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MODELING CLOUD COMPUTING ADOPTION IN IT-RELATED EDUCATIONAL INSTITUTIONS: AN EMPIRICAL INVESTIGATION USING THE DIFFUSION OF INNOVATION THEORY

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cloud computing adoption in education, diffusion of innovation, determinants of cloud computing adoption, compatibility, relative advantage, observability, complexity, trialability.

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Abstract
This paper examined the factors that influence the acceptance and use of cloud-based services in education. The study used a quantitative cross-sectional methodology, collecting data from 194 IT learners from two IT universities in Hyderabad, Pakistan, via a Likert scale questionnaire. The study is theoretically based on the Diffusion of Innovation theory and used structural equation modeling in Amos to discover the influencing factors for adoption. The path analysis revealed that Cloud Computing Adoption is positively and significantly influenced by Compatibility ($\beta = 0.227$, CR = 2.392, $p = 0.017$) and Relative Advantage ($\beta = 0.402$, CR = 4.262, $p < 0.001$). and Observability ($\beta = 0.11$, CR = 1.964, $p = 0.049$). Meanwhile, contrary to the original DOI assumption, complexity had a positive and significant impact on cloud computing adoption ($\beta = 0.399$, CR = 4.115, $p < 0.001$). Furthermore, the relationship from Trialability to Cloud Computing Adoption was negative and non-significant ($\beta = -0.07$, CR = -0.714, $p = 0.475$). The study contributes to the field by investigating the cloud computing adoption factors in education from the perspectives of developing countries.

INTRODUCTION

Cloud computing is the delivery of online services and resources made available to people via the Internet. Cloud computing reduces the actual costs of implementation and maintenance. It also increases accessibility; users can access cloud computing services whenever and wherever they need through an Internet connection. Due to its several benefits in services offered to the commercial industry, cloud computing is very common and gaining significant relevance. Firms from all over the world have deployed data centers to offer cloud services globally.

As a developing country, educational institutions in Pakistan face extreme financial challenges, particularly in the field of IT. On the other hand, the number of internet users is significantly increasing. Moreover, the IT industry in the country has extensively expanded after the government announced IT policies and action plans to increase IT use (Kundi & Shah, 2009). Additionally, the government has been promoting initiatives for the incorporation of new technologies to raise the quality of education.

Problem Statement

Despite cloud technology's advantages, adoption is still a major issue, especially in technical education (Behrend et al., 2011). From an academic, administrative, and planning standpoint, it is crucial to comprehend the features that lead learners to embrace this technology (Venkatesh & Bala, 2008). The technological success ratio is influenced by the user's perspective of technology adoption (Low et al., 2011).

Although cloud computing adoption in education has been extensively studied in various educational settings, the literature limits empirical investigation of the factors influencing its adoption in learners in IT-related educational settings in a developing country context. Hence, there is a need to investigate the factors that influence cloud computing adoption from the perspective of learners in a developing country context.

This paper is an extension of the previous paper by Agha et al., 2026) on the perceived determinants of cloud computing adoption, which explores the users' perception of cloud computing adoption in education. This paper extends the research by examining the factors that contribute to cloud computing adoption in educational settings in Pakistan.

Research Aim

This study aims to investigate the determining factors of cloud computing adoption among learners of IT using the Diffusion of Innovation framework.

