The Bioscan
AN INTERNATIONAL QUARTERLY JOURNAL OF LIFE SCIENCES
19(1): 53-56, 2024 www.thebioscan.com

Studying the Role of Social Influence on Adoption of Artificial Intelligence (AI) in Financial Services

***Mr. Vaibhav Sinha [1], Dr. Ajit Kumar [2]**

[1] Research Scholar, Amity Business School, Amity University, Patna, Bihar, India

[2] Associate Professor, Amity Business School, Amity University, Patna, Bihar, India

Corresponding author: vaibhav1381@gmail.com, vaibhav1@s.amity.edu

Emails of co-authors: akumar@ptn.amity.edu

DOI: https://doi.org/10.63001/tbs.2024.v19.i01.pp53-56

KEYWORDS
Artificial intelligence,
performance expectancy,
effort expectancy,
social influence,
financial services.

Received on:

10-11-2024

Accepted on:

05-12-2024

Published on:

14-01-2025

ABSTRACT

This paper studies the impact of the role of social influence on adoption of artificial intelligence on financial services. The research model used is the modified Unified Theory of Acceptance and Use of Technology (UTAUT) model. Independent variables likely, performance expectancy, effort expectancy and social influence and their effect on adoption of AI in financial services has been researched using questionnaire method. Judgemental sampling technique was used and the data was analysed using two-step structural equation modelling. Results reveal that performance expectancy, effort expectancy and social influence have a positive influence on the adoption of artificial intelligence on financial services. The findings may help the corporate, technology firms, fintech companies to formulate strategies in accordance to use and adoption of artificial intelligence in the financial services industry. The major limitation of the study is that it does not include the effects of other demographic characteristics like gender, income level, literacy rate, living conditions, and these could be further investigated to have a more holistic understanding of the adaptability of artificial intelligence in the field of finance.

INTRODUCTION

Artificial Intelligence (AI) can be defined as a social and cognitive phenomena that enables a machine to integrate with a society and perform competitive tasks which requires cognitive processes and communicate with other entities by exchanging messages with high information content and shorter representations.[1] AI having its foundations in computer science, linguistics, psychology, mathematics, and philosophy has been a powerful tool in financial services. It improves adaptive pattern recognition using statistical methods and data to reach the 'best guess' answer to any specific and narrowly-defined problem set.[2] This principle of dialectic symmetry assumes the existence of a hierarchy of information objects which reflects different levels of organization of matter i.e. mechanical, chemical, biological, social, which in turn allows us to interpret the essence of both artificial intelligence and the intelligence that a human being in a similar manner.[3] AI also helps in reduction of cost.[4]

The Finance industry is under continuous development by using and adapting to new technological opportunities —like Artificial Intelligence (AI) and Data Analytics—that shape the private and working lives worldwide.[5] [6] The financial industry benefits from technological advances like the artificial intelligence.[7] [8] AI has become a major component of modern finance. It has made finance cheaper, faster, larger, more accessible, more profitable, and more efficient.[9] It is rapidly transforming the global financial services industry. Along with machine learning (ML) and deep learning (DL), AI has the potential to disrupt and refine the existing financial services industry.[10] It has been found out that the application of artificial intelligence and machine learning has been helpful in understanding the bankruptcy prediction, stock price prediction, portfolio management, oil price prediction, anti-money laundering, behavioural finance, big data analytics, and blockchain.[11]

THEORETICAL BACKGROUND & HYPOTHESES FORMULATION

Previous research in the field of AI have confirmed that the UTAUT model (Unified theory of acceptance and use of technology) can partially predict the likelihood of AI and related technologies adoption intentions among librarians. The model showed that performance expectancy (PE) and attitude toward use (ATU) of AI and related technologies had significant effects on librarians' intention to adopt AI and related technologies.[12] Earlier studies have proved that all three of these pillars—expectation of performance, expectancy of effort, and social influence—significantly and positively impact auditors' intentions to adopt and use artificial intelligence.[13] Another study in the construction of the user acceptance model of AI music, the influencing factors which have an effect on users' intentions were Performance Expectancy and Effort Expectancy.[14] Social influence positively affects perceived value, which directly influences the intention to use AI-based recruitment systems, introducing a new aspect to AI-based recruitment adoption in Thailand.[15] In a study on healthcare workers' adoption intention of AI-assisted diagnosis and treatment the results showed that performance expectancy and effort expectancy were both positively influence their adoption of the same.[16] A study for those with experience in using AI chatbots for mental health suggested that the performance expectancy, price value, descriptive norm, and injunctive norm are positively related to the intention of continuing to use AI chatbots.[17] Another research suggested that facilitating conditions, performance expectancy, effort expectancy, and social influence are the main factors affecting the use of artificial intelligence by teachers and students.[18] The research on societal impact of artificial intelligence revealed that the entangled evolution of individual strategy and network structure constitutes a key mechanism for the sustainability of utilitarian and human-conscious AI.[19] An empirical analysis, using data from 152 firms, based on the Unified Theory of Acceptance and Use of Technology and related approaches revealed that social influence on adoption significantly affects both the peer groups and adopters and non-adopters of the influence.[20]

Basis the above understanding and study of existing literature the below research model was suggested and hypotheses has been formulated. Expanded UTAUT has been considered the basic research model including social influence as an added independent variable.

