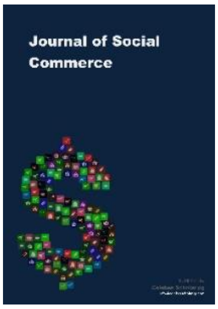

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SWACAM and the Future of Self-Service: a TAM Study of Perceptions, Attitudes, and Intentions to Use

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Article History

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Abstract

This study aims to analyze customer acceptance of the SWACAM feature in the PLN Mobile application using the Technology Acceptance Model (TAM). Based on data from 181 postpaid customers at PLN UP3 Serpong, this research empirically investigates the impact of perceived ease of use and perceived usefulness on users' attitudes and their intention to use the SWACAM feature. The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. The findings reveal that both perceived ease of use and perceived usefulness significantly affect user attitudes and intentions. Attitude also mediates the relationship between perception and intention. These results provide practical insights for PLN to enhance the adoption of self-service technologies.

Introduction

The COVID-19 pandemic that has hit since early 2020 has accelerated the digitalization process in various sectors, including the energy and public services sectors. PT PLN (Persero), as the national electricity provider, is faced with the challenge of maintaining continuity and quality of service while limiting physical contact between customers and officers in the field. In response to this challenge, PT PLN (Persero) launched the New PLN Mobile application with new features and a new appearance as a superior digital platform to meet all customer needs, providing convenience and a different electricity service experience (Kusuma & Rahim, 2021; Pradipta & Aruan, 2024; Afrianti & Nugroho, 2024). One of the new features presented in this application is the SWACAM (Swadaya Catat Meter) feature, which allows postpaid customers to record and submit electricity meter readings by uploading photos independently, rather than waiting for direct recording by officers. Although this feature has functional benefits, its adoption is still low, with only around 25 percent of postpaid customers in the PLN UP3 Serpong work area actively using this feature (PLN UP3 Serpong, internal data, 2025). This indicates a gap between the availability of digital innovation and actual acceptance from customers. Therefore, it is important to understand the factors that influence customer

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acceptance of this feature (Boukrouh et al., 2024; Wang & Lee, 2021; Pelau et al., 2021; Zhang et al., 2021; Yoon & Lee, 2021).

The Technology Acceptance Model developed by Davis (1989) states that two primary factors influencing technology acceptance are perceived ease of use and perceived usefulness. These two factors shape a person's attitude toward a technology, which then influences their intention to use it. Previous studies have shown that perceived usefulness is a key determinant of intention to use a technology. This finding is also confirmed by Pavlou (2003), who found that perceived usefulness consistently influences transaction intention. Meanwhile, perceived ease of use plays a more significant role in the initial stages of technology use. Research by Chen et al. (2001) showed that perceived ease of use has a direct influence on attitude and perceived usefulness, which ultimately drives intention to use. However, few studies have specifically examined the use of the SWACAM feature separately from the PLN Mobile application as a whole. Customer perceptions of specific features can vary depending on their experience and needs (Liu et al., 2022; Jiang & Hong, 2023; Yang et al., 2021). Therefore, this study was conducted to examine how perceived ease of use and usefulness influence attitudes and intentions to use the SWACAM feature, as well as the role of attitude as a bridge in this relationship.

Literature Review

The Technology Acceptance Model (TAM) is a theoretical framework developed by Davis (1989) to explain how and why individuals accept or reject the use of technology. This model emphasizes two main factors influencing acceptance: perceived usefulness and perceived ease of use. Perceived usefulness refers to the view that technology can help complete tasks more quickly, effectively, and efficiently (Prastiawan et al., 2021; Siagian et al., 2022; Kim et al., 2021). Meanwhile, perceived ease of use relates to the extent to which a technology is perceived as easy to learn, understand, and use without requiring much effort. If someone perceives a technology as useful and easy to use, their tendency to accept and use it will be higher (Davis et al., 1989; Bansah & Darko Agyei, 2022; Zou & Huang, 2023).

These two factors shape attitudes toward technology use, namely an individual's assessment of how comfortable, confident, or happy they are when using the technology. A positive attitude will strengthen the intention to use, which is the internal drive from within a person to actually utilize the technology in their daily activities. This intention is a key indicator before actual usage behavior occurs. Further research by Venkatesh et al. (2003) emphasized that the intention to use technology is strongly influenced by user attitudes, which are formed from perceptions of the ease and benefits of the system. Similar findings were obtained from research by Munoz-Leiva et al. (2016) in the context of digital financial services, and Al-Rahmi et. al., (2019) in the field of online education. They concluded that attitudes and intentions play a crucial role in driving technology adoption (Huang et al., 2021; Hőgye-Nagy et al., 2023; Vafaei-Zadeh et al., 2021). Therefore, for providers of digital-based public services, understanding how to shape user perceptions, attitudes, and intentions is crucial to ensure that the technology developed is optimally utilized by the public.

