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Determinants of Online Transportation Adoption: An Extended UTAUT2 Model with Loyalty Program

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ABSTRACT

This study investigates the factors influencing the adoption of online transportation services, focusing on loyalty programs within the UTAUT2 framework. Online transportation platforms, such as Gojek and Grab, have revolutionized service delivery in Indonesia, yet customer retention remains a challenge. Utilizing an extended UTAUT2 model, this research incorporates constructs like Hedonic Motivation, Price Value, and Habit, alongside moderating variables such as Age, Gender, and Experience. Data from 413 active users in Medan City were analyzed using Structural Equation Modeling (SEM) via SmartPLS 3. Results highlight the critical role of loyalty programs in enhancing user engagement and retention by boosting behavioral intentions and actual usage behaviors. Findings offer actionable insights for platform providers to optimize marketing strategies and improve customer loyalty through tailored program designs.

Keyword: Loyalty programs, online transportation, UTAUT2 model

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1. INTRODUCTION

Information technology plays a critical role in human interaction across various life domains, particularly in transportation (Arts et al., 2021). In Indonesia, the transportation sector has significantly driven economic growth, influencing the production, distribution, and consumption of goods and services. With the nation's growing population, the demand for transportation has also risen, making the transportation industry increasingly lucrative. Concurrently, there is a notable shift from conventional transportation services to online platforms, a transition driven by globalization and the digitalization of daily activities (Chung, 2021; Siswadi et al., 2023).

Online transportation platforms provide several conveniences, including easy access to services, seamless payment options, and the ability to order food and beverages via smartphones at any time or place (Ashari et al., 2021). Despite these advantages, many customers remain hesitant to repeatedly use online transportation applications. Enhancing application quality is therefore crucial to promoting customer retention. Implementing loyalty programs emerges as a promising strategy to encourage repeated usage and foster customer loyalty, ultimately boosting repurchase rates (Chen et al., 2021).

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been extensively utilized to study technology adoption, particularly in organizational settings (Erjavec & Manfreda, 2022). This model explains up to 70% of the variance in behavioral intentions toward technology adoption (Bu et al., 2021; Yu et al., 2021). However, its initial focus on employee technology adoption limits its applicability in consumer contexts. To address this gap, the UTAUT2 model was developed with additional constructs tailored to consumer behavior (Zaid Kilani et al., 2023).

UTAUT2 expands upon the original UTAUT by incorporating three consumer-related constructs: Hedonic Motivation, Price Value, and Habit. It also includes moderating variables such as Age, Gender, and Experience, all of which impact Behavioral Intention and Usage Behavior. Research shows that UTAUT2 enhances the explanatory power for variance in behavioral intention (56%-74%) and usage behavior (40%-52%) (Gupta et al., 2018; Venkatesh et al., 2012).

Despite the widespread application of UTAUT2, the integration of Loyalty Programs within this framework, particularly in online transportation services, remains underexplored. Given the diverse designs, incentives, and implementations of loyalty programs across platforms, it is critical to examine how perceived benefits of these programs influence behavioral intention and usage behavior in services like Gojek and Grab. This study aims to analyze the role of loyalty programs in shaping consumer behavior within the UTAUT2 framework, providing insights into effective strategies to enhance user retention and satisfaction in online transportation platforms.

2. LITERATURE REVIEW, HYPOTHESES, AND METHODS

2.1 Literature Review

Loyalty programs serve as a strategic marketing tool that combines personalized promotional activities with effective communication to enhance customer relationships. These programs offer both tangible rewards, such as discounts, vouchers, or gifts, and intangible benefits, including exclusive services, elevated status, or tailored information. Studies have demonstrated the effectiveness of loyalty programs in increasing consumer-perceived value, motivating participation, and strengthening purchasing behavior and brand loyalty (Chen et al., 2021). For instance, research by Hwang & Choi (2020) highlights that gamified loyalty programs significantly boost consumer loyalty and behavioral intentions, with enjoyment and positive attitudes acting as critical mediating factors. These findings underscore the importance of designing loyalty programs that not only retain customers but also foster sustained active engagement, providing actionable insights for businesses seeking to optimize their marketing strategies.

2.2 Conceptual Framework for Problem Solving

The conceptual framework for problem solving provides a structured and systematic approach to understanding, analyzing, and addressing problems efficiently. This framework serves as a guide for identifying key issues, evaluating potential solutions, and implementing strategies to resolve them effectively. The evaluation results of the measurement model, as depicted in Figure 1, illustrate the application of this framework, highlighting its utility in achieving robust problem-solving outcomes.

2.3 Hypotheses

Building upon the previously discussed issues, this study proposes a set of hypotheses to address the identified research problems, focusing on factors influencing the use of online transportation services in Medan. The following hypotheses are proposed:

H1: Performance Expectancy (X1) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.

H2: Effort Expectancy (X2) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.

H3: Social Influence (X3) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.

H4: Facilitation Conditions (X4) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.

H5: Facilitation Conditions (X4) positively influences Use Behavior (Y2) to use online transportation services in Medan.

H6: Hedonic Motivation (X5) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.
H7: Price Value (X6) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.
H8: Habit (X7) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.
H9: Habit (X7) positively influences Use Behavior (Y2) to use online transportation services in Medan.
H10: Loyalty Program (X8) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan.
H11: Behavioral Intentions (Y1) positively influences Use Behavior (Y2) to use online transportation services in Medan.
H12a-i: Age moderates the relationships between key variables (such as Performance Expectancy (X1), Effort Expectancy (X2), Social Influence (X3), Facilitation Conditions (X4), Hedonic Motivation (X5), Price Value (X6), and Habit (X7)) and both Behavioral Intentions (Y1) and Use Behavior (Y2) in Medan.
H13a-h: Gender moderates the relationships between key variables (such as Performance Expectancy (X1), Effort Expectancy (X2), Social Influence (X3), Facilitation Conditions (X4), Hedonic Motivation (X5), Price Value (X6), and Habit (X7)) and both Behavioral Intentions (Y1) and Use Behavior (Y2) in Medan.
H14a-h: Experience moderates the relationships between key variables (such as Effort Expectancy (X2), Social Influence (X3), Facilitation Conditions (X4), Hedonic Motivation (X5), and Habit (X7)) and both Behavioral Intentions (Y1) and Use Behavior (Y2) in Medan.

