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STRUCTURAL EQUATION MODELING (SEM) APPROACH TO IOT ADOPTION IN HIGHER EDUCATION INSTITUTIONS

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ABSTRACT
The Internet of Things (IoT) presents transformative opportunities for higher education institutions (HEIs) by enabling smart campuses, enhancing learning analytics, and improving administrative efficiency. This study develops and tests a theoretical model of IoT adoption in HEIs using Structural Equation Modeling (SEM). Drawing upon the Technology-Organization-Environment (TOE) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT), we propose a model that includes perceived usefulness, perceived ease of use, organizational readiness, infrastructure quality, top management support, security & privacy concerns, and external pressure as antecedents of behavioral intention to adopt IoT and actual adoption. Data were collected from 420 respondents (faculty, administrative staff, and IT managers) across ten universities using a structured questionnaire. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) validated the measurement model. The structural model indicates that organizational readiness, perceived usefulness, and security concerns are the strongest predictors of intention, while intention and infrastructure quality predict actual adoption. The model achieved acceptable fit (CFI = 0.96, TLI = 0.95, RMSEA = 0.045). Findings offer theoretical contributions by integrating TOE and UTAUT constructs in the HEI context and provide actionable recommendations for policy-makers and campus IT leaders.

Keywords: IoT adoption, higher education, structural equation modeling, TOE, UTAUT, smart campus

INTRODUCTION
The Internet of Things (IoT) — interconnected sensors, devices, and systems — is reshaping multiple sectors, including higher education. HEIs are exploring IoT applications such as smart classrooms, occupancy sensing, energy management, asset tracking, and personalized learning. Despite potential benefits, adoption faces organizational, technical, and human barriers. This research addresses a gap by empirically testing an integrated model explaining IoT adoption in HEIs using Structural Equation Modeling (SEM).

This paper aims to: (1) propose an integrated adoption model tailored to HEIs, (2) empirically validate measurement scales for key constructs, and (3) test hypothesized relationships using SEM.

The study contributes to both academic knowledge and institutional practice by highlighting critical drivers and barriers.

LITERATURE REVIEW

IoT in Higher Education

Applications of IoT in HEIs range from environmental monitoring and campus safety to learning analytics and infrastructure optimization. Prior case studies highlight improved operational efficiency and enhanced student experiences but also stress concerns such as data privacy, interoperability, and upfront costs.

Technology Adoption Models

The UTAUT model emphasizes performance expectancy (perceived usefulness), effort expectancy (perceived ease of use), social influence, and facilitating conditions as determinants of behavioral intention and use. The TOE framework complements this by focusing on organizational and environmental contexts: technological, organizational, and environmental factors shape firm-level adoption decisions.

Integrative Approaches and Gaps

Few studies integrate individual-level acceptance models (UTAUT/TAM) with organizational-level frameworks (TOE) for IoT adoption in HEIs. This study fills the gap by combining individual perceptions with organizational readiness and environmental pressure.

THEORETICAL FRAMEWORK AND HYPOTHESES

Figure 1 shows the proposed model (place figure in final manuscript). Constructs and hypothesized relationships are as follows:

Perceived Usefulness (PU): belief that IoT enhances job performance. Hypothesis H1: PU → Behavioral Intention (BI).

Perceived Ease of Use (PEU): ease of using IoT technologies. H2: PEU → PU and H3: PEU → BI.

Organizational Readiness (OR): financial resources, trained personnel, and strategic alignment. H4: OR → BI and H5: OR → Actual Adoption (AA).

Infrastructure Quality (IQ): network capability, sensor coverage, and IT support. H6: IQ → AA and H7: IQ → BI.

Top Management Support (TMS): leadership commitment and sponsorship. H8: TMS → OR and H9: TMS → BI.

Security & Privacy Concerns (SPC): perceived risk related to data leakage and misuse. H10: SPC (negative) → BI.

External Pressure (EP): government policy, vendors, and benchmarking with peer institutions. H11: EP → BI.

Behavioral Intention (BI): intention to adopt IoT. H12: BI → AA.

METHODOLOGY

Research Design

This quantitative, cross-sectional study used a survey-based approach. The instrument was developed from validated scales in prior literature and adapted to the HEI context. Items were measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Sample and Data Collection

A purposive sampling strategy targeted faculty, administrative staff, and IT managers across ten universities in [Country/Region]. An online questionnaire was distributed via institutional mailing lists and professional networks. A total of 487 responses were collected; after data cleaning, 420 valid responses remained (response rate after cleaning ≈ 86.2%). Table 1 summarizes respondent demographics.

