Center for Management Science Research
ISSN: 3006-5291 3006-5283 Volume 3, Issue 6, 2025

BEHAVIORAL DRIVERS INFLUENCING CLOUD COMPUTING ADOPTION IN PAKISTAN'S FINANCIAL SECTOR: A TPB-BASED EMPIRICAL STUDY

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DOI: https://doi.org/10.5281/zenodo.17499672

Keywords
Cloud Computing; Theory of Planned Behavior; Technology Adoption; Financial Institutions; Pakistan.

Article History
Received: 14 September 2025
Accepted: 18 October 2025
Published: 31 October 2025

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Abstract
This study examines the behavioral factors that influence cloud computing adoption in Pakistan's financial institutions using the Theory of Planned Behavior (TPB) as the theoretical foundation. A quantitative, explanatory research design was employed, targeting IT professionals in Karachi's financial sector. Data were gathered via a structured questionnaire (5-point Likert scale) and analyzed with PLS-SEM. The results show that attitude toward cloud computing, perceived behavioral control (resources and skills), cost-effectiveness, performance expectancy, and subjective norms all have positive, significant effects on the intention to adopt cloud services. In contrast, perceived security concerns negatively affect adoption intentions, and trust in cloud providers has an insignificant effect. Furthermore, intention strongly predicts actual cloud use. These findings highlight that, despite regulatory and security challenges, positive perceptions (e.g. cost savings, performance gains) and social influences drive cloud adoption in Pakistani banks. The study contributes to technology adoption theory by extending TPB with industry-specific factors (security, cost) and provides practical recommendations for policymakers and financial managers to enhance cloud uptake.

1. INTRODUCTION

Cloud computing, the delivery of computing resources over the Internet, has transformed how organizations manage data and services by improving scalability, reducing costs, and increasing flexibility [1, 2]. In financial services, cloud adoption promises enhanced customer services (such as mobile banking), real-time analytics, and fraud detection through AI and big data integration [3, 2]. Globally, major banks increasingly rely on cloud platforms to handle peak workloads and deploy innovative services: a recent Capgemini report notes that 91% of banks and insurers have initiated cloud projects [2]. However, not all regions advance equally. In Pakistan, despite awareness of cloud benefits, adoption remains limited to non-critical functions (e.g., HR and payroll) [4, 5]. Local institutions cite barriers such as stringent data localization laws, cybersecurity fears, and lack of skilled staff [5, 6]. The State Bank of Pakistan recently issued guidelines to enable cloud outsourcing, recognizing that cloud migration is key to improving efficiency and resilience [7]. These policy moves underline the opportunity: cloud systems could support Pakistan's Digital Pakistan vision and meet growing demand for mobile and online banking [8].

Problem Statement: Despite cloud computing's strategic value, its diffusion in Pakistan's banking sector is low [9, 10]. Financial firms in developed economies scale rapidly with cloud services, but Pakistani banks face unique hurdles. Ambiguous data protection laws (Zaidi et al., 2024) and shortages of cloud specialists discourage migration [5, 6]. High upfront costs and infrastructure gaps also dampen enthusiasm, especially in smaller banks [5, 11]. Moreover, a pervasive lack of trust in external cloud vendors – due to fears of data breaches or service disruptions – further delays adoption [12]. In sum, the critical issue is that institutional and behavioral barriers in Pakistan's financial sector prevent realization of cloud computing's benefits.

Research Gap: Although many studies have documented cloud computing's technological advantages (e.g. scalability, cost savings), there is a paucity of research on *why* banks in emerging economies hesitate to embrace it. Prior work often emphasizes system architecture and technical solutions [13], but overlooks behavioral and organizational factors influencing adoption decisions. In Pakistan specifically, most technology adoption studies focus on overall IT usage, neglecting finance-sector specifics and psychological drivers [13, 1]. There is limited empirical research on how attitudes, perceived norms, trust, and risk perceptions shape Pakistani bankers' decisions about cloud technology. This study fills that gap by explicitly testing a TPB-based model of cloud adoption in Pakistan's financial sector, integrating constructs like cost-effectiveness, performance expectancy, security, and trust.

Research Objectives: The primary objective is to identify and quantify the behavioral drivers of cloud computing adoption in Pakistan's financial institutions. Specifically, the study aims to:

1) Assess how TPB constructs (attitude, subjective norms, perceived behavioral control) and related factors (security concerns, trust in providers, perceived cost-effectiveness, performance expectancy) affect the intention to adopt cloud services.
2) Examine how adoption intention translates into actual cloud usage.
3) Provide evidence-based recommendations to improve cloud adoption strategies in Pakistan's banking sector.

