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Classification of Consumers on Usage Intentions: Multi-Layer Perception Approach

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ABSTRACT

Fintech has significantly transformed the usage of financial services and changed how individuals engage with these innovations. This study aims to validate the Unified Theory of Acceptance and Use of Technology (UTAUT) in the context of Fintech adoption in Northeast India. Importantly, this study intends to predict usage intention based on Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI). Analyzing 454 responses using a multi-layer perceptron neural network approach, the study achieved a prediction accuracy of 86%. This high level of accuracy demonstrates the UTAUT model's effectiveness in identifying individuals with high or low usage intention and confirms its validity in the context of Fintech adoption.

Keywords: Classification, Multi-Layer Perception, Fintech, Northeast India, UTAUT Model

INTENTION TO FINTECH ADOPTION

Financial technology (Fintech) has changed a lot about how financial services are offered and how people use them. Mobile payment apps, robotic advisors, crowdfunding platforms, blockchain, and digital currencies, among others, are some of the most prominent Fintech innovations. The intention to adopt Fintech is an individual's desire or willingness to use and adopt Fintech innovations.

Adoption of Fintech can make usage of financial services, easier, cheaper, accessible, and better. It could also help more people get access to financial services. But despite these benefits, not everyone uses fintech services. The rates of acceptance vary between people, demographic groups, and geographic areas.

Frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT) model, the Technology Acceptance Model (TAM), and the Theory of Planned Behaviour (TPB) are used to understand the intention of adopting fintech innovation (Deka,2020). These models show that perceived usefulness, ease of use, social influence, trust, perceived risk, and individual attitudes are some of the most important determinants of fintech adoption.

Also, the decision to use Fintech is affected by factors such as demographics, cultural values, financial literacy, and prevalent rules and regulations. Understanding how these factors interact with psychological constructs in the process of adoption is also important.

UTAUT

The Unified Theory of Acceptance & Use of Technology (UTAUT), developed by Venkatesh, Morris, Davis, and Davis in 2003, offers a comprehensive framework for understanding technology acceptance and use in organizational settings. This model integrates key elements from several established theories, including the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Innovation Diffusion Theory (IDT) (Chang, 2012).

UTAUT identifies four primary constructs—Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI)—as critical factors in predicting technology usage intentions and behaviors (Priyadarshini, 2018). PE parallels Perceived Usefulness from TAM, while EE is akin to Perceived Ease of Use from TAM. Similarly, FC corresponds to Perceived Behavioral Control from TPB (Priyadarshini, 2018). The impact of these constructs on behavioral intention is moderated by demographic and psychographic variables such as age and gender (Slade et al., 2013).

The UTAUT model has been extensively applied across various domains, including information systems, mobile technologies, e-commerce, social media, and fintech. In the context of fintech adoption, studies extending UTAUT have identified additional determinants such as trust, perceived benefits, perceived risks (Hassan et al., 2022), and financial literacy. The theory's robustness is further supported by its validation across diverse geographical contexts worldwide.

Xie et. al., (2021) extended UTAUT with an addition of Perceived Value and Perceived Risk. The study was based in China. This study, conducted to analyse adoption intention in the context of wealth management platforms, found perceived value to be an important determinant of adoption intention.

Aljaafreh et. al., (2023) while extending UTAUT2 in the context of Fintech Adoption included two additional variables, electronic word of mouth (eWOM) and COVID19 perceived risks. The study was based in Jordan. eWOM is described as a statement, either negative or positive, made about any product, service or innovation. It is said to impact an individual's behavioural intention of adopting new technology. COVID19 related risks are said in the paper to have made an unprecedented impact on human emotion and behaviour. Adopting Fintech is understood to be an important way to avoid catching the deadly COVID19 virus. People are willing to avoid using physical money and adopt cashless methods of transactions through various technological mediums.

PERFORMANCE EXPECTANCY (PE)

Performance Expectancy (PE) is defined as the degree to which users believe that using a technology will enhance their performance and provide benefits (Venkatesh et al., 2003). It reflects user expectations regarding the utility of the technology, closely aligning with the Perceived Usefulness (PU) construct from the Technology Acceptance Model (TAM) (Davis, 1989). PE measures how much users believe that fintech solutions will enhance their financial management and transactions. It often includes perceived benefits such as increased convenience, faster transactions, and better financial control. Research consistently shows that higher performance expectancy correlates with greater intention to adopt fintech solutions. For example, users who believe that a mobile payment system or investment platform will improve their financial outcomes are more likely to use these technologies (Hassan et al., 2022). PE is instrumental in influencing technology adoption and continued use. For example, Mensah et al. (2021) found that PE significantly impacts the sustained acceptance of WeChat mobile payment systems in China, highlighting its critical role in user engagement and technology persistence.

