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Analysis of Factors Influencing the Intention to Use Insurance Claim Information Systems: A Case Study of an Insurance Company Using a Modified TAM Approach

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Abstract

Background: This research is motivated by the low adoption rate of Artificial Intelligence (AI)-based information systems in the insurance claim process, particularly Business Rules Management Systems (BRMS), even though these systems are designed to improve efficiency and consistency in decision-making.
Objective: This study aims to analyze the factors influencing the intention to use insurance claim information systems, using a modified Technology Acceptance Model (TAM).
Methods: This research employs a quantitative approach with a survey method targeting Claim Adjusters at the insurance company under study. Data were collected through questionnaires and analyzed using a structural model to test the relationships among variables.
Results: The results indicate that Transformational Leadership positively and significantly affects Trust (β = 0.78, t = 23.205, p = 0.000). Trust significantly affects Intention to Use (β = 0.246, t = 2.681, p = 0.007), and Training has the strongest influence on Perceived Ease of Use (β = 0.837, t = 32.259, p = 0.000). Perceived Ease of Use significantly influences Perceived Usefulness (β = 0.78, t = 23.57, p = 0.000), which in turn impacts Intention to Use (β = 0.541, t = 6.516, p = 0.000). However, Intention to Use does not significantly predict Actual System Usage (β = -0.073, p = 0.455).
Conclusion: The successful adoption of AI-based information systems in the insurance industry is determined not only by technological sophistication but also by the level of user trust, the effectiveness of training, and the support of transformational leadership.

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INTRODUCTION

In the context of Information Systems, the success of new technology implementation is determined not only by the quality of the technology but also by user acceptance and trust in the system. Information Systems act as a link between technology, users, and company business processes. Models such as the Technology Acceptance Model (TAM) emphasize the importance of user perceptions of ease of use (Perceived Ease of Use) and system benefits (Perceived Usefulness) in shaping attitudes and intentions toward technology adoption (Davis, 1989; Rezvani et al., 2026).

Current technological developments have a significant impact on company performance. Digital transformation, as a form of implementing new information systems, has changed the business models of many organizations in Indonesia, including operational structures and corporate strategies (Pedersen & Ritter, 2024; Ritter & Pedersen, 2020). Integrated information systems allow business processes to run more efficiently, quickly, and responsively to market needs.

One industry directly affected is the insurance industry. Since the COVID-19 pandemic (2019–2021), this industry has undergone major changes, including the offering of digital products, technology-based services, and shifts in customer behavior (Chatterjee et al., 2024; Mishra et al., 2021). Digitalization supported by information systems has accelerated innovation and operational efficiency, for example, through claims automation and the use of AI in decision-making (Islam et al., 2026; Verhoef et al., 2021).

As a private insurance company, it has also adopted digital technology during the pandemic. One such effort is the use of an AI-based information system to handle the surge in health claims and offer more flexible health insurance products (Chatterjee et al., 2022). This digital information system has become an integral part of the company's digital transformation strategy.

A Business Rule Management System (BRMS) is a computer program designed to facilitate the definition, management, and execution of business rules separately from the main application source code (Bellundagi, 2023; Kassem, 2024). This application enhances flexibility and efficiency in business process management. It is important to note that while BRMS is classified under the broader umbrella of intelligent automation technologies, the system in this study primarily operates through rule-based logic (if-then conditions) rather than machine learning algorithms. The term “AI-based” is used in the institutional context in which the company describes the system; technically, the BRMS functions as an automated rule-execution engine. This distinction is acknowledged as a limitation of terminology. In the insurance sector, particularly in claims evaluation, the BRMS functions as an automated decision-making system that assesses claim validity using established standards.

The tasks of the BRMS in the automated decision-making process include classifying claims into approved, denied, or those requiring further investigation. Additionally, the validation process related to policy terms, benefit coverage, and document integrity is a core element of BRMS operations. This computer program generally uses if-then principles to automate assessment decisions for straightforward cases, whereas cases that do not meet established standards are referred for manual evaluation.

