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Decoding AI adoption in banking: Insights from artificial neural network modelling

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***Abstract*---**AI is revolutionizing the banking sector addressing intricate challenges, streamlining operations, and enhancing customer experiences. This research delves into the key elements affecting customers' decisions to adopt Artificial Intelligence (AI) in the banking industry, filling a significant gap in the current literature. By combining various components from the '*Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)', such as 'Performance Expectancy', 'Effort Expectancy', 'Social Influence', 'Hedonic Motivation', 'Facilitating Conditions', 'Behavioural Intentions',* and *'Habit',* with additional dimensions like '*Knowledge', 'Openness to Change',* and *'Perceived Risk'*, the study proposes a holistic framework to understand AI adoption. Drawing on primary data from 511 banking customers in India, the research utilizes '*Artificial Neural Network (ANN)*' modelling to assess the relative significance of these factors. Sensitivity analysis indicates *'Habit'* as the most influential factor (normalized importance: 100%), followed by *'Openness to Change'* (70%) and *'Facilitating Conditions'* (67%). This highlights the significance of routine behavior, flexibility, and infrastructure. Moderate influences were found for *'Effort Expectancy'* (45%) and *'Hedonic Motivation'* (33%), while *'Social*

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Influence', 'Knowledge', and *'Perceived Risk'* had a relatively minor effect. This study's uniqueness lies in its integration of theoretical constructs and innovative analytical methods. The results provide valuable guidance for banks to develop AI solutions that cater to customer needs, focusing on habit formation and adaptability, while offering a solid basis for further exploration in this field.

***Keywords*---**Artificial Intelligence (AI), Artificial Neural Networks (ANN), Banking Sector, Fin-Tech, UTAUT-2, Perceived Risk, Knowledge, Openness to Change.

1. Introduction

The financial services sector is undergoing a paradigm shift, driven by the proliferation of Artificial Intelligence technologies. Of the numerous developments changing the face of industry, AI has been one of the biggest factors in the transformation of operations, decision-making processes, and customer engagement in the banking sector. From fraud detection and credit scoring to personalized financial advice and automated processes, AI integration in banking represents a transformative wave of innovation aimed at improving efficiency, lowering costs, and bettering customer experiences. The present study reflects an effort to understand and model the complex patterns of AI adoption within this dynamic sector. The adoption of AI in banking is no longer an operational upgrade but a strategic necessity for banks to remain competitive in a highly digitalized market.

This means that traditional banking processes, which have always been labour-intensive and prone to human error, can now be reinvented with speed, accuracy, and scalability via AI-driven solutions. For example, technologies like Artificial Neural Networks give power to advanced predictive analytics, customer segmentation, and decision-making in real-time. All these prove paramount in handling the growing challenges of rising competition, regulatory complexity, and changing customer demands. However, this path of adoption is neither linear nor uniform; it is a multi-factorial one, driven by technological readiness, organizational strategies, market dynamics, and customer acceptance. The confluence of banking and AI technologies has elicited substantial academic and industrial interest over the past couple of years. During the last decade, there has been a rapid increase in the deployment of AI technologies to enhance operational capabilities and service delivery within the banking industry.

Today's modern banking ecosystem is filled with AI applications, starting with chatbot-based customer service and going up to algorithmic trading, risk assessment, and compliance automation. Still, there remains unexplored potential with several banks at various stages of adoption. The adoption journey for AI in banking follows the stages, viz. awareness, exploration, pilot implementation, scaling, and finally, institutionalization. Each of these stages unfolds with opportunities and challenges unique to that stage and further moderated by factors such as organizational culture, regulatory constraints, technological infrastructure, and market readiness. The complexity of this adoption trajectory needs strong analytic frameworks that bring forth patterns, enable the prediction of trends, and provide strategic guidance.

'Artificial Neural Networks (ANNs)' provide a very powerful methodological tool for analysing large datasets and identifying nonlinear relationships that make outcome predictions accurate. Thus, the current study has adopted ANN models to give nuanced insight into the adoption trajectory of AI in banking by highlighting the interplay between technological, organizational, and market factors.

The present research is based on some of the theoretical foundations of the '*Unified Theory of Acceptance and Use of Technology (UTAUT)'*. The study also integrates *'Knowledge', 'Openness to Change',* and *'Perceived Risk'* as the additional factors influencing AI Adoption in the banking sector. These frameworks represent complementary views of the factors influencing technology adoption at an individual, organizational, and societal level. For example, UTAUT points out that *'Performance Expectancy', 'Effort Expectancy', 'Social Influence',* and *'Facilitating Conditions'* are the major factors that shape *'User Acceptance of Technology'*. The *Technology-Organization-Environment (TOE)* framework highlights the role of *'Technological Capabilities', 'Organizational Characteristics',* and *'Environmental Factors'* as significant determinants in the adoption of innovations. *Diffusion of Innovation Theory* goes further to explain how innovations are diffused within and across organizations through the influence of characteristics such as *'Relative Advantage', 'Compatibility', 'Complexity', 'Trialability',* and *'Observability'*. Introducing these theoretical perspectives, this study follows a holistic approach to examine the adoption trajectory of AI in the banking sector.

Specifically, this study uses ANN models to analyze the influence of multidimensional factors—ranging from technological attributes to the role of *'Openness to Change', 'Knowledge',* and *'Perceived Risk'* in the adoption process. ANN models allow the possibility of showing complex relationships that are not easily established using traditional regression-based analyses. This ANN methodology provides a much more holistic understanding of the dynamics at play in the adoption of AI in banking.

