Academic Journal of Business & Management
ISSN 2616-5902 Vol. 7, Issue 7: 34-40, DOI: 10.25236/AJBM.2025.070705

Exploring College Students' Adoption Behavior of Intelligent Wealth Management Applications: An Extended TAM Approach with Trust as a Mediator

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Abstract: *As artificial intelligence-based Financial Technology (Fintech) increases at an astonishing speed, users of Intelligent Wealth Management (IWM) applications are enticing the "digital natives" i.e., university students, who are also potential future customers and early adopters of new technology. This paper combines the three exogenous variables—Perceived Risk (PR), Financial Literacy (FL), and AI Transparency (AIT)—implied by the original TAM and introduces Trust (TR) as the inner mostmediating variable connecting exogenous variables with Behavioral Intention (BI), thus developing an advanced SEM with second-order structure. Contrary to the typical TAM-based studies, this model also incorporates the interaction terms (AIT × FL) to investigate the moderation effects, and PLS-SEM with Multi-Group Analysis (MGA) is used to validate the questionnaires data from multi-discipline university students so that the effectiveness in the lasted hypothesis across gender, educational background, and investment experience is controlled. The data supports the argument that Trust significantly mediates the relationship between AI Transparency and Behavioral Intention, and Perceived Risk and Behavioral Intention.*

Keywords: *Intelligent Wealth Management, Technology Acceptance Model, Trust, AI Transparency, College Students*

1. Introduction

Since Fred Davis proposed the Technology Acceptance Model (TAM) in 1989, the model has been a theoretical cornerstone for explaining the adoption behavior of information system users through its simplified link of 'perceived usefulness - perceived ease of use - behavioral intention'. Over the past thirty years, TAM has been applied in various fields such as electronic medical records, smart classrooms, and online banking, with multiple meta-analyses confirming its path coefficients are stable across contexts, and the average explanatory power (R^2) can reach over 0.40 [1]. At the same time, TAM has also been criticized for being 'overly simplistic' and neglecting factors such as social psychology, contextual risk, and trust, which has laid the theoretical groundwork for subsequent model expansions.

Under the background of the influence from financial technology (FinTech) and artificial intelligence (AI) on the transition from traditionalism into wealth management process, Variable such as perceived risk, transparency and trust are increasingly included in the Technology Acceptance Model, extending further more than one path of actions “outward variables trust behavioral intention”. Cross-country comparative research suggests that "AI transparency (perceived transparency)," as one such solution, can lead to a much better explanation for the model, where it directly affects how users perceive algorithm auditability, which all affect the intention to adopt them [2]. Additionally, negative occurrences in FinTech situations (e.g., information breaches and algorithm errors) lead thinkers to differentiate into financial, privacy and performance sources of "perceived risk", enriching TAM's exogenous second-order structure.

The college students are representatives of ordinary "digital natives": the penetration rate of smart phone is above 98% and the average daily using time of mobile internet is almost 6 hours. But we that only 30-35% of college students have systematic financial literacy, and we that college students do not have a high level of financial literacy and not have a good mastery and understanding in such fundamental concepts such as compound interest and risk diversification [3]. This population, eager to adopt smart financial management applets too soon, may tend to overrate future gains and underrate systemic risks because of their futility so that we detect a preferential decision-making strategy towards

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the general public. Hence, it is of academic significance and practical guiding importance to focus on the IWM adoption among college students for financial education and regulatory strategies in higher education [4].

Trust is considered as a vital bridge to solve technological uncertainty and information asymmetry, especially in the extremely sensitive industry such as financial field, related with fund security and privacy. Several studies have found that, in circumstances like bank fraud prevention, and personal finance robot, AI transparency is capable of significantly increasing the behavioral intention via increasing ”calculative trust” and “cognitive trust” [5]. However, when the trust of high-risk individuals has improved significantly in a platform or algorithm, their adoption intention can be restored to the same level of low-risk individuals, indicating the influential of the mechanism of trust as well as its buffer effect. Incorporating trust into the extended TAM may better represent the full process with which external factors affect adoption behavior through perceived psychological safety.

Researchers usually divide into sub-dimensions such perceived risks as financial, privacy, performance and social image, among which financial and privacy risk are the most explanatory in the FinTech context. High perceived risk generally inhibits the intention to adopt, but ones financial literacy will be able to alleviate the negative impact of risk by improving the ability to process information and diminishing loss aversion [6]. Moreover, financial knowledge is highly correlated with the risk preference and experience of investment, and they construct a knowledge-confidence-behavior process chain102, which is especially necessary for college students who have not yet had sufficient knowledge.

