



Adoption of Auto-replenishment as Digital Transformation Solution for Supply Chain Operation in Gas Station Using TAM-TOE Framework

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Abstract

Indonesia's downstream oil and gas sector faces persistent supply chain challenges due to manual processes and high demand variability. This study aims to investigate the determinants influencing the behavioral intention of Indonesian Gas Station (SPBU) operators and supervisors to adopt the Auto-Replenishment system. Data were collected from 419 valid respondents of gas station operators and supervisors who had completed the Digitalisasi SPBU e-learning. The model comprises nine latent constructs from Technology Organization Environment and Technology Acceptance Model Framework. Data were analyzed using Partial Least Squares-Structural Equation Modelling (PLS-SEM), and reveals that Top Management Support and Organizational Readiness are the strongest drivers, significantly enhancing both Perceived Usefulness and Perceived Ease of Use. Environmental factors, specifically Regulatory Support and Vendor Support, significantly impact Perceived Ease of Use. Technological Readiness influenced Perceived Usefulness but failed to significantly affect Perceived Ease of Use. In line with TAM, both Perceived Usefulness and Perceived Ease of Use have significant positive effects on Behavioral Intention, and mediation analysis confirms that these TAM constructs transmit a substantial portion of TOE effects to adoption intention.

Introduction

Indonesia holds a critical position in the global energy market as the largest oil consumer in Southeast Asia, with petroleum demand exceeding one million barrels per day, driven by sustained economic growth, rapid urbanization, and an expanding motorized vehicle fleet (IEA, 2025; Badan Pusat Statistik (BPS), 2024). Within this context, PT Pertamina Patra Niaga dominates the downstream fuel retail sector, operating the majority of Indonesia's approximately 15,000 fuel outlets and competing with an increasing number of private and foreign retailers in a deregulated market (da et al., 2022).

Ensuring reliable, efficient, and transparent fuel distribution is therefore both an operational imperative and a strategic national priority (Rehman et al., 2012; Dimitriou et al., 2025). In response, the Indonesian government and Pertamina launched a large-scale digitalization program for fuel stations (SPBU), mandating the deployment of Automatic Tank Gauging (ATG) sensors, Internet of Things (IoT) infrastructures, Big Data Analytics (BDA), and an

Auto-Replenishment (Autorep) system integrated through enterprise platforms such as MS2 and SAP. This initiative is designed to replace fragmented manual processes with real-time, data-driven supply chain operations that improve stock visibility, enable predictive replenishment, and support targeted subsidy control (Kanyepe, 2025;).

Despite this strong strategic rationale and substantial capital outlay, the effectiveness of the digitalization program is compromised by uneven adoption at the operational level. Pertamina internal data indicate that, as of September 2025, only 4,430 of 5,986 registered SPBU (approximately 74%) had actually used the Auto-Replenishment feature to generate Sales Orders (SO), leaving roughly 26% of stations as inactive users; overall performance achievement stands at 78.34% of the corporate target. Non-adoption forces stations to revert to the legacy “as-is” model characterized by manual stock estimation, ad-hoc ordering, and fragmented coordination, which increases the risk of stockouts, overstocking, higher logistics costs, and service failures that erode customer trust (Bhavikatta, 2025; Zheng et al., 2025; Ranjan & Puri, 2012).

Existing studies on digitalization in the oil and gas sector have mainly focused on upstream and midstream domains (such as digital oil fields, production optimization, or pipeline monitoring) leaving the downstream retail supply chain comparatively underexplored, particularly in terms of how frontline workers adopt and use auto-replenishment solutions in regulated environments. This creates a substantive empirical gap: there is limited evidence on the determinants of digital transformation solution adoption for supply chain operations at fuel stations in emerging markets, despite these sites being where service quality and stock availability are directly experienced by end consumers.

From a theoretical standpoint, prior research has frequently relied on single adoption models such as the Technology Acceptance Model (TAM) or the Technology Organization Environment (TOE) framework. TAM explains individual-level acceptance through perceived usefulness (PU) and perceived ease of use (PEOU), but it has been criticized for its limited attention to organizational and environmental context (Rahimi, R. A., & Oh, 2025; Davis, 1989). Conversely, the TOE framework offers a macro-level view by capturing technological, organizational, and environmental conditions that influence adoption, yet it is often criticized for its lack of behavioral specificity and psychological depth (Raj & Jeyaraj, 2023; Ahad & Busch, 2024; Mahmoudian et al., 2025; Seshadrinathan, S., & Chandra, 2025; Mpanza, 2025).

Recent work suggests that hybrid models combining TAM and TOE can more comprehensively explain digital adoption by linking firm-level attributes to individual user perceptions, particularly in complex enterprise settings (Gangwar et al., 2015). However, such hybrid TAM–TOE approaches have rarely been applied to downstream energy supply chains or mandated digital solutions in state-owned enterprises. To address these gaps, this study investigates the determinants of auto-replenishment adoption as a digital transformation solution for supply chain operations in Pertamina gas stations (SPBU) from the perspective of frontline operators and supervisors.

Drawing on an integrated TAM–TOE framework, the research models how technological readiness and compatibility, organizational readiness and top management support, and environmental factors such as regulatory pressure and vendor support shape perceived usefulness and ease of use, and ultimately influence adoption intention and behavior. Specifically, the study seeks to answer four research questions: (1) How Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) influence the intention of SPBU workers to use

digital transformation technologies in supply-chain operations (2) How Technological Readiness, Compatibility, Top Management Support, Organizational Readiness, Government Regulatory Support, and Vendor Support shape the user's perception of ease and usefulness. (3) How Perceived Usefulness and Perceived Ease of Use mediate the relationships between the contextual TOE factors and the intention to adopt digital transformation technologies. (4) How does the integrated TOE and TAM framework explain the adoption intention of digital transformation technologies within SPBU supply-chain operations.

