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# Understanding Adoption of PELNI Mobile: Effects of Barriers, Quality, Trust, and Value

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**ABSTRACT**

The increasing number of PT PELNI passengers, reaching 5.15 million in 2025, has not been matched by a shift toward digital ticketing: PELNI Mobile is used by only about 10% of the national passenger base, suggesting barriers to broader adoption among potential users. This study examines effects of Usage Barrier, Risk Barrier, and Information Quality on Trust; Information Quality on Perceived Value; and Trust and Perceived Value on Adoption Intention, integrating Innovation Resistance Theory (IRT) with information quality dimensions to explain trust formation among potential users of a historically conventional maritime service. Data were collected via purposive sampling from 281 national respondents who use PELNI's sea services, are aware of PELNI Mobile, but have not used it, analyzed using SEM-PLS 4. The model explains 62.7% of variance in Trust, 72.5% in Perceived Value, and 71.7% in Adoption Intention, with good predictive relevance ($Q^2$predict > 0); six of seven hypotheses were supported. Information Quality was the strongest predictor of Trust ($\beta$ = 0.688; p = 0.000), while Risk Barrier was a significant barrier ($\beta$ = -0.239; p = 0.000), far more influential than Usage Barrier, which had no significant effect ($\beta$ = -0.011; p = 0.852). Perceived Value was the most dominant predictor of Adoption Intention ($\beta$ = 0.666; p = 0.000). These results show that transaction-security concerns shape trust more than usability complexity among prospective users of maritime mobile ticketing, a novelty distinguishing this study from other transport-adoption research, with implications for IRT and PELNI's digital adoption efforts.



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## 1. INTRODUCTION

Maritime transportation plays a strategic role for Indonesia as an archipelagic nation, particularly in connecting regions that are inaccessible by land or air. Data from the Central Statistics Agency (BPS) shows that the number of maritime passengers nationwide reached 24,669,332 in 2023 and rose to 30,390,912 in 2024 [1]. PT PELNI plays a vital role as the national shipping company providing passenger transport services to various regions across Indonesia, with the number of passengers served increasing by 1.12% to 5.15 million in 2025 [2]. This increase reflects the high public demand for maritime transportation services and underscores the importance of efforts to improve the quality of service provided by PT PELNI. As passenger volumes continue to rise, digital ticketing systems become increasingly important to support scalable and efficient service delivery, positioning digital adoption as a natural extension of this broader push toward improved service quality.

Technological advancements have also driven digital transformation in the maritime transportation sector, as reflected in a study on the digital readiness of ports in archipelagic nations [3]. In response to this need, PT PELNI launched the PELNI Mobile app to make it easier for passengers to book ferry tickets online. Since its launch, the number of users of this app has increased from 195,000 in 2022 to more than 531,000 in 2025 [4]. However, when set against PELNI's total national passenger volume of 5.15 million in 2025 [2], the number of registered app users represents only around 10% of that figure. Although this comparison is not a precise adoption rate, since unique app users do not map directly onto passenger counts and a single user may account for multiple trips, it nonetheless points to a considerable gap between the app's availability and its actual use among passengers, as evidenced, among other things, by the company's continued need to actively urge tens of thousands of passengers to use PELNI Mobile ahead of the peak Eid homecoming travel period [5].

This phenomenon reflects a pattern of user resistance consistent with findings from studies on mobile ticketing [6], public transportation apps [7], and transit payment systems [8], [9]. Referring to the patterns identified in these studies, barriers to the use of transportation apps may stem from perceptions of operational complexity (classified as a Usage Barrier, UB), as well as concerns about financial loss and personal data security (classified as a Risk Barrier, RB) [10], [11], [12], [13]. Similar patterns tend to contribute to the low intention to use PELNI Mobile, leading some passengers to continue relying on conventional booking methods.

Efforts to understand this phenomenon of resistance in greater depth were undertaken by applying the Innovation Resistance Theory (IRT) developed by [14], as this theory explains that resistance to technology is influenced not only by a lack of Perceived Value (PV) but also by functional barriers (UB and RB). On the other hand, to mitigate these barriers and foster users' adoption intentions, the establishment of trust (Trust/TR) is required. Referring to [15] information systems success model, the establishment of user trust is highly dependent on the quality of information (Information Quality/IQ) presented by an application. This aligns with the findings of [16], which show that when users perceive limited value in a mobile payment solution, this perception can outweigh the influence of usability and risk-related barriers in shaping resistance, underscoring the central role that value considerations play alongside functional barriers. Rather than treating value as a separate barrier construct, however, the present study incorporates this dimension through Perceived Value (PV), positioned as an outcome shaped by TR and IQ that in turn drives Adoption Intention (AI), consistent with variations in how IRT-based studies operationalize value-related resistance. These findings indicate that the lack of clarity in the information conveyed by the application hinders the formation of user trust, thereby leading to a decline in the intention to continue using the service [17], [18], [19].

