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Determinants Of Robotics Process Automation Acceptance in Digital Banking Onboarding: Evidence from Malaysian Banking Customers

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Abstract

This study examines customer acceptance of Robotic Process Automation (RPA) in the banking onboarding process within the Malaysian banking sector. Customer onboarding represents a critical first interaction between banks and new customers, yet it is often marred by inefficiencies, manual bottlenecks, and regulatory complexities that negatively affect customer satisfaction and retention. As the Malaysian banking sector accelerates its digital transformation, RPA has emerged as a promising solution to automate repetitive, rule-based tasks, improve process efficiency, and deliver faster, error-free onboarding experiences. Grounded in the Technology Acceptance Model (TAM), this research proposes and tests a conceptual framework integrating constructs such as Perceived Ease of Use (PEU), Perceived Process Efficiency (PPE), Perceived Security and Privacy (PSP), Perceived Attribute of Accessibility (PAA), and RPA Acceptance (RA). A quantitative methodology was employed using a structured survey administered to banking customers in Malaysia. The data were analyzed using Structural Equation Modelling (SEM) to evaluate the hypothesized relationships. The findings indicate that PEU and PSP significantly influence RA, whereas PPE and PAA do not demonstrate significant effects. The study further examines the moderating role of age in shaping these relationships. The findings enhance understanding of RPA acceptance in banking onboarding processes and inform automation adoption strategies.

Keywords: Robotics Process Automation, Customer Onboarding, RPA Acceptance, Digital transformation, Technology Acceptance Model.

1. Introduction

The banking sector plays a fundamental role in supporting economic development by facilitating financial transactions, mobilizing savings, and providing credit to individuals and businesses (Lottu et al., 2023). In recent years, rapid technological advancements and evolving customer expectations have accelerated digital transformation initiatives across the global banking industry (Mandych et al., 2023). Financial institutions are increasingly leveraging digital technologies to enhance operational efficiency, improve service quality, and strengthen customer engagement while maintaining regulatory compliance and risk

management standards (Pham et al., 2022). The widespread adoption of digital banking services has transformed the way customers interact with financial institutions, creating increasing demand for seamless, convenient, and efficient banking experiences. This trend is particularly evident across both developed and emerging economies, where increasing digitalization, internet penetration, and changing customer expectations have accelerated the adoption of digital banking services and technology-enabled financial solutions (Lottu et al., 2023).

Despite these advancements, customer onboarding remains a critical and often complex process involving identity verification, documentation, customer due diligence, and regulatory compliance requirements (Sumanti & Damle, 2025). These activities frequently rely on repetitive and rule-based procedures that may contribute to processing delays, operational inefficiencies, and increased administrative workload when performed manually (Garlapati, 2024). To address these challenges, financial institutions are increasingly exploring RPA as a means of automating routine tasks, improving process consistency, reducing processing time, and enhancing operational effectiveness (Bueno et al., 2024). RPA enables software robots to emulate human interactions with digital systems, making the technology particularly suitable for high-volume and structured banking processes (Delagrammatikas et al., 2025). As banks continue to advance their digital transformation agendas, understanding the factors that influence customer acceptance of RPA-enabled onboarding processes has become increasingly important for achieving successful technology implementation and maximizing the benefits of automation initiatives (Somda et al., 2023).

Research Objectives

Considering the challenges and opportunities associated with the adoption of automation technologies in the banking sector, this study seeks to examine the factors influencing customer acceptance of RPA in the onboarding process within Malaysian banks. Drawing upon TAM, the study investigates the extent to which PEU, PPE, PSP, and PAA influence RA. In addition, the study evaluates whether age moderates the relationships between these factors and RA. By examining these relationships, the research aims to provide a deeper understanding of the key determinants that shape customers' willingness to accept RPA-enabled onboarding processes in the Malaysian banking context.

Specifically, the objectives of this study are to examine the impact of PEU on RA, to investigate the impact of PPE on RA, to assess the impact of PSP on RA, and to determine the impact of PAA on RA. Furthermore, the study seeks to examine the moderating effect of age on the relationships between PEU, PPE, PSP, and PAA and RA.

