the same widespread methods used for mode choice models. The author, furthermore, lays stress on the behavioral reactions of individuals.

In particular, social psychology has studied the decision-making process on the basis of various theories. Technology Acceptance Model (TAM; Davis, 1989) deals with actual system use, behavioral intention, attitude and antecedents of attitude. Theory of Planned Behavior (TPB; Ajzen, 1991) seeks for structural relationship between attitude, social norms, perceived behavioral control, intention and behavior. Health Action Process Approach (HAPA; Schwarzer, 1992) considers motivational self-efficacy, outcome-expectancies and risk perception as predictors of intention. Toward the actual use, recovery-self-efficacy and planning are mediators of motivational self-efficacy and intention respectively. Four-stage loyalty model (Oliver, 1997) focuses on consequent connection between cognitive loyalty, affective loyalty, conative loyalty and action loyalty.

Among the above mentioned theories, under a view that potential users are future customers, it seems that loyalty-based theory has the closest relationship with the concept of potential users. Customer loyalty is a preeminent concept which guides managers on matters of customer retention, repurchase, long-term relationship and profitability. In particular, users with a high in retention will probably have a high in future service patronage, thus, the possibility for them to be potential users is high. With such essence, the loyalty concept takes a significant role in term of recognizing potential users. Therefore, it is reasonable to measure the potential users based on loyalty frame work.

Although researchers realized the potential application of loyalty modeling in service choices (Minser and Webb, 2010), the application of loyalty concept in quantifying potential users is still a new research topic, at least in a context of public transportation. Some of the initial attempts for transportation service were to measure loyalty based on performance of service and individual's socioeconomic characteristics (e.g., Figler *et al*., 2011; Foote *et al*., 2001). Furthermore, some researchers focused on the relationship between loyalty and its determinants (e.g., Minser and Webb, 2010; Joewondo and Kubota, 2007; Wen *et al*., 2005). However, those mentioned studies have not studied customer loyalty under a view of human decision making process. Therefore, in the context of public transportation, it is a challenge to model user demand based on loyalty framework.

Literature records a number of loyalty frameworks, but those frameworks are insufficient for modeling demand. An aim of a demand forecasting model prefers concept of loyalty to be closed with decision making process. Thus, among numerous definitions of loyalty, a concept suggested by Oliver (1997, 1999) emerges as an outstanding reference of various studies. Oliver (1997, 1999) proposed a sequential concept of loyalty starting with cognitive loyalty, followed by affective loyalty, conative loyalty and finally action loyalty. However, the concept does not catch up with a recent development of attitude studies that promotes a multi-facet of attitude (e.g., Aizen, 2001). Furthermore, the concept is insufficient regard to suggestions in the field of transportation such as the existences of habitual impact, social impact, risky attitude as well as a diversity in passengers' perception (e.g., Schaap *et al*., 2012). Therefore, it should be necessary that a rational approach for future study is to focus on a more comprehensive framework of loyalty which integrates up-to-date findings found in transportation service.

Recently, Hoang-Tung *et al*. (forthcoming) proposed a constituent relationship of loyalty for bus service setting. The loyalty concept has been decomposed into three major phases including attitudinal loyalty, conative loyalty (intention) and action loyalty. Furthermore, the loyalty model demonstrated cognitive loyalty, affective loyalty and implicit loyalty as three aspects of attitudinal loyalty. In addition, impacts of social norm and habit were considered in the loyalty model. As such, it is possible to see that the developed loyalty model was adhered with the human decision-making process with a supplement of the up-to-date related findings such as a multi-facet of attitude and the existences of habitual impact and social impact. Furthermore, based on the developed model, the authors pointed out that bus service demand is a function of determinants in which the impacts of determinants are consequential.

Although there were models working toward psychological aspects (e.g., Sunitiyoso and Matsumoto, 2009), however, most of them are complicated and not easy to apply in practice. Thus, practical implication of bus service requires an easy-to-apply demand model which is capable to provide a connection between service quality, other determinants and frequency of use. The failure in preventing reduction of passengers (Balcomebe *et al*., 2004) creates a financial burden on bus providers, specially with small bus enterprises. As such, the accessibility of bus managers toward computational models in complex systems is out of the reach because of a high investment cost. Furthermore, the systems often need a massive amount of input data for operation. Thus, a simplified and creditable demand model is necessary for managers.