LITERATURE REVIEW

Diffusion of Innovation Theory

Rogers' Diffusion of Innovation model, also called the diffusion model, is the most extensively tested and used model for identifying and assessing the elements that help or impede the expected diffusion rate of technology evaluation, adoption, and implementation. DOI provides clearly defined concepts and techniques. (Robert G. Fichman, 1992). In general, factors involved in the diffusion process can be divided into three categories: innovation traits, innovative construct, and innovation decision-making process. Rogers did not, however, originate the concept of dissemination. Transcultural diffusion was one of the earliest studies on innovation transmission conducted by Ratzel et al. (1928). Another study that questioned people's voting habits was carried out by researchers (Lazarsfeld et al., 1969). This study demonstrated how crucial opinion leaders' attitudes are in influencing voters' decisions. Subsequently, a different researcher examined the variables that affected the dissemination of seed corn in two Iowa villages (Bass, 1969). The 1960s saw the convergence of those research methods and the emergence of a new theory of innovation. Finding the elements influencing a society's adoption of a new idea or technology is the goal of the most recent edition of DOI (Everett M. Rogers, 2003). This hypothesis seeks to explain why some innovations in a society successfully spread while others do not. Rogers has identified certain elements that influence the frequency of diffusion in a community.

Attributes of Innovation of Diffusion Theory

The Theory of Invention aims to explain the key factors and mechanisms of invention diffusion. The primary aspects include innovation, communication channels, time, and social systems, as well as their impact on the rate of innovation adoption. The adopted DOI categories were previously stated in conjunction with this. The properties or elements of DOI are listed below. Innovation Theory highlights a number of elements that influence innovation and its pace of diffusion. These factors influence the rate of acceptance of an innovation (Everett M. Rogers,

2010). Rogers described the following innovation constructs:
Trialability: the extent to which an invention can be tried for a period of time.
Compatibility: an innovation's assessment of current values, historical views, and the demands of potential adoptees.
Relative advantage: the degree to which the invention outperforms the original idea.
Complexity: the degree to which an innovation is seen as somewhat difficult to learn and use.
Observability: the degree to which others can witness the outcomes of an innovation.

Application of DOI
Since the 1960s, Rogers' Innovation Theory has been applied to study a wide range of technologies, from agricultural implements to organizational innovation (Buyya et al., 2009). Researchers in technological adoption have long held the innovation idea in high regard. For example, the Innovation Theory has been used in a variety of contexts, including studies into technology adoption determinants (V. K. Narayanan, 2001).
The factors influencing adoption vary from study to study. Similar to prior studies, researchers discovered that strong relative benefit and compatibility innovations are easy to deploy. (Jurison, 2000). Another researcher discovered that, in addition to possible benefits, sociocultural influences considerably impact decision-making (Tung & Rieck, 2005). Another study discovered that both external (mass media, advertising) and interpersonal (friends, family) factors influence variables. In addition to usefulness and compatibility, it had a significant impact on adoption decisions (Parthasarathy & Bhattacherjee, 1998). Another study found that technology compatibility influences technology diffusion because it must fit with the current technological context.

Cloud Computing Adoption in Education and DOI
To assess this study, this study utilizes the DOI model to understand how dependable and useful the deployment of cloud-based education systems in IT-based institutions is. Rogers outlined five key steps in the inventive decision-making process. The organization has to make the right decisions and motivate its users at the appropriate time. Knowledge, persuasive ability, and decision-making are the three most essential structures that influence the decision to pursue innovation. Researchers describe the innovation diffusion process as "a process for reducing uncertainties," and it provides innovative qualities that aid in lowering uncertainty regarding innovation.

The five innovation constructs are trialability, compatibility, relative advantages, complexity, and observability. According to researchers, people's views of this trait determine the rate at which innovations are adopted. (Everett M. Rogers, 2003) (Pavlou & El Sawy, 2006). This study looks at the role of constructions and the relationships between constructs in the adoption of cloud computing (Everett M. Rogers, 2003).
Cloud computing is one of the innovative approaches to improving organizational performance. The DOI can be applied to communication systems in the current situation. It will aid in policy alignment and evaluating how intended users perceive the adoption process (Everett M. Rogers, 2010).

FRAMEWORK OF THE STUDY
The framework of the study is based on the Roger's Diffusion of Innovation theory.

