Exploring the Dynamics of eLearning: A Comprehensive Analysis of ECM and TAM

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Abstract. Understanding user behavior and adoption is essential in the rapidly changing world of online. In this context, this article performs an in-depth analysis of the technology acceptance model, encompassing TAM, TAM 2 and TAM as well as the expectation confirmation model. The article examines the usefulness of ECM and TAM in online by carefully reviewing the literature and carefully considering the advantages, disadvantages and consequences of each approach. By dissecting these models within the eLearning landscape, the article aims to deepen comprehension of their effectiveness in enhancing student engagement and optimizing learning outcomes. Additionally, it critically assesses their suitability, addressing challenges identified in prior studies. Embracing a critical perspective, this article contributes to the ongoing discourse surrounding ECM and TAM's relevance in eLearning environments, urging further investigation to tackle the intricacies of online education.

Keywords: eLearning, User behavior, Technology acceptance, ECM, TAM, Student engagement, Learning outcomes.

1 Introduction

The shift from traditional classroom settings to digital platforms has gained substantial popularity in the rapidly developing field of e-learning. Teachers and students who were raised in traditional classrooms are under pressure from numerous institutions to accept e-learning as the new standard. This change poses a significant challenge: how to ensure the acceptance and effective reuse of new digital learning platforms? Within this framework, two well-known theories—the Technology Acceptance Model (TAM) and the Expectation Confirmation Model (ECM)—emerge as essential instruments for comprehending and managing user behavior in e-learning settings. ECM explores consumers' post-adoption experiences, illuminating how expectations affect continuous usage. Conversely, Technology Acceptance Models (TAM)—TAM, TAM2, and TAM3—concentrate on how technology is first accepted and used, looking at things like perceived usefulness and ease of use. Although each of these models has advantages, a thorough investigation of these models in the context of e-learning has not yet been accomplished. This paper aims to close this gap by thoroughly examining TAM and ECM in the particular situation of e-learning, providing valuable insights for educators and institutions navigating this digital transformation.

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2 The Expectation Confirmation Model (ECM):

Originating from Richard L. Oliver's pioneering work during the 1970s and 1980s, the Expectation Confirmation Theory (ECT) explores post-adoption satisfaction by examining expectations, perceived outcomes, and belief disconfirmation. In contrast, Bhattacherjee introduced the Expectation Confirmation Model (ECM) in 2001, which applies ECT's concepts to the realm of Information Systems (IS), emphasizing user satisfaction and the desire to continue using IS. Consequently, ECM represents a specialized version of ECT designed specifically for the IS sector, shifting the focus from consumer behavior and marketing to user satisfaction and continuous IS utilization. Figure 1 outlines the components of ECM.

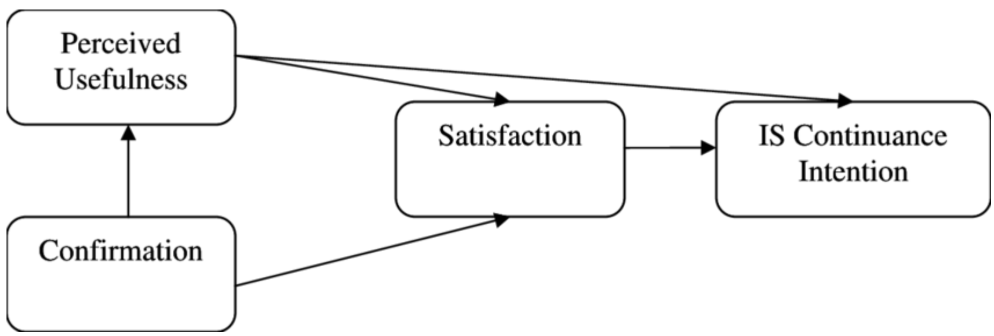

Fig. 1: Bhattacherjee's 2001 ECM Model

As we can see in the figure, the model comprises four essential components:

- Perceived usefulness: It gauges users' perception of the system's benefits.
- Confirmation: This evaluates the alignment between user expectations and actual system performance.
- Satisfaction: This measures users' overall emotional response to their system experience.
- IS Continuance intention: It indicates users' intent to persist in using the system and serves as the primary predictive target of the model.

Several studies have utilized the ECM to determine if students plan to keep using the e-learning platform. The initial adoption of the platform holds significance for students, yet its true value lies in its continuous reuse. Cheng (2020) conducted a study published in Education & Training, exploring how the ECM can help understand student satisfaction and intentions regarding e-learning. The study emphasized the significance of meeting students' expectations of online learning platforms to enhance their satisfaction and intention to continue using them.