While there is increased interest in AI applications in the banking sector, most existing research focuses on specific cases, such as fraud detection, customer profiling, or risk assessment, with little attention paid to the broader adoption trajectory of AI technologies. Besides, the majority of these studies have adopted conventional analytical approaches that may be inadequate for examining complex and highly dynamic AI adoption processes. There is scant research that takes a systematic mapping of the adoption trajectory of AI in banking, weaving in multiple dimensions and using the latest analytical techniques, such as ANNs, to arrive at conclusions. Thus, this study tries to fill this research gap by offering an in-depth analysis of the adoption trajectory for the benefit of both practitioners and policy implementers. Therefore, the overall objective of this research is to explore the factors influencing the adoption of AI in banking using ANN modelling.

2. Literature Review

Artificial intelligence is pivotal in driving growth in developing economies, particularly in the Industry 4.0 era (Veglianti et al., 2022). The banking sector is regarded as the backbone of economy and AI has significantly enhanced its efficiency and functionality. Applications of AI in banking include credit evaluation (Sharma & Ahuja, 2024), credit risk management (Mall, 2018), customer engagement (Payne et al., 2020), and bolstering cybersecurity (Swamy, 2023). AI elevates the quality of banking services, especially those with technical requirements (Boustani, 2022).

Previous research has extensively explored mobile banking adoption among Indian consumers (Deb & Agrawal, 2017). Studies indicate that individuals with a negative orientation toward innovation are resistant to adopting modern technologies like chatbots (Méndez-Suárez et al., 2023). Conversely, consumers with an innovative mindset are more inclined toward adopting AI in banking (Xian, 2021). Age-related disparities also play a role, as older customers often perceive technological innovations as more complex compared to younger customers (Laukkanen et al., 2007; Méndez-Suárez et al., 2023), leading to negative perceptions about the desirability and feasibility of such technologies (Park et al., 2021).

Artificial intelligence serves as a transformative tool for addressing banking challenges. Jarrahi (2018) illustrated how AI and humans can collaborate to optimize business operations amid uncertainty and complexity. Rather than replacing employees, AI is positioned to complement their work (De Cremer & Kasparov, 2021). Xu et al. (2018) found that consumers preferred AI for low-complexity tasks, while human interaction was favoured for more complex banking activities. Similarly, Ris et al. (2020) demonstrated that AI-powered virtual assistants enhanced banking performance through improved speed, reliability, and reduced dependency on human intervention.

Technological advancements are continuous and dynamic, necessitating ongoing studies on societal acceptance. The UTAUT, developed by Venkatesh et al. (2003), remains a foundational framework for examining technological adoption. This study utilizes the extended UTAUT model, commonly known as UTAUT 2 (Venkatesh et al., 2012), which incorporates six key variables—'*Performance Expectancy (PE)', 'Effort Expectancy (EE)', 'Social Influence (SI)', 'Hedonic Motivation (HM)', 'Facilitating Conditions (FC)', and 'Habit (HB'*—to assess *'Behavioral Intention (BI)'* towards technological adoption. This model has been widely adopted by researchers (Yu et al., 2021; Pobee, 2022; Tiwari et al., 2023; Trang et al., 2024).

To broaden the study's scope, additional constructs such as *'Knowledge (KE)'* (Lankton & Wilson, 2007; Lin & Filieri, 2015), *'Perceived Risk (PR)'* (Forsythe et al., 2006; Featherman & Wells, 2004), and *'Openness to Change (OC)'* (Bardi & Schwartz, 2003) have been included. *'Knowledge'* is the familiarity and proficiency acquired from previous service-related experiences (Lankton & Wilson, 2007). A system or technology's *'Perceived Risk'* is the users' subjective assessment of the possibility of suffering losses while utilizing it (Marriott &

Williams, 2018). *'Openness to Change'* reflects an individual's willingness to explore new technologies and adapt to evolving environments. This study incorporates three dimensions of *'Openness to Change': 'Stimulation', 'Hedonism',* and *'Self-direction'* (Bardi & Schwartz, 2003). Past studies have examined *'Openness to Change'* as a dependent variable (Yue et al., 2019), an independent variable (Ndiango et al., 2023), and as a moderating factor (Tiwari et al., 2023). Openness to adopting new technologies is a critical factor influencing consumer adoption of AI-driven technologies (Nunkoo et al., 2024). The Research framework is shown in Figure 1.

