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Antecedents of Automation Practices in Fostering Operational Efficiency in Selected Banks of Karnataka: A Study Utilizing TAM

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Abstract: This study examines automation adoption in Karnataka's regional banks using the Technology Acceptance Model (TAM). Analyzing data from 156 banking professionals, it investigates how Perceived Ease of Use (PE) and Perceived Usefulness (PU) influence Behavioral Intention (BI) and User Satisfaction (SU). Results show PE strongly impacts both PU (β=0.611) and BI (β=0.865), while PU significantly affects BI (β=0.565). BI emerges as a key predictor of SU (β=0.779), confirming its mediating role.

Three major adoption barriers are identified: inadequate infrastructure, resistance to change, and insufficient training. These obstacles limit automation's potential to enhance operational efficiency and service quality.

The study offers practical recommendations: banks should prioritize user-friendly design and comprehensive training, while policymakers need to improve digital infrastructure and create supportive incentives. Theoretically, it extends TAM's application to India's regional banking context and suggests future research directions, including examining additional variables like trust, conducting cross-sector comparisons, and longitudinal studies.

These findings provide valuable insights for financial institutions undergoing digital transformation, helping them implement automation technologies effectively while ensuring employee acceptance and satisfaction. The research contributes to both academic literature on technology adoption and practical strategies for digital transition in emerging banking markets.

Keywords: Automation practices, operational efficiency, Technology acceptance model, banking institutions.

I. INTRODUCTION

Automation has emerged as a transformative force in the modern banking landscape, reshaping how financial institutions operate by enhancing efficiency, accuracy, and speed. By minimizing human error, reducing operational costs, and enabling round-the-clock service delivery, automation technologies play a pivotal role in improving organizational performance and maintaining competitiveness in an increasingly digital world (Davenport &Ronanki, 2018). As global banks accelerate the adoption of automation to streamline processes and elevate customer experiences, it has become imperative for regional banks to keep pace with these advancements to avoid obsolescence.

However, the integration of automation practices remains uneven across different regions and sectors. In the context of Karnataka's regional banking sector, the adoption of automation technologies has been notably sluggish. Despite the widely recognized benefits—such as enhanced operational efficiency, improved compliance, and faster transaction processing—many banks in the region continue to rely on traditional, manual processes. This resistance to adopting automation is a critical challenge that hampers the sector’s overall growth and competitiveness.

This study is poised to generate practical and theoretical value. The primary stakeholders and beneficiaries of the research include banking institutions, policymakers, and academic researchers. Banks will benefit from actionable insights into the enablers and barriers of automation adoption, allowing them to develop more effective implementation strategies. Policymakers, on the other hand, can use the findings to craft supportive regulatory frameworks and incentive structures that foster innovation and digital transformation across the sector. For researchers, this study contributes to the growing body of knowledge on technology adoption, offering a contextualized application of the Technology Acceptance Model (TAM) within the Indian banking environment (Venkatesh et al., 2003). It also opens avenues for future research into the broader impacts of digital transformation in financial services.With reference to above the aim of this study revolves around the following objectives

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II. OBJECTIVES

1) To examine how automation practices can enable operational efficiency in banks using the TAM framework.
2) To analyze how banks can integrate automation practices in day-to-day operations
3) To examine what constitutes the preceding steps of the process in enabling automation in banks

III. LITERATURE REVIEW

Carretta et al. (2024) investigate consumer expectations of bank automation compared to human employees, focusing on the concept of the perfect automation schema (PAS). Their survey of 500 Italian adults shows that cognitive schemas significantly influence consumer expectations, with strong PAS correlating with positive views on automated banking (Carretta et al., 2024). Romão, Costa, and Costa (2019) discuss Robotic Process Automation (RPA) as a tool to improve efficiency in repetitive tasks within banks. Despite its benefits, such as task automation and speed, RPA also presents risks like productivity decline from immature models (Romão et al., 2019). Wojciechowska-Filipek (2019) examines the automation of bank secret inquiries, demonstrating how RPA reduced the inquiry process from seven to three stages in a Polish bank, thereby enhancing efficiency and security (Wojciechowska-Filipek, 2019).