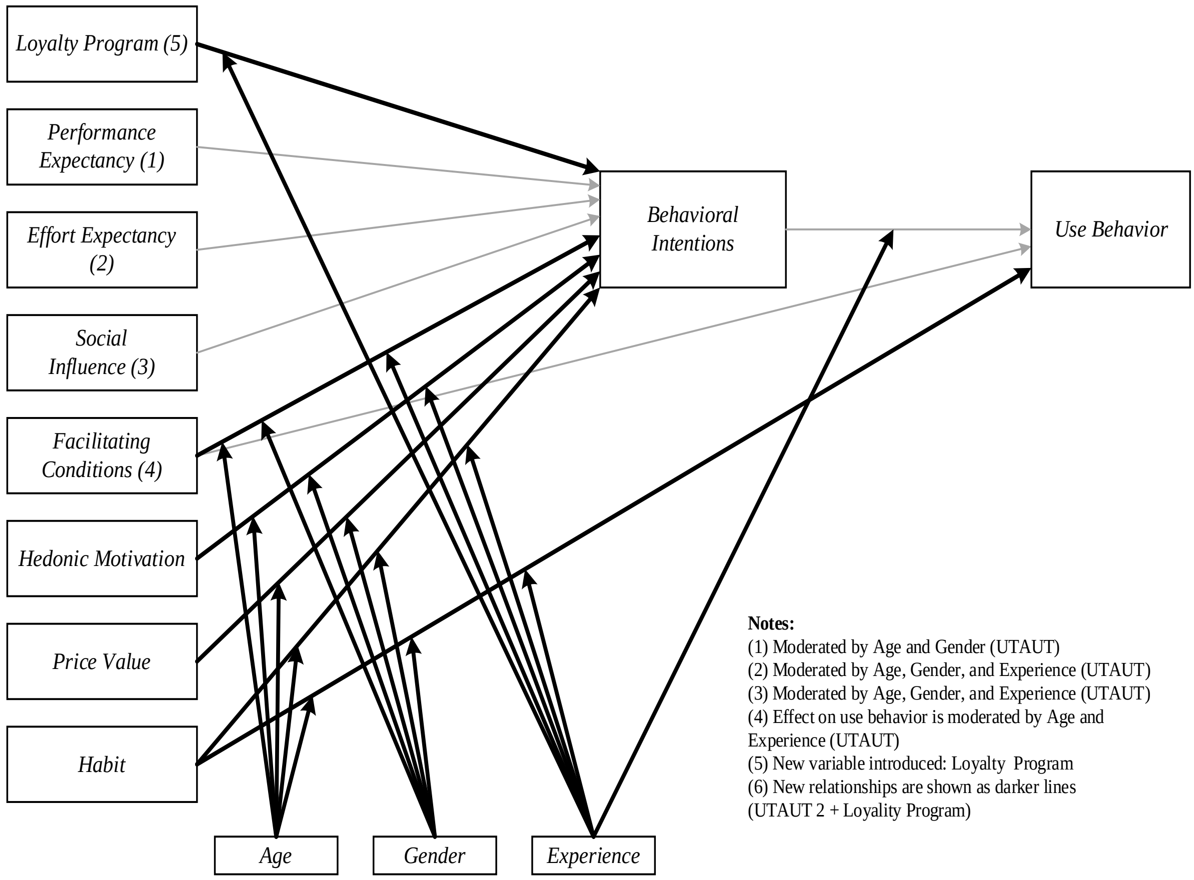

Figure 1. Evaluation of relationships among key variables in the measurement model

2.4 Method

This study adopts a quantitative methodology, employing surveys as the primary data collection tool. To ensure the inclusion of only active users of online transportation services (Gojek and Grab), the questionnaire begins with a filter question: *"How often do you use Online Transportation services (Gojek and Grab)?"* Respondents indicating any usage frequency are categorized as active users and allowed to proceed with the survey. Conversely, those selecting *"Never"* or *"Only use one application"* are classified as inactive users and excluded from further participation. Consequently, data collection is limited to active users of online transportation applications.

The research process, as outlined in Figure 2, begins with the identification of the core research problem and the design of a structured questionnaire using Google Forms, which is distributed to participants via a sharable link. The collected responses are first organized in Microsoft Excel and subsequently analyzed using SmartPLS 3 software. The analytical phase involves hypothesis testing and a comprehensive results analysis, culminating in final conclusions. To validate the proposed hypotheses, the study employs multiple regression analysis and Structural Equation Modeling (SEM), with SmartPLS 3 serving as the primary analytical tool. The ultimate objective is to examine how various factors influence behavioral intention and usage behavior regarding online transportation services, focusing on Gojek and Grab users in Medan.

