

International Conference on Optimization, Simulation and Control Adoption of Artificial intelligence in the banking sector: Evidence from Mongolia

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Abstract

The purpose of this study is to understand the current situation of the importance of adopting artificial intelligence in the Mongolian banking sector and to study the current situation of customers in the case of adopting artificial intelligence to banking services. In order to identify the importance and need for adopting artificial intelligence in the banking sector, a quantitative survey was conducted on 220 customers of 6 major Mongolian banks, using the results of Smart PLS 3.0 software. In determining how customers adopt artificial intelligence in banking we used factors such as awareness, perceived ease of use, perceived usefulness, perceived risk, perceived trust, subjective norms, attitude towards AI, intention to adopt AI in banking, and knowledge of technology. This study will provide banking sector policymakers with insights into addressing the challenges of introducing artificial intelligence to banks and increasing their consumption. It is one of the studies to identify the important factors influencing the adoption of artificial intelligence in Mongolian banking services. The results also show that attitude towards AI significantly mediates the relationship between perceived usefulness and intention to adopt AI in banking services.

Keywords: Artificial intelligence, Bank customers, Intention to adopt

Introduction

Mongolian banks are rapidly providing financial services based on fintech technology to increase access to finance in the economy and ensure the efficiency of the financial system. To stay competitive in the marketplace, banks are now seeking AI solutions to replace expensive, tedious, and routine activities. AI become a step-forward game-changer in transforming and digitalizing modern businesses. Basic AI applications used in banks, such as chat-bots, personalized services, and even AI robots for self-servicing, could generate more efficiency than traditional human advisory services.

While Mongolian customers are prepared to use banking services that rely on AI, it is still crucial to clearly understand the factors that may influence their decisions. Extending on the technology acceptance model (TAM), this study examines important factors in investigating consumers' intention to adopt AI (INT) in the banking industry in Mongolia.

To keep up with the technological transformation of the banking sector, banks need to better understand the customers' needs to effectively introduce AI. Moreover, this study identifies the key determinants that affect the consumers' decision to adopt AI tools.

Hypotheses	Std. Beta	Mean SE	T Values	95% CI	P values	Decision	ES
H1 PEOU->ATT	0.009	0.11 0.09	1.118	[-0.09, 0.29]	0.264	NS	0.009
H2 PU->ATT	0.281	0.613 0.09	6.754	[0.43, 0.78]	0.000	S	0.281
H3 ATT->INT	0.285	0.567 0.07	7.324	[0.41, 0.72]	0.000	S	0.285
H4 PEOU->INT	0.001	-0.028 0.08	0.309	[-0.19, 0.13]	0.759	NS	0.001
H5 PU->INT	0.002	0.048 0.08	0.589	[-0.11, 0.20]	0.556	NS	0.002
H6 AW->INT	0.016	0.084 0.04	1.673	[-0.00, 0.18]	0.094	NS	0.016
H7 PR->INT	0.002	-0.016 0.04	0.562	[-0.10, 0.06]	0.574	NS	0.002
H8 PT->INT	0.005	0.069 0.07	0.951	[-0.07, 0.20]	0.342	NS	0.005
H9 SN->INT	0.015	0.142 0.09	1.581	[-0.03, 0.31]	0.114	NS	0.015
Mediation analysis							
H10 PEOU->ATT->INT	0.062	0.062 0.05	1.106	[-0.05, 0.17]	0.269	NS	
H11 PU->ATT->INT	0.351	0.348 0.07	4.737	[0.22, 0.50]	0.000	S	

Note(s): SE = Standard Error, CI=Confidence Interval, S=Supported, NS=Not supported, ES=Effect size

Table 1. Structural model analysis.

Methods and Materials

A self-administrated structured questionnaire was used to obtain the data needed. The target respondents include those clients who have customers of Mongolian biggest 6 banks. The research framework in Figure 1 illustrates the direct and indirect effect of selected variables on the INT in banking services. There are seven direct effects, and two indirect effects on AI intention in the model, which are presented using the following equations:

$$INT_i = \alpha_0 + \alpha_1 PEOU_i + \alpha_2 PU_i + \alpha_3 AW_i + \alpha_4 PR_i + \alpha_5 PT_i + \alpha_6 SN_i + \alpha_7 ATT_i + \varepsilon_i \quad (1)$$

$$ATT_i = \beta_0 + \beta_1 PEOU_i + \beta_2 PU_i + u_i \quad (2)$$

$$INT_i = \beta_0 + \beta_1 \alpha_7 PEOU_i + \beta_2 \alpha_7 PU_i + u_i \quad (3)$$

INT is the customer intention to adopt AI in banking, PEOU is perceived ease of use, PU is perceived usefulness, AW is awareness, PR is perceived risk, PT is perceived trust, SN is subjective norms, ATT is attitude toward AI in Banking, $\alpha_0 - \alpha_7; \beta_0 - \beta_2;$ are the coefficients for the direct and indirect effects. Equation (1) shows the direct relationships between independent variables and the INT in banking. Equation (2) presents the indirect effect of the two independent variables (PEOU and PU) of INT in banking through the ATT in banking. This study applied the SEM techniques to estimate the path coefficients hypothesis in Figure 1.