Adewumi et al. (2024) explore data-driven automation in banking, highlighting improvements in efficiency, customer experience, and profitability. However, they also address potential challenges, including job displacement and cybersecurity risks (Adewumi et al., 2024). Oshri and Plugge (2021) provide a case study of KAS Bank's RPA implementation, outlining challenges such as employee resistance and data quality issues. Despite these, the automation initiative succeeded in improving financial process efficiency (Oshri& Plugge, 2021). Nikolaidou et al. (2000) address business process modeling and automation in the Loan Monitoring Department, using the Modified Petri-Net model for enhanced business coordination (Nikolaidou et al., 2000). Lastly, Patri (2020) identifies RPA implementation challenges in banking, particularly security concerns, and proposes solutions to enhance reliability and processing speed (Patri, 2020).

Alkaf et al. (2021) conducted a literature review on service improvement strategies, emphasizing that organizational adaptation to technological advancements is crucial for enhancing efficiency. They identified internal factors (like implementing efficient systems) and external factors (such as economic conditions) as vital for service quality. Challenges include outdated systems and the difficulty of updating knowledge among members (Alkaf et al., 2021). Villareal et al. (2012) proposed a waste elimination scheme for distribution operations, focusing on availability, performance, and quality wastes. Using Value Stream Mapping, they demonstrated that reducing transportation and warehousing inefficiencies improves distribution efficiency (Villareal et al., 2012) J.P. Morgan (2024) examined operational efficiency challenges in private markets, emphasizing the need for innovative data management solutions to handle the complexities of managing both public and private asset data. The study recommended outsourcing data management and adopting cloud-native systems to streamline processing and enhance efficiency (J.P. Morgan, 2024).

Harris (2006) explored enhancing airline efficiency through human factors, arguing that holistic approaches yield better results than isolated changes. By examining airport ramp operations and flight crew management, the study highlighted the need for a socio-technical perspective (Harris, 2006). Jeong and Phillips (2001) focused on equipment utilization in capital-intensive industries. They introduced a new loss classification scheme for Overall Equipment Effectiveness (OEE) to address inadequacies in traditional metrics, emphasizing the importance of identifying hidden time losses (Jeong & Phillips, 2001). Banker et al. (1991) investigated IT's impact on operational efficiency, using a case study at Hardee's Inc. They found that new point-of-sale technology reduced input material costs by enhancing productivity (Banker et al., 1991). Cheng et al. (2018) assessed internal control's role in financial reporting, finding that effective controls enhance operational efficiency, particularly for smaller firms. Addressing material weaknesses led to improved decision-making and resource management (Cheng et al., 2018).

Rabiu et al. (2019) explored E-banking's impact on operational efficiency at Diamond Bank Plc, Nigeria. The study found that internet and mobile banking improved efficiency by reducing service times, enabling online account management, and cutting costs. Recommendations include enhancing online platforms and integrating biometric ATMs for security (Rabiu et al., 2019). Banu (2019) conducted a comparative analysis of Indian banking sectors, finding that foreign banks excel in liquidity and solvency metrics, while private banks lead in profitability. Public banks, however, maintain consistent liquidity but lag in profitability (Banu, 2019). Ali and Abu-AlSondos (2020) reviewed the role of Accounting Information Systems (AIS) in banking, advocating for broader AIS adoption to optimize efficiency and reduce costs. The study highlights the need for adequate training and comprehensive implementation (Ali & Abu-AlSondos, 2020)

The study by Avcı Yücel and Gülbahar (2013) provides a comprehensive qualitative review of 50 studies conducted between 1999 and 2010, focusing on predictors within the Technology Acceptance Model (TAM). The review identifies the core TAM constructs—perceived usefulness, perceived ease of use, and behavioral intention—as the most effective and consistent predictors of technology acceptance across fields such as education and business. Perceived usefulness emerged as the most influential factor, while anxiety was found to be the least effective predictor (Avcı Yücel & Gülbahar, 2013). Technology Acceptance Model (TAM), originally introduced by Davis (1989), was developed to explain users' acceptance of technology through two primary beliefs: perceived usefulness and perceived ease of use. These beliefs influence users' attitudes and behavioral intentions toward system usage, ultimately affecting actual use (Davis, 1989). While other models like the Theory of Reasoned Action and the Theory of Planned Behavior incorporate subjective norms, TAM differentiates itself through its focus on cognitive evaluations rather than social influences.

