



Review

The Development and Adoption of Online Learning in Pre- and Post-COVID-19: Combination of Technological System Evolution Theory and Unified Theory of Acceptance and Use of Technology

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Abstract: After the outbreak of COVID-19, schools heavily depend on e-learning technologies and tools to shift from in-person class to online. This review article analyzes the changes of technology evolution and technology adoption of e-learning in pre- and post-COVID-19 based on the Technology System Evaluation Theory (TSET) and technology adoption of e-learning based on the Unified Theory of Acceptance and Use of Technology (UTAUT). We intend to explore the interaction of technology evolution and technology adoption in the different focus of e-learning technology in the two stages and the particularity and heterogeneity of the UTAUT model. The results indicate that (1) The moderating results of technology evolution are proposed and evaluated under the UTAUT model before the COVID-19 outbreak. Studies after the COVID-19 pandemic paid more attention to technology efficiency rather than effectiveness; (2) Research on e-learning focuses on the infrastructure to reach more users after the outbreak of COVID-19 because e-learning is the only way to continue education; (3) COVID-19 fear moderates the relationship between the external factors and the behavior intention of e-learning users. The lack of financial support on technology evolution will directly weaken the implementation of new technology. Social Isolation offers more opportunities for students to engage in e-learning. Meanwhile, it slows down the implementation of e-learning because of out-to-date hardware and software. This article offers an enhanced understanding of the interaction of technology evolution and technology adoption under unexpected environments and provides practical insights into how to promote new technology in a way that users will accept and use easily. This study can be tested and extended by empirical research in the future.

Keywords: COVID-19; education; e-learning; technology system evaluation theory (TSET); TRIZ; unified theory of acceptance and use of technology (UTAUT)

1. Introduction

The outbreak of COVID-19 occurred significant changes in different industries (Yue et al. 2020a, 2020b), especially in the field of education. Most businesses are affected, and citizens and employees are encouraged or forced to do business remotely from home. The demand for using appropriate technologies is increasing (Sepasgozar et al. 2020). More than 1.5 billion students ranging from primary school to university had to study at home highly relying on digital education platforms during the COVID-19 pandemic (UNESCO 2020). E-learning has become an irreplaceable part of the home class and home office (Almaiah et al. 2020; Siriwardhana et al. 2020; Smalley 2020; Wu et al. 2020; Ye 2020). This situation turns e-learning from an option to support face-to-face teaching into a necessary

reality. The department of Education of Australia announced to offer online education to the students who are affected by COVID-19 and its travel ban ([The Department of Education and Skills and Employment, Australian Government 2020](#)). In the United States, in-person classes were either canceled or shifted to online learning in the spring semester of 2020 ([Smalley 2020](#)). The Ministry of Education of China delayed the spring semester of 2020 ([Ministry of Education, PRC 2020](#)) and instructed schools to conduct online classes to obey the government's quarantine order ([Yuan 2020](#)). The necessity of e-learning could promote capital investment and technological innovation.

The unexpected pandemic in 2020 accelerated the exposure of opportunities and challenges of e-learning. Early initiatives of e-learning were focused on the functional understanding and technical skills of information and communication technologies ([Klasnic et al. 2008](#)). The previous research directions were oriented to personal satisfaction, motivation and contextualization which are reflected in the quality of e-learning ([Klasnic et al. 2008](#)). However, when e-learning became a necessity nowadays, the reality is that e-learning is excluded from many undeveloped countries geographically due to the lack of internet facilities and computers or the inability to afford the high cost of accessing the Internet. It should be noted that how e-learning can be improved in the respective of its technology evolution if it is the only way for education when facing new influencer, such as COVID-19 in this case.