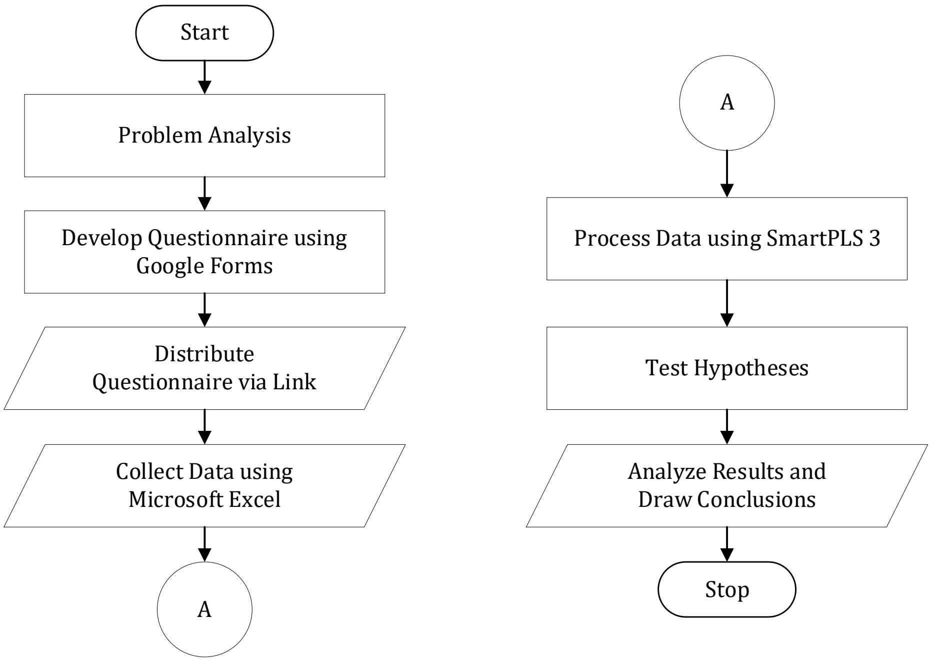

Figure 2. Research method

2.5 Research Object

This study focuses on the residents of Medan City who are active users of online transportation applications, specifically Gojek and Grab, across various areas in the city. To ensure the inclusion of only relevant respondents, a filter question is incorporated at the beginning of the questionnaire. The question asks, *"How often do you use online transportation services (Gojek and Grab)?"* Respondents who report any usage frequency are identified as active users and are allowed to proceed with the survey. Conversely, those who answer *"Never"* or *"Only one of them"* are classified as inactive users and are excluded from further participation. Data collection is therefore restricted to individuals who actively use both Gojek and Grab applications.

The sample for this research comprises all active users of online transportation services (Gojek and Grab) in Medan. A non-probability sampling approach is employed, incorporating methods such as convenience sampling, sample matching, and network sampling. Among these, convenience sampling is selected due to its practical advantages in locating and recruiting participants. This approach also simplifies participation for respondents, as the questionnaire is easily distributed via Google Forms.

2.6 Sample and Data Collection Method

The minimum required sample size for this study is determined using the Lemeshow formula, which is appropriate for populations with an unknown size. The formula is expressed in Equation (1):

$$n = \frac{Z^2 . P . (1 - P)}{d^2} \quad (1)$$

Explanation:

n : Required sample size

Z : The critical value from the standard normal distribution for a given confidence level: Z = 1.96 for a 95% confidence level; Z = 1.645 for a 90% confidence level; Z = 2.576 for a 99% confidence level.

P : Proportion of the population expected to have the attribute of interest. If unknown, p = 0.5 is commonly used to ensure maximum variability and the largest possible sample size.

d : Desired margin of error or precision level (e.g., d = 0.05 for 5%)

Using this formula, the sample size required for the study is calculated as:

$$n = \frac{(1.96)^2 . 0.5 . (1 - 0.5)}{(0.05)^2} = 385\ respondents$$

Thus, the minimum required sample size is 385 respondents, representing active users of online transportation applications (Gojek and Grab) in Medan City. To ensure that the sample aligns with the research objectives, only active users are included in the study, as determined by a filter question at the beginning of the survey.

To collect data from this sample, the study employs a quantitative framework, emphasizing surveys as the primary tool. This approach is chosen to gather statistically reliable information while addressing potential variations within the dataset (Rooshenas et al., 2019). A structured questionnaire, developed with a five-point Likert scale, is utilized to capture participants' opinions and attitudes. The Likert scale provides five distinct response levels, enabling respondents to articulate their perspectives on key aspects of online transportation services. This method ensures consistency in data collection across the calculated sample size, facilitating robust analysis and hypothesis testing.

3. RESULTS AND DISCUSSION

Based on 413 valid responses collected through distributed surveys, Table 1 provides a detailed summary of the respondents' characteristics, categorized by district, age, gender, and experience. The table highlights the geographic distribution of participants across various districts in Medan, their age groups, gender composition, and frequency of using online transportation services.

Table 1. Respondent characteristics

Dimension	Category	Count
District	Medan Amplas	16
	Medan Area	47
	Medan Barat	11
	Medan Baru	12
	Medan Belawan	3
	Medan Deli	17
	Medan Denai	27
	Medan Helvetia	20

Table 1. Respondent characteristics (continued)

Dimension	Category	Count
District	Medan Johor	20
	Medan Kota	91
	Medan Labuhan	9
	Medan Maimun	4
	Medan Marelan	9
	Medan Perjuangan	25
	Medan Petisah	7
	Medan Polonia	2
	Medan Sunggal	19
	Medan Selayang	11
	Medan Tembung	36
	Medan Tuntungan	9
	Medan Timur	18
Age	15 - 24 years	333
	25 - 34 years	67
	35 - 44 years	9
	45 - 54 years	4
Gender	Male	191
	Female	222
Experience	At least once a week	209
	At least once a month	204

3.1 Evaluation of the Measurement Model

The evaluation of the measurement model aims to assess how effectively the indicators reflect their respective latent variables. This process involves examining convergent validity, discriminant validity, and composite reliability using the SmartPLS 3 application. The results of this evaluation are depicted in Figure 3.