Hypothesis Development

In technology acceptance studies, perceived ease of use plays a crucial role in shaping the assessment of a system's usefulness. When users perceive a technology as easy to use, they tend to perceive it as providing tangible benefits. Davis (1989) stated that a system's ease of use can enhance a person's perception of its usefulness. This finding is further supported by the research of Shroff et al. (2011) and Chen et al. (2001), which found that perceived ease of use significantly influences perceived usefulness. Ilham & Zarnelly (2021) added that the higher the perceived ease of use, the more positive the assessment of the technology's usefulness. Based on this reasoning, the following hypothesis is proposed:

H1: Perceived ease of use has a positive effect on perceived usefulness.

In addition to influencing perceived usefulness, perceived ease and perceived usefulness also shape users' attitudes toward technology use. Adams et al. (1992) stated that even if a system is not particularly easy to use, users will still accept it if they perceive it to provide significant benefits. This finding is also supported by the research of Putra et al. (2022) on freemium apps, which stated that perceived usefulness positively influences attitudes toward using freemium apps. Meanwhile, Cendika et al. (2023) showed that perceived usefulness has a more dominant influence on user attitudes than perceived ease of use. Another study by Mai and Cuong (2020), in the context of smart home appliances, concluded that both perceived usefulness and ease of use have a positive influence on user attitudes. Therefore, the proposed hypothesis is:

H2: Perceived ease of use has a positive influence on attitudes

H3: Perceived usefulness has a positive influence on attitudes.

Furthermore, both perceived usefulness and user attitudes play a role in shaping user intentions to use technology. Davis (1989) suggested that perceived usefulness is a key determinant of intention to use a system. Research by Adams et al. (1992), Shroff et al. (2011), and Pikkarainen et al. (2004) consistently shows that the greater the perceived usefulness, the stronger the user's desire to use the technology.

Conversely, attitude is an important factor driving intention to use. Muñoz-Leiva et al. (2016) stated that in the use of digital banking applications, user attitude is a strong factor influencing intention to use. Before someone intends to purchase or use an application, they will first evaluate and determine their attitude (Putra et al., 2020; Cheung & To, 2017; Papakostas et al., 2023; Dirsehan & Cankat, 2021). Research by Chou (2020) suggests that attitude can mediate the influence of perception on behavioral intention to use. Therefore, the following hypotheses are proposed:

H4: Perceived usefulness has a positive effect on intention to use.

H5: Attitude toward use has a positive effect on intention to use.

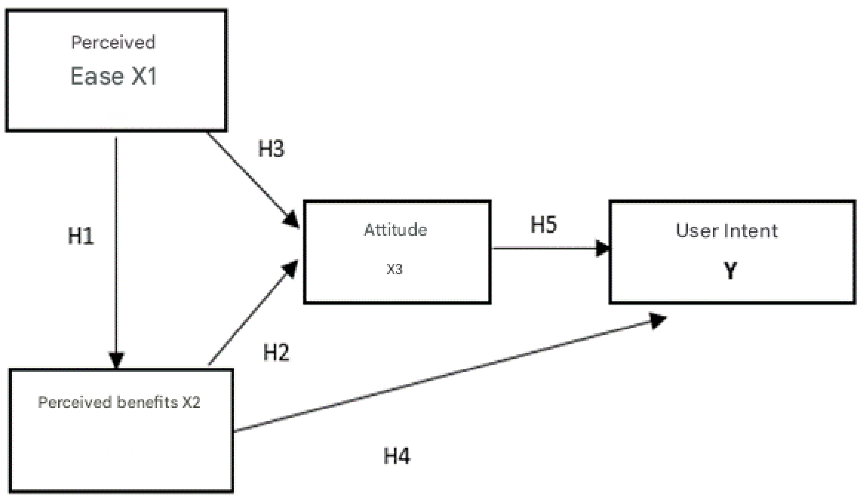

Figure 1. Research Model

Methods

This study used a quantitative research design to examine determinants of customer acceptance of the SWACAM (Swadaya Catat Meter) feature within the PLN Mobile application, applying the Technology Acceptance Model (TAM) as the theoretical basis. The structural relationships among Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude toward Use (ATT), and Behavioral Intention to Use (INT) were tested using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach. SmartPLS software was employed to estimate both the measurement (outer) and structural (inner) models because PLS-SEM is well suited for prediction and for models with latent constructs measured by reflective indicators.