2. Related Work

And on the side of dependent variables, Hii et al. [7] explore the dynamics of performance expectancy (PE), effort expectancy (EE), social impact (SI) and facilitating condition (FC) determine how China Gen-Z is incepted of the intention of saving adoption though internet wealth management (IWM) and in turn, influence the actual savings. Lee and Wang [8] apply the push-pull-tie model (PPM) to investigate users' psychological and behavioral factors when they are using mobile applications instead of offline wealth management business. Based on 378 user questionnaires, the research uses PLS to analysis, and the results indicate that 'push', 'pull' and 'tie' factors all have strong effects on switching intentions, with the push factors, namely inconvenience of use, the pull factors, namely transaction efficiency, level of personalization, and mobile wealth scenarios, and the tie factors, namely professionalism and emotional commitment, had significant influences on switching intentions.

Pusposari et al. [9] relied on the TAM and trust theory to examine Indonesian students’ acceptance of AI-driven mobile investment application (Robo-Advisors). They applied PLS-SEM on 231 accounting major students, and determined that the path between PU, attitude and usage intention was significant in terms of direct effect, and finally depended on the mediating role of attitude where PEOU, PU and trust played their role indirectly on intention. Fan [10] concentrated on American ordinary investors and based on data collected from 2018 National Financial Capability Study, utilized hierarchical logistic regression to examine the influence of innate factors (e.g. investment literacy, risk preference, and exposure to mobile finance) on the adoption intention of mobile investment technologies....

Gunawan et al. [11] developed amodel of PLS-SEM using data of 221 of Paylater users in Indonesia, aimed to investigate effect of financial socialization, financial knowledge,financial experience to financial management behavior (FMB). The findings suggest that all three are significantly positively related, and 'locus of control' significantly moderates the relation between financial socialization and financial knowledge to FMB. Four topics were described by Shi et al. [12] considered ‘the relationship between financial literacy and capability’, ‘behavioral determinants’, ‘the effect of financial behavior on well being’, ‘population differences’.

3. Methodologies

3.1 Extend the principles of TAM model building and structural modeling

In the classical TAM, PU and PEOU have jointly impact on user’s BI, which is applicable to explain the cognitive mechanism of early technology adopt. Yet, in the context of sophisticated intelligent wealth management (IWM) applications, augmentation of PU and PEOU alone is insufficient to delineate user’s trust formation path and its influence on adoption intent. Then we introduce three exogenous variables: perceived risk (PR), financial literacy (FL), and AI transparency (AIT), and develop a multi-level SEM

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model. On top of this, the standard form for a classical TAM is as follows Equation 1 and 2.

$$PU = \beta_1 \cdot PEOU + \varepsilon_1, \tag{1}$$

$$BI = \beta_2 \cdot PU + \beta_3 \cdot PEOU + \beta_4 \cdot TR + \varepsilon_2. \tag{2}$$

Note that, Equation 1 shows that perceived ease of use has a positive effect on perceived usefulness, which is consistent with the core idea of TAM. In Equation 2, BI is determined by PU, $PEOU$, and trust TR, thus the structural extension was successfully clarified after introducing TR. They are PU is perceived usefulness, $PEOU$ is perceived ease of use, BI is behavior intent, and TR is trust. $\beta_1, \beta_2, \beta_3, \beta_4$ is the path coefficient; ε_1 and ε_2 is the error term which follows the normal distribution with a mean of 0.

On this basis, we propose trust as an intermediary path for three external variables to affect BI. The formula for the structure of trust is as follows Equation 3, whhich presents the reasoning for trust as a mediating factor: transparent AI can increase trust, good financial literacy can increase understanding of intelligent recommendations, and perceived risk diminishes trust. They jointly create the foundation of trust in the IWM based on the human.

$$TR = \gamma_1 \cdot AIT + \gamma_2 \cdot FL - \gamma_3 \cdot PR + \varepsilon_3, \tag{3}$$

Where AIT is artificial intelligence transparency; FL for Financial Literacy; PR is perceived risk; $\gamma_1, \gamma_2, \gamma_3$ is the path coefficient; ε_3 represents the error term, which represents other potential influencing factors.