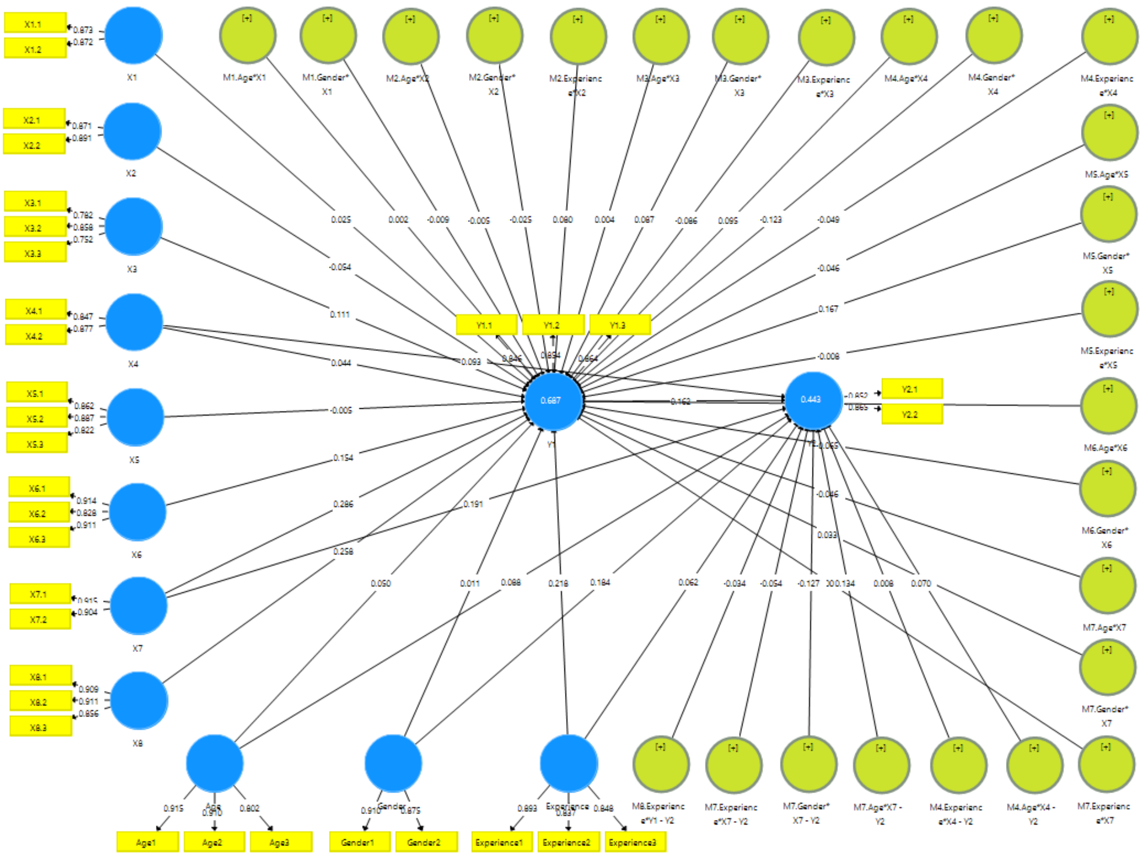

Figure 3. Diagram of measurement model evaluation results

1. Convergent Validity Test

Convergent validity assesses whether indicators of a variable correlate strongly with their construct. Using the SmartPLS 3 application, convergent validity is determined by two criteria: (1) The loading factor between the indicator and its latent variable should exceed 0.7 (Loading Factor ≥ 0.7); (2) The Average Variance Extracted (AVE) value should be greater than 0.5 (AVE ≥ 0.5). Table 2 shows the results of the convergent validity test, where all indicators meet the specified criteria.

Table 2. Convergent validity test results

Variable	Indicator	Loading Factor	AVE	Remark
Performance Expectancy (X1)	X1.1	0.873	0.762	✓
	X1.2	0.872		✓
Effort Expectancy (X2)	X2.1	0.871	0.776	✓
	X2.2	0.891		✓
Social Influence (X3)	X3.1	0.782	0.638	✓
	X3.2	0.858		✓
	X3.3	0.752		✓
Facilitation Conditions (X4)	X4.1	0.847	0.744	✓
	X4.2	0.877		✓
Hedonic Motivation (X5)	X5.1	0.862	0.735	✓
	X5.2	0.887		✓
	X5.3	0.822		✓
Price Value (X6)	X6.1	0.914	0.784	✓
	X6.2	0.828		✓
	X6.3	0.911		✓
Habit (X7)	X7.1	0.915	0.827	✓
	X7.2	0.904		✓
Loyalty Program (X8)	X8.1	0.909	0.797	✓
	X8.2	0.911		✓
	X8.3	0.856		✓
Behavioral Intentions (Y1)	Y1.1	0.846	0.730	✓
	Y1.2	0.854		✓
	Y1.3	0.864		✓
Use Behavior (Y2)	Y2.1	0.852	0.737	✓
	Y2.2	0.865		✓
Age	Age1	0.915	0.769	✓
	Age2	0.910		✓
	Age3	0.802		✓
Gender	Gender1	0.910	0.797	✓
	Gender2	0.875		✓
Experience	Experience1	0.893	0.739	✓
	Experience2	0.837		✓
	Experience3	0.848		✓

2. Discriminant Validity Test

Discriminant validity evaluates whether an indicator is more strongly associated with its assigned variable than with other variables. This is assessed by examining cross-loading values. Table 3 illustrates the results, with shaded cells highlighting stronger correlations between each indicator and its corresponding construct.

3. Composite Reliability

Composite reliability tests the consistency of indicators within a variable, using Cronbach's Alpha and Composite Reliability values. Variables are categorized as: (1) Reliable: Cronbach's Alpha ≥ 0.7 and Composite Reliability; (2) Moderately Reliable: Cronbach's Alpha < 0.7, but Composite Reliability ≥ 0.7; (3) Highly Reliable: Both metrics achieve perfect scores of 1.000.

