



Exploring the Determinants of Technology Acceptance Among Students of Higher Education Institutions in West Bengal: A Critical Review

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The Technology Acceptance Model (TAM) has been widely used to explain student adoption of educational technology, but its traditional focus on perceived usefulness and ease of use overlooks emotional, social, and contextual influences. This review critically evaluates recent extensions of TAM, concentrating on higher education institutions in West Bengal, India. It synthesizes contemporary findings, identifies unresolved gaps, and proposes an extended framework integrating cognitive, affective, social, and contextual determinants. The resulting model offers a richer, region-sensitive understanding of student behaviour in digitally diverse settings.

Keywords: technology acceptance, higher education, west bengal, tam, critical review, digital learning

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1. Introduction

Technology continues to reshape education by enabling flexible, personalized, and collaborative learning. Despite these benefits, adoption remains uneven across regions, particularly in developing contexts such as West Bengal, where socio-economic and infrastructural challenges persist.

The Technology Acceptance Model (TAM), introduced by Davis (1989), provides a theoretical base for explaining why individuals adopt or resist technology. It emphasizes two core beliefs—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—which influence users' behavioral intentions. While TAM has been validated across contexts, critics argue that it simplifies adoption by ignoring emotional, cultural, and contextual factors.

In West Bengal, student adoption of technology is shaped not only by utility and usability but also by peer influence, trust, and socio-economic conditions. The need to extend TAM to reflect these broader realities motivates this critical review.

2. Literature Review

Since its inception, TAM has evolved through various extensions that attempt to incorporate additional determinants influencing technology acceptance. These extensions recognize that cognitive evaluation alone does not fully explain behavior in real-world educational contexts.

This review systematically examines studies published between 2010 and 2024 that apply or extend TAM within higher education. Literature was identified through Scopus and Google Scholar using keywords such as Technology Acceptance Model, higher education, and India. Inclusion criteria required peer-reviewed works addressing cognitive, affective, or contextual variables.

2.1 Classic TAM and Cognitive Determinants

TAM's core constructs—PU and PEOU—remain central across studies (Davis, 1989; Venkatesh & Davis, 2000). Students are more inclined to adopt digital tools when they find them both useful and easy to use.

2.2 Social and Cultural Influence

Social norms, faculty encouragement, and peer support strongly affect student adoption decisions (Venkatesh et al., 2003).

In collectivist cultures such as India, social validation often outweighs individual perception, amplifying these effects.

2.3 Affective Determinants

Enjoyment, self-efficacy, technostress, and anxiety shape emotional readiness for technology. Enjoyment enhances motivation, while fear of complexity or prior failure discourages experimentation (Tarhini et al., 2017; Compeau & Higgins, 1995).

2.4 Contextual Determinants

Infrastructure, affordability, and digital literacy influence how effectively students engage with learning systems (Dwivedi et al., 2019). Within West Bengal, adoption differs sharply between urban and rural institutions. Urban campuses benefit from reliable connectivity and ICT resources, whereas rural colleges often face unstable networks, shared devices, and language barriers. Institutional funding and administrative priorities further moderate these dynamics.

2.5 Emerging AI-Era Factors

The rise of AI-driven and data-intensive platforms introduces new determinants such as trust, privacy, and perceived risk (Al-Emran et al., 2021). These factors redefine user acceptance, demanding continuous revision of classical frameworks.

3. Research Questions and Propositions

Drawing from the reviewed studies and identified gaps, the following research questions guide this synthesis:

RQ1: Which cognitive, social, affective, and contextual factors most strongly influence technology acceptance among students in West Bengal's higher education institutions?

RQ2: How do social and emotional factors interact with cognitive perceptions in shaping behavioral intentions?

RQ3: How do contextual conditions—such as infrastructure, institutional support, and culture—affect actual technology use?

Propositions for Future Testing

P1: Perceived Usefulness and Ease of Use positively influence behavioral intention.

P2: Social and emotional factors moderate the relationship between usefulness and intention.

P3: Contextual variables indirectly affect actual use through behavioral intention.

4. Research Gaps

Despite the progress in understanding technology acceptance, several research gaps persist:

1. Over-reliance on quantitative surveys limits insights into student attitudes and emotions.

2. Lack of contextual focus on socio-economically diverse areas like West Bengal.

3. Insufficient exploration of trust and risk factors in adoption of AI-based tools.

4. Minimal longitudinal studies to track how attitudes evolve with continued technology exposure.

These gaps indicate the need for a broader and culturally responsive framework that extends beyond traditional TAM constructs.

5. Proposed Extended TAM Framework

In response to the identified gaps, this paper proposes an extended TAM framework. This model integrates four categories of influencing variables:

Cognitive Variables: Perceived Usefulness (PU), Perceived Ease of Use (PEOU)

Social Variables: Peer Influence, Instructor Support

Affective Variables: Enjoyment, Technostress, Anxiety, Self-Efficacy

Contextual Variables: Access to Devices, Infrastructure, Cultural Values, Trust, and Risk Perception

These determinants collectively influence students' **Behavioral Intention**, which in turn leads to **Actual Usage** of technology.

This holistic model is more suitable for regions like West Bengal, where students face unique structural and emotional challenges.

6. Methodological Orientation

Although this study is theoretical, it follows a systematic review approach. Searches covering 2010–2024 identified peer-reviewed articles that examined technology adoption in higher education. Keywords included TAM, UTAUT, AI trust, and India.

For future empirical validation, scholars can apply established measurement scales (e.g., Davis 1989 for PU/PEOU; Venkatesh & Davis 2000 for social influence). Sampling should ensure diversity across college types and locations. Reliability and bias checks—such as Cronbach's alpha and Harman's single-factor test—can enhance credibility.

7. Discussion

Findings reaffirm TAM as a useful foundation yet insufficient in capturing complex behavioral drivers in education. In West Bengal, students' decisions reflect not only perceived utility but also peer context, emotional comfort, and infrastructure constraints.

Integrating social and affective determinants aligns with recent global trends that emphasize trust and cultural variations. The extended model offers policy guidance for institutions to design training programs, enhance digital literacy, and build confidence in technology use.

8. Conclusion

This review extends the traditional TAM by incorporating cognitive, social, affective, and contextual factors that shape students' technology adoption in West Bengal. The proposed framework provides a more holistic and culturally sensitive lens for understanding student behavior in higher education.

Future studies should test this model empirically using mixed methods and longitudinal designs. Comparisons across urban and rural colleges, and between disciplines, will help clarify how context modifies key determinants of acceptance.

Limitations and Future Work

This paper synthesizes literature but does not include empirical testing.

Subsequent research could use two-wave or multi-group designs to observe behavior over time and compare institution types. Further, as AI-based platforms expand, variables such as trust, privacy, and algorithmic transparency should be integrated. Such approaches will strengthen the validity and relevance of TAM in the AI era.

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