Perceived Impact of Artificial Intelligence Applications on Financial Forecasting Accuracy in Sri Lankan Commercial Banks

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ABSTRACT

Artificial Intelligence (AI) is increasingly used in banking, yet evidence on how specific AI applications relate to forecasting activities in Sri Lankan commercial banks remains limited. This study examines the perceived associations of Expert Systems (ES), Machine Learning (ML), and Robotic Process Automation (RPA) with three forecasting-related outcomes: Customer Churn Prediction, Debt Repayment Prediction, and Investment Analysis. A quantitative cross-sectional survey was conducted between 14 and 27 July 2026 using a five-point Likert-scale questionnaire adapted from Alassuli et al. (2026). Purposive and convenience sampling yielded 93 valid responses from employees of 14 licensed commercial banks who prepare, review, or use financial forecasts. Partial least squares structural equation modelling (PLS-SEM) was performed in SmartPLS 4 with 5,000 bootstrap resamples and two-tailed tests. All nine path coefficients were positive, and four were statistically significant. ML was associated with Customer Churn Prediction ($\beta = 0.471$) and Investment Analysis ($\beta = 0.421$), RPA with Debt Repayment Prediction ($\beta = 0.659$), and ES with Investment Analysis ($\beta = 0.299$), although the confidence interval for the last path marginally included zero. The results suggest that the perceived contribution of AI is task-specific rather than uniform. Because all measures are self-reported perceptions from a single source, discriminant validity was not fully established for several construct pairs, and common-method variance cannot be ruled out, the findings are interpreted as perceived associations rather than causal effects on objective forecast accuracy. Drawing on the Resource-Based View and Information Processing Theory, the study provides context-specific evidence to support task-level evaluation of AI investments in banking.

Keywords: *Artificial Intelligence; Expert Systems; Financial Forecasting; Machine Learning; Robotic Process Automation; Sri Lanka*

JEL Classification: *C53; G21; O33*

1. INTRODUCTION

Accurate forecasting underpins lending, liquidity management, investment allocation, customer retention, and risk management in commercial banking. Banks operate in information-intensive environments in which large volumes of customer, transaction, credit, and market data must be interpreted under uncertainty, and inaccurate or delayed forecasts can lead to mispriced risk and inefficient resource allocation (Wasserbacher & Spindler, 2022). Conventional statistical methods remain strong competitors (Makridakis et al., 2018), but the growing volume and complexity of banking data have encouraged the use of AI to complement them in credit scoring, customer management, risk assessment, investment services, and process automation (Herrmann & Masawi, 2022; Vuković et al., 2025).

This study focuses on three AI applications that may support forecasting through different mechanisms. Expert Systems apply codified knowledge and decision rules to structured decisions; Machine Learning derives patterns from historical data and suits complex or nonlinear problems; and RPA automates repetitive, rule-based processing such as data entry, reconciliation, and reporting, supporting forecasting indirectly by improving the timeliness and consistency of information (Lacity & Willcocks, 2016; Alassuli et al., 2026). Treating AI as a single construct may therefore conceal meaningful differences in how individual technologies relate to specific forecasting tasks.

Sri Lankan research has documented digital transformation, digital resilience, and RPA adoption in banking (Herath & Gamlath, 2024; Jayasundara & Wickramarachchi, 2024; Perera et al., 2024), but has rarely examined how specific AI applications relate to forecasting activities. International studies, meanwhile, tend to evaluate individual algorithms for isolated tasks such as credit scoring or churn prediction (Khandani et al., 2010; Lessmann et al., 2015; Coussement & Van den Poel, 2008), and their findings may not transfer to settings with different data infrastructure, skills, and regulation. This study addresses these gaps by examining nine technology–task relationships within a single framework, using the perceptions of banking employees who prepare, review, or use financial forecasts.