Before immersing themselves in an online learning platform, students establish expectations based on factors such as its layout, user-friendliness, and perceived usefulness. As they actively engage with the platform, these pre-existing expectations shape their assessment of its effectiveness in aiding their goal achievement. Over time, they measure their experiences on the platform against these expectations. When the platform meets or surpasses their expectations, students feel validated, leading to heightened satisfaction.

However, students may feel let down and experience a drop in pleasure or even discontent if the platform falls short of their expectations. Confirmation of expectations can be described as a person's belief that expectations and performance align (Bhattacherjee, 2001).

Chow, Wing S. (2013) initiated a study aimed at delving into the realm of e-learning, exploring how students' initial expectations influence their satisfaction and ongoing engagement with e-learning systems. This study took an innovative approach by expanding the Expectation-Confirmation Model (ECM) to focus specifically on four key aspects of e-learning: the learning process, tutor interaction, peer interaction, and course design. Through this lens, Chow sought to measure students' expectations after they had begun using e-learning. The study uncovered that when students' expectations concerning these four dimensions of e-learning were validated—meaning the e-learning system met or surpassed their expectations—it resulted in a positive impact on their satisfaction with e-learning. This positive effect was evident for both their expectations (termed Post-Adoption Expectation or PAE) and their overall satisfaction with using e-learning. Furthermore, the study highlighted the pivotal roles played by the process of learning and curriculum design in influencing both students' satisfaction levels and their commitment to continued e-learning usage, it’s crucial to emphasize the importance of urging e-learning practitioners to design e-learning course structures that are clear and logically organized, along with well-designed course materials. In the other hand, the study found that the effects of instructor and peer interaction on satisfaction with online learning and intentions to continue are not statistically significant. This could be attributed to the fact that in many universities, Students' adoption of online learning primarily focuses on accessing educational materials rather than on communication and collaboration.Njenga & Fourie (2010) have also discussed the importance of communication in e-learning systems, suggesting that greater efforts are required to enhance communication and facilitate interaction between students and tutors.

Within the e-learning framework, Chow, Wing S. (2013) identified several critical factors influencing the overall experience, including the learning process, tutor interaction, peer interaction, and course design. However, alongside these foundational elements lies a factor of equal importance – perceived enjoyment. Perceived enjoyment, as defined by Venkatesh (2000), refers to the extent to which individuals derive pleasure from utilizing a specific system, irrespective of its outcomes or performance implications. Studies have consistently shown a positive correlation between confirmation, where users' experiences align with their expectations, and perceived enjoyment. This alignment not only fosters enjoyment but also enhances the intention to adopt or continue using online learning platforms. Li Li, Qing Wang, and Jinhui Li (2022) further proposed a hypothesis suggesting the positive influence of enjoyment on students' satisfaction with online learning. Their analysis supported this hypothesis, revealing a significant relationship between the enjoyment derived from online learning activities and subsequent satisfaction levels among students.

2.1 Limitations of ECM

Several limitations prevent the Expectation Confirmation Model (ECM) from accurately capturing the nuances of user happiness with technology, particularly in online learning contexts.

First of all, pedagogy, technology, social interaction, and psychology are all interwoven in the intricate and multifaceted nature of online learning settings. These nuances, especially the way that technology, course design, and social interactions interact to influence learners' experiences and expectations, may be missed by the ECM.

Additionally, e-learning expectations are dynamic, changing as students interact with the platform, acquire experience, and get feedback. Since perceptions on usefulness and satisfaction shift over time, the ECM's emphasis on the immediate post-adoption experiences might not be sufficient to address these changes. Furthermore, the ECM assumes that system performance and user satisfaction are causally related. However, there are a number of variables that might affect user satisfaction, including the user experience, ease of use, and environment. User satisfaction may be impacted by mediating variables, which are overlooked in this oversimplification. Lastly, the long-term consequences of satisfaction on users' actions and attitudes toward technology may not be sufficiently captured by the ECM. It ignores changes in usage habits and satisfaction over time in favor of concentrating exclusively on the immediate post-adoption experiences. To sum up, although the ECM offers insightful information on how satisfied users are with technology, its constraints prevent it from accurately capturing the changing nature of user experiences and attitudes in online learning environments.