Problem Statement

Financial institutions continue to face challenges in customer onboarding due to complex procedures, extensive documentation requirements, lengthy processing times, and the potential for operational errors (Garlapati, 2024; Fagbore et al., 2022). Although banks have increasingly adopted digital technologies to improve service delivery, the application of RPA within customer onboarding processes remains relatively underexplored from the customer perspective and as a result, there is limited understanding of the factors that influence customers' acceptance of RPA-enabled onboarding processes in the banking sector (Kim et al., 2022). Customers may perceive onboarding processes as complicated and difficult to navigate, which can influence their willingness to accept automated solutions (Pham et al., 2022). Similarly, inefficiencies such as delays, repetitive procedures, and lengthy processing times may affect perceptions of RPA-enabled

onboarding services (Chang & Benson, 2022). Concerns relating to data security, privacy protection, and the safeguarding of personal information may further shape customers' acceptance of automation in banking environments (Rosati et al., 2022). In addition, accessibility issues, including the availability of support and the ease of accessing onboarding services across different channels, may influence customers' evaluations of RPA-enabled processes (Bellahcene & Latreche, 2023).

Despite the growing adoption of automation technologies in the financial sector, there remains limited empirical evidence regarding the collective influence of PEU, PPE, PSP, and PAA on RA within the Malaysian banking onboarding context. Furthermore, the extent to which age influences the relationships between these factors and RA remains insufficiently understood. Addressing these gaps is important for both theory and practice, as a better understanding of the determinants of RPA acceptance can support the successful implementation of automation technologies in banking onboarding processes.

Accordingly, this study seeks to address these gaps by empirically investigating the factors influencing RA in the onboarding processes of Malaysian banks, while examining the moderating effect of age on the proposed relationships.

Scope of the Study

This study focuses on the customer onboarding process within the Malaysian banking sector and examines the factors influencing customer acceptance of RPA in onboarding activities. Specifically, the study investigates the influence of PEU, PPE, PSP, and PAA on RA. In addition, the study examines the moderating effect of age on the relationships between these factors and RPA acceptance. The research adopts a quantitative cross-sectional design and utilizes structured questionnaires administered to banking customers who have experienced onboarding processes. The collected data are analyzed using statistical techniques to evaluate the proposed relationships and provide insights into customer acceptance of RPA within the Malaysian banking context.

Significance of the study

This study contributes to the existing literature by extending TAM within the context of RPA acceptance in banking onboarding processes (Shaikh et al., 2020; Abdalla, 2025). By examining the influence of PEU, PPE, PSP, and PAA on RA, the research enriches the growing body of knowledge on technology acceptance and adoption in financial services (Legass & Durmus, 2024; Abdalla, 2025). In addition, the study advances the understanding of customer–technology interactions in automated service environments (Garlapati, 2024; Somda et al., 2023) and provides empirical evidence on the factors influencing the acceptance of RPA-enabled banking solutions (Delagrammatikas et al., 2025).

From a practical perspective, the findings offer valuable insights for banking institutions seeking to implement RPA technologies within onboarding processes (Delagrammatikas et al., 2025). By identifying the factors that influence RPA acceptance, the study enables banks to better understand customer perceptions towards automation and the determinants of successful adoption (Kusairi et al., 2025). These insights can support the development and implementation of RPA-enabled onboarding solutions that align with customer expectations, improve adoption outcomes, enhance operational effectiveness, and contribute to broader digital transformation initiatives (Delagrammatikas et al., 2025; Garlapati, 2024). Furthermore, examining the moderating effect of age provides banks with a deeper understanding of how different customer segments respond to automated onboarding processes, thereby supporting the design of more inclusive and customer-centric strategies (Abdalla, 2025).

The study also has policy implications. The findings provide empirical evidence that may assist regulatory authorities and policymakers in understanding the factors that influence customer acceptance of automation technologies in banking services (Singh et al., 2025). Such insights can support the formulation of policies and guidelines that encourage digital transformation while maintaining appropriate standards of security, privacy, and regulatory compliance (Eskandarany, 2024). Moreover, the results may contribute to initiatives aimed at promoting greater accessibility and financial inclusion through the responsible adoption of digital technologies within the banking sector (Singh et al., 2025; Eskandarany, 2024).