Trust (TR) is a crucial element in mitigating the risks of digital transactions, particularly through commitments to data security in accordance with Law of the Republic of Indonesia No. 27 of 2022 on Personal Data Protection [20], and in this study is defined based on the multidimensional typology of trust proposed by [21]. Trust is positioned as a construct influenced by UB, RB, and IQ, in line with recent studies that integrate IRT with the constructs of trust and information quality in the context of technology adoption [22], [23]. On the other hand, Perceived Value (PV), defined as an evaluation of the rewards for users' sacrifices [24], also contributes to increased satisfaction and the intention to continue using the technology [25], [26].

This study addresses this gap by analyzing the resistance factors that hinder the adoption of PELNI Mobile through a combination of IRT [14] and the IS Success Model [15], using a model that incorporates the variables UB, RB, IQ, TR, and PV in relation to Adoption Intention (AI). Specifically, this study aims to examine the effects of Usage Barrier, Risk Barrier, and Information Quality on Trust; the effect of Information Quality on Perceived Value; and the effects of Trust and Perceived Value on Adoption Intention among prospective users of PELNI Mobile. The contribution of this study lies not merely in the fact that few empirical studies have examined IRT barriers in Indonesia's digital maritime transportation context, but in articulating the specific mechanism through which these barriers operate: usage and risk barriers, alongside information quality, shape the formation of trust, which in turn drives perceived value and ultimately adoption intention. This integrated barrier-to-trust-to-value pathway distinguishes the present model from prior single-theory approaches to technology adoption in transportation. Theoretically, this study is expected to contribute to the development of Information Systems and digital service marketing, while practically, the results are expected to provide insights for PT PELNI and app developers in reducing barriers and risks associated with usage, as well as improving information quality and security to build user trust. The four research questions (RQs) posed in this study are as follows.

**RQ1**. How do UB, RB, and IQ affect the TR of prospective users of PELNI Mobile?
**RQ2**. How does TR affect the PV and AI of prospective users of PELNI Mobile?
**RQ3**. How does IQ affect the PV of prospective users of PELNI Mobile?
**RQ4**. How does PV affect the AI of prospective users of PELNI Mobile?

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## 2. LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

### 2.1. Innovation Resistance Barriers and Trust Formation

The tendency of users to reject, delay, or avoid adopting an innovation even though it offers better objective benefits than existing alternatives [14], by classifying resistance into functional barriers (Usage Barrier, Value Barrier, Risk Barrier) and psychological barriers (Tradition Barrier, Image Barrier), with usage barriers (UB) and risk barriers (RB) proven to be significant predictors of user resistance in the context of digital services [8]. UB refers to resistance resulting from the innovation's incompatibility with users' habits and workflows [6], [7], while RB refers to resistance resulting from uncertainty regarding the consequences of use, including functional, financial, and privacy risks [10], [12]; in this study, both are measured through the complexity of the booking process and the difficulty of learning the app, as well as concerns about data security and the risk of transaction failure. The mismatch between PELNI Mobile and the habit of manual transactions at ticket counters has the potential to create a perception of complexity that triggers doubts about the app's reliability, as users tend to associate difficulties in using a system with poor system quality [6], [7], while concerns about payment failures, tickets not being issued, or data breaches also constitute risks that are directly perceived, given that trust is established when perceived risks are at an acceptable level [10], [11], [12]. The resulting low TR from these two barriers ultimately weakens AI, defined as an individual's willingness to begin using an innovation, a variable that consistently serves as the outcome construct in technology acceptance models such as the Technology Acceptance Model (TAM) [27] and the Theory of Planned Behavior [28]. In this study, AI is measured through the intention to use PELNI Mobile for subsequent bookings, preference for it over conventional methods, and the intention to make it the primary ticket-booking channel [7]. Based on this discussion, the following hypotheses are formulated:

**H1: Usage Barriers influence the trust of PELNI Mobile users.**
**H2: The Risk Barrier influences PELNI Mobile user's trust.**

### 2.2. The Role of Information Quality in Building Trust and Transaction Intentions

One of the key dimensions of the IS Success Model developed by [15] is the quality of information system output, assessed in terms of the accuracy, relevance, completeness, consistency, and timeliness of information presentation. Its relevance as a determinant of user trust and satisfaction is confirmed in a systematic review of information systems [17] as well as in the testing of the IS Success Model on a mobile travel application [19]; In this study, Information Quality (IQ) is operationalized through the accuracy of departure schedules, the accuracy of fare information, the clarity of ticket availability status, and real-time information updates [17]. Accurate and real-time updated information provides tangible evidence to users that the system is functioning as intended, thereby strengthening confidence in the overall reliability of the app [17], [19], while the clarity of this information also makes it easier for users to assess the time efficiency and convenience offered by the app compared to manual processes at the ticket counter; thus, IQ is also hypothesized to have a direct influence on PV beyond the mediating role of TR [17], [19]. Good perceived information quality not only shapes TR but also directly fosters PV regarding the app's convenience and efficiency; consequently, both factors collectively drive the strengthening of AI (i.e., users' tendency to choose PELNI Mobile as a more reliable option over manual processes at the ticket counter for subsequent bookings) [7], [29]. Based on the above discussion, the following hypotheses are formulated:

**H3: Information Quality influences the trust of PELNI Mobile users.**
**H4: Information Quality influences the perceived value of PELNI Mobile users.**

### 2.3. User Confidence as a Driver of Intent to Conduct Digital Transactions

Drawing on [30] benefit-sacrifice trade-off principle, confidence in PELNI's competence and integrity as a service provider reduces perceived risk as a form of non-financial sacrifice, causing the proportion of perceived benefits to become more dominant relative to the potential losses that may arise from using the application [22], [23]. This trust not only serves as a balancing factor between benefits and risks but also provides a psychological foundation for users in assessing the suitability of PELNI Mobile as a secure and reliable transaction channel. In line with the Theory of Planned Behavior [28], which asserts that beliefs about an object help shape the intention to behave in relation to that object, trust in transaction security and PELNI's commitment is believed to directly drive the intention to use the app, without the need for prior benefit evaluation as established beliefs tend to accelerate users' decision-making processes [22], [23]. The higher the level of trust (TR) users have in the system's reliability and the service provider's good faith, the greater their tendency to set aside any remaining doubts and decide to switch from the habit of manual transactions at the ticket counter. This belief thus leads to the reinforcement of AI, namely the tendency for users to choose PELNI Mobile as a more reliable option compared to the manual process at the ticket counter for their next booking [7], [29]. Based on this discussion, the following hypothesis is formulated:

**H5: Trust influences the Perceived Value of PELNI Mobile users.**
**H6: Trust influences the adoption intention of PELNI Mobile users.**

### 2.4. Perceived Value as a Determinant of Technology Adoption

Users' overall assessment of a service's utility, based on a comparison between perceived benefits and perceived sacrifices was identified by [30] as the primary basis for evaluating the suitability of a product or service for use. This study operationalizes this construct through a group of benefits (time efficiency, ease of access to information, practicality) and a group of sacrifices (technical complexity and estimated costs of digital transactions), given their relevance as determinants of satisfaction and willingness to switch to a digital platform [25], [26], [31]. The greater the benefits perceived by users compared to the sacrifices made, whether in terms of cost, time, or risk, the higher the Perceived Value (PV) that is formed, consistent with the findings of various studies regarding its influence on willingness to use in the context of adopting new digital platforms [25], [26], [31]. The dominance of perceived benefits over these sacrifices ultimately drives the reinforcement of AI (i.e., the tendency for users to choose PELNI Mobile as a more reliable option compared to the manual process at the ticket counter for subsequent bookings) [7], [29]. Based on this discussion, the following hypothesis is formulated:

**H7: Perceived Value influences the Adoption Intention of PELNI Mobile users.**

These seven hypotheses position UB, RB, and IQ as antecedents of TR, with IQ also directly influencing PV; TR then influences PV and AI, while PV also drives AI. TR and PV thus serve as mediators linking resistance barriers and information quality to users' adoption intentions, as illustrated in Figure 1.

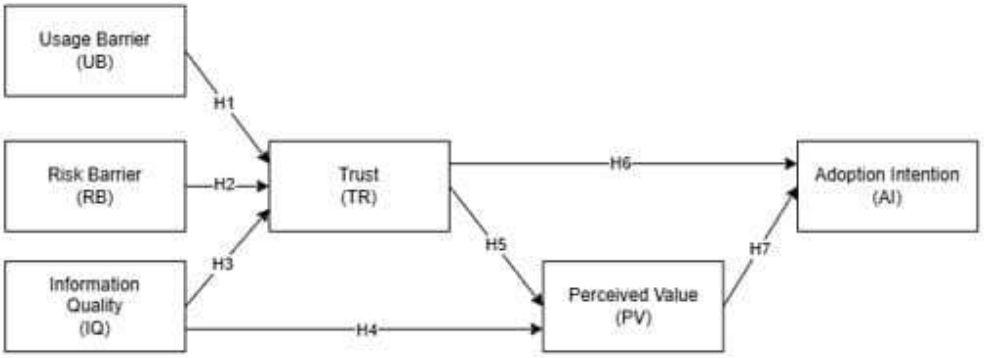


Figure 1. Research Framework

## 3. METHOD

To investigate the relationships among UB, RB, IQ, TR, PV, and AI among PELNI Mobile users, this study employed an exploratory quantitative design as its research method. The exploratory quantitative method was used to test hypotheses derived from theory in order to determine causal relationships among latent variables [30]. A similar design has been used in research on resistance to the adoption of digital transportation, which combined quantitative surveys with PLS-SEM 4 structural modeling [7], as well as in research on digital application services that examined the relationships among information system success variables through structural path modeling [19].

### 3.1. Research Design

This study employs a quantitative approach with an explanatory research design, a research design aimed at explaining causal relationships among variables and testing hypotheses formulated based on a theoretical review [14], [31]. This approach was chosen because it can systematically measure the magnitude of the influence between variables through numerical data analyzed statistically, making it suitable for research with a causal-predictive nature. This design was used to analyze the influence of UB, RB, IQ, TR, PV, and AI on PELNI Mobile users, as formulated in the seven research hypotheses (H1–H7).