2.2 Conclusion

In conclusion, the Expectation-Confirmation Model (ECM) is instrumental in Information Systems (IS) research, including e-learning, for understanding user satisfaction and continued usage. ECM, an extension of the Expectation-Confirmation Theory (ECT), shifts the focus from pre-consumption to post-consumption expectations, particularly emphasizing perceived usefulness. This shift recognizes that users' initial expectations can evolve based on their experience with the system, impacting satisfaction and intention to continue usage. However, while the ECM provides valuable insights, its scope is somewhat limited, and certain components may not fully illuminate learners' success expectations in online learning environments. Therefore, incorporating explanatory factors related to continuity intentions would be advantageous. By doing so, educators, developers, and policymakers can gain a more comprehensive understanding of user behaviors and preferences, ultimately facilitating the design and implementation of e-learning solutions that enhance satisfaction and promote effective usage across educational settings.

3 The Technology Acceptance Model (TAM)

Based on Fishbein and Ajzen's (1975) theory of reasoned action (TRA), the Technology Acceptance Model (TAM) was developed. The psychology of human behavior is explored by TRA, which contends that people are more likely to act in ways they perceive to get particular results. TAM applies these ideas to the adoption of technology and was first presented by Davis, Bagozzi, and Warshaw in 1989. As a crucial and often used theories in the field of information systems (IS), TAM has garnered recognition ever since it was first proposed.

It is important in today's world to comprehend and forecast people's adoption and use of technology. The idea is that people's intentions, which are shaped by their opinions about a technology's usefulness. (PU) and ease of use (PEOU), ultimately determine how a technology is actually used.People's opinions about the advantages they would experience from utilizing a certain technology are known as Perceived Usefulness (PU). PEOU, or perceived ease of use, is a measure of people's expectations of how simple it will be to use the technology. The ideas presented here are summarized in Figure 2, which shows the Technology Acceptance Model (TAM).

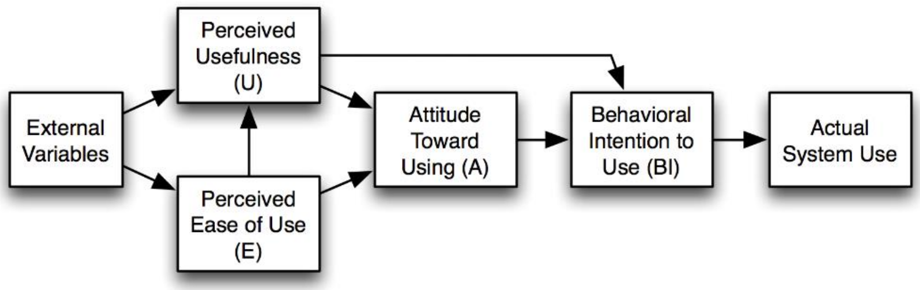

Fig. 2: Davis et al.'s 1989 TAM Model

Masrom (2007) and Chen (2022) findings reveal that perceived ease of use strongly impacts perceived usefulness. When users view a technology as easy to operate, they're more likely to deem it effective and valuable for their objectives. This favorable usability perception enriches user experience, fostering deeper interaction with its functions. As users grow more accustomed to the technology, their perception of its usefulness solidifies. This influence is also evident in online learning environments, where ease of use affects perceived effectiveness and value. However, it's apparent from another angle that while a platform may be user-friendly, it might lack quality content. This disparity between ease of use and perceived usefulness can lead to user dissatisfaction, despite the intuitive interface. It emphasizes the significance of not just ease of use, but also evaluating the content or services' quality. It underscores that while technology design and usability are pivotal, the derived value, encompassing content quality, relevance, and usability, holds an equally, if not more, crucial role in shaping user behavior.

Ibrahim et al. (2017) conducted a study to increase students' acceptance of online learning in higher education. Based on the Technology Acceptance Model (TAM), they put out a complete model that included six essential components: the characteristics of the teacher, computer self-efficacy, course design, perceived usefulness, perceived ease of use, and intention to use online learning. In order to evaluate the degree of assistance and accommodations offered by teachers, the qualities of the instructors were looked at. Surprisingly, the study found that instructor characteristics did not have a significant effect on student adoption of online learning, indicating a predominant reliance on published resources rather than interactive engagement with instructors. Additionally, research consistently highlights the strong correlation between students' computer self-efficacy and their perceived ease of using online learning platforms. This underscores the critical need for universities to assess and enhance students' self-efficacy levels in navigating digital learning environments. Effective training programs should transcend technical proficiency, encompassing strategies for efficient navigation and active participation in online courses. Students benefit from guidance that equips them with the skills to navigate online platforms seamlessly, access resources efficiently, and engage actively in their learning journey. By providing comprehensive training initiatives tailored to students, universities can empower them to embrace e-learning confidently and proficiently, fostering a dynamic and inclusive educational environment.

