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THE ROLE OF ARTIFICIAL INTELLIGENCE IN ENHANCING LOAN RECOVERY STRATEGIES IN SRI LANKA

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ABSTRACT

Sri Lankan Licensed commercial banks maintain economic stability and financial inclusion, but struggle with loan recovery which affect their financial stability. The increasing Non-Performing Loan (NPL) ratios shows that the loan recovery process has become inefficient, creating financial risks for sustainability. Despite traditional recovery methods, challenges such as regulatory constraints, operational inefficiencies, and borrower behavior continue to delay loan repayment. Hence, this research addresses a research gap by examining how Artificial Intelligence (AI) can improve loan recovery processes, making them more effective and efficient. This study primarily aimed to identify whether performance expectancy, effort expectancy, and social influence impact the intention to use an AI-based loan recovery system in Sri Lanka. By focusing on these key constructs, the study focuses on providing empirical evidence on how individual perceptions and social factors shape employees' readiness to adopt AI technologies in the loan recovery process. This research adopts a positive philosophy and a quantitative research strategy. The objective is to be achieved using quantitative analysis from the data collected through structured questionnaires from a sample of 100 loan recovery officers selected using the Purposive sampling method from the population of recovery officers across Western Province branches. The findings indicate that effort expectancy and social influence are significant factors affecting the adoption of AI-based loan recovery, and performance expectancy is not significant. These findings shows that the banks should focus on ease of use, and peer and organizational support, as well as equipping them with sufficient infrastructure and resources to motivate the adoption of AI systems to improve the NPL ratios and financial sustainability of the banking sector in Sri Lanka.

Keywords: Artificial Intelligence, Banking, Loan Recovery, Non-Performing Loans

1. Introduction

Technological advancements, particularly in Artificial Intelligence (AI), have introduced a revolutionary era of transformation into the banking sector of the world, revolutionizing traditional practices of operation and risk management (Dewasiri et al., 2023; Bueno et al., 2024). The predictive modeling, process automation, and data analytics strengths of AI have been leveraged to enhance credit scoring, fraud detection, and customer service, leading to enhanced operational efficiency and financial stability (World Economic Forum, 2021). In addition to the effects on operational effectiveness, the consequences of adopting AI also include strategic risk management redefinition, autonomy in decision-making, and interaction with customers. The AI systems will enable the real-time observation of the borrower behavior, adjustive credit score and recovery strategies based on data, which can substantially decrease the risk of the defaults. In the Sri Lankan context, adoption of AI in recovery systems is not only an upgrade in terms of technology but also a financial necessity to maintain the stability of the banking sector in the context of the rapidly growing NPL ratios. The potential applications of AI systems in banking are vast; for instance, machine learning algorithms can analyze vast datasets to predict the likelihood of loans defaults and assist in proactive measures and substantially improve recovery rates (Sadok et al., 2022;Athukorala, 2024). The implementation of such AI-driven strategies has the potential to revolutionize banking operations, improve risk assessment protocols, and improve financial outcomes (Baffour Gyau et al., 2024).

Among the fundamental challenges facing banking institutions worldwide is the handling of Non-Performing Loans (NPLs), which impact profitability and threaten financial stability (Kumarasinghe, 2017; Ughulu & Odion, 2023). In Sri Lanka, the case is particularly grim, with Licensed Commercial Banks facing a phenomenal rise in NPL percentages from 4.7% in 2020 to 13% in 2023, a rate that persisted in 2024 (Central Bank of Sri Lanka, 2023). This surge indicates inefficiencies in traditional loan recovery processes, which are often hampered by manual intercessions, regulator constraints, and inability to realize and act fast in terms of borrower distress signals (Keshani & Jayatilake, 2021;Saliya, 2023). Consequently, banks face reduced profitability due to higher provisioning costs, constrained liquidity and a restricted capacity to extend new credit, which in turn stifles economic growth and recovery (Preuss & Königsgruber, 2021).