Table 3. Discriminant validity test results

Indicator	X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2	Age	Gender	Experience
X1.1	0.873	0.514	0.209	0.468	0.524	0.272	0.368	0.389	0.393	0.458	0.279	0.488	0.491
X1.2	0.872	0.401	0.307	0.389	0.446	0.373	0.390	0.314	0.392	0.423	0.303	0.427	0.444
X2.1	0.473	0.871	0.256	0.524	0.502	0.272	0.287	0.386	0.324	0.392	0.246	0.420	0.452
X2.2	0.452	0.891	0.212	0.546	0.515	0.266	0.290	0.383	0.351	0.283	0.207	0.349	0.437
X3.1	0.246	0.209	0.782	0.258	0.330	0.299	0.191	0.258	0.309	0.277	0.289	0.274	0.290
X3.2	0.221	0.201	0.858	0.236	0.262	0.259	0.243	0.236	0.367	0.170	0.343	0.272	0.304
X3.3	0.244	0.225	0.752	0.327	0.260	0.287	0.220	0.288	0.328	0.261	0.335	0.362	0.318
X4.1	0.457	0.564	0.281	0.847	0.541	0.323	0.348	0.450	0.403	0.361	0.300	0.501	0.526
X4.2	0.394	0.489	0.306	0.877	0.539	0.464	0.340	0.528	0.466	0.376	0.301	0.417	0.453
X5.1	0.479	0.531	0.325	0.541	0.862	0.396	0.400	0.498	0.463	0.419	0.307	0.456	0.552
X5.2	0.528	0.524	0.343	0.547	0.887	0.452	0.471	0.516	0.528	0.448	0.325	0.541	0.613
X5.3	0.416	0.429	0.236	0.521	0.822	0.362	0.382	0.554	0.466	0.380	0.271	0.440	0.536
X6.1	0.311	0.251	0.314	0.392	0.393	0.914	0.494	0.467	0.522	0.241	0.295	0.237	0.342
X6.2	0.417	0.320	0.290	0.463	0.502	0.828	0.532	0.493	0.507	0.318	0.384	0.395	0.495
X6.3	0.260	0.244	0.326	0.371	0.366	0.911	0.500	0.478	0.552	0.255	0.336	0.261	0.328
X7.1	0.377	0.259	0.238	0.313	0.451	0.539	0.915	0.364	0.600	0.430	0.285	0.371	0.432
X7.2	0.413	0.338	0.262	0.414	0.439	0.504	0.904	0.360	0.534	0.445	0.302	0.404	0.467
X8.1	0.398	0.409	0.308	0.534	0.566	0.511	0.356	0.909	0.599	0.377	0.318	0.496	0.594
X8.2	0.354	0.443	0.285	0.558	0.597	0.500	0.328	0.911	0.605	0.391	0.312	0.466	0.597
X8.3	0.324	0.311	0.275	0.427	0.460	0.434	0.384	0.856	0.559	0.320	0.314	0.387	0.524
Y1.1	0.391	0.330	0.288	0.396	0.485	0.542	0.565	0.524	0.846	0.492	0.309	0.405	0.483
Y1.2	0.384	0.349	0.354	0.467	0.510	0.438	0.532	0.565	0.854	0.442	0.397	0.495	0.646
Y1.3	0.378	0.303	0.434	0.433	0.461	0.548	0.505	0.599	0.864	0.435	0.442	0.447	0.574
Y2.1	0.417	0.304	0.267	0.337	0.391	0.299	0.365	0.358	0.506	0.852	0.351	0.432	0.412
Y2.2	0.450	0.348	0.233	0.396	0.441	0.228	0.459	0.342	0.413	0.865	0.323	0.460	0.475
Age1	0.282	0.229	0.364	0.318	0.335	0.374	0.288	0.324	0.427	0.361	0.915	0.371	0.363
Age2	0.271	0.193	0.360	0.267	0.292	0.376	0.253	0.295	0.393	0.317	0.910	0.345	0.341
Age3	0.324	0.254	0.341	0.331	0.296	0.248	0.306	0.306	0.355	0.351	0.802	0.514	0.467
Gender1	0.500	0.403	0.321	0.497	0.534	0.308	0.432	0.461	0.494	0.508	0.386	0.910	0.601
Gender2	0.432	0.372	0.356	0.445	0.464	0.288	0.320	0.440	0.442	0.413	0.452	0.875	0.594
Experience1	0.502	0.487	0.299	0.524	0.623	0.382	0.458	0.570	0.600	0.472	0.391	0.614	0.893
Experience2	0.472	0.433	0.286	0.471	0.540	0.305	0.396	0.477	0.440	0.464	0.329	0.586	0.837
Experience3	0.411	0.382	0.391	0.462	0.544	0.427	0.417	0.597	0.653	0.404	0.416	0.529	0.848

Table 4. Composite reliability test results

Variable	Cronbach's Alpha	Composite Reliability	Remarks
PE (X1)	0.687	0.865	✓
EE (X2)	0.711	0.874	✓
SI (X3)	0.715	0.840	✓
FC (X4)	0.656	0.853	✓
HM (X5)	0.820	0.893	✓
PV (X6)	0.861	0.916	✓
H (X7)	0.791	0.905	✓
LP (X8)	0.872	0.921	✓
BI (Y1)	0.815	0.890	✓
UB (Y2)	0.643	0.849	✓
Age	0.848	0.909	✓
Gender	0.747	0.887	✓
Experience	0.824	0.895	✓
M1.Age*X1 (BI)	1.000	1.000	✓

Table 4. Composite reliability test results (continued)

Variable	Cronbach's Alpha	Composite Reliability	Remarks
M1.Gender*X1 (BI)	1.000	1.000	✓
M2.Age*X2 (BI)	1.000	1.000	✓
M2.Gender*X2 (BI)	1.000	1.000	✓
M2.Experience*X2 (BI)	1.000	1.000	✓
M3.Age*X3 (BI)	1.000	1.000	✓
M3.Gender*X3 (BI)	1.000	1.000	✓
M3.Experience*X3 (BI)	1.000	1.000	✓
M4.Age*X4 (BI)	1.000	1.000	✓
M4.Gender*X4 (BI)	1.000	1.000	✓
M4.Experience*X4 (BI)	1.000	1.000	✓
M4.Age*X4 (UB)	1.000	1.000	✓
M4.Experience*X4 (UB)	1.000	1.000	✓
M5.Age*X5 (BI)	1.000	1.000	✓
M5.Gender*X5 (BI)	1.000	1.000	✓
M5.Experience*X5 (BI)	1.000	1.000	✓
M6.Age*X6 (BI)	1.000	1.000	✓
M6.Gender*X6 (BI)	1.000	1.000	✓
M7.Age*X7 (BI)	1.000	1.000	✓
M7.Gender*X7 (BI)	1.000	1.000	✓
M7.Experience*X7 (BI)	1.000	1.000	✓
M7.Age*X7 (UB)	1.000	1.000	✓
M7.Gender*X7 (UB)	1.000	1.000	✓
M7.Experience*X7 (UB)	1.000	1.000	✓
M8.Experience*Y1 (UB)	1.000	1.000	✓

Table 4 highlights the reliability of the variables analyzed in this study. Most variables exhibit strong reliability, as indicated by their Cronbach's Alpha and Composite Reliability values. While a few variables have Cronbach's Alpha scores below 0.7, their high Composite Reliability values demonstrate adequate internal consistency. The reliability breakdown is as follows:

a. Reliable Variables: Variables with Cronbach's Alpha scores of 0.7 or higher and Composite Reliability values of at least 0.7 are categorized as reliable. These include X2, X3, X5, X6, X7, X8, Y1, age, gender, and experience.
b. Moderately Reliable Variables: Variables with Cronbach's Alpha scores below 0.7 but Composite Reliability values above 0.7 are considered moderately reliable. These variables, including X1, X4, and Y2, show sufficient reliability despite slightly lower internal consistency.
c. Highly Reliable Variables: Mediators (M1 to M8) achieved perfect scores for both Cronbach's Alpha and Composite Reliability (1.000), demonstrating exceptional consistency and reliability.