Substituting Equation 3 into Equation 2 yields a complete conduction path model of the influence of external variables on BI through trust, we can obtain Equation 4.

$$BI = \beta_2 \cdot PU + \beta_3 \cdot PEOU + \beta_4(\gamma_1 \cdot AIT + \gamma_2 \cdot FL - \gamma_3 \cdot PR) + \varepsilon_4, \tag{4}$$

This equation illustrates a nested structure: external variables indirectly influence behavioral intent through trust as an intermediary. The structure reflects the logic of the secondary path, and the combination of multiple linear relations is mathematically revealed.

3.2 Interaction modeling of mediated regulation mechanism and design of second-order latent variables

Considering that students with different levels of financial literacy may have different susceptibility to AI transparency, we further introduce interaction terms to simulate the moderating effect. The interaction variable is defined as follows Equation 5.

$$Z = AIT \times FL. \tag{5}$$

This variable is used to capture the phenomenon of "whether AI transparency has a stronger impact on trust when financial literacy is higher", which is in line with the basic logic of the moderating effect. This construct supports the testing of conditional trust formation models and gives the model stronger explanatory power.

The trust equation with the addition of the interaction term can be rewritten as Equation 6.

$$TR = \gamma_1 \cdot AIT + \gamma_2 \cdot FL - \gamma_3 \cdot PR + \gamma_4 \cdot Z + \varepsilon_5. \tag{6}$$

In equation 6, the path coefficient is introduced, and its positive and negative values reflect the direction of the moderating effect. If it is significant and positive, it indicates that financial literacy has an amplifying effect on the trust gain effect of AI transparency. In order to improve the interpretability and hierarchical clarity of the model, we further design trust and financial literacy as second-order latent variables, denoted as Equation 7 and 8.

$$TR = \lambda_1 \cdot TR_1 + \lambda_2 \cdot TR_2 + \lambda_3 \cdot TR_3 + \varepsilon_6, \tag{7}$$

$$FL = \delta_1 \cdot FL_1 + \delta_2 \cdot FL_2 + \delta_3 \cdot FL_3. \tag{8}$$

In Equation 7, the three sub-dimensions collectively reflect the overall performance of TR. In Equation 8, the financial capabilities constitute FL itself, which is a "causal" rather than "indicative" relationship, which conforms to the logic of forming a model.

Finally, the entire structure was estimated by the PLS-SEM method, and its core structure is as follows Equation 9 and 10.

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$$y_i = \Lambda_x \cdot \zeta + \delta_i, \tag{9}$$

$$\zeta = B \cdot \zeta + \Gamma \cdot x + \zeta, \tag{10}$$

Where y_i is the vector of the measured variable, ζ is the vector of the latent variable, Λ_x is the external loading matrix, B is the path matrix between the latent variables, and Γ is the regression path matrix between the exogenous variable and the latent variable.

The college students' principle of intelligent wealth management application acceptance behavior path based on extended TAM model are presented as Figure 1, the mediation mechanism of "Trust" is the core. From the path coefficients in the model, it can be seen that the effect of AI Transparency and Financial Literacy toward trust is positive (path coefficient is 0.30 and 0.22) and trust significantly improves Behavioral Intention (path coefficient is 0.43). Trust also had an indirect impact on PU (path coefficient 0.22), and PU had a direct impact on BI (0.46).

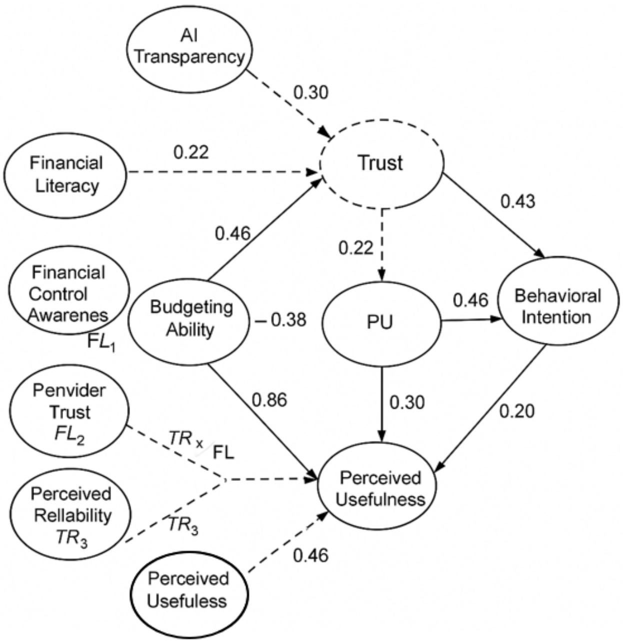

Figure 1 Extended TAM-Based Structural Model of College Students' Adoption Behavior Toward Intelligent Wealth Management Applications