Across the globe, major banks have employed AI to address these same problems. Global case studies show the efficacy of AI in recovering loans. To name an example, ICICI Bank in India employs AI and machine learning for data analysis, which enables specific customer outreach and automated payment reminders, and this resulted in a 15-20% boost in loan recoveries (McKinsey & Company., 2022). Similarly, the deployment of AI chatbots and voicebots by HDFC Bank has mechanized its reminder mechanism, enhancing collection management efficiency without having to incur major manpower deployment (World Economic Forum, 2021). These international applications confirm that modern institutions require technology-based solutions to strengthen stability and promote sustainable loan management practices (Khan et al., 2024).

However, despite its proven global success, its integration of AI-based loan recovery systems in Sri Lanka's banking sector, particularly in its priority Domestic Systemically Important Banks (D-SIBs), is underdeveloped (Central Bank of Sri Lanka, 2024; Ari et al., 2021). This creates a significant research gap. Most Importantly, the successful adoption of any new technology is not merely a technical issue but is deeply influenced by the behavioral intentions of end users. This study is based on the Unified Theory of Acceptance and the Use of Technology (UTAUT), which posits that major aspects directly influence the intention to use a new system. Performance Expectancy (the degree to which users believe the system will help them achieve gains in job performance) is critical because recovery officers must be convinced that an AI system will genuinely enhance recovery rates and efficiency (Venkatesh et al., 2003). Effort Expectancy (the perceived ease of use of the system) is vital for ensuring that the technology is not seen as overly complex, thereby encouraging adoption (Venkatesh et al., 2003). Furthermore, Social Influence (the degree to which users perceive that important others believe they should use the system) can drive acceptance within the organizational culture of a bank (Venkatesh et al., 2003). Understanding these factors is a major precursor to the effective development and implementation of AI solutions, but the willingness and perceptions of the recovery officers have been largely overlooked in the Sri Lankan context.

Accordingly, the objective of this study is to identify whether performance expectancy, effort expectancy, and social influence impact the intention to use an AI-based loan recovery system in Sri Lanka. This is informed by the UTAUT by Venkatesh et al., (2003) , which suggests that people's behavioral intentions toward new technology are shaped by perceived usefulness, ease of use, and social encouragement. Gaining an understanding of these behavioral determinants is a key prerequisite for the successful implementation of AI solutions in operationally critical functions of the bank such as loan recovery.

The major contribution of this research lies in its empirical validation of behavioral factors influencing AI adoption in the Sri Lankan banking sector. By integrating the UTAUT framework in the context of loan recovery, this study provides managerial implications for improving technological readiness, enhancing employee acceptance, and designing more effective AI-based recovery systems to address the growing NPL problem.

The remaining part of the paper is organized as follows: first chapter presents the literature review, next, it outlines the research methodology, third chapter shows the results and discussions, and the last chapter provides the conclusion, implications, limitations and future research.

2. Literature Review

Artificial Intelligence (AI) is increasingly transforming the global financial sector, particularly in credit rating, fraud detection, and loan recovery (Kumar et al., 2020).AI-based loan recovery systems improve efficiency by predicting payment behavior, identifying early potential defaults, and automating the collection process. The border implications of AI adoption in banking also involve the possibility to encourage transparency, data-driven accountability, and efficiency in compliance. AI-driven insights can empower regulatory reporting and recovery operations that are aligned with the guidelines of central banks, thereby reinforcing systemic trust. The integration of AI ensures sustainability in finance by limiting human bias in recovery decisions and supports ethical strategies for debt collection. However, in Sri Lanka, there is limited AI adoption in banking due to infrastructural shortcomings, low awareness, and employee resistance (Ranasinghe & Perera, 2022). Currently, recovery of loans in Sri Lanka is mainly done by use of traditional means like reminder calls, written notices, field visits carried out by recovery officers, and court proceedings in instances of defaults. Such processes are very intensive, time-consuming and they usually cause customers unfavorable experiences to banks as well as making their operations expensive (Ranasinghe & Perera, 2022).