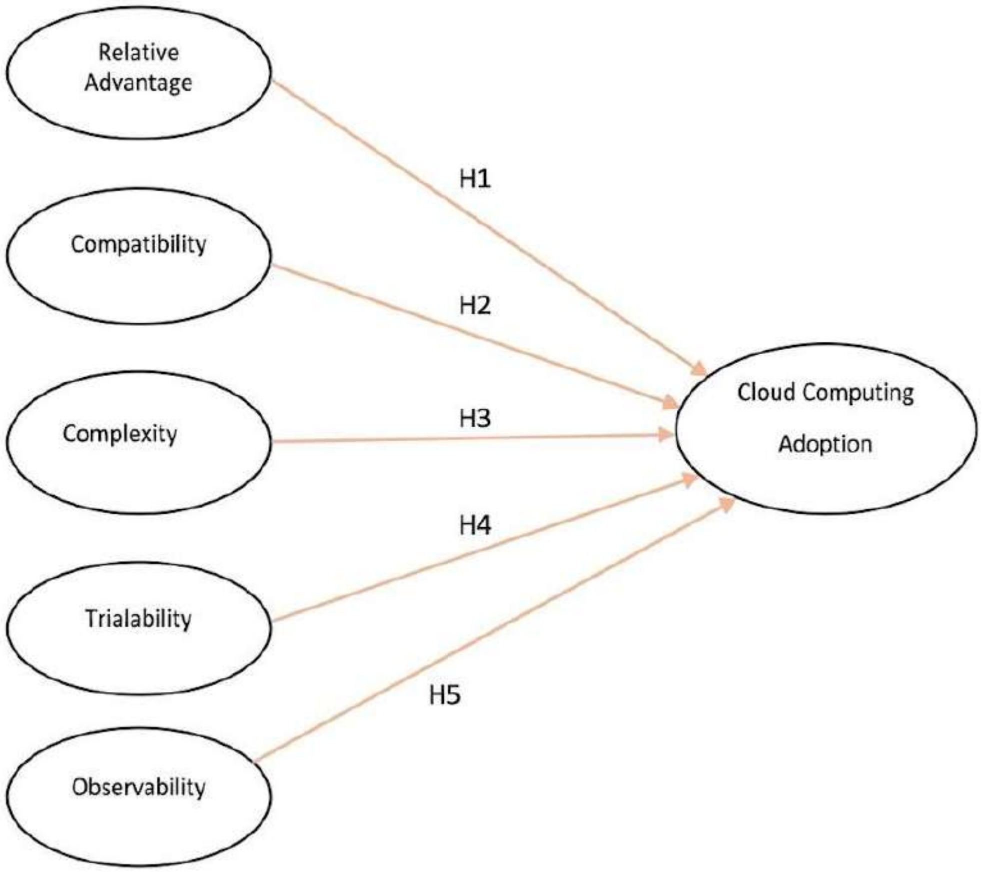

Figure 1. Framework of the study

The framework of the study hypothesizes that

H1: β RA, CCA> 0, and is significant.
H2: β Comp, CCA> 0, and is significant.
H3: β Compx, CCA< 0, and is significant.
H4: β TR, CCA> 0, and is significant.
H5: β OB, CCA> 0, and is significant.

RESEARCH METHODOLOGY

Research Design

To achieve the aim and objective, the study employs a quantitative cross-sectional research design using a survey method to collect responses from the targeted sample to investigate the factors influencing the adoption of cloud services among IT-related learners.

Data Collection Tool and Procedure

This study used a well-structured and validated questionnaire to collect users' perceptions of factors for cloud computing adoption in education in Pakistan. The questionnaire consisted of three sections. The first section served as a cover letter for describing the research and the demographic data of the respondents, the second section contained 7-point Likert scale items to represent the constructs of the study framework, these items were adapted from the literature, and the third and final section of the questionnaire was for comments and suggestions regarding the experience of attempting the questionnaire. The questions in the questionnaire were kept simple, short, and straightforward.

To collect sufficient responses to investigate the problem, 300 questionnaires were distributed among the learners, and 200 were returned. After a thorough check, 194 of the returned questionnaires were deemed correctly filled and considered for data analysis.