### 3.2. Respondents

The population in this study consists of users of PT PELNI's maritime transportation services throughout Indonesia who are aware of the PELNI Mobile app but have not yet actively used it to book tickets, consistent with the population characteristics identified in a study on barriers to the adoption of IRT-based

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mobile ticketing apps [6] and a study on barriers to the adoption of public transportation apps in Indonesia [7]. The sample was determined using a non-probability sampling technique, specifically purposive sampling, based on three main criteria: respondents must be users of PT PELNI's maritime transportation services, must be aware of the PELNI Mobile app, and must not yet have actively adopted the app for ticket transactions, as a representation of the adoption resistance segment within the IRT framework. Based on these criteria, the sample size was determined by referring to the guidelines for determining the minimum sample size in SEM-PLS analysis (rule of thumb), so that it would meet the requirements and support the stability of model parameter estimates [32].

### 3.3. Data Collection

Data collection was conducted through a survey using a structured questionnaire in the form of Google Forms, with a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) to measure respondents' perceptions [29]. Data were collected through a survey using a structured questionnaire, employing a cross-sectional research design; that is, data were collected at a specific point in time (June–August 2026) to describe the perceptions and adoption intentions of potential users during that period, rather than changes over time [30].

### 3.4. Instrument

The research instrument consists of 28 indicators reflecting six latent constructs, namely UB, RB, IQ, TR, PV, and AI, which are presented in full in Table 1. This study first conducted a pilot test on 31 respondents with a degree of freedom (df) of 29 and a significance level of 5%, yielding a table r value of 0.355. The validity test results showed that all statement items across the six research variables (UB, RB, IQ, TR, PV, and AI) were deemed valid because the calculated r values for each item, ranging from 0.776 to 0.968, were greater than the table r value. Furthermore, the results of the reliability test using Cronbach's alpha coefficient showed that the six variables had alpha values ranging from 0.881 to 0.957, all of which exceeded the minimum threshold of 0.70. Thus, this research instrument can be deemed valid and reliable, making it suitable for data collection in subsequent research stages.

Table 1. Research Instruments

| Variable | Code | Indicator | Source |
|---|---|---|---|
| Usage Barrier (UB) | UB1 | I feel that learning how to use Pelni Mobile requires a lot of effort.S | [6] |
| | UB2 | The steps for using Pelni Mobile seem complicated to me. | [7] |
| | UB3 | It took me quite a long time to understand how Pelni Mobile works. | [6] |
| | UB4 | As a new user, I find Pelni Mobile difficult to use. | [6] |
| | UB5 | The process of booking tickets through Pelni Mobile is quite confusing. | [7] |
| Risk Barrier (RB) | RB1 | I'm concerned that my personal data isn't protected when using Pelni Mobile. | [10] |
| | RB2 | I'm worried about payment failures. | [11] |
| | RB3 | I feel that transactions through Pelni Mobile carry a high risk. | [10], [12] |
| | RB4 | I'm concerned that the information I enter could be misused. | [10] |
| Information Quality (IQ) | IQ1 | The information on Pelni Mobile matches the actual conditions (accurate schedules and fares). | [15], [19] |
| | IQ2 | Information regarding schedules, fares, and ticket availability is presented comprehensively. | [15], [17] |
| | IQ3 | The information on Pelni Mobile is always updated to reflect the latest conditions. | [18] |
| | IQ4 | The information displayed matches the context of my search. | [19] |
| | IQ5 | The information on Pelni Mobile is easy to understand and not confusing. | [15], [17] |
| Trust (TR) | TR1 | I believe Pelni Mobile can be used to book tickets safely. | [23] |
| | TR2 | I am confident that PT PELNI, as the service provider, has a good reputation and credibility. | [22] |
| | TR3 | I feel that Pelni Mobile is capable of delivering on its promises to users. | [23] |
| | TR4 | I trust that my data and transactions are protected when using Pelni Mobile. | [22] |
| | TR5 | Overall, I have confidence in Pelni Mobile. | [22], [23] |
| Perceived Value | PV1 | Using Pelni Mobile provides benefits that are worth the time and effort I put in. | [24] |

| Variable | Code | Indicator | Source |
|---|---|---|---|
| (PV) | PV2 | Pelni Mobile makes the ticket booking process more efficient than conventional methods. | [33] |
| | PV3 | Compared to the cost and time I spend, the features I get from Pelni Mobile are well worth it. | [24] |
| | PV4 | Pelni Mobile helps me save time and effort when booking tickets. | [25] |
| | PV5 | Pelni Mobile offers additional convenience in planning my trips compared to manual methods. | [26] |
| Adoption Intention (AI) | AI1 | I intend to use Pelni Mobile when booking ferry tickets in the future. | [27] |
| | AI2 | I will choose Pelni Mobile as one of my primary methods for purchasing ferry tickets. | [8] |
| | AI3 | I am willing to switch from manual purchases to Pelni Mobile. | [12] |
| | AI4 | I plan to use Pelni Mobile regularly whenever I need to purchase tickets. | [28] |

### 3.5. Data Analysis

Data analysis was conducted using the SEM-PLS approach via SmartPLS 4 software, which is suitable for testing research models with latent variables and stepwise mediation relationships as designed in this study [29]. Data analysis was conducted through the following steps.