The rest of the paper is structured as follows. First, Section 2 presents the theoretical background and develops a conceptual model. Section 3 discusses the research methodology, while Section 4 analyses the data and presents the results. Section 5 discusses the results with respect to the available literature. Finally, Section 6 provides concluding remarks

Theoretical Background

Technology Acceptance Model (TAM), introduced by Davis (1989), posits that an individual's intention to use a technology is primarily determined by two beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is defined as the extent to which a person believes that using a system will enhance job performance, while PEOU refers to the degree to which using the system is free of effort (Davis, 1989; Zhang & Lee, 2023). When users perceive a system as both useful and easy to use, they are more likely to develop favorable attitudes and stronger intentions to adopt it (Venkatesh et al., 2003). Empirical studies consistently show that PU and PEOU explain a substantial share of variance in behavioral intention across diverse digital technologies, which explains the extensive use of TAM in information systems and supply-chain contexts.

However, TAM has been criticized for focusing mainly on individual cognitive beliefs while under-representing broader organizational structures and external environmental forces that shape technology implementation, especially in complex inter-organizational supply chains (Nguyen et al., 2022; Tichavavamwe & Rachmawati, 2024). This limitation motivates the incorporation of a more contextual framework. The Technological, Organizational Environment (TOE) framework, developed by Tornatzky and Fleischer, explains organizational technology adoption as a function of three contextual dimensions: (i) the technological context (e.g., characteristics and availability of technologies), (ii) the organizational context (e.g., structure, resources, and management support), and (iii) the environmental context (e.g., industry structure, competition, and regulation). Within digital supply chains, the technological context captures infrastructure, integration capability, and innovation attributes; the organizational context captures internal capabilities and readiness; and the environmental context captures institutional pressures, regulatory requirements, and relationships with external stakeholders such as vendors and regulators (Gangwar et al., 2015; Raj & Jeyaraj, 2023).

TOE has been used extensively to study the adoption of e-business, cloud computing, blockchain, and advanced analytics in logistics and supply-chain environments, where firms must respond to regulatory demands and competitive pressures while ensuring sufficient internal readiness. In Indonesia's fuel retail (SPBU) supply chain, such environmental forces include government digitalization mandates, BPH Migas regulations, and partnerships with technology vendors that provide IoT telemetry and digital POS solutions. Recent research increasingly advocates integrating TAM and TOE to capture both user-level perceptions and contextual antecedents of technology adoption (Zhang & Lee, 2023; Gangwar et al., 2014; Virmani et al., 2025; Tichavavamwe, 2024). Integrated TAM–TOE models have been applied

to mobile commerce, e-supply-chain management, blockchain, and AI adoption, showing that technological, organizational, and environmental enablers shape PU and PEOU, which then drive behavioral intention (Chatterjee et al., 2021; Moreno et al., 2024; Legesse et al., 2024; Virmani et al., 2025).

Conceptually, this integration is consistent with the original formulation of TAM, in which PU and PEOU were designed as mediators of the effects of external variables (system attributes, social influence, or organizational conditions) on behavioral intention and use (Davis, 1989). In the present study, these “external variables” are operationalized via TOE constructs (technological, organizational, and environmental factors), while PU and PEOU function as cognitive mediators translating contextual enablers into intention to adopt Pertamina’s auto-replenishment system. Given the multi-level nature of SPBU digitalization, where frontline operators and supervisors use systems that are deployed, financed, and regulated at higher organizational and governmental levels an integrated TAM–TOE framework provides an appropriate theoretical basis to capture both micro-level user perceptions and macro-level structural conditions.

Proposed Conceptual Model and Hypotheses Formulation

Technology Readiness refers to the extent to which SPBU possess the necessary IT infrastructure, network resources, and skills to implement and operate the auto-replenishment system (Gangwar et al., 2015). When infrastructure is reliable and staff are technologically competent, users are more likely to perceive the system as beneficial for controlling inventory, reducing stockouts, and improving decision-making, and to view interaction with the system as less demanding. Prior TAM–TOE studies show that technology readiness tends to enhance PU and, in some cases, PEOU for digital supply-chain and analytics solutions (Moreno et al., 2024; Tasnim et al., 2023; Virmani et al., 2025). Thus, this leads to the formulation of the following hypothesis

H1a: Technology Readiness positively influences Perceived Usefulness.

H1b: Technology Readiness positively influences Perceived Ease of Use.

Compatibility captures the degree to which the auto-replenishment system fits existing work practices, operational processes, and technical platforms at the SPBU level. Technologies that align with current routines, reporting formats, and hardware/software environments are typically experienced as easier to operate and more smoothly integrated into daily tasks (Awa et al., 2015). Empirical work in supply-chain and cloud-computing adoption confirms that compatibility is a robust predictor of PEOU and, in some contexts, PU (Gangwar et al., 2015; 2025; Bounfour et al., 2022). Accordingly:

H2a: Compatibility positively influences Perceived Usefulness.

H2b: Compatibility positively influences Perceived Ease of Use.

Top Management Support represents the extent to which SPBU managers and Pertamina leadership visibly champion the digitalization program by prioritizing system use, allocating budgets, monitoring key performance indicators, and embedding system outputs in daily decision-making (Gangwar et al., 2015). Strong leadership support signals strategic importance, reduces resistance, and provides guidance, which tends to enhance both perceived usefulness (through demonstrating performance benefits) and perceived ease of use (through facilitating training and problem resolution) (Awa et al., 2015; Wong et al., 2024). Consequently, the following hypothesis is formulated:

H3a: Top Management Support positively influences Perceived Usefulness.

H3b: Top Management Support positively influences Perceived Ease of Use.

Organizational Readiness reflects the availability of financial resources, technological infrastructure, and human capabilities needed to adopt and sustain digital systems. Organizations with sufficient budgets, IT infrastructure, and trained personnel are more likely to perceive digital tools as both useful and easy to use (Tasnim et al., 2023; Tichavavamwe & Rachmawati, 2024; Bounfour et al., 2022). In the SPBU context, high readiness (installed ATG sensors, integrated POS systems, and staff trained on dashboards) should enhance operators perceptions of the benefits and usability of the auto-replenishment system. As a result, the hypothesis is proposed:

H4a: Organizational Readiness positively influences Perceived Usefulness.

H4b: Organizational Readiness positively influences Perceived Ease of Use.