In the context of Sri Lanka, the Domestic Systemically Important Banks (D-SIBs) are defined by the Central Bank of Sri Lanka (2024), as banks whose distress or failure would have a significant impact on the domestic financial system and economy mandate takes on special significance due to their size, interconnectedness, and substitutability, and complexity. With their huge portfolios of loans and systemic significance in maintaining financial stability, these banks need to adopt state-of-the-art solutions to improve operational efficiency, including loan recovery, with a sense of urgency (Central Bank of Sri Lanka, 2024).

AI-based systems would have a special benefit for D-SIBs as it can help them automate routine collection efforts, identify high-risk consumers, and optimize resource allocation, thereby minimizing non-performing loans and managing systemic risk. Thus, for D-SIBs, AI adoption is no longer just a question of a tool for operational improvement but a strategic requirement in terms of national financial stability, systemic risk mitigation, and economic recovery. However, AI adoption in D-SIBs remains limited due to infrastructure, regulatory, and employee-related challenges, highlighting a gap this study aims to address.

Although AI has already proved to be successful in enhancing loan recovery efficiency in many countries around the world, there is still a lack of empirical studies on behavioral and organizational readiness concerning AI adoption in Sri Lanka. Most previous studies have focused more on the technical potential of AI itself without giving due consideration to human factors, such as employees' perceptions, training, and social support, which eventually make AI projects successful. This study therefore closes this gap by investigating the behavioral intentions of recovery officers toward the adoption of AI-based loan recovery systems.

To examine such dynamics, the study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) Venkatesh et al. (2003), which posits that performance expectancy, effort expectancy, and social influence are key determinants of technology adoption. Based on this theory, a conceptual framework was developed in which these three constructions were employed as independent variables influencing behavioral intention to adopt AI in loan recovery. The constructs were operationalized using a items adopted from validated measures in prior studies: performance expectancy with perceived improvements in recovery efficiency, effort expectancy with perceived ease of use of the system, social influence with encouragement from managers and peers, and behavioral intention as the dependent variable, measured using willingness to deploy AI systems in recovery operations (Venkatesh et al., 2003).

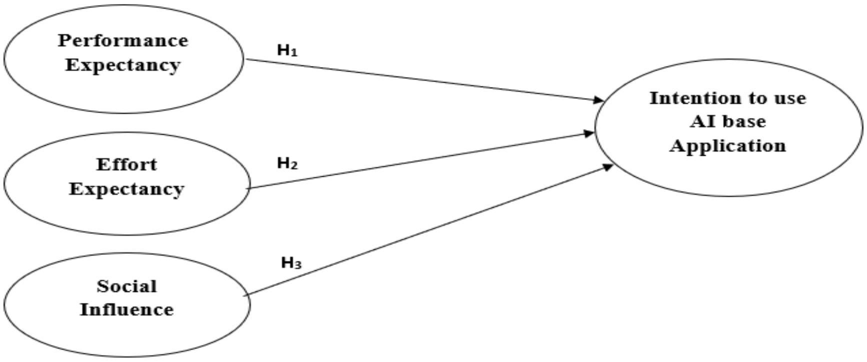

Figure 1: Conceptual Model *(Based on the UTAUT Model Author developed)*

Based on the proposed model, the following hypotheses are developed
H1: Performance Expectancy has a significant impact on the Intention to accept the AI-based loan recovery application.
H2: Effort Expectancy has a significant effect on the Intention to accept the AI-based loan recovery application.
H3: Social Influence has a significant effect on the intention to accept the AI-based loan recovery application.