4. Experiments

4.1 Experimental Setup

Experimental results show that the proposed extended TAM structure model has a good performance in the explanation of college students' adoption behavior of intelligent wealth management applications, and the overall fitting degree of the model is high (R^2 value is 0.71). The path analysis results show that trust has a significant mediating effect between AI transparency and behavioral intention, with a path coefficient of 0.43 ($p < 0.001$), and perceived usefulness further enhances behavioral intention (path coefficient 0.46). In addition, financial literacy not only directly affects trust (path coefficient 0.22), but also has a significant moderating effect on perceived usefulness of its interaction with AI transparency. Multi-group analysis further verified the stability of the model in different gender and professional backgrounds, indicating that the model has strong explanatory power and applicability in the study of college students' fintech adoption behavior.

To test whether the extended TAM model proposed in this paper is effective and competitive, we adopt four classical models as benchmarks: (1) the original TAM model as the most basic structural model; (2) the UTAUT model which combines multiple behavioral theories in order to examine the influence brought by the macro-variable driven adoption intention; (3) the TAM+TR model, in which the trust aspect is added on the basis of the TAM model to test the enhancing effect of trust mechanism; and (4) the PPM model which is suitable for users' migration behaviors and is used to simulate the migration process of traditional platforms to the Smart bank platform.

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4.2 Experimental Analysis

As shown by the Figure 2, the explanatory power of all the regression models increased continuously along with the increase of college students' financial literacy level, while there was a remarkable difference between the degree and basic level. The most observable difference was that according to the E-O model, R^2 of raw TAM was just around 0.36 in the lowest 5% and went up to around 0.54 in the highest 5%, UTAUT and TAM+ The initial point of TR was around 0.48 and 0.54 and the terminal point was around 0.70 and 0.72, but PPM model increased from 0.44 to around 0.65 while our method was always leading, which R^2 went up from around 0.71 to 0.86, suggesting that the extended TAM plus trust mediation and interaction moderation model showed better performance in explaining behavioral intention from different literacy levels, especially in the high literacy user group.