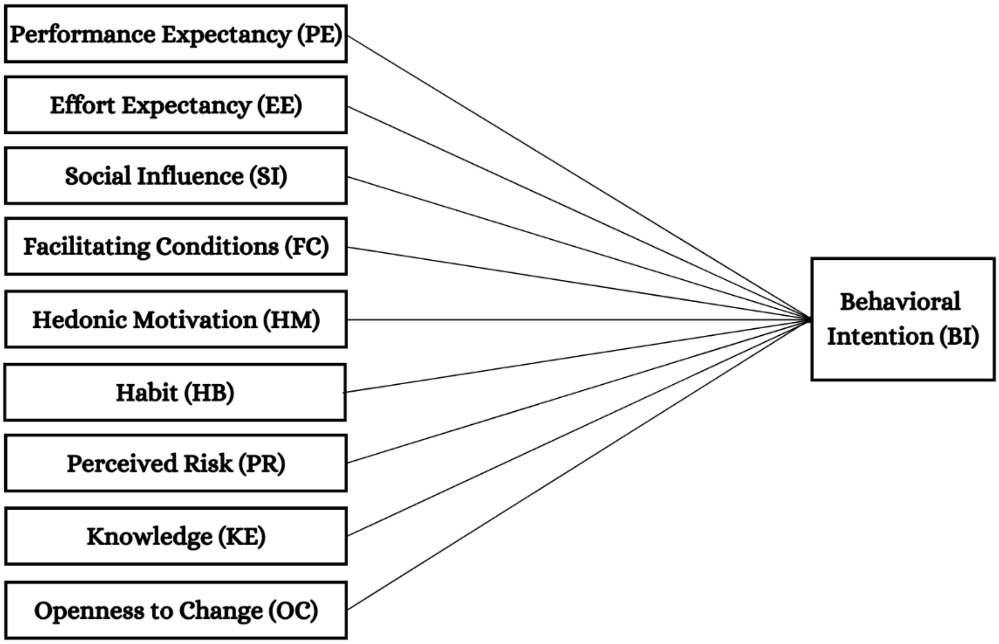

Figure 1: Research Framework
Source: Author's compilation

3. Research Methodology

This descriptive research is based on primary data collected from 511 banking customers across India. A structured questionnaire was designed by integrating constructs validated in previous studies. Core constructs, including *'Performance Expectancy (PE)', 'Effort Expectancy (EE)', 'Social Influence (SI)', 'Hedonic Motivation (HM)', 'Facilitating Conditions (FC)', 'Behavioral Intentions (BI)',* and *'Habit (HB)'*, were adapted from Venkatesh et al. (2012). Additional constructs, such as *'Knowledge (KE)', 'Openness to Change (OC)',* and *'Perceived Risk (PR)'* are drawn from other pertinent studies. ANN Modelling has been utilized to explore the adoption of technology in various sectors (Priyadarshinee et al., 2017; Mustafa et al., 2022; Parhi et al., 2022). In this study, ANN is conducted using SPSS to investigate the importance of each factor in the adoption of AI in the banking sector. The constructs along with the supporting references are shown in Table 1.

Table 1: Constructs and supporting references

Construct and their Items	**Source**
'Performance Expectancy' (4 Items)	Venkatesh et al. (2012)
'I find AI based Banking useful in my daily life' 'Using AI based Banking helps me accomplish things quicker'	
'Effort Expectancy' (4 Items)	Venkatesh et al (2012)
'I find AI based Banking easy to use' 'Learning how to use AI based Banking is easy for me'	Al-Somali et al (2009) Venkatesh et al. (2012)
'Social Influence' (3 Items)	
'People who are important to me think that I should use AI based Banking' 'People whose opinions that I value prefer that I should use AI based Banking'	Venkatesh et al. (2012)
'Facilitating Condition' (4 Items)	
'I have the resources necessary to use AI based Banking' 'I have the knowledge necessary to use AI based Banking'	Venkatesh et al. (2012)
'Hedonic Motivation' (3 Items)	Venkatesh et al. (2012)
'Using AI based Banking is fun' 'Using AI based Banking is enjoyable'	
'Habit' (4 Items)	
'The use of AI based Banking has become a habit for me' 'Using AI based Banking has become natural to me'	Al-Somali et al (2009) Venkatesh et al. (2012)
'Behavioural Intention' (3 Items)	
'I intend to continue using AI based Banking in the future' 'I will always try to use AI based Banking in my daily life'	Featherman and Wells (2004) Forsythe et al. (2006)
'Perceived Risk' (3 Items)	
'I do not have personal touch in AI based Banking' 'I found AI based Banking complicated to do tasks'	Lankton and Wilson (2007) Lin & Filieri (2015)
'Knowledge' (3 Items)	
'I know pretty much about AI based Banking' 'I am an expert user of AI based Banking'	Bardi & Schwartz (2003)
'Openness to Change' (3 Items)	
'I feel very comfortable using AI based Banking' 'I feel a different experience using AI based Banking'	

4. Data Analysis

4.1 Demographic Profile

The demographic profile analysis provides insights into the characteristics of the sample population (N=511). The age distribution indicates a majority of respondents fall within the 26–60 age group (54.0%), followed by the 18–25 group (45.4%), and a minimal representation from those aged 61 and above (0.6%) (Table 2). Gender representation is nearly balanced, with females slightly outnumbering males (51.5% vs. 48.3%, respectively), while "Others" constitutes only 0.2% (Table 3). Regarding marital status, most respondents are single (65.8%), followed by married individuals (33.5%), with widowed and divorced participants comprising 0.6% and 0.2%, respectively (Table 4). In terms of income level, nearly half (46.6%) earn under 1 lakh annually, while the remaining are distributed across higher income brackets, with 9.2% earning 10 lakh and above (Table 5). The educational qualification of respondents shows a predominantly well-educated population, with 52.8% holding a Master's degree and 20.2% having a Doctorate, whereas only 1.6% have qualifications below high school (Table 6). The occupational profile reveals that students form the largest group (48.7%), followed by individuals in private jobs (24.7%) and government jobs (12.1%) (Table 7). Other categories such as self-employed, unemployed, housewives, and freelancers collectively account for smaller proportions. Lastly, bank preference highlights a strong inclination towards public sector banks (65.6%), with private sector banks (28.8%) being the second-most chosen, and minimal reliance on regional rural, cooperative, and foreign banks (Table 8)**.**