Government & Regulatory Support encompasses external policies, legal frameworks, incentives, and compliance requirements that shape the environment for SPBU digitalization. Favorable regulations, clear guidelines, and supportive oversight reduce uncertainty and can make digital systems feel more straightforward to use (Awa et al., 2015; Raj & Jeyaraj, 2023). In Indonesia's fuel retail sector, Presidential Decree No. 191 and BPH Migas regulations, along with Pertamina's internal digitalization policies, create regulatory pressure and incentives for using telemetry and auto-replenishment systems. Such support is expected to increase both PU (by linking system use to strategic and compliance benefits) and PEOU (by standardizing procedures and reducing ambiguity). Therefore, a hypothesis is proposed:

H5a: Government & Regulatory Support positively influences Perceived Usefulness.

H5b: Government & Regulatory Support positively influences Perceived Ease of Use.

Vendor Support refers to the technical assistance, training, maintenance, and integration services provided by technology providers and implementation partners. Prior studies show that strong vendor support facilitates successful implementation and reduces the effort users perceive in operating complex digital systems, while also highlighting performance benefits (Chatterjee et al., 2021; Virmani et al., 2025). In the SPBU digitalization program, vendor teams who provide reliable helpdesks, on-site training, and troubleshooting are expected to improve both PU and PEOU for front-line users. Therefore:

H6a: Vendor Support positively influences Perceived Usefulness.

H6b: Vendor Support positively influences Perceived Ease of Use.

Within TAM, PEOU and PU are not only influenced by external factors but also related to each other and to behavioral intention. PEOU is theorized to enhance PU because systems that are easier to use are more likely to be perceived as performance-enhancing (Davis, 1989). Numerous studies confirm that both PU and PEOU are strong predictors of behavioral intention to adopt digital technologies in organizational settings (Venkatesh & Davis, 2000; Moreno et al., 2024; Legesse et al., 2024). In the context of Pertamina's auto-replenishment system, SPBU operators and supervisors are therefore expected to intend to use the system when they find it easy to operate in daily tasks and clearly beneficial for improving inventory control, reducing stockouts, and simplifying reporting. Accordingly:

H7: Perceived Ease of Use positively influences Perceived Usefulness.

H8: Perceived Usefulness positively influences Behavioral Intention to use the auto-replenishment system.

H9: Perceived Ease of Use positively influences Behavioral Intention to use the auto-replenishment system

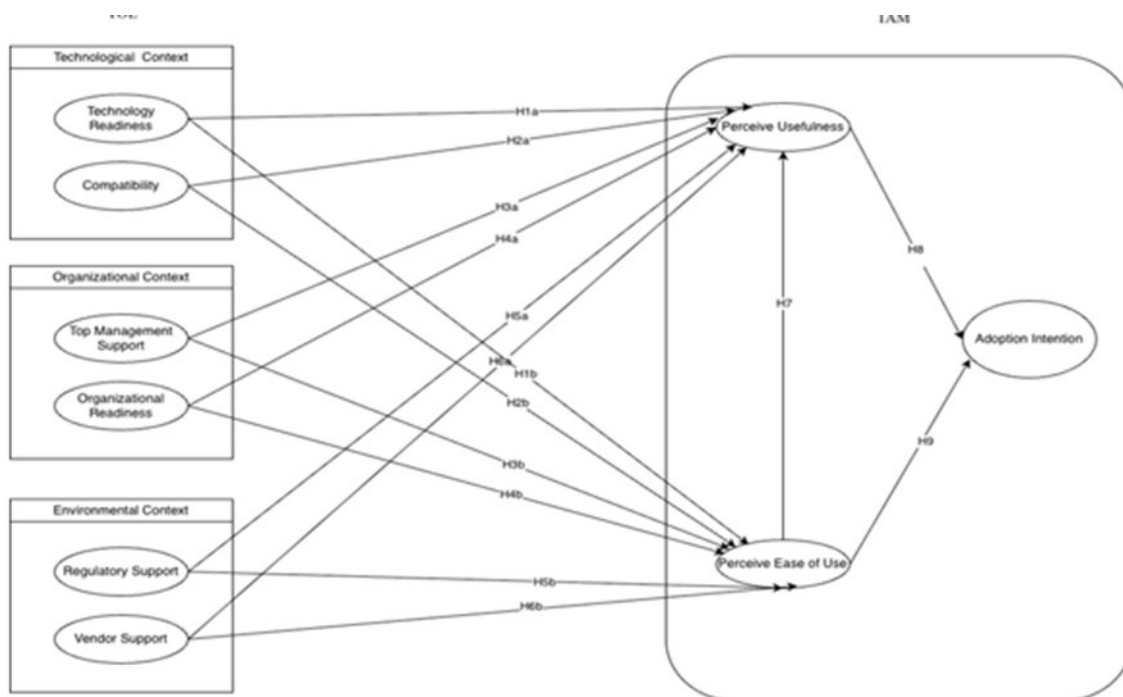


Figure 1. Proposed Model

Source : Extraction From Virmani et al. (2025), Moreno et al., (2024), Das (2022)

Methods

Research Instrument

This study used a quantitative survey design. The questionnaire was developed by identifying constructs from relevant theory and prior studies, then adapting items to operationalize each construct in the proposed research model. The instrument was pretested to ensure clarity and measurement adequacy before the main data collection (Creswell & Creswell, 2017). The questionnaire was first reviewed in the pilot test by 20 SPBU operator and supervisor in selected SPBU in Jakarta. Then, the questionnaire was again piloted with them to ensure that the respondents would be able to understand the measures and provide appropriate responses to the questions. The questionnaire had 36 questions covering all the important concepts. The answers were given by answering these questions. We used a 5-point Likert scale for the measures used for constructs for the purpose of data collection, with '1' representing 'strongly disagree' and '5' representing 'strongly agree' (Sekaran & Bougie, 2016). To ensure a robust empirical investigation, each construct was meticulously operationalized. Appendix 1 presents a comprehensive summary of these constructs, detailing their conceptual definitions, specific measurement items, and the seminal literature from which they were adapted.