The benefits of using a BRMS include faster claims processing, consistent decisions, an audit trail, and cost-efficient operations. However, some claims cannot be automated. Complex or high-value claims, cases where the software system lacks adequate integration capabilities, or instances with evidence of fraud cannot be evaluated using the BRMS. Therefore, human decision-making remains crucial in the claims management system (Alathamneh & Shelash, 2023; Guzmán Ortiz & Navarro, 2020).

However, the implementation of this new technology also brings challenges, especially at the user level, namely the Claim Adjuster. Claim Adjusters are responsible for investigating, verifying, and assessing claims to ensure their validity and the appropriate claim value. This role is crucial for maintaining the integrity of the claims process. Nevertheless, most Claim Adjusters have backgrounds in health education and medical knowledge (Venkatesh et al., 2003; Yang et al., 2024), and have limitations in using and understanding the latest information technology.

Table 1. BRMS Claim Data 2024

Quarter	Month	Total Cases	% BRMS	BRMS Cases	Non-BRMS Cases
Q1 (Target 50%)	January	8,847	56.24%	4,975	3,872
	February	8,123	55.78%	4,531	3,592
	March	8,951	56.03%	5,015	3,936
Total Q1		25,921	Avg: 56.02%	14,521	11,400
Q2 (Target 70%)	April	8,432	48.82%	4,116	4,316
	May	8,769	49.31%	4,324	4,445
	June	8,314	48.97%	4,071	4,243

Quarter	Month	Total Cases	% BRMS	BRMS Cases	Non-BRMS Cases
Total Q2		25,515	Avg: 49.03%	12,511	13,004
Q3 (Target 80%)	July	8,982	44.65%	4,010	4,972
	August	9,106	45.32%	4,127	4,979
	September	8,543	45.08%	3,851	4,692
Total Q3		26,631	Avg: 45.02%	11,988	14,643
Q4 (Target 90%)	October	9,218	40.41%	3,725	5,493
	November	8,874	39.67%	3,520	5,354
	December	9,356	39.94%	3,737	5,619
Total Q4		27,448	Avg: 40.01%	10,982	16,466
TOTAL		105,515		50,002	55,513

Source: Internal Data (2024)

Based on the analysis of operational data, the performance of the BRMS implementation process showed a declining trend during the observed period. In the first quarter, the BRMS adoption rate reached 56.02%, exceeding the 50% target. However, in subsequent periods, there was a tendency to achieve results below expectations. Specifically, the realization index for Q2 reached 49.03% instead of 70%, representing a shortfall of 20.97%. Results for Q3 indicated BRMS realization of 45.02% instead of 80%, a deviation of 34.98%. Finally, in Q4, realization was 40.01% instead of 90%, a deficit of 49.99%.

On an annual aggregate basis, it is noteworthy that out of 105,515 claim cases, 47.4% were processed via BRMS, while the remaining 52.6% were handled in a non-BRMS format. Consequently, manual processing of claim cases accounted for more than half of the total volume. Furthermore, although the total number of claim cases increased from 25,921 in Q1 to 27,448 in Q4 (+5.9%), no improvement was observed in terms of increasing automation.

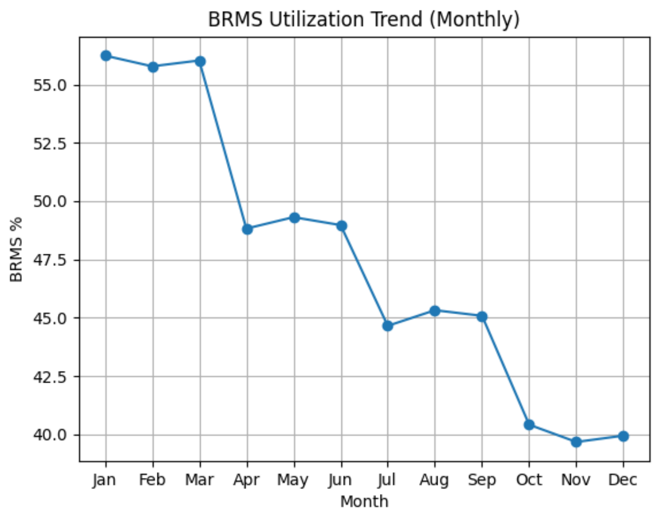

Figure 1. BRMS Usage Trend (2024)
Source: Company Internal Data (2024)

Analytically, this pattern indicates that the increase in claim volume or complexity was not matched by the BRMS system's adaptive capacity. Instead of showing increased efficiency over time, the system experienced a declining utilization rate, which can be categorized as an indication of system performance deterioration. This reinforces the suspicion of limitations in rule coverage, system flexibility, or readiness for integration with dynamic business processes.