Table 2: Age Profile

Serial No	Age	Frequency	Percentage
1	18-25	232	45.4
2	26-60	276	54.0
3	61 and above	3	0.6
	Total	511	100.0

Source: Author's compilation

Table 3: Gender Profile

Serial No	Gender	Frequency	Percentage
1	Male	247	48.3
2	Female	263	51.5
3	Others	1	0.2
	Total	511	100%

Source: Author's compilation

Table 4: Marital Status

Serial No	Marital Status	Frequency	Percentage
1	Single	336	65.8
2	Married	171	33.5
3	Widowed	3	0.6
4	Divorced	1	0.2
	Total	511	100.0

Source: Author's compilation

Table 5: Income Level			
Serial No	**Income Level**	**Frequency**	**Percentage**
1	Under 1 Lakh	238	46.6
2	1 Lakh to 5 Lakh	158	30.9
3	5 Lakh to 10 Lakh	68	13.3
4	10 Lakh and above	47	9.2
	Total	511	100.0

Source: Author's compilation

Table 6: Educational Qualification			
Serial No	**Educational Qualification**	**Frequency**	**Percentage**
1	Lower than a high school	8	1.6
2	High school or equivalent	25	4.9
3	Bachelor's degree/ Diploma	89	17.4
4	Master's degree / Diploma	270	52.8
5	Doctorate Degree	103	20.2
6	Post Doctorate Degree	16	3.1
	Total	511	100.0

Source: Author's compilation

Table 7: Occupation			
Serial No	**Occupation**	**Frequency**	**Percentage**
1	Government Job	62	12.1
2	Private Job	126	24.7
3	Self-employed	27	5.3
4	Unemployed	27	5.3
5	Housewife	11	2.2
6	Freelancer	7	1.4
7	Retired	2	0.4
8	Student	249	48.7
	Total	511	100.0

Source: Author's compilation

Table 8: Type of Bank			
Serial No	**Type of Bank**	**Frequency**	**Percentage**
1	Public Sector Bank	335	65.6
2	Private Sector Bank	147	28.8
3	Regional Rural Bank	14	2.7
4	Co-operative Banks	10	2.0
5	Foreign Banks	5	1.0
	Total	511	100.0

Source: Author's compilation

4.2 ANN Modelling for Factors Influencing Adoption of AI in Banking

The ANN is a complex, nonlinear, and parallel information processing system based on the studies of the human brains (Haykin, 1999). ANN has become prominent system for modelling, pattern recognition and prediction in many disciplines (Abiodun et al., 2018).

The ANN analysis is robust against noise, outliers, and small sample sizes. It also accommodates non-compensatory models, where a decrease in one factor does not necessitate an increase in another. The analysis was conducted using the SPSS Neural Network module. During the training process, the algorithm predicted results using a feed-forward-backward-propagation (FFBP) approach, where inputs are propagated forward, and estimated errors are adjusted backward (Taneja & Arora, 2019). The model, illustrated in Figure 2, used multilayer perceptrons with input and hidden layers that have sigmoid activation functions (Sharma et al., 2020). Similarly, a study by Rathi and Rathi (2020) used ANN to optimize the manufacturing process.

Following the approach of Leong et al. (2018), 90% of the samples were allocated for training, with the remaining 10% reserved for testing. To mitigate overfitting and estimate the root mean square error (RMSE), we employed a ten-fold cross-validation technique (Ooi & Tan, 2016). The sample sizes and RMSE values for both the training and testing phases using this technique are shown in Table 9. The mean value of RMSE for the Training and Testing model comes to be .29 and .25 respectively, which shows the accuracy of the ANN model.