Data Collection Strategy

The target population included SPBU operators and supervisors enrolled in the Digitalization SPBU e-learning modules. The total population consists of 64,726 individuals. The broadcast

message from the internal Pertamina system is sent to the entire population. The response distribution reveals that only 1,258 of the 64,726 SPBU workers completed the questionnaire as mandated. The 1,258 respondents can be regarded as a sample for this research. In contrast, 839 of the submitted responses (0.66%) did not meet the required completion criteria. After careful curation and selection, this is attributed to incomplete responses, respondents not meeting the criteria as operators or supervisors, or failing to pass screening filters that require only one individual to represent each gas station. After data cleansing and eligibility verification, 419 responses (0.33% of the population) were considered valid for analysis. The final percentage of analyzable responses may seem small compared to the total population, but the sample of 419 respondents is still good for multivariate analysis, including structural equation modeling, because it is larger than the minimum recommended sample size (Hair et al., 2019). It also meet the criteria of proportionate stratified random sampling technique for operator and supervisor which ideal minimum sample size using slovin formula is 398 respondents (279 operator & 119 supervisor) (Creswell & Creswell, 2017).

Table 1. Distribution and Response of Quisioner

| Responden Criteria | Frequency (n) |
|---|----------------------|
| Operator/Supervisor SPBU that response questionnaire | 1,258 |
| Response answered that do not meet the filling criteria | 839 |
| Response used in analysis | 419 |

Source: 2025 processed original data

Data Analysis Technique

The principal methodology employed for data analysis in this research is Partial Least Squares Structural Equation Modelling (PLS-SEM). PLS-SEM has been selected due to its capacity to manage intricate models comprising numerous constructs and indicators, particularly in contexts where theoretical models are still in developmental stages or the primary aim of the study is predictive (Hair et al., 2015). PLS-SEM facilitates the use of smaller sample sizes, emphasizes prediction-oriented research, and demonstrates greater robustness to non-normal data distributions compared to Covariance-Based SEM (CB-SEM). The analysis was conducted in a two-stage process as recommended in the literature: (1) Assessment of the Measurement Model (Outer Model). This stage evaluated the reliability and validity of the instrument as Fornell & Larcker (1981) explained. It included assessing indicator reliability (outer loadings), internal consistency (Cronbach's Alpha and Composite Reliability), convergent validity (Average Variance Extracted - AVE), and discriminant validity. To supplement the Fornell and Larcker criteria, a heterotrait-monotrait (HTMT) correlational ratio test was performed using ratio. (Henseler et al., 2015). (2) Assessment of the Structural Model (Inner Model). This stage evaluated the predictive power of the model and tested the hypothesized relationships. It involved checking for collinearity (VIF), assessing the coefficient of determination (R^2), calculating predictive relevance (Q^2), and determining the significance of the path coefficients through a bootstrapping procedure. It also employ mediation analysis to determine how TOE construct influence Behavioral Intention directly or indirectly through the perceptual constructs of TAM.

Results and Discussion

The study's findings are based on data collected from 419 valid survey responses from SPBU personnel across Indonesia. The demographic and operational characteristics of these

respondents provide a clear context for interpreting the results of the technology adoption analysis. A detailed breakdown of the respondent profile is presented in the table below.

Table 2. Profile of Survey Respondents and Operational Context

| Characteristic | Category | Frequency (n) | Percentage (%) |
|----------------------------------|---------------------------------|---------------|----------------|
| Gender | Male | 346 | 82.58% |
| | Female | 73 | 17.42% |
| Age Group | ≤ 20 years | 13 | 3.10% |
| | 21 - 25 years | 91 | 21.72% |
| | 26 - 30 years | 110 | 26.25% |
| | 31 - 40 years | 141 | 33.65% |
| | > 40 years | 64 | 15.27% |
| Education Level | Junior High School | 2 | 0.48% |
| | High School / Vocational School | 306 | 73.03% |
| | Diploma (D1-D3) | 63 | 15.04% |
| | Bachelor's Degree (S1) | 42 | 10.02% |
| | Postgraduate (S2/S3) | 5 | 1.19% |
| Work Experience | < 1 year | 51 | 12.26% |
| | 2 - 3 years | 99 | 23.80% |
| | 4 - 6 years | 100 | 24.04% |
| | > 6 years | 166 | 39.90% |
| Job Title | Operator | 266 | 63.48% |
| | Supervisor | 114 | 27.21% |
| | Manager | 23 | 5.49% |
| | Others | 16 | 3.82% |
| SPBU Type | Dealer-Owned (DODO) | 190 | 45.35% |
| | Company-Owned (COCO) | 143 | 34.13% |
| | Modular / Others | 86 | 20.52% |
| Digital SPBU Training Attendance | Completed (with e-certificate) | 244 | 58.23% |
| | Accessed (not yet completed) | 175 | 41.77% |

Source: 2025 processed original data

The workforce is primarily male (82.58%) and possesses significant operational experience, as nearly 40% of respondents report over six years of service. A majority of personnel possess a high school or vocational qualification (73.03%), indicating the operational emphasis of frontline SPBU positions. The sample includes respondents from dealer-owned (DODO) and company-owned (COCO) stations, along with modular formats, thereby ensuring that the analysis encompasses diverse operating environments within Pertamina's downstream network. Notably, 58.23% of respondents have completed the "Digitalisasi SPBU" e-learning module and received an e-certificate, while the remaining participants have at least accessed

the training. This pattern indicates that the workforce is being actively prepared for digital transformation initiatives. Previous studies in digital supply chains and fuel retail indicate that front-line employees and supervisors play a crucial role in harnessing the advantages of IoT, telemetry, and automation, as they are responsible for operating these systems and integrating them into everyday practices (Das, 2019; Talukdar, 2021).