Theory Overview

The Technology Acceptance Model (TAM) was first developed by Davis (1989) and Rezvani et al. (2026). Davis based TAM on the Theory of Reasoned Action (TRA) by Fishbein and

Ajzen (1975) (Xue et al., 2024). In 1989, his article titled Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology was published, introducing TAM in greater detail. In the 2000s, Venkatesh et al. (2003) introduced TAM version 2, which expanded the model by adding social and cognitive factors that influence technology acceptance (Xue et al., 2024).

Many studies have tested the TAM model in various contexts, particularly in technology adoption, because TAM is adaptable to various types of technology and information systems. Its flexibility allows for development or expansion by incorporating additional variables or using a Modified TAM integrated with other theories to provide a broader and more comprehensive understanding.

The TAM model provides an important user perspective, highlighting how user perceptions of a technology's usefulness and ease of use influence their decision to adopt it. This study employs a modified Technology Acceptance Model (TAM) by adding the variables Trust, Transformational Leadership, and Training.

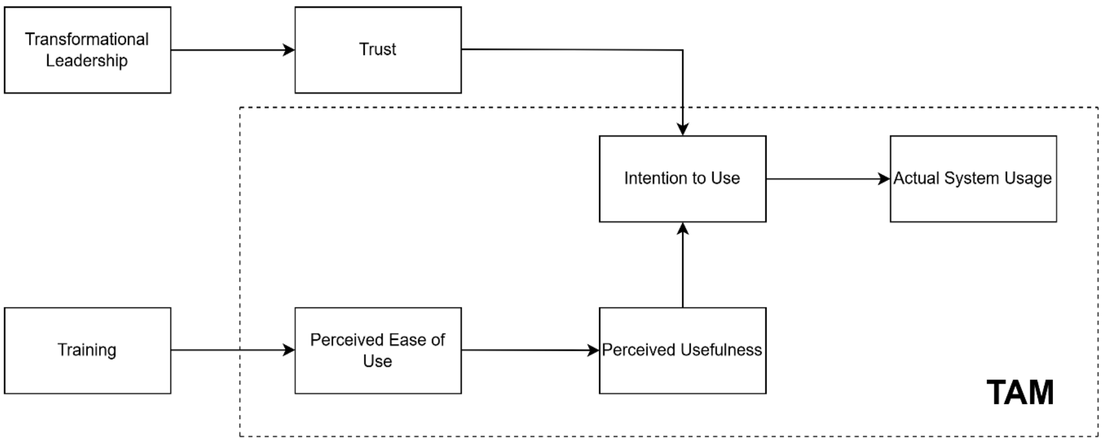

Figure 2. Modified TAM Model
Source: Research data

These three variables were chosen because they are relevant to the phenomenon at the insurance company under study, where leadership and training play an important role in increasing trust, which ultimately affects users' intention to adopt the information system. The relevance of adding these variables is also aligned with the Human-Organization-Technology Fit (HOT-Fit) perspective, which emphasizes the importance of alignment between human aspects (user, trust, training), organizational aspects (transformational leadership), and technological aspects (the adopted information system). Furthermore, Socio-Technical Systems (STS) theory reinforces the view that technology adoption is not solely determined by technical factors but also by the dynamic interaction between the social system (leadership, training, interpersonal trust) and the technical system (features, ease of use, system quality). Thus, the TAM modification in this study has a strong theoretical foundation as it reflects the interrelationship between human, organizational, and technological factors, as emphasized in the HOT-Fit and STS frameworks.