Giving teachers the same level of attention is crucial when it comes to training. It is critical that teachers have the resources and know-how necessary to interact with students in virtual learning environments and convey course material. To promote learning and engagement among students, teachers need assistance in creating interesting online content, facilitating debates, and giving prompt feedback. Academic institutions may foster a cooperative learning atmosphere that fully utilizes e-learning resources by allocating substantial resources to training programs for instructors and students.

The study also discovered a larger inclination to use online learning platforms was associated with perceived ease of use. This indicates that the perception of platforms as accessible and user-friendly by students increases the likelihood of students engaging in digital learning, underscoring the importance of platform design in encouraging student involvement. Overall, these results demonstrate how critical it is to improve perceived ease of use and address students' computer self-efficacy in order to encourage the uptake of online learning in educational settings. In addition, the perceived utility (PU) of e-learning platforms significantly impacts users' decisions to keep using them. Users who find the platform advantageous for their educational needs are more likely to maintain their engagement. This underscores the importance of ensuring e-learning platforms are perceived as useful. Jiyun Chen's (2022) research confirms this relationship, emphasizing the vital role of perceived usefulness (PU) in fostering continued engagement with e-learning platforms.

Understanding the factors influencing technology acceptance in e-learning environments may be accomplished with the help of the Technology Acceptance Model (TAM). It particularly focuses on perceived usefulness and ease of use.There are still more nuances to investigate as we dig deeper into this area. This provides opportunities for more study and advancement, which could take us to TAM 2 and beyond. E-learning systems may be better designed to address the changing demands of educators and learners by continuously improving our understanding of user attitudes and intents.

4 Technology Acceptance Model 2 (TAM2)

In 2000, Davis and Venkatesh introduced an extension to the model, known as TAM2. Recognizing the necessity for deeper analysis, they understood that simply stating technology's utility was insufficient. They aimed to uncover the specific factors influencing individuals' perceptions of technology's usefulness.

TAM2 expanded the initial model by introducing new theoretical constructs that explore both social influence mechanisms and cognitive instrumental factors, including experience and voluntariness. This extension aimed to enhance the understanding of why users perceive technology as useful. While the significance of this perception in adoption decisions was evident, it was necessary to pinpoint the specific factors influencing it. Thus, the TAM2 model introduced additional theoretical components concerning social influence dynamics (subjective norm, voluntariness, and image), as well as cognitive instrumental aspects (job relevance, output quality, result demonstrability, and perceived ease of use). In Figure 3, TAM 2 is depicted graphically, showing the model's components and their relationships.

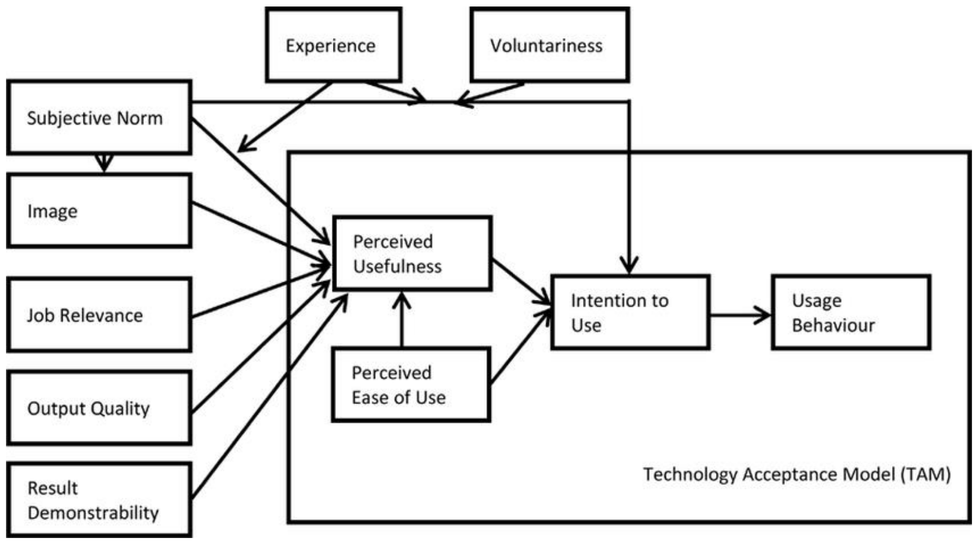

Fig. 3: TAM2 Model

Subjective norms are fundamental in determining how people feel about e-learning. It represents how they see the expectations and societal pressures of using e-learning platforms or courses. For instance, if learners feel that their peers, teachers, or supervisors support and encourage them to participate in eLearning activities, They are probably going to feel more motivated. Their intention to use eLearning systems and their subsequent usage habits are ultimately influenced by this incentive. On the other hand, learners can be less likely to engage in eLearning if they feel that it is not supported or endorsed. This association was confirmed by Guohua Wan's (2010) research, which showed a favorable correlation between one's willingness to accept technology and the subjective norm.