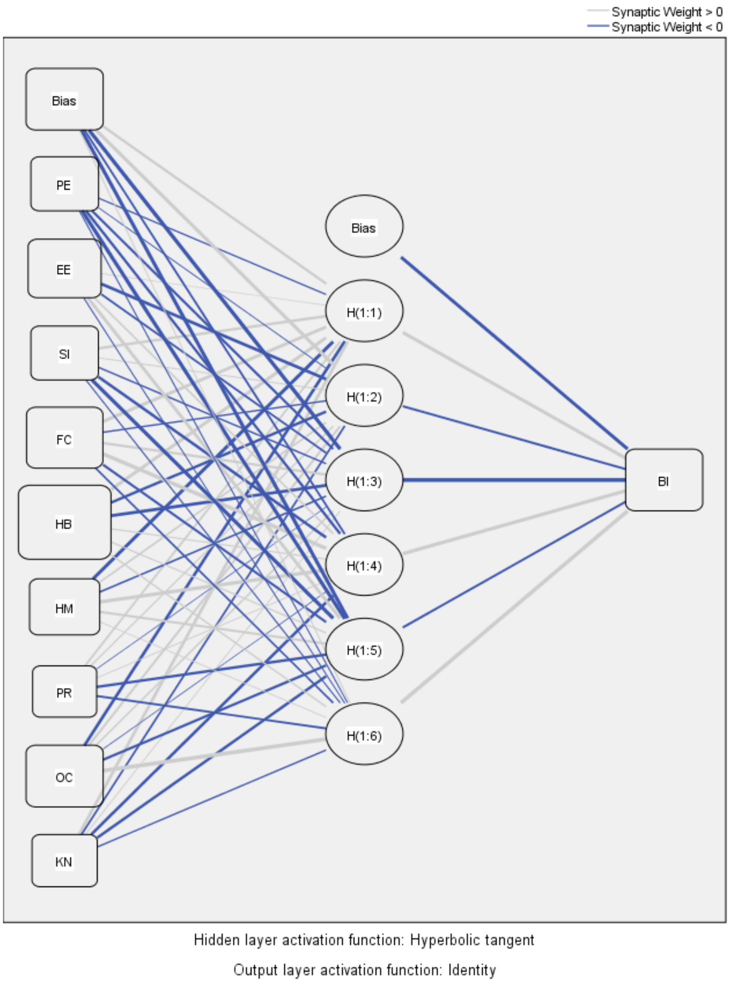

Figure 2: ANN Model for AI Adoption in Banking
Source: SPSS Output

Table 9: RMSE Values for Neural Network (Input Neurons: PE, EE, FC, SI, HM, HB, PR, OC, KN; Output Neuron: BI)							
Network	N (Training)	SSE (Training)	RMSE (Training)	N Testing	SSE (Testing)	RMSE (Testing)	N (Total)
1	458	41.7	0.301742	53	4.180	0.281	511
2	449	46.77	0.304751	62	6.8	0.331	511
3	459	41.05	0.299054	52	0.179	0.059	511
4	452	38.9	0.293363	59	2.6	0.210	511
5	468	40.6	0.294537	43	3.7	0.293	511
6	461	38	0.287105	50	4.3	0.293	511
7	452	34.77	0.277353	59	4.2	0.267	511
8	452	43.2	0.309152	59	5.5	0.305	511
9	460	40.8	0.297818	51	4.2	0.287	511
10	456	37.9	0.288295	55	3.9	0.266	511

Source: SPSS Output

Table 10: Sensitivity Analysis									
	PE	**EE**	**SI**	**FC**	**HB**	**HM**	**PR**	**OC**	**KN**
N1	0.31	0.39	0.21	0.81	1.00	0.24	0.11	0.81	0.13
N2	0.16	0.59	0.39	0.69	1.00	0.59	0.21	0.71	0.17
N3	0.22	0.56	0.12	0.75	1.00	0.19	0.08	0.73	0.18
N4	0.35	0.30	0.21	0.48	1.00	0.23	0.16	0.57	0.15
N5	0.07	0.44	0.14	0.83	1.00	0.44	0.06	0.73	0.21
N6	0.26	0.45	0.24	0.68	1.00	0.33	0.10	0.72	0.25
N7	0.21	0.25	0.18	0.52	1.00	0.29	0.11	0.69	0.26
N8	0.42	0.69	0.46	0.89	1.00	0.43	0.26	0.75	0.23
N9	0.17	0.50	0.13	0.58	1.00	0.25	0.11	0.74	0.20
N10	0.19	0.37	0.19	0.48	1.00	0.28	0.08	0.50	0.12
Normalise Importance Score	24%	45%	23%	67%	100%	33%	13%	70%	19%
RANK	VI	IV	VII	IIII	I	V	IX	II	VIII

Source: SPSS Output

The sensitivity analysis (Table 10) evaluates the relative importance of various factors influencing the output of an ANN model. It identifies critical elements, ranks their significance, and provides a roadmap for optimizing outcomes. Among the factors analyzed, *'Habit (HB)'* emerges as the most influential, with a normalized importance score of 100%. This underscores the critical role of habitual behavior in shaping the system's adoption and performance. Ranked second is *'Openness to Change (OC)'* with 70%, indicating the significance of users' adaptability to new systems. *'Facilitating Conditions (FC)'*, which represent the availability of resources and support, ranks third with 67%, emphasizing the importance of infrastructure in ensuring smooth system use.

The mid-tier factors include *'Effort Expectancy (EE)'*, ranked fourth at 45%, and *'Hedonic Motivation (HM)'*, ranked fifth at 33%. This shows that ease of use and the enjoyment derived from using the system moderately influence the ANN model's output. Additionally, *'Performance Expectancy (PE)'*, ranked sixth at 24%, suggests that perceived performance while relevant plays a comparatively smaller role. These findings imply that user-centric designs should balance functionality with ease of use and enjoyment to enhance system adoption.

The analysis further identifies less influential factors, with *'Social Influence (SI)'* ranked seventh at 23%, '*Knowledge (KN)'* at 19%, and *'Perceived Risk (PR)'* at 13%. These low-ranked factors indicate that external pressures, user knowledge, and concerns about potential negative consequences have minimal impact in this context. While not primary drivers, they could still be relevant in niche applications or specific scenarios, such as addressing user concerns about risks in high-stakes environments.

5. Findings and Discussions

The findings of this study reveal significant insights into the factors driving customer adoption of AI in banking. *'Facilitating Conditions (FC)'* emerged as a critical determinant, emphasizing the importance of infrastructural support, ease of access, and technological readiness in fostering adoption. *'Habit (HB)' and 'Openness to Change (OC)'* also played pivotal roles, highlighting the influence of customers' behavioural tendencies and their willingness to embrace innovation. These results underline the behavioural and environmental aspects as key enablers for AI adoption in banking, suggesting that familiarity and readiness to adapt are integral to customer decision-making processes.