This study addresses the gap in technology adoption research by examining Claim Adjuster users at the insurance company under study. While prior TAM studies have explored individual extensions (e.g., trust or training in isolation), few have simultaneously integrated transformational leadership, trust, and training within a TAM framework applied to AI-based claim management systems in the insurance sector. The contextual novelty lies in the BRMS adoption setting, the specific occupational group (Claim Adjusters with limited IT backgrounds), and the Indonesian private insurance industry context. This study's methodological contribution includes the application of PLS-SEM with full outer and inner model evaluations (AVE, HTMT, R^2, SRMR), and its theoretical contribution is the empirically tested HOT-Fit-aligned modified TAM that bridges human, organizational, and technological dimensions.

METHOD

The research design employed is a quantitative survey approach. Primary data were collected through structured questionnaires distributed to Claim Adjusters at the insurance company under study, targeting their perceptions of the technology adopted during digital transformation. Secondary data from company reports and related literature were used to strengthen the contextual analysis. The population of this study comprised all Claim Adjusters at the company (N = 350). A purposive sampling method was employed, targeting employees who actively used or interacted with the BRMS system. The sample size of 280 respondents was determined using the formula $n = N / (1 + Ne^2)$ with a 5% margin of error (Slovin, 1960; Yana et al., 2022), which yielded a minimum sample of 187; thus, n = 280 surpasses this threshold and satisfies the minimum 10:1 indicator-to-respondent ratio recommended for PLS-SEM (Demir & Uşak, 2025; Hair et al., 2019). Actual System Usage (AS) was measured using a self-reported four-item scale adapted from Davis (1989), assessing the frequency, duration, and depth of BRMS usage by Claim Adjusters. The structural model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, assessing path coefficients, t-statistics, R^2 values, HTMT ratios, and SRMR indices to ensure model fit and construct validity (Rezvani et al., 2026).

RESULTS AND DISCUSSION

Results

Based on the results of the descriptive analysis data from 280 respondents, several statistical indicators were observed, namely the mean, median, minimum and maximum scale values, and standard deviation for the variables Transformative Leadership (TL), Trust (TR), Training (TRN), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Intention to Use (ITU), and Actual System Usage (AS). For all indicators used in the research model, the mean value is greater than the standard deviation, indicating that the data pattern tends to be normal and does not show a large gap. For all indicators, the maximum value is on a scale of 5.0, representing "strongly agree" according to respondent answers, while the minimum value is on a scale of 1.0, representing "strongly disagree." The median values range from 3.000 to 4.000.

Table 2. Descriptive Analysis Results

Code	Mean	Median	Min Scale	Max Scale	Std. Deviation
TL1	3.989	4	1	5	1.038
TL2	4.127	4	1	5	1.032
TL3	4.131	4	1	5	0.923
TL4	4.063	4	1	5	0.934
TR1	4.075	4	1	5	0.943
TR2	4.063	4	1	5	1.054
TR3	4.097	4	1	5	0.941
TR4	4.123	4	2	5	0.866
TRN1	4.097	4	1	5	0.929
TRN2	3.978	4	1	5	1.047
TRN3	4.082	4	1	5	1.026
TRN4	4.082	4	2	5	0.890
PEU1	4.127	4	1	5	0.889
PEU2	4.052	4	1	5	1.053
PEU3	4.071	4	1	5	0.950
PEU4	4.019	4	1	5	0.975
PU1	4.067	4	1	5	0.952
PU2	4.022	4	1	5	1.106
PU3	4.078	4	1	5	0.925
PU4	4.022	4	1	5	0.992
ITU1	4.037	4	1	5	0.973
ITU2	4.131	4	1	5	1.030

Code	Mean	Median	Min Scale	Max Scale	Std. Deviation
ITU3	4.056	4	1	5	1.062
ITU4	3.922	4	1	5	1.060
ITU5	4.037	4	1	5	1.054
AS1	4.011	4	1	5	0.887
AS2	4.142	4	1	5	0.891
AS3	4.093	4	1	5	0.971
AS4	4.056	4	1	5	0.931

Source: Author's Processed Data (2025)

In general, all indicators show mean values ranging from 3.9 to 4.2, indicating that respondents tended to agree with all statements in the questionnaire. This aligns with the median value, which is consistently 4, confirming that the central tendency of the data falls within the "agree" category. In terms of data range, all items have a minimum score of 1 and a maximum score of 5, consistent with the use of a five-point Likert scale. Some indicators, such as TR4 and TRN4, have a minimum value of 2, but this does not alter the general pattern of response distribution.