Over the years, TAM has been extended with variables such as trust, compatibility, and technology readiness to broaden its applicability in various settings (Lee et al., 2003). For instance, Masrom (2007) validated TAM in the Malaysian e-learning context, finding that perceived usefulness significantly predicted intention, even more than users' attitudes. However, some scholars argue TAM's simplicity

may limit its explanatory power in complex, real-world settings (Legris et al., 2003; Chuttur, 2009). Ultimately, while TAM continues to serve as a robust and parsimonious model for predicting technology acceptance, researchers are encouraged to explore its applicability in emerging technologies and diverse domains, integrating it with broader theoretical frameworks (Avcı Yücel & Gülbahar, 2013; Chen et al., 2011).

Kamath and Pai (2022) analyzed the profitability of Canara Bank and Karnataka Bank, revealing that an optimal advance-to-deposit ratio is critical for maximizing profits. They found that advances, through interest income, enhance profits, whereas excessive deposits may increase credit risk and reduce profitability (Kamath & Pai, 2022). Baligatti and Danappanavar (2016) evaluated the Karnataka Vikas Grameena Bank's priority sector lending, noting significant contributions to agriculture but insufficient attention to allied sectors. This reflects an imbalance in rural financial support (Baligatti&Danappanavar, 2016). Basavarajappa (2013) explored electronic banking in Karnataka, highlighting overall customer satisfaction but underscoring persistent concerns over digital security, reflecting challenges in the adoption of online banking services (Basavarajappa, 2013). Lohith (2021) assessed financial inclusion in Karnataka, revealing superior banking penetration compared to national averages. However, rural areas still lag, indicating infrastructure disparities. The study suggests that a denser distribution of bank branches significantly improves access to financial services (Lohith, 2021). Malathy and Subhashinisrivatsa (2018) examined the impact of Core Banking Solutions (CBS), finding it enhanced efficiency but posed employment and technical challenges, particularly concerning security and workforce adaptation (Malathy &Subhashinisrivatsa, 2018). Kishore and Sequeira (2016) focused on mobile banking in rural Karnataka, emphasizing how behavioral factors like attitude, risk perception, and demographics influence adoption. Lastly, Maheswari and Sudha (2017) provided a financial analysis of Karnataka Bank, revealing profitability trends and recommending improvements in capital management and expense control for long-term growth (Maheswari & Sudha, 2017).

IV. RESEARCH GAP

At a macro level, the slow pace of automation adoption in Karnataka's banking industry can be attributed to several interrelated factors. Key barriers include insufficient technological infrastructure, a lack of staff preparedness, limited awareness of automation's strategic value, and resistance to change (Venkatesh & Davis, 2000). Furthermore, without adequate training and a clear roadmap for implementation, banking personnel often struggle to embrace automation tools effectively. These challenges result in continued inefficiencies, heightened operational risks, and suboptimal customer experiences—ultimately threatening the long-term sustainability of regional banks.

By identifying and understanding the key factors that influence the adoption of automation practices, banking institutions can design informed strategies that align with evolving technological trends. Strategic adoption of automation not only facilitates internal process optimization but also enhances service delivery, reduces turnaround times, and strengthens customer relationships. As Chuang & Lin (2015) suggest, successful integration of automation can lead to improved resource utilization, increased profitability, and a sustainable competitive advantage.