The study population comprised postpaid customers of PT PLN (Persero) UP3 Serpong (South Tangerang and surrounding areas), since postpaid customers are the primary target users of the SWACAM feature. Sampling was purposive: only respondents who were postpaid customers and potentially exposed to the PLN Mobile application were invited to participate. Sample size was determined with reference to Hair et al. (2013), which recommends a minimum of 150 respondents for models with up to seven constructs; to satisfy and exceed this guideline, data were collected until 181 valid responses were obtained. Data collection was performed via an online questionnaire distributed between 16 June and 6 July 2025. Prior to analysis responses were screened for completeness and relevance; only complete questionnaires from eligible respondents were retained for analysis.

The measurement instrument was a structured questionnaire adapted from Davis (1989) and subsequent TAM literature. Each construct was operationalized with reflective indicators as follows: Perceived Ease of Use (four items), Perceived Usefulness (three items), Attitude toward Use (three items), and Intention to Use (two items). All items used a five-point Likert scale ranging from 1 = Strongly disagree to 5 = Strongly agree. Respondents received a brief explanation of the study's purpose and were informed that participation was voluntary and responses would be treated confidentially. Demographic and usage questions were included to characterise the sample (gender, age group, education, PLN Mobile installation status, self-reported frequency of SWACAM use, and awareness of the feature); these descriptive statistics are presented in the Results section.

Data analysis followed a two-stage PLS-SEM procedure. In the first stage the measurement model was evaluated to establish reliability and validity. Convergent validity was assessed via indicator loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). The evaluation criteria applied were consistent with common SEM practice and Hair et al. (2013): indicator loadings were expected to be at least 0.50 (with preferable values ≥0.70 for well-defined constructs), AVE > 0.50, and CR and Cronbach's alpha > 0.70 to indicate internal consistency reliability. Discriminant validity was examined using the Fornell–Larcker criterion and cross-loadings to ensure each construct captured unique variance. In the second stage the structural model was tested to examine hypothesized paths and effect sizes. Goodness-of-fit and model quality were assessed with indices appropriate for PLS-SEM (SRMR, d_ULS, d_G, Chi-square and NFI), and path significance was evaluated using nonparametric bootstrapping. Specifically, hypotheses were tested with bootstrapping; the significance decision rule used standard thresholds (two-tailed test; $p < 0.05$ and $|t| \geq 1.96$). Mediation (indirect) effects were assessed by examining the significance of indirect paths in the bootstrapping output rather than by relying solely on product-of-coefficients approximations; the presence of statistically significant indirect effects supports mediation claims. All modeling, estimation and hypothesis testing were implemented in SmartPLS to ensure consistency between measurement and structural evaluation.

participation was voluntary, respondents were informed about the study's objectives and confidentiality of their answers, and only aggregated results are reported. The Methods as described provide sufficient detail to reproduce the measurement and analytical procedure: the instrument items (adapted from Davis, 1989) and the exact PLS-SEM evaluation criteria (indicator loading thresholds, AVE, CR, Cronbach's alpha, Fornell–Larcker, SRMR/d_ULS/d_G/NFI, and bootstrapping significance tests) together form a transparent, replicable approach to empirically testing the TAM propositions for the SWACAM feature.

Results and Discussion

The sample was collected through the distribution of questionnaires from June 16 to July 6, 2025, targeting postpaid customers within the service area of PLN UP3 Serpong. A total of 181 respondents participated in the study. Based on respondent profiles, the majority were female (62.43%) and within the productive age range of 26–35 years (49.17%). Most respondents had at least a secondary education, with university graduates forming the largest group (36.46%). Furthermore, 66.85% of respondents had installed the PLN Mobile application; however, more than half (55.80%) had never used the SWACAM feature. Nevertheless, over 50% reported being aware of its existence. These findings highlight a gap between the level of awareness and the actual usage of the SWACAM feature.