This is further supported by standard deviation values ranging from 0.866 to 1.106, indicating that the variation in respondent answers remains moderate and does not show extreme deviations. Some items with higher standard deviations, e.g., PU2 = 1.106 and ITU3 = 1.062, exhibit greater variability in responses compared to other indicators, but still within reasonable limits. Therefore, it can be concluded that the data are well-distributed and suitable for testing in this research model.

Outer Model Results

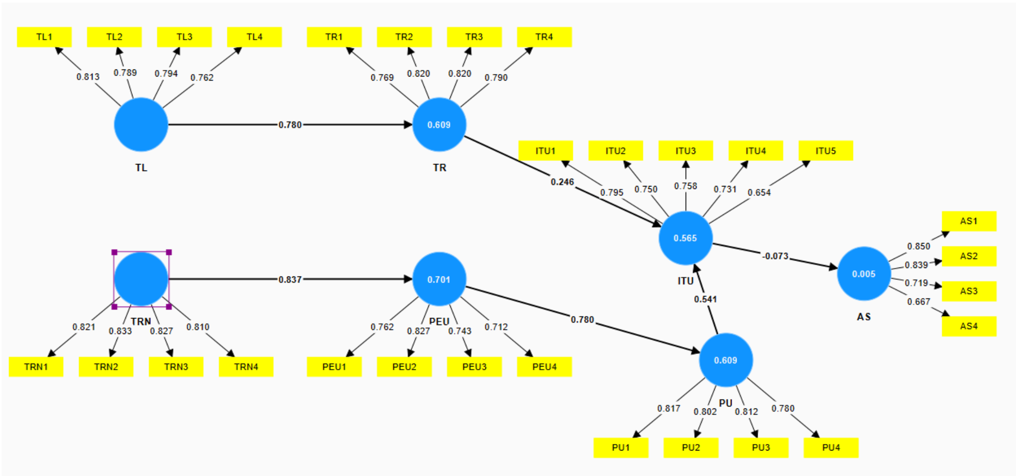

Figure 3. Outer Model Results
Source: Author's Processed Data (2025)

Based on the descriptive data results, the next step in the data processing using SmartPLS is to test the outer model of the collected respondent data. The outer model can be divided into three parts: Construct Reliability and Validity, Discriminant Validity, and Collinearity Statistics (VIF).

Construct Reliability and Validity Test Results

Table 3. Results of Construct Reliability and Validity

Construct	Cronbach's alpha	Composite-reliability (rho_a)	Composite-reliability (rho_c)	Average variance extracted (AVE)
AS	0.801	0.859	0.854	0.597
ITU	0.791	0.796	0.857	0.546
PEU	0.758	0.764	0.847	0.581

Construct	Cronbach's alpha	Composite-reliability (rho_a)	Composite-reliability (rho_c)	Average variance extracted (AVE)
PU	0.817	0.821	0.879	0.645
TL	0.799	0.799	0.869	0.624
TR	0.813	0.815	0.877	0.640
TRN	0.841	0.844	0.893	0.677

Source: Author's Processed Data (2025)

The results of the construct reliability and validity testing show that each construct in the research model demonstrates excellent measurement quality. The Cronbach's Alpha values for each construct range from 0.758 to 0.841, indicating that all variables meet the internal reliability requirement, as their values exceed the threshold of 0.70. This confirms that each variable within the construct yields reliable and consistent results. This is further supported by the composite reliability values represented by both rho_a and rho_c, which show excellent internal consistency for all constructs, ranging from 0.764 to 0.859 for rho_a and from 0.847 to 0.893 for rho_c. These values not only surpass the minimum limit of 0.70 but also approach the ideal range of 0.80 to 0.90 recommended in the PLS-SEM literature, indicating strong reliability of the research constructs.