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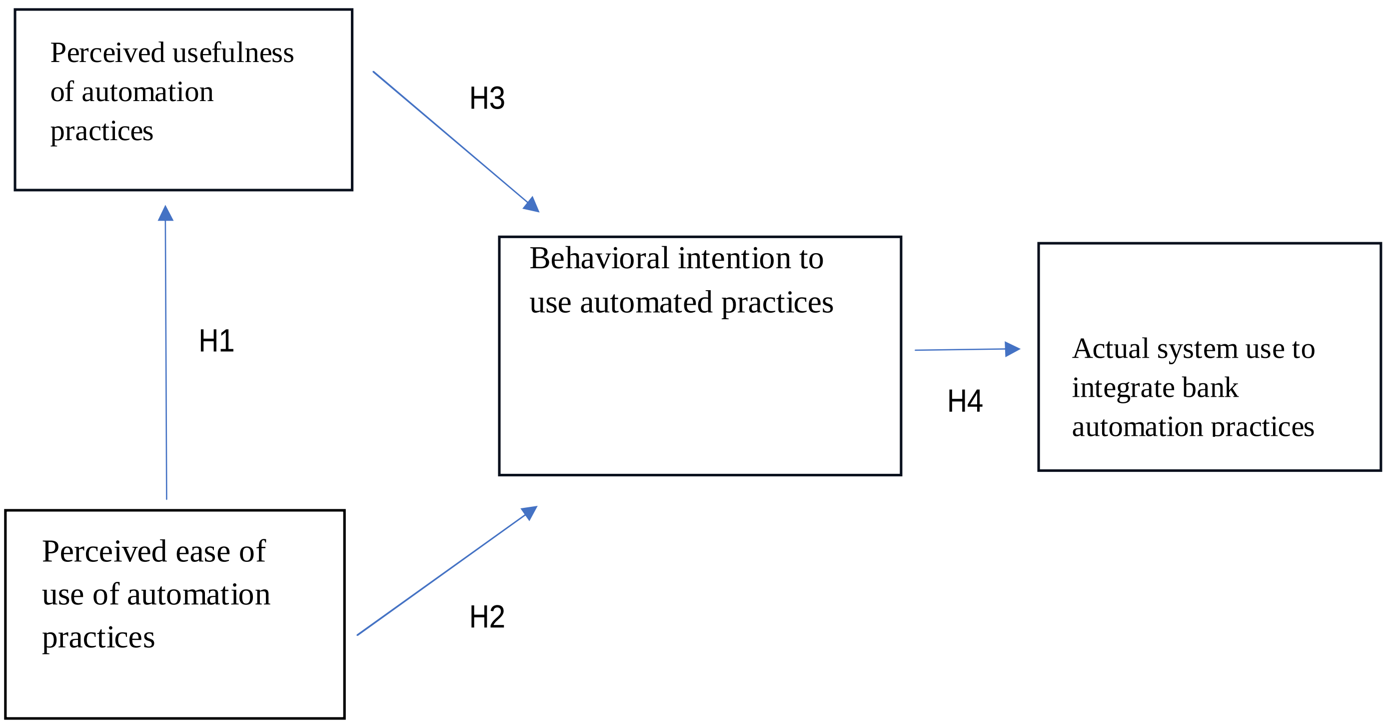
TAM MODEL



Hypothesis formation
H1: Perceived ease of use of automation practices positively impacts perceived usefulness of automation practices
H2: Perceived ease of use of automation practices impacts behavioral intention to use automated practices
H3: Perceived usefulness of automation practices positively impacts behavioral intention to use automated practices
H4: Behavioral intention to use automated practices mediates actual system use to integrate bank automation practices

V. RESEARCH METHODOLGY

Quantitative research is essential for objectively measuring variables, testing hypotheses, and generating statistical data to generalize findings across populations (Creswell, 2014). Its structured approach enables replicability and precision, which strengthens the validity and reliability of research outcomes (Babbie, 2020). This methodology is ideal for establishing patterns and causal relationships.

Sources of data:

Primary data collected through questionnaires is relevant for a sample size of 156, as it allows for standardized data collection, ensuring consistency and comparability across responses (Saunders et al., 2019). This method is efficient for gathering quantifiable insights from a moderately sized sample, enhancing the reliability of statistical analysis (Creswell, 2014).

SAMPLING TECHNIQUES- Purposive Sampling:

Purposive sampling is appropriate for studying the antecedents of automation practices in fostering operational efficiency in selected banks of Karnataka using the Technology Acceptance Model (TAM), as it enables the selection of participants with specific knowledge and experience relevant to technology adoption in banking (Etikan, Musa, &Alkassim, 2016). This ensures rich, relevant, and insightful data aligned with the study's objectives (Palinkas et al., 2015).

VI. DATA ANALYSIS

	Parameters	Frequency	Percent
Age	18-25	46	29.5
	25-35	39	25
	35-45	45	28.8

	45-55	20	12.8
	55 & above	6	3.8
gender	Total	156	100
	Female	103	66
	Male	53	34
education	Below Graduation	7	4.5
	Graduation	41	26.3
	Post Graduation	87	55.8
	Professional certification	21	13.5
	Total	156	100
bank type	Private Sector	84	53.8
	Public Sector	72	46.2
	Total	156	100
role	Customer Service Representative	35	22.4
	Fresher	1	0.6
	IT Specialist	35	22.4
	Manager	26	16.7
	Operations Officer	57	36.5
	Senior Associate	1	0.6
	Shared services	1	0.6
	Total	156	100
year of experience	1-3 years	47	30.1
	3-5 years	47	30.1
	Less than 1 year	32	20.5
	More than 5 years	30	19.2
	Total	156	100

Path Coefficients:

Path	Path Coefficient (β)	Significance
BI -> SU	0.779	Significant
PE -> BI	0.865	Significant
PE -> PU	0.611	Significant
PU -> BI	0.565	Significant

Perceived Ease (PE) has a strong influence on Behavioral Intention (BI), with a path coefficient of 0.865 (significant at $p < 0.05$). This suggests that when individuals perceive an activity as easier, they are more likely to intend to engage in it. Perceived Ease (PE) also positively affects Perceived Usefulness (PU), with a path coefficient of 0.611 (significant at $p < 0.05$). This shows that individuals who find a system or activity easier to use tend to view it as more useful Venkatesh & Davis (2000). Perceived Usefulness (PU) influences Behavioral Intention (BI) to a moderate extent, with a coefficient of 0.565 (significant at $p < 0.05$), indicating that individuals who perceive something as useful are more likely to intend to use it Venkatesh & Morris (2000) found a similar relationship, showing that users' behavioral intention is positively influenced by their perception of the system's usefulness.. Behavioral Intention (BI) significantly predicts Satisfaction (SU), with a path coefficient of 0.779 (significant at $p < 0.05$). This suggests that individuals who intend to use a system or activity are more likely to be satisfied with their experience.

These findings align with prior studies by Bhattacherjee (2001) and confirm the theoretical framework guiding this research.

Total Effects

Path	Direct Effect (β)	Indirect Effect (β)	Significance
PE -> BI -> SU	0.47	0.285	Significant
PU -> BI -> SU	0.237	0.362	Significant
PE -> PU -> BI -> **SU**	0.362	0.185	Significant
PE -> PU -> **BI**	0.465	0.237	Significant

Direct Effect (β) = 0.470: This indicates that Perceived Ease (PE) has a moderate positive effect on Behavioral Intention (BI), meaning that as users perceive a system or activity as easier to use, they are more likely to intend to use it. Indirect Effect (β) = 0.285: This is the effect of PE on Satisfaction (SU) that works through Behavioral Intention (BI). It shows that part of the way PE affects Satisfaction (SU) is by first influencing BI. The indirect effect is positive and moderate, meaning that PE contributes to satisfaction indirectly by enhancing the intention to use the system, which then influences satisfaction. Direct Effect (β) = 0.237: Perceived Usefulness (PU) has a moderate positive effect on Behavioral Intention (BI), meaning that the more useful users perceive a system or activity to be, the more likely they are to intend to use it. Indirect Effect (β) = 0.362: This is the effect of PU on Satisfaction (SU) through Behavioral Intention (BI). A positive indirect effect of 0.362 indicates that PU indirectly affects Satisfaction through its influence on BI. Direct Effect (β) = 0.362: This is the direct effect of Perceived Ease (PE) on Perceived Usefulness (PU), suggesting that PE has a positive effect on how useful users perceive a system or activity to be. A higher PE leads to higher PU. Indirect Effect (β) = 0.185: This is the indirect effect of PE on Satisfaction (SU), which flows through PU and BI. The indirect effect suggests that PE influences satisfaction indirectly by increasing perceived usefulness, which in turn influences the intention to use the system and, ultimately, satisfaction. Direct Effect (β) = 0.465: Perceived Ease (PE) has a relatively strong positive effect on Perceived Usefulness (PU), meaning that easier-to-use systems are generally perceived as more useful. Indirect Effect (β) = 0.237: This indicates the indirect effect of PE on Behavioral Intention (BI) through PU. As PE increases PU, this in turn increases BI.

OuterLoadings-Theouterloadingsofallindicatorsexceededtherecommendedthresholdof(Hairetal.,2017), confirming good indicator reliability.

OuterLoadings

Construct	Indicator	Outer Loading (β)	Decision
BI -> SU	BI	0.779	Highly Related
PE -> BI	PE	0.603	Highly Related
PE -> PU	PU	0.511	Highly Related
PE -> SU	SU	0.47	Related
PU -> BI	BI	0.465	Related
PU -> SU	SU	0.362	Moderately related

The analysis of the outer loadings (β) indicates the strength of the relationships between constructs and their indicators. Each relationship was assessed based on the magnitude of the outer loading, with thresholds used to determine whether the relationships are highly related, related, or moderately related. BI → SU (Behavioral Intention → Satisfaction) Outer Loading (β) = 0.779. Decision: Highly Related