In addition, with various purposes, bus providers and transport planners are interested in the highest level of service patronage. However, the available models can not yield such indicator. Therefore, this paper seeks to provide a maximum value of potential users. The maximum value of potential users, within this study, can be understood as a max in frequency of bus use for a given resident area in case service providers provide a supposed ideal service that satisfies everybody. This figure can be considered as ceiling value for bus managers when deciding a strategy plan such as opening a new route or something similar. According the awareness of the authors, there is no researcher aim to the value as one of their objectives.

Taking all the mentioned issues, objective of this study is to provide a simplified model for measuring frequency of bus use. The model was developed based on a loyalty framework in which a bunch of latent factors including affective loyalty, cognitive loyalty, implicit loyalty, descriptive norm and habit were considered. The model aims to quantify users' frequency of use and measure the maximum values of bus patronage respect to various cases of perceived ideal bus service.

2. METHODOLOGY

2.1 Modeling Approach

The proposed model was based on a loyalty framework which comprises attitudinal loyalty and behavioral loyalty as discussed detail in Hoang-Tung *et al*. (forthcoming). Attitudinal loyalty implies a general evaluation of a person toward a given service, whereas, behavioral loyalty is a respective feedback respect to the general evaluation. Based on the definitions, attitudinal loyalty has been considered in a form of a higher-order formative construct with three causal factors including cognitive loyalty, affective loyalty and implicit loyalty. In particular, cognitive loyalty refers to perceived attributes of service quality. Affective loyalty implies an emotion and satisfaction related to perceived service quality. Implicit loyalty represents for people's perception which is not activated by attributes of service quality. Besides, behavioral loyalty covers two phases. The initial phase is about behavioral intention (conative loyalty). The second phase is about frequency of use (action loyalty). Figure 1 illustrates the whole structure of the loyalty concept.

The mentioned loyalty framework has already provided a list of the key determinants of frequency of use. For modal diversion, Diana (2010) categorizes investigated factors into three classes including instrumental elements (e.g., characteristics of mode choices), subjective factors (e.g., attitude and personal traits) and situational variables (e.g., habit and socioeconomic characteristics). Following this classification, a procedure to model the human decision making process should naturally base on a consequential order of instrumental elements-subjective and situational variables – actual behavior. In other words, the impacts of instrumental elements will be reflected via subjective factors. Then, after getting influences from situational variables, subjective factors will yield actual behavior. Under the light of the mentioned understanding, a consideration of subjective factors in demand models indirectly accounts the impacts of instrumental elements. Therefore, with the consideration of cognitive loyalty, affective loyalty, implicit loyalty, descriptive norm, habit and intention, the developed loyalty framework provided a good spectrum on determinants of actual behavior.