On the other hand, the study identified a moderate impact of *'Hedonic Motivation (HM)'*, suggesting that while enjoyable and engaging AI-driven experiences enhance adoption, they are secondary to functional and contextual factors in the banking domain. Interestingly, *'Social Influence (SI)'* and *'Knowledge (KN)'* were found to have relatively lower importance, challenging traditional assumptions about their roles. The limited effect of social influence suggests that customers prioritize individual preferences and trust over peer or societal opinions when adopting AI for financial decisions. Similarly, the low influence of knowledge implies that intuitive designs and seamless interactions reduce the need for customers to possess technical expertise, making AI services more accessible.

The findings validate the relevance of UTAUT2 constructs while emphasizing the need to refine existing models for domain-specific applications. The prominence of *'Facilitating Conditions (FC)'* aligns with the *Technology-Organization-Environment (TOE)* Framework, reinforcing the necessity of robust infrastructural and organizational support in AI adoption. The behavioral dimensions, such as *'Habit'* and *'Openness to Change'*, suggest that integrating insights from the *Theory of Planned Behavior (TPB)* and *Habit Formation Theory* can enhance existing models. These findings offer valuable implications for both academia and practitioners, providing a foundation for designing AI-driven banking services that align with customer needs and preferences.

6. Implications

6.1 Theoretical Implications

The theoretical implications of this study significantly advance the understanding of technology adoption for AI in the Banking Sector. The result validated key constructs of *'Habit', 'Openness to Change'*, and the presence of *'Facilitating Conditions'*, thereby underlining the appropriateness of established models like UTAUT and UTAUT2 in understanding customer behavior toward AI-driven banking services. The study identifies the critical role of *'Facilitating Conditions'*. This underlines the importance of infrastructural and environmental support, such as a reliable digital platform, a safe network, and customer assistance. It needs to be well integrated within theories of adoption for a reflection of the unique operational context of the banking industry.

This study has a strong focus on the behavioral and psychological dimensions of AI adoption—especially the impact of *'Habit'* and *'Openness to Change'*. These findings are indicative of the fact that models for banking customers need to include insights from theories such as the *Theory of Planned Behavior* and *Habit Formation Theory*, where the repeated interactions with AI systems and the readiness of customers to embrace new technologies have significant influences on adoption decisions. Moreover, the moderate role of *'Hedonic Motivation'* shows that customer enjoyment and positive experience with AI-driven services—be it personalized recommendations or captivating interfaces—do play a supporting role in adoption. This is coherent with *Self-determination Theory* and further underlines the need for balancing both functional and affective factors within theoretical frameworks.

Interestingly, the limited effect of '*Social Influence'* in this context does challenge traditional views on its role in technology adoption. This finding would imply that the decision to adopt AI in banking may be less guided by peer opinions or social norms, perhaps owing to the personal nature of financial decisions. Likewise, the relatively low importance of *'Knowledge'* may underline the fact that the customer's technical understanding of AI systems may be overshadowed by other aspects, such as ease of use, trust in the system, and contextual enablers. These insights suggest that future theories must carefully contextualize constructs like *'Social Influence' and 'Knowledge'* based on the specificity of AI applications in banking.

This study also contributes to the development of AI-specific adoption theories. It fills the gaps in the current frameworks by identifying and prioritizing constructs relevant to AI in banking. The current frameworks are mainly focused on general-purpose technologies. In so doing, this informs the development of domain-specific theories, tailor-made for financial technologies that add dimensions such as trust, data security, and regulatory compliance.

This would further mean that sensitivity analysis, applied as a methodological tool, would reveal its potential to quantify the assessment and ranking of adoption factors. Such an innovative approach would help the refinement of the existing theoretical models and validation of assumptions in banking contexts.

These findings suggest several promising avenues for advancing theories beyond those mentioned, including dynamic models, interdisciplinary approaches combining psychological and financial behaviors, and cross-cultural studies accounting for variations in banking preferences. This enhances the theoretical understanding of the issue by highlighting behavioral, contextual, and motivational dimensions in the adoption of AI in banking.

6.2 Practical implications

This paper identifies the most important system adoption factors, where *'Habit' and 'Openness to Change'* are the strongest. Managers should design systems that fit seamlessly into users' 'habits through routine training, gamification, and incentives while fostering openness through effective change management and inclusive decision-making. Equally important are the *'Facilitating Conditions'*, which call for sufficient infrastructure, training, and technical support that will make the user confident and satisfied. More moderate in their influence are *'Effort Expectancy' and 'Hedonic Motivation'*, emphasizing the need for a user-friendly and enjoyable design to increase engagement. Ranked lower is the *'Perceived Risk'*, although concern about security and reliability still has to be overcome. Resource allocation should focus on habit formation and openness, with less emphasis on factors such as *'Social Influence'*. Socially, the findings indicate the creation of a culture of technological adaptation through education and community engagement to ensure that support is equitably provided to bridge the digital divide and embed positive behavioral changes for societal benefits. Building trust in technology through transparency and encouraging collaborative efforts across communities supports innovation diffusion and broad adoption.

7. Conclusion and Future Research Direction

This study advances theoretical understanding by highlighting the behavioral, contextual, and motivational dimensions of ANN adoption. It reinforces the validity of existing models, challenges traditional assumptions about social and knowledge factors, and provides a foundation for AI-specific theoretical developments. The findings encourage scholars to refine and expand theoretical frameworks, ensuring they remain relevant and comprehensive in explaining technology adoption in rapidly evolving digital landscapes.