EFFORT EXPECTANCY (EE)

Effort Expectancy (EE) is defined as the degree to which users perceive that using a new technology will be effortless and not require significant effort (Venkatesh et al., 2003). This construct parallels the Perceived Ease of Use (PEU) from the Technology Acceptance Model (TAM), as well as concepts of complexity and learning outcomes identified in other technology adoption frameworks.

In the context of fintech platforms, the ability to execute transactions with minimal effort is a fundamental factor influencing user adoption. This underscores the importance of designing technologies that are user-friendly and require little cognitive or operational effort from users. Studies have found that lower perceived effort or complexity is associated with higher adoption rates. Fintech platforms that offer user-friendly interfaces and straightforward functionalities tend to attract more users (Venkatesh et al., 2003).

FACILITATING CONDITIONS (FC)

Facilitating Conditions (FC) are defined as the perceived organizational and technological infrastructure that supports the effective use of technology (Venkatesh et al., 2003). FC is a critical determinant in the adoption of fintech, as it encompasses the external factors that can either facilitate or obstruct technology utilization. Key components of FC include the adequacy of technical infrastructure, the availability of IT support, the compatibility with existing systems, and the overall resource availability. Adequate facilitating conditions are crucial for fintech adoption. Research indicates that users are more likely to adopt fintech solutions when they have reliable access to the necessary infrastructure and support (Hassan et al., 2022). For instance, the presence of reliable internet connectivity is a fundamental facilitating condition that significantly impacts fintech adoption (Das & Das, 2020). Favorable facilitating conditions positively influence users' intentions to adopt fintech by ensuring that the requisite support structures and infrastructure are accessible and functional.s

SOCIAL INFLUENCES (SI)

Social Influences (SI) refer to the impact of peers and social networks on an individual's decision to adopt and continue using technology (Venkatesh et al., 2003). Research consistently shows that SI significantly affects technology adoption intentions (Priyadarshini, 2018). In fintech, factors such as word-of-mouth and electronic Word-of-Mouth (eWOM) play crucial roles, influencing user decisions through social endorsement (Slazus & Bick, 2020; Aljaafreh et al., 2023). For instance, Halim et al. (2020) found that social influence is a major driver of e-wallet adoption among Generation Z, underscoring the importance of social factors in technology acceptance.

METHODOLOGY

The study aims to provide conclusive insights into the acceptance of fintech in Northeast India by validating the UTAUT model within this distinct region. Northeast India, characterized by its unique geographical, socio-economic, and cultural attributes, differs significantly from the rest of the country. Although socio-economic development in the region has been relatively recent, the Government of India's Look-East policy has significantly accelerated development, fostering technological and social integration with mainland India.

The study utilizes a sample size of 454 participants to predict usage intention based on Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI). Analysis is conducted using a multi-layer perceptron neural network approach, providing a sophisticated method for evaluating the impact of these factors on fintech adoption.

RESULT AND DISCUSSION

Results have been discussed here under. Table 1 provides details of the case summary from which we find that out of 454 cases, 310 (68.4%) have been used for training while the rest 143 (31.6%) have been used for testing.

Table 1: Case Processing Summary

		N	Percentage
Sample	Training	310	68.4%
	Testing	143	31.6%
Valid		453	100.0%
Excluded		1	
Total		454	

Table 2 provides the network information. Input layers are Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC) and Social Influence (SI). Number of hidden layers is one.

Table 2: Network Information

Input Layer	Factors	1	PETOT
		2	EETOT
		3	SITOT
		4	FCTOT
	Number of Units[a]		55
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	AICATG
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy
a. Excluding the bias unit			

Table 3 provides the model summary. We find cross-entropy error for training is 139.5 and the corresponding percent of incorrect predictions is 20.3%, which is moderately high. Testing values are 67.3% (cross entropy error) and 21.7% (percentage incorrect predictions).

Table 3: Model Summary		
Training	Cross Entropy Error	139.540
	Percent Incorrect Predictions	20.3%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error.
	Training Time	0:00:00.16
Testing	Cross Entropy Error	67.290
	Percent Incorrect Predictions	21.7%
Dependent Variable: AICATG		
a. Error computations are based on the testing sample.		