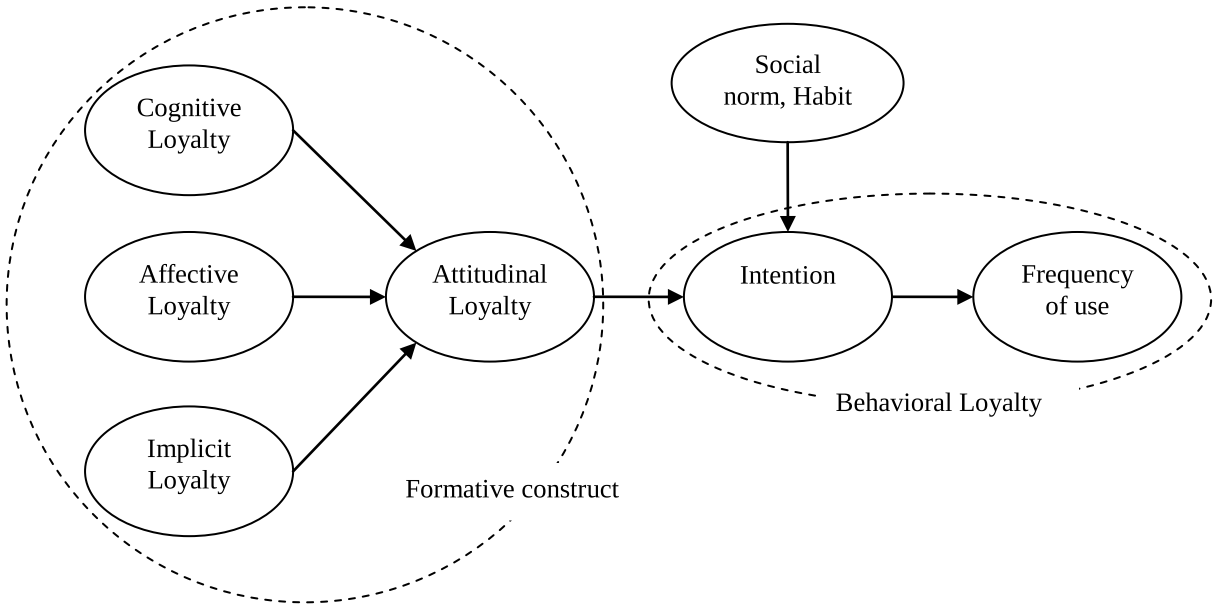

Figure 1. Loyalty framework (adapted from Hoang-Tung *et al.*)

Although the above structural constituent relationship of loyalty has a good support for loyalty concept, however, due to the numerous relationships of the structure, it could not be directly used to quantify users' frequency of use. Originated from the foundation of latent variable structural equation modeling (SEM), the technique results a statistical model upon theoretical relationships. As such, the huge number of relationships may yields a complicated model with a high error of measurement. Put a stronger weight on the static essence, the proposed demand model seeks to a direct connection between determinants (independent variables) and frequency of use (dependent variable).

A technique of SEM with latent variables is an appropriate solution which represents the direct connection between frequency of use and its determinants. Latent variables are random variables in which their realized values are hidden. Latent variable modeling has been recognized as a part of mainstream statistics (Skrondal and Rabe-Hesketh, 2007). The modeling branch has been applied in various disciplines (e.g., Sutton *et al*., 2000; Verbeke & Molenberghs, 2000; Train, 2003; Rue and Held, 2005; Carroll *et al*., 2006). Among different types of latent variable models, SEM with latent variables follows relations specified between continuous latent dependent variables and continuous latent explanatory variables. The SEM's foundation lies in factor analysis and multiple regression analysis (Hair *et al*., 2005). Thus, a direct connection between dependent and independent variables can be understood as a direct latent variable multiple regression between the variables. This study uses 5-point Likert scale for measuring latent constructs of determinants and 4-point scale for measuring frequency of use. Hence, all the recorded data can be assumed as continuous. Therefore, it is suitable to apply the technique for the data.

However, a direct latent variable multiple regression between frequency of use and its determinants including cognitive loyalty, affective loyalty, implicit loyalty, descriptive norm, habit and intention may not bring an expected outcome. First, the mentioned loyalty framework does not cover all key determinants of frequency of use. For instance, Schwarzer (1992) points out that planning is a mediator between intention and actual behavior. The lack of considering planning may lead to a low fit of the proposed model. Second, the direct regression will put intention on the same layer compared with other determinants. This will hide the consequential order of impacts in which intention takes the later and the most significant impact on frequency of use.

A possible solution for building the model is to consider a two-phase estimation. First phase comes with a latent variable multiple regression between intention and its determinants. In the second phase, based on the relationship between intention and frequency of use obtained from Hoang-Tung *et al*.'s model, the final model will express the relationship between frequency of use and intention's determinants. The loyalty framework covers most of the key determinants of intention. Thus, a regression between intention and the determinants is creditable. In addition, the correlation coefficient between intention and frequency of use obtained from the mentioned model has been developed with a consideration of consequential order of impacts. Therefore, employing the coefficient will make the proposed model close to the nature of human decision making process. Figure 2 illustrates the proposed model approach.