Results

Features the demographic profile of the respondents. Females were more willing to participate than males, with 69.91% females and 30.09% males. The majority of the respondents belong to the living in UB (81.48%) are between 18 and 45 years old. A total of 87.04% of the respondents completed either Bachelor's or Master's degree. Almost 90.3% of respondents are employed, of which about 33.8% have experience working in the banking, finance industry, and Information technology. As all measurement models of the research framework are reflective, the internal consistency reliability and convergent validity were examined based on composite reliability (CR), Cronbach's alpha (CA), factor loading, and average variance extracted (AVE). Table 3. Next, the discriminant validity of study constructs was investigated using Fornell-Larcker's (FL) ratio of correlations criteria. Table 2. The research model consists of a total of 11 hypotheses. The results are in Table 1. As one of the major statistical objectives of SEM is to estimate the prediction accuracy of the research model, coefficient of determination (R^2) and effect size (f^2) values were evaluated (Hair et al., 2017b). Results showed that the proposed research model explained 49.6% variance in ATT and 72.6% variance in INT. Results in Table 1 demonstrate that in predicting ATT, INT has a large effect size of 0.285. Besides, in predicting PU, ATT has a strong effect size ($f^2 = 0.281$), whereas other antecedents have a marginally small practical effect.

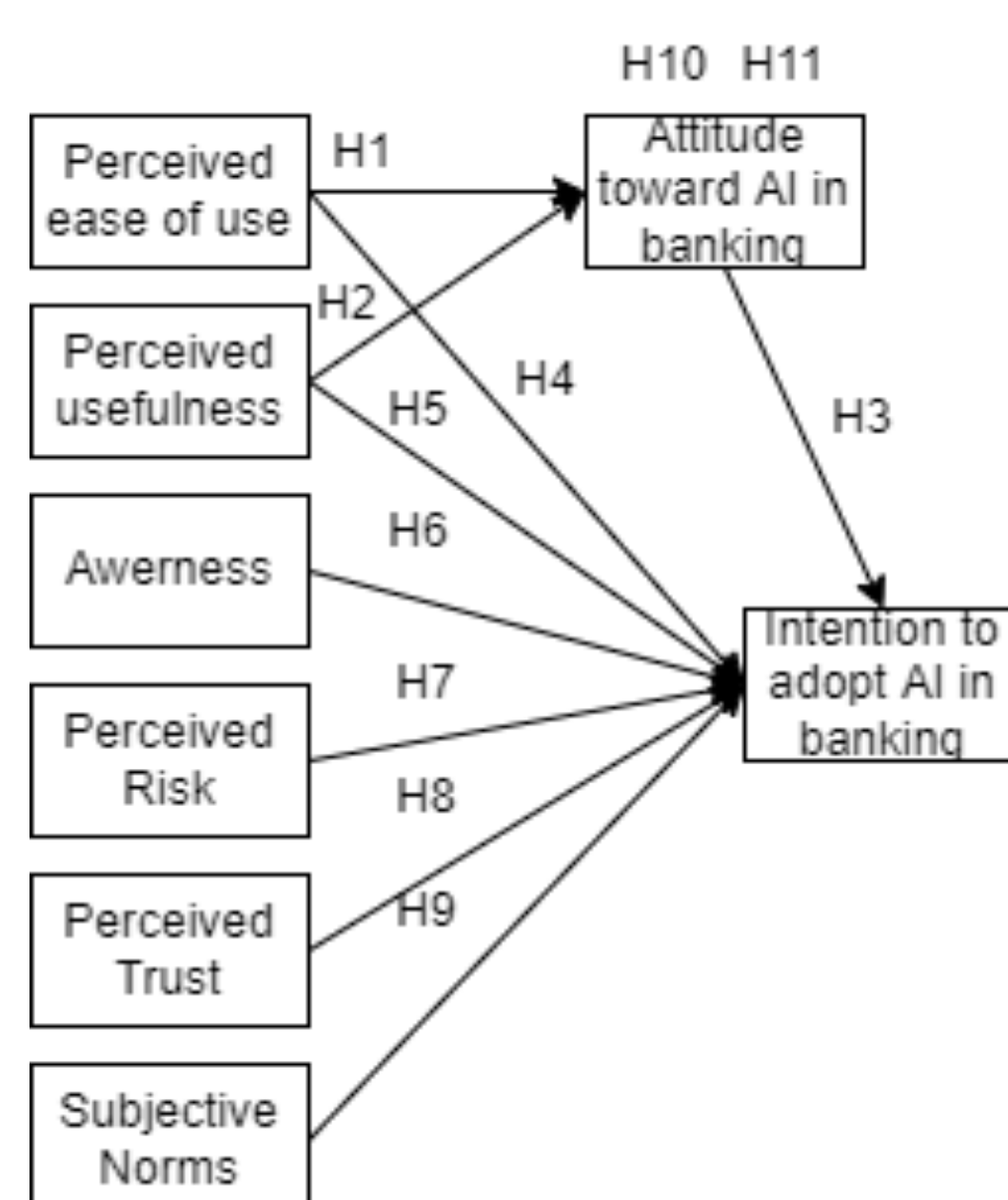


Figure 1. Research Framework

Fornell-Larcker criterion	ATT	AW	INT	PR	PT	PU	PEOU	SN
ATT	0.919							
AW	0.407	0.903						
INT	0.835	0.437	0.882					
PR	0.221	0.085	0.193	0.865				
PT	0.760	0.485	0.705	0.246	0.863			
PU	0.701	0.430	0.648	0.293	0.705	0.917		
PEOU	0.595	0.544	0.560	0.162	0.658	0.791	0.862	
SN	0.849	0.427	0.774	0.288	0.776	0.724	0.604	0.843

Note(s): Diagonal values (Underline) are the square root of the AVE, while the off-diagonals are correlations

Table 2. Latent variable correlation results

Discussion

This study offers practical implications for the management of banks. The empirical findings of this research confirmed that seven factors (i.e. AW, PR, PT, SN, ATT, PU, and PEOU) account for 72.6% of the variance in the AI adoption intention in banking services. The findings explain that all these seven variables are essential for predicting AI adoption intention. However, all the hypothesized relationships between these predictors