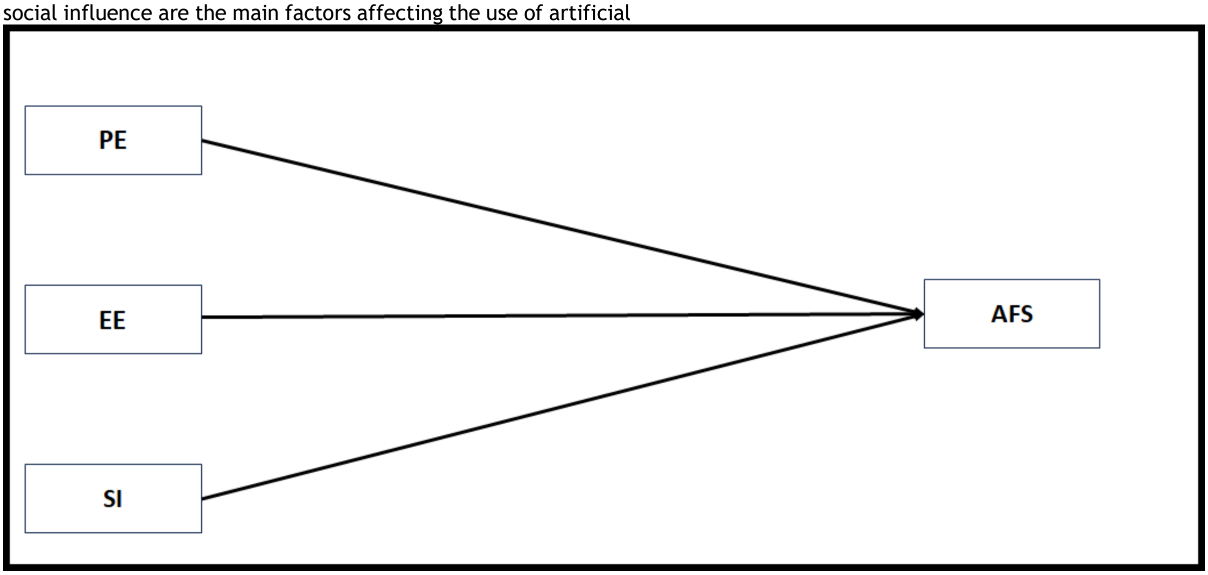

Figure 1. Proposed hypothesised model

H1: Performance Expectancy (PE) has a positive impact on Adoption of Artificial Intelligence in Financial Services (AFS)

H2: Effort Expectancy (EE) has a positive impact on Adoption of Artificial Intelligence in Financial Services (AFS)

H3: Social Influence (SI) has a positive impact on Adoption of Artificial Intelligence in Financial Services (AFS)

DATA COLLECTION & DATA ANALYSIS

A structured questionnaire having two sections, was designed to collect data. The first section recorded demographic details while the second recorded measurement items (on Likert scale) and responses were collected for the constructs of the hypothesized model. In order to avoid discrepancies and to ensure content validity, a pilot study was conducted on 40 respondents from industry and academia. The questionnaire was finalized after making relevant modifications as suggested in the pilot study. Judgmental sampling was used where the majority of respondents were from fields related to fintech, sustainability and financial inclusion. A total of 500 respondents were interviewed and a total of 454 valid responses were accepted. Most of respondents were working professionals with 57% were from urban areas and the remaining 43% from rural parts of the country.

The data was analysed on SPSS and AMOS software. SPSS was used to check for multi collinearity and common method bias. The multicollinearity of all independent variables was tested using VIF (variance inflation factor) and tolerance. The values for VIF and tolerance for performance expectancy (PE) were 1.806 and 0.554, respectively. The VIF for effort expectancy (EE) was 1.884, and the tolerance was 0.531. The VIF and tolerance for social influence (SI) were 1.636 and 0.611 respectively. Finally, the VIF for adoption of artificial intelligence in financial services (AFS) was 2.197, and the tolerance was 0.455. Further, Harman's single-factor test was used to determine if the total variance extracted by one factor was less than 50% and this was found to be 29.646%, which is considerably less than the 50% criterion hence, the study has no method bias. These findings are in line with standard benchmark and has been earlier suggested and used by various researchers.[21] [22]