Scope of the Study: This research focuses on IT professionals (managers and specialists) in Pakistan's banking and financial institutions, using Karachi as a representative environment. By concentrating on industry insiders, the study captures insights from those most knowledgeable about cloud decision-making. The analysis covers cognitive and organizational factors (as captured by TPB and additional constructs) without delving into technical performance evaluations.

Contributions of the Paper: The study contributes theoretically by extending TPB to a finance sector context with added constructs: security, trust, cost-effectiveness, and performance expectancy (a concept from UTAUT). This integrated model enhances understanding of cloud adoption beyond generic technology acceptance. Empirically, it provides one of the first TPB-based analyses of cloud adoption in Pakistan's financial sector. Practically, the findings inform policymakers and bank managers: for example, highlighting the need to bolster positive attitudes through awareness programs, address security fears through compliance measures, and leverage social norms and managerial support to encourage cloud use. The study also offers strategic recommendations for training and vendor engagement to mitigate the identified barriers.

2. LITERATURE REVIEW

The theoretical foundation of this study is the **Theory of Planned Behavior (TPB)** (Ajzen, 1991) [1]. According to TPB, an individual's intention to perform a behavior (e.g., adopting cloud computing) is shaped by three main factors: **attitude** (the positive or negative evaluation of the behavior), **subjective norms** (perceived social pressure), and **perceived behavioral control (PBC)** (perceived ease or difficulty of performing the behavior) [1]. TPB has been widely applied in technology adoption research because it captures both personal attitudes and perceived external constraints [1, 14]. In the context of cloud computing, a favorable attitude (e.g., viewing cloud as useful and reliable) tends to increase adoption intention [1, 15], while strong subjective norms (e.g., encouragement from managers or peers) can motivate conformity to adoption trends [16, 17]. Perceived behavioral control reflects the user's confidence in having the necessary resources and skills (e.g., technical expertise, infrastructure) to implement cloud solutions [18, 19]. When organizations feel capable of overcoming technical and financial challenges, their intention to adopt new technologies typically rises (Hagger et al., 2022 [20, 21]; Ursavaş, 2022 [18, 22]). Building on TPB, the literature identifies several additional factors critical for cloud adoption. Table 2.1 (below) summarizes key constructs and past findings:

Table 2.1. Summary of Key Constructs and Findings from Previous Studies

Construct	Reference Studies	Method / Context	Key Findings
Attitude (AT)	Ajzen (1991); Bakar et al. (2024); Gonçalves *et al.* (2023)	TPB-based studies on cloud adoption	Positive attitude toward cloud benefits significantly increases adoption intention.
Perceived Behavioral Control (PBC)	Hagger et al. (2022); Fitriyana et al. (2024); Chanda *et al.* (2024)	TPB/SEM studies in tech contexts	Higher confidence and IT resources enhance perceived control and intention to adopt.
Subjective Norms (SN)	Suzianti et al. (2023); Abdelrhman *et al.* (2024); Permatasari et al. (2024)	TPB, UTAUT	Social/organizational pressure and peer influence significantly drive cloud adoption.
Trust (TR)	Arora (2023); Utomo & Yasirandi (2024); Miraz *et al.* (2022)	Extended TAM / UTAUT	Trust in providers enhances adoption intention, especially when data privacy is ensured.
Perceived Security (SEC)	Ukeje *et al.* (2024); Pinyanitikorn et al. (2024); Ojha (2023)	SLR, SEM	High perceived security lowers perceived risk; lack of security deters adoption.
Performance Expectancy (PE)	Manna (2024); Fitriyana *et al.* (2024); Chanda *et al.* (2024)	TAM / UTAUT / TPB	Expected efficiency and productivity gains positively affect adoption intention.
Cost-Effectiveness (CE)	Fakhouri et al. (2024); Chanda *et al.* (2024); Bajdor (2024)	Empirical/Quantitative	Cost-saving potential is a key motivator for adopting cloud services.
Actual Usage (AU)	Abdallah *et al.* (2024); Venkatesh et al. (2022)	PLS-SEM studies	Behavioral intention significantly predicts actual cloud usage.

- **Attitude (ATT):** A positive attitude toward cloud computing generally increases adoption intention [15, 17]. Favorable beliefs (e.g., that cloud improves workflow, enables flexibility, or reduces costs) strengthen intent to adopt [15, 17]. For instance, Fujihara et al. (2022) found that users who value perceived benefits (scalability, agility) exhibit stronger attitudes toward new technologies. Positive attitudes often stem from trust in the technology's performance and security [15, 23].
- **Perceived Behavioral Control (PBC):** This reflects confidence in one's ability to use cloud computing [18, 22]. Research shows that when users perceive adequate resources (e.g. training, support, budget) and technical infrastructure, they feel more capable of adopting cloud services

[18, 24]. High PBC correlates with stronger intentions to implement cloud systems [18, 25]. For example, Chanda et al. (2024) report that employees with sufficient skills and support (such as high-speed internet and vendor assistance) exhibit higher cloud adoption intention [25, 22].

