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Task–Technology Fit as a Foundational Antecedent of Technology Acceptance: Evidence from Compliance-Intensive Financial Management Information Systems

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Abstract

Financial Management Information Systems (FMIS) are increasingly developed in-house by higher education institutions to accommodate institution-specific governance requirements. However, user acceptance of such systems remains insufficiently understood. Integrating the Technology Acceptance Model (TAM) with Task–Technology Fit (TTF) theory, this study examines behavioral intention toward a self-developed FMIS in a Chinese vocational college. Survey data from 181 users were analyzed using PLS-SEM. The results indicate that TTF significantly affects perceived ease of use (β = 0.599) and perceived usefulness (β = 0.377), and directly influences behavioral intention (β = 0.284). The model accounts for a substantial proportion of variance in behavioral intention (R^2 = 0.574), indicating strong explanatory capability in institutional financial system contexts. Mediation analysis reveals significant parallel and sequential indirect effects, with cognitive pathways accounting for 56% of the total effect. These findings suggest that in compliance-intensive institutional contexts, user acceptance is structurally anchored in task–technology alignment. This study contributes to technology acceptance theory by demonstrating that TTF functions as a foundational antecedent within TAM in task-constrained environments.

Keywords: Task–Technology Fit; Technology Acceptance; Compliance-Intensive Systems; Financial Management Information Systems

1. Introduction

Financial Management Information Systems (FMIS) have become critical infrastructures for budgeting control, accounting processes, and institutional financial governance in higher education institutions. With the acceleration of digital transformation, many universities—particularly in rapidly developing regions—have increasingly adopted self-developed financial systems tailored to their internal governance structures and regulatory compliance requirements. Unlike commercial off-the-shelf solutions, institution-specific systems are primarily designed to support operational tasks rather than optimize general usability. This structural orientation raises an important theoretical question regarding how users form acceptance beliefs in environments where system functionality is task-driven and usage is institutionally mandated.

The FMIS investigated in this study is a self-developed system currently implemented in a higher vocational college in Guangzhou, China. In this setting, system use is embedded within routine, compliance-sensitive financial procedures, and users have limited autonomy to substitute alternative tools. Such conditions differ fundamentally from voluntary consumer technology contexts that dominate the technology acceptance literature. In compliance-intensive systems, users' cognitive evaluations may be less preference-based and more strongly anchored in the alignment between task requirements and technological functionality.

This theoretical concern motivates the integration of Task–Technology Fit (TTF) with the Technology Acceptance Model (TAM). While prior research has combined these frameworks, most empirical studies examine voluntary adoption scenarios or enterprise systems characterized by discretionary usage. Limited attention has been paid to contexts where technology use is operationally mandated and task accuracy is critical. Under such conditions, task–technology fit may function not merely as an additional predictor but as a structural antecedent that shapes perceived ease of use and perceived usefulness. Addressing this contextual and theoretical gap, the present study investigates TAM–TTF integration within a self-developed financial system operating under compliance constraints.Accordingly, this study addresses the following research question:How does task–technology fit condition the formation of perceived usefulness, perceived ease of use, and behavioral intention in compliance-intensive institutional systems?

Extant technology acceptance research consistently identifies perceived usefulness (PU) as a central determinant of behavioral intention. Empirical studies in financial decision-making environments demonstrate that PU significantly predicts adoption intention, often exhibiting stronger effects than perceived ease of use (Yu feifei & Wang lei. ,2024). Similar findings have been reported in extended TAM applications within educational digital platforms, where usefulness perceptions emerge as one of the most influential determinants of user acceptance (Sasongko et al., 2025). These findings underscore the theoretical importance of examining how contextual factors—such as task alignment—shape usefulness evaluations in institutional settings.

2. Literature Review and Hypothesis Development

2.1. Task–Technology Fit and User Perceptions

Task–Technology Fit (TTF) theory asserts that information systems are more likely to be utilized and valued when their functionalities align with users' task requirements (Goodhue &

Thompson, 1995). In financial management contexts, such alignment includes support for accurate data processing, compliance assurance, integrated reporting, and efficient workflow execution. When financial systems exhibit high task–technology fit, users expend less cognitive effort in completing tasks and experience fewer operational frictions.

