EXPLORING THE FACTORS AFFECTING E-LEARNING ADOPTION AMONG ENTREPRENEURSHIP STUDENTS DURING PANDEMICS

Reza Mohammadkazemi, Professor of Entreprenurship at University of Tehran
Aref Golivari, PhD Candidate of Entreprenurship at University of Tehran
Nader Goudarzi, PhD Candidate of Entreprenurship at University of Tehran

ABSTRACT

This research investigates the factors influencing the adoption of electronic learning (e-learning) systems during the COVID-19 pandemic among university students majoring entrepreneurship in Iran. Understanding these factors helps students, instructors, and educational institutions optimize the use of e-learning systems in challenging situations. The Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) theory were used as the theoretical foundation for building a conceptual framework, with the addition of Perceived Trust to provide a comprehensive model. A questionnaire was distributed to 380 entrepreneurship students, from which 321 valid responses were collected. The data was analyzed using Structural Equation Modeling (SEM) through AMOS software to examine the relationships between key constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust, Task-Technology Fit (TTF), Behavioral Intention (BI), and Actual Use. The findings revealed that while PU and PEOU positively influence students' attitudes toward e-learning, Trust plays a pivotal role in driving Behavioral Intention. However, the fit between technology and educational tasks (TTF) had a weaker impact on actual engagement. These insights highlight the importance of trust and system-task alignment for successful e-learning adoption.

Keywords: E-learning Adoption, TAM, TTF, Trust, COVID-19, Structural Equation Modeling.

INTRODUCTION

The COVID-19 pandemic has caused a significant transformation in educational environments worldwide, particularly in higher education. By early 2020, universities and colleges were grappling with the challenges of transitioning from traditional face-to-face learning to e-learning (Jin et al., 2021; Rapanta et al., 2020). Quarantine measures and social distancing to curb the spread of COVID-19 led to a sharp decline in physical presence and in-person instruction, which in turn spurred a global rise in e-learning and distance education, which can be categorized under the concept of green entrepreneurial orientation (Asad, et al., 2024; Asad, et al., 2024. Governments, in their bid to neutralize the negative effects of school closures, promoted e-learning as an essential tool (Ho et al., 2020). For instance, in countries like Iran, where distance learning became mandatory, e-learning ensured the continuity of education while mitigating the spread of the virus (Toquero, 2020; Mohammadkazemi &

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Golivari, 2023). Given this abrupt transition, investigating the factors influencing e-learning adoption has become crucial, particularly in developing nations such as Iran, where traditional education methods are often prioritized due to constraints such as insufficient financial resources and lack of adequately trained personnel (Kanwal & Rehman, 2017; Tarhini et al., 2017).

Before the pandemic, e-learning was not the dominant form of education in most institutions; however, with the shift to online classes due to COVID-19, the importance of studying different aspects of e-learning, which is considered as an entrepreneurial opportunity (Satar, et al., 2024), has significantly increased (Jin et al., 2021). The internet, now a central component of education and research, has empowered students and instructors to exchange and access information effortlessly (Malik & Rana, 2014; Nafisi & Mohammadkazemi, 2024). The rapid advancements in information and communication technologies (Kanaan, et al., 2024), alongside the proliferation of virtual learning environments, have been key drivers in the expansion of e-learning platforms (Gunasinghe et al., 2020). E-learning is set to continue its growth trajectory, as forecasted by Statista (2020), which predicts the global e-learning market will surpass $243 billion by 2022.

Defining e-learning, however, is not straightforward. The concept encompasses a variety of applications, processes, and learning methods, making it difficult to provide a universal definition (Malik & Rana, 2014). Nonetheless, Rodrigues et al. (2019) offer a more recent and comprehensive definition that suits current technological contexts: “E-learning is an innovative web-based system based on digital technologies and other forms of educational materials whose primary goal is to provide students with a personalized, learner-centered, open, enjoyable and interactive learning environment supporting and enhancing the learning processes.” This definition highlights how e-learning leverages technology to create a more engaging, interactive, and accessible learning experience for students.