Table 4 provides the classification details. For training data out of 130 low AICATG 89 have been predicted correctly whereas 41 have been predicted wrongly. Similarly, out of 180 high AICTAG 158 are predicted correct and 22 have been predicted wrong. This provides an accuracy of 79.7%.

Table 4: Classification				
Sample	Observed	Predicted		
		1.00	2.00	Percent Correct
Training	1.00	89	41	68.5%
	2.00	22	158	87.8%
	Overall Percent	35.8%	64.2%	79.7%
Testing	1.00	40	23	63.5%
	2.00	8	72	90.0%
	Overall Percent	33.6%	66.4%	78.3%
Dependent Variable: AICATG				

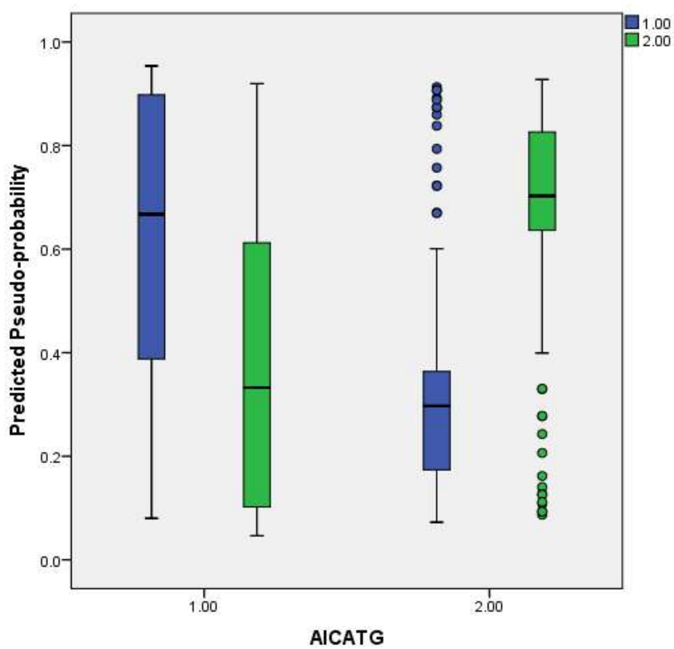

Figure 1: Predicted by Observed Chart

Predicted by Observed chart shown in Figure 1 displays clustered boxplots of predicted pseudo-probabilities for the combined training and testing samples. The x-axis corresponds to the observed response categories, and the legend corresponds to the predicted categories.

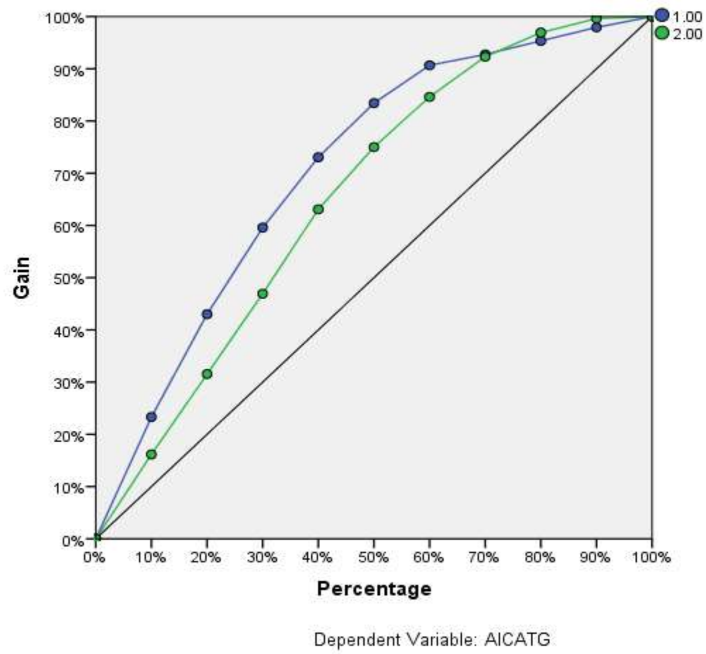

Figure 2: Cumulative Benefit Chart

The Cumulative Benefit chart given in Figure 2 shows the percentage of total cases in a "achieved" category targeting the percentage of total cases. For example, the first point on the curve for the category Yes is (10%, 23%), which means that if you grid the dataset and order all cases by the predicted pseudo probability of Yes, one would expect the top 10%, which contains about 23% of all cases that actually belong to the Yes category. Similarly, the top 20 percent would have about 45 percent of defaults, the top 30 percent would have 60 percent, and so on.