3.2 Structural Model Evaluation

The evaluation of the structural model focuses on assessing the relationships between latent constructs within the research framework. The structural model analysis was conducted using the bootstrapping technique in SmartPLS 3, with the results presented in Figure 4. This evaluation involves three main stages: testing the coefficient of determination (R-Square), testing predictive relevance (Q-Square), and conducting hypothesis testing to verify relationships between latent variables.

1. Testing the Coefficient of Determination (R-Square)

The R-Square test measures how well the model explains the variability of the dependent variables. The results, shown in Table 5, classify R-Square values as weak ($R^2 < 0.33$), moderate ($0.33 \leq R^2 \leq 0.67$), or strong ($R^2 > 0.67$).

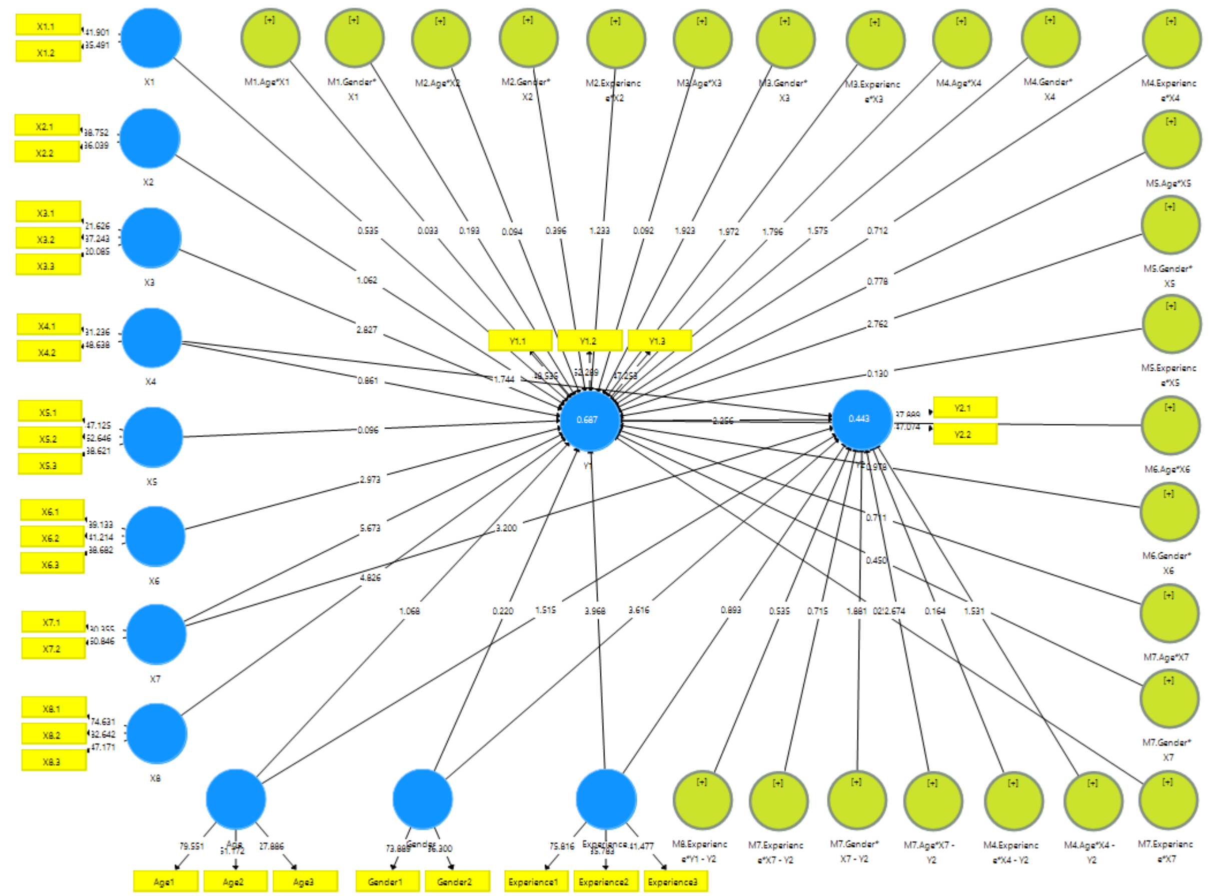

Figure 4. Results of structural model evaluation

Table 5. R-Square values

Variable	R-Square	R-Square Adjusted	Description
Behavioral Intentions	0.687	0.662	Good
Use Behavior	0.443	0.426	Moderate

The results indicate that the model explains 68.7% of the variance in Behavioral Intentions, with the remaining 31.3% influenced by external factors. For Use Behavior, 44.3% of the variance is explained by the model, while 55.7% is attributed to external factors. These values suggest that the structural model provides acceptable explanatory power.

2. Testing Predictive Relevance (Q-Square)

The Q-Square test evaluates the model's ability to predict actual outcomes. A Q-Square value greater than 0 indicates good predictive relevance, while a value less than or equal to 0 suggests weak predictive significance. The results, displayed in Table 6, demonstrate that the model exhibits strong predictive relevance.

Table 6. Q-Square values

Variable	Q-Square	Description
Behavioral Intentions	0.462	Predictive Relevance
Use Behavior	0.291	

The Q-Square value of 0.462 for Behavioral Intentions indicates that 46.2% of the variance is accounted for by the model, while 53.8% stems from external influences. Similarly, the Q-Square value of 0.291 for Use Behavior shows that 29.1% of the variance is explained by the model, with the remaining 70.9% attributed to external factors.

3. Hypothesis Testing

Hypotheses were tested using the bootstrapping technique in SmartPLS 3 at a 5% significance level ($p < 0.05$). Relationships were deemed significant if the T-statistic exceeded 1.96 and the p-value was below 0.05. The results are summarized in Table 7.

