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Understanding AI Technology Adoption in Educational Settings: A Review of Theoretical Frameworks and their Applications

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Abstract: Artificial Intelligence (AI) technologies are increasingly integrated into educational environments, promising transformative impacts on learning experiences and administrative efficiencies. This review synthesizes prominent theoretical frameworks used to understand AI technology adoption among students and educators in educational settings. The Value-based Adoption Model (VAM), Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), and Technology Acceptance Model (TAM) are examined for their strengths and limitations in explaining the factors influencing technology adoption. Through a comprehensive analysis of recent literature, this paper highlights the involvement of user acceptance, incorporating cognitive, social, and emotional dimensions. Understanding theoretical frameworks related to AI technology adoption could provide a comprehensive overview of existing theoretical frameworks related to AI technology adoption in educational settings, integrating findings into a cohesive narrative.

Keywords: *Artificial Intelligence, AI adoption, educational technology, technology acceptance models, VAM, TPB, UTAUT, TAM, educational settings*

1. Introduction and Background

Artificial intelligence (AI) technologies are increasingly being used in educational settings, with the potential to significantly improve learning experiences, expedite administrative work, and provide personalized instructional support. Coppin (2004) defines artificial intelligence as a machine's ability to solve issues, answer questions, devise strategies, and execute a variety of other functions that need a level of intelligence generally found in humans. From intelligent tutoring systems and adaptive learning platforms to AI-powered analytics and virtual assistants, these technologies have the potential to disrupt existing educational paradigms (Holmes et al., 2019).

The successful adoption of AI technology by users—students and educators—is dependent on several factors that determine its acceptability and use (Kizilcec, 2024). Understanding the factors that influence or impede the adoption of AI technology in educational contexts is critical to realizing their potential benefits (Radhakrishnan & Chattopadhyay, 2020). Several theoretical frameworks have been established to investigate technology adoption, with each providing unique insights into the process. These frameworks assist in identifying major factors of user acceptance and assist in building and implementing AI technology in more user-friendly ways.

However, only a few studies have thoroughly studied the technology acceptance paradigm in the educational setting (Antonietti, Cattaneo, & Amenduni, 2022). Thus, the goal of this research is to examine various models and theories accessible from the user's viewpoint of technological adoption in educational settings. By synthesizing recent research findings, this study aims to provide insights for future research as well as practical recommendations for improving the uptake and effective use of AI in education.

2. Technology Adoption Related Models

Computer and information communication technologies have evolved, resulting in the creation of artificial intelligence (Zerfass, Hagelstein, and Tench, 2020). The opportunities have connected students, educators, and technologies, generating widespread interest among researchers and practitioners. This is related to the fact that more scholars appear to be interested in how students and teachers use technology. This has resulted in the development of numerous technological acceptance models (Xu et al. 2021). Based on a review of the literature, this study identified a variety of theories and models that are commonly used to understand what motivates people to accept and use a particular technology in their educational activities. Table 1 illustrates this by providing some well-known underlying theories and models.

Table 1: Prominent Technology-Related Models (Author own compilation, 2024)

Theory / Model	Acronym	Author(s)
Value-based Adoption Model	VAM	Kim et al. (2007)
Theory of Planned Behavior	TPB	Ajzen (1991)
Unified Theory of Acceptance and Use of Technology	UTAUT	Venkatesh et al. (2003)
Technology Acceptance Model	TAM	Davis (1989)

Value-Based Adoption Model (VAM): The Value-based Adoption Model (VAM) is a theoretical framework designed to understand the factors influencing users' adoption of technology by focusing on perceived value. This model posits that adoption decisions are driven by users' overall assessment of the value provided by a technology, which is determined by both the benefits and sacrifices associated with its use (Kim et al., 2007). VAM has been particularly useful in contexts where perceived value is a critical determinant of user acceptance, such as emerging technologies like AI.