The benefits of e-learning have become more evident during the pandemic. E-learning systems offer a cost-effective, flexible, and ubiquitous mode of education, providing learners with the ability to access content from any location at any time (Almaiah et al., 2020; Kanwal & Rehman, 2017). These systems are also highly interactive, fostering an engaging and enjoyable learning environment (Samsudeen & Mohamed, 2019; Ekbatani et al., 2024). Furthermore, e-learning supports learning providers by helping them plan, manage, deliver, and track the teaching process efficiently, particularly in situations where in-person instruction is not feasible (Almaiah et al., 2020). For institutions, e-learning not only enhances teaching capacity but also facilitates more effective knowledge transfer (Samsudeen & Mohamed, 2019). Offering both online and offline learning options, e-learning platforms provide learners with a convenient and flexible approach to education, making it particularly valuable in a time when mobility and face-to-face interactions are limited.

The success of e-learning systems, however, hinges on students’ attitudes toward adopting the technology (Saberi, et al., 2024). Their perceptions and willingness to engage with e-learning platforms are critical to the success or failure of such systems (Kanwal & Rehman, 2017). As the integration of technology in education becomes increasingly vital for enhancing both learning and teaching, understanding the factors that influence technology adoption has gained importance (Cheng, 2019). Therefore, exploring the determinants of e-learning adoption offers higher education institutions valuable insights into students’ needs, which can lead to the development of more efficient and user-friendly systems (Almaiah et al., 2020). Furthermore, examining the factors influencing e-learning adoption can ensure that

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the lessons learned during this crisis are applied in future emergencies, helping researchers, businesses, and governments are better prepared for similar situations.

In recent years, several studies have explored factors influencing e-learning adoption, using various technology adoption models. For example, Mo et al. (2021) investigated Chinese students' continuance intentions to engage in online learning during the pandemic using the Technology Acceptance Model (TAM). Their study incorporated expanded variables such as instructor attitudes, family support, and Task-Technology Fit (TTF), recognizing the differences between COVID-19-induced online learning and regular e-learning environments. Similarly, Ho et al. (2020) used TAM to identify the key factors affecting students' adoption of e-learning in Vietnam during the pandemic. Nikou and Maslov (2021) extended TAM to study the impact of the pandemic on students' intentions to adopt e-learning technologies. Jin et al. (2021), meanwhile, employed the push-pull-mooring model to investigate the factors influencing Chinese students' decisions to switch from traditional learning to e-learning during the pandemic.

In this research, we aim to investigate the determinants of e-learning adoption in Iran during the COVID-19 pandemic by integrating two prominent models: the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF). TAM, which is widely used to predict technology acceptance, has been proven to be a useful model for explaining students' intentions to adopt e-learning (Teo, 2012; Park, 2009). Several researchers have extended or modified TAM in their studies to better fit the e-learning context (e.g., Park, 2009; Kanwal & Rehman, 2017; Ho et al., 2020). In contrast, the TTF model focuses on the degree to which a technology fits the tasks it supports, emphasizing the functional benefits of technology adoption (Dishaw & Strong, 1998). TTF assumes that users are more likely to adopt a technology if it enhances their performance, regardless of their personal attitudes toward it.

Combining TAM and TTF provides a more comprehensive understanding of e-learning adoption by capturing both the attitudinal and functional dimensions of technology use (Mo et al., 2021; Wu & Chen, 2016). While TAM is focused on user beliefs and attitudes, TTF offers a more rational perspective by considering how well the system supports users' tasks. Integrating these two models allows us to explore how e-learning systems fit both students' tasks and their technology adoption intentions.

Additionally, in this study, we incorporate the concept of trust into our combined model, as trust is a critical factor influencing technology adoption. Trust plays a vital role in building confidence in the e-learning system, especially when students are required to shift from traditional to online learning environments (Gefen et al., 2003). In the context of e-learning, trust is essential for ensuring that students feel secure in using the system and believe that it will effectively improve their knowledge and skills. Therefore, examining the impact of trust on e-learning adoption provides a more thorough investigation into the factors that drive students to embrace online learning platforms during a pandemic.

REVIEW OF LITERATURE

TAM and TTF Models

The Technology Acceptance Model (TAM), first introduced by Davis (1989), has become one of the most widely used frameworks for understanding the factors that influence the adoption of technology (Marangunić & Granić, 2015). At the core of TAM are two primary constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which

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shape an individual's intention to use a technology (Davis et al., 1989). PU refers to the degree to which a person believes that using a particular system would enhance their performance, while PEOU focuses on the extent to which the system is perceived as free from effort. This model has been extensively applied across various domains, including e-learning, to explore the acceptance and use of technology.