Table 1. Respondent Data Analysis

Category	Subcategory	Number of people)	Percentage (%)
Gender	Female	113	62,43%
	Male	68	37,57%
Age	< 25 years	28	15,47%
	26–35 years	89	49,17%
	36–45 years	48	26,52%
	> 45 years	16	8,84%
Last education	Elementary School	2	1,10%
	Junior High School	13	7,18%
	High School/Vocational School	52	28,73%
	Diploma	41	22,65%
	Bachelor's Degree	66	36,46%
	Master's Degree	7	3,87%
PLN Mobile Installation Status	Installed	121	66,85%
	Not yet installed	60	33,15%
SWACAM Usage Frequency	Never	101	55,80%
	1–2 times	42	23,20%
	3–5 times	29	16,02%
	> 5 times	9	4,97%
Knowledge about SWACAM	Knowing	99	54,70%
	Don't know	82	45,30%

Data analysis was conducted using the Structural Equation Modeling (SEM) approach using SmartPLS software. Before proceeding to the data analysis stage, the measurement model (Outer model) was first tested by measuring the validity and reliability of the variables. According to Hair et al. (2013), convergent validity is met if the AVE value is above 0.50, an indicator is said to be valid if it has a loading value of at least 0.50 and a variable is said to have good reliability if the Cronbach's alpha and Composite Reliability values are each more than 0.70. From the test results, all variables have AVE values above 0.50, all indicators in the model have Outer Loading values above 0.70 and Cronbach's alpha and Composite Reliability values for each variable are above 0.70. Thus, all variables in this model have met the validity and reliability criteria.

Table 2. Validity and Reliability Test Results

Indicator	Outer loadings	Cronbach's alpha	CR	AVE
Perceived Ease 1	0.838	0,842	0,842	0,678
Perceived Ease 2	0.801			
Perceived Ease 3	0.813			
Perceived Ease 4	0.842			
Perceived Benefit 1	0.794	0,711	0,715	0,633
Perceived Benefit 2	0.788			
Perceived Benefit 3	0.804			
Attitude 1	0.823	0,762	0,776	0,678
Attitude 2	0.763			
Attitude 3	0.881			
Intention to Use 1	0.921	0,809	0,811	0,839
Intention to Use 2	0.911			

To evaluate the suitability between the constructed model and the analyzed data, a Goodness of Fit (GOF) test was conducted. The test results are presented in Table 2 below. The test results indicate that the structural model has an adequate level of suitability with an SRMR value of 0.076, d_ULS of 0.461, and NFI of 0.747, making it suitable for use in analyzing the relationship between latent variables.

Table 3. Results of the goodness of fit test

Indicator	Saturated Model	Estimated Model	Status
SRMR	0,076	0,077	Good
d_ULS	0,454	0,461	Good
d_G	0,249	0,25	Good
Chi-Square	282,681	282,988	Good
NFI	0,747	0,747	Good

Next, a structural model test (Inner Model) was conducted. This test aims to assess how strong and significant the relationship between latent variables in the developed model is. From the testing that has gone through the Bootstrapping process in the SmartPLS application, the results showed that all relationships between variables in this research model are positive and significant. First, Perceived Ease of Use is proven to have a significant effect on Perceived Benefit with a coefficient value of 0.667 and a p-value <0.05, so that hypothesis 1 (H1) is accepted. Second, Perceived Benefit also has a significant effect on Attitude with a coefficient of 0.363 and a p-value <0.05, so that hypothesis 2 (H2) is accepted. Third, Perceived Ease of Use has a significant effect on Attitude with a coefficient value of 0.431 and a p-value <0.05, which means hypothesis 3 (H3) is accepted. Fourth, Perceived Benefit has a significant effect on Intention to Use, indicated by a coefficient of 0.362 and a p-value <0.05, so that hypothesis 4 (H4) is accepted. Fifth, the influence of attitude on intention is measured through direct and indirect relationship measurements. The results of the direct relationship measurement of attitude have a positive and significant effect on Intention to Use with a coefficient of 0.430 and p-value <0.05. While the results of the indirect relationship show that Attitude significantly mediates the relationship between Perceived Ease and Intention to Use, with a coefficient of 0.242 and p-value <0.05. Similarly, Attitude significantly mediates the relationship between Perceived Benefit and Intention to Use (coefficient 0.156; p <0.05), thus Hypothesis 5 is accepted.

