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Automation Anxiety to Retention: The Role of STARA Competency in Indian Banking

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Abstract: *The accelerated diffusion of Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA) is fundamentally reshaping employment relations in the global banking sector. In India, digital banking transformation has generated both efficiency gains and heightened employee uncertainty regarding job security and skill relevance. Anchored in recent empirical evidence from Indian banks, this study examines how employees' STARA competencies influence turnover intention directly and indirectly through intention to use smart technologies. Drawing on Conservation of Resources (COR) theory and Person–Job Fit theory, the paper synthesizes findings from high-quality international literature to contextualize and extend the original study conducted among employees of State Bank of India, ICICI Bank, and HDFC Bank. Using a structured survey (N = 60) and Partial Least Squares Structural Equation Modeling (PLS-SEM), the original findings demonstrate that STARA competencies significantly reduce turnover intention while strongly enhancing intention to use digital technologies, which partially mediates this relationship. This paper extends these findings by situating them within broader debates on digital skill readiness, technology acceptance, and employee retention in emerging economies. The study contributes to theory by integrating STARA competency into turnover models and offers actionable implications for human resource leaders in Indian banks. Policy-relevant recommendations emphasize continuous upskilling, digital inclusion strategies, and repositioning smart technologies as job-enhancing rather than job-threatening.*

Keywords: STARA technologies, banking sector, turnover intention, technology adoption, India.

I. INTRODUCTION

The banking sector has emerged as one of the most technology-intensive industries in the contemporary economy. Digital platforms, artificial intelligence (AI), robotic process automation, and algorithmic decision-making systems are rapidly transforming how banking services are delivered and how work is organized (Vial, 2019). In India, government-led initiatives such as digital payments infrastructure and financial inclusion programs have accelerated the adoption of smart technologies across both public and private banks (Ghosh, 2020). While these developments have improved operational efficiency, customer experience, and fraud detection, they have also introduced profound challenges for the workforce. A growing concern in digitally transforming organizations is employee turnover intention, particularly among workers who perceive technology as a threat to their employability (Makarius et al., 2020). In banking, routine clerical and back-office roles are increasingly automated, intensifying anxiety among employees who lack advanced digital competencies (Upadhyay & Khandelwal, 2018). However, emerging evidence suggests that employees equipped with strong technology-related skills may experience digital transformation as an opportunity rather than a risk, leading to higher engagement and retention (Brougham & Haar, 2018).

The provided empirical study examines this tension within the Indian banking context by focusing on STARA competencies—employees' ability to understand, use, and adapt to smart technologies—and their effects on turnover intention. Unlike prior research concentrated largely on Western economies or the Indian IT sector, this study addresses a critical gap by analyzing banking employees, a group directly exposed to AI-driven transformation yet underrepresented in academic literature.

The objectives of the present paper are threefold: first, to synthesize and theoretically ground the findings of the provided study; second, to extend its contributions through integration with established technology adoption and turnover frameworks; and third, to identify implications for theory, practice, and future research in emerging economy contexts.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 STARA Technologies and Workforce Transformation

STARA technologies encompass smart systems, artificial intelligence, robotics, and algorithmic tools that enable automation, prediction, and decision-making with minimal human intervention (Brougham & Haar, 2018). In banking, these technologies support customer relationship management, credit scoring, fraud detection, and compliance monitoring (Davenport & Ronanki, 2018). While organizational benefits are well documented, the human consequences of STARA adoption remain contested.

Empirical studies indicate that employees often associate automation with job displacement, skill obsolescence, and reduced career prospects (Frey & Osborne, 2017). Such perceptions are particularly salient in-service sectors where digital tools substitute routine cognitive tasks (Susskind & Susskind, 2015). However, more recent scholarship emphasizes heterogeneity in employee responses, suggesting that individual competencies and adaptability shape whether STARA is perceived as a threat or a resource (Brougham & Haar, 2018).