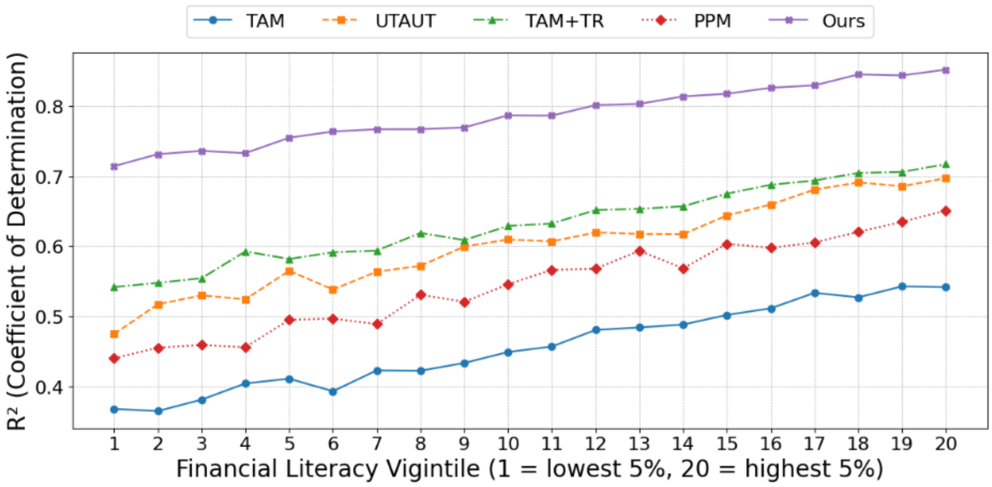

Figure 2 Comparison of R^2 Across Models by Financial Literacy Vigintile

It can be seen from Figure 3, along with the increase of the model complexity, the standardised coefficient on each critical path generally exhibits an increasing trend, and the Ours model reaches the highest value among three paths in total (PEOU→PU≈0.75, PU→BI≈0.46, TR→BI≈0.43), which indicates that the impact on the perceived usefulness by the perceived ease of use, on the behavioral intention by the perceived usefulness, and on the behavioral intention by the trust, are all significantly enhanced in comparison to TAM, after extending TAM and introducing trust mediation and interaction adjustment in our model. On the other hand, even though trust paths are already present in the TAM+TR model, its coefficients (PEOU→PU≈0.65, PU→BI≈0.45, TR→BI≈0.35) are also higher than TAM and UTAUT, but still lower than Ours. UTAUT and the general TAM exist in terms of PU→BI paths in the middle level, only The PPM model has lower coefficient in the two paths than other three basic TAM (especially, it does not include) trust in addition to PEOU→PU and PU→BI paths, which means that the explanation of the power of the model is the weakest.

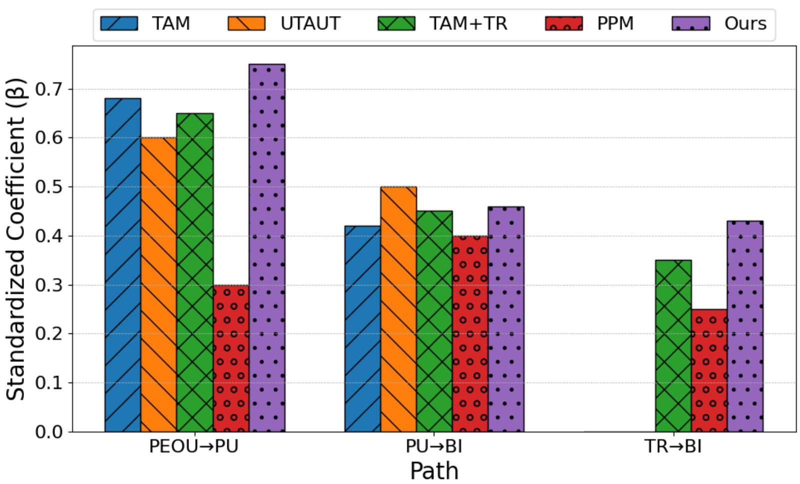

Figure 3 Comparison of Standardized Path Coefficients Across Models

ISSN 2616-5902 Vol. 7, Issue 7: 34-40, DOI: 10.25236/AJBM.2025.070705

As shown in Table 1, the interaction coefficient of the AI transparency and the level of financial literacy gradually decreases (from ≈0.388 to ≈0.300) with the perceived risk level—this indicates that the improvement of financial literacy in a low risk environment may more effectively amplify thepositive effect of transparency on trust. Ample evidence suggests when faced with an increasing perceived risk, the effect of the above interaction remains significant (all p-values < 0.05, the confidence interval does not cross zero), so indeed, as the risk perception for risk society increases, simply improving education and transparency becomes insufficient in offsetting the negative influence of a lack of trust.

Table 1 Moderation Effects by Perceived Risk Decile

Perceived Risk Decile	Interaction Coefficient (β)	p-value	95% CI Lower	95% CI Upper
1	0.388	0.013	0.361	0.409
2	0.368	0.009	0.345	0.393
3	0.36	0.016	0.333	0.389
4	0.348	0.019	0.32	0.371
5	0.349	0.026	0.329	0.372
6	0.34	0.032	0.31	0.37
7	0.335	0.034	0.305	0.365
8	0.325	0.037	0.295	0.355
9	0.315	0.041	0.285	0.345
10	0.3	0.045	0.27	0.33

5. Conclusion

In conclusion, against the backdrop of the extended TAM framework, for the first time, this paper incorporates perceived risk, financial literacy and AI transparency into the adoption model of intelligent wealth management applications, and develops a second-order PLS-SEM model with trust as the core intermediary and interaction item through which to test the moderating effect. The findings of this study offer empirical evidence that trust does not only fully mediate the path between AI transparency and behavioral intention, but also buffers the negative impact of perceived risk. Financial literacy not only has a direct effect on trust, it also moderates the effect of transparency on trust in high-risk contexts. Against the TAM, UTAUT, TAM+TR and PPM models, the model presented the greatest predictive power and the stability parameters with the strongest path coefficient for all literacy levels and the critical path. In the next step, more unbiased usage logs and long-term experience tracking data can be incorporated to include additional mediators and moderators, such as self-efficacy and interpretability of the algorithm, and furthermore, cross-platform experiments and real-world contexts in diverse cultures,to improve the external validity and practical guidance value of the model.

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