Interpretation: There is a strong and significant positive relationship between Behavioral Intention (BI) and Satisfaction (SU). This suggests that individuals who intend to use a system or activity are likely to report higher levels of satisfaction with their experience.
PE → BI (Perceived Ease → Behavioral Intention)
Outer Loading (β) = 0.603. Decision: Highly Related. Interpretation: Perceived Ease (PE) has a strong effect on Behavioral Intention (BI), meaning that users who find a system easy to use are more likely to intend to engage with it. This finding is consistent with models like the Technology Acceptance Model (TAM), which highlights ease of use as a key factor influencing user behavior. PE → PU (Perceived Ease → Perceived Usefulness) Outer Loading (β) = 0.511. Decision: Highly Related
Interpretation: Perceived Ease (PE) significantly influences Perceived Usefulness (PU), suggesting that users who perceive a system as easy to use are more likely to view it as useful. This relationship emphasizes the role of ease of use in shaping users' perceptions of a system's value. PE → SU (Perceived Ease → Satisfaction). Outer Loading (β) = 0.470 Decision: Related. Interpretation: The relationship between Perceived Ease (PE) and Satisfaction (SU) is positive and statistically significant, though somewhat weaker compared to other relationships. This indicates that while ease of use contributes to satisfaction, its effect is not as strong as the effects of PE on BI or PU. PU → BI (Perceived Usefulness → Behavioral Intention) Outer Loading (β) = 0.465. Decision: Related.
Interpretation: Perceived Usefulness (PU) has a moderate positive effect on Behavioral Intention (BI), suggesting that users are more likely to intend to use a system if they find it useful. However, the effect is not as strong as that of Perceived Ease (PE) on BI. PU → SU (Perceived Usefulness → Satisfaction) Outer Loading (β) = 0.362. Decision: Moderately Related. Interpretation: The relationship between Perceived Usefulness (PU) and Satisfaction (SU) is moderate, indicating that while PU does influence SU, its effect is weaker compared to the other paths (especially PE → BI or BI → SU).

ConstructReliabilityandValidity

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE	Decision
BI	0.822	0.826	0.587	reliable and valid.
PE	0.883	0.884	0.686	highly reliable and valid.
PU	0.874	0.878	0.668	reliable and valid.
SU	0.817	0.826	0.578	reliable and valid.

Behavioral Intention (BI): Cronbach's Alpha (α) = 0.822: This value exceeds the threshold of 0.7, indicating good internal consistency for BI. Composite Reliability (CR) = 0.826: This value is above 0.7, confirming that BI has good composite reliability, meaning that the indicators of this construct reliably measure the latent variable. Average Variance Extracted (AVE) = 0.587: Since AVE is above the 0.5 threshold, it indicates adequate convergent validity for BI, meaning the indicators collectively explain more than 50% of the variance in the construct.
Perceived Ease (PE): Cronbach's Alpha (α) = 0.883: This high value indicates excellent internal consistency for the PE construct. Composite Reliability (CR) = 0.884: With a CR value above 0.7, PE has strong composite reliability, confirming that the items used to measure this construct are highly reliable. Average Variance Extracted (AVE) = 0.686: The AVE value exceeds the 0.5 threshold, indicating that PE has good convergent validity and that the indicators collectively explain a substantial proportion of the construct's variance.
Perceived Usefulness (PU): Cronbach's Alpha (α) = 0.874: This value demonstrates good internal consistency, well above the acceptable threshold of 0.7 for PU. Composite Reliability (CR) = 0.878: A CR value above 0.7 confirms strong reliability for PU. Average Variance Extracted (AVE) = 0.668:
The AVE value for PU also exceeds the 0.5 threshold, suggesting good convergent validity.

Satisfaction (SU): Cronbach's Alpha (α) = 0.817: This value is above the threshold of 0.7, indicating that SU has good internal consistency. Composite Reliability (CR) = 0.826: The CR value confirms the reliability of the SU construct, as it is above the required threshold of 0.7. Average Variance Extracted (AVE) = 0.578: The AVE value is above the acceptable 0.5 threshold, indicating that SU has sufficient convergent validity.

Heterotrait-monotrait ratio (HTMT)- Reliability measure

	BI	PE	PU	SU
BI	1.000			
PE	0.709	1.000		
PU	0.763	0.579	1.000	
SU	0.942	0.655	0.863	1.000

Behavioral Intention (BI) → Perceived Ease (PE) Correlation = 0.709. Interpretation: There is a strong positive relationship between Behavioral Intention (BI) and Perceived Ease (PE). This indicates that as users find a system easier to use, their intention to use it increases.