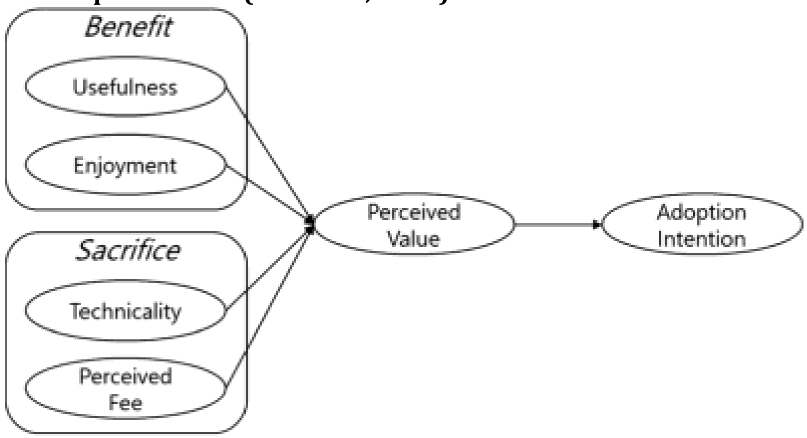
One of the primary strengths of VAM is its emphasis on perceived value as a central construct. This construct encompasses perceived benefits, such as convenience and usefulness, as well as perceived sacrifices, including cost and effort (Kim et al., 2007). By focusing on these aspects, VAM allows researchers to capture a comprehensive view of user motivations and barriers. The model has been successfully applied across various domains, including mobile services, online banking, and social media platforms, providing valuable insights into user adoption behavior in these contexts (Oh et al., 2020). In educational settings, VAM can help understand how students and educators perceive the value of AI technologies, balancing the benefits of enhanced learning experiences against potential drawbacks like data privacy concerns and learning curve challenges.

Furthermore, VAM can inform the design and implementation of technologies. By identifying key value determinants, the model helps designers and policymakers create and implement technologies that align with user expectations and maximize perceived value (Park & Kwon, 2019). For instance, in the adoption of AI in education, understanding the value perceptions of different user groups can inform targeted interventions to enhance acceptance and usage.

Despite its strengths, VAM also has several limitations that need to be considered. One significant limitation is the potential oversimplification of the complex nature of technology adoption. VAM's focus on perceived value may not fully capture the influence of other significant factors, such as social influences, habitual behavior, and emotional responses (Wu & Chen, 2017). While perceived value is crucial, technology adoption often involves a more nuanced interplay of various psychological and contextual factors. Additionally, the determinants of perceived value can vary significantly across different contexts and user groups, limiting the generalizability of VAM. What constitutes value in one setting might not be relevant in another (Huang et al., 2020). This contextual dependency requires researchers to adapt VAM to specific scenarios, potentially complicating its application.

Moreover, VAM typically focuses on the initial adoption decision, providing limited insight into the long-term usage and post-adoption behavior (Choi et al., 2021). Factors influencing continued use or discontinuation of technology might differ from those affecting initial adoption, and VAM's framework does not adequately address these dynamics. Additionally, accurately measuring perceived value and its components can be challenging due to its subjective nature. Differences in individual perceptions and expectations can complicate the operationalization of value constructs (Oh et al., 2020). This measurement difficulty can affect the reliability and validity of research findings using VAM.

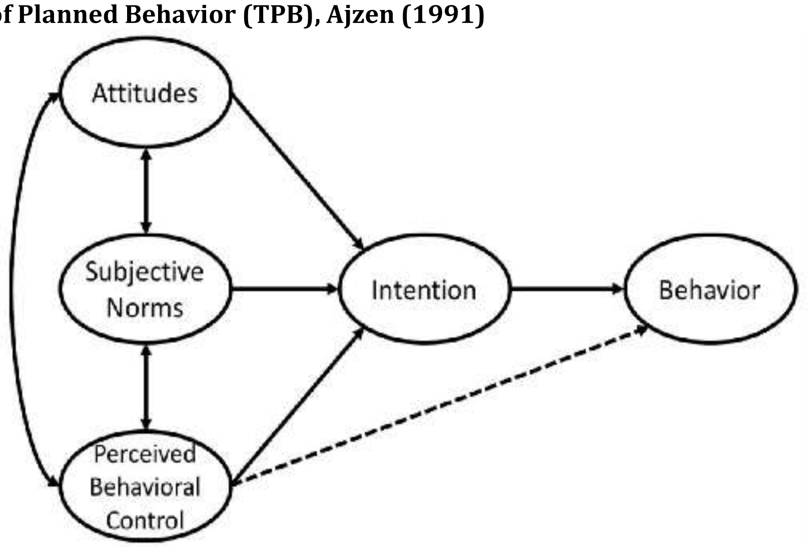
Figure 1: Value-based Adoption Model (Kim et al., 2007)