In the context of e-learning, TAM's emphasis on user perceptions of technology's ease of use and usefulness is particularly relevant. With online learning systems becoming integral to modern education, TAM helps explain the motivations behind students' adoption and continued use of such platforms. However, while TAM has demonstrated its utility, some scholars argue that it does not fully capture the nuances of task-oriented environments like e-learning, where the alignment between the task and the technology plays a critical role.

This is where the Task-Technology Fit (TTF) model, developed by Goodhue and Thompson (1995), comes into play. TTF evaluates the degree to which a technology supports the tasks that users need to accomplish. The idea is that technology will be more readily adopted if it provides adequate support for completing specific tasks. In the case of e-learning, TTF looks at how well the e-learning system aligns with the educational tasks students must perform. When the system is perceived to be a good fit for these tasks, students are more likely to experience higher satisfaction and efficiency, leading to greater technology adoption (Mo et al., 2021).

The correspondence between task requirements and the capabilities of e-learning systems plays a crucial role in perceived TTF. E-learning platforms that are designed to meet students' specific needs not only enhance learning outcomes but also improve engagement and motivation. This further supports the argument that technology adoption is not merely a matter of attitude, as TAM suggests, but also depends on how well the technology fulfills the user's task requirements (Goodhue & Thompson, 1995). Thus, the integration of both TAM and TTF provides a more comprehensive view of the factors influencing technology adoption.

Integrating Two Models

The integration of TAM and TTF was pioneered by Dishaw and Strong (1998), who recognized that TAM focuses on the user's behavioral intentions, while TTF places emphasis on how technology supports task performance. They suggested that combining these models offers a more holistic understanding of technology adoption. While TAM explains users' attitudes and intentions based on perceived usefulness and ease of use, TTF captures the rational, performance-driven aspect of technology adoption, focusing on how well the technology meets the functional needs of the user (Dishaw & Strong, 1998).

In the context of e-learning, many researchers have applied this integrated model to gain deeper insights into technology adoption. For instance, Mo et al. (2021) and Wu & Chen (2016) have explored the combination of TAM and TTF to analyze the factors influencing online learning adoption during the COVID-19 pandemic. Their research demonstrates that both models contribute unique insights: TAM helps explain students' perceptions and attitudes toward using e-learning platforms, while TTF explains the extent to which these platforms align with their educational tasks and enhance learning outcomes.

The integrated TAM-TTF model acknowledges that technology adoption is influenced not only by user perceptions (PU and PEOU) but also by the practical fit of the technology to the task at hand. Dishaw and Strong (1998) asserted that TAM applications

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focus early in the result chain, predicting the intention to use or actual use, while TTF applications address actual use or individual performance later in the result chain. This dual approach enriches the explanatory power of each model and provides a more comprehensive framework for understanding e-learning adoption, especially in situations where task performance and technology alignment are crucial (Dishaw & Strong, 1998).

Research supports the notion that an integrated model holds greater explanatory power than either model alone, particularly in complex environments like e-learning (Vanduhe et al., 2020). By combining both constructs, researchers can better assess how students decide to adopt e-learning systems based on not only how easy and useful they perceive the platform to be but also how well it meets the demands of their educational tasks. Therefore, the integration of TAM and TTF is increasingly seen as a necessary framework for exploring e-learning adoption (Mo et al., 2021; Wu & Chen, 2016).

Adding Trust to the Model

In recent years, trust has emerged as a crucial factor in understanding technology adoption, especially in online environments where direct control is limited, and uncertainty is high (Roca et al., 2009; Wang, 2014). Trust plays a vital role in encouraging users to engage with technology, particularly when users cannot physically verify the quality or effectiveness of the system, as is often the case in e-learning. This makes trust an essential component in the adoption of e-learning platforms, where learners must rely on the system's ability to provide valuable and secure educational experiences (Shin, 2010).

Trust has been integrated into technology adoption models to enhance their explanatory power, particularly in contexts where security and reliability are significant concerns. For instance, Baby and Kannammal (2020) proposed an enhanced TAM3 for e-learning, where trust affects the behavioral intention to use such systems. They argued that traditional TAM models are more suited for general e-commerce or retailing but need modifications for specific contexts like e-learning, where trust in the system and the institution offering it becomes even more crucial.