Table 4. Inner Model Test Results

Relationships Between Variables	Sample (O)	T Statistics	P Value	Hypothesis
Perceived Ease → Perceived Benefit	0,667	13,85	0	Accepted
Perceived Benefit → Attitude	0,363	4,009	0	Accepted
Perceived Ease → Attitude	0,431	5,165	0	Accepted
Perceived Benefit → Intention to Use	0,362	4,898	0	Accepted
Attitude → Intention to Use	0,43	6,36	0	Accepted
Perceived Ease → Attitude → Intention to Use	0,242	3,508	0	Accepted
Perceived Benefit → Attitude → Intention to Use	0,156	3,085	0,001	Accepted

Bridging the Gap in Digital Service Adoption

The findings of this study demonstrate that perceived ease of use is a fundamental driver of customer perceptions toward the SWACAM feature. When users find that a system can be operated with minimal effort, they are more likely to view it as a supportive tool that can help them achieve their goals more efficiently. This observation is consistent with earlier research by Chen et al. (2001) and Shroff et al. (2011), who found that ease of use reduces the psychological burden of learning and encourages experimentation with new digital features. The role of ease of use as a determinant of adoption has long been emphasized in technology acceptance studies, beginning with Davis (1989), and remains relevant in contemporary digital environments where users expect interfaces to be simple and intuitive. Venkatesh et al. (2003) also highlighted that perceived ease of use does not only facilitate initial trial but also fosters confidence in technology, which is essential for the development of stable user attitudes. In the case of SWACAM, the finding suggests that technical simplicity is not just a design attribute but also an entry point that influences whether customers recognize the potential benefits of the feature.

The relationship between perceived usefulness and customer attitude also emerged as significant. When users are convinced that a feature delivers tangible benefits such as convenience, time efficiency, and accuracy, they tend to develop positive attitudes toward its use. Adams et al. (1992) explained that usefulness may even outweigh challenges in ease of use, because individuals are often willing to invest effort in systems that provide high value. Putra et al. (2022) confirmed this logic in their study on freemium applications, showing that usefulness consistently drives favorable evaluations even when the system is somewhat complex. Similarly, Cendika et al. (2023) observed that usefulness plays a dominant role in shaping positive perceptions of innovations within public service applications. Evidence from research on consumer appliances by Mai and Cuong (2020) further supports this finding, as customers who clearly perceive functional advantages are more inclined to accept and integrate digital tools into their routines. The convergence of these studies underscores that perceived usefulness is a powerful construct, acting not only as a cognitive assessment but also as a strong emotional motivator in shaping favorable attitudes.

The analysis also confirmed that perceived usefulness directly influences behavioral intention, supporting the theoretical assumptions of Davis (1989). This result echoes empirical findings by Pikkarainen et al. (2004), Shroff et al. (2011), and Adams et al. (1992), which consistently show that usefulness predicts an individual's likelihood of adopting technology. When customers perceive SWACAM as an effective way to manage electricity usage, they translate this perception into a stronger intention to use the feature in the future. At the same time, attitude was also found to be a significant predictor of intention, which aligns with research in other digital contexts. Muñoz-Leiva et al. (2016) found that in mobile banking, positive attitudes strongly predicted willingness to adopt, while Chou (2020) demonstrated that attitudes mediate the effect of cognitive evaluations on behavioral decisions in mobile services. These studies reinforce the conclusion that attitudes bridge the gap between rational assessments and behavioral outcomes. In the present study, this mediating effect of attitude illustrates how cognitive perceptions of ease and usefulness are transformed into intentions through affective evaluations.

Although the TAM framework was confirmed, the descriptive data revealed a notable gap between intention and actual usage of the SWACAM feature. While more than half of the respondents expressed awareness and willingness to adopt, the majority had not used the feature in practice. This discrepancy is consistent with the intention–behavior gap widely documented in information systems research. Limayem et al. (2007) explained that habitual behaviors often undermine the predictive power of intention, as users tend to continue with established routines even when new technologies offer advantages. In this case, the longstanding habit of waiting for meter officers may prevent customers from actively adopting self-service tools. Trust is another critical factor. Gefen et al. (2003) demonstrated that in online shopping, trust is essential for overcoming uncertainty and risk, and Pavlou (2003) argued that trust must be integrated with TAM to explain why users hesitate despite recognizing benefits. Customers may doubt the accuracy of self-reported data or question whether the system will protect their information, which creates hesitation even in the presence of positive perceptions and attitudes.

Beyond individual perceptions, social influence and norms also appear relevant to the low adoption of SWACAM. Venkatesh et al. (2003) emphasized that social contexts and peer influence strongly shape technology usage decisions. For many customers, interaction with PLN officers has long served not only as a service function but also as a source of social reassurance and validation. Replacing this familiar interpersonal contact with a digital interface may feel less trustworthy or less socially acceptable, leading to resistance. Al-Rahmi et al. (2019) highlighted similar dynamics in their study of e-learning, where peer norms and community influences significantly shaped adoption behavior. This suggests that digital tools do not exist in isolation but are interpreted through social contexts and collective practices that reinforce or hinder individual choices.