Measurement Model

Before testing the structural relationships that lie at the core of the research model, the measurement model must be rigorously assessed. Measurement model evaluation in PLS-SEM focuses on internal consistency reliability, convergent validity, and discriminant validity for reflective constructs. Establishing a robust measurement model ensures that the indicators accurately reflect the latent constructs and that subsequent structural path estimates are trustworthy. Internal consistency reliability was evaluated using Cronbach's alpha and Composite Reliability (ρ_c), while convergent validity was assessed using the Average Variance Extracted (AVE). Recommended thresholds in PLS-SEM suggest values above 0.70 for both Cronbach's alpha and Composite Reliability, and AVE values of at least 0.50. In terms of collinearity, the value of the Variance Inflation Factor (VIF) for all indicators is in the range of 1,473 (VS1) to 4,114 (BI1). This range falls below the threshold of 5 which is widely used as the starting limit of serious collinearity problems in the context of PLS-SEM (Hair et al., 2019; Sarstedt et al., 2017).

Table 3. Measurement Model Summary (Reliability, Convergent Validity, Outer Loadings, and VIF)

| Construct | Indicator | VIF (Inner) | Outer Loading | Cronbach's Alpha | Composite Reliability (ρ_c) | AVE |
|-------------------------------|-----------|-------------|---------------|------------------|------------------------------------|-------|
| Behavioral Intention (BI) | BI1 | 4.114 | 0.928 | 0.942 | 0.959 | 0.852 |
| | BI2 | 4.111 | 0.929 | | | |
| | BI3 | 3.731 | 0.920 | | | |
| | BI4 | 3.669 | 0.916 | | | |
| Compatibility (COMP) | COMP1 | 1.873 | 0.831 | 0.838 | 0.891 | 0.673 |
| | COMP2 | 1.875 | 0.825 | | | |
| | COMP3 | 1.805 | 0.818 | | | |
| | COMP4 | 1.725 | 0.805 | | | |
| Regulatory Support (GRS) | GRS1 | 1.851 | 0.820 | 0.834 | 0.889 | 0.668 |
| | GRS2 | 1.672 | 0.801 | | | |
| | GRS3 | 1.929 | 0.828 | | | |
| | GRS4 | 1.784 | 0.819 | | | |
| Organizational Readiness (OR) | OR1 | 1.844 | 0.830 | 0.831 | 0.888 | 0.664 |
| | OR2 | 1.691 | 0.801 | | | |
| | OR3 | 1.782 | 0.810 | | | |
| | OR4 | 1.768 | 0.817 | | | |
| Perceived Ease of Use (PEOU) | PEOU1 | 1.960 | 0.832 | 0.870 | 0.911 | 0.720 |
| | PEOU2 | 2.177 | 0.854 | | | |
| | PEOU3 | 2.109 | 0.853 | | | |
| | PEOU4 | 2.194 | 0.856 | | | |
| | PU1 | 2.253 | 0.857 | 0.886 | 0.921 | 0.745 |

| | | | | | | |
|------------------------------|------|-------|-------|-------|-------|-------|
| Perceived Usefulness (PU) | PU2 | 2.502 | 0.877 | | | |
| | PU3 | 2.291 | 0.864 | | | |
| | PU4 | 2.184 | 0.854 | | | |
| Top Management Support (TMS) | TMS1 | 1.926 | 0.832 | 0.845 | 0.896 | 0.683 |
| | TMS2 | 1.806 | 0.816 | | | |
| | TMS3 | 1.914 | 0.826 | | | |
| | TMS4 | 1.878 | 0.831 | | | |
| Technology Readiness (TR) | TR1 | 1.698 | 0.793 | 0.823 | 0.883 | 0.653 |
| | TR2 | 1.816 | 0.814 | | | |
| | TR3 | 1.871 | 0.820 | | | |
| | TR4 | 1.795 | 0.806 | | | |
| Vendor Support (VS) | VS1 | 1.473 | 0.754 | 0.810 | 0.876 | 0.638 |
| | VS2 | 1.741 | 0.809 | | | |
| | VS3 | 1.960 | 0.831 | | | |
| | VS4 | 1.723 | 0.799 | | | |

Discriminant validity test

Discriminant validity ensures that each construct in the model is empirically distinct and captures a unique theoretical domain. It was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio of correlations. The Fornell–Larcker criterion requires that the square root of a construct’s AVE exceed its correlations with other constructs. In addition, HTMT values below 0.85 or 0.90 are typically regarded as evidence of discriminant validity in variance-based SEM (Henseler et al., 2015a; Roemer et al., 2021). Across all constructs, the square root of AVE on the diagonal is greater than the corresponding inter-construct correlations, indicating that the Fornell–Larcker criterion is satisfied. Complementary HTMT analysis (not tabulated here) yielded values below the conservative threshold of 0.90, further confirming discriminant validity. This dual evidence aligns with current recommendations that Fornell–Larcker and HTMT be jointly used when evaluating discriminant validity in PLS-SEM (Hair et al., 2019; Henseler et al., 2015b).

Table 4. Fornell-Larcker Criterion Results

| | BI/ITAB | COMP | GRS | OR | PEOU | PU | TMS | TR | VS |
|---------|---------|-------|-------|-------|-------|-------|-------|-------|--------------|
| BI/ITAB | 0.923 | | | | | | | | |
| COMP | 0.67 | 0.82 | | | | | | | |
| GRS | 0.713 | 0.748 | 0.817 | | | | | | |
| OR | 0.706 | 0.742 | 0.769 | 0.815 | | | | | |
| PEOU | 0.834 | 0.721 | 0.766 | 0.748 | 0.849 | | | | |
| PU | 0.842 | 0.722 | 0.762 | 0.774 | 0.826 | 0.863 | | | |
| TMS | 0.719 | 0.77 | 0.764 | 0.794 | 0.743 | 0.77 | 0.826 | | |
| TR | 0.661 | 0.702 | 0.727 | 0.721 | 0.686 | 0.717 | 0.724 | 0.808 | |
| VS | 0.604 | 0.729 | 0.748 | 0.734 | 0.711 | 0.691 | 0.719 | 0.666 | 0.799 |

Source: 2025 processed original data

Table 5. HTMT Results

| | BI/ITAB | COMP | OR | PEOU | PU | RS | TMS | TR | VS |
|---------|---------|-------|-------|-------|-------|-------|-------|-------|----|
| BI/ITAB | | | | | | | | | |
| COMP | 0.681 | | | | | | | | |
| OR | 0.765 | 0.702 | | | | | | | |
| PEOU | 0.748 | 0.779 | 0.729 | | | | | | |
| PU | 0.812 | 0.763 | 0.789 | 0.776 | | | | | |
| RS | 0.713 | 0.667 | 0.693 | 0.686 | 0.731 | | | | |
| TMS | 0.779 | 0.709 | 0.835 | 0.742 | 0.822 | 0.734 | | | |
| TR | 0.660 | 0.738 | 0.673 | 0.765 | 0.704 | 0.651 | 0.692 | | |
| VS | 0.668 | 0.691 | 0.681 | 0.709 | 0.719 | 0.676 | 0.704 | 0.723 | |

Source: 2025 processed original data

With reliability, convergent validity, and discriminant validity firmly established, the measurement model can be considered robust. The analysis thus proceeds to the evaluation of the structural model and hypothesis testing.