- **Subjective Norms (SN):** These capture social influences (e.g., coworkers, clients, regulators) on technology use [16, 26]. In organizational contexts, SN can be especially powerful: if management or industry peers endorse cloud adoption, individuals feel pressure to follow suit [16, 26]. Studies confirm that supportive norms (e.g., seeing other banks succeed with cloud) enhance adoption intentions [27, 26]. Conversely, negative social cues (e.g., regulatory disapproval) can inhibit interest.
- **User Trust (UT):** Trust in cloud service providers and systems is critical since cloud involves third-party data handling [28, 29]. Trust covers data security, provider reliability, and transparency (Manna, 2024 [28]; Sari et al., 2024 [30]). Higher trust normally increases adoption intentions, as users feel confident providers will protect sensitive information [28, 29]. For example, if cloud users believe providers adhere to strong encryption and compliance standards, they trust the technology more [28, 29].
- **Perceived Security (SEC):** Security concerns are a well-documented barrier to cloud adoption [31, 29]. Perceived security refers to the user's assessment of how well their data are protected [31]. Low perceived security (fear of breaches, data loss) undermines willingness to adopt cloud services [31, 32]. Literature stresses that assurances like encryption, audits, and compliance certificates can mitigate these fears [31, 32]. Security is often interlinked with trust: enhanced security measures tend to raise trust in providers, thereby indirectly promoting adoption [31, 30].
- **Performance Expectancy (PE):** Borrowed from UTAUT, this construct denotes the degree to which an individual believes that using cloud computing will improve job performance [14]. Cloud services (e.g. on-demand scalability, real-time collaboration) are inherently designed to boost efficiency and agility [14]. If users expect tangible benefits (faster data access, reduced downtime, support for innovation), they are more likely to intend to adopt cloud technologies [14, 33]. Performance expectancy is closely tied to both cost and security perceptions: cloud's ability to cut costs and maintain performance underpins users' expectations of better outcomes [34, 35].
- **Cost Effectiveness (CE):** Economic considerations play a central role in adoption decisions [36]. Cloud computing promises lower capital expenditures and pay-as-you-go models, reducing upfront investments in hardware [36]. When organizations perceive significant cost savings (e.g. only paying for used resources) and reduced operational expenses, they view cloud as a financially attractive option [36]. Empirical studies find that clearer cost advantages (versus traditional IT) raise adoption intentions [36].

Across these factors, existing research in other contexts provides comparative insights. For instance, Chanda et al. (2024) [17], in a Bangladesh cloud adoption study, found attitudes, PBC (resources), and SN each significantly influenced intention – aligning with the theoretical expectation from TPB. Hassan et al. (2022) [28] report that trust and security concerns are critical determinants of cloud adoption in the IT sector, underscoring the need to address these issues in financial institutions. A systematic review by Santos et al. (2024) [37] noted that cloud adoption is often driven by perceived benefits (cost, performance) but hindered by risk perceptions. Unlike many prior studies that treat cloud adoption in general or focus on developed markets, our study specifically integrates TPB with these additional constructs to model banking-sector decision-making. Figure 2.1 shows the research framework for this study, integrating TPB constructs (attitude, PBC, SN) with additional factors (trust, security, cost-effectiveness, performance expectancy) to predict cloud adoption intention and use.