LITERATURE REVIEW

The banking industry has significantly embraced digital transformation, leveraging emerging technologies such as cloud computing, Artificial Intelligence (AI), RPA to enhance operational efficiency and customer service quality (Madakam et al., 2022). AI and machine learning, specifically, have improved banks' analytical capabilities in fraud detection, credit assessments, and customer relationship management, thus enabling more personalized and context-driven interactions (Singh et al., 2025). RPA, a central component of banking modernization, utilizes software robots to automate repetitive, rule-based tasks including account management, transaction processing, and regulatory compliance activities (Syed et al., 2020). Unlike traditional automation, RPA interacts at the user-interface level, reducing integration complexity with legacy systems and enhancing scalability and flexibility (Rizk et al., 2020). RPA platforms, notably UiPath, Automation Anywhere, and Blue Prism, facilitate rapid deployment, minimize operational errors, and significantly improve banking processes, thereby contributing directly to customer satisfaction and operational agility.

Customer Onboarding: Challenges and Expectations

Customer onboarding remains a critical yet challenging process in the banking sector, characterized by stringent regulatory compliance demands such as Know Your Customer (KYC) and Anti-Money Laundering (AML) verification (Sumanti & Damle, 2025). Complex onboarding procedures often result in customer dissatisfaction, delays, and abandonment, negatively impacting customer retention and acquisition. Today's banking customers have heightened expectations driven by seamless experiences in other digital services. They demand personalized, efficient, and secure onboarding processes comparable to those offered by digital-native platforms. Clear, consistent communication, digital convenience through tools like biometric verification, and proactive, personalized customer service are now prerequisites for successful onboarding (Barjaktarović Rakočević et al., 2025). Managing these expectations effectively by ensuring transparency and regular updates significantly enhances trust and satisfaction, fostering long-term customer loyalty (Kusairi et al., 2025).

RPA Adoption in Malaysian Banks: Current Status and Challenges

RPA adoption among Malaysian banks has progressively gained traction, with larger institutions such as Maybank and CIMB already integrating RPA into operations such as compliance, account reconciliation, and customer onboarding, achieving substantial improvements in efficiency and accuracy (Razak & Ismail, 2022). However, broader adoption remains inconsistent, particularly among smaller banks, constrained by limited infrastructure investments, lack of organizational readiness, and uncertainties regarding RPA's tangible benefits (Syed et al., 2020). Regulatory guidelines from Bank Negara Malaysia further shape RPA adoption, emphasizing the importance of compliance and robust data security

frameworks. Banks must balance technological innovation with stringent regulatory standards, adding complexity to RPA deployment decisions (Rahman et al., 2023).

Integration of RPA and Customer Experience (CX)

The strategic implementation of RPA positively impacts customer experience in banking by streamlining critical processes such as onboarding, transaction handling, and customer support, thereby improving speed, accuracy, and reliability (Axmann & Harmoko, 2021). Automated processes reduce waiting times, minimize operational errors, and offer a consistent omnichannel experience that meets modern customer expectations for immediacy and efficiency. These underscores the capability of RPA to transform customer interactions and reinforce customer trust.

Challenges in RPA Implementation and Integration

Despite its benefits, RPA implementation poses multiple challenges for banks, notably process complexity, cybersecurity risks, regulatory compliance burdens, and employee resistance (Syed et al., 2020; Yadav et al., 2025). Complex banking processes, stringent regulatory frameworks, and data security concerns require meticulous planning and robust governance frameworks. Employee apprehension about potential job displacement necessitates effective change management, transparent communication, and comprehensive training programs to ensure smooth RPA adoption (Yadav et al., 2025). Addressing these human-centric challenges alongside technical and regulatory considerations remains essential for successful RPA deployment.