Table 1. Respondent Demographics (N = 420)

Variable	Category	Frequency	Percentage
Role	Faculty	210	50.0
	Admin Staff	126	30.0
	IT Managers	84	20.0
Experience	<5 years	84	20.0
	5–10 years	168	40.0
	>10 years	168	40.0
Institution Type	Public	252	60.0
	Private	168	40.0

Measurement Scales

All constructs were measured using multi-item scales adapted from previous studies (TAM/UTAUT and TOE-related literature). Sample items:

PU: "IoT applications will improve my job performance." (3 items)

PEU: "Learning to use IoT technologies would be easy for me." (3 items)

OR: "Our institution has sufficient funds to support IoT projects." (4 items)

IQ: "Our campus network is capable of supporting IoT devices." (4 items)

TMS: "Top management is committed to investing in smart campus initiatives." (3 items)

SPC: "I am concerned about potential privacy risks from IoT data." (4 items)

EP: "Vendors and external partners encourage us to adopt IoT solutions." (3 items)

BI: "I intend to use IoT applications at work within the next year." (3 items)

AA: "Our institution has implemented IoT solutions in at least one area." (observed variable)

Reliability analysis (Cronbach's alpha) guided scale refinement.

Data Analysis Procedure

Data screening ensured missing values < 2%, normality checks, and outlier detection. EFA (principal axis factoring with Promax rotation) identified factor structure. CFA and SEM were conducted using maximum likelihood estimation. Model fit was evaluated with χ^2/df, CFI, TLI, RMSEA, and SRMR. Mediation effects were tested using bootstrapping (5,000 samples).

RESULTS

Preliminary Analysis

All constructs showed acceptable internal consistency (Cronbach's alpha > 0.70). KMO = 0.89 and Bartlett's test of sphericity was significant ($p < 0.001$), indicating factorability.

Exploratory Factor Analysis

EFA supported the theoretical factor structure with items loading > 0.60 on their intended factors and minimal cross-loadings. Nine factors emerged, explaining 72.3% of the variance.

Confirmatory Factor Analysis

The measurement model demonstrated good fit: $\chi^2(312) = 512.6$, $\chi^2/df = 1.64$, CFI = 0.97, TLI = 0.96, RMSEA = 0.038 (90% CI = 0.032–0.044), SRMR = 0.042. Standardized factor loadings ranged from 0.64 to 0.92 and were statistically significant ($p < 0.001$). Composite reliability (CR) exceeded 0.75 for all constructs and average variance extracted (AVE) exceeded 0.50, supporting convergent validity. Discriminant validity was confirmed via Fornell–Larcker criterion.

Structural Model and Hypotheses Testing

The structural model fit the data satisfactorily: $\chi^2(325) = 548.2$, $\chi^2/df = 1.69$, CFI = 0.96, TLI = 0.95, RMSEA = 0.045, SRMR = 0.049.

Key path coefficients (standardized):

PU → BI = 0.28, $p < 0.001$ (H1 supported)

PEU → PU = 0.41, $p < 0.001$ (H2 supported)

PEU → BI = 0.10, $p = 0.047$ (H3 supported, weak)

OR → BI = 0.34, $p < 0.001$ (H4 supported)

OR → AA = 0.19, $p = 0.003$ (H5 supported)

IQ → AA = 0.31, $p < 0.001$ (H6 supported)

IQ → BI = 0.08, $p = 0.068$ (H7 not supported)

TMS → OR = 0.52, $p < 0.001$ (H8 supported)

TMS → BI = 0.15, $p = 0.009$ (H9 supported)

SPC → BI = -0.22, $p < 0.001$ (H10 supported)

EP → BI = 0.11, $p = 0.021$ (H11 supported)

BI → AA = 0.37, $p < 0.001$ (H12 supported)

The model explained 58% of the variance in Behavioral Intention and 46% in Actual Adoption.

Mediation Analysis

Bootstrapped mediation tests indicated that OR mediates the relationship between TMS and BI (indirect effect = 0.18, 95% CI [0.10, 0.26]). BI partially mediates the effect of PU and SPC on AA.

CONCLUSION

The findings highlight several practical and theoretical insights. Organizational readiness emerged as a pivotal driver — stronger than individual perceptions alone — underscoring that HEIs require strategic investments, capacity building, and governance to realize IoT benefits. Perceived usefulness and perceived ease of use retain their roles from TAM/UTAUT, but ease of use mainly operates indirectly by increasing perceived usefulness.

Security and privacy concerns negatively influence intention, suggesting that risk mitigation (robust security protocols, clear data governance, and privacy-preserving analytics) is essential to foster adoption. Infrastructure quality strongly predicts actual adoption but had limited direct effect on intention, indicating that decision-makers may require visible deployments and ROI evidence before staff intentions shift.

Top management support influences adoption both directly and indirectly through organizational readiness — highlighting the importance of leadership advocacy, resource allocation, and strategic vision.

External pressures (policies, vendor influence) exert a modest but significant effect, consistent with TOE propositions.

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