Structural Model

To evaluate the hypotheses, a structural model is constructed by conducting a path analysis among the latent variables utilizing PLS-SEM. We conducted hypothesis testing by analyzing the path coefficients among latent variables and their significance. Figure 2 illustrates the structural model, encompassing the path coefficients and their significance among the latent variables.

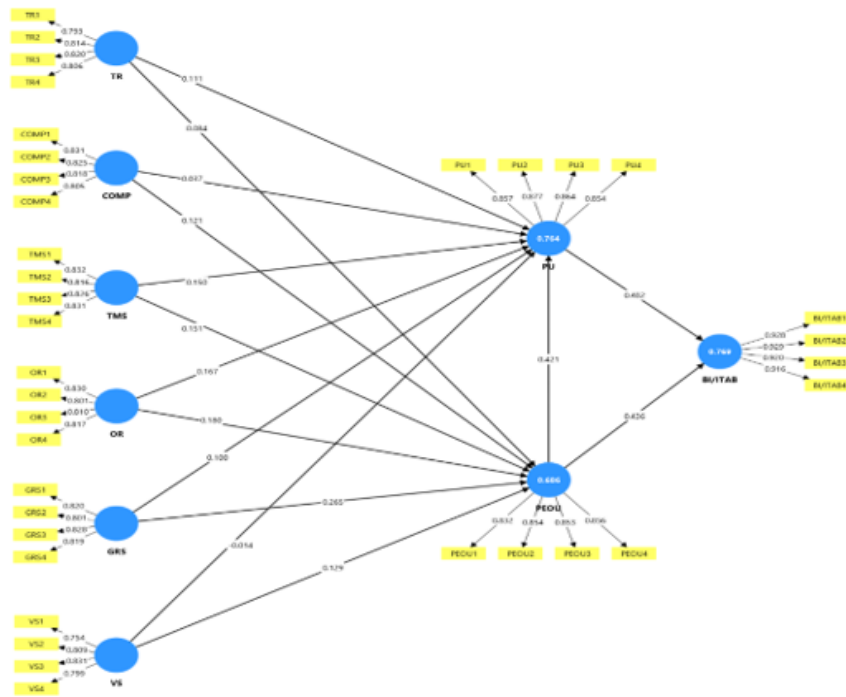


Figure 2. Validated Research Model

Table 6. Table R² and Q²

| Metric | Value | Interpretation |
|--------|-------|----------------|
|--------|-------|----------------|

| | | |
|-------------------------|-------|--|
| R ² for PEOU | 0.769 | Substantial explanatory power |
| R ² for PU | 0.686 | Substantial explanatory power |
| R ² for BI | 0.764 | Substantial explanatory power |
| Q ² for PEOU | 0.675 | Strong predictive relevance (Q ² > 0) |
| Q ² for PU | 0.700 | Strong predictive relevance (Q ² > 0) |
| Q ² for BI | 0.597 | Strong predictive relevance (Q ² > 0) |
| SRMR | 0.040 | Good overall model fit (SRMR < 0.08) |

Source: 2025 processed original data

The integrated TAM–TOE model explains 76.4% of the variance in Behavioral Intention (BI), which is considered substantial in behavioral research. The model also accounts for 76.9% of the variance in Perceived Ease of Use (PEOU) and 68.6% in Perceived Usefulness (PU). All Q² values exceed zero by a wide margin, indicating strong out-of-sample predictive relevance. The SRMR of 0.040 is well below the 0.08 threshold, suggesting good global model fit. These indicators collectively demonstrate that the integrated model is both explanatory and predictive, consistent with recent TAM–TOE applications in digital supply chains, blockchain adoption, and AI adoption studies (Anderson & Lee, 2021; Chatterjee et al., 2021; Virmani et al., 2025).

Hypotheses testing

Hypotheses were tested using bootstrapping to obtain path coefficients (β), t-statistics, and p-values. The results are summarized in Table below:

Table 7. Hypotesis Testing Result

| Hypothesis | Path | β | t-Statistic | p-Value | Result |
|------------|-------------|---------|-------------|---------|---------------|
| H1a | TR → PU | 0.111 | 2.606 | 0.005 | Supported |
| H1b | TR → PEOU | 0.084 | 1.759 | 0.079 | Not supported |
| H2a | COMP → PU | 0.037 | 0.725 | 0.469 | Not supported |
| H2b | COMP → PEOU | 0.121 | 2.078 | 0.019 | Supported |
| H3a | TMS → PU | 0.150 | 2.793 | 0.003 | Supported |
| H3b | TMS → PEOU | 0.151 | 2.408 | 0.008 | Supported |
| H4a | OR → PU | 0.167 | 2.836 | 0.002 | Supported |
| H4b | OR → PEOU | 0.180 | 3.084 | 0.001 | Supported |
| H5a | GRS → PU | 0.100 | 1.910 | 0.056 | Not supported |
| H5b | GRS → PEOU | 0.265 | 4.304 | 0.000 | Supported |
| H6a | VS → PU | -0.014 | 0.307 | 0.759 | Not supported |
| H6b | VS → PEOU | 0.129 | 2.267 | 0.012 | Supported |
| H7 | PEOU → PU | 0.421 | 8.693 | 0.000 | Supported |
| H8 | PU → BI | 0.482 | 9.931 | 0.000 | Supported |
| H9 | PEOU → BI | 0.436 | 8.724 | 0.000 | Supported |