In e-learning, trust can be seen as an essential mediator that influences students' perceptions of both the usefulness and ease of use of the platform. When learners trust that the system will protect their data, offer relevant content, and effectively enhance their knowledge, their willingness to adopt and engage with the platform increases. Trust, therefore, adds another layer of complexity to the TAM-TTF framework, as it addresses the psychological and emotional dimensions of technology adoption, which are particularly important in the online learning context (Roca et al., 2009; Baby & Kannammal, 2020).

Trust can also affect the long-term success of e-learning systems. Without trust, students may be hesitant to engage deeply with the platform or continue using it over time, regardless of how well the system fits their tasks or how useful it appears to be. Thus, adding trust to the TAM-TTF model can provide a more nuanced understanding of the factors that influence not only initial adoption but also the sustained use of e-learning systems.

The integration of TAM and TTF provides a robust framework for analyzing e-learning adoption by capturing both attitudinal and functional aspects of technology use. While TAM focuses on user perceptions of ease of use and usefulness, TTF evaluates the extent to which the technology aligns with users' tasks. Adding trust to this integrated model further enhances its explanatory power, particularly in the e-learning context, where trust in the platform plays a pivotal role in shaping user intentions. Understanding these factors is

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critical, not only for improving the effectiveness of e-learning systems but also for ensuring their sustained use, particularly during crises like the COVID-19 pandemic. By combining TAM, TTF, and trust, researchers and educators can gain a more comprehensive understanding of the factors that influence e-learning adoption and develop more effective strategies to support students in their transition to online learning environments.

RESEARCH METHODOLOGY

Research Model

Using the TAM (Davis, 1989) and the TTF model (Goodhue & Thompson, 1995), we propose a research model in which e-learning adoption and actual use of e-learning systems during the pandemic are predicted by several determinants. In addition to the TAM and TTF's constructs, we extend the model by adding Perceived Trust (PT). The relationship between the constructs is depicted in Figure 1.

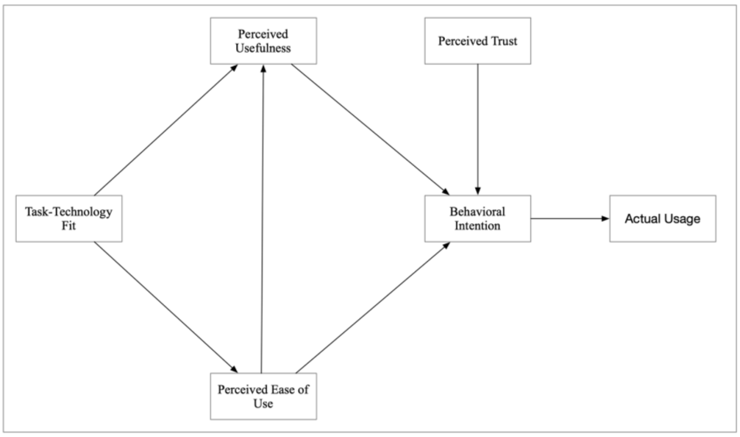

FIGURE 1
PROPOSED RESEARCH MODEL

Hypothesis

PU is "*the degree to which a person believes that using a particular system would enhance his or her job performance*," and PEOU is defined as "*the degree to which a person believes that using a particular system would be free of effort*" (Davis, 1989). In the e-learning context, learners' intention to adopt the system increases when they realize the system is advantageous. On the other hand, users tend to use an e-learning system if they find out it is easy to use. Many studies affirmed that PU positively affects Behavioral Intention (BI) (Agudo-Peregrina et al., 2014; Al-Gahtani, 2016; Eksail & Afari, 2020; Jaiyeoba & Iloanya, 2019; Kanwal & Rehman, 2017; Nikou & Maslov, 2021; Siron et al., 2020; Tarhini et al., 2017), and PEOU positively predicts BI (Al-Gahtani, 2016; Jaiyeoba & Iloanya, 2019; Mo et al., 2021; Siron et al., 2020; Tarhini et al., 2017; Wu & Chen, 2016). Hence, in our study, PU and PEOU are considered BI's predictors. Accordingly, we hypothesize:

H_1: *PU positively predicts BI to use e-learning systems.*

H_2: *PEOU positively predicts BI to use e-learning systems.*

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Built upon the TAM, our research model proposes that PEOU is a determinant of PU. Many researchers have confirmed that PEOU significantly affects PU (Al-Gahtani, 2016; Al-Rahmi et al., 2019; Eksail & Afari, 2020; Huang et al., 2019; Kanwal & Rehman, 2017; Mo et al., 2021; Nikou & Maslov, 2021; Park, 2009; Siron et al., 2020; Vanduhe et al., 2020; Wu & Chen, 2016). These studies indicated if the usage of the system is effortless, users will perceive it functional. Therefore, we hypothesize that:

H*$_3$*: *PEOU positively predicts PU of e-learning systems.*

PT by students is defined as *"the degree to which a student is willing to rely on the e-learning system and has faith and confidence in the instructor or the educational institution to take appropriate steps that help the student achieve his or her learning objectives"* (Wang, 2014). In fact, trust refers to the reliability and trustworthiness of e-learning systems (Almaiah & Al Mulhem, 2019). Whereas trust widely have been studied in e-commerce contexts (such as Fang et al., 2014 and Gefen et al., 2003), it has been investigated insufficiently in the context of e-learning (Wang, 2014). Since the impact of trust might differ in every culture and technology (Salloum et al., 2019), we examine its importance in Iran and from e-learners perspectives. Trust predicts BI because learners are willing to use the system when they feel it is secure and trustable (El-Masri & Tarhini, 2017). As many researchers believe, trust affects the adoption rate. When the level of trust is satisfying, learners' tendency to adopt the system increases (El-Masri & Tarhini, 2017). Hence, in addition to PU and PEOU, PT affects BI positively. So, we posit:

H*$_4$*: *PT positively predicts BI to use e-learning systems.*

TTF is considered the determinant of both PU and PEOU. TTF is the correspondence between task requirements, individual abilities, and the functionality of the technology, according to Goodhue & Thompson (1995). In the current circumstance, e-learning, adopted to prevent the spread of the virus, is the technology, learning goals are the task under the Covid-19 pandemic (Lin et al., 2021), and learners are the performer of the task. It is highly likely that users accept the technology if the technology matches the job (Vanduhe et al., 2020). Previous studies showed that TTF has a significant influence on both PEOU and PU (Mo et al., 2021). However, some studies confirmed that TTF only affects PEOU, not PU (Vanduhe et al., 2020; Wu & Chen, 2016). When learners realize the technology used in an e-learning system is capable of meeting the objectives, users' perception of the system usefulness improves. On the other hand, the match between task requirements and the functionality of the technology makes tasks effortless for users. Accordingly, we assert:

H*$_5$*: *TTF positively predicts PU of e-learning systems.*

H*$_6$*: *TTF positively predicts PEOU of e-learning systems.*

Finally, Actual Use of e-learning systems by students is determined by BI. BI is defined as *"a measure of the strength of an individual's willingness to perform a behavior"*(Kim et al., 2009). Students will adopt e-learning systems if they are ready to use. BI significantly affects adoption of technology in many previous studies (Jaiyeoba & Iloanya, 2019; Tarhini et al., 2017). Hence, we hypothesize:

H*$_7$*: *BI positively predicts Actual Use of e-learning systems.*

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DISCUSSION

This study analyzed the factors influencing e-learning adoption during the COVID-19 pandemic, based on a sample of **321 valid responses** collected from **entrepreneurship students in Iran**. To explore the relationships between the key constructs, **Structural Equation Modeling (SEM)** was employed using **AMOS** software, allowing for an in-depth analysis of the factors driving the adoption of e-learning platforms.

Table 1 presents the correlation matrix, showcasing the relationships between the variables in the study, while Table 2 provides descriptive statistics for the data set.

Table 1
CORRELATION MATRIX OF CONSTRUCTS

Construct	PU	PEOU	Trust	TTF	BI	Actual Use
Perceived Usefulness (PU)	1	0.09	0.07	0.07	-0.02	0.05
Perceived Ease of Use (PEOU)	0.09	1	0.03	0.09	-0.04	-0.09
Trust	0.07	0.03	1	-0.04	0.07	0.03
Task Technology Fit (TTF)	0.07	0.09	-0.04	1	0	0.03
Behavioral Intention (BI)	-0.02	-0.04	0.07	0	1	0.01
Actual Use	0.05	-0.09	0.03	0.03	0.01	1

The analysis showed that **Perceived Usefulness (PU)** had a mean of 4.01, and while it is critical for positive attitudes toward e-learning systems, its influence on **Behavioral Intention (BI)** was limited (-0.02 correlation). This suggests that while students find e-learning beneficial, other factors significantly influence their actual intention to adopt the technology.