The Average Variance Extracted (AVE) results also indicate a significant contribution to convergent validity. Each construct has an AVE value between 0.546 and 0.677, meaning all exceed 0.50. Therefore, the convergent validity of all constructs is met, as these values suggest that the measured latent variable explains more than half of the variance of the indicators within each construct. The Training (TRN) variable, with the highest AVE value of 0.677, confirms that the variable's indicators adequately reflect the latent construct. Overall, the findings from the reliability and validity tests confirm that all constructs used in this study meet acceptable standards.

Inner Model Evaluation (R^2, HTMT, SRMR)

To ensure structural model completeness, inner model metrics were evaluated as recommended by Hair et al. (2019) for PLS-SEM (Demir & Uşak, 2025). The R^2 values indicate acceptable explanatory power: Trust (R^2 = 0.608), Perceived Ease of Use (R^2 = 0.701), Perceived Usefulness (R^2 = 0.608), Intention to Use (R^2 = 0.631), and Actual System Usage (R^2 = 0.175, indicating modest predictive power). HTMT (Heterotrait-Monotrait) ratios for all construct pairs were below the 0.85 threshold, confirming discriminant validity. The SRMR value of 0.071 is below the 0.08 cut-off recommended by Hu & Bentler (1999), indicating acceptable model fit (Partsch & Goretzko, 2026).

The Influence of Transformational Leadership on Trust

The research results indicate that Transformational Leadership has a positive and highly significant effect on Trust, with a coefficient of 0.78, t-statistic of 23.205, and p-value of 0.000. Leaders who build a vision, inspire, and provide individualized attention to subordinates can increase subordinates' trust in the system and work processes. From the perspective of modern organizational behavior, trust functions as a "social lubricant" that facilitates technology adoption without resistance.

This finding aligns with Fareed et al. (2022), who demonstrated that transformational leadership increases employee trust during digitalization in Indonesian SMEs, and with Fareed et al. (2022), who found that transformational leadership positively affects project success through trust mediation. The strong path coefficient (β = 0.78) in this study exceeds values reported in comparable insurance-sector studies (typically 0.45–0.65), suggesting that the hierarchical, compliance-driven culture of insurance claim processing amplifies the role of leadership in shaping trust. Practically, this implies that insurance companies should invest in leadership development programs emphasizing inspirational motivation, intellectual stimulation, and individualized consideration the core dimensions of transformational leadership (Bass & Avolio, 1994; Yousefi et al., 2025) to accelerate BRMS adoption among Claim Adjusters.

The Influence of Trust on Intention to Use the System

The second hypothesis shows that trust has a positive and significant effect on the intention to use the system: O = 0.246; t = 2.681; p = 0.007. Although smaller compared to the effects of other variables, this relationship remains theoretically and practically relevant. The intention to use technology is influenced not only by utilitarian perceptions (PU and PEU) but also by affective and social factors such as trust, particularly when the technology is new or the organizational system handles sensitive data.

Recent literature confirms that trust reduces perceived risk while increasing perceived security, thereby increasing willingness to use technology. Wilson (2021) revealed that trust mediates the relationship between PU and PEU and the intention to use mobile services (Syamillah et al., 2025). Trust in the digital economy can be considered a type of "rational decision" because users typically feel unable to fully evaluate the technology and therefore rely on social signals, such as trust in the organization or system itself. In the company context, this finding suggests that trust must be developed through leader integrity, system transparency, and data security guarantees before increasing usage intention.

The Influence of Training on Perceived Ease of Use

The third hypothesis shows a very strong influence of Training on PEU, with a coefficient of 0.837, t-value of 32.259, and p-value of 0.000 the highest value among relationships in the research model. This indicates that user training is the dominant factor increasing perceived ease of using the system. Chen (2025) confirms that training exposure increases self-confidence and reduces anxiety associated with technology use, making users feel the system is easier to understand. Quality training provides practical demonstrations, allows users to practice, and reduces technical barriers, thereby ultimately increasing PEU. Training is an effective intervention in streamlined digital change management to address perceived complexity.