Theory of Planned Behavior (TPB): The Theory of Planned Behavior (TPB), developed by Ajzen (1991), was designed for predicting and understanding human behavior, including technology adoption. TPB posits that an individual's intention to engage in a behavior is primarily determined by their attitude toward the behavior, subjective norms, and perceived behavioral control.

In educational settings, TPB provides valuable insights into AI adoption. Users' attitudes toward AI, such as their belief in its benefits for enhancing learning and improving efficiency, play a crucial role. Positive attitudes toward AI technologies increase the likelihood of their adoption (Teo et al., 2019). Moreover, subjective norms, or the perceived social pressure to adopt AI from peers, colleagues, and institutional policies, significantly influence users' decisions (Mohammadi, 2015). For example, strong advocacy from school administrations for AI-based learning platforms can motivate educators to integrate these tools into their teaching practices.

Figure 2: Theory of Planned Behavior (TPB), Ajzen (1991)



Perceived behavioral control, which reflects users' confidence in their ability to use AI technologies and access necessary resources, also affects adoption. Comprehensive training and technical support can enhance perceived behavioral control, facilitating the use of AI tools (Cheok & Wong, 2015). When users feel capable and supported, they are more likely to adopt AI technologies.

Despite its strengths, TPB has limitations in this context. The model primarily focuses on intentional behavior, potentially overlooking spontaneous or habitual actions that influence technology adoption (Venkatesh et al., 2020). Additionally, TPB does not account for emotional factors, such as anxiety, which can impact willingness to adopt new technologies (Teo et al., 2019). The assumption of a linear relationship between intention and behavior may not hold in complex educational environments, where external factors like institutional barriers and technical issues can disrupt this link (Mohammadi, 2015).

Unified Theory of Acceptance and Use of Technology (UTAUT): The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), provides a comprehensive framework for understanding technology adoption by integrating elements from multiple models (Abbad, 2021). UTAUT identifies four key determinants of technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions.

In educational settings, UTAUT offers valuable insights into AI adoption. Performance expectancy, which refers to users' beliefs that using AI technologies will improve their educational outcomes, is crucial. When students and educators perceive AI tools as enhancing learning efficiency, improving academic performance, and providing personalized learning experiences, they are more likely to adopt these technologies (Huang et al., 2020). For instance, AI-driven adaptive learning platforms that tailor educational content to individual needs can significantly boost performance expectancy.

Effort expectancy, or the perceived ease of using AI technologies, is another vital factor. AI tools in education must be user-friendly and require minimal effort to learn and operate. If students and educators find AI technologies intuitive and easy to integrate into their routines, adoption rates are likely to increase (Teo, 2019). For example, seamless integration of AI-powered learning management systems with existing educational platforms can reduce the perceived effort required, facilitating adoption.