The findings of this study therefore resonate with the broader literature showing that TAM alone cannot fully explain digital adoption behavior. Pavlou (2003) expanded the TAM framework by integrating trust and risk, showing that acceptance is not only cognitive but also emotional and relational. Gefen et al. (2003) further emphasized that trust operates together with usefulness to determine adoption, especially in online and self-service environments.

Research on freemium applications by Putra et al. (2020) added that prior evaluations and perceived risks influence willingness to pay, highlighting that digital behavior often reflects a blend of rational and emotional considerations. Studies by Mai and Cuong (2020) and Muñoz-Leiva et al. (2016) similarly demonstrate that user decisions are driven by a combination of functional benefits, affective responses, and contextual influences. Collectively, these findings suggest that while ease of use and usefulness remain central constructs, they interact with trust, habit, and social norms to determine whether users move from intention to actual adoption.

The present study extend the understanding of customer adoption of digital public services by demonstrating that attitudes and intentions, while necessary, are not sufficient for explaining actual behavior. Integrating trust, habit, and social influence into the model, as suggested by Davis (1989), Venkatesh et al. (2003), Pavlou (2003), and Limayem et al. (2007), offers a more comprehensive perspective. Such an expanded framework aligns with evidence from online commerce (Chen et al., 2001), mobile services (Chou, 2020), smart home technology (Mai & Cuong, 2020), and educational platforms (Al-Rahmi et al., 2019). These studies collectively illustrate that digital adoption is shaped by a convergence of cognitive assessments, affective responses, and social contexts. The contribution of this study lies in demonstrating how these dynamics manifest in a utility-based application, where adoption requires not only perceived efficiency but also changes in trust, habits, and social interaction.

Conclusion

This study examined the effects of perceived ease of use, perceived usefulness, and attitude on the intention to use the SWACAM feature in the PLN Mobile application using the Technology Acceptance Model (TAM). The results show that ease of use positively influences usefulness, and both factors significantly shape user attitudes, which in turn drive intention. Attitude also mediates the relationship between perceptions and intention, highlighting the importance of these constructs in fostering digital adoption. Nevertheless, descriptive findings reveal an intention–behavior gap: although many users recognize the benefits and express willingness to use SWACAM, actual usage remains low. This suggests that TAM variables alone cannot fully explain adoption behavior in public digital services. Factors such as habit, trust, and social norms are likely to influence actual use and should be integrated into future research for a more comprehensive understanding. Practically, PLN should strengthen trust through data transparency, address entrenched user habits via continuous education, and provide incentives such as rewards or gamification. These strategies can help narrow the gap between intention and behavior and accelerate the adoption of digital services.

References

Adams, D. A., Nelson, R., Todd, P. A., & Nelson, R. R. (1992). Perceived Usefulness, Ease of Use, and Usage of Information Technology: A Replication Increasing Systems Usage Perceived Usefulness, Ease of Use, and Usage of Information Technology: A Replication. *Source: MIS Quarterly*, *16*(2), 227–247. https://doi.org/10.2307/249577

Afrianti, A. D., & Nugroho, R. H. (2024). The Role of Service Staff in Digitalization at PT. PLN (Persero) ULP Rungkut. *Business and Investment Review*, *2*(6). https://doi.org/10.61292/birev.150

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating Technology Acceptance Model with

Innovation Diffusion Theory: An Empirical Investigation on Students' Intention to Use E-Learning Systems. *IEEE Access*, *7*, 26797–26809. https://doi.org/10.1109/ACCESS.2019.2899368

Bansah, A. K., & Darko Agyei, D. (2022). Perceived convenience, usefulness, effectiveness and user acceptance of information technology: evaluating students' experiences of a Learning Management System. *Technology, Pedagogy and Education*, *31*(4), 431-449. http://dx.doi.org/10.1080/1475939X.2022.2027267

Boukrouh, I., Tayalati, F., & Azmani, A. (2024, October). Feature importance in predicting customer offer acceptance in online retail. In *IET Conference Proceedings CP906* (Vol. 2024, No. 34, pp. 346-351). Stevenage, UK: The Institution of Engineering and Technology. http://dx.doi.org/10.1049/icp.2025.0107

Chen, L. da, Gillenson, M. L., & Sherrell, D. L. (2001). Enticing online consumers: An extended technology acceptance perspective. *Information and Management*, *39*(8), 705–719. https://doi.org/10.1016/S0378-7206(01)00127-6

Cheung, M. F., & To, W. M. (2017). The influence of the propensity to trust on mobile users' attitudes toward in-app advertisements: An extension of the theory of planned behavior. *Computers in human behavior*, *76*, 102-111. http://dx.doi.org/10.1016/j.chb.2017.07.011

Chou, T.-Y. (2020). AT positively affect BI significantly. *The International Journal of Organizational Innovation*, *13*(2), 96. http://www.ijoi-online.org/http://www.ijoi-online.org/

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). Davis1989 (1).Pdf. *Management Science*, *35*(July 2018), 982–1003.