#### 3.5.1. Evaluation of the Measurement Model (Outer Model)

The measurement model was tested by examining convergent validity, construct reliability, and discriminant validity. Convergent validity was evaluated using outer loadings ≥ 0.70 and Average Variance Extracted (AVE) ≥ 0.50 [32]. Construct reliability was analyzed using Cronbach's alpha and composite reliability, both of which were required to be ≥ 0.70 [34]. The Fornell-Larcker criteria and the heterotrait-monotrait ratio (HTMT) were used to assess discriminant validity, with an HTMT value below 0.90 considered acceptable [32].

#### 3.5.2. Evaluation of Structural Models (Inner Models)

The structural model was tested using the Variance Inflation Factor (VIF) to detect multicollinearity among the independent variables, the coefficient of determination ($R^2$) to verify the ability of the independent variables to explain the dependent variable, and the effect size ($F^2$) to identify the degree of influence of each independent variable on the model.

### 3.6. Hypothesis Testing

The hypotheses were tested by examining the significance of the structural paths using a bootstrapping procedure. All statistical tests were conducted at a 5% significance level ($\alpha = 0.05$) to ensure that the relationships among the variables were statistically significant.

## 4. RESULTS AND DISCUSSION

### 4.1. Respondent Demographics

The demographic analysis of the respondents in this study was conducted to provide a contextual foundation for understanding the characteristics of the individuals in the study sample, while also ensuring that the respondents selected met the previously established criteria for the target population. Based on the data collection process, a total of 281 respondents met the study's criteria, with the demographic characteristics presented in Table 2.

Table 2. Respondent Demographics

| Respondent Demographic (N=281) | | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Female | 169 | 60,1 |
| | Male | 112 | 39,9 |
| Age | < 18 | 37 | 13,2 |
| | 18 – 25 | 182 | 64,8 |
| | 26 – 35 | 26 | 9,3 |
| | 36 – 45 | 11 | 3,9 |
| | > 45 | 25 | 8,9 |
| Profession | Students | 187 | 66,5 |
| | Civil Servants | 17 | 6,0 |

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| Respondent Demographic (N=281) | | Frequency | Percentage (%) |
|---|---|---|---|
| | Private-Sector Employees | 24 | 8,5 |
| | Self-Employed | 19 | 6,8 |
| | Stay-at-Home Mothers | 13 | 4,6 |
| | Other | 21 | 7,5 |
| Education | Junior High School | 4 | 1,4 |
| | High School/Vocational High School | 173 | 61,6 |
| | Diploma | 12 | 4,3 |
| | Bachelor's Degree | 85 | 30,2 |
| | Master's Degree | 7 | 2,5 |
| Residence | Sumatera | 10 | 3,6 |
| | Jawa | 145 | 51,6 |
| | Kalimantan | 79 | 28,1 |
| | Sulawesi | 22 | 7,8 |
| | Bali &Nusa Tenggara | 11 | 3,9 |
| | Maluku & Papua | 14 | 5,0 |

### 4.2. Measurement Model Evaluation (Outer Model)

The outer loading test was conducted to examine the convergent validity of each indicator against its construct. The initial outer loading results showed that all indicators had outer loading values above 0.7, except for indicator UB1 in the Usage Barrier (UB) variable, which obtained a value of 0.638; thus, it did not meet the criteria for convergent validity and had to be eliminated from the model. After removing indicator UB1, the outer loading test was re-run, producing the output presented in Table 3. The results of the retest showed that all indicators for the six research variables had outer loading values above 0.7, with the lowest value observed for indicator IQ1 at 0.705 and the highest for indicator TR2 at 0.905. Thus, it can be concluded that all indicators in this research model have met the criteria for convergent validity and are suitable for use in the subsequent model testing phase.

Table 3. Outer Loading Result

| Construct | Outer loadings |
|---|---|
| **UB2 <- UB** | 0.844 |
| **UB3 <- UB** | 0.871 |
| **UB4 <- UB** | 0.862 |
| **UB5 <- UB** | 0.877 |
| **RB1 <- RB** | 0.880 |
| **RB2 <- RB** | 0.832 |
| **RB3 <- RB** | 0.820 |
| **RB4 <- RB** | 0.892 |
| **IQ1 <- IQ** | 0.705 |
| **IQ2 <- IQ** | 0.800 |
| **IQ3 <- IQ** | 0.847 |
| **IQ4 <- IQ** | 0.880 |
| **IQ5 <- IQ** | 0.823 |
| **TR1 <- TR** | 0.898 |
| **TR2 <- TR** | 0.905 |
| **TR3 <- TR** | 0.874 |
| **TR4 <- TR** | 0.870 |
| **TR5 <- TR** | 0.829 |
| **PV1 <- PV** | 0.844 |
| **PV2 <- PV** | 0.891 |
| **PV3 <- PV** | 0.875 |
| **PV4 <- PV** | 0.851 |
| **PV5 <- PV** | 0.884 |
| **AI1 <- AI** | 0.907 |
| **AI2 <- AI** | 0.907 |
| **AI3 <- AI** | 0.823 |
| **AI4 <- AI** | 0.898 |