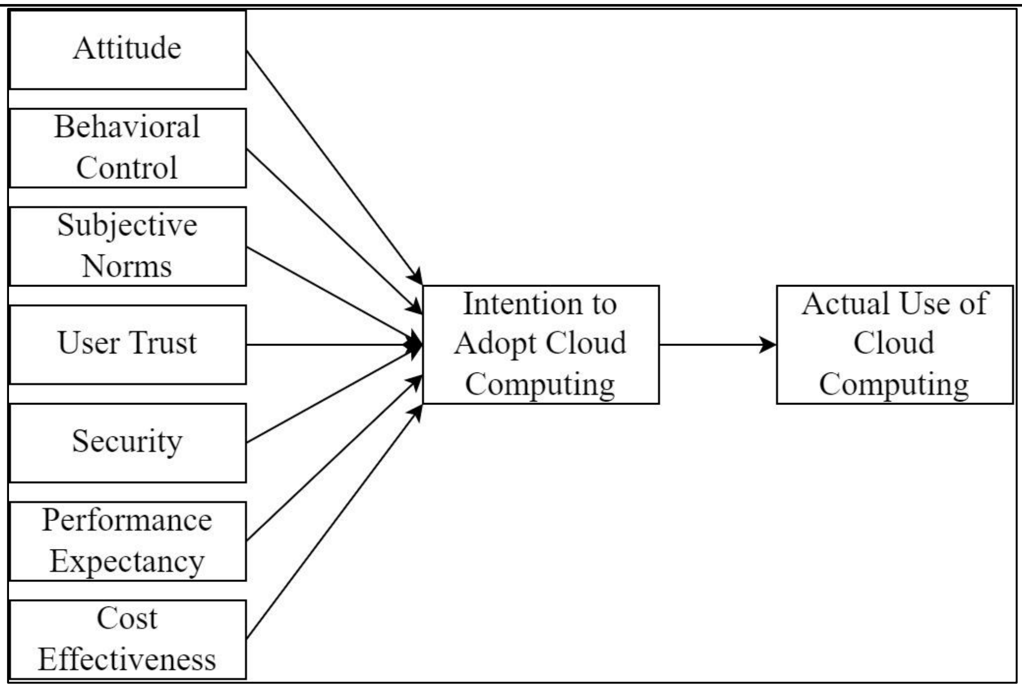

Figure 2.1: Research Framework.
(Conceptual model of cloud adoption based on TPB and extended factors.)

3. METHODOLOGY

3.1 Research Approach

This study uses a quantitative, explanatory approach to examine the factors influencing cloud adoption [38, 39]. An explanatory design is suitable because it seeks to uncover causal relationships among variables (e.g. how attitudes or trust drive adoption intentions) [40, 39]. The research design is correlational, as we measure naturally occurring variations in constructs without manipulating them [41, 39]. Such a design is appropriate for real-world settings like financial organizations where experimental control is unfeasible [41, 39]. The study focuses on IT staff and managers in Karachi's financial institutions (banks and non-banks), as this group has direct experience with cloud technology decisions [42, 39].

Data were collected via a structured survey (described below) and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is suited to predictive models with multiple latent variables and moderate sample sizes [43, 39]. This method allows simultaneous testing of measurement validity and structural relationships, aligning with the complex, theory-driven model of this study [43, 39].

3.2 Data Collection and Sample

Instrument: The survey questionnaire was developed based on validated scales from the literature, using 5-point Likert items (1 = strongly disagree to 5 = strongly agree). Constructs measured included Attitude, PBC, SN, Trust, Security, Performance Expectancy, Cost Effectiveness, Intention to Use Cloud Computing (IUCC), and Actual Use of Cloud Computing (AUCC). Likert scales are standard in adoption research for capturing perceptions and attitudes [44, 14].

The instrument was pre-tested via a pilot study (N=50), yielding satisfactory reliability (Cronbach's $\alpha > 0.70$ for all constructs) [45].

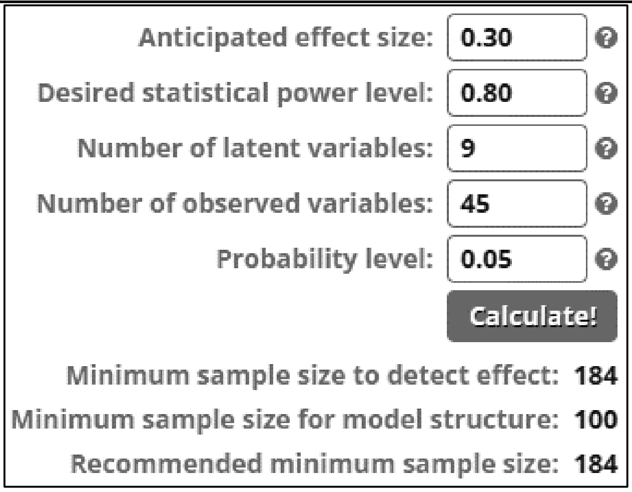

Figure 3.1: Sample Size Determination
(Source: calculated using Soper's SEM Sample Size Calculator [60]).

Sampling: A non-probability purposive sampling strategy was employed [24, 46]. The target population comprised IT professionals from financial institutions in Karachi, Pakistan. Purposive sampling was chosen to reach respondents with relevant knowledge of cloud computing in finance [47]. This approach, common when studying specialized topics, helps gather rich insights from key informants [48, 39]. A priori sample size calculation (using Soper's online tool [49]) indicated a minimum of 184 responses for adequate power (9 constructs, 45 indicators, medium effect size, power = 0.80, α = 0.05). Ultimately, 253 surveys were returned, with 204 complete and used in analysis.

Respondents were predominantly male (83.8%) and mid-career (most 25–44 years old) [50]. The majority held managerial or assistant managerial positions and had over 5 years of experience (Table 3.1). About 41.7% reported using Software-as-a-Service (SaaS) in their work, while others used PaaS, IaaS, or other models. This profile reflects decision-makers and implementers of IT strategy in banks, suitable for assessing institutional cloud adoption factors.