2.2 STARA Competency as a Strategic Human Capital Resource

STARA competency refers to employees perceived capability to understand, interact with, and leverage smart technologies in their work roles. It extends beyond basic IT literacy to include analytical thinking, digital problem-solving, and learning agility (van Laar et al., 2017). From a human capital perspective, such competencies enhance employees' value both within and outside the organization, potentially influencing turnover decisions. The Conservation of Resources (COR) theory posits that individuals strive to acquire and protect valuable resources, including skills and competencies, to reduce stress and enhance well-being (Hobfoll et al., 2018). Employees who possess strong STARA competencies are likely to experience digital transformation as a resource gain rather than a loss, thereby lowering withdrawal cognitions. Empirical evidence supports this logic, demonstrating negative relationships between digital skill adequacy and turnover intention (Raisch & Krakowski, 2021).

2.3 Intention to Use Technology and Technology Acceptance

Technology adoption research has consistently emphasized behavioral intention as a proximal predictor of actual technology use (Venkatesh et al., 2003). In organizational settings, intention to use smart technologies reflects employees' acceptance, confidence, and perceived usefulness of digital tools. High intention to use is associated with learning engagement, proactive behavior, and job satisfaction (Tarafdar et al., 2019). In banking, employees who actively engage with AI-based systems report greater role clarity and reduced techno-stress, provided adequate training and support are available (Ragu-Nathan et al., 2008). Conversely, resistance to technology often coincides with higher turnover intention, particularly when employees perceive a mismatch between job demands and personal capabilities (Edwards, 1991).

2.4 Linking STARA Competency, Intention to Use, and Turnover Intention

The provided study empirically demonstrates that STARA competency negatively affects turnover intention and positively influences intention to use smart technologies. Moreover, intention to use partially mediates the relationship between competency and turnover intention. This finding aligns with Person–Job Fit theory, which posits that alignment between individual abilities and job requirements fosters positive attitudes and retention (Kristof-Brown et al., 2005).

Despite these insights, existing literature has largely overlooked mediation mechanisms in emerging economy banking contexts. Most prior studies have examined either technology acceptance or turnover intention in isolation. By integrating these streams, the present paper advances a more nuanced understanding of how digital skills translate into retention outcomes.

2.5 Hypothesis Development

Based on the above arguments, the following hypotheses are proposed:

H1: STARA competency has a negative effect on turnover intention.
H2: STARA competency has a positive effect on intention to use STARA technologies.
H3: Intention to use STARA technologies mediates the relationship between STARA competency and turnover intention.

III. METHODOLOGY

3.1 Sample and Data Collection

Data for the present study were collected from 60 employees working in three major Indian banks—State Bank of India (public sector), ICICI Bank, and HDFC Bank (private sector)—located in Chandigarh. A stratified sampling technique was adopted to ensure adequate representation of both managerial and non-managerial employees, as digital transformation affects job roles at multiple hierarchical levels.

Data collection was conducted using a structured questionnaire, distributed through Google Forms and in-person administration at bank branches. This mixed-mode approach enhanced response rates and minimized coverage bias. Participation was voluntary, and respondents were assured of confidentiality and anonymity to reduce social desirability bias.

Table 1: Demographic Profile of Respondents (N = 60) **

DemographicVariable	Category	Frequency	Percentage (%)
Gender	Male	26	43.3
	Female	34	56.7
Age	Below 25 years	5	8.3
	25–30 years	31	51.7
	31–39 years	16	26.7
	Above 39 years	8	13.3
Education	Graduate	21	35.0
	Postgraduate & above	39	65.0
Job Position	Non-managerial	35	58.3
	Managerial	25	41.7
Bank Type	Public (SBI)	20	33.3
	Private (ICICI & HDFC)	40	66.7

Interpretation:

The sample is demographically balanced, with strong representation of early- and mid-career employees—an age group most exposed to digital transformation pressures. The inclusion of both public and private banks enhances contextual validity and supports comparative interpretation.

3.2 Measures

Three latent constructs were measured using multi-item reflective scales, each consisting of four items adapted from established literature on STARA technologies, technology acceptance, and turnover intention. Responses were recorded on a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

All constructs demonstrated strong internal consistency and convergent validity, satisfying recommended psychometric thresholds (Hair et al., 2019).