Empirical research suggests that strong task–technology fit enhances perceived ease of use by reducing learning barriers and simplifying task execution. In professional software environments, better task support enables users to focus on task outcomes rather than system operation (Wei weiet al., 2022). Therefore, this study proposes:H1: Task–Technology Fit positively influences Perceived Ease of Use.

Task–technology fit also shapes users' evaluations of a system's instrumental value. When system capabilities closely match task requirements, users are more likely to perceive the system as useful for improving performance and decision quality. Prior studies have identified task–technology fit as a significant antecedent of perceived usefulness in enterprise systems (Gangwar et al., 2020). Thus, the following hypothesis is proposed:H2: Task–Technology Fit positively influences Perceived Usefulness.

2.2. Relationship Between Perceived Ease of Use and Perceived Usefulness

According to TAM, perceived ease of use contributes to perceived usefulness because systems that require less effort allow users to achieve performance gains more efficiently (Davis, 1989).

In financial management systems, ease of use facilitates smoother data entry, reduces error rates, and supports timely financial analysis, thereby enhancing perceived usefulness.Previous research in technology acceptance contexts has consistently found that perceived usefulness is a primary determinant of behavioral intention, often exerting stronger influence than perceived ease of use (Sasongko et al., 2025). Hence, this study proposes:H3: Perceived Ease of Use positively influences Perceived Usefulness.

2.3. Determinants of Behavioral Intention

Behavioral intention reflects users' willingness to adopt and continue using a system and is a key predictor of actual usage. In task-intensive financial systems, perceived usefulness reflects users' assessment of whether the system meaningfully enhances task accuracy, efficiency, and decision quality. Therefore, usefulness perceptions are expected to play a dominant role in shaping behavioral intention. When users believe that a financial system enhances work effectiveness and decision quality, they are more inclined to use it consistently. Empirical research in digital service adoption contexts has shown that perceived usefulness often serves as a key predictor of behavioral intention, sometimes exerting a stronger influence than perceived ease of use in determining user acceptance (Tian, 2024). Accordingly, this study proposes:H4: Perceived Usefulness positively influences Behavioral Intention.

Although perceived ease of use often affects behavioral intention indirectly through perceived usefulness, prior research indicates that it may also exert a direct influence, especially when users are forming adoption judgments or interacting with complex systems. Therefore:H5:

Perceived Ease of Use positively influences Behavioral Intention.

2.4. Research Model

The proposed research model integrates TTF and TAM by positioning task–technology fit as an exogenous construct influencing perceived ease of use and perceived usefulness. Perceived ease of use further affects perceived usefulness, while both perceptual constructs directly influence behavioral intention. This integrated framework enables an examination of both direct and indirect mechanisms underlying financial system adoption.3. Materials and Methods

3.1. Research Design

This study adopted a quantitative research design to examine the relationships among task characteristics, technology characteristics, task–technology fit, and technology acceptance variables. A structured questionnaire survey was employed to collect empirical data, Data analysis was conducted using SmartPLS 4.0. PLS-SEM was selected because the study emphasizes prediction and theory extension rather than covariance-based model confirmation. Additionally, the relatively moderate sample size (n = 181) and the model's inclusion of higher-order explanatory paths make variance-based SEM more appropriate (Hair et al., 2019).

3.2. Measurement Instrument

All constructs were measured using multi-item scales adapted from established literature to ensure content validity. Task characteristics (TAC) and technology characteristics (TEC) were measured to capture the nature of task requirements and technology features. Task–technology fit (TTF) assessed the degree to which the technology supported task performance. Technology acceptance variables included perceived ease of use (PEOU), perceived usefulness (PU), and behavioral intention to use (BI).

Each construct was measured using four items. All items were assessed on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). Minor wording adjustments were made to suit the research context while preserving the original meaning of the items. Prior to formal data collection, the questionnaire was reviewed to ensure clarity and comprehensibility.

3.3. Data Collection and Sample

A total of 220 eligible FMIS users were invited to participate in the survey using a census approach. Of these, 181 responses were returned after data screening, yielding a response rate of 82.3%. Participants included finance officers and administrative staff who regularly used the system. Participation was voluntary and anonymous. Respondents were informed about the academic purpose of the study and provided informed consent prior to survey completion.