Population and Sample

The research population consists of students registered in IT institutes in Hyderabad, Pakistan, taking courses that use a cloud-based virtual lab. The administrators of eight IT institutes were personally approached to convince them to take part in the study. Five of them agreed to participate in the research survey under the condition that no information about the institutes would be disclosed during the study. Due to time constraints and the nature of the research study, only two of the five IT institutes were selected to conduct the survey. For ease of reference, the chosen institutes were designated as Institute A and Institute B.

The study used purposive sampling with random sample selection for the study. This sample approach was deemed appropriate because the study seeks users with expertise and experience in cloud computing in education who are eager to participate in order to gain better insights and representation of the study objectives.

Factors and Measures

Table 1. Factors and measures of the study

Factors	Items and measures	References
Relative Advantage	RA1 – Cloud computing allows you to manage heavy IT software for IT education. RA2 – The use of cloud computing services improves the quality of IT education. RA3- Compared to traditional computing, cloud computing would make data-intensive computing faster	(Ifinedo, 2011) (Tehrani & Shirazi, 2014)(Ghobakhloo et al., 2011).
Compatibility	COMP1 – The use of cloud computing fits the education style of the IT institutes. COMP2 – The use of cloud computing is fully compatible with current education standards COMP3 – The use of cloud computing will be compatible with existing hardware and software in the IT institutes.	(Ifinedo, 2011) (Thiesse et al., 2011) (Zhu et al., 2006).
Complexity	COMPX1 – The use of cloud computing requires a lot of mental effort. COMPX2 – The use of cloud computing is frustrating. COMPX3 – The use of cloud computing is too complex for remote education.	(Thiesse et al., 2011)
Trialability	TR1: I have a great deal of opportunity to try various types of cloud-based education for IT. TR2: Cloud computing is available to me to adequately test run various applications adequately test run various applications TR3: Before deciding whether to use any cloud-based education for IT students, I would be able to properly try them out. TR4: I am permitted to use cloud education on a trial basis long enough to see what it would do.	(Tehrani & Shirazi, 2014)
Observability	OB1: Cloud-based education for IT students can be accessed anytime & anywhere in Pakistan.	

	OB2: Cloud-based education for IT students can be accessed anywhere in Pakistan. OB3: I can see the effect of a response to software that is used by students easily.	(Ibrahim M Al-Jabri & M. Sadiq Sohail, 2012)
Cloud Computing Adoption	CCA1: I intent to use cloud computing. CCA2: I plan to continue using cloud computing in the future. CCA3: I recommend it to others. CCA4: I more often use it.	

Results and Discussion

Demographic Information

The study collected gender, age, IT Background, and employment status demographic information of the participants.

Table 2. Demographics statistics

Variable	Categories	Frequency	Percentage
Gender	Male	130	67.01
	Female	64	32.99
Age	Up to 20	55	28.35
	21 to 30	106	54.63
	31 to 40	28	14.43
	41 and above	5	2.57
Technological Skills	Skilled	137	70.61
	Un skilled	57	29.38
Employment	Employed	60	30.92

	Un-Employed	134	69.07

According to gender demographics, males account for two-thirds of respondents (67.01%) and females for 32.99%. The age demographic data show that the majority of participants are young adults aged up to 30; they make up 82.98% of all participants, and they are more likely to be involved with technology and cloud-based education systems. According to the IT skills demographics statistics, the majority of responding learners have IT skills (70.61%), indicating that they have the necessary technological knowledge and expertise to understand and evaluate cloud-based computing usage and acceptance. According to the employment status statistics, the vast majority of respondents (69.07%) are learners who are not formally employed.

Descriptive Analysis

Descriptive analysis was performed to explore IT learners' perception of cloud-based education.