and the dependent variable were not statistically significant (refer to Table 1). Although PU was found to have a significant positive effect, PEOU was insignificant in affecting INT in banking services. The findings suggest that bank clients prioritize the benefits of using AI over user-friendliness. This study also confirmed that ATT had the largest positive significant ($\beta = 0.285$) effect on the INT in banking services. In the banking service, the adoption of AI should mitigate clients' safety and security concerns while offering greater convenience and user-friendliness of the new system.

Constructs	Items	Loading	CA	CR	AVE	Constructs	Items	Loading	CA	CR	AVE
Attitude toward AI in banking	ATT1	0.905	0.907	0.942	0.844	Perceived risk	PR1	0.876	0.894	0.922	0.747
	ATT2	0.928					PR2	0.913			
	ATT3	0.923					PR3	0.829			
Awareness	AW1	0.885	0.887	0.930	0.815	Perceived Trust	PT1	0.828	0.885	0.921	0.744
	AW2	0.906					PT2	0.848			
	AW3	0.891					PT3	0.901			
	AW4	0.147					PT4	0.871			
Intention to adopt AI in banking	INT1	0.906	0.856	0.913	0.778	Perceived Usefulness	PU1	0.915	0.937	0.955	0.84
	INT2	0.925					PU2	0.933			
Perceived ease of use	PEOU1	0.803	0.885	0.900	0.744	Subjective Norms	PU3	0.925			
	PEOU2	0.853					PU4	0.893			
	PEOU3	0.917					SN1	0.717	0.863	0.907	0.71
	PEOU4	0.873					SN2	0.908			
						SN3	0.896				
						SN4	0.836				

Note(s): AW4 was deleted due to the poor factor loading, CA=Cronbach's Alpha, CR=Composite Reliability, AVE=Average Variance Extracted

Table 3. Reliability and convergent validity for the measurement model.

Conclusions

With the help of artificial intelligence in the banking sector, there is a huge opportunity to make business processes more efficient and offer more sophisticated services to customers. This study adopts the TAM by incorporating important variables such as AW, PR, PT, and SN.

The study findings provide some useful insights for bank management in formulating AI banking strategies. For instance, attitude had the strongest direct effect on the INT in banking. The mediating effect of attitude also substantiated that the effect of PU on intention via attitude was the strongest and most significant. Therefore, increasing the usefulness of AI technology should give higher importance to banking services and applications. Bank management must take the necessary steps to make AI banking services more reliable and attractive by increasing security and improving the customer service experience.

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