3.4. Data Analysis Procedure

Data analysis was conducted using PLS-SEM following a two-stage approach. First, the measurement model was evaluated to assess reliability and validity. Internal consistency reliability was examined using Cronbach's alpha and composite reliability. Convergent validity was assessed through factor loadings and average variance extracted (AVE). Discriminant validity was evaluated using the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio.Second, the structural model was assessed by examining path coefficients, coefficients of determination (R^2), predictive relevance (Q^2), effect sizes (f^2), and collinearity diagnostics. Bootstrapping with 5,000 resamples was employed to test the statistical significance of the hypothesized relationships.

3.5. Mediation Analysis

To examine indirect effects, a bias-corrected bootstrapping procedure with 5,000 resamples was applied. Mediation effects were evaluated by inspecting indirect path coefficients and their 95% confidence intervals. An indirect effect was considered significant when the confidence interval did not include zero. Both direct and indirect effects were assessed to determine the presence of partial or full mediation among the studied constructs.

3.6 Common Method Bias

Procedural remedies were implemented to mitigate common method bias, including anonymity assurance and scale separation. Statistically, full collinearity VIF values were examined and all were below the recommended threshold of 3.3, suggesting that common method bias is unlikely to threaten the validity of the findings.

A Harman's single-factor test was conducted, and the first factor accounted for 38.7% of total variance, below the 50% threshold, further indicating that common method variance is unlikely to significantly bias the results.Additionally, a common latent factor approach was tested, and results confirmed that no single factor accounted for a majority of the variance.

4. Results and Discussion

4.1. Sample Profile

As shown in Table4.1,A total of 181 valid responses were obtained. The gender distribution was relatively balanced, Among the respondents, 51.93% were male and 48.07% were female. This distribution reduces potential gender bias and supports the robustness of subsequent analyses.

Gender	Number	(%)
Male	94	51.934
Female	87	48.066
Total	181	100.0

Table4.1:Description of the total sample size

4.2. Measurement Model Evaluation

Reliability and Convergent Validity

Internal consistency reliability and convergent validity were assessed using Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE). As shown in Table4.2 , all Cronbach's alpha values ranged from 0.839 to 0.878, exceeding the recommended threshold of 0.70. Composite reliability values ranged from 0.841 to 0.883, indicating satisfactory internal consistency.

Variable	Topic	Factor loading	T statistics	P	Cronbach's alpha	CR	AVE
TAC	TAC1	0.872	53.980	0.000	0.878	0.883	0.732
	TAC2	0.859	45.927	0.000			
	TAC3	0.828	28.702	0.000			
	TAC4	0.863	49.422	0.000			
TEC	TEC1	0.837	30.073	0.000	0.866	0.870	0.714
	TEC2	0.825	33.699	0.000			
	TEC3	0.851	40.046	0.000			
	TEC4	0.866	47.312	0.000			
TTF	TTF1	0.844	36.786	0.000	0.855	0.857	0.696
	TTF2	0.848	36.032	0.000			
	TTF3	0.815	33.418	0.000			
	TTF4	0.831	32.900	0.000			
Peou	Peou1	0.809	32.860	0.000	0.839	0.841	0.674
	Peou2	0.832	37.744	0.000			
	Peou3	0.843	35.481	0.000			
	Peou4	0.800	28.119	0.000			
PU	PU1	0.859	45.540	0.000	0.871	0.873	0.721
	PU2	0.833	35.564	0.000			
	PU3	0.863	46.904	0.000			
	PU4	0.841	38.416	0.000			
BI	BI1	0.848	35.598	0.000	0.848	0.855	0.687
	BI2	0.857	38.890	0.000			

BI3	0.797	27.657	0.000
BI4	0.811	31.774	0.000

Table4.2:Reliability and validity analysis

All factor loadings were above 0.80 and statistically significant ($p < 0.001$), suggesting strong indicator reliability. AVE values ranged from 0.674 to 0.732, exceeding the recommended benchmark of 0.50, thereby confirming convergent validity.