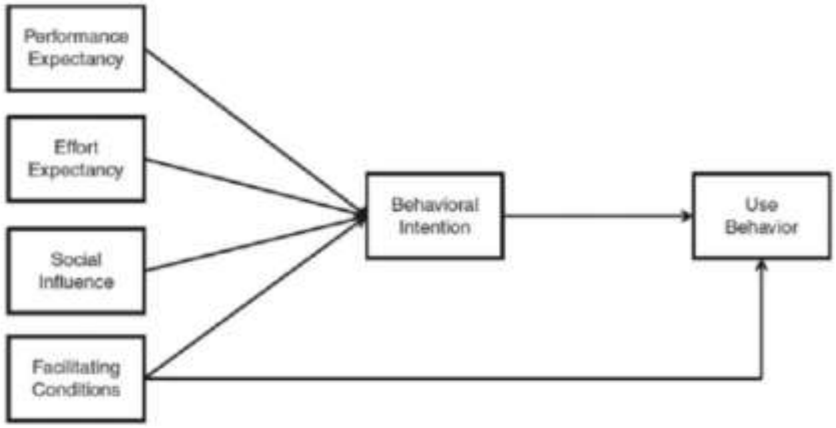
Social influence, defined as the degree to which individuals perceive that important others believe they should use the new technology, also plays a significant role in AI adoption. In educational settings, the endorsements and recommendations from peers, colleagues, and institutional leaders can substantially impact adoption decisions. When influential figures within the educational community advocate for AI technologies, it creates a supportive social environment that encourages their use (Al-Maroof & Al-Emran, 2018). For example, active promotion of AI tools by university administration can motivate both faculty and students to adopt these technologies.

Facilitating conditions, or the availability of resources and support for using AI technologies, are essential for adoption. This includes access to necessary infrastructure, technical support, and training. Ensuring that users have the required resources and assistance can significantly enhance their willingness to adopt AI technologies (Venkatesh et al., 2016). Comprehensive training sessions and ongoing technical support, for instance, can boost educators' and students' confidence in using AI tools, thereby promoting adoption.

Despite its strengths, UTAUT has certain limitations when applied to AI adoption in educational settings. One major limitation is its primary focus on the initial adoption phase, potentially overlooking long-term usage and post-adoption behavior. Factors influencing continued use or discontinuation of AI technologies might differ from those affecting initial adoption, and UTAUT does not fully capture these dynamics (Venkatesh et al., 2016). Additionally, UTAUT's focus on cognitive and social determinants may overlook emotional and psychological factors that can impact technology adoption. Users' anxiety about data privacy or fears of obsolescence due to AI advancements, for example, can influence their decisions to adopt new technologies (Al-Maroof & Al-Emran, 2018).

Furthermore, UTAUT assumes a relatively stable environment, which may not account for the rapidly evolving nature of AI technologies and the educational landscape. The model's applicability may vary across different cultural contexts, necessitating adaptations to fit specific educational environments and user groups. Moreover, UTAUT's linear approach to intention and behavior may not always hold in complex educational settings, where various external factors can intervene (Venkatesh et al., 2016).

Figure 3: Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)



Technology Acceptance Model (TAM): The Technology Acceptance Model (TAM), developed by Davis (1989), is a prominent framework for understanding technology adoption, focusing on two primary determinants: perceived usefulness (PU) and perceived ease of use (PEOU). These factors significantly influence users' attitudes toward technology and their subsequent intention to use it.

In educational settings, TAM offers valuable insights into AI adoption. Perceived usefulness (PU) refers to the degree to which students and educators believe that AI technologies will enhance their learning and teaching outcomes. When users perceive AI tools as beneficial for improving academic performance, facilitating personalized learning, and increasing overall educational efficiency, they are more likely to adopt these technologies (Huang et al., 2020). For example, AI-driven tutoring systems that provide real-time feedback and adaptive learning paths can be perceived as highly useful, encouraging their adoption among students.

Perceived ease of use (PEOU) pertains to the extent to which users believe that using AI technologies will be free of effort. In educational contexts, AI tools must be user-friendly and easy to integrate into existing workflows. When students and educators find AI applications intuitive and straightforward to use, their likelihood of adoption increases (Teo, 2019). For instance, an AI-based learning management system with a simple, user-friendly interface can enhance perceived ease of use, thereby facilitating adoption.