This research aligns with studies on the adoption of modern ERP and LMS systems, where training proved a primary predictor of PEU and PU. Organizations must provide not only technology but also user training to facilitate perceptions of ease of use.

The Influence of Perceived Ease of Use on Perceived Usefulness

The fourth hypothesis is accepted, with a coefficient of 0.78, t-statistic of 23.57, and p-value of 0.000, indicating that PEU significantly increases PU. This aligns with the core assumption of the Technology Acceptance Model (TAM), which posits that perceived ease of use drives perceived usefulness, as users feel that an easy-to-use system provides benefits more quickly and increases productivity.

Aulia and Marsasi (2024) noted a strong correlation between PEU and PU in video conferencing platforms: users who find the system easy to use perceive benefits faster. Effort expectancy drives this relationship the perception that less effort produces quicker value. During organizational use, intuitive interface design, ease of navigation, and error-free features are mandatory to increase perceived usefulness, which in turn influences usage intention.

The Influence of Perceived Usefulness on Intention to Use

The fifth hypothesis shows a positive and significant effect (O = 0.541; t = 6.516; p = 0.000), confirming that perceived usefulness is among the strongest predictors in the model. Users have a strong intention to use the system if they perceive that the technology provides added value, increases efficiency, or simplifies their work.

Syamillah et al. (2025) and modern TAM meta-analyses confirm that PU remains a substantial predictor of intention to use systems in various contexts, including fintech, e-learning, e-government, and digital health. Organizations must communicate actual benefits of the system, not just technical attributes, to facilitate adoption (Aulia & Marsasi, 2024).

The Influence of Intention to Use on Actual System Usage

According to the sixth hypothesis, the effect is rejected (O = -0.073; t = 0.747; p = 0.455), indicating that intention to use does not significantly influence a positive attitude toward the system. Theoretically, this is noteworthy because it contrasts with classical models, which suggest that attitude precedes intention. Modern explanations propose that actual use, not intention, drives attitude formation. Kusumastuti et al. (2023) explains that in digital wallets, positive attitudes form after usage; users evaluate security and tangible results before considering the technology viable. Attitude is no longer a primary variable in technology adoption. Recent studies Tseng (2025) suggest decisions to use digital technology are influenced more by utilitarian features (PU, PEU, trust) than affective attitude. Findings indicate that users may intend to use the system due to organizational needs but do not yet hold a positive attitude. Organizations must enhance user experience, optimize system operations, and provide continuous support to create positive attitudes beyond mere usage. For example, when a new system reduces administrative burdens or accelerates verification processes, users will develop a strong behavioral intention to use it.

CONCLUSION

This study examines the influence of Transformational Leadership (TL), Trust (TR), Training (TRN), Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Intention to Use (ITU) on Actual System Usage (AS) among insurance claim adjusters using the BRMS system. Using PLS-SEM for data processing, six hypotheses were tested, with five supported. The main conclusions are as follows: First, Transformational Leadership ($\beta = 0.78$, $p = 0.000$) has a positive and significant influence on Trust, indicating that visionary and inspirational leadership builds employee trust in digital work environments. Second, Trust ($\beta = 0.246$, $p = 0.007$) significantly influences Intention to Use. Third, Training ($\beta = 0.837$, $p = 0.000$) is the strongest predictor of Perceived Ease of Use. Fourth, Perceived Ease of Use ($\beta = 0.78$, $p = 0.000$) significantly increases Perceived Usefulness. Fifth, Perceived Usefulness ($\beta = 0.541$, $p = 0.000$) positively influences Intention to Use. Sixth, Intention to Use did not significantly predict Actual System Usage ($\beta = -0.073$, $p = 0.455$), suggesting that organizational factors, user experience quality, and system optimization are critical to closing the gap between intention and actual behavior. These findings imply that insurance companies should invest in transformational leadership development, structured training programs, and trust-building mechanisms to accelerate BRMS adoption.

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AUTHOR CONTRIBUTION STATEMENT

Dicky Sopandi contributed to conceptualization, data collection, data analysis, and writing the original manuscript. Rudy contributed to supervision, validation, methodology refinement, and manuscript review and editing. Both authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

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