The instrument's reliability was tested by calculating Cronbach's Alpha for each variable. The test results in Table 4 show that all variables have Cronbach's Alpha values above the 0.70 threshold. Consequently, the entire instrument was deemed reliable and suitable for testing the structural model.

Table 4. Cronbach's Alpha, CR, and AVE Result

| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|
| **UB** | 0.887 | 0.895 | 0.922 | 0.746 |
| **RB** | 0.879 | 0.892 | 0.917 | 0.734 |
| **IQ** | 0.872 | 0.892 | 0.907 | 0.661 |
| **TR** | 0.924 | 0.926 | 0.943 | 0.767 |
| **PV** | 0.919 | 0.921 | 0.939 | 0.756 |
| **AI** | 0.907 | 0.911 | 0.935 | 0.782 |

Discriminant validity was tested using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. The test results showed that the root-mean-square AVE values for all constructs were higher than their correlation values with other constructs, thus fulfilling the Fornell-Larcker criteria in Table 6 for the entire model. The HTMT test results in Table 5 show that the highest value is found in the PV and AI pair (0.918), followed by TR and PV (0.905) and TR and AI (0.832), while the lowest value is found in the RB and IQ pair (0.285). Although the HTMT values for the PV-AI and TR-PV pairs slightly exceeded the conservative threshold of 0.90, HTMT inference testing through bootstrapping (5,000 subsamples, bias-corrected and accelerated method) showed that the 95% confidence intervals for both pairs did not include the value of 1 (PV-AI: 0.868–0.957; TR-PV: 0.859–0.942), indicating that the two constructs remain statistically distinguishable despite their conceptually close relationship within the sequential IQ-TR-PV-AI pathway of the research model [34].

Table 5. HTMT Result

| Construct | Heterotrait-monotrait ratio (HTMT) |
|---|---|
| **UB <-> RB** | 0.707 |
| **UB <-> IQ** | 0.406 |
| **UB <-> TR** | 0.454 |
| **UB <-> PV** | 0.467 |
| **UB <-> AI** | 0.470 |
| **RB <-> IQ** | 0.285 |
| **RB <-> PV** | 0.368 |
| **RB <-> AI** | 0.341 |
| **IQ <-> AI** | 0.781 |
| **TR <-> RB** | 0.473 |
| **TR <-> IQ** | 0.820 |
| **TR <-> PV** | 0.905 |
| **TR <-> AI** | 0.832 |
| **PV <-> IQ** | 0.806 |
| **PV <-> AI** | 0.918 |

The discriminant validity test was conducted using the Fornell-Larcker criterion, which involves comparing the square root of the Average Variance Extracted (AVE) for each variable with the correlation coefficients between that variable and the other latent variables [29]. A variable is considered to have good

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discriminant validity if its AVE value (shown on the diagonal of the table) is greater than its correlation values with other variables. The test results in Table 6 show that all diagonal values are higher than the correlation values between variables in the same rows and columns; thus, the discriminant validity of all constructs in this research model is deemed to have been met.

Table 6. Fornell-Lacker Result

| | AI | IQ | PV | RB | TR | UB |
|---|---|---|---|---|---|---|
| **AI** | 0.884 | | | | | |
| **IQ** | 0.706 | 0.813 | | | | |
| **PV** | 0.839 | 0.740 | 0.869 | | | |
| **RB** | -0.307 | -0.266 | -0.333 | 0.857 | | |
| **TR** | 0.764 | 0.755 | 0.835 | -0.429 | 0.876 | |
| **UB** | -0.424 | -0.371 | -0.426 | 0.624 | -0.415 | 0.864 |

A multicollinearity test was conducted by calculating the Variance Inflation Factor (VIF) for each path between variables to ensure there was no excessive correlation among exogenous variables that could compromise the accuracy of the model estimates [29]. A path is considered free of multicollinearity if the VIF value is below the threshold of 5. The test results in Table 7 show that all VIF values for each path fall within the range of 1.162 to 3.306, meaning that all values are below the required threshold; therefore, the model in this study is deemed free of multicollinearity.