The present hypothesized framework was examined using two-step structural equation modelling (SEM). At first, the reliability and validity of constructs were examined using confirmatory factor analysis (CFA). The outcomes of CFA indicate the goodness of fit (GOF) of the data. The reliability and validity of questionnaire items are reported in Table 1. Cronbach alpha scores for PE, EE, SI, and AFS were 0.898, 0.896, 0.878, and 0.899 respectively. The Cronbach alpha score of all items range between 0.878 and 0.899, which is higher than the recommended value of 0.7, indicating acceptable internal consistency.[23] [24] For establishing convergent validity, three components, namely, factor loading, composite reliability (CR), and average variance explained (AVE). Factor loadings and CR values of PE, EE, SI, and AFS meet the suggested level of 0.6 or higher. The values of AVE for all the constructs also lie within the range of the acceptance criterion of convergent validity.[25] All these important observations are reported in Table 1. The AVE and squared correlation between the constructs were used to determine discriminant validity and are reported in Table 1. As reported in Table 2, the squared root of AVE for all constructs range between 0.841 to 0.879, which was greater than the squared correlation between the constructs, suggesting that the constructs used in the analysis met an agreed-upon criterion for discriminant validity.[26]

Construct	Items	Factor Loading	Squired Multiple Correlation	Composite Reliability (CR)	Cronbach Alpha	Average Variance Explained

PE	PE3	0.824	0.68	0.190	0.898	0.772
	PE2	0.822	0.676			
	PE1	0.98	0.96			
EE	EE3	0.839	0.703	0.898	0.896	0.747
	EE2	0.932	0.869			
	EE1	0.818	0.669			
SI	SI3	0.847	0.718	0.878	0.878	0.707
	SI2	0.853	0.728			
	SI1	0.821	0.674			
AFS	AFS3	0.768	0.589	0.908	0.899	0.767
	AFS2	0.929	0.863			
	AFS1	0.922	0.85			

Table 1. Measurement Model Analysis: Reliability and Validity

	CR	AVE	MSV	MaxR(H)	PE	EE	SI	AFS
PE	0.910	0.772	0.278	0.966	**0.879**			
EE	0.898	0.747	0.278	0.917	0.527***	**0.864**		
SI	0.878	0.707	0.223	0.879	0.458***	0.473***	**0.841**	
AFS	0.908	0.767	0.242	0.931	0.488***	0.438***	0.311***	**0.876**

Table 2. Discriminant Validity

The GOF statistics were analysed to assess the overall predicting power of the model (x2 = 409.095, x2/df = 1.826, Goodness-of-Fit Index = 0.929, Normed Fit Index = 0.949, Tucker Lewis Index = 0.971, Comparative Fit Index = 0.976, and Incremental Fit Index = 0.976, Relative Fit Index = 0.937) which showed a reasonably fit data set. Furthermore, the RMSEA value (0.043) and SRMR value (0.048) are less than the recommended guideline of 0.06 and 0.08 respectively. The PClose value of 0.968 is more than the recommended value of 0.05. The hypothesized model was further analysed in SPSS AMOS and the results are depicted in Table 3. The observations indicate that performance expectancy or PE (β = 0.254, p = .00, and t = 5.795) and effort expectancy or EE (β = 0.171, p = .00, and t = 3.793) positively influences the Adoption of Artificial Intelligence in Financial Services (AFS). Also, it is observed that social influence or SI (β = 0.118, p = .002, and t = 3.171), positively affects the Adoption of Artificial Intelligence in Financial Services (AFS). Thus, the hypotheses H1, H2, H3 stands supported. These are in line with previous studies in this sector.[27] [28] [29]

Hypotheses	Path			Estimate	S.E.	C.R.	P	Results
H1	AFS	<---	PE	0.254	0.044	5.795	***	Supported
H2	AFS	<---	EE	0.171	0.045	3.793	***	Supported
H3	AFS	<---	SI	0.118	0.037	3.171	0.002	Supported

Table 3: Structural Model: Hypotheses Result

Note: *** = p

CONCLUSION

The study investigated the role of social influence on the adoption of artificial intelligence (AI) in financial services using extended UTAUT model. The finding revealed that performance expectancy, effort expectancy and social influence significant positive impact on the adoption of artificial intelligence in financial services. It can be concluded that the performance and convenience to use artificial intelligence-based solutions increase its adoptability and intention to use. It has also been concluded that the social influence supporting the AI based solutions help in increasing its adaptability and usage. Also, government agencies, market conditions that facilitate the spread of AI based solutioning helps in its adaptability. The above findings could contribute to the research in the area of adaptability of artificial intelligence in financial services. Also, these may add to the literature on the UTAUT model and confirm its applicability in this context. The findings have significant contribution in formulating strategies to increase the adoption of Artificial intelligence in financial services by corporates, fintech firms and government agencies. These findings shall help technology firms to develop their artificial intelligence platforms suitable for better and faster adoption in the field of finance.

While the study helps to understand the behaviour of users' adoption of artificial intelligence in financial services, its global generalization cannot be assured. The findings must be confirmed by similar studies undertaken in other nations to gain a global perspective. Also, effects of other demographic characteristics like gender, income level, literacy rate, living conditions, could be further investigated to have a more holistic understanding of the adaptability of artificial intelligence in the field of finance. and other resources.

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