2. AIMS/OBJECTIVES

The primary objective is to examine the perceived associations of Expert Systems, Machine Learning, and Robotic Process Automation with three forecasting-related outcomes—Customer Churn Prediction, Debt Repayment Prediction, and Investment Analysis—among employees of Sri Lankan licensed commercial banks. The secondary objective is to assess whether these associations are uniform across tasks or task-specific. The study measures employees' perceptions of how AI supports each forecasting task; it does not measure objective forecast error, and its

findings are therefore framed as perceived associations rather than causal effects on forecasting accuracy.

3. THEORY

The study combines the Resource-Based View (RBV) and Information Processing Theory (IPT). RBV holds that performance depends on valuable resources that are effectively deployed (Barney, 1991); AI technologies create value only when combined with suitable data, infrastructure, expertise, and routines. ES, ML, and RPA represent distinct capabilities—codified knowledge, predictive analytics, and process automation—whose usefulness depends on fit with the task. IPT explains how organisations manage uncertainty by increasing information-processing capacity (Galbraith, 1973). ML may expand analytical capacity for complex, changing data; ES may improve consistency in applying structured criteria; and RPA may increase the speed and reliability of routine information flows. Together, the theories imply that associations between AI and forecasting outcomes should vary by task.

Accordingly, nine hypotheses were proposed (Figure 1). H1–H3 state that ES is positively associated with Customer Churn Prediction (CUS), Debt Repayment Prediction (DEB), and Investment Analysis (INV), respectively; H4–H6 state the same for ML; and H7–H9 state the same for RPA.

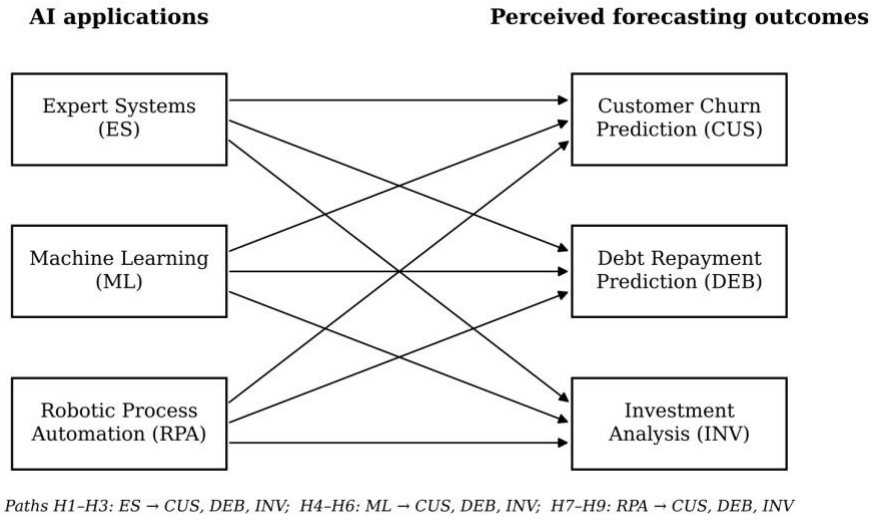

Figure 1. ***Conceptual Framework***
Source: Adapted from Alassuli et al. (2026).

4. METHODS

A positivist, deductive, quantitative cross-sectional survey design was adopted (Saunders et al., 2019). The target population comprised employees of Sri Lankan licensed commercial banks who prepare, review, analyse, or use financial forecasts

and AI-assisted financial information. Because no complete sampling frame was available, purposive and convenience sampling were combined. Invitations were distributed through LinkedIn, professional contacts, email, and direct approaches to banks, and responses were collected through Google Forms between 14 and 27 July 2026. Participation was voluntary and anonymous, and informed consent was obtained.

The final sample comprised 93 complete responses from 14 licensed commercial banks: two state-owned banks (n = 32; 34.4%), eleven domestic private banks (n = 60; 64.5%), and one foreign bank (n = 1; 1.1%). The largest contributions came from Bank of Ceylon (n = 22), Commercial Bank of Ceylon (n = 13), and People's Bank (n = 10). Respondent suitability was assessed with two screening items: involvement in preparing, reviewing, or using financial forecasts, and frequency of engagement with forecasting. Of the 93 respondents, 89 reported direct involvement; the remaining four were retained because their roles involved reviewing or using forecast-related information. Only one respondent reported engaging with forecasting rarely. The questionnaire recorded job position rather than functional department; position is therefore reported as the closest available indicator of role (Table 1).