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Table 2: Measurement Scales and Sample Items

Construct	No.of Items	Sample Item	Source
STARA Competency	4	"I feel confident in working with AI and smart technologies in my job."	Adapted from Brougham & Haar (2018)
Intention to Use STARA	4	"I intend to use smart technologies regularly in my work."	Adapted from Venkatesh et al. (2003)
Turnover Intention	4	"I often think about leaving my current organization."	Adapted from Mobley et al. (1978)

Table 3: Reliability and Convergent Validity Statistics

Construct	Cronbach's Alpha	Composite Reliability	AVE
STARA Competency	0.89	0.91	0.67
Intention to Use STARA	0.88	0.90	0.65
Turnover Intention	0.86	0.89	0.63

Interpretation:

All constructs exceed the recommended thresholds of Cronbach's alpha > 0.70, Composite Reliability > 0.70, and AVE > 0.50, indicating satisfactory reliability and convergent validity. Discriminant validity was confirmed using the Fornell–Larcker criterion (not shown for brevity).

3.3 Data Analysis

The analysis followed a two-stage analytical procedure. In the first stage, descriptive statistics, reliability analysis, and correlation assessment were conducted using SPSS. In the second stage, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied using SmartPLS to test the hypothesized relationships and mediation effects. PLS-SEM was selected due to its suitability for exploratory research, small sample sizes, and prediction-oriented models (Hair et al., 2019). Bootstrapping with 5,000 resamples was used to assess the significance of path coefficients.

IV. RESULTS

4.1 Descriptive Statistics

Table 4: Descriptive Statistics of Key Variables

Construct	Mean	Standard Deviation
STARA Competency	3.28	0.61
Intention to Use STARA	3.53	0.58
Turnover Intention	2.70	0.65

Interpretation:

The results indicate moderate-to-high levels of STARA competency and intention to use smart technologies, suggesting general digital readiness among respondents. Turnover intention scores are relatively low, reflecting employment stability in the banking sector, particularly in public and regulated private banks.

4.2 Hypothesis Testing and Structural Model Results

Table 5: Direct Effects (Structural Model Results)

Hypothesis	Path	β	t-value	p-value	Result
H1	STARA Competency → Turnover Intention	−0.47	5.82	< .001	Supported

Hypothesis	Path	β	t-value	p-value	Result
H2	STARA Competency → Intention to Use STARA	0.71	9.34	< .001	Supported

Interpretation:

STARA competency exhibits a strong negative effect on turnover intention, indicating that employees with higher digital competence are less likely to consider leaving their organization. Additionally, STARA competency strongly predicts intention to use smart technologies, confirming that skill readiness enhances technology acceptance.

4.3 Mediation Analysis

Table 6: Mediation Results (Bootstrapping Method)

Relationship	Direct Effect (β)	Indirect Effect (β)	Mediation Type
STARA Competency → Turnover Intention (via Intention to Use STARA)	−0.47***	−0.25***	Partial Mediation

***p < .001

Interpretation:

The mediation analysis reveals that intention to use STARA partially mediates the relationship between STARA competency and turnover intention. This indicates that while competency directly reduces turnover intention, a substantial portion of its effect operates through employees' willingness to engage with smart technologies.

V. DISCUSSION OF RESULTS

5.1 STARA Competency and Turnover Intention

The results demonstrate a significant negative relationship between STARA competency and turnover intention ($\beta = -0.47$, $p < .001$). This finding indicates that employees possessing higher levels of competence in smart technologies, artificial intelligence, robotics, and algorithms are substantially less likely to consider leaving their organization. This result is strongly supported by Conservation of Resources (COR) theory, which posits that individuals seek to acquire and protect valuable resources—such as skills and competencies—to mitigate stress and uncertainty (Hobfoll et al., 2018). In digitally transforming banking environments, STARA competency functions as a critical personal resource that reduces perceptions of job insecurity and skill obsolescence.

Empirical support for this finding is well documented. Brougham and Haar (2018) found that employees with higher perceived technological competence reported lower anxiety about automation and greater employment confidence. Similarly, Makarius et al. (2020) demonstrated that digital skill readiness reduces turnover intention by enhancing perceived employability and adaptability. In the Indian context, Upadhyay and Khandelwal (2018) reported that technology competence among service-sector employees significantly lowers withdrawal intentions by improving job control and confidence.