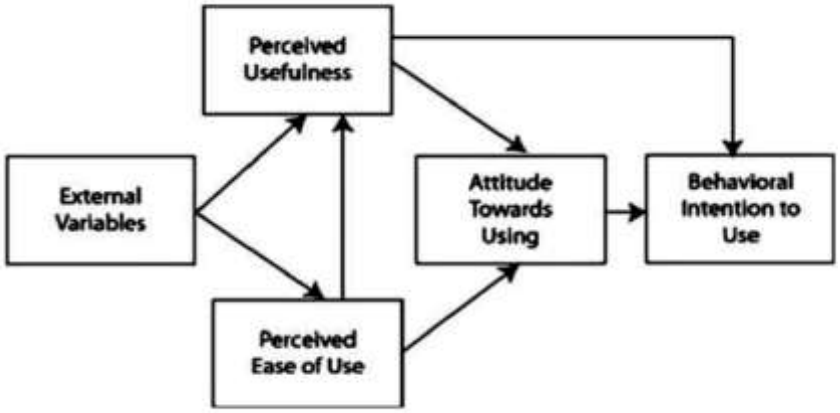
TAM also emphasizes the role of external variables, such as individual differences, system characteristics, and situational constraints, which can indirectly affect technology acceptance by influencing PU and PEOU. In educational settings, these external variables can include factors like prior experience with technology, the availability of training and support, and the technological infrastructure of the institution (Cheung & Vogel, 2013). By considering these variables, TAM provides a comprehensive framework for understanding the multifaceted nature of AI adoption in education.

Despite its strengths, TAM has several limitations when applied to AI adoption in educational settings. One significant limitation is its focus on individual perceptions of usefulness and ease of use, potentially overlooking other important factors that can influence technology adoption. For instance, TAM does not explicitly account for social influence and facilitating conditions, which are emphasized in other models like the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2016). In educational environments, social factors such as peer influence and institutional support can play a crucial role in technology adoption.

Additionally, TAM primarily addresses the initial acceptance of technology and may not fully capture long-term usage behaviors and post-adoption outcomes. The model's focus on cognitive perceptions might not adequately explain the sustained use of AI technologies over time, especially in dynamic educational settings where continuous interaction with technology is essential (Bagozzi, 2007). For example, initial positive perceptions of AI tools may not translate into long-term use if ongoing support and updates are lacking.

Moreover, TAM assumes a relatively linear and rational decision-making process, which may not always reflect the complex and sometimes irrational nature of technology adoption behaviors. Emotional and psychological factors, such as anxiety about using new technologies or excitement about innovative tools, are not explicitly considered in TAM (Park et al., 2015). These factors can significantly impact users' willingness to adopt AI technologies in educational settings.

Figure 4: Technology Acceptance Model (TAM), Davis (1989)



3. Conclusion and Recommendations

This study synthesizes prominent theoretical frameworks to provide a comprehensive overview of AI technology adoption in educational settings. By examining the Value-based Adoption Model (VAM), Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), and Technology Acceptance Model (TAM), the study highlights the strengths and limitations of these models in elucidating the factors influencing AI adoption among students and educators. By bringing together these diverse frameworks, the study creates a more holistic understanding of how AI technologies are being adopted in educational settings.

Contribution of the study: This comprehensive overview highlights the strengths of the existing frameworks, showing how they have successfully addressed certain aspects of AI adoption, such as technological readiness, user acceptance, and the pedagogical impact of AI tools. By identifying these strengths, the study underscores the effective strategies and principles that can be leveraged in future AI implementations.

Practical Policy Implications: Inclusive Policy Development involving educators, students, and parents in the policy development process will ensure that AI adoption in education is guided by the needs and perspectives of those directly affected. Creating platforms for student feedback on AI tools will ensure that their experiences and insights are considered in the continuous improvement of AI technologies. By addressing these practical policy implications, educational policymakers can create a comprehensive and inclusive framework for the adoption of AI technologies in education. This approach ensures that AI integration is effective, ethical, and equitable, aligning with broader educational goals and societal values.

Recommendations for Future Research: Understanding AI technology adoption in educational settings requires a multifaceted approach that considers the strengths and limitations of various theoretical models. Future research should aim to integrate these models, addressing their limitations and capturing the dynamic, context-dependent nature of technology adoption. By doing so, researchers and practitioners can develop more effective strategies to enhance the adoption and effective use of AI technologies in education.

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