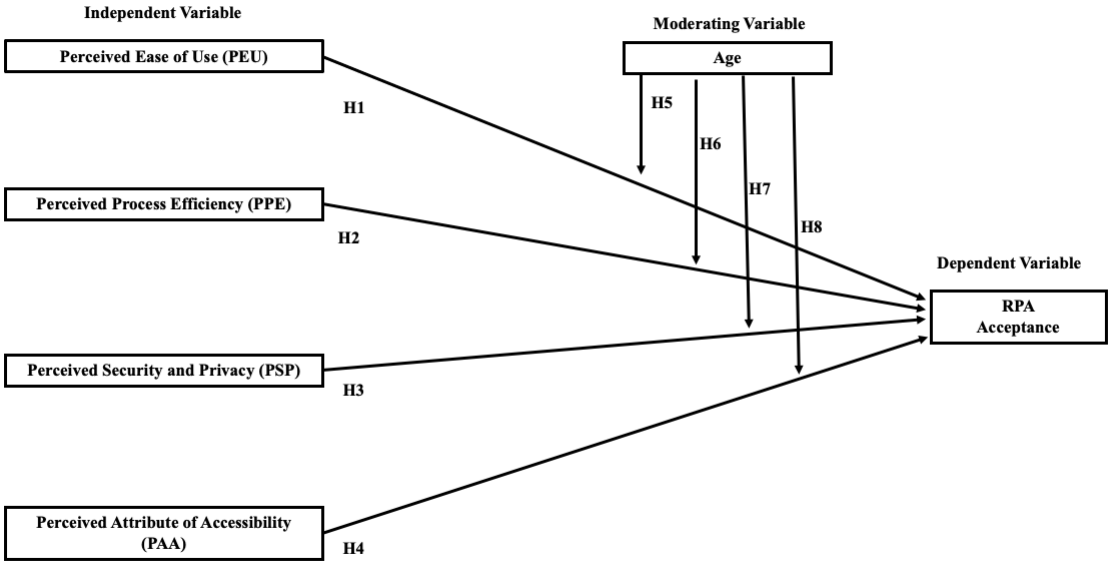
Theoretical Underpinning: TAM

TAM, proposed by Davis (1989), provides a theoretical foundation for understanding user acceptance of technology, emphasizing two primary constructs: PEU and perceived usefulness (PU) (Davis, 1989). In the banking context, PU relates to the degree customers perceive RPA as enhancing onboarding efficiency, while PEU refers to how effortlessly customers interact with automated systems (Song et al., 2025). Extensions of TAM, such as TAM2 and TAM3, incorporate additional elements including social influence and system quality, providing deeper insights into technology acceptance dynamics within organizational contexts (Davis & Granić, 2024). These constructs significantly inform the research framework, enabling a comprehensive analysis of customer acceptance and experience with RPA-driven onboarding solutions.

Conceptual Framework and Hypotheses Development

The proposed framework aims to explain the factors influencing customer acceptance of RPA in the banking onboarding process. Specifically, the framework examines the relationships between PEU, PPE, PSP, and PAA and their influence on RA. In addition, the framework investigates the moderating effect of age on these relationships to determine whether customers from different age groups exhibit varying levels of acceptance towards RPA-enabled onboarding processes. By providing a structured representation of these relationships, the framework contributes to a better understanding of the key determinants of RPA acceptance within the Malaysian banking sector. The conceptual framework of this research is shown in Figure 1.

Figure 1. CONCEPTUAL FRAMEWORK OF THIS RESEARCH



Source: The authors

Grounded in TAM, this study investigates the influence of PEU, PPE, PSP, and PAA on RA within the context of banking onboarding processes. Furthermore, the framework evaluates the moderating effect of age on these relationships. Based on the proposed framework, the following hypotheses are developed and tested (Table 1):

Table 1. HYPOTHESIS OF THE CONCEPTUAL FRAMEWORK

ID	Hypothesis
H1	Perceived Ease of Use is positively associated with RPA Acceptance.
H2	Perceived Process Efficiency is positively associated with RPA Acceptance.
H3	Perceived Security and Privacy is positively associated with RPA Acceptance.
H4	Perceived Attribute of Accessibility is positively associated with RPA Acceptance.
H5	Age moderates the relationship between Perceived Ease of Use and RPA Acceptance.
H6	Age moderates the relationship between Perceived Process Efficiency and RPA Acceptance.
H7	Age moderates the relationship between Perceived Security and Privacy and RPA Acceptance.
H8	Age moderates the relationship between Perceived Attribute of Accessibility and RPA Acceptance.

Source: The authors

METHODOLOGY

The study employed a quantitative research design guided by the positivist paradigm, enabling empirical validation through statistical analysis and hypothesis testing. A structured online survey was used to collect data on customers' perceptions of PEU, PPE, PSP, and PAA, as well as their acceptance of RPA in banking onboarding processes. This quantitative approach facilitates objective measurement of the relationships among the study variables and supports the testing of the proposed hypotheses. Furthermore, it enables the generation of statistically robust findings that contribute to both theoretical understanding and practical implementation of RPA within the Malaysian banking sector.

Sampling and Data Collection

A purposive sampling method was adopted, targeting Malaysian bank customers aged 18 and above. The sample size was determined using Krejcie & Morgan's formula, yielding a minimum of 384 respondents for robust statistical analysis (Krejcie & Morgan, 1970). Data were collected via an online survey administered through Google Forms, facilitating wide geographic coverage and respondent convenience. Data collection was conducted over a period of approximately three and a half months, from 3 December 2024 to 15 March 2025. The questionnaire employed a five-point Likert scale, enabling precise quantification of subjective perceptions. Prior to full-scale implementation, a pilot study involving 35 respondents was conducted, confirming questionnaire clarity, reliability (Cronbach's $\alpha > 0.7$), and construct validity.