3. Methodology

3.1. Research Design

In this study, the objective is to identify factors influencing recovery officers' adoption of an AI-based loan recovery system. Therefore, the study takes a positive research philosophy, founded on objectivity, empirical evidence, and the use of systematic methodology (Maretha, 2023). Quantitative research design is employed in which numerical data are captured through structured questionnaires and statistically analyzed. Quantitative research is able to provide general and factual conclusions, making it suitable for the evaluation of AI-based loan recovery solutions (Creswell & Creswell, 2020). Further it allows the quantification of officers' perceptions and the testing of behavioral factors such as performance expectancy, effort expectancy, and social influence.

3.2. Population and Sampling

The study targeted loan recovery officers in Domestic Systemically Important Banks (D-SIBs) in Sri Lanka's Western Province as the study sample. Domestic Systemically Important Banks were selected because they manage a significant amount of the country's loan portfolios and face the highest risk of non-performing loans, making them crucial players in driving the success of AI-driven recovery mechanisms and Western Province has been chosen due to its high concentration of bank branches, diverse customer base, and significant volume of Non-Performing Loans (Central Bank of Sri Lanka, 2024). The study obtained a sample of 100 recovery officers. A similar study in Sri Lanka by Khan et al. (2021) used the same sample size of 100 recovery officers, confirming that the sample size is adequate and justifiable. Purposive sampling was used in selecting participants because it allows sampling from individuals of specific expertise and relevance to the study topic (Etikan, 2016).

3.3. Data Collection

The study used a structured questionnaire distributed via Google Forms to loan recovery officers in Domestic Systemically Important Banks (D-SIBs) in Sri Lanka's Western Province. The questionnaire was developed in English, to capture officers' perceptions, challenges, and willingness to adopt AI-powered applications in loan recovery. Each item was measured using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

3.4. Pilot Survey

A pilot survey was conducted using two senior bankers and two academic experts to test the clarity, jargon, and applicability of the questionnaire. The feedback resulted in rephrasing several items, removal of redundant questions, and the inclusion of new context-specific questions to improve validity. The questionnaire was revised based on insights from the pilot survey.

3.5. Data Analysis

The collected data were analyzed in two stages. First, descriptive statistics were computed using SPSS to summarize demographic characteristics and give an overview of the respondents. In the second step, SMART PLS 4 was conducted to test the relationships among the hypothesized variables derived from the UTAUT model. Tests of reliability by means of Cronbach's alpha and composite reliability were followed by tests for validity using Average Variance Extracted and HTMT ratios to evaluate the strength and significance of relationships between constructs. Since the research consisted of descriptive and inferential results, the combination of SPSS and SMART PLS was highly suitable for offering strong empirical support for the research objectives.

4. Results and Discussion

4.1. Composition of the Sample

A total of 100 loan recovery officers in the Domestic Systemically Important Banks answered the questionnaire. A majority of the respondents were men (63%), while women accounted for 37%. Most respondents were above 26 years of age 96%. Over 55% of them had a bachelor's degree. Regarding banking experience, 55% had more than six years and in loan recovery, specifically, had 13 years. As far as workload is concerned, more than 54% responded to more than 30 recovery cases per month. Significantly, 97% said they had issues with the existing loan recovery process without AI.

4.2. Reliability and Validity of the Constructs

The Measurement model was evaluated by the Cronbach Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), Fornell-Larcker and HTMT ratios. All constructs in obtained acceptable reliability with Cronbach Alpha ranged between 0.768 (SI) and 0.900 (PE) and CR between 0.836 (SI) and 0.915 (PE), exceeding the recommended value of 0.70 (Hair, 2014). In convergent validity, PE (0.545) and IU (0.507) had higher values than the 0.50 target AVE values, whereas the others (EE 0.434) and SI (0.469) were slightly lower. Nevertheless, because the CR values of all constructs are over 0.70, it is convenient to regard convergent validity as satisfactory (Hair, 2014). The Fornell-Larcker criterion was used to confirm discriminant validity, as well as the HTMT ratios. AVE values were square rooted, and HTMT ratios (0.560881) were lower than the 0.85 criterion Henseler et al. (2015), which represents satisfactory discriminant validity.