The instrument contained 18 items, three per construct, adapted from Alassuli et al. (2026) and measured on a five-point scale (1 = strongly disagree to 5 = strongly agree); all items are listed in Appendix A. Each outcome item asks the extent to which AI systems help the respondent's bank perform a forecasting task, so the outcomes capture *perceived* forecasting performance rather than objective accuracy. Customer Churn Prediction reflects the perceived ability to anticipate which customers will leave, and Debt Repayment Prediction the perceived ability to anticipate borrowers' repayment behaviour. Investment Analysis is broader: one item refers directly to investment forecasting accuracy, while the others refer to forward-looking assessment of risks and returns and to the quality of investment decisions. This construct is therefore interpreted as perceived forecasting-related decision support for investments, not as accuracy alone.

SPSS 26 was used for screening and descriptive analysis. Kolmogorov–Smirnov and Shapiro–Wilk tests indicated non-normality for all constructs ($p < 0.001$), supporting PLS-SEM in SmartPLS 4 (Hair et al., 2022) with the path weighting scheme. The measurement model was assessed through outer loadings, Cronbach's alpha, composite reliability (ρc), average variance extracted (AVE), the Fornell–Larcker criterion, the heterotrait–monotrait ratio (HTMT; Henseler et al., 2015), and cross-loadings. The structural model was assessed through collinearity (VIF), R^2, path coefficients, and f^2. Significance was tested by bootstrapping with 5,000 resamples, two-tailed tests at $\alpha = 0.05$, and percentile 95% confidence intervals. Because all data came from a single self-report source, common-method variance was examined using full-collinearity VIFs (Kock, 2015).

Green's (1991) rule ($N \geq 50 + 8m$) gives a minimum of 74 for three predictors, but it was developed for multiple regression and does not account for the latent-variable model or the size of the effects tested. Sample adequacy was therefore also evaluated with the inverse square root method (Kock & Hadaya, 2018) and post-hoc power analysis in SmartPLS 4. With $N = 93$, the minimum path coefficient detectable at $\alpha = 0.05$ with 80% power is approximately $|\beta| = 0.258$.

5. RESULTS

5.1. Sample Profile

Table 1: Respondent Profile (N = 93)

Variable	Category	n	%
Gender	Male	46	49.5
	Female	47	50.5
Age	19–29 years	54	58.1
	30–45 years	35	37.6
	46–61 years	4	4.3
Bank ownership	State-owned (2 banks)	32	34.4
	Domestic private (11 banks)	60	64.5
	Foreign (1 bank)	1	1.1
Position	Senior Manager	5	5.4
	Manager	18	19.4
	Assistant Manager	40	43.0
	Senior Executive	10	10.8
	Executive Officer	8	8.6
	Finance Assistant	12	12.9
Work experience	Less than 5 years[a]	48	51.6
	6–10 years	21	22.6
	11–15 years	12	12.9
	Above 15 years	12	12.9
Involved in forecasting	Yes	89	95.7
	No (reviews or uses forecasts)	4	4.3

Note. [a] *The questionnaire offered "Less than 5 years" and "6–10 years"; respondents with exactly five years of experience had no exact category and most likely selected the first option. This is acknowledged as a limitation of the instrument. Source: Survey data (2026).*

5.2. Measurement Model

All 18 outer loadings exceeded 0.70 (0.775–0.897). Cronbach's alpha (0.743–0.801) and composite reliability (0.854–0.883) indicated adequate internal consistency, and all AVE values exceeded 0.50 (0.661–0.716), supporting convergent validity (Table 2).