Table 7. VIF Result

| | VIF |
|---|---|
| **IQ -> PV** | 2.330 |
| **IQ -> TR** | 1.162 |
| **PV -> AI** | 3.306 |
| **RB -> TR** | 1.640 |
| **TR -> AI** | 3.306 |
| **TR -> PV** | 2.330 |
| **UB -> TR** | 1.767 |

The model's predictive ability was evaluated using the PLSpredict procedure, which aims to assess the model's predictive relevance on out-of-sample data through the $Q^2$predict value, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) [29]. A dependent variable is considered to have good predictive relevance if the $Q^2$predict value is positive. The test results in Table 8 show that all three dependent variables have positive $Q^2$predict values with relatively low RMSE and MAE values, indicating that the model in this study has adequate predictive capability.

Table 8. PLSPredict LV Summary

| | $Q^2$predict | RMSE | MAE |
|---|---|---|---|
| **TR** | 0.601 | 0.636 | 0.452 |
| **PV** | 0.544 | 0.680 | 0.502 |
| **AI** | 0.495 | 0.716 | 0.540 |

Effect size tests were conducted by calculating the f-square value for each path to determine the extent of an exogenous variable's contribution to the endogenous variable in the structural model. According to commonly used guidelines, f-square values of 0.02, 0.15, and 0.35 indicate small, moderate, and large effects, respectively [29]. The test results in Table 9 show variations in the magnitude of the effect across each path, with the highest value found in the TR-to-PV path and the lowest in the UB-to-TR path; thus, it can be concluded that each exogenous variable makes a different contribution to the endogenous variables in this research model.

Table 9. F-Square (Matrix)

| | AI | IQ | PV | RB | TR | UB |
|---|---|---|---|---|---|---|
| **AI** | | | | | | |
| **IQ** | | | 0.101 | | 1.090 | |
| **PV** | 0.475 | | | | | |
| **RB** | | | | | 0.093 | |
| **TR** | 0.046 | | 0.647 | | | |
| **UB** | | | | | 0.000 | |

The coefficient of determination was tested by calculating the R-squared and adjusted R-squared values to determine the proportion of variance in the endogenous variables that could be explained by the exogenous variables in the research model [29]. The test results in Table 10 show that the R-squared values for the AI, PV, and TR variables were 0.717, 0.725, and 0.627, respectively, with relatively consistent adjusted R-squared values of 0.715, 0.723, and 0.623. These values indicate that this research model has a fairly strong explanatory power regarding the variance of each endogenous variable.

Table 10. R-Square and R-Square Adjusted

| | R-square | R-square adjusted |
|---|---|---|
| **AI** | 0.717 | 0.715 |
| **PV** | 0.725 | 0.723 |
| **TR** | 0.627 | 0.623 |

### 4.3. Structural Model Evaluation (Inner Model)

The structural model was evaluated by examining the coefficient of determination ($R^2$) and the path coefficients between constructs. The results of the coefficient of determination ($R^2$) test showed that the TR construct had an $R^2$ value of 0.627, meaning that the UB, RB, and IQ variables jointly explained 62.7% of the variance in the TR construct. The PV construct had an $R^2$ value of 0.725, indicating that IQ and TR explained 72.5% of the variance in PV. Meanwhile, the AI construct had an $R^2$ value of 0.717, meaning that TR and PV explained 71.7% of the variance in the AI construct. The path coefficient analysis results showed that IQ had the strongest effect on TR (β = 0.688), followed by the effect of TR on PV (β = 0.643), and the effect of PV on AI (β = 0.666). Meanwhile, RB showed a negative effect on TR (β = -0.239), which is theoretically plausible, as higher perceived risk tends to reduce users' level of trust. UB also showed a negative effect on TR, although it was very weak and practically insignificant (β = -0.011). TR further showed a positive effect on AI (β = 0.207), while IQ showed a direct positive effect on PV (β = 0.254).