Source: 2025 processed original data

Most hypothesized paths are supported, particularly those linking organizational readiness (OR), top management support (TMS), and regulatory support (GRS) to user perceptions, as well as the core TAM relationships among PEOU, PU, and BI. The pattern is broadly consistent with prior TAM–TOE studies in supply chain and industrial settings, where PU and PEOU typically emerge as the strongest direct predictors of behavioral intention, while

technological and organizational context variables shape these perceptions (Chatterjee et al., 2021; Lee & Yoon, 2022; Suradi, 2025)

Moderation Analysis

The mediation analysis, estimated via a bootstrapping procedure, strongly supports the centrality of TAM constructs as mediators. Across the different pathways tested, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) emerge as statistically significant mediators in most relationships between TOE factors and Behavioral Intention (BI/ITAB). This pattern aligns with prior TAM-based research, which consistently finds PU and PEOU to be the most proximal predictors of technology adoption. Table 9 summarizes the bootstrapped indirect effects, including the original coefficient (O), sample mean (M), standard deviation (STDEV), t-statistics, p-values, and mediation type. Several robust patterns emerge:

Table 8. Mediation Analysis Results for Indirect Effects

| Path | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics ((O/STDEV)) | P values | Mediation Type |
|-------------------------|----------------------------|------------------------|-----------------------------------|---------------------------------|-----------------|--|
| TMS -> PU -> BI | 0.072 | 0.073 | 0.028 | 2.619 | 0.004 | Full (indirect-only) mediation to BI |
| TR -> PU -> BI | 0.054 | 0.054 | 0.022 | 2.441 | 0.007 | Full (indirect-only) mediation to BI |
| VS -> PU -> BI | -0.007 | -0.007 | 0.022 | 0.306 | 0.38 | No mediation (indirect effect not significant) |
| VS -> PEOU -> PU -> BI | 0.026 | 0.026 | 0.013 | 2.052 | 0.02 | Full (indirect-only) chain mediation to BI |
| TMS -> PEOU -> PU -> BI | 0.031 | 0.031 | 0.013 | 2.277 | 0.011 | Full (indirect-only) chain mediation to BI |
| GRS -> PEOU -> PU -> BI | 0.054 | 0.054 | 0.015 | 3.541 | 0 | Full (indirect-only) chain mediation to BI |
| COMP -> PEOU -> BI | 0.053 | 0.053 | 0.026 | 2.002 | 0.023 | Full (indirect-only) mediation to BI |
| GRS -> PEOU -> BI | 0.115 | 0.116 | 0.03 | 3.829 | 0 | Full (indirect-only) mediation to BI |
| OR -> PEOU -> BI | 0.078 | 0.077 | 0.027 | 2.935 | 0.002 | Full (indirect-only) mediation to BI |
| COMP -> PEOU -> PU | 0.051 | 0.051 | 0.025 | 2.023 | 0.022 | Full mediation to PU (direct COMP → PU is not significant) |

| | | | | | | |
|-------------------------|-------|-------|-------|-------|-------|---|
| TMS -> PEOU -> BI | 0.066 | 0.067 | 0.029 | 2.256 | 0.012 | Full (indirect-only) mediation to BI |
| GRS -> PEOU -> PU | 0.111 | 0.113 | 0.03 | 3.752 | 0 | Full mediation to PU (direct GRS → PU is not significant) |
| TR -> PEOU -> BI | 0.037 | 0.037 | 0.022 | 1.697 | 0.045 | Full (indirect-only) mediation to BI |
| OR -> PEOU -> PU | 0.076 | 0.074 | 0.025 | 2.983 | 0.001 | Partial mediation to PU (direct OR → PU is significant) |
| VS -> PEOU -> BI | 0.056 | 0.056 | 0.025 | 2.233 | 0.013 | Full (indirect-only) mediation to BI |

Source : 2025 processed original data

This study shows that digital technology adoption in Pertamina’s fuel supply chain is best understood as a multi-layered process where contextual enablers from the Technology–Organization–Environment (TOE) framework shape user perceptions in the Technology Acceptance Model (TAM), which then drive behavioral intention. The strong explanatory power of the integrated model (high R² for PEOU, PU, and BI) confirms that combining individual-level and organizational-level perspectives is appropriate for complex, infrastructure-intensive contexts such as SPBU operations (Davis, 1989).

Within the technological context, Technology Readiness (TR) and Compatibility (COMP) play clearly differentiated roles. Robust infrastructure and stable connectivity strengthen Perceived Usefulness (PU) by making the benefits of real-time monitoring, auto-replenishment, and accurate inventory data tangible for operators, but do not automatically make the system feel easier to use. In other side, COMP mainly improves Perceived Ease of Use (PEOU) by aligning new digital workflows with existing ordering and reporting routines, thereby lowering cognitive effort without, by itself, guaranteeing that users regard the system as superior in performance. This pattern is consistent with TOE-based findings that relative advantage and compatibility affect different dimensions of user evaluation (Ghobakhloo & Ching, 2019).

The organizational context emerges as the strongest and most consistent driver of both PU and PEOU. Top Management Support (TMS) and Organizational Readiness (OR) jointly provide strategic justification (“why this system matters”) and operational feasibility (“how we can actually use it”). Visible leadership endorsement, budget allocation, training, calibrated ATG devices, working POS terminals, and responsive internal support create a supportive ecosystem in which SPBU staff both can and want to use the system. This aligns with prior TOE research that highlights top management support, resources, and digital maturity as central to successful technology implementation in organizations (Awa et al., 2015; Tichavavamwe & Rachmawati, 2024).

Environmental factors Government/Regulatory Support (GRS) and Vendor Support (VS) exert a more selective effect. Clear corporate and regulatory guidelines for subsidy management and compliance, as well as responsive vendor assistance, significantly increase PEOU by reducing ambiguity, standardizing procedures, and lowering troubleshooting

burdens. However, they do not directly raise PU, suggesting that operators interpret regulation and vendor help primarily as conditions for doing the job “correctly” rather than as sources of extra performance value. This echoes evidence that external pressures and support mainly operate as facilitating conditions rather than direct value drivers (Raj & Jeyaraj, 2023; Venkatesh et al., 2003).