Table 2. Reliability and Convergent Validity

Construct	Loadings	α	ρc	AVE
Expert Systems (ES)	0.786–0.826	0.743	0.854	0.661
Machine Learning (ML)	0.808–0.897	0.801	0.883	0.716
Robotic Process Automation (RPA)	0.775–0.840	0.755	0.858	0.669
Customer Churn Prediction (CUS)	0.811–0.851	0.770	0.867	0.685
Debt Repayment Prediction (DEB)	0.796–0.883	0.793	0.879	0.708
Investment Analysis (INV)	0.794–0.861	0.773	0.869	0.689

Source: SmartPLS 4 output (2026).

Discriminant validity was not fully established. Under the Fornell–Larcker criterion, the square root of the AVE for RPA (0.818) was below its correlation with DEB (0.840). The complete HTMT matrix (Table 3) shows that 11 of the 15 construct pairs exceeded the 0.90 threshold, and two pairs exceeded 1.0: RPA–DEB (1.071) and RPA–ML (1.011). Cross-loadings were more favourable, with every item loading highest on its intended construct. Inspection of item wording suggests two sources of overlap. First, all nine outcome items share the stem "AI systems help…", which may inflate correlations among the three outcomes. Second, the RPA items concern data accuracy and processing speed, while the debt-repayment items—especially monitoring repayment behaviour by tracking late payments and repayment history—describe a task that is largely automated in practice; RPA3 cross-loaded at 0.769 on DEB. The RPA, DEB, INV, and ML paths should therefore be read with caution.

Table 3. Heterotrait–Monotrait Ratio (HTMT)

Construct	CUS	DEB	ES	INV	ML
DEB	**0.933**				
ES	0.806	0.900			
INV	**0.915**	0.898	**0.957**		
ML	**0.902**	**0.911**	**0.954**	**0.967**	
RPA	0.840	**1.071**	**0.991**	**0.920**	**1.011**

Note. Values in bold exceed the 0.90 threshold (Henseler et al., 2015). Source: SmartPLS 4 output (2026).

Full-collinearity VIFs, computed from the latent-variable correlations, ranged from 2.71 to 4.76 and exceeded Kock's (2015) 3.3 threshold for DEB (4.25), ML (3.82), and RPA (4.76). Common-method variance and conceptual overlap therefore cannot be ruled out.

5.3. Structural Model

Structural VIFs ranged from 2.59 to 3.14, below the threshold of 5 (Hair et al., 2022). The model explained 53.3% of the variance in CUS (adjusted $R^2 = 0.517$), 72.1% in DEB (0.712), and 65.0% in INV (0.638); SRMR was 0.080. All nine paths were positive and four were significant (Table 4). ML was associated with CUS ($\beta = 0.471$, $t = 3.48$, $p = 0.001$) and INV ($\beta = 0.421$, $t = 3.32$, $p = 0.001$), and RPA with DEB ($\beta = 0.659$, $t = 4.35$, $p < 0.001$), each with a medium-to-large effect. ES was

associated with INV (β = 0.299, t = 2.05, p = 0.041, f^2 = 0.098), but its percentile confidence interval marginally included zero (−0.049 to 0.555); H3 is therefore regarded as only weakly supported. The paths for H1 (t = 0.81, p = 0.421), H2 (t = 0.77, p = 0.443), H5 (t = 0.99, p = 0.324), H7 (t = 1.14, p = 0.255), and H9 (t = 1.14, p = 0.254) were not significant.

Table 4. Hypothesis Testing (5,000 Bootstrap Resamples, Two-Tailed)