The study provides insights into the factors that affect customer adoption of AI in banking, highlighting the critical role of facilitating conditions, habit, and openness to change; while challenging traditional assumptions regarding the impact of social influence and knowledge. The findings bear important implications for financial institutions to focus on the creation of supportive environments that enhance user experience and address the behavioral dynamics that foster AI adoption. Theoretical models, such as UTAUT2, are validated in this context, with some recommended additions to include AI-specific dimensions: openness to change, knowledge & perceived risk that are especially important to represent the distinguishing characteristics of banking services.

Future research should investigate the dynamics of AI adoption using a Longitudinal study to capture the shifts in customer attitudes and behaviors over time, growing in exposure and familiarity. Investigating the interaction between trust, data privacy, and regulatory compliance with adoption constructs would allow a deeper exploration into overcoming resistance to AI technologies. Cross-cultural research would further deepen the understanding by establishing regional and demographic differences in adoption patterns. It could also be enhanced by using more advanced analytical methods, such as machine learning and interpretive structural modeling (ISM), to discover hidden relationships among constructs and to better understand adoption behaviors. By addressing these avenues, future research can contribute to the development of strong frameworks and workable strategies for the promotion of AI adoption in banking, ensuring a fit with customer needs and expectations within an increasingly digital financial ecosystem.

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References

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

Al-Somali, S. A., Gholami, R., & Clegg, B. (2009). An investigation into the acceptance of online banking in Saudi Arabia. *Technovation, 29*(2), 130–141. https://doi.org/10.1016/j.technovation.2008.07.004

Bardi, A., & Schwartz, S. H. (2003). Values and Behaviour: Strength and Structure of Relations. *Personality and Social Psychology Bulletin, 29*(10), 1207–1220. https://doi.org/10.1177/0146167203254602

Boustani, N.M. (2022). Artificial intelligence impact on banks clients and employees in an Asian developing country. Journal of Asia Business Studies, 16 (2), 267-278. https://doi.org/10.1108/JABS-09-2020-0376

Deb, M. and Agrawal, A. (2017). Factors impacting the adoption of m-banking: understanding brand India's potential for financial inclusion. Journal of Asia Business Studies, 11(1), 22-40. https://doi.org/10.1108/JABS-11-2015-0191

De Cremer, D., & Kasparov, G. (2021, March 18). AI Should Augment Human Intelligence, Not Replace It. *Harvard Business Review*. Retrieved June 15, 2024, from https://hbr.org/2021/03/ai-should-augment-human-intelligence-not-replace-it

Featherman, M. S., Miyazaki, A. D., & Sprott, D. E. (2010). Reducing online privacy risk to facilitate e-service adoption: The influence of perceived ease of use and corporate credibility. *Journal of Services Marketing*, *24*(3), 219-229. https://doi.org/10.1108/08876041011040622

Forsythe, S., Liu, C., Shannon, D., & Gardner, L. C. (2006). *Development of a scale to measure the perceived benefits and risks of online shopping. Journal of Interactive Marketing, 20*(2), 55–75. https://doi.org/10.1002/dir.20061

Haykin, S. (1999). *Neural Networks—A comprehensive foundations.* 2nd Edition, Prentice- Hall International, New Jersey. https://shorturl.at/JQrMq

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Lankton, N. K., & Wilson, E. V. (2007). Factors Influencing Expectations of e-Health Services within a Direct-Effects Model of User Satisfaction. *E- Services Journal*, *5*(2), 85-112. https://doi.org/10.2979/esj.2007.5.2.85

Laukkanen, T., Sinkkonen, S., Kivijärvi, M., & Laukkanen, P. (2007). Innovation resistance among mature consumers. *Journal of Consumer Marketing*, *24*(7), 419-427. https://doi.org/10.1108/07363760710834834

Lin, Z., & Filieri, R. (2015). Airline passengers' continuance intention towards online check-in services: The role of personal innovativeness and subjective knowledge. *Transportation Research Part E: Logistics and Transportation Review, 81*, 158–168. https://doi.org/10.1016/j.tre.2015.07.001

Mall, S. (2018). An empirical study on credit risk management: The case of nonbanking financial companies. *Journal of Credit Risk*, *14*(3), 49-66. https://doi.org/10.21314/JCR.2017.239

Marriott, H. R., & Williams, M. D. (2018). Exploring consumers perceived risk and trust for mobile shopping: A theoretical framework and empirical study. Journal of Retailing and Consumer Services, 42, 133–146. https://doi.org/10.1016/j.jretconser.2018.01.017

Méndez-Suárez, M., Monfort , A., & Hervas-Oliver , J. L. (2023). Are you adopting artificial intelligence products? Social-demographic factors to explain customer acceptance. *European Research on Management and Business Economics*, *29*, 100223. https://doi.org/10.1016/j.iedeen.2023.100223

Mustafa, S., Zhang, W., Anwar, S., Jamil, K., & Rana, S. (2022). An integrated model of UTAUT2 to understand consumers' 5G technology acceptance using SEM-ANN approach. *Scientific Reports*, *12*(1). https://doi.org/10.1038/s41598-022-24532-8

Ndiango, S., Kumburu, N. P., & Jaffu, R. (2023). The influence of openness to change on academics' research publication in public higher education institutions in Tanzania. *LBS Journal of Management & Research*, *21*(2), 186-196. https://doi.org/10.1108/LBSJMR-01-2023-0004