At the core of the model, the TAM relationships are very strong: PEOU significantly enhances PU, and both constructs strongly predict Behavioral Intention (BI), with PU emerging as the dominant driver. This is consistent with the original TAM and its extensions, which emphasize performance gains as the key reason for sustained use, especially among experienced professional users (Davis, 1989; Venkatesh et al., 2003). The mediation analysis confirms that TOE factors rarely affect BI directly; instead, their influence is transmitted through PEOU and PU, in line with recent integrated TOE–TAM models in digital transformation and supply chain settings (Truong, 2023; Virmani et al., 2025). In practical terms, organizational, technological, and environmental conditions “set the stage,” but adoption decisions ultimately pass through the cognitive filters of perceived usefulness and ease of use.

Crucially, the mediation analysis clarifies *how* TOE factors exert their influence: contextual factors rarely affect BI directly; instead, their impact is transmitted through PEOU and PU. In terms, most TOE → BI relationships display “indirect-only” (full) mediation, where the indirect effect via TAM constructs is significant while the direct path is not. For example, TMS and TR influence intention through PU, whereas COMP, GRS, OR, and VS primarily influence BI via PEOU, sometimes through a chain PEOU → PU → BI. OR presents a notable case of partial mediation, where both the direct effect on PU and the indirect effect via PEOU are significant, yielding a “double dividend”: readiness makes the system seem more useful directly and also by making it easier to use. These patterns are consistent with recent integrated TOE–TAM models in digital transformation and supply chain research (Truong, 2023; Virmani et al., 2025), and they empirically support the idea that macro-level conditions are translated into micro-level behavioral intent through the cognitive filters of perceived ease of use and perceived usefulness.

For Theoretical implications, the findings strengthen the case for using an integrated TAM–TOE framework to study digital transformation in state-owned energy supply chains a context that has received comparatively limited empirical attention. The model’s high explanatory power demonstrates that combining individual beliefs (PEOU, PU) with organizational and environmental enablers provides a richer explanation than either framework alone, extending earlier work on technology adoption in SMEs, net-zero supply chains, and digital supply chain management (Tasnim et al., 2023; Virmani et al., 2025). The confirmation of PU as the strongest predictor of BI also supports extended TAM research emphasizing performance outcomes for experienced users (Venkatesh et al., 2003).

Managerial implications. First, leadership and organizational capacity are central levers. Because TMS and OR jointly shape both PEOU and PU, Pertamina should maintain strong visible sponsorship of digital initiatives, link system usage to strategic KPIs, and ensure that every SPBU has adequate hardware, connectivity, and access to training and internal support. This aligns with broader digital transformation literature that highlights alignment of strategy, resources, and capabilities as a prerequisite for realizing value from technology (Awa et al., 2015; Vial, 2019).

Second, investments in Technology Readiness must be prioritized in parallel with front-line experience. Reliable connectivity, properly integrated ATG sensors, and stable back-office systems are non-negotiable if operators are to perceive the system as genuinely useful for preventing stockouts, improving inventory accuracy, and simplifying reporting. Third, the design of training and change management should explicitly emphasize “why-to,” not only “how-to”: training that demonstrates concrete gains in productivity, compliance, and financial performance will more effectively raise PU and, consequently, BI.

Fourth, strengthening readiness at the SPBU level through local “digital champions,” responsive helpdesks, and clear SOPs can convert organizational intent into day-to-day usage. Finally, environmental actors regulators and vendors should focus on simplifying workflows and reducing complexity. Policies and vendor interventions that embed rules into system logic, standardize procedures, and provide proactive support will most effectively raise PEOU, thereby indirectly boosting adoption intention. Together, these strategies translate abstract digitalization goals into a more usable, valuable, and trusted system for SPBU personnel.

Conclusion

The study concludes that digital technology adoption in Pertamina’s SPBU network is driven primarily by users’ perceptions of usefulness and ease of use, which mediate the influence of technological, organizational, and environmental factors. PEOU and PU both significantly boost Behavioral Intention, with PU being a little stronger. This shows how important perceived performance gains are for experienced fuel-station workers (Davis, 1989; Venkatesh et al., 2003). The most consistent factors that make these perceptions possible are organizational ones, such as Top Management Support and Organizational Readiness. Other factors that help are Technology Readiness (for PU), Compatibility (for PEOU), and environmental supports that mainly make things less complicated. The integrated TAM–TOE model elucidates a significant portion of the variance in BI, PEOU, and PU, exhibiting robust predictive relevance, thereby validating its applicability for the analysis of digital transformation within Pertamina’s supply chain (Tasnim et al., 2023; Wiyantirta & Ishak, 2022).

It is important to recognize a number of limitations. The cross-sectional design inhibits the examination of the temporal evolution of perceptions and adoption behaviors. The focus on one organization and one country may make it hard to apply the findings to other fuel retailers or regulatory situations. The dependence on self-reported survey data creates a risk of common method bias, and the emphasis on auto-replenishment and back-office tools suggests that the results may not comprehensively reflect the adoption drivers for alternative digital solutions, such as mobile payment or loyalty applications.

Subsequent research may expand upon this study in various avenues. Longitudinal designs could monitor the evolution of PEOU, PU, and BI as systems develop and become institutionalized. Comparative studies could investigate whether the significance of TAM and TOE factors varies among different categories of digital solutions (operational versus customer-facing). The model could be enhanced with constructs such as trust, resistance to change, or perceived security risk, which are particularly significant in critical infrastructure contexts. Including depots, transport partners, and regional managers in the unit of analysis would help create a more complete, multi-stakeholder view of digital integration. Lastly, mixed-methods designs that use PLS-SEM along with interviews or case studies could help us better understand how formal structures, local practices, and organizational culture all work

together to shape the real-world path of digital transformation in Pertamina and similar businesses.

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