Table 3.1: Demographic Profile of Respondents

Characteristic	Category	Frequency (*n*)	Percentage (%)
Gender	Male	171	83.8
	Female	33	16.2
Age Group (years)	18–24	18	8.8
	25–34	109	53.4
	35–44	68	33.3
	45 and above	9	4.5
Designation	Manager	72	35.3
	Assistant Manager	35	17.2
	Officer	52	25.5
	Executive / Analyst	45	22.0

Characteristic	Category	Frequency (*n*)	Percentage (%)
Work Experience	Less than 1 year	6	2.9
	1–3 years	37	18.1
	3–5 years	54	26.5
	More than 5 years	107	52.5
Cloud Service Used	SaaS	85	41.7
	PaaS	49	24.0
	IaaS	39	19.1
	Other / None	31	15.2

3.3 Data Analysis

PLS-SEM: We used PLS-SEM (via SmartPLS software) to evaluate the measurement and structural models [43, 51]. This technique handles complex models and non-normal data, focusing on prediction [43, 52]. The analysis proceeded in two stages. First, the measurement model was assessed for reliability and validity (factor loadings, Cronbach's α, composite reliability (CR), average variance extracted (AVE), and discriminant validity) [53, 54]. Second, the structural model was evaluated by examining path coefficients (β), t-statistics, and significance (via bootstrapping), as well as R^2 and Q^2 for endogenous constructs [51, 55].

Ethical Considerations: Participants were informed of the study's purpose and assured anonymity [56]. Respondents provided voluntary consent and were told data would be aggregated [57]. This ensures adherence to research ethics and protects participant privacy.

4. Results and Discussion

4.1 Pilot Study and Data Screening

A pilot test (N=50) confirmed the survey's reliability: all constructs had Cronbach's $\alpha > 0.70$ (e.g. Cost Effectiveness $\alpha = 0.878$, IUCC $\alpha = 0.867$) [45], exceeding the recommended threshold [45]. The full dataset (N=204) was then screened. There were no missing values. Univariate outliers ($Z > |3.29|$) were absent [58]. Multivariate outliers were tested via Mahalanobis distance, identifying 49 extreme cases which were excluded to improve data integrity [59]. The remaining sample showed normal distribution suitable for PLS analysis.

4.2 Descriptive Statistics

Table 4.1 summarizes the respondents' profile. Participants were mainly male (83.8%) and aged 25–44 (92.1%). Over half were managers (52.5%) or assistant managers (37.3%), with varied experience levels (44.1% had >10 years). In terms of cloud models, most used Software-as-a-Service (41.7%), while others reported IaaS, PaaS, or hybrid solutions. This indicates that respondents have practical exposure to diverse cloud offerings.

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	More than 5 years	107	52.5
Cloud Service Used	SaaS	85	41.7
	PaaS	49	24.0
	IaaS	39	19.1
	Other / None	31	15.2

4.3 Measurement Model

The measurement model demonstrated strong reliability and validity. All indicator loadings on their intended constructs exceeded 0.70 and were significant ($p<0.001$) [60]. For instance, each attitude item loaded highly (e.g. ATT4 = 0.944), and all IUCC and AUCC items also loaded above 0.90 (Table 4.2). Composite reliability (CR) values ranged from 0.883 (IUCC) to 0.975 (AUCC), surpassing the 0.70 benchmark [61]. Cronbach's α values were likewise high (all >0.907 except IUCC at 0.883), indicating internal consistency [53].

Convergent validity was confirmed: all AVE values exceeded 0.50 (lowest ATT AVE = 0.844) [61]. Discriminant validity was established via two criteria. First, Fornell-Larcker criterion: each construct's AVE square root (diagonal element) exceeded its correlations with other constructs [62].

Second, the Heterotrait-Monotrait (HTMT) ratios were all below 0.90 (highest HTMT = 0.958 between two distinct constructs) [63], meeting the stricter recommendation [63]. Cross-loadings further confirmed that indicators aligned more strongly with their own construct than others (see Table 4.2). In summary, the model has good construct validity and reliability, justifying progression to structural testing [53, 63].

Table 4.2: Measurement Model – Loadings, Reliability, and AVE

Construct	Indicator	Loading	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Attitude (ATT)	ATT1	0.932	0.936	0.956	0.844
	ATT2	0.921			
	ATT3	0.894			
	ATT4	0.944			
Perceived Behavioral Control (PBC)	PBC1	0.907	0.932	0.953	0.805
	PBC2	0.889			