Table 3. Descriptive analysis of the items

Items	Mean	Std. Deviation
RA1	4.97	1.708
RA2	4.83	1.756
RA3	4.93	1.729
Comp1	4.96	1.758
Comp2	4.88	1.827
Comp3	4.91	1.781
Compx1	4.66	1.724
Compx2	4.77	1.813
Compx3	4.86	1.720
Tr1	4.88	1.743
Tr2	4.74	1.768
Tr3	4.82	1.667
Tr4	4.78	1.739
Ob1	4.47	1.943
Ob2	4.68	1.804
Ob3	4.85	1.822
Cloud1	5.03	1.870
Cloud2	5.02	1.876
Cloud3	4.81	1.909
Cloud4	4.98	1.744

Descriptive analysis statistics indicate that the learners generally perceive the use of cloud computing services in education positively, as reflected by the high mean scores from 4.47 to 5.03, specifically for Cloud computing adoption items, with mean scores 5.03 to 4.81. Additionally, the items measuring cloud computing adoption had high mean scores, ranging from 4.81 to 5.03, indicating that respondents had a favorable level of intention to use cloud computing services.

Structural Equation Modeling

The SEM assesses the causal relationships between various measuring items and constructs. SEM can handle complex models because of its robust statistical techniques (Hair et al., 2019; Barbara G.

Tabachnick & Linda S. Fidell, 2021). A measurement model and a structural model are the two basic components of SEM. They specify the degree to which particular variables can predict other specific variables. This study used a two-way approach to perform SEM (Anderson & Gerbing, 1988). The first step involved the measurement of the interrelationship between measured and latent variables of the measurement model. In the second phase, hypothesis testing was performed.

i) Measurement Model

The measurement model is the first part of the model assessment, and its validity and reliability are assessed using CFA. To assess the degree of the load on its underlying construct of the observed variables, the measurement or outer model employs factor analysis (Chin, 1998).

Table 4. measurement model

Index	X^2 Chi-Square	Df degree of freedom	X^2/df	GFI Goodness of fit index	RMSEA Root mean square error of approximation	NFI Normed fit index	CFI Comparative fit index	AGFI Adjusted goodness of fit index
Type			Absolute fit measures			Incremental fit measures		Parsimony fit measures
Obtained	184.932	155	1.193	0.917	0.032	0.938	0.989	0.888
Criteria	>0.05		>1.0 and <3.0	≥0.90	<0.05	≥0.09	≥0.09	≥0.09

All fit indices met the suggested threshold values, indicating that the model suited the data well (Ahmed et al., 2023). The chi-square/degrees of freedom ratio (χ^2/df = 1.193) was lower than the acceptable limit of 3.0, indicating a good model fit. The GFI (0.917), NFI (0.938), and CFI (0.989) were all above the required value of 0.90, while the RMSEA value (0.032) was less than the 0.05 criterion, indicating an excellent fit. Furthermore, the AGFI value (0.888) was within acceptable limits. These findings demonstrate that the measurement model fits the data well and supports the validity of the proposed constructs.

ii) Confirmatory Factor Analysis

To validate the measuring model and determine whether the observed items accurately reflect the corresponding latent constructs of the study framework, Confirmatory Factor Analysis (CFA) was carried out. CFA was used to evaluate the model fit, construct reliability, convergent validity, and discriminant validity before using structural equation modeling to investigate the proposed relationships between constructs.