These findings indicate that the measurement model demonstrates strong internal consistency and convergent validity.For all constructs, the square roots of AVE exceeded inter-construct correlations (Table 4.3). In addition, all HTMT values were below the conservative threshold of 0.85 , confirming that the constructs were empirically distinct (Henseler et al., 2015).

	TAC	TEC	TTF	Peou	PU	BI
TAC	0.856					
TEC	0.599	0.845				
TTF	0.670	0.675	0.835			
Peou	0.410	0.439	0.599	0.821		
PU	0.424	0.458	0.601	0.600	0.849	
BI	0.383	0.504	0.645	0.644	0.658	0.829

Table 4.3Fornell–Larcker Criterion Results

4.3. Structural Model Results

The model exhibited moderate to substantial explanatory power. The standardized root mean square residual (SRMR) was 0.062, below the recommended threshold of 0.08, indicating acceptable model fit.The R^2 values were 0.566 for TTF, 0.359 for PEOU, 0.451 for PU, and 0.574 for BI. In particular, the model explains 57.4% of the variance in behavioral intention, indicating strong predictive capacity for user adoption behavior in institutional financial systems.

Blindfolding procedures were conducted to assess predictive relevance (Q^2). All endogenous constructs yielded positive Q^2 values (TTF = 0.557; PEOU = 0.218; PU = 0.236; BI = 0.242), indicating that the model possesses satisfactory predictive relevance.

Bootstrapping with 5,000 resamples confirmed that all hypothesized paths were statistically significant ($p < 0.001$; Table 4). Task characteristics ($\beta = 0.413$) and technology characteristics ($\beta = 0.428$) both exerted strong positive effects on task–technology fit. In turn, task–technology fit significantly influenced perceived ease of use ($\beta = 0.599$), perceived usefulness ($\beta = 0.377$), and behavioral intention ($\beta = 0.284$).Perceived ease of use positively affected perceived usefulness ($\beta = 0.373$) and behavioral intention ($\beta = 0.283$), while perceived usefulness also showed a significant positive effect on behavioral intention ($\beta = 0.318$). These results support the proposed structural relationships and are consistent with established technology acceptance research.The path coefficients of the structural model are shown in the figure4.1.