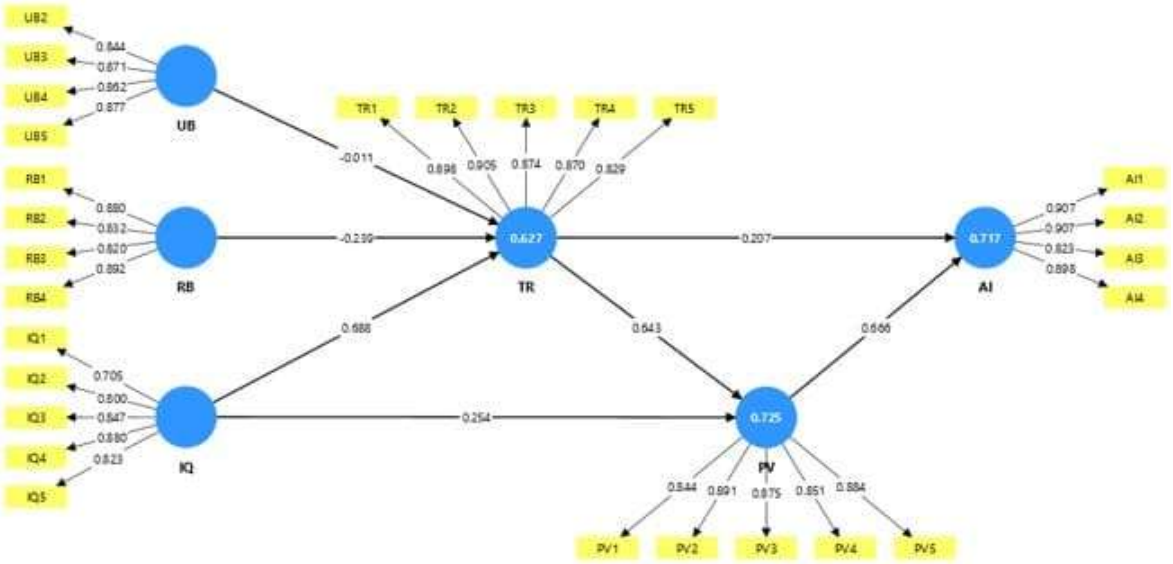


Figure 2. Result of PLS-SEM

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### 4.4. Hypothesis Testing Results

Hypothesis testing was conducted using bootstrapping in PLS-SEM, applying the criterion of $t > 1.96$ and $p < 0.05$. As summarized in Table 8, six of the seven hypothesized relationships were supported, while H1 was rejected.

Table 8. Hipothesis Result

| Hypothesis | Relations | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values | Decision |
|---|---|---|---|---|---|---|---|
| **H1** | **UB -> TR** | -0.011 | -0.011 | 0.059 | 0.187 | 0.852 | Rejected |
| **H2** | **RB -> TR** | -0.239 | -0.236 | 0.061 | 3.926 | 0.000 | Accepted |
| **H3** | **IQ -> TR** | 0.688 | 0.692 | 0.062 | 11.082 | 0.000 | Accepted |
| **H4** | **IQ -> PV** | 0.254 | 0.256 | 0.090 | 2.832 | 0.005 | Accepted |
| **H5** | **TR -> PV** | 0.643 | 0.641 | 0.070 | 9.235 | 0.000 | Accepted |
| **H6** | **TR -> AI** | 0.207 | 0.208 | 0.084 | 2.457 | 0.014 | Accepted |
| **H7** | **PV -> AI** | 0.666 | 0.666 | 0.075 | 8.838 | 0.000 | Accepted |

UB did not significantly affect TR ($\beta = -0.011$; $p = 0.852$), rejecting H1. This likely reflects the predominantly young, student respondent profile (64.8% aged 18–25; 66.5% students), who tend to be adaptable to mobile interfaces, diverging from prior transport-app findings where usage barriers reduced trust [7], [32]. RB significantly and negatively affected TR ($\beta = -0.239$; $p = 0.000$), supporting H2 and confirming risk as a key resistance driver in mobile ticketing and fintech adoption [6], [10], [12]. IQ strongly predicted TR ($\beta = 0.688$; $f^2 = 1.090$), confirming H3 as the model's dominant path and aligning with the IS Success Model's emphasis on information quality as a direct trust determinant [15], [19]. IQ also positively influenced PV ($\beta = 0.254$), supporting H4, consistent with information quality's established role in shaping value perceptions [17], [18].

TR strongly predicted PV ($\beta = 0.643$; $f^2 = 0.647$), confirming H5, while its direct effect on AI was comparatively smaller ($\beta = 0.207$; $f^2 = 0.046$), supporting H6. This contrast indicates that trust functions as a distal antecedent whose influence on adoption intention is largely channeled through PV rather than acting directly, consistent with trust-value-intention sequences observed in digital financial services [21], [22]. PV exerted the strongest effect on AI ($\beta = 0.666$; $f^2 = 0.475$), confirming H7 and positioning perceived value as the primary driver of adoption intention, consistent with meta-analytic and satisfaction-based adoption evidence [26], [33]. Together, these results confirm the IQ-TR-PV-AI pathway as the model's core mechanism, further supported by positive $Q^2$predict values (TR = 0.601; PV = 0.544; AI = 0.495) indicating adequate predictive relevance. Theoretically, these findings show that within a historically conventional maritime service, perceived risk outweighs usability concerns as a barrier to trust, while information quality emerges as trust's strongest driver, offering a nuanced account of resistance that distinguishes this context from more digitally mature transportation sectors.

## 5. CONCLUSION

This study examined the factors shaping prospective users' intention to adopt the PELNI Mobile app by integrating Innovation Resistance Theory (IRT) with information quality dimensions, based on 281 respondents analyzed via SmartPLS 4. Perceived risk, not usability complexity, emerged as the dominant barrier to trust, while information quality proved to be trust's strongest driver; trust in turn shaped adoption intention largely through perceived value, which stood as the strongest overall predictor, confirming an IQ-to-TR-to-PV-to-AI pathway as the core adoption mechanism. These findings extend IRT by showing that in a historically conventional maritime service, risk perception outweighs usability as a resistance driver, reflecting the security-sensitive nature of digital transactions. Practically, this suggests PT PELNI should prioritize information transparency and transaction security over usability simplification. This study is limited by its cross-sectional design and respondent scope, and longitudinal designs and additional moderating or mediating variables are recommended for future research.

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