Subjective norm not only affects your technology usage through social pressure but also influence your perceived image. Image refers to how using a specific technology enhances your social status (Moore & Benbasat, 1991). According to TAM2, there's a positive correlation between subjective norm and image. In simpler terms, if important individuals in your life suggest using a certain technology, it can shape how others perceive your social standing. Findings from prior studies (Pfeffer, 1992; Chassin, Presson & Sherman, 1990) corroborate this relationship. Additionally, while TAM2 suggests a linkage between 'image' and 'perceived usefulness,' it underscores the importance of recognizing the varied viewpoints and experiences of individuals. In the context of e-learning, users may prioritize practical aspects such as functionality and content quality over the perceived social image associated with a technology. The assumption that social status significantly influences perceptions of usefulness may not universally apply. This highlights concerns regarding the wide applicability of the proposed relationship and emphasizes the necessity of considering individual differences in technology adoption.

As an independent variable that indicates how suitable the target system is to a person's professional position, work relevance is the third factor influencing perceived usefulness (Venkatesh & Davis, 2000). Job relevance in eLearning refers to the alignment between the skills, knowledge, and information gained in a course with the requirements, objectives, and tasks of a learner's current or future job. Consider a beginner in marketing who signs up for a sophisticated online course. Advanced subjects like SEO, PPC advertising, and content marketing tactics are covered in the course through thorough tutorials, practical exercises, and real-life case studies to help students comprehend and successfully apply complicated marketing ideas. The student is therefore more motivated to interact with the content and use the newly acquired information in their professional activities as they believe the course to be extremely relevant to their line of work. It functions as a measure for evaluating how well e-learning resources match the expectations and practical needs of the workplace, improving the professional capabilities of the learners. Therefore, job relevance is significant and has a direct and interactive effect on perceived usefulness, according to Venkatesh and Davis (2000). Making a clear link between eLearning tools and learners' professional responsibilities or academic objectives is a crucial component of job relevance, which enhances perceived usefulness. This alignment not only encourages the intention to use but also drives actual usage behavior.

Output quality, as defined by Venkatesh & Davis (2000) as the perceived effectiveness of a system in accomplishing tasks, is a critical factor in technology acceptance. In e-learning, it encompasses various elements such as the clarity of course materials and the effectiveness of interactive features. For instance, an online programming course with well-structured lectures, interactive coding exercises, and real-world project assignments would be perceived as high in output quality. It effectively supports users' learning objectives and practical skill development. However, it's not just about delivering content—it's about demonstrating tangible outcomes. Result demonstrability, as emphasized by Moore & Benbasat (1991), refers to users' ability to directly observe the benefits of technology usage. In e-learning, this might involve showcasing improved coding proficiency through project showcases or demonstrating problem-solving skills gained from interactive exercises. When users can witness the positive impact of using a technology, their perception of its usefulness is reinforced. Therefore, by ensuring both high output quality and clear result demonstrability, educational online platforms can effectively enhance user satisfaction and promote adoption.

Adding to our understanding of technology acceptance, voluntariness, as described by Venkatesh & Davis (2000), represents how much potential users perceive adopting a technology as optional. When examining situations where voluntariness is low, such as when technology use is compulsory, the importance of subjective norm, which reflect the opinions of influential people, might be questioned. For example, if a student has to use a specific e-learning platform mandated by their school, their use of the platform is mandatory, so they don't have much choice in the matter. While subjective norm might still matter somewhat, voluntariness influences its impact. Conversely, in contexts characterized by high voluntariness where individuals have the choice to adopt a technology, subjective norms may play a more significant role. Consequently, the relevance of subjective norm in technology acceptance models can change based on how much choice users perceive they have.

Shifting our focus, experience within technology acceptance encompasses users' familiarity and comprehension of a specific system or technology over time. Venkatesh & Davis (2000) observed that as users become more experienced with a system, the direct impact of subjective norm on intentions may diminish. Initially, users heavily consider the opinions of others, as indicated by subjective norm, particularly when they are less acquainted with the technology. However, with increasing experience and proficiency, users tend to rely less on external influences and develop their own assessments of the technology's utility and ease of use. Furthermore, hands-on experience with the system directly influences perceived usefulness. Through interaction, users achieve a more profound comprehension of the technology's capabilities and its alignment with their needs. Consequently, experienced users can make more informed judgments about the technology's effectiveness in accomplishing tasks or meeting objectives. Therefore, experience plays a pivotal role in both moderating the influence of subjective norm and shaping the perception of usefulness in technology acceptance models.