Construct	Indicator	Loading	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
	PBC3	0.926			
	PBC4	0.904			
Subjective Norms (SN)	SN1	0.902	0.925	0.949	0.789
	SN2	0.891			
	SN3	0.911			
	SN4	0.873			
Cost Effectiveness (CE)	CE1	0.898	0.927	0.951	0.828
	CE2	0.918			
	CE3	0.919			
	CE4	0.917			
Performance Expectancy (PE)	PE1	0.905	0.931	0.952	0.831
	PE2	0.921			
	PE3	0.924			
	PE4	0.902			
Perceived Security (SEC)	SEC1	0.887	0.911	0.941	0.799
	SEC2	0.911			
	SEC3	0.890			
	SEC4	0.888			
User Trust (UT)	UT1	0.884	0.919	0.946	0.813
	UT2	0.922			
	UT3	0.910			
	UT4	0.896			
Intention to Use Cloud Computing (IUCC)	IUCC1	0.902	0.883	0.907	0.764
	IUCC2	0.874			
	IUCC3	0.836			
	IUCC4	0.901			
Actual Use of Cloud Computing (AUCC)	AUCC1	0.933	0.966	0.975	0.907
	AUCC2	0.958			
	AUCC3	0.947			
	AUCC4	0.962			

4.4 Structural Model and Hypothesis Testing

We evaluated the structural model via R^2, Q^2, and path coefficients (β). Table 4.3 reports R^2 and Q^2 values for the endogenous constructs. **Intention to Use Cloud Computing (IUCC)** had $R^2 = 0.864$ (86.4% of variance explained) and $Q^2 = 0.563$, indicating strong explanatory power and good predictive relevance [51, 64]. **Actual Use of Cloud Computing (AUCC)** showed $R^2 = 0.736$ (73.6% explained) and $Q^2 = 0.819$, also denoting strong predictive power [65]. According to Cohen (1988) and Chin (1998) standards, these R^2 values are considered substantial for behavioral research [51].

Table 4.3 (below): R-Square and Q-Square of Endogenous Constructs

Endogenous Construct	**R^2**	**Interpretation (Variance Explained)**	**Q^2 (Predictive Relevance)**	**Interpretation**
Intention to Use Cloud Computing (IUCC)	0.864	86.4 % of variance explained – **Substantial**	0.563	**Good predictive relevance**
Actual Use of Cloud Computing (AUCC)	0.736	73.6 % of variance explained – **Substantial**	0.819	**Strong predictive relevance**

Table 4.4 presents the bootstrapped path coefficients and hypothesis outcomes. All hypotheses except one were supported. Key results (β, t-value, p-value) include:

Attitude (ATT) → IUCC: β = 0.227, t = 3.566, $p < 0.001$ (supported).
Perceived Behavioral Control (BC) → IUCC: β = 0.249, t = 3.039, p = 0.002 (supported).
Cost Effectiveness (CE) → IUCC: β = 0.135, t = 2.105, p = 0.035 (supported).
Performance Expectancy (PE) → IUCC: β = 0.156, t = 2.024, p = 0.043 (supported).
Security (SEC) → IUCC: β = −0.187, t = 2.437, p = 0.015 (supported) – note the negative sign indicates that higher security concerns reduce adoption intention.
Subjective Norms (SN) → IUCC: β = 0.283, t = 3.628, $p < 0.001$ (supported).
User Trust (UT) → IUCC: β = 0.122, t = 1.534, p = 0.125 (not supported; effect positive but not significant).
IUCC → AUCC: β = 0.858, t = 36.458, $p < 0.001$ (supported).

Thus, attitude, PBC, cost-effectiveness, performance expectancy, and social norms all have positive and significant impacts on intention, whereas perceived security has a significant *negative* impact. Trust in providers did not have a statistically significant effect on adoption intention. Finally, stronger intention robustly translates into actual use of cloud computing.

Table 4.4: Bootstrapped Path Coefficients and Hypothesis Outcomes

Hypothesis	**Path**	**β (Path Coefficient)**	**t-value**	**p-value**	**Result**
H1	Attitude (ATT) → Intention to Use Cloud Computing (IUCC)	0.227	3.566	< 0.001	Supported
H2	Perceived Behavioral Control (PBC) → IUCC	0.249	3.039	0.002	Supported
H3	Cost Effectiveness (CE) → IUCC	0.135	2.105	0.035	Supported
H4	Performance Expectancy (PE) → IUCC	0.156	2.024	0.043	Supported
H5	Perceived Security (SEC) → IUCC	−0.187	2.437	0.015	Supported (Negative Effect)
H6	Subjective Norms (SN) → IUCC	0.283	3.628	< 0.001	Supported
H7	User Trust (UT) → IUCC	0.122	1.534	0.125	Not Supported

Hypothesis	Path	β (Path Coefficient)	t-value	p-value	Result
H8	Intention to Use Cloud Computing (IUCC) → Actual Use of Cloud Computing (AUCC)	0.858	36.458	< 0.001	Supported