Perceived Ease of Use (PEOU) showed the highest mean score (4.49), indicating that students find e-learning systems user-friendly. However, the correlation with **Actual Use** (-0.09) suggests that ease of use alone does not drive engagement with e-learning platforms, a finding consistent with existing literature that ease of use must be complemented by engagement and relevance (Al-Gahtani, 2016).

Trust in the e-learning platform had a mean of 4.06, playing a vital role in students' willingness to use these systems. The positive correlation between **Trust** and **Behavioral Intention** (0.07) highlights the importance of building secure, reliable platforms, especially in remote learning environments (Wang, 2014).

Task Technology Fit (TTF) had a mean score of 4.26, indicating that students perceive e-learning systems as a good match for their academic tasks. However, its weak correlation with **Behavioral Intention** (-0.00) suggests that while students believe the system is technically capable, other motivational factors, such as content quality and instructor involvement, are necessary to drive their intention to use it.

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Table 2
DESCRIPTIVE STATISTICS

Construct	Mean	Standard Deviation	Min	Max
Perceived Usefulness (PU)	4.01	0.58	2.06	6.31
Perceived Ease of Use (PEOU)	4.49	0.5	3.26	6.04
Trust	4.06	0.68	2.11	5.84
Task Technology Fit (TTF)	4.26	0.66	2.32	5.88
Behavioral Intention (BI)	4.32	0.61	2.55	5.86
Actual Use	4.14	0.67	2.21	6.34

Practical Implications

Based on the analysis conducted using **AMOS** and the **SEM** methodology, several practical implications arise for educational institutions aiming to improve e-learning adoption. First, they must prioritize building **trust** in their platforms. As shown in the results, trust is positively associated with **Behavioral Intention** and can be enhanced through measures like improved data security, reliable performance, and consistent technical support.

Second, while **Perceived Ease of Use** is essential, it is not enough to drive **Actual Use**. Institutions should also ensure that the e-learning platform fits students' tasks (high **Task Technology Fit**) and engages them through interactive tools and personalized learning paths. This alignment between technology and tasks is critical for fostering sustained engagement.

FUTURE DIRECTIONS

Future research should consider expanding the sample size and incorporating cross-cultural studies to understand how e-learning adoption differs between countries. Comparing the results between **developing and developed nations** would provide additional insights into how technological infrastructure and access influence the adoption of e-learning.

Additionally, longitudinal studies would allow researchers to track changes in student attitudes over time, as the initial forced shift to e-learning due to the pandemic may differ from voluntary engagement in the future. This would provide a clearer understanding of long-term adoption trends.

Incorporating variables like **social influence**, **instructor digital competency**, and **peer support** could also reveal other factors affecting e-learning usage, providing a more holistic picture of what drives student engagement in different settings.

LIMITATIONS

This study has several limitations. The data was collected solely from **university students majoring entrepreneurship in Iran**, which limits the generalizability of the findings. Furthermore, the study was conducted during the pandemic, when e-learning was mandatory, potentially introducing biases into the responses. Future research should consider

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a more **voluntary** e-learning environment to examine whether the findings hold in non-crisis contexts.

Additionally, the study focused exclusively on students' perspectives, overlooking the **roles of instructors and administrators**. Including these groups in future research would provide a more comprehensive understanding of e-learning adoption, as their involvement is crucial to the system's success.

The use of **self-reported data** may also introduce biases such as **social desirability** or **recall bias**. Future studies could complement quantitative approaches like SEM with qualitative methods such as interviews or focus groups to gain deeper insights.

CONCLUSION

The findings from this study provide valuable insights into the factors affecting e-learning adoption during the COVID-19 pandemic. Based on a sample of **321 students**, analyzed using **Structural Equation Modeling (SEM)** via **AMOS software**, the study demonstrates that **Perceived Usefulness**, **Perceived Ease of Use**, **Trust**, and **Task Technology Fit** all play critical roles in shaping students' **Behavioral Intention** and **Actual Use** of e-learning platforms.

Educational institutions must go beyond ease of use to build trust and ensure that e-learning systems align with students' academic tasks. By doing so, they can improve the adoption and effectiveness of these systems, ensuring their success even in a post-pandemic educational landscape.

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