Table 7. Hypothesis testing results

Hypothesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Description
PE (X1) → BI (Y1)	0.025	0.029	0.047	0.535	0.593	Rejected
EE (X2) → BI (Y1)	-0.054	-0.046	0.050	1.062	0.289	Rejected
SI (X3) → BI (Y1)	0.111	0.109	0.039	2.827	0.005	Accepted
FC (X4) → BI (Y1)	0.044	0.036	0.052	0.861	0.389	Rejected
FC (X4) → UB (Y2)	0.093	0.094	0.053	1.744	0.082	Rejected
HM (X5) → BI (Y1)	-0.005	-0.008	0.055	0.096	0.924	Rejected
PV (X6) → BI (Y1)	0.154	0.161	0.052	2.973	0.003	Accepted
H (X7) → BI (Y1)	0.286	0.290	0.050	5.673	0.000	Accepted
H (X7) → UB (Y2)	0.191	0.193	0.060	3.200	0.001	Accepted
LP (X8) → BI (Y1)	0.258	0.257	0.053	4.826	0.000	Accepted
BI (Y1) → UB (Y2)	0.162	0.158	0.072	2.256	0.024	Accepted
M1.Age*PE (X1) → BI (Y1)	0.002	-0.005	0.049	0.033	0.973	Rejected
M2.Age*EE (X2) → BI (Y1)	-0.005	-0.010	0.058	0.094	0.925	Rejected
M3.Age*SI (X3) → BI (Y1)	0.004	0.000	0.045	0.092	0.927	Rejected
M4.Age*FC (X4) → BI (Y1)	0.095	0.090	0.053	1.796	0.073	Rejected
M4.Age*FC (X4) → UB (Y2)	0.070	0.074	0.046	1.531	0.126	Rejected
M5.Age*HM (X5) → BI (Y1)	-0.046	-0.045	0.059	0.778	0.437	Rejected
M6.Age*PV (X6) → BI (Y1)	0.073	0.074	0.056	1.296	0.196	Rejected
M7.Age*H (X7) → BI (Y1)	-0.046	-0.040	0.065	0.711	0.478	Rejected
M7.Age*H (X7) → UB (Y2)	0.134	0.133	0.050	2.674	0.008	Accepted
M1.Gender*PE (X1) → BI (Y1)	-0.009	-0.007	0.046	0.193	0.847	Rejected
M2.Gender*EE (X2) → BI (Y1)	-0.025	-0.031	0.064	0.396	0.692	Rejected
M3.Gender*SI (X3) → BI (Y1)	0.087	0.093	0.045	1.923	0.055	Rejected
M4.Gender*FC (X4) → BI (Y1)	-0.123	-0.095	0.078	1.575	0.116	Rejected
M5.Gender*HM (X5) → BI (Y1)	0.167	0.163	0.061	2.762	0.006	Accepted
M6.Gender*PV (X6) → BI (Y1)	-0.065	-0.079	0.066	0.978	0.329	Rejected
M7.Gender*H (X7) → BI (Y1)	0.033	0.027	0.073	0.450	0.653	Rejected
M7.Gender*H (X7) → UB (Y2)	-0.127	-0.120	0.067	1.881	0.061	Rejected
M2.Experience*EE (X2) → BI (Y1)	0.080	0.081	0.065	1.233	0.218	Rejected
M3.Experience*SI (X3) → BI (Y1)	-0.086	-0.083	0.044	1.972	0.049	Accepted
M4.Experience*FC (X4) → BI (Y1)	-0.049	-0.049	0.069	0.712	0.476	Rejected
M4.Experience*FC (X4) → UB (Y2)	0.008	0.004	0.050	0.164	0.870	Rejected
M5.Experience*HM (X5) → BI (Y1)	-0.008	-0.012	0.065	0.130	0.897	Rejected
M7.Experience*H (X7) → BI (Y1)	-0.002	-0.001	0.071	0.025	0.980	Rejected
M7.Experience*H (X7) → UB (Y2)	-0.054	-0.052	0.076	0.715	0.475	Rejected
M8.Experience*BI (Y1) → UB (Y2)	-0.034	-0.030	0.063	0.535	0.593	Rejected

3.3 Discussion

H3: Social Influence (X3) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan

According to the findings of the hypothesis test, Social Influence (X3) has a sample mean of 0.111, a T-Statistic of 2.827 (> 1.96), and a P-Value of 0.005 (< 0.05). This result validates the hypothesis by showing that Behavioral Intentions (Y1) is greatly and favorably impacted by Social Influence (X3) when it comes to using online transportation services (like Gojek and Grab) in Medan. The social support Medan inhabitants receive—such as referrals and encouragement to use these services from friends, family, or coworkers—is the source of this effect. Research has shown that social influence has a beneficial effect on behavioral intentions (Alomari & Abdullah, 2023; An et al., 2023; Ginting et al., 2023; Khatimah et al., 2019; Panjaitan & Budiarto, 2019; Saragih et al., 2023). The results of this study are in line with previous findings. However, contrasting findings exist, with some studies indicating a negative impact on Behavioral Intentions (Y1), diverging from this study's results (Purwanto & Loisa, 2020; Syamsudin et al., 2018).

H7: Price Value (X6) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan

According to the findings of the hypothesis test, Price Value (X6) has a sample mean of 0.154, a T-Statistic of 2.973 (> 1.96), and a P-Value of 0.003 (< 0.05). The hypothesis is supported by this result, which demonstrates that Price Value (X6) significantly and favorably affects Behavioral Intentions (Y1) for Medan's online transportation services (Gojek and Grab). This effect is ascribed to the prices' affordability, which attracts customers to these services. Users are more inclined to stick with these services if they believe they are getting good value for their money. These results are consistent with earlier studies that discovered a favorable relationship between price value and behavioral intention (Osei et al., 2022).

H8: Habit (X7) positively influences Behavioral Intentions (Y1) to use online transportation services in Medan

According to the findings of the hypothesis test, Habit (X7) has a sample mean of 0.286, a T-Statistic of 5.673 (> 1.96), and a P-Value of 0.000 (< 0.05). This result validates the hypothesis by showing that Habit (X7) significantly and favorably affects Behavioral Intentions (Y1) for Medan's online transportation services (Gojek and Grab). The people of Medan, who frequently use these services, is said to have developed habits that have contributed to this influence. Regular use improves opinions about the dependability and effectiveness of the service, which increases customers' desire to keep utilizing internet transit in their daily lives. The study's findings are in line with earlier research that shows habit positively affects behavioral intention (Sinaga et al., 2024; Syamsudin et al., 2018).