H	Path	β	t	p	95% CI	f^2	VIF	Decision
H1	ES → CUS	0.134	0.81	0.421	[−0.181, 0.476]	0.015	2.59	Not supported
H2	ES → DEB	0.103	0.77	0.443	[−0.155, 0.370]	0.015	2.59	Not supported
H3	ES → INV	0.299	2.05	0.041	[−0.049, 0.555]	0.098	2.59	Weakly supported
H4	ML → CUS	0.471	3.48	0.001	[0.168, 0.708]	0.155	3.06	Supported
H5	ML → DEB	0.133	0.99	0.324	[−0.122, 0.406]	0.021	3.06	Not supported
H6	ML → INV	0.421	3.32	0.001	[0.170, 0.662]	0.165	3.06	Supported
H7	RPA → CUS	0.179	1.14	0.255	[−0.152, 0.456]	0.022	3.14	Not supported
H8	RPA → DEB	0.659	4.35	<0.001	[0.361, 0.917]	0.497	3.14	Supported
H9	RPA → INV	0.156	1.14	0.254	[−0.113, 0.423]	0.022	3.14	Not supported

Note. CI = percentile confidence interval; f^2 of 0.02, 0.15, and 0.35 indicate small, medium, and large effects. Source: SmartPLS 4 output (2026).

The non-significant paths had coefficients of 0.103–0.179, below the minimum detectable effect of 0.258, and post-hoc power for these paths at α = 0.05 ranged from 0.26 to 0.53. Their non-significance may therefore partly reflect limited statistical power rather than the absence of an association.

6. DISCUSSION

The results indicate that the perceived contribution of AI differs by forecasting task. The ML associations with churn prediction and investment analysis are consistent with research showing the value of data-driven methods for identifying behavioural patterns associated with customer defection (Coussement & Van den Poel, 2008; Verbeke et al., 2012) and for modelling complex financial relationships (Fischer & Krauss, 2018). Both tasks involve many interacting and potentially nonlinear signals, where pattern recognition is most useful. The non-significant ML–debt repayment path contrasts with evidence on machine-learning credit models (Khandani et al., 2010; Lessmann et al., 2015); this may reflect the perceptual measures, differences in ML maturity across banks, the dominance of policy rules in repayment decisions, or the limited power noted above.

The RPA–debt repayment association is consistent with the process-intensive nature of repayment monitoring, which depends on timely and accurate records of payment histories, overdue balances, and reconciliations (Lacity & Willcocks, 2016; Mamede et al., 2023). However, this is also the construct pair with the most serious discriminant-validity problem (HTMT = 1.071), so the strength of the path may partly reflect overlapping perceptions of automated data processing and repayment monitoring rather than two clearly distinct constructs. The ES–investment analysis

association fits the structured, criteria-based nature of many investment decisions, but given its confidence interval it should be treated as tentative.

Theoretically, the pattern supports the RBV view that technology is valuable when matched to the task and the IPT view that a technology's usefulness depends on whether its information-processing capability fits the task's uncertainty: ML for complex pattern recognition, RPA for routine information flows, and possibly ES for structured evaluation. These interpretations concern perceived associations and should be confirmed with objective data and measures with stronger discriminant validity.

7. IMPLICATIONS AND LIMITATIONS

For practice, the findings suggest that banks should evaluate AI investments at the level of the forecasting task rather than adopting technologies because they are generally regarded as advanced. ML may merit priority for customer analytics and investment-related prediction, and RPA for repayment data and credit-monitoring processes. Relationships that were not supported should be tested in each bank's own data environment before substantial investment, and all AI tools should complement professional judgement and established governance.

Several limitations apply. First, all constructs are self-reported perceptions from a single source, so the study cannot speak to objective accuracy measures such as forecast error, realised churn, or default-prediction accuracy; full-collinearity VIFs above 3.3 indicate that common-method variance cannot be excluded. Second, discriminant validity was not established for several construct pairs, including two HTMT values above 1.0, partly because of similar item wording; future studies should refine the instrument, particularly by differentiating RPA items from debt-repayment items and varying the outcome stems. Third, the purposive and convenience sample of 93 respondents is concentrated in state-owned and a few large private banks and lacks functional-area data, which limits generalisation; the sample also has limited power for small effects. Fourth, the cross-sectional design precludes causal inference, and the work-experience categories omitted exactly five years. Future research should use larger probability-based samples, objective forecasting-performance data, longitudinal designs, and procedural remedies for common-method bias (Podsakoff et al., 2003).

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