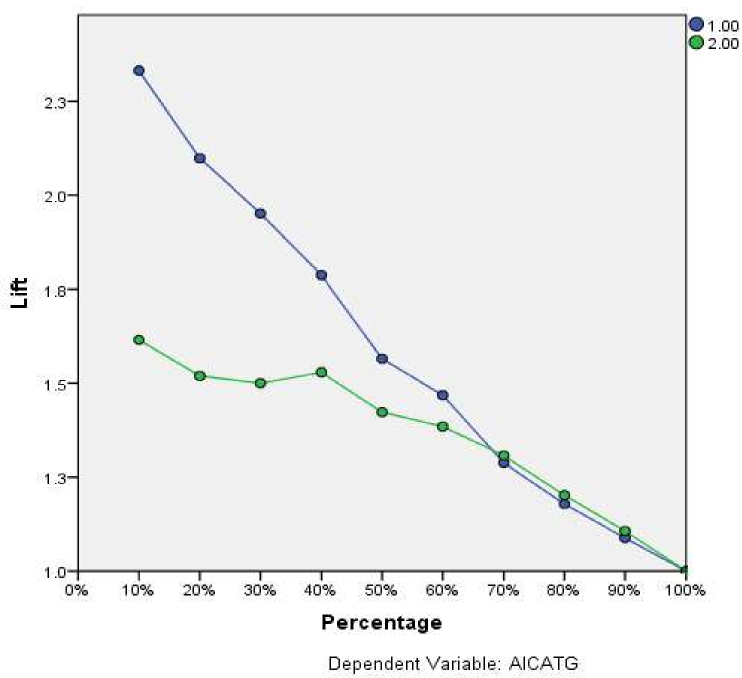

Figure 3: Lift Chart

The Lift Chart is derived from the cumulative earnings chart and offers an alternative perspective on cumulative profit data. In this chart, the y-axis values represent the ratio of the cumulative gain for each curve relative to the baseline. For instance, if there is a 10% increase in the "Yes" category, this would result in a lift value of 23% / 10% = 2.3. This ratio indicates how much more effective the model is at identifying the positive category compared to random selection, providing a clear view of the model's performance in terms of cumulative profit.