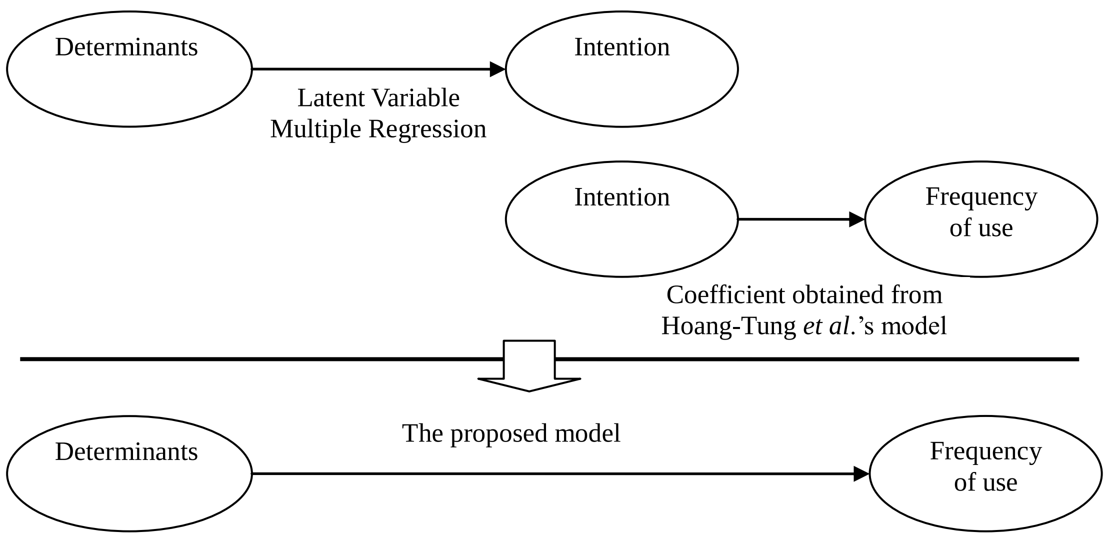

Figure 2. Modeling approach

Although the proposed model includes cognitive loyalty and/or affective loyalty as explanatory variables, it must not be strictly adhered with both existences of cognitive loyalty and affective loyalty. According to Ajzen (2001), people rely differently on cognition versus affection as determinants of attitude and the two components have different weights on different objects. Haddock and Zanna (1998) also categorize people into two types. One type is identified as thinkers who lean on cognition when making decisions. The other type is feelers who make decision base on affection. Furthermore, Shiv and Fedorikhin (2002) provide evidences showing the moment and the goal of the decision may decide people are thinkers or feelers.

The inclusion of affective loyalty and/or cognitive loyalty makes the proposed model enable to calculate the maximum number of potential users. As already mentioned in previous section, the maximum value was built on an assumption of an ideal scenario of service quality. In other words, with different ideal scenarios of service quality, there will be respective maximum values of potential users. To reflect any supposed level of service quality, it is possible to use the proposed model with the respective supposed level of affective loyalty and/or cognitive loyalty. For example, to describe an ideal service quality that satisfies everybody, the value of affective loyalty and/or cognitive loyalty will be pushed to the best value. This study estimated different values of potential users by changing different values of affective loyalty and/or cognitive loyalty. In addition, there was an assumption toward other determinants that they are separate with service quality so that they will keep the same average values for every change of service quality. In particular, implicit loyalty, descriptive norm and habit were assumed to be non-affected factors regards to service quality. This assumption is compatible with the nature of those determinants.

According to Diamantopoulos and Winklhofer (2001), the validity assessment of the proposed model was considered via individual indicator validity and the overall fit indexes. The γ-parameters stand for the influences of the individual indicators to constructs. Therefore, items with the non-significant parameters should be eliminated (Bollen, 1989). In addition, based on suggestions of Hair *et al.* (2005), this study uses several indexes to assess the fit of the model. Goodness-of-Fit Index (GFI), Adjusted Goodness-of- Fit Index (AGFI), Normed Fit Index (NFI) allow values equal or higher than a cutoff value of 0.9. The value of Root Mean Square Error of Approximation (RMSEA) is less than or equal to 0.07. The value of Comparative Fit Index (CFI) is higher than or equal to 0.92. Furthermore, of the multiple regression analysis, since the proposed model does not focus on the magnitude of individual contribution, then the issue of multicolinearity does not influence to the final estimation results.

2.2 Data Collection

A questionnaire survey in Hidaka city, Saitama prefecture, Japan was conducted from September 24, 2012 to October 5, 2012. Participants received the questionnaire and sent their feed backs via post. The content of the questionnaires comprises items for the proposed constructs and socio-demographic characteristics of participants. There are a total of 7500 questionnaires distributed. The rate of receiving questionnaire is 7.39% (554 questionnaires). Because of some uncompleted answers, 333 (4.44%) questionnaires were used for analysis. Table 1 provides general characteristics of respondents.