As we explore technology acceptance models further, the transition from TAM2 to TAM3 marks a big step forward in understanding how people and organizations adopt new technologies. This evolution shows how technology adoption processes change over time and emphasizes the need for ongoing research and adaptation in this area.

5 Technology Acceptance Model 3 (TAM3)

We have thoroughly reviewed the determinants influencing perceived usefulness in TAM 2. Now, we will shift our attention to the novel components introduced in the model, specifically aimed at predicting perceived ease of use. In 2008, Venkatesh and Bala merged the Technology Acceptance Model 2 (TAM2) with the Determinants of Perceived Ease of Use model, resulting in the creation of the Global Technology Acceptance Model 3 (TAM3). This integration aimed to enrich the understanding of technology acceptance by incorporating additional factors. TAM3 retained elements from TAM2, including subjective norm, image, job relevance, output quality, and result demonstrability, which contributes to perceived usefulness. Additionally, TAM3 introduced new predictors directly related to perceived ease of use. In Figure 3, TAM 3 is visually illustrated.

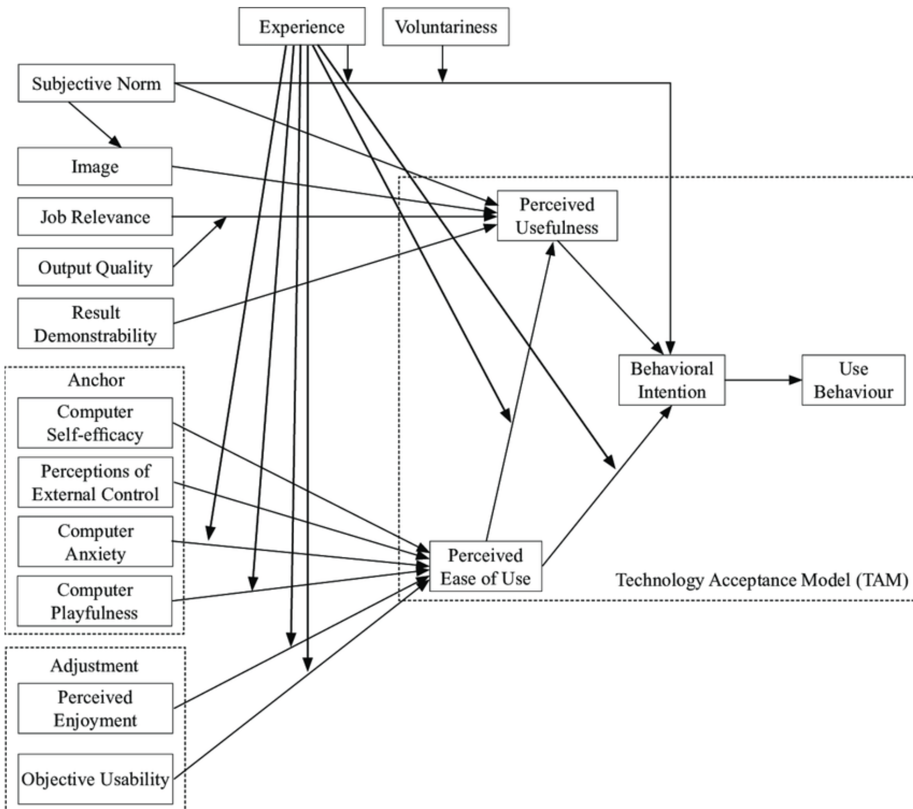

Fig. 4: TAM3 Model

TAM3 introduced two concepts: anchoring and adjustments. The concept of anchoring and adjustment in human decision-making is presented in TAM3. It introduces constructs like perception of external control (PEC), computer self-efficacy (CSE), computer anxiety (CANX), and computer playfulness (CP) to illustrate how people anchor their perceptions of a system's ease of use to their existing beliefs. These anchors reflect individuals' fundamental convictions and attitudes before interacting with technology, shaping their initial perspective on it. On the other hand, adjustment arises from direct experience with the technology in question and aims to modify the user's viewpoint towards it. It encompasses factors that influence people's perception of a system's ease of use, such as subjective enjoyment (SENJ) and objective usability. Hence, TAM 3 proves invaluable in comprehending the uptake of e-learning platforms by shedding light on how variables like PEC, CSE, CANX, and CP influence teachers' and students' utilization of these tools. The initial three factors mirror users' confidence levels regarding technology and its application, as outlined by Venkatesh and Bala in 2008. If we consider computer self-efficacy (CSE) as an example, which refers to confidence in one's computer skills, it becomes evident how pivotal it is in molding individuals' attitudes and actions within digital learning contexts. Compeau and Higgins (1995) conducted research that underscored its importance, demonstrating a strong connection between heightened levels of self-efficacy and optimistic expectations regarding learning outcomes. Lim's (2001) study further highlighted its impact on adult distance learners' satisfaction and future participation in digital learning. Recent research by Lin and Yu (2023) supports a direct relationship between higher education students' self-confidence in utilizing digital academic reading tools and their perceived ease of use. This correlation is grounded in the idea that individuals who feel confident in their technological abilities, such as university faculty members during emergency remote teaching, are more likely to perceive online teaching as easy.

Conversely, those who have low computer self-efficacy might experience confusion or anxiety, which could prevent them from engaging in digital learning activities. As a result, computer self-efficacy has a significant role in shaping people's views and experiences in digital learning contexts, which has consequences for encouraging positive attitudes and active participation in these settings. In a study, researchers looked at the relationship between people's tendency to stick with online systems and their level of computer confidence, or computer self-efficacy, or CSE. Interestingly, they discovered that individuals with elevated CSE levels were less likely to stick with these online platforms. This unexpected finding suggests that confident users may attribute their success more to their computer skills rather