4.3. Test of Linearity and Normality of the Data

Since the data were not normally distributed and the data were presented in the form of Likert-scale items, covariance-based SEM (CB-SEM) was not appropriate. Hence, as proposed by Hair (2014) , Partial Least Squares SEM (PLS-SEM) was used.

4.4. Model Assessment

In PLS-SEM, there are two steps in model assessment. The measurement model should be assessed in terms of reliability and validity, and the structural model should be assessed in terms of collinearity, path significance, explanatory power, and effect sizes. Lastly, the stability of the results is ensured by running model fit indices (Hair, 2014).

4.5. Assessing the Structural Model for Collinearity

Prior to the evaluation of the structural model, the collinearity between the predictor constructs had to be evaluated. Collinearity magnifies the regression estimates and threatens the reliability of results. The diagnostic indicator was the Variance Inflation Factor (VIF). Hair (2014) state that VIF values must not go above 3.3.

Table 1: Collinearity of VIF Inner Values

	IU
EE	2.407
PE	3.043
SI	2.060

All predictor constructs in the Table have values that fall below this value. Effort Expectancy (EE) = 2.407, Performance Expectancy (PE) = 3.043, and Social Influence (SI) = 2.060. These findings support the conclusion that multicollinearity was not present, and the individual constructions were used to explain Intention to Use AI-based applications.

4.6. Assessment of Relevance of the Significance of the Structural Models Relationships

Results of the PLS-SEM model, shown in Figure 2, display the standardized regression coefficients of the hypothesized paths, as well as the R^2 value of 0.558 of the endogenous constructs, Intention to Use (IU). Social Influence (0.660) turned out to be the most significant predictor, and then Effort Expectancy (0.347). Performance Expectancy (–0.197), on the other hand, revealed a negative and statistically insignificant impact, which implies that it has no significant impact on the intentions of users.

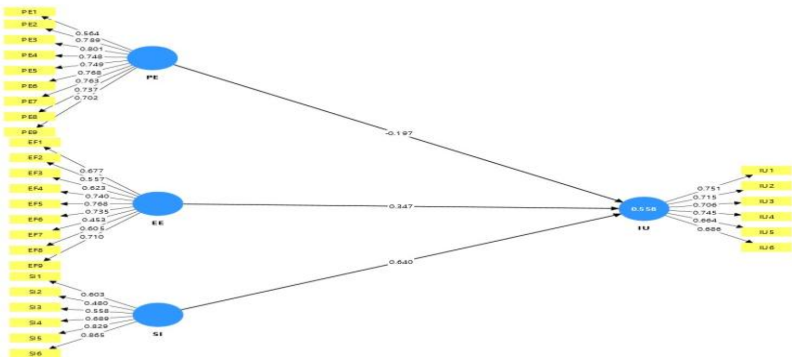

Figure 2: Path Coefficients of the Model

Three hypotheses that tested these relationships were formulated: H_2 the influence of Effort Expectancy on IU. H_1, the influence of Performance Expectancy, and the influence of Social Influence. In line with the previous methodological principles (Hair, 2014;Venkatesh et al., 2003) the constructions were measured separately so that the contribution of each construct could be better defined. After the measurement model met the criteria of validity and reliability, the structural model was validated by means of the PLS-SEM bootstrapping process. The results of hypothesis testing are shown in Table 2.