Table 1. General characteristics of respondents

Characteristics	Statistics
Gender	Male (48.0%), Female (52.0%)
Age (year old)	≤17 (1.2%), 18-29 (6.0%), 30-39 (8.1%), 40-49 (14.1%), 50-54 (6.6%), 55-59 (9.3%), 60-64 (13.8%), 65-69 (13.5%), 70-74 (18.6%), 75-79 (5.7%), ≥80 (3.0%)
Time of residence (year)	≤1 (3.3%), 1-5 (7.8%), 5-10 (12.6%), 10-30 (35.7%), ≥30 (40.2%), unknown (0.3%)
Driving license	Have (76.9%), Don't have (21.0%), Other (2.1%)

2.3 Measures

Each of the unobservable constructs has been measured by one to three items. With each of the items, respondents pick up one answer ranged from 1 (strongly agree) to 5 (strongly disagree) in Likert-type scale.

Cognitive loyalty was measured by two items including "Overall, bus service quality is good" and "Compared with the price you pay, the service is valuable". The cronbach's alpha of these two items is 0.79. Affective loyalty was revealed by two items having cronbach's alpha of 0.90: "You love to use bus in your daily life" and "Compared to other transport mode, you prefer to use bus in your daily life". Implicit loyalty comes with three measure items: "You find no difficulty to use bus in daily life", "Using bus is an easy thing for you to do" and "Your freedom to use bus in daily life is high". The three items have a cronbach's alpha of 0.81. Two items having cronbach's alpha of 0.93 were used to measure descriptive norm: "Number of people using bus is increasing nowadays" and "Most of people you know tend to use bus more nowadays". Habit was manifested by one item: "If you have alternatives, you can easily change your most frequent-use transport mode". Intention was reported through three measure items: "Bus is one of priorities for your daily travel", "You strongly intend to use bus in your daily life" and "The possibility to daily use bus is high". The three items come with a cronbach's alpha of 0.94. Exceptionally, frequency of use was measured by a question whose the answer comes with real number filled by respondents. Answers for frequency of use (days/week) were divided into 4 point scale by coding. The code is as the follows: 1.(Frequency≥5), 2.(2≤Frequency<5), 3.(0<Frequency<2), 4. (Frequency=0).

3. RESULT

3.1 Descriptive Analysis

This study revealed individual's frequency of bus use by asking them to state their perceptions on some key determinants of the frequency.

The data showed that people do not use bus much. On average, people have a low on bus use with a score of 3.43 as showed in Table 2. There is 34.5% of respondents stated that they are using bus. The mentioned percentage of the actual use is quite close to the 39.9% of people who reported that their intention to use bus is high. This probably suggests that an increase in people' intention may help to increase actual bus use.

Although people stated a good quality in bus service, it is likely that their emotions and satisfactions are slightly different compared with the perceived service quality. Contradict to a high average cognitive loyalty score of 2.43, respondents reported a low of affective loyalty with a mean score of 3.07. This indicates that there is a room for increasing people's affection toward bus service.

Regarding to affective scores, there are some significant differences between groups of respondents. Men seem to be stricter than women regarding the emotion and satisfaction toward bus service. The data showed that women give an average score of 2.86 which is higher than that of men of 3.28 ($F(1,331)=10.650$, $p<0.01$). The difference is also recorded between people having car driving license and those without car driving license. Car drivers gave a worse score compared with that of non-car drivers. The average score of car drivers is 3.22 compare with a score of 2.52 of non-driving license people ($F(1,331)=22.007$, $p<0.001$).

In addition, people seem to have no hidden concern or pressure toward bus service. In particular, the mean score of implicit loyalty of 2.40 falls in a range in which people have positive thoughts about bus service (i.e., people do not have many concerns about bus use). For more detail, when being asked about difficulties of using bus, 63.9 % of participants return their feedback saying no difficulty in using bus.

Table 2. Perceived respondents' opinions on measured constructs

	Min	Max	Mean	SD
Affective loyalty	1(Strongly Agree)	5(Strongly disagree)	3.07	1.20
Cognitive loyalty	1(Strongly Agree)	5(Strongly disagree)	2.43	0.94
Implicit loyalty	1(Strongly Agree)	5(Strongly disagree)	2.40	1.10
Descriptive norm	1(Strongly Agree)	5(Strongly disagree)	3.76	1.07
Habit	1(Strongly Agree)	5(Strongly disagree)	3.74	1.13
Intention	1(Strongly Agree)	5(Strongly disagree)	3.16	1.38
Frequency of use	1 (everyday use)	4 (do not use)	3.43	0.89

The data also provided information about how people attach to their frequent-use mode and how they perceive about bus use in their community. It is possible to say that people quite adhere with their most frequent-use mode. As can be seen from Table 2, the average score of 3.74 for changing frequent-use mode if having alternatives indicates that respondents find difficulty in doing the change. The data revealed 56.1% of participants report a disagreement in changing their frequent-use mode. Besides, 60% respondents showed their disagreement about an increase in number of people using bus. This leads to a low in average score of 3.76 for descriptive norm.