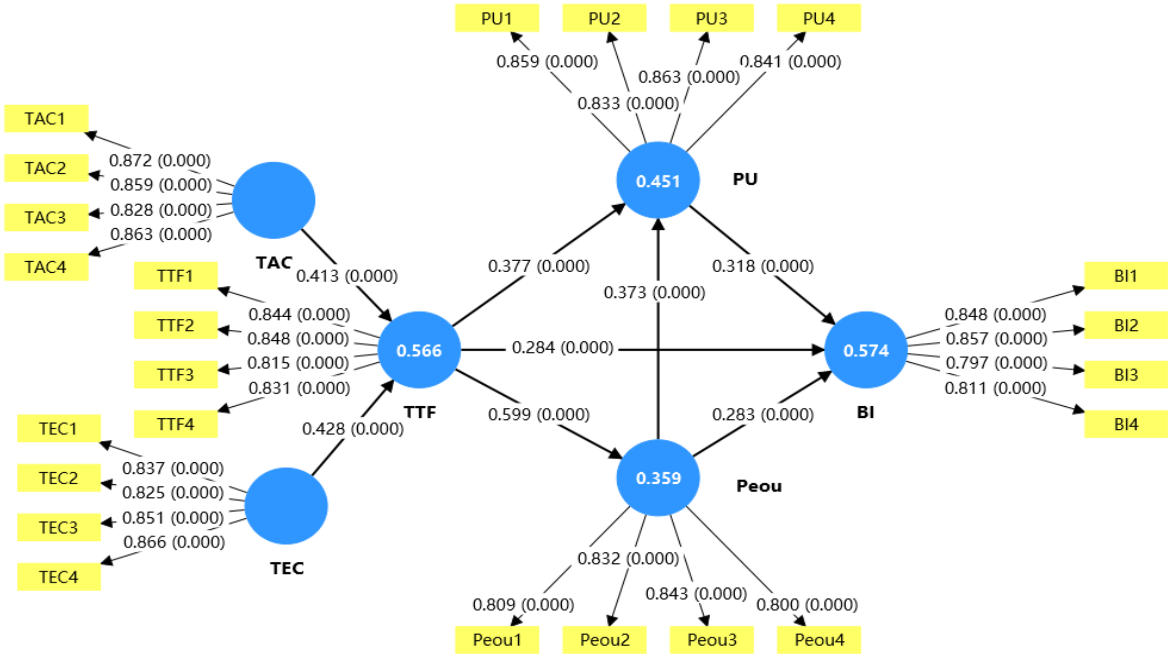

Figure4.1 Structural Model with Path Coefficients

Effect size analysis indicated that task–technology fit had a large effect on perceived ease of use (f^2 = 0.560) and medium effects on perceived usefulness and behavioral intention. Task and technology characteristics also showed large effects on task–technology fit (f^2 = 0.252–0.270). Other relationships exhibited small to medium effect sizes, indicating meaningful practical significance (Table 4.4).

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
TAC -> TTF	0.413	0.412	0.055	7.521	0.000
TEC -> TTF	0.428	0.430	0.056	7.588	0.000
TTF -> Peou	0.599	0.601	0.051	11.698	0.000
TTF -> PU	0.377	0.376	0.070	5.428	0.000
TTF ->BI	0.284	0.285	0.069	4.146	0.000
Peou -> PU	0.373	0.376	0.068	5.505	0.000
Peou -> BI	0.283	0.281	0.065	4.368	0.000
PU -> BI	0.318	0.319	0.063	5.010	0.000

Table 4.4 Path coefficient table of the PLS structural equation model

4.4. Mediation Effects

Mediation analysis using bias-corrected bootstrapping revealed both parallel and sequential mediation effects. The indirect effects via PU (β = 0.120), PEOU (β = 0.169), and the sequential pathway (β = 0.071) were all statistically significant.

The direct effect of TTF on BI remained significant (β = 0.284), indicating partial mediation. Notably, the combined indirect effects accounted for more than half of the total effect (56%), suggesting that TTF shapes behavioral intention primarily through cognitive evaluations rather than direct influence alone.

This finding highlights a structured cognitive mechanism wherein task alignment first reduces effort perceptions and subsequently enhances perceived usefulness before translating into adoption intention.

4.5. Discussion

This study provides empirical support for an integrated task–technology fit and technology acceptance framework, with results indicating strong measurement properties and substantial explanatory power for behavioral intention.Consistent with task–technology fit theory (Goodhue & Thompson, 1995), task and technology characteristics significantly contribute to task–technology fit, which in turn plays a central role in shaping users' acceptance beliefs.

When system functionalities align with task requirements, users perceive the system as easier to use, which subsequently enhances perceived usefulness and adoption intention.

The mediation analysis further demonstrates that task–technology fit influences behavioral intention through both direct and indirect pathways. In addition to its direct effect, task–technology fit operates through perceived ease of use and perceived usefulness, including a sequential cognitive mechanism. This study extends the traditional Technology Acceptance Model in task-intensive system contexts. Practically, the findings highlight the importance of aligning system design with task demands to enhance user acceptance, particularly for complex or professional applications.

This study contributes to the literature in three ways. First, it empirically extends TAM by incorporating task–technology fit in a compliance-intensive setting. Second, it clarifies the cognitive mechanisms linking task alignment to behavioral intention. Third, it highlights contextual boundary conditions under mandated system usage.

4.6 Limitations and Future Research

Despite its contributions, this study has several limitations. First, the data were collected from a single institution, which may limit the generalizability of the findings. Second, the cross-sectional design restricts causal inference. Third, all variables were measured using self-reported perceptions. Future research should employ multi-site sampling, longitudinal designs, and objective usage data to enhance robustness.

5. Conclusion

This study provides empirical evidence that task–technology fit serves as the cognitive foundation for belief formation in compliance-intensive institutional systems. By explaining a substantial proportion of variance in behavioral intention and identifying structured mediation mechanisms, the findings demonstrate that task alignment fundamentally restructures technology acceptance processes under mandated usage conditions. These insights refine the boundary conditions of TAM and underscore the strategic importance of aligning system functionality with task requirements in institutional contexts.

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