than the effectiveness of the online systems. In other words, they might believe that they can achieve their goals using any system, regardless of its effectiveness or usability. As a result, they may not feel the need to continue using a specific online platform if they believe they can accomplish the same tasks elsewhere or differently. This goes against the common belief that proficient computer users would be more likely to want to keep using online systems. While this study offers a unique perspective, it's important to consider the broader body of research, which often supports the idea that individuals with high self-efficacy are more inclined to engage with technology.

After talking about computer self-efficacy, it's critical to investigate how e-learning experiences are impacted by computer anxiety and perception of external control (PEC). PEC, as defined by Venkatesh et al. (2003), is the measure of how people view technical and organizational support for utilizing the system, which affects how confident they are in its usability. On the other hand, as highlighted by Venkatesh (2000), computer anxiety is characterized by individuals' unease or reluctance to engage with computers in online learning settings. These aspects wield considerable influence over users' perceptions of e-learning platform's ease of use, their inclination to adopt them, and their actual patterns of usage. Users with elevated PEC levels and minimal computer anxiety tend to perceive e-learning platforms as user-friendly, fostering stronger intentions to utilize them and heightened actual usage. Conversely, those with low PEC and heightened computer anxiety may encounter challenges with e-learning systems, leading to diminished intentions to use them and decreased actual engagement. A deep understanding of PEC and computer anxiety roles is essential in crafting e-learning platforms that effectively meet users' preferences, ultimately amplifying user engagement and learning efficacy. Furthermore, Researchers and developers must prioritize designing eLearning platforms that not only fulfill functional needs but also offer enjoyable and engaging experiences for users. Boredom can lead students to abandon online platforms, irrespective of their perceived usefulness. Computer Playfulness (Independent), defined by Webster & Martocchio in 1992, measures the spontaneity and creativity users bring to interactions with microcomputers, including eLearning systems. Research shows that playful interaction correlates with creativity and exploration, offering practical implications for enhancing engagement and satisfaction in eLearning contexts. By incorporating elements of Computer Playfulness into platform design, educators can create environments that inspire curiosity and promote active learning.

Transitioning to Adjustment in TAM3, we explore two crucial elements: Perceived Enjoyment and Objective Usability. Perceived Enjoyment (Independent), as defined by Venkatesh (2000) describes hedonic motivation as the degree to which using a particular system is perceived as enjoyable in itself, regardless of the performance outcomes derived from its use. This concept, highlighted in this article within the context of ECM, plays a pivotal role in predicting technology reuse.

Objective Usability (Independent), also delineated by Venkatesh (2000), provides a more tangible perspective by assessing systems based on the actual effort required to complete tasks. This objective evaluation offers valuable insights into system efficiency, informing enhancements to optimize user experience in e-learning environments. TAM 3 directs its attention toward two pivotal dimensions: perceived usefulness (PU) and perceived ease of use (PEU). In contrast to TAM 2's primary focus on perceived usefulness, TAM 3 broadens its scope by integrating perceived ease of use. This expanded perspective enables TAM 3 to offer a more comprehensive understanding of technology acceptance, examining both the perceived benefits and the ease of utilizing technology. With this dual focus, TAM 3 enhances its capability to predict and elucidate technology adoption, as it considers the impact of both perceived usefulness and perceived ease of use on users' intentions to use and actual usage of technology.