H9: Habit (X7) positively influences Use Behavior (Y2) of online transportation services in Medan

According to the findings of the hypothesis test, Habit (X7) obtains a sample mean of 0.191, a T-Statistic of 3.200 (> 1.96), and a P-Value of 0.001 (< 0.05). This outcome validates the hypothesis, showing that Habit (X7) significantly improves Use Behavior (Y2) for Medan's online transportation services (Gojek and Grab). The development of regular usage patterns among users is probably the cause of this effect. Because online transportation services are so convenient, easy to use, and effective, people often continue to use them once they've incorporated them into their daily routines. The results of this study are consistent with earlier research that highlights the importance of habit in fostering consistent and long-term usage behavior (Khatimah et al., 2019).

H10: Loyalty Program (X8) positively influence Behavioral Intentions (Y1) to use online transportation services in Medan

According to the findings of the hypothesis test, Loyalty Programs (X8) have a sample mean of 0.258, a T-Statistic of 4.826 (> 1.96), and a P-Value of 0.000 (< 0.05). This result validates the hypothesis by showing that Behavioral Intentions (Y1) in Medan is significantly influenced favorably by Loyalty Program

(X8) to use online transportation services like Gojek and Grab. Discounts, reward points, and special promotions are just a few of the alluring incentives and prizes created for devoted customers that are responsible for this impact. Users' intention to keep using online transportation services is strengthened by these loyalty rewards, which raise user pleasure and engagement. The study's findings support other research that indicates loyalty programs have a beneficial impact on users' inclinations to use the service repeatedly (Hwang & Choi, 2020; Sinaga et al., 2024).

H11: Behavioral Intentions (Y1) positively influences Use Behavior (Y2) of online transportation services in Medan

The findings reveal that Behavioral Intentions (Y1) significantly affect Use Behavior (Y2) in the context of online transportation services, as shown by a T-statistic of 2.256, exceeding the 1.96 threshold, and a P-value of 0.024. The sample estimate was 0.162. This confirms that strong user intentions lead to increased utilization of services like Gojek and Grab in Medan. Factors such as perceived advantages, prior satisfaction, and social recommendations can intensify these intentions. Users demonstrating a higher intent to engage with online transportation services are more likely to integrate them into their daily routines. This result aligns with earlier research highlighting a positive link between Behavioral Intentions and Use Behavior (Purwanto & Loisa, 2020; Sinaga et al., 2024).

H12i: Age moderates the effect of Habit (X7) on Use Behavior (Y2) of online transportation services in Medan

The analysis indicates that Age significantly affects the relationship between Habit (X7) and Use Behavior (Y2) within the context of online transportation services, such as Gojek and Grab, in Medan, as evidenced by a T-statistic of 2.674, surpassing the critical value of 1.96, and a P-value of 0.008, which is less than the 0.05 threshold. The moderation effect of Age is thus confirmed, based on an original sample estimate of 0.134. Furthermore, this study's findings present some deviations from earlier research. Specifically, while previous studies found positive correlations between Performance Expectancy (X1) and Behavioral Intentions (Y1), Effort Expectancy (X2) and Behavioral Intentions (Y1), as well as Facilitation Conditions (X4) and Use Behavior (Y2), this study reveals nuanced variations Ginting et al. (2023).

H13e: Gender moderates the effect of Hedonic Motivation (X5) on Behavioral Intentions (Y1) of online transportation services in Medan

The analysis confirms that Gender moderates the connection between Hedonic Motivation (X5) and Behavioral Intentions (Y1) in the context of online transportation services such as Gojek and Grab in Medan, as indicated by a T-statistic of 2.762, surpassing the critical threshold of 1.96, and a P-value of 0.006, which is below 0.05. The observed sample value is 0.167. This finding highlights the role of gender-based differences in perceptions of enjoyment and satisfaction when using these services. Notably, this outcome diverges from earlier studies, which reported Gender's significant influence on Use Behavior (Y2) at a 10% significance level (Panjaitan & Budiarto, 2019).

H14b: Experience moderates the effect of Social Influence (X3) on Behavioral Intentions (Y1) of online transportation services in Medan

The results show that Experience acts as a moderator in the relationship between Social Influence (X3) and Behavioral Intentions (Y1) within the scope of online transportation services like Gojek and Grab in Medan, with a T-statistic of 1.972, which exceeds the cutoff of 1.96, and a P-value of 0.049. The sample value recorded was -0.086. This suggests that individuals with more extensive experience using these services are more receptive to social recommendations and feedback from their networks, such as friends, family, or peers. However, these findings vary slightly from prior studies, which found no moderating effect of Experience on Behavioral Intention (Panjaitan & Budiarto, 2019).

4. CONCLUSION

The study's findings indicate that Behavioral Intentions (Y1) toward online transportation services like Gojek and Grab in Medan are significantly influenced by Social Influence (X3), Price Value (X6), Habit (X7), and Loyalty Programs (X8). Additionally, actual Use Behavior (Y2) is driven by Habit (X7) and Behavioral Intentions (Y1). However, variables such as Performance Expectancy (X1), Effort Expectancy (X2), Facilitating Conditions (X4), and Hedonic Motivation (X5) do not show a significant effect on Behavioral Intentions (Y1). Moderating factors like age, gender, and experience amplify the impact of certain variables on Y1 and Y2.

To enhance practical recommendations, online transportation providers can adopt successful loyalty programs from other markets. For instance, they could introduce point-based discounts for frequent rides, similar to tiered reward systems that allow users to earn free trips after accumulating points. Providers can also integrate their services with popular e-wallets or partner apps, enabling users to receive cashback, bundled offers, or additional incentives when booking rides alongside other services like food delivery or shopping. Referral programs offering discounts to both new and existing users can further encourage platform adoption and retention.

In terms of limitations, the study's reliance on non-probability sampling and its geographically limited scope—focusing solely on Medan—may restrict the generalizability of the findings. These factors can introduce sampling bias and limit the applicability of the results to broader populations. Future research should address this limitation by using probability sampling techniques and expanding the sample to include respondents from multiple cities across Indonesia. This would ensure more diverse and representative results, enabling a broader understanding of user behavior toward online transportation services.

By focusing on strengthening Social Influence (X3), enhancing Price Value (X6), fostering Habitual Use (X7), and implementing effective Loyalty Programs (X8)—while accounting for age, gender, and experience—service providers can boost user loyalty and improve both Behavioral Intentions (Y1) and Use Behavior (Y2). These measures will help providers like Gojek, and Grab maintain a competitive edge in the market.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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