3.2 Estimation of the Proposed Model

As already mentioned in previous sections, the two-phase simulation was conducted to produce the proposed model. First, SEM technique running on AMOS software was employed to yield a latent variable multiple regression between intention and its determinants including affective loyalty, cognitive loyalty, implicit loyalty, descriptive norm and habit. However, due to the non significant relationship, the final model excludes cognitive loyalty out of the estimation. Second, the coefficients adapted from the already mentioned loyalty framework were used to describe the relationship between intention and frequency of use. Coefficients for the final proposed model estimation can be seen in Table 3.

Table 3. Coefficients of the proposed model

	Coefficient	P	Note
Intention ← Affective Loyalty	.824	***	p<0.001
Intention ← Implicit Loyalty	.165	.012	p<0.05
Intention ← Descriptive Norm	.196	***	p<0.001
Intention ← Habit	-.088	.016	p<0.05
Interception to calculate Intention	0		
Correlation			
Affective Loyalty ←→ Implicit Loyalty	.952	***	p<0.001
Implicit Loyalty ←→ Descriptive Norm	.425	***	p<0.001
Affective Loyalty ←→ Descriptive Norm	.570	***	p<0.001
Affective Loyalty ←→ Habit	.081	.259	-
Implicit Loyalty ←→ Habit	.146	.062	-
Descriptive Norm ←→ Habit	.160	.013	p<0.05
Model fit indexes			
Goodness-of-Fit Index (GFI)	.977		Acceptable
Adjusted Goodness-of- Fit Index (AGFI)	.957		Acceptable
Normed Fit Index (NFI)	.985		Acceptable
Root Mean Square Error of Approximation (RMSEA)	.028		Acceptable
Comparative Fit Index (CFI)	.997		Acceptable
Adapted from Hoang-Tung *et al.* (SEM results)			
Intention → Frequency of use	.441	***	p<0.001
Interception to calculate frequency of use	1.99		
Item1 ← Intention	.986	***	p<0.001
Interception to calculate Item1	3.28	***	p<0.001
Item2 ← Intention	1.03	***	p<0.001
Interception to calculate Item2	3.50	***	p<0.001
Item3 ← Intention	3.56	***	p<0.001
Interception to calculate Item3	1.00		

Of the initial phase, the proposed model has a good support from data. As presented in Table 3, all of the relationships have been confirmed on trend and significance of impacts. The data showed that affective loyalty, implicit loyalty, descriptive norm have positive relationships with intention. In other words, a high in any of the mentioned factors will lead to a high in intention and reverse. There is only a negative relationship between habit and intention. It means that a high in changing frequent-use mode will contribute to a low in intention and reverse. In addition, an interception for calculating intention was assumed to be zero due to a fact that intention is a latent variable. Finally, all the fit indexes fall within the acceptable range. Even there was a high correlation score between affective loyalty and implicit loyalty. However, as already explained in previous sections, the correlation does not influence to the final estimation of the proposed model.

The second stage of simulation is to illustrate the relationship between intention and frequency of use. A 1.0 loading factor has been arbitrarily assigned to item3 of the three measure items. In other words, intention was indirectly adjusted by item3. Therefore, the relationship between intention and frequency of use could be derived by using an equation between frequency of use and item3. A logical calculation leads to an interception of 1.99 for calculating frequency of use. To conclude, the intention-frequency relationship is represented via a regression having a regression coefficient of 0.441 and an interception of 1.99.

3.3 Measuring Maximum Potential Frequency of Bus Use

As discussed by Gehlert *et al*. (2012), the difference in people' perception toward a given service is one of questions remaining for transportation. This creates a challenge for bus managers when they aim to an ideal service that satisfies everybody. Therefore, the present study suggested a concept of ideal perceived service quality indicating a service being judged as perfect service based on customers' perception. The present study considered various scenarios to assist bus managers on the mentioned issue.