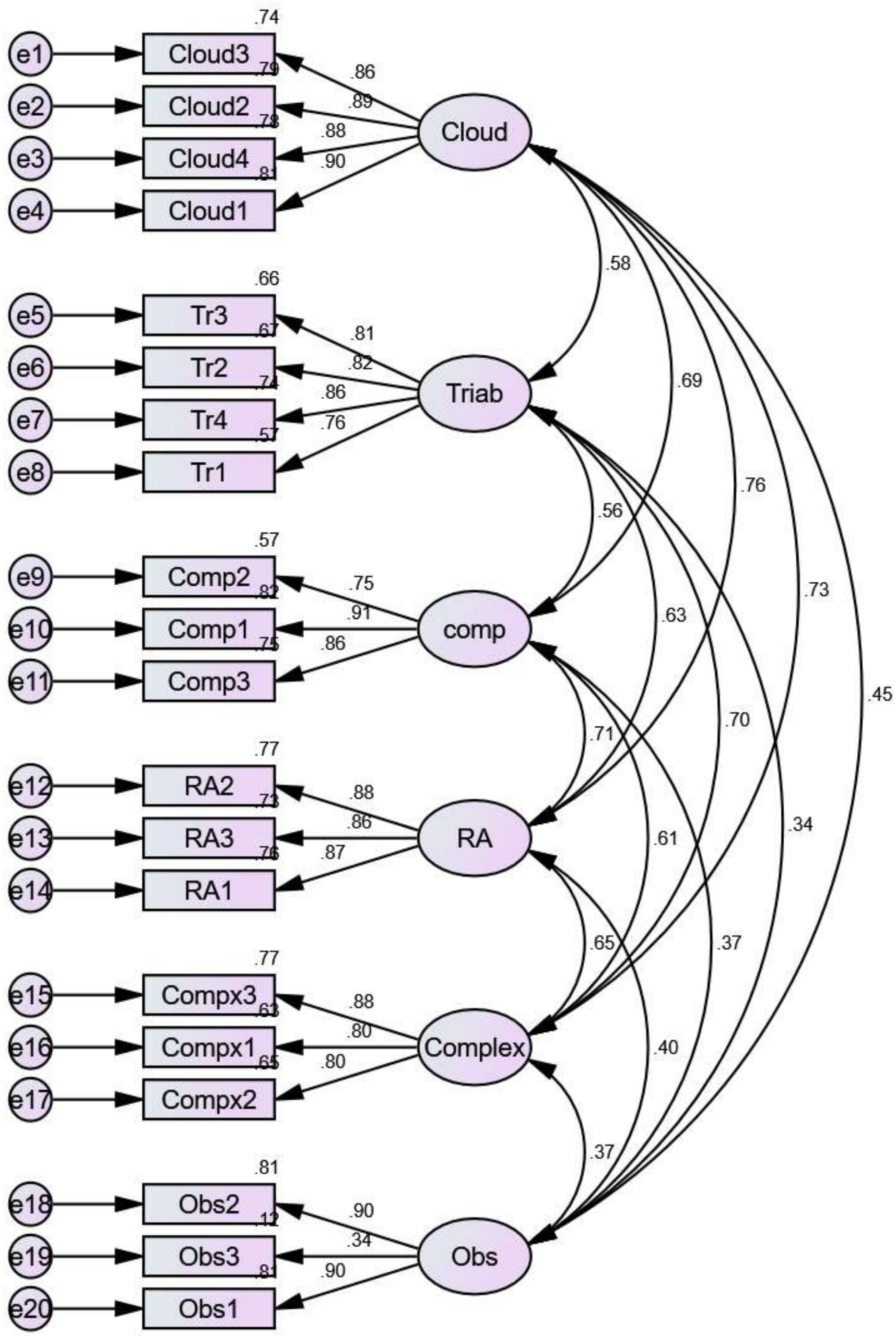

Figure 2. Confirmatory factor analysis

iii) CONSTRUCT RELIABILITY

The reliability of a measurement is the level to which the measurement is error-free, and therefore shows coherent results, i.e., consistency of the measuring procedure. Cronbach's alpha is a common reliability measurement that evaluates the degree of internal consistency or uniformity between the items measuring the same variable. The coefficient's value ranges from 0 to 1.

Table 5. Constructs Cronbach's alpha reliability test results

Constructs	TR	COMP	RA	COMPX	OBS	Cloud
Cronbach's Alpha	0.976	0.880	0.901	0.966	0.764	0.963

iv) Construct Validity

The degree to which an operational measure aligns with the theoretical idea under study is known as construct validity. In this study, convergent and discriminant validity, and the entire measurement model was assessed using a confirmatory factor analysis.

v) Convergent Validity

Convergent validity confirms that all items of a construct aiming to measure the same construct "converge" or move together.