6 Unveiling the Advantages and Limitations of TAM

TAM, a well-established theoretical framework, demonstrates strong predictive power in determining individuals' willingness to adopt technology. TAM emerged as the pioneering theory in explaining why people adopt information systems, filling a crucial gap in information systems research and practice (Goodhue, 2007). Its enduring relevance and predictive capability have made it a foundational framework for understanding user behavior towards technology adoption. With its comprehensive framework encompassing internal and external factors, TAM offers a nuanced understanding of technology adoption dynamics across various domains, including e-commerce, healthcare, education, and beyond. Its adaptability allows for tailored applications in specific contexts or technologies, ensuring relevance and effectiveness. TAM's influence on technology design ensures the development of user-centric solutions, enhancing user satisfaction and engagement. By incorporating emotional factors, TAM offers insights into the nuanced motivations driving technology adoption, contributing to the creation of impactful solutions. With its wide application and support for decision-making processes, TAM emerges as a valuable tool for informing technology adoption strategies and fostering innovation across various industries and sectors.

As TAM has cemented its position as a foundational theory in understanding technology adoption, it's imperative to acknowledge its limitations. These constraints highlight areas where further refinement and adaptation may be necessary for a more comprehensive understanding of technology acceptance. Several constraints have been deliberated in TAM and its subsequent developments throughout the years. Previous research has raised concerns about TAM's simplicity and its limited understanding of the factors influencing technology acceptance, such as perceived usefulness and ease of use (Venkatesh, Davis & Morris, 2007; Lee, Kozar & Larsen, 2003). Additionally, TAM research have mainly centered on understanding the factors driving technology adoption and usage, overlooking how actual technology utilization affects performance outcomes (Goodhue, 2007). This oversight hampers the broader understanding of technology's impact on individual and organizational effectiveness, potentially impeding the development of strategies to optimize technology usage for enhanced performance. Furthermore, extended models of technology acceptance, such as TAM2, have faced criticism for their contextual specificity, often being tailored primarily to organizational settings (Venkatesh, Thong & Xu, 2012). This limitation highlights the importance of contextual relevance in technology acceptance models to ensure their applicability and accuracy across diverse domains.

Additionally, other difficulties have been noted (Venkatesh & Davis, 2000; Venkatesh, Thong & Xu, 2012), including the dependence on self-reported usage intentions and the possibility of common method bias. Researchers might not always capture the best picture since they frequently rely on people's stated intentions rather than watching them in action. Furthermore, biases that affect the results may be introduced by the methods used by researchers to gather data, such as surveys or interviews. The validity of the results may thus be impacted by these issues, regardless of whether TAM is a helpful framework for understanding how people embrace technology.

7 Conclusion and future work

In conclusion, while the Expectation Confirmation Model (ECM) and the Technology Acceptance Model (TAM) were not originally designed for educational contexts, this article has discussed their relevance in the realm of online learning. By examining these models, including different iterations like TAM, TAM 2, and TAM 3, within digital education, we've emphasized their importance in understanding user behavior and technology acceptance. Through a thorough review of existing research, we've emphasized the practical insights offered by ECM and TAM in enhancing student engagement and improving learning outcomes in online educational settings. However, it's apparent that while these models provide valuable frameworks, there's a need for a more tailored approach. Developing a model explicitly crafted for educational purposes could yield even more profound insights and guidance for educators and researchers grappling with the intricacies of online education. Therefore, while ECM and TAM are effective tools, there's an opportunity for further refinement to better address the unique challenges and dynamics inherent in the educational landscape.

Looking ahead, the endeavor to enhance online learning experiences persists in developing a groundbreaking model finely attuned to the evolving landscape of digital education. The project ahead involves creating a detailed framework that merges the fundamental concepts of the Expectation Confirmation Model (ECM) and the Technology Acceptance Model (TAM). This framework is designed exclusively for educational settings and digital learning contexts. Its goal is to provide educational institutions with a strategic plan to boost user interaction and encourage the broader use of online learning tools. Future researchers are encouraged to embark on collaborative and innovative research projects in online education. The collaboration will hopefully lead to the creation of a revolutionary framework that will advance online learning projects and improve learning opportunities for students worldwide. This innovative project has the power to completely transform the online learning environment, encouraging creativity and raising the caliber and efficacy of digital education worldwide.

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