Measurement and Operationalization of Constructs

The measurement model was developed based on the proposed conceptual framework and comprised five primary constructs. PEU refers to customers' perceptions of the simplicity, clarity, and ease associated with completing the banking onboarding process. PPE reflects customers' evaluations of the timeliness, speed, and overall effectiveness of the onboarding procedures. PSP captures customers' confidence in the security of their personal information, the adequacy of privacy protection measures, and compliance with regulatory requirements throughout the onboarding process. PAA represents customers' perceptions of the ease of accessing onboarding services, resources, and support through available channels and devices. RA refers to customers' willingness to accept and adopt RPA-enabled onboarding processes based on their perceptions of the technology and its potential benefits.

In addition to the primary constructs, demographic information was collected to provide a profile of the respondents. Age was specifically incorporated as a moderating variable to examine its influence on the relationships between PEU, PPE, PSP, and PAA and RA.

Data Analysis

Data analysis encompassed both descriptive and inferential statistical methods. Descriptive statistics summarized initial data trends, including central tendency and variability. Multivariate assumption checks (normality, linearity, homoscedasticity, multicollinearity) were performed to ensure appropriateness for further analysis. Structural Equation Modeling (SEM) was selected as the core analytical technique due to its capability to simultaneously examine relationships among observed and latent variables, measure model fit, and account for measurement errors. SEM involved the validation of structural and measurement models using fit indices ensuring robust and reliable analytical outcomes (Wooldredge, 2023).

Common Method Bias and Ethical Considerations

Procedural and statistical controls were implemented to mitigate Common Method Bias (CMB). Procedurally, survey anonymity, question clarity, and counterbalanced item order minimized potential bias. Statistically, Harman's single-factor and marker variable tests confirmed minimal bias impact. Participant confidentiality and anonymity were rigorously maintained throughout data collection, analysis, and reporting, adhering strictly to ethical research standards (Creswell, 2023).

Methods Limitations

The study acknowledges several limitations associated with the quantitative research approach. While the use of structured surveys enabled the collection of data from a larger sample and facilitated statistical analysis and hypothesis testing, it limited the ability to explore respondents' underlying motivations and perceptions in greater depth. Furthermore, the study relied on self-reported data, which may be subject to response bias and individual interpretation. Nevertheless, pilot testing was conducted to enhance the reliability and validity of the measurement instrument, while established statistical procedures were employed to ensure the robustness of the findings. Despite these limitations, the quantitative approach was considered appropriate for examining the relationships between PEU, PPE, PSP, PAA, and RA, as well as the moderating effect of age.

RESULTS AND FINDINGS

Data collection was conducted through an online survey distributed to banking customers in Malaysia, achieving a final sample size of 423 valid responses after data cleansing. Demographic analysis revealed most respondents aged between 26-35 years (37%), followed by 18-25 years (26%), 36-50 years (22%), and above 50 years (15%).

Descriptive Statistics and Data Normality

Descriptive analysis assessed key constructs using a 5-point Likert scale. The mean scores were: Perceived Ease of Use (2.46), Perceived Process Efficiency (2.55), Perceived Security and Privacy (2.52), Perceived Attribute of Accessibility (2.46), and RPA Acceptance (3.55). Normality checks via skewness (-0.87 to 0.49) and kurtosis (-1.65 to -0.61) confirmed data suitability for Structural Equation Modeling (SEM), meeting the standard range (±2) (Hair et al., 2022).

Measurement Model Validation

The measurement model was rigorously tested using Cronbach's alpha (≥ 0.7), Composite Reliability (≥ 0.7), and Average Variance Extracted (AVE ≥ 0.5) to ensure reliability and convergent validity (Hair et al., 2022). All constructs met these thresholds, confirming strong internal consistency and convergent validity shown in Table 2.

Table 2. MEASUREMENT MODEL VALIDATION

Construct	Cronbach's α	Composite Reliability	AVE
PEU	0.946	0.946	0.85
PPE	0.936	0.936	0.75
PSP	0.958	0.958	0.85
PAA	0.953	0.953	0.80
RA	0.972	0.972	0.87

Source: The authors

Discriminant validity was established via the Fornell-Larcker criterion and the HTMT ratio (below 0.85), confirming distinctiveness among constructs.