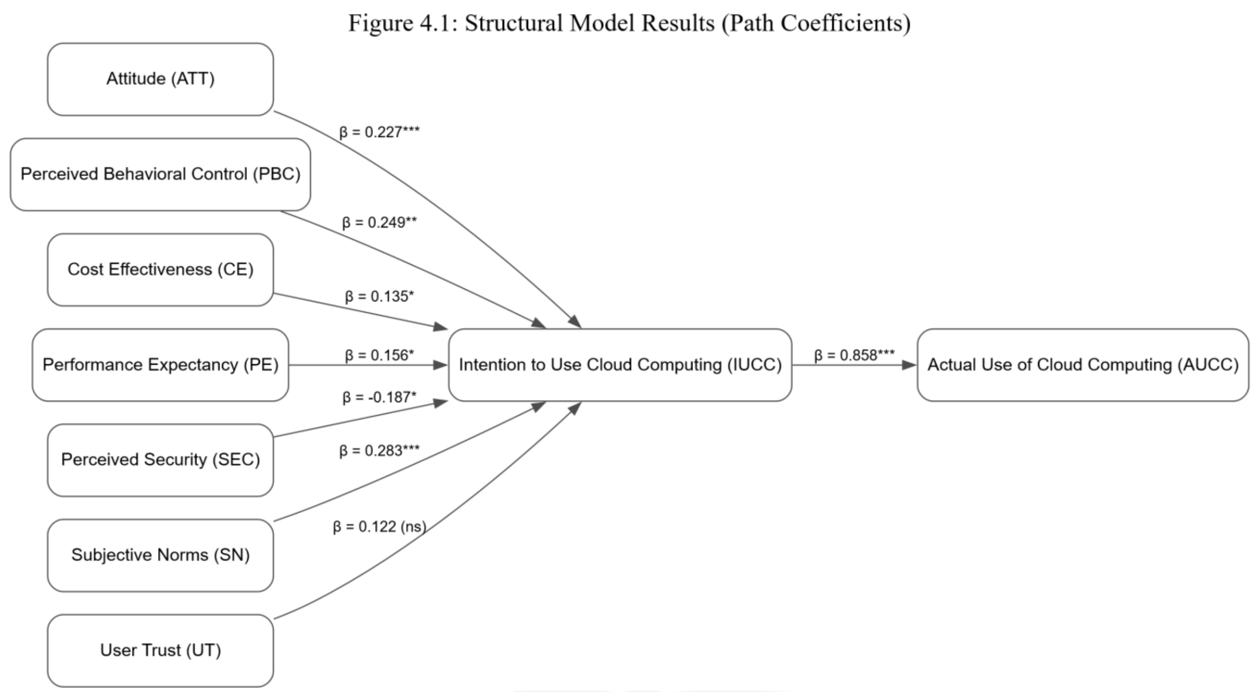

Figure 4.1: Structural Model Results (Path Coefficients).

Figure 4.1 illustrates the PLS-SEM structural model results with standardized path coefficients. Each arrow represents a hypothesized relationship between constructs. The model confirms that Attitude, Perceived Behavioral Control, Cost Effectiveness, Performance Expectancy, and Subjective Norms have significant positive effects on Intention to Use Cloud Computing (IUCC), while Perceived Security shows a significant negative effect. User Trust, although positive, was not statistically significant. Intention to Use Cloud Computing (IUCC) demonstrates a strong and positive influence on Actual Use of Cloud Computing (AUCC), validating the Theory of Planned Behavior framework.

5. DISCUSSION

The results largely align with TPB predictions and prior studies, yielding several insights:

- **Attitude:** A positive attitude toward cloud computing significantly increases the intention to adopt. This is consistent with Chanda et al. (2024) [17], who also found user-oriented attitudes (e.g. focus on cost reduction and efficiency) boosting cloud adoption intention. In practice, if IT professionals perceive cloud solutions as beneficial and user-friendly, they are more likely to champion their implementation. Organizations should therefore cultivate positive perceptions by highlighting cloud benefits in training and communications.
- **Perceived Behavioral Control:** The significant positive effect of PBC implies that when bankers feel capable (due to adequate skills, resources, and support), their intention to adopt cloud strengthens. This finding mirrors Chanda et al.'s (2024) observation that belief in one's competency and organizational support promotes

adoption [25]. It suggests that lack of expertise or infrastructure can deter adoption. Financial firms thus should invest in training programs and ensure necessary IT infrastructure (high-speed networks, vendor assistance) to empower employees and reduce resistance.