Nunkoo, R., Pillai, R., Sivathanu, B., & Rana, N. P. (2024). Drivers and inhibitors of consumers' adoption of AI-driven drone food delivery services. International Journal of Hospitality Management, *123*, 103913. https://doi.org/10.1016/j.ijhm.2024.103913

Ooi, K., & Tan, G. W. (2016). Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. Expert Systems with Applications, 59, 33–46. https://doi.org/10.1016/j.eswa.2016.04.015

Parhi, S., Joshi, K., Wuest, T., & Akarte, M. (2022). Factors affecting Industry 4.0 adoption – A hybrid SEM-ANN approach. *Computers & Industrial Engineering*, *168*, 108062. https://doi.org/10.1016/j.cie.2022.108062

Park, J., Kim, D., & Hyun, H. (2021). Understanding self-service technology adoption by "older" consumers. *Journal of Services Marketing*, *35*(1), 78-97. https://doi.org/10.1108/JSM-10-2019-0420

Pobee, F. (2022). Non-Probabilistic Approach to e-Banking Adoption: The Moderating Impact of Trialability. *Management and Labour Studies, 47*(2), 183-198. https://doi.org/10.1177/0258042X211054248

Priyadarshini, P., Raut, R. D., Jha, M. K., & Gardas, B. B. (2017). Understanding and predicting the determinants of cloud computing adoption: A two staged hybrid SEM - Neural networks approach. *Computers in Human Behavior*, *76*, 341–362. https://doi.org/10.1016/j.chb.2017.07.027

Rathi, N. K., & Rathi, N. (2020). An application of ANN for modelling and optimisation of process parameters of manufacturing process: a review. *International Journal of Engineering Applied Sciences and Technology*, *4*(12), 127–134. https://doi.org/10.33564/ijeast.2020.v04i12.017

Ris, K., Stankovic, Z., & Avramovic , Z. (2020). Implications of Implementation of Artificial Intelligence in the Banking Business with Correlation to the Human Factor. *Journal of Computer and Communications*, *8*(11), 130-144. https://doi.org/10.4236/jcc.2020.811010

Sharma, S., & Ahuja, M. (2024). Algorithmic Brilliance: Unveiling the Power of AI in Credit Evaluation. *Bank Quest: The Journal of Indian Institute of Banking & Finance*, *95*(1), 12-23.

Sharma, S., Sharma, S., & Athaiya, A. (2020). ACTIVATION FUNCTIONS IN NEURAL NETWORKS. *International Journal of Engineering Applied Sciences and Technology*, *04*(12), 310–316. https://doi.org/10.33564/ijeast.2020.v04i12.054

Swamy, V. (2023). Adapting to Digital Disruption: A digital transformation strategy for Indian Banks. *Bank Quest: The Journal of Indian Institute of Banking & Finance*, *94*(3), 9-17.

Taneja, A., & Arora, A. (2018). Modelling user preferences using neural networks and tensor factorization model. *International Journal of Information Management*, *45*, 132–148. https://doi.org/10.1016/j.ijinfomgt.2018.10.010

Tewari, A., Singh, R., Mathur, S., & Pande, S. (2023). A modified UTAUT framework to predict students' intention to adopt online learning: Moderating role of openness to change. *The International Journal of Information and Learning Technology*, *40*(2), 130-147. https://doi.org/10.1108/IJILT-04-2022-0093

Trang, T. T. N., Chien Thang, P., Hai, L. D., Phuong, V. T., & Quy, T. Q. (2024). Understanding the Adoption of Artificial Intelligence in Journalism: An Empirical Study in Vietnam. S*age Open,* *14*(2). https://doi.org/10.1177/21582440241255241

Turning, A. M. (1950). Computing Machinery and Intelligence. *Mind*, *49*(236), 433-460. https://doi.org/10.1093/mind/LIX.236.433

Veglianti, E., Li, Y., Magnaghi, E. and De Marco, M. (2022). Understanding artificial intelligence: insights on China. Journal of Asia Business Studies, 16 (2), 324-339. https://doi.org/10.1108/JABS-10-2020-0391

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157-178. https://www.jstor.org/stable/41410412

Venkatesh, V. Morris, M. Davis, G. & Davis, F. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27*(3), 425-478. https://www.jstor.org/stable/30036540

Xian, X. (2021). Psychological Factors in Consumer Acceptance of Artificial Intelligence in Leisure Economy: A Structural Equation Model. *Journal of Internet Technology*, *22*(3), 697-705. https://doi.org/10.3966/160792642021052203018

Xu, Y., Shieh, C. H., Van Esch, P., & Ling, I. L. (2018). AI customer service: Task complexity, problem-solving ability, and usage intention. *Australasian Marketing Journal*, *28*(4), 189-199. https://doi.org/10.1016/j.ausmj.2020.03.005

Yu, C.-W., Chao, C.-M., Chang, C.-F., Chen, R.-J., Chen, P.-C., & Liu, Y.-X. (2021). Exploring Behavioural Intention to Use a Mobile Health Education Website: An Extension of the UTAUT 2 Model. Sage Open, 11(4). https://doi.org/10.1177/21582440211055721

Yue, C. A., Men, L. R., & Ferguson, M. A. (2019). Bridging transformational leadership, transparent communication, and employee openness to change: The mediating role of trust. *Public Relations Review*, *45*(3), 101779. https://doi.org/10.1016/j.pubrev.2019.04.012