Table 2: Hypothesis Testing

	Original sample (O)	**Sample mean (M)**	**Std deviation (STDEV)**	**T stat (|O/ STDEV|)**	**P values**	**Result**
EE -> IU	0.347	0.347	0.120	2.901	0.004	Accepted
PE -> IU	-0.197	-0.173	0.139	1.411	0.158	Rejected
SI -> IU	0.640	0.628	0.148	4.321	0.000	Accepted

The statistical significance of hypothesized relationships was calculated by bootstrapping with 5,000 resamples. The findings indicated that Effort Expectancy had a positive statistically significant influence on Intention to Use AI-based applications ($\beta = 0.347$, $t = 2.901$, $p = 0.004$). Herein, it indicates that the easier AI-based applications are perceived to be by users, the more likely they are to adopt such technologies. Social Influence showed a significant and very powerful effect on Intention to Use ($\beta = 0.640$, $t = 4.321$, $p = 0.000$). This observation suggests that peer pressure, social networks, and social expectations play a significant role in influencing the choices people make to embrace AI-based applications. Conversely, Intention to Use was not affected statistically by Performance Expectancy ($\beta = -0.197$, $t = 1.411$, $p = 0.158$). This indicates that perceptions of performance gain or usefulness of AI-based applications could not be the decisive factor in intentions to adopt in this scenario.

4.7. Assessment of the Level of R^2

Table 3: Assessment of the Level of R^2

	R-square	R-square adjusted
IU	0.558	0.544

The coefficient of determination was used to determine the explanatory power of the model. It was found that under the table 3 model explained 55.8% of the variance in Intention to Use (R^2 = 0.558), adjusted R^2 = 0.544. Hair (2014) state that the weak, moderate, and strong explanatory power are represented by R^2 equals 0.25, 0.50, and 0.75. The model therefore shows moderate to significant power to explain IU, meaning that over half of the variance of IU is explained by the three independent variables.

4.8. Assessment of the f^2 Effect Size

Table 4: Assessment of the f^2 Effect Size

	IU
EE	0.113
PE	0.029
SI	0.450

The effect size analysis was carried out to ascertain the relative contribution of each predictor construct to IU. According to the recommendations given by Cohen (1988), f^2 of 0.02, 0.15, and 0.35 will show a small effect, medium and large effect, respectively. Under the table 4, results indicated that the effect of Social Influence was significant (f^2 = 0.450), which proves its paramount importance in influencing the intention to use AI-based apps. Effort Expectancy exhibited a small to medium effect (f^2 = 0.113), which is significant. On the contrary, the influence of the Performance Expectancy was only insignificant (f^2 = 0.029), supporting the weak role.

4.9. Model Fit Summary of PLS-SEM

The adequacy of the overall model was evaluated in terms of the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), discrepancies (D_ULS, D_G), and Chi-square statistics. In Table 5 shows the SRMR was 0.104, just above the suggested value of 0.08, which means a marginally satisfactory fit. The NFI value is 0.579 (lower than the benchmark of 0.90), indicating that the model is a relatively weak fit to the global data. The measures of discrepancy were d ULS = 5.064 and d G = 1.624, and Chi-square = 804.113. The global model fit indices are not of very high standards, but it is noteworthy that PLS-SEM pays more attention to the predictive power of the model and its explanatory power than absolute fit (Hair et al., 2019). Since the model explains over half of the variations in IU and shows good contributions of Effort Expectancy and Social Influence, it would be sufficient to understand the behavioral intentions in this study.

Table 5: Model Fit Summary

	Value
SRMR	0.104
D_ULS	5.064
D_G	1.624
Chi-square	804.113
NFI	0.579

5. Discussion

This study aimed to examine the impact of Effort Expectancy (EE), Performance Expectancy (PE), and Social Influence (SI) on Intention to Use (IU) AI-based applications. The results obtained with the PLS-SEM showed that EE and SI were significant predictors of IU, but PE did not become a major predictor. These results are discussed below based on theories and previous research.

It is surprising that the importance of Performance Expectancy is relatively low since the concept is at the heart of the majority of models of technology adoption. Performance-related beliefs are very strong predictors of behavioral intention in both the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989; Venkatesh et al., 2003). As one example, researchers in the field of mobile banking Rahi et al. (2019), and e-government services Gupta et al. (2008), have shown consistently that performance expectancy was among the strongest constructs. Nevertheless, this work is consistent with previously emerging studies that propose PE may not always be important in situations in which the utility of technology is already assumed (Jadil et al., 2021). In the context of AI-based applications, users can take high performance as a baseline feature that diminishes its influence on adoption decisions.