A set of scenarios were created due to a supposed set of perceived service qualities. Scenarios were studied base on information revealed from the data with differences between groups such as women vs. men and car drivers and non-car drivers. There were five cases including "ideal perceived service quality for everybody", "ideal perceived service toward men only", "ideal perceived service toward women only", "ideal perceived service toward car driver only" and "ideal perceived service toward car driver only". With each the cases, the change in service quality was only reflected via a change in affection. According to that, when everybody perceives an ideal service quality, then the mean affective score is 1. For other cases, the mean scores of affection will be calculated in order to estimate the respective frequency of use. Of the other determinants, the average values which have been used in a base case, was assigned to other cases when conducting the estimation.

Comparisons were made between each of the supposed cases and the base case. The comparisons help to see how frequency of use changes accordingly. It should be noted that the base case illustrates for the current service quality. As can be seen from Table 4, the highest increase of 21.7% was with a case in which everybody perceives an ideal bus service. The second increase of 18.1% was with a case when car drivers perceive an ideal bus service. The increases for men and women to perceive ideal service are 11.6% and 10.25 % respectively. The lowest increase of 3.8% was with a group of non-car drivers.

Table 4. Frequency changed due to improvement of perceived service quality

Model	Description	Affection	Intention	Frequency of use	% change vs. base case
Base case	current service quality	3.07	3.72	3.46	-
Max 0	ideal perceived service toward everybody	1.00	2.01	2.71	21.74
Max 1	ideal perceived service toward men only	1.97	2.81	3.06	11.58
Max 2	ideal perceived service toward women only	2.09	2.91	3.11	10.25
Max 3	ideal perceived service toward car driver only	1.35	2.30	2.84	18.05
Max 4	ideal perceived service toward non-car driver only	2.71	3.42	3.33	03.81

4. DISCUSSION

This study was an effort to provide a psychological demand model using data collected from bus service. The proposed model was successful described with a good support from SEM results. Based on a framework of loyalty, the proposed model has considered impacts of various latent factors related to human decision-making process. In addition, the proposed model demonstrated its advantage on visualizing the bus demand (frequency of use). Furthermore, it was superior in term of an ability to provide different frequencies of bus use respect to different perceived service qualities. It was also proved as an useful tool for bus service managers when providing a ceiling reference on potential frequency of bus use. Finally, the present study can be seen as the first effort providing a psychological demand model that based on loyalty framework in the context of bus service industry.

A number of latent factors have been integrated in the proposed model. The proposed model considered most of the outstanding latent variables suggested by literature which influence to the individual behavior. Affection and cognition are two constructs related to current service quality, whereas, factors which are not related to current service quality are implicit loyalty, descriptive norm and habit. Although there was an absence of cognitive loyalty due to insignificant statistic coefficient in the proposed model, it is not necessary to exclude the factor out of the generalized model. A possible reason to explain for the case is that people have different reliance on cognition versus affection (e.g., Ajzen, 2001). Of the present study, the data showed that people give a strong reliance on affection as a perceived service quality.

The two-stage simulation approach has been demonstrated via a good estimation for the proposed loyalty-based demand model in which loyalty was decomposed into three main phases including attitudinal loyalty, conative loyalty and action loyalty. First, a direct latent variable multiple regression between frequency of use and the mentioned determinants may not get a good support from data due to the ignorance of factors which happen during the transfer time from intention to actual use. An example for the mentioned factors can be listed as planning (e.g., Schwarzer, 1992). As such, a regression between the mentioned determinants and intention guarantees a good estimation result because most of the key determinants of intention have been considered in the model. Second, one of the weaknesses of regression technique is that it does not consider the consequential order of impacts. However, by adapting path coefficients between intention and frequency of use provided by the SEM model describing the whole structure of loyalty, the proposed model has indirectly added up the effect of consequential impacts because the coefficients were yielded based on a structural analysis.

The proposed model has an advantage respect to predictive capability compared to some conventional demand models. Within public transportation, although there is a dominant number of studies on demand modeling focus on factors influencing to mode choice (e.g., Eriksson *et al*., 2013; Rojo *el al*., 2012; Diana, 2010; Sunitiyoso and Matsumoto, 2009), this study defines its different territory regarding to demand measurement. Specifically, the proposed model does not impress on the magnitude of impacts of factors toward the outcome (frequency of use). In stead, it focuses on the magnitude of the outcome due to changes of perceive service quality. With such attention, the proposed model was more flexible compared with conventional studies in term of considering different scenarios of service quality.