Table 6: Convergent validity test results

Constructs	Items	CR	AVE
Complex	COMPX1 COMPX2 COMPX3	0.866	0.684
Cloud	CLOUD1 CLOUD2 CLOUD3	0.933	0.778
Triab	Tr1 Tr2 Tr3 Tr4	0.886	0.662
Comp	COMP1 COMP2 COMP3	0.880	0.711
RA	RA1 RA2 RA3	0.901	0.752
Obs	Obs1 Obs2 Obs3	0.784	0.578

Convergent validity is evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE). The minimum threshold value of 0.70 was obtained by the composite reliability of several measures. Additionally, AVE met the researcher's recommended minimum threshold of 0.50 for all constructs (Hair et al., 2019). This demonstrates that each item can accurately represent the associated construct.

vi) Discriminant Validity

When an indicator or construct has a stronger relationship to its own latent construct than to other constructs in the model, discriminant validity is proven. Constructs may not be sufficiently distinct and may overlap in measuring comparable underlying concepts if discriminant validity is not proven. Because of this, the validity of the structural linkages may be weakened, making it challenging to ascertain whether the proposed relationships are influenced by statistical overlap or represent actual theoretical effects (Farrell, 2008).

Table 7 Discriminant validity test result

	MSV	MaxR(H)	COMPX	Cloud	TR	COMP	RA	OBS
COMPX	0.533	0.874	0.827					
Cloud	0.578	0.955	0.730	0.882				
TR	0.494	0.967	0.703	0.582	0.813			
COMP	0.498	0.974	0.606	0.689	0.563	0.843		
RA	0.578	0.979	0.653	0.760	0.626	0.706	0.867	
OBS	0.201	0.982	0.374	0.448	0.343	0.372	0.398	0.760

Correlations between exogenous constructs should be less than 0.85, according to a widely accepted standard. Because the correlations between the constructs were within acceptable bounds and did not exceed the suggested threshold, discriminant validity in this study was considered adequate.