In comparison, Effort Expectancy was a significant and positive influence on Intention to Use. This validates the position of ease of use identified in TAM and supported in UTAUT (Davis, 1989; Venkatesh et al., 2003). This finding is supported by prior empirical literature, Baptista & Oliveira (2015) demonstrated ease of use was a key factor to drive the use of mobile payments, whereas Zhou et al. (2010) also identified the same factor in mobile banking. It means that complexity is still a burning barrier to adoption; users will be more willing to accept AI-based applications when their perception of those apps is that they are simple and easy to use. Therefore, usability and reducing the learning load are critical adoption-enhancing tactics.

Social Influence was the strongest predictor in this research, with a large and significant effect on Intention to Use. The present finding is consistent with the UTAUT framework and system in which SI is identified as a driver of behavioral intention (Venkatesh et al., 2003). It also echoes research focused on the social aspect of adoption of technology. The use of peers and trusted social networks in the AI context offers a sense of security and decreases ambiguity in situations where users might feel that they are dealing with a level of uncertainty or risk (Islam et al., 2023). The high effect size of this research indicates that the adoption of AI is firmly rooted in social norms and social behavior.

These findings suggest that the implications of AI adoption in the loan recovery area are not merely technological but also organizational and cultural. The readiness of human capital, management support, and digital infrastructure are all prerequisite to leveraging all the potentials of AI. When properly enacted, AI can transform recovery operations into predictive, proactive systems that contribute to a more stable and inclusive financial ecosystem.

Combined, these results demonstrate that ease and social endorsement perceptions are more direct drivers of adoption of AI-based applications compared to perceived usefulness. This expands on previous models of adoption by demonstrating that, in technologically sophisticated situations, certain constructions (like PE) can decline in salience and other constructs (like SI) can increase in saliency. It further highlights the importance of addressing cultural and contextual differences in the implementation of UTAUT because the adoption of drivers can vary among environments.

6. Conclusion, implications, limitations and future research

6.1. Conclusion

This study concludes that the intention to adopt AI-based loan recovery systems is strongly influenced by effort expectancy and social influence. Performance expectancy plays a lesser role. This finding shows that recovery officers are more likely to use AI tools when they find them easy to operate and when their peers and management encourage them, rather than expecting major performance improvements.

From a management perspective, this highlights the need for banks to invest in user-friendly AI systems, ongoing training, and strong support from management to build confidence among recovery officers. Creating a culture that promotes digital readiness, and teamwork can significantly improve successful AI adoption. Looking ahead, further research can explore behavioral and organizational factors like trust, motivation, and change management in AI adoption. Expanding the study to other regions or types of banks could also provide broader insights into how AI can enhance loan recovery practices in various contexts.

6.2. Practical Implications of Findings

Findings of this research indicated that the most significant predictors of intention to use AI-based loan recovery systems amongst recovery officers in Sri Lanka are the effort expectancy and social influence. Practically, this means that banks need to focus on creating easy-to-use AI platforms and offer training on the benefits of such systems in reducing workload through automating reminders, prioritizing cases and tracking repayments. Meanwhile management and peer influence are determining factors in adoption, so senior leaders and early adopters must be champions to influence broader adoption, and recognition and reward schemes can foster positive peer pressure. Social influence not only shapes employees' willingness to adopt new systems but also helps build trust and confidence in AI technologies, making collective acceptance more likely. By focusing on these factors, Sri Lankan banks can improve recovery efficiency and reduce non-performing loans.

6.3. Limitations and Future Research

This study is limited to recovery officers of Domestic Systemically Important Banks (D-SIBs) in the Western Province of Sri Lanka, which can restrict the generalizability of the findings to the wider banking sector. Future research can expand the scope of other provinces, other financial institutions, and longitudinal studies to ascertain adoption over time.

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