Behavioral Intention (BI) → Perceived Usefulness (PU) Correlation = 0.763. Interpretation: BI is strongly positively correlated with PU. This means that users who intend to use the system are more likely to perceive it as useful. This relationship suggests that behavioral intention plays a key role in enhancing the perceived usefulness of the system.

Behavioral Intention (BI) → Satisfaction (SU) Correlation = 0.942. Interpretation: The very strong positive correlation between BI and SU suggests that users who intend to use a system are highly likely to report greater satisfaction with it. This is an important finding, highlighting that behavioral intention is a key predictor of user satisfaction.

Perceived Ease (PE) → Perceived Usefulness (PU) Correlation = 0.579. Interpretation: There is a moderate positive correlation between PE and PU, indicating that as users find a system easier to use, they are more likely to perceive it as useful. While not as strong as the PE → BI relationship, this correlation still suggests that ease of use contributes to perceptions of usefulness.

Perceived Ease (PE) → Satisfaction (SU) Correlation = 0.655. Interpretation: There is a strong positive relationship between PE and SU, meaning that as users find a system easier to use, their satisfaction with the system increases. This suggests that making a system easy to use can directly influence user satisfaction.

Perceived Usefulness (PU) → Satisfaction (SU). Correlation = 0.863. Interpretation: There is a very strong positive correlation between PU and SU, suggesting that users who perceive a system as useful are highly likely to be satisfied with it. This supports the idea that perceived usefulness is a major driver of user satisfaction.

VII.DISCUSSION

The findings of this study provide strong empirical support for the theoretical framework that connects Perceived Ease (PE), Perceived Usefulness (PU), Behavioral Intention (BI), and Satisfaction (SU). The structural model shows that PE significantly influences both PU (β = 0.611) and BI (β = 0.865), indicating that ease of use not only makes a system seem more useful but also enhances users' intentions to engage with it. This is consistent with earlier work by Venkatesh and Davis (2000), who emphasized the centrality of ease of use in technology adoption models.

PU also exerts a significant positive influence on BI (β = 0.565), affirming that users' perception of usefulness is a key determinant of their intention to use a system. The impact of BI on SU is particularly noteworthy (β = 0.779), suggesting that users' intention to use a system strongly predicts their eventual satisfaction—echoing the conclusions of Bhattacherjee (2001).

The total effects further illuminate the indirect pathways: PE has both a direct effect on BI and a cascading influence on SU through PU and BI (total indirect effect = 0.285), reinforcing the pivotal role of perceived ease. PU similarly contributes to SU both directly and indirectly via BI (total indirect effect = 0.362), supporting the premise that perceived usefulness is a significant antecedent of user satisfaction.

The outer loadings support the robustness of the measurement model, with all constructs showing loadings above the threshold suggested by Hair et al. (2017), confirming indicator reliability. BI → SU demonstrated the highest outer loading (β = 0.779), reinforcing the central role of behavioral intention in user satisfaction.

Assessment of construct reliability and validity shows that all constructs meet or exceed the accepted thresholds for Cronbach's Alpha (α > 0.7), Composite Reliability (CR > 0.7), and Average Variance Extracted (AVE > 0.5), indicating high internal consistency and convergent validity.

Moreover, the Heterotrait-Monotrait (HTMT) ratios and confirm discriminant validity among constructs. The strongest HTMT correlation was observed between BI and SU (0.942), suggesting a very close relationship, while all values remained below the acceptable threshold, confirming that constructs are distinct despite their strong interrelations.

Overall, these results affirm the validity of the model in predicting user satisfaction based on perceived ease, usefulness, and behavioral intentions. The findings emphasize the importance of designing user-friendly and functionally valuable systems to foster positive user experiences and sustained engagement.

VIII. IMPLICATION AND CONCLUSION

The findings of this study carry important implications for both academic research and practical implementation. From a research perspective, the results reinforce and extend the Technology Acceptance Model (TAM) by demonstrating that Perceived Ease (PE) and Perceived Usefulness (PU) significantly influence Behavioral Intention (BI), which in turn is a strong predictor of user Satisfaction (SU). The mediating role of BI suggests that future studies should pay close attention to how intention acts as a bridge between perception and experience. Moreover, the strong indirect effects and validated model structure encourage further exploration of multi-layered relationships and the adaptation of this framework across various domains and user contexts.