vii) Hypotheses Testing

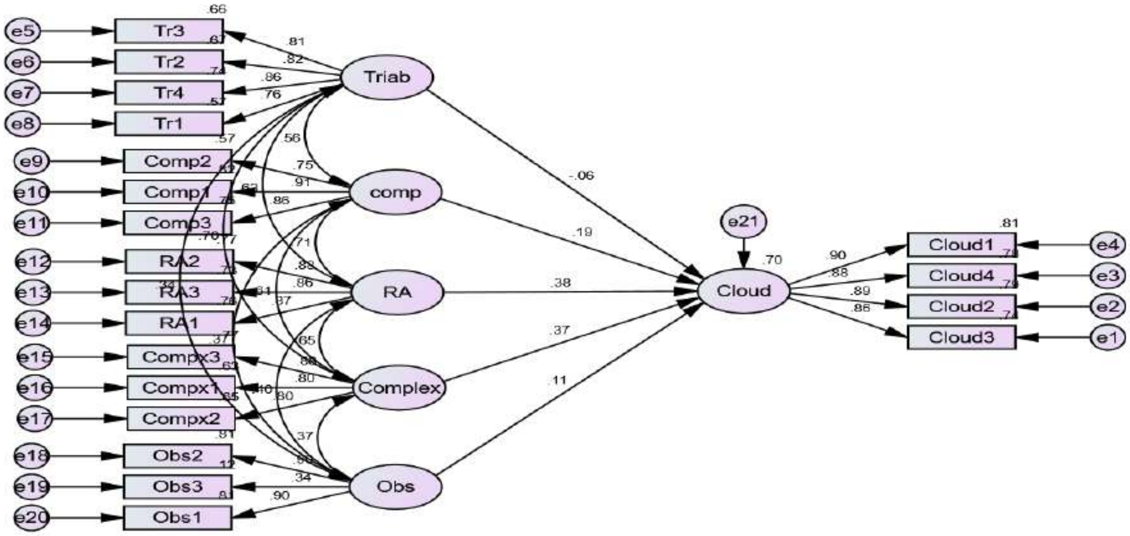

Figure 3. Structural Model

The findings provide some support for the Diffusion of Innovation theory in explaining cloud computing adoption behavior. Relative Advantage appears to be the most influential variable, followed by Compatibility and Observability, but Trialability has no significant impact on adoption decisions in this study scenario. These findings indicate that students' adoption of cloud computing is mostly motivated by perceived benefits and institutional fit, rather than experimentation or trial use.

Table 8. Standard Estimation

Hypothesized Path	Estimate	S.E.	C.R.	P	Label
CCA ← TR	-0.07	0.098	-0.714	0.475	par_15
CCA ← COMP	**0.227**	**0.095**	**2.392**	**0.017**	**par_16**

CCA ← RA	**0.402**	**0.094**	**4.262**	***	**par_17**
CCA ← COMPX	0.399	0.097	4.115	***	par_18
CCA ← OBS	**0.11**	**0.056**	**1.964**	**0.049**	**par_19**

The path analysis results in Amos revealed that; Cloud Computing Adoption is positively and significantly influenced by Compatibility (β = 0.227, CR = 2.392, p = 0.017) and Relative Advantage (β = 0.402, CR = 4.262, p < 0.001). and Observability (β = 0.11, CR = 1.964, p = 0.049).
The results also indicate that complexity has a positive and significant impact on cloud computing adoption (β = 0.399, CR = 4.115, p < 0.001). However, according to the DOI theory, complexity is predicted to have a detrimental impact on innovation adoption. The positive association found in this study contradicts the original DOI concept, implying that in the context of technical education, respondents may not see complexity as a barrier to adoption. Furthermore, the relationship from Trialability to Cloud Computing Adoption is negative and non-significant (β = -0.07, CR = -0.714, p = 0.475), indicating that trialability has no significant influence on students' cloud computing adoption in this study.

Conclusion

Conceptually based on the Diffusion of Innovation theory and its characteristics, this study aimed to examine the determining factors for the adoption of cloud computing among IT learners in Pakistan. The study used a quantitative cross-sectional research design using a survey approach for data collection. Structural Equation Modeling in AMOS was used to examine data from 194 respondents.
The results of the path analysis showed that cloud computing adoption in education is influenced by compatibility, relative benefits, and observability. Relative advantage was found to be the strongest predictor, suggesting that students are more inclined to use cloud computing when they see obvious educational advantages. Additionally, compatibility showed a strong positive impact, indicating that adoption of cloud computing rises when the technology is compatible with the infrastructure of current educational processes. The relevance of observable advantages and results in promoting adoption is highlighted by observability as a positive and significant element. Interestingly, contrary to the DOI's original assumption, complexity was discovered to have a strong and positive link with cloud computing adoption. This shows that IT learners may view complexity as a challenge that comes with increased technology capabilities rather than a barrier to adoption. Additionally, Trialability was found to have no significant influence on adoption, implying that the ability to experiment with cloud computing services does not always affect learners' intentions to adopt them.
Overall, the study supports the use of DOI theory to explain cloud computing adoption in educational settings, while also emphasizing the particular impact of complexity in the context of IT education. The findings are useful for educational institutions, legislators, and technology suppliers looking to increase cloud computing usage and improve technology-enabled learning environments in education.

Limitations and Future Work Directions

This study was limited to the quantitative data collected from the 194 IT learners from 2 Cloud-Based IT institutes from Hyderabad, Pakistan, using a cross-sectional research design due to time and resource constraints. Future studies may broaden the scope by increasing sample size to collect data across different provinces and regions of the country and at different times, as well as incorporating qualitative methods to gain a deeper understanding of the subject matter.

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