Dirsehan, T., & Cankat, E. (2021). Role of mobile food-ordering applications in developing restaurants' brand satisfaction and loyalty in the pandemic period. *Journal of Retailing and Consumer Services*, *62*, 102608. https://doi.org/10.1016/j.jretconser.2021.102608

Gefen, D., Karahanna, E., & Straub, D. W. (2003). *Trust and TAM in online shopping: An integrated model*. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

Hair, J. F. (2009). Multivariate data analysis. In *Neuromarketing in India: Understanding the Indian Consumer*. https://doi.org/10.4324/9781351269360

Hőgye-Nagy, Á., Kovács, G., & Kurucz, G. (2023). Acceptance of self-driving cars among the university community: Effects of gender, previous experience, technology adoption propensity, and attitudes toward autonomous vehicles. *Transportation research part F: traffic psychology and behaviour*, *94*, 353-361. https://doi.org/10.1016/j.trf.2023.03.005

Huang, X., Lin, Y., Lim, M. K., Tseng, M. L., & Zhou, F. (2021). The influence of knowledge management on adoption intention of electric vehicles: perspective on technological knowledge. *Industrial Management & Data Systems*, *121*(7), 1481-1495. http://dx.doi.org/10.1108/IMDS-07-2020-0411

Ilham, M., & Zarnelly, Z. (2021). Analisis Penerimaan Aplikasi PLN Mobile Menggunakan Technology Accpetance Model (TAM). *Jurnal Ilmiah Rekayasa dan Manajemen Sistem Informasi*, *7*(1), 58-62. https://doi.org/10.24014/RMSI.V7I1.11549

Jiang, Y., & Hong, F. (2023). Examining the relationship between customer-perceived value of night-time tourism and destination attachment among Generation Z tourists in China. *Tourism Recreation Research*, *48*(2), 220-233. http://dx.doi.org/10.1080/02508281.2021.1915621

Kim, J., Merrill Jr, K., & Collins, C. (2021). AI as a friend or assistant: The mediating role of perceived usefulness in social AI vs. functional AI. *Telematics and Informatics*, *64*, 101694. https://doi.org/10.1016/j.tele.2021.101694

Kusuma, M. H., & Rahim, S. E. (2021, November). The effectiveness of the new PLN mobile application in improving service quality, customer satisfaction, and electrifying lifestyle during the new normal period in Tanjung pandan city. In *IOP Conference Series: Earth and Environmental Science* (Vol. 913, No. 1, p. 012050). IOP Publishing. https://doi.org/10.59581/harmoni-widyakarya.v2i4.4431

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). *How habit limits the predictive power of intention: The case of information systems continuance*. MIS Quarterly, 31(4), 705–737. https://doi.org/10.2307/25148817

Liu, J., Ellies-Oury, M. P., Stoyanchev, T., & Hocquette, J. F. (2022). Consumer perception of beef quality and how to control, improve and predict it? Focus on eating quality. *Foods*, *11*(12), 1732. https://doi.org/10.3390/foods11121732

Mai, S. M., & Cuong, T. (2020). Relationships between Service Quality, Brand Image, Customer Satisfaction, and Customer Loyalty. *Journal of Asian Finance, Economics and Business*, *8*(3), 585–593. https://doi.org/10.13106/jafeb.2021.vol8.no3.0585

Muñoz-Leiva, F., Climent-Climent, S., & Liébana-Cabanillas, F. (2016). Determinantes de la intención de uso de las aplicaciones de banca para móviles: una extensión del modelo TAM clásico. *Spanish Journal of Marketing - ESIC*, *21*(1), 25–38. https://doi.org/10.1016/j.sjme.2016.12.001

Papakostas, C., Troussas, C., Krouska, A., & Sgouropoulou, C. (2023). Exploring users' behavioral intention to adopt mobile augmented reality in education through an extended technology acceptance model. *International Journal of Human–Computer Interaction*, *39*(6), 1294-1302. http://dx.doi.org/10.1080/10447318.2022.2062551

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

Pelau, C., Dabija, D. C., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. *Computers in Human Behavior*, *122*, 106855. https://doi.org/10.1016/j.chb.2021.106855

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: An extension of the technology acceptance model. *Internet Research*, *14*(3), 224–235. https://doi.org/10.1108/10662240410542652

Cendika, P., Parawansa, D. A., & Baumassepe, A. N. (2023). NEW PLN MOBILE INNOVATION: TECHNOLOGY ACCEPTANCE MODEL. *Paulus Journal of Accounting (PJA)*, *4*(2), 1-9.