Measurement Model Assessment and Hypothesis Testing

The measurement model assessment depicted in Table 3 was developed to fulfil the objectives of this study, specifically to identify the factors influencing RPA Acceptance in Malaysian banks. These factors were assessed based on the model fit indices and the R-square values.

Table 3. MEASUREMENT MODEL ASSESSMENT

Construct	Indicators Retained	Loading Range
PEU	PEU1, PEU2, PEU3, PEU4, PEU5	0.778 – 0.935
PPE	PPE1, PPE3, PPE4, PPE5	0.763 – 0.944
PSP	PSP1, PSP3, PSP4, PSP5	0.827 – 0.907
PAA	PAA1, PAA3, PAA4, PAA5	0.858 – 0.907
RA	RA1, RA2	0.934 – 0.943

Source: The authors

The retained indicators represent the questionnaire items used to measure each latent construct. For example, PPE1–PPE5 correspond to the items measuring customers' perceptions of process efficiency, while PEU1–PEU5, PSP1–PSP5, PAA1–PAA5, and RA1–RA2 represent the respective measurement items for PEU, PSP, PAA, and RA. Indicators that did not meet the recommended loading threshold were excluded from the final measurement model. SEM using SmartPLS was conducted to evaluate hypothesized relationships. Goodness-of-fit indices showed a strong fit (SRMR = 0.035; NFI = 0.919). The structural model explained 61% of the variance in RPA Acceptance. Path coefficients revealed significant relationships as shown in Table 4.

Table 4. PATH COEFFICIENT ASSESSMENT

Hypothesis	Path	O	M	t-value	p-value	Result
H1	PEU → RA	0.086	-0.192	3.99	0.000	Significant (Negative)
H2	PPE → RA	-0.065	-0.067	1.015	0.310	Not significant
H3	PSP → RA	-0.115	-0.122	2.353	0.019	Significant (Negative)
H4	PAA → RA	-0.191	0.089	1.215	0.225	Not significant

Note: O=Original Sample, M= Sample Mean

Source: The authors

The findings demonstrate that PEU and PSP have significant effects on RA, while PPE and PAA do not show statistically significant direct relationships with RA.

Moderation Analysis by Age Demographic

Moderation analysis was conducted using multi-group comparisons to examine whether age influenced the structural relationships between PEU, PPE, PSP, PAA, and RA. The results indicate that age did not

exert a statistically significant moderating effect on the relationships between the independent variables and RA. However, differences were observed in the significance of predictors across age groups. Among respondents aged 18–25, PSP emerged as the most influential factor affecting RA. For respondents aged 26–35 and those above 50 years, PEU was identified as the most significant predictor of RA. In contrast, no dominant predictor was observed among respondents aged 36–50. These findings suggest that while age does not significantly moderate the proposed relationships, customers from different age groups may place varying levels of importance on specific factors when evaluating the acceptance of RPA in banking onboarding processes.

Table 5. SUMMARY OF AGE PREDICTOR BY DEMOGRAPHICS SEGMENTS

Demographic Segment	Significant Predictors
Age: Above 50 years	PEU
Age: 36-50 years	None significant
Age: 26-35 years	PEU
Age: 18-25 years	PSP

Source: The authors

These moderation insights provide valuable guidance for banks to strategically address different concerns and priorities across varied demographic groups when implementing RPA solutions.

CONCLUSION

This study aimed to examine the factors influencing RA in the onboarding processes of Malaysian banks. Guided by TAM, the research investigated the effects of PEU, PPE, PSP, and PAA on RA, while also assessing the moderating effect of age. The findings revealed that PEU and PSP significantly influenced RA, whereas PPE and PAA did not exhibit statistically significant direct effects. The significant negative relationship between PEU and RA contrasts with the traditional assumptions of TAM, which posit that technologies perceived as easier to use are more likely to be accepted by users. One possible explanation is that customers may associate highly simplified onboarding processes with reduced transparency, control, or procedural robustness, particularly in the highly regulated banking environment where security and verification procedures are expected (Zhang et al., 2023). As a result, excessive simplification may unintentionally reduce customer confidence in the effectiveness of RPA-enabled onboarding processes. Similarly, PSP was found to have a significant negative effect on RA, indicating that concerns relating to data security, privacy protection, and the handling of personal information remain important barriers to the acceptance of automation in banking onboarding activities. This finding is consistent with previous studies that identify privacy and security concerns as critical determinants of technology acceptance, particularly in digital financial services where customers are required to share sensitive personal and financial information (Zhang et al., 2023; Martínez-Navalón et al., 2023). In contrast, PPE and PAA did not significantly influence RA. Although process efficiency and accessibility are generally regarded as important attributes of digital services, the findings suggest that these factors alone may not be sufficient to drive customer acceptance of RPA within the onboarding context. Customers may perceive efficiency and accessibility as baseline service expectations rather than distinguishing factors that influence their acceptance of automation (Barjaktarović Rakočević et al., 2025; Bueno et al., 2024). Consequently, improvements in efficiency and accessibility may not necessarily translate into higher levels of RPA