Practically, the study highlights that user-centered design is critical—systems that are easy to use and perceived as useful are more likely to be adopted and lead to higher satisfaction. Developers and service providers should focus on optimizing usability to enhance perceived usefulness, thereby increasing user commitment and satisfaction. Additionally, emphasizing the practical benefits of a system during onboarding or training can foster positive behavioral intentions. Organizations should consider behavioral intention as a strategic metric, shaping their user engagement, communication, and support strategies to reinforce long-term satisfaction and adoption.

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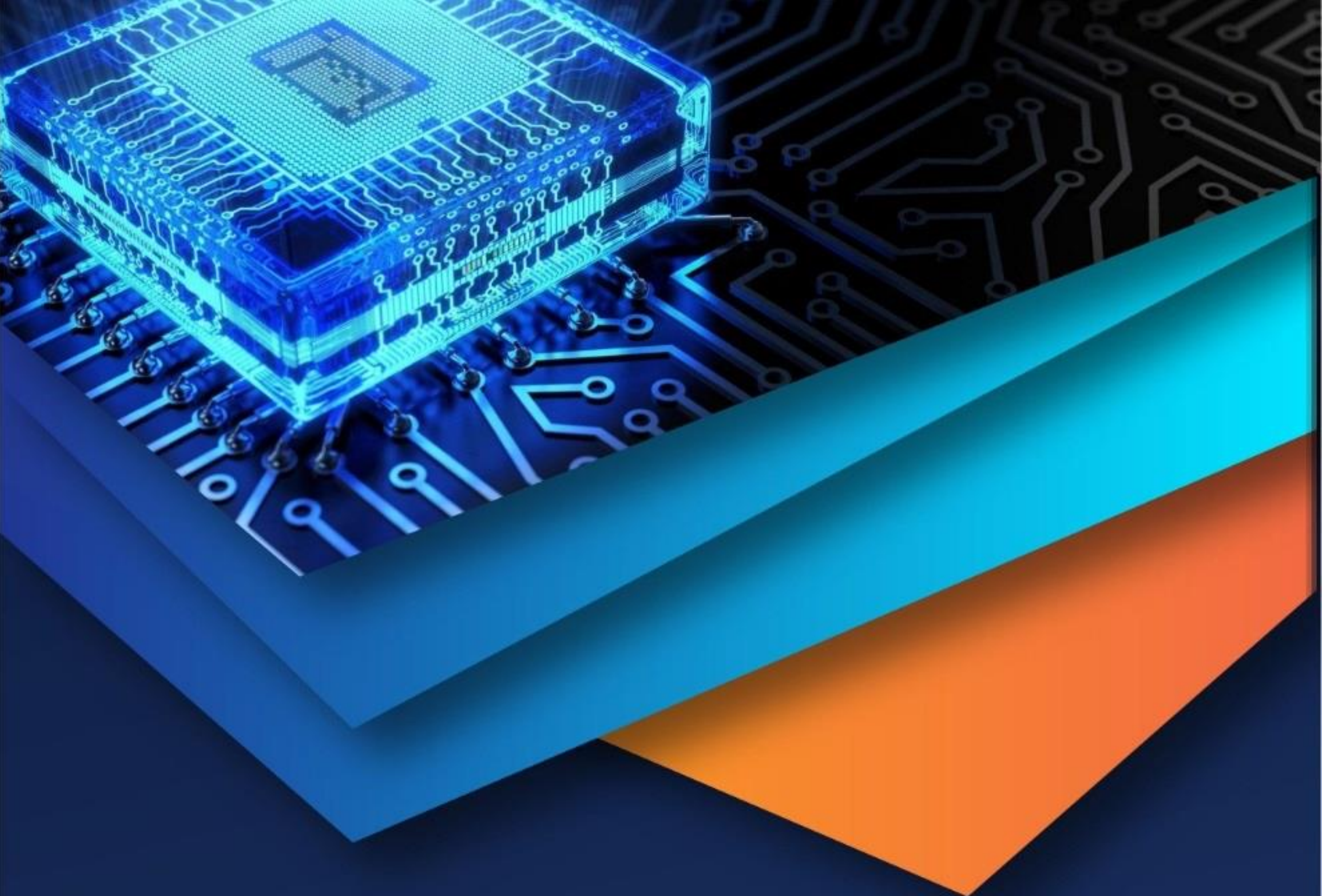

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