Pradipta, F., & Aruan, D. T. H. (2024). Powering Up User Loyalty: Exploring Multidimensional Platform Value And Service Quality In The Pln Mobile Electricity Service Application Platform. *Journal of Syntax Literate*, *9*(12). https://doi.org/10.36418/syntax-literate.v9i12.55140

Prastiawan, D. I., Aisjah, S., & Rofiaty, R. (2021). The effect of perceived usefulness, perceived ease of use, and social influence on the use of mobile banking through the mediation of attitude toward use. *APMBA (Asia Pacific Management and Business Application)*, *9*(3), 243-260. https://doi.org/10.21776/ub.apmba.2021.009.03.4

Putra, H. B., Pradita, N., & Hayuningtias, K. A. (2020). Prediksi Niat Penggunaan Aplikasi Dan Permainan Daring Freemium Versi Berbayar Dengan Menggunakan Model Tpb. *Managament Insight: Jurnal Ilmiah Manajemen*, *15*(2), 130–143. https://doi.org/10.33369/insight.15.2.130-143

Shroff, R. H., Deneen, C. C., & Ng, E. M. W. (2011). Analysis of the technology acceptance model in examining students' behavioural intention to use an e-portfolio system. *Australasian Journal of Educational Technology*, *27*(4), 600–618. https://doi.org/10.14742/ajet.940

Siagian, H., Tarigan, Z. J. H., Basana, S. R., & Basuki, R. (2022). *The effect of perceived security, perceived ease of use, and perceived usefulness on consumer behavioral intention through trust in digital payment platform* (Doctoral dissertation, Petra Christian University).

Tao, D., Fu, P., Wang, Y., Zhang, T., & Qu, X. (2022). Key characteristics in designing massive open online courses (MOOCs) for user acceptance: An application of the extended technology acceptance model. *Interactive Learning Environments*, *30*(5), 882-895. https://psycnet.apa.org/doi/10.1080/10494820.2019.1695214

Vafaei-Zadeh, A., Ng, S. X., Hanifah, H., Teoh, A. P., & Nawaser, K. (2021). Safety technology adoption: predicting intention to use car dashcams in an emerging country. *International Journal of Innovation and Technology Management*, *18*(05), 2150022. http://dx.doi.org/10.1142/S021987702150022X

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478. https://doi.org/10.1016/j.inoche.2016.03.015

Wang, C., Ahmad, S. F., Ayassrah, A. Y. B. A., Awwad, E. M., Irshad, M., Ali, Y. A., ... & Han, H. (2023). An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. *Heliyon*, *9*(8). http://dx.doi.org/10.1016/j.heliyon.2023.e18349

Wang, L., & Lee, J. H. (2021). The impact of K-beauty social media influencers, sponsorship, and product exposure on consumer acceptance of new products. *Fashion and Textiles*, *8*(1), 15. http://dx.doi.org/10.1186/s40691-020-00239-0

Yang, F., Tang, J., Men, J., & Zheng, X. (2021). Consumer perceived value and impulse buying behavior on mobile commerce: The moderating effect of social influence. *Journal of Retailing and Consumer Services*, *63*, 102683. https://doi.org/10.1016/j.jretconser.2021.102683

Yoon, N., & Lee, H. K. (2021). AI recommendation service acceptance: Assessing the effects of perceived empathy and need for cognition. *Journal of Theoretical and Applied*

Electronic Commerce Research, *16*(5), 1912-1928. https://doi.org/10.3390/jtaer16050107

Zhang, M., Gursoy, D., Zhu, Z., & Shi, S. (2021). Impact of anthropomorphic features of artificially intelligent service robots on consumer acceptance: moderating role of sense of humor. *International Journal of Contemporary Hospitality Management*, *33*(11), 3883-3905. http://dx.doi.org/10.1108/IJCHM-11-2020-1256

Zou, M., & Huang, L. (2023). To use or not to use? Understanding doctoral students' acceptance of ChatGPT in writing through technology acceptance model. *Frontiers in Psychology*, *14*, 1259531. https://doi.org/10.3389/fpsyg.2023.1259531