acceptance unless accompanied by stronger perceptions of trust, security, and confidence in the automated process. The moderation analysis further revealed that age did not significantly influence the relationships between PEU, PPE, PSP, PAA, and RA. This finding suggests that the factors influencing RPA acceptance are relatively consistent across different age groups. Nevertheless, variations in the significance of predictors across age categories indicate that customers may place differing levels of importance on specific factors when evaluating RPA-enabled onboarding processes, although these differences were not sufficiently strong to produce statistically significant moderating effects (Kusairi et al., 2025; Manasreh et al., 2025; Murugesh-Warren et al., 2015).

Practical Implications for Banking Operations

The findings of this study provide several practical implications for banking institutions implementing RPA-enabled onboarding processes. Given the influence of PEU on RA, banks should prioritize the development of onboarding interfaces that are intuitive, user-friendly, and require minimal effort or technological expertise to navigate. The results also highlight the importance of PSP, suggesting that financial institutions should strengthen and clearly communicate their data protection, privacy, and security practices, particularly to customer segments that may be more sensitive to such concerns. Furthermore, banks may benefit from adopting segment-specific strategies that consider the differing needs and expectations of customers across age groups. Communicating the benefits of RPA, including reduced processing times, real-time updates, and improved accuracy, can further enhance customer awareness and acceptance of automated onboarding solutions. Finally, institutions should promote inclusive design principles by offering multiple onboarding channels and accessible support mechanisms to accommodate customers with varying levels of digital literacy and technology experience (Naik, 2024; Singh et al., 2025).

Policy and Regulatory Implications

The implementation of RPA within banking operations requires careful consideration of Malaysia's regulatory landscape, including the Financial Services Act 2013, Islamic Financial Services Act 2013, and the Personal Data Protection Act 2010 (Razak & Ismail, 2022). To ensure compliance, transparency, and responsible adoption of automation technologies, banking institutions should maintain close engagement with regulatory authorities to remain aligned with evolving requirements and industry standards. In addition, robust data governance frameworks should be established to safeguard customer information and ensure adherence to privacy and security obligations. Banks should also implement appropriate audit and monitoring mechanisms to enhance transparency, accountability, and traceability within automated processes. Furthermore, the development of ethical governance frameworks can assist institutions in addressing concerns relating to automation, including its implications for employment, decision-making accountability, and transparency in customer-facing services (Singh et al., 2025).

Limitation and Recommendation for Future Research

Several limitations should be considered when interpreting the findings of this study. First, the scope of the research was confined to PEU, PPE, PSP, PAA, and RA. While these constructs were selected based on the proposed conceptual framework, the inclusion of additional variables such as perceived usefulness, system quality, and organizational trust may provide a more comprehensive understanding of customer acceptance of RPA-enabled onboarding processes. Second, the cross-sectional nature of the research

design limits the ability to establish causal relationships among the study variables. Future studies may benefit from adopting longitudinal approaches to examine changes in customer perceptions and acceptance over time. Third, the study was conducted within the Malaysian banking sector, which may limit the generalizability of the findings to other industries or geographical settings. Comparative studies across sectors and countries could provide additional insights into the determinants of RPA acceptance. Finally, variations in respondent demographics may influence the applicability of the findings to broader populations. Future research should therefore consider more diverse samples and larger respondent groups. In addition, future studies may explore hybrid human–RPA service models, adopt mixed-method approaches, and examine the role of artificial intelligence in supporting customer segmentation and personalized service delivery.

Declaration of Conflicting Interests

The authors declare no conflict of interest with respect to the research, authorship, and/or publication of this article.

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