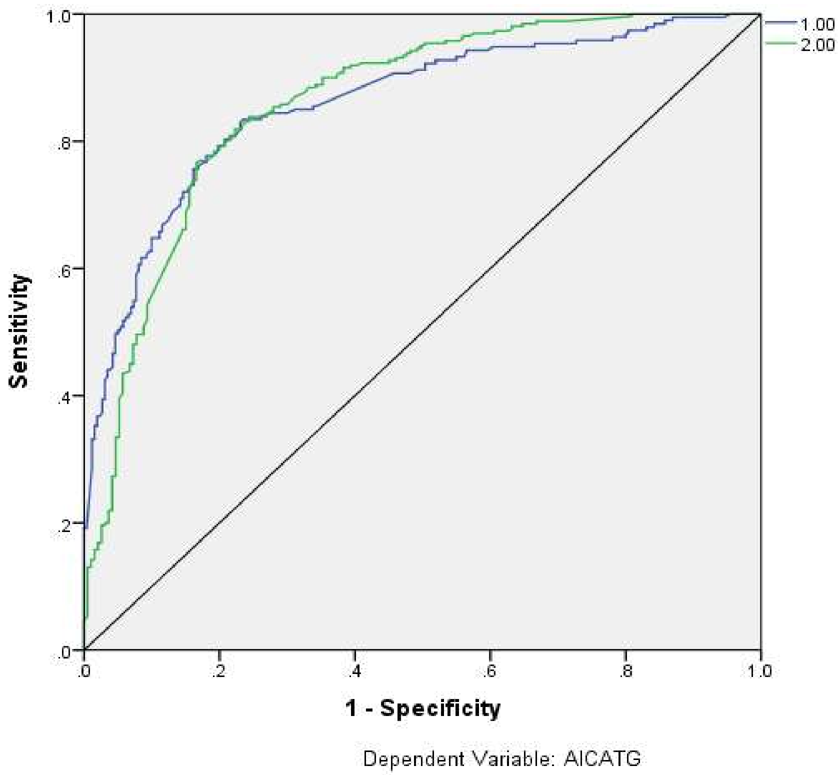

Figure 4: ROC (Receiver Operating Characteristic) Curve

Figure 4 presents Receiver Operating Characteristic (ROC) curves for each categorical dependent variable, with a corresponding table that provides the area under each curve. For a given dependent variable, the ROC chart includes one curve for each category, where each curve assesses one category as the positive state against the remaining category. In the case of a dependent variable with two categories, the ROC curve differentiates the positive state from the other category. The total area under the curve, as summarized in Table 5, is 0.86. This value, which exceeds the acceptable threshold of 0.5, indicates that the model's ability to predict high versus low usage intention is highly effective.

Table 5: Area Under the Curve

		Area
AICATG	1.00	.860
	2.00	.860

CONCLUSION

This study was undertaken to investigate the possibility of predicting low or high usage intention of Fintech by any individual based on their scores of Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC) and Social Influence (SI). Analysis has been done using the multi-layer perception of the neural network approach. Results have shown that the prediction is 86% correct which provides a basis to identify individuals with high or low usage intention. This detail could be of value to financial institutions for targeting the right consumers. The results also validate The Unified Theory of Acceptance and provide a theoretical basis for such studies in other areas of research on technology usage.

REFERENCES

Aljaafreh, A., Qatawneh, N., Awad, R., Alamro, H., & Ma'aitah, S.: FinTech Adoption in Jordan: Extending

UTAUT2 with eWOM and COVID-19 Perceived Risk. The Implementation of Smart Technologies for Business Success and Sustainability 91-97 (2023).

Chang, A.: UTAUT and UTAUT 2: A review and agenda for future research. The Winners 13(2), 10-114 (2012).

Dakduk, S., Santalla-Banderali, Z., & Siqueira, J. R.: Acceptance of mobile commerce in low-income consumers: evidence from an emerging economy. Heliyon 6(11), (2020).

Das, A., & Das, D.: Perception, Adoption, and Pattern of Usage of FinTech Services by Bank Customers: Evidences from Hojai District of Assam. Emerging Economy Studies 6 (1), (2020).

Deka, P. K.: Intention to use mobile wallet by youths in northeast India. Journal of Management in Practice (Online Only) 5(1) (2020).

Halim, F., Efendi, E., Butarbutar, M., Malau, A. R., & Sudirman, A.: Constituents Driving Interest in Using E-Wallets in Generation Z. Proceeding on International Conference of Science Management Art Research Technology 1(1), 101-116 (2020).

Hassan, Md. S., Islam, Md. A., Sobhani, F. A., Nasir, H., Mahmud, I., & Zahra, F. T.: Drivers Influencing the Adoption Intention towards Mobile Fintech Services: A Study on the Emerging Bangladesh Market. Information 13(7), 349 (2022).

Mensah, I. K., Liu, Y., & Luo, C.: Factors Influencing the Continued Acceptance of WeChat Mobile Payments by Chinese Vendors. Information Resources Management Journal (IRMJ) 34(4), 28-47 (2021).

Priyadarshini, V.: Determinants of customer's intentions to adopt banking channel innovations in India. (Doctoral dissertation, University of Hyderabad) (2018).

Slade, E. L., Williams, M. D., & Dwivedi, Y. K.: Devising a research model to examine adoption of mobile payments: An extension of UTAUT2. The Marketing Review 14(3), 310-335 (2014).

Slazus, B. J., & Bick, G.: Factors that influence fintech adoption in South Africa: A study of consumer behaviour towards branchless mobile banking. Athens Journal of Business & Economics 6, 1-21 (2020).

Solarz, M. & Swacha-Lech, M.: Determinants of the Adoption of Innovative Fintech Services by Millennials. E & M Ekonomie a Management 24(3), (2021).

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D.: User acceptance of information technology: Toward a unified view. MIS Quarterly, 425-478 (2003).

Venkatesh, V., Thong, J. Y. L., & Xu, X.: Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly 36(1), 157–178 (2012).

Xie, J., Ye, L., Huang, W., & Ye, M.: Understanding FinTech Platform Adoption: Impacts of Perceived Value and Perceived Risk. Journal of Theoretical and Applied Electronic Commerce Research 16(5), 1893–1911 (2021).