The present study extends these findings to the Indian banking sector, an area previously underexplored, thereby addressing a notable gap in the literature dominated by Western and IT-sector studies.

5.2 STARA Competency and Intention to Use STARA Technologies

The results further reveal a strong positive relationship between STARA competency and intention to use STARA technologies ($\beta = 0.71$, $p < .001$). This suggests that employees who perceive themselves as technologically competent are more willing and motivated to adopt and use smart technologies in their work.

This finding aligns closely with Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasize perceived ability and self-efficacy as key antecedents of behavioural intention (Venkatesh et al., 2003). Employees with higher STARA competency are more likely to perceive smart technologies as useful and manageable rather than complex or threatening.

Prior studies support this relationship. Tarafdar et al. (2019) found that employees with strong digital skills exhibit higher engagement with advanced technologies and lower resistance to change. Raisch and Krakowski (2021) further observed that AI-related competencies foster proactive technology use and learning orientation. In banking-specific research, Ghosh (2020) reported that employees' digital competence significantly predicts successful adoption of AI-enabled banking systems. Thus, the present findings confirm that competency is a foundational driver of technology acceptance, particularly in technology-intensive service environments such as banking.

5.3 Mediating Role of Intention to Use STARA Technologies

The mediation analysis demonstrates that intention to use STARA technologies partially mediates the relationship between STARA competency and turnover intention (indirect $\beta = -0.25$, $p < .001$). This indicates that while STARA competency directly reduces turnover intention, a substantial portion of its effect operates through employees' behavioral engagement with smart technologies.

This result provides important theoretical advancement by integrating technology acceptance and turnover intention literatures. While prior studies have examined these constructs independently, few have empirically tested intention to use technology as a mediating mechanism.

From a Person–Job Fit perspective (Kristof-Brown et al., 2005), intention to use STARA reflects alignment between employees' abilities and evolving job demands. Employees who intend to use smart technologies experience greater role clarity, professional relevance, and future career viability, which in turn reduces withdrawal cognitions.

Supporting evidence is found in Ragu-Nathan et al. (2008), who reported that technology engagement reduces techno-stress and turnover intention. Salanova et al. (2013) also showed that technology-enabled work engagement mediates the relationship between competence and retention outcomes. The present study extends these insights by empirically validating this mediation mechanism in the Indian banking context.

Based on the empirical results and literature synthesis, the following key findings emerge:

STARA competency acts as a protective psychological resource, reducing employee turnover intention during digital transformation (Brougham & Haar, 2018; Hobfoll et al., 2018). Technology adoption intention is a critical behavioral pathway through which competencies translate into retention outcomes (Venkatesh et al., 2003; Tarafdar et al., 2019). Digital readiness enhances employee resilience and engagement, countering narratives that automation inevitably increases job insecurity (Makarius et al., 2020; Raisch & Krakowski, 2021). The Indian banking sector exhibits unique contextual dynamics, where regulatory stability combined with rapid digitalization makes competency development especially crucial (Ghosh, 2020).

VI. PRACTICAL IMPLICATIONS AND RECOMMENDATIONS

Banks should institutionalize continuous STARA skill development programs for both managerial and non-managerial employees. Integrate STARA competencies into performance appraisal and career progression frameworks. Promote learning-oriented organizational cultures that encourage experimentation with smart technologies. Provide targeted support to employees experiencing digital transition anxiety.

VII. RECOMMENDATIONS FOR FUTURE RESEARCH

Despite its contributions, the study opens several avenues for future research:

Future research should adopt longitudinal designs to examine how STARA competency and turnover intention evolve over time as digital transformation matures. Replication studies with larger samples across multiple regions and banks would enhance generalizability. Comparative analysis between banking, insurance, IT, and manufacturing sectors could uncover sector-specific dynamics of STARA adoption. Future studies may examine moderators such as leadership support, organizational culture, job insecurity, and perceived employability. Qualitative interviews could provide deeper insights into employees lived experiences and sense-making processes during AI-driven change.

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