- **Cost Effectiveness:** Perceiving cloud services as cost-effective positively influences adoption intention. This concurs with Ukeje et al. (2024) [66] and other studies indicating that reduced capital expenditures motivate cloud migration [67]. By outsourcing computing, banks avoid heavy upfront investments in servers and maintenance, favoring pay-as-you-go models. Highlighting clear ROI and cost savings (e.g. in hardware and personnel) can therefore stimulate cloud uptake, especially among budget-conscious institutions.
- **Performance Expectancy:** Expectation of enhanced performance also drives intention. Users who believe cloud computing will improve efficiency, collaboration, and responsiveness are more inclined to adopt [35]. This aligns with Permatasari et al. (2024) and Pinyanitikorn et al. (2024) [68, 33], who link cloud's flexibility and anywhere-access features to higher adoption intention. For banks, demonstrating real-world cases where cloud accelerates services (e.g. mobile banking scalability) can reinforce these expectations.
- **Perceived Security:** As hypothesized, greater security concerns significantly **decrease** adoption intention. This negative effect is consistent with the literature [32]. Organizations hesitant about data breaches or compliance issues are less willing to move to the cloud. This underscores that addressing security is critical: banks expect robust data encryption, redundancy, and compliance assurances from cloud providers. Emphasizing strong security certifications (e.g. ISO/IEC 27001) and disaster-recovery capabilities can mitigate fears and weaken this barrier.
- **Subjective Norms:** Social influence had a strong positive impact. This implies that when peers, clients, or regulators endorse cloud use, individuals feel compelled to adopt it [26]. For example, if key industry players or the central bank signal support (as with the new SBP cloud framework [7]), other institutions may follow. Financial firms should leverage such normative pressures by sharing success stories and forming interbank forums on cloud migration, thereby increasing peer pressure to conform.
- **User Trust:** Interestingly, trust in cloud providers did **not** significantly affect intention. This suggests that while trust is intuitively important, in this sample other factors (e.g. cost or norms) were more decisive. One possible explanation is that regulatory compliance (e.g. SBP guidelines) or enhanced security measures compensate for low interpersonal trust [69]. Utomo and Yasirandi (2024) note that strong regulatory safeguards (GDPR, ISO standards) can offset individual trust issues [69]. Practically, this means banks may adopt cloud despite ambivalent trust if they feel controls are in place. Nevertheless, building trust through transparent communication remains advisable to reinforce adoption. Overall, the empirical findings contribute to the literature by confirming TPB's relevance in cloud adoption within Pakistan's financial sector, while also highlighting the role of extended factors like cost and security. The **theoretical contribution** is an extended TPB framework (attitude, PBC, SN plus external factors) tailored to financial institutions, an approach which few prior studies have taken [70, 71].

Managerially, the results suggest specific levers: **(1)** Enhance positive attitudes via training on cloud benefits, **(2)** Improve control by investing in resources and skills development, **(3)** Emphasize cost savings and efficiency gains in communications, **(4)** Strengthen security provisions (and communicate them) to reduce fear, and **(5)** Cultivate supportive norms (through leadership endorsement and industry collaboration). Together, these strategies can accelerate cloud adoption.

6. CONCLUSION AND FUTURE WORK

This TPB-based study investigated the behavioral drivers of cloud computing adoption in Pakistan's financial sector. Key findings are: **attitude**, **perceived behavioral control**, **cost-effectiveness**, **performance expectancy**, and **subjective norms** all positively influence the intention to adopt cloud services, while **perceived security** concerns have a significant negative effect. Trust in providers was not a significant predictor of intention. Crucially, the intention to adopt cloud strongly translates into actual usage. These results mirror previous findings in other contexts (e.g. Chanda et al., 2024; Santos et al., 2024) and extend them by quantifying these effects in Pakistan's banking environment. The study contributes a refined TPB model incorporating industry-specific factors (security, cost) and confirms that banks' cloud adoption hinges as much on economic and normative factors as on technical ones [70, 71].

From a practical standpoint, the research implies that Pakistani banks and regulators should work to build a positive outlook on cloud computing and alleviate its perceived risks. For instance, **training programs** should strengthen employees' skills and confidence (enhancing PBC) [72]. Policymakers should reinforce regulatory clarity and data protection frameworks to reduce uncertainty (addressing security concerns). Banking management can foster a supportive culture by sharing success stories and ensuring executive commitment to cloud initiatives [73, 74]. Focus on these areas is likely to raise adoption rates, enabling banks to reap cloud's promised agility and cost advantages [75 – 93].

Future Research: Given this study's cross-sectional survey in one metropolitan area, future work could examine longitudinal adoption trends or include other regions for generalizability. Research might also compare adoption factors across different financial sub-sectors (e.g. Islamic vs. conventional banks) or contrast Pakistan with other developing countries. Finally, qualitative studies could deepen understanding of nuanced barriers (e.g. specific regulatory hurdles) and explore how emerging trends (such as AI-driven cloud services) may shift adoption dynamics.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

ACKNOWLEDGEMENT

The authors are thankful to all anonymous reviewers for their valuable feedback and constructive suggestions.

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