An innovative understanding of potential users has been successfully described in the model. It is popular to define that potential users are people who may use a given clear-stated service. A possible reason for the school of thought is probably due to a widespread use of stated preference data in which researchers must specify alternatives for respondents to select. This study excavated the concept of potential users in a different angle. According to that, the focus of the demand model lies on the room for development of bus service. In particular, a limit for the service development was explored. The limit was measured by a maximum frequency of use in case people perceive an ideal bus service. Based on the values of maximum frequency of bus use, bus managers are able to figure out how far their efforts on service improvement will go.

Maximum potential bus usage, which is the valuable information for bus service providers as well as transport planner, has been successfully revealed. This study figured out the value by conducting an analysis to find out how the frequency changes due to an improvement of perceived service quality. The result showed that the frequency will increase 21.74% if everybody perceives an ideal bus service. In fact, practical service operation may probably never get such percentage due to a conflict of satisfaction between groups of people. For example, elder people want a long transfer time from bus to train, but young people want the short transfer time. Thus, it should be more realistic to consider ideal case for each of potential user groups. Data analysis showed that an improvement to ideal perceived service quality toward the group of car drivers will increase the bus patronage up to of 18.05%. The increase puts the group of car drivers at the first priority for service improvement. The second and third priorities for service improvement should give to groups of men and women with increases of 11.58% and 10.25% respectively. Finally, there should be a warn to bus managers if they want to focus on non-car drivers group because the group only plus 3.81 % of bus use with their highest affective score.

By integrating psychological factors in a well-constructed model, results provided by this study can probably be more reliable than those of the comparable study. A previous study by Santoso *et al.* (2012) conducted in Hidaka city, Japan (the same study area), showed a figure of 14% regard to the increase in bus ridership in case there is an improvement in service quality. The value is different compared with that of the present study probably because of some reasons. First, the increase of 14% was for the group of train commuter. Beside, data derived from the authors' data showed that 85% of the train commuters do not use cars. Thus, it is logical to assume that the 14% increase is mostly for the group of non-car drivers. As such, the result found by Santoso *et al.* (2012) is quite high compared to the present study with an increase of 3.81% for the group of non-car driver regard to the supposed ideal perceived service. A possible reason explained for the difference may come from the fact that Santoso *et al.* (2012) provided their estimation based on a simple procedure. They simply add up some optimistic cases extracted from their data. And the authors narrow their concerns on service quality and do not consider impacts of psychological factors.

According to analysis results, bus managers and transport planner should pay attention on the existence of the non-service-quality factors. As can be seen from Table 4, when service quality gets the highest level (ideal service to everybody), the average score for bus patronage is of 2.71 within a rage from 4 (don't use) to 1 (everyday use). It means that bus service will not become an everybody - daily-travel mode if the service providers solely focus on service quality. Therefore, an appropriate suggestion for bus managers is to make efforts on impacts of non-service-quality factors such as descriptive norm, habit and implicit loyalty.

5. CONCLUSIONS

As an additional supplement to the literature of demand models, this study has successfully proposed a psychological demand model for bus service industry. The proposed model's foundation was close to the nature of human decision-making process as well as the concept of potential users. An excavation on both service-quality-rated factors (cognitive loyalty and affective loyalty) and non-service-quality-factors (implicit loyalty, descriptive norm, habit) makes the proposed model outstanding in term of capability in predicting and explaining different practical scenarios. This study insists its distinction as the first attempt to quantify bus patronage based on loyalty framework. Furthermore, it introduces a new examination on the concept of potential users by providing the maximum values of bus patronage respect to various proposed ideal service qualities. Overall, the present study has substantially contributed to the body knowledge of bus demand modeling.

Empirical findings in this study are critical for bus service managers as well as transport planner. First, it provides a reliable the demand model to predict bus patronage. According to the final model, people seem to pay their reliance on affection when perceiving service quality. It means people judge service quality based on both satisfaction and emotion related to the target service quality. Therefore, an effort toward bus service improvement should cover both people' satisfaction and emotion. Second, maximum values of bus patronage regard to different scenarios can be considered as reference limits for bus managers when making strategy at any bus service of a given resident area. The data also suggested that the group of car divers with a potential increase 18.05% should be the first priority for improving of bus service quality, whereas, the group of non-car drivers was close to its limit of bus patronage with a small increase of 3.81%. Thus, the later group should be at the lowest priority rank for service improvement. Finally, the data showed that even bus service reaches the highest quality, bus patronage can still be increased if there is an improvement in descriptive norm, habit and/or implicit loyalty.

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