This article also investigates the role of COVID-19 in the relationships between the behavior intention of e-learning users and its exogenous factors (i.e., performance expectancy, effort expectancy, social influence, facilitating condition). During the COVID-19 pandemic, the effectiveness and efficacy of e-learning for students in different age groups have been challenges. Their intention to accept and use e-learning was changed because of the decrease of financial support on education as well as the increase of social isolation. While e-learning is actively promoted, there are potential inequalities in the educational system worldwide. That is why we study the technology evolution and technology adoption of e-learning in this article to better understand and implement e-learning in the future.

The theoretical foundation for our research study is drawn from the Technology System Evaluation Theory (TSET) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Technology System Evaluation Theory (TSET) demonstrates the principles of technology evolution ([Wang et al. 2010](#); [Gadd 2011](#); [Sun and Tan 2012](#); [Ilevbare et al. 2013](#); [Hou et al. 2015](#)). Unified Theory of Acceptance and Use of Technology (UTAUT) details the acceptance and the use of technology ([Marchewka and Kostiwa 2007](#); [Venkatesh et al. 2016](#)).

This study will contribute to relevant research from three aspects. First, we implement Technology System Evaluation Theory (TSET) to compare the changes of e-learning technologies in pre- and post-COVID-19. It helps to enhance the understanding of the technology evolution of e-learning given the unexpected global pandemic, in particular, the increasing number of e-learning research into relative infrastructure including 5G and IoT. Second, we apply the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze the change of the behavior intention of e-learning in COVID-19. The UTAUT model is expanded with a moderator factor named COVID-19 fear. We discover financial support and social influence as new external factors in the updated model. The expended UTAUT model offers a guideline to analyze technology adoption in different scenarios. It also specifies social isolation and the importance of financial support in the case of COVID-19. Third, after realizing technology evolution and technology adoption are not isolated in practical, we combine Technology System Evaluation Theory (TSET) and Unified Theory of Acceptance and Use of Technology (UTAUT) to answer our research questions. This combination extends the research boundary of these two theories as well as explains the interaction of COVID-19-related external factors, e-learning changes and behavior intention of e-learning users. These contributions provide significant suggestions for technology developers and policymakers in practice through considering influential factors of user intention.

The rest of the paper is organized as follows. We begin with the introduction of two foundational theories: Technology System Evaluation Theory (TSET) and Unified

Theory of Acceptance and Use of Technology (UTAUT). Then, we discuss the development trend of e-learning technology under Technology System Evaluation Theory (TSET) before the COVID-19 pandemic and after the pandemic, respectively. After that, we review the influence of each external factor on the behavior intention of e-learning users before COVID-19 and then expand the Unified Theory of Acceptance and Use of Technology (UTAUT) by adding COVID-19 fear as a new moderator factor to monitor the change of behavior intention affected by social isolation and insufficient financial support.

2. Theoretical Frameworks

2.1. Technology System Evolution Theory (TSET)

Before discussing Technology System Evolution Theory (TSET), another theory—Theory of Inventive Problem Solving (TRIZ) by Dr. Genrich S. Altshuller—will be introduced first because Technology System Evolution Theory (TSET) is one of the most essential sub-theories of Theory of Inventive Problem Solving (TRIZ) (Hou et al. 2015). Theory of Inventive Problem Solving (TRIZ) is the theory that aims to solve problems and then to create new ideas and innovation (Ilevbare et al. 2013). Technological systems generally follow certain regularities that are translated into eight evolution patterns for better problem solutions and evolution prediction (Gadd 2011; Ilevbare et al. 2013; Hou et al. 2015). The eight patterns are (1) principles of completion, (2) principles of energy transfer, (3) principles of harmonization, (4) increasing dynamism and controllability, (5) increasing ideality, (6) uneven development of subsystems, (7) increasing complexity followed by simplicity through integration, (8) transition from macro-systems to micro-systems (Hou et al. 2015).

2.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

A number of theoretical models have been proposed to facilitate the understanding of factors impacting the acceptance of information technologies (Marchewka and Kostiwa 2007). Among these studies, Technology Acceptance Model (TAM) is one of the most influential and robust models in explaining IT/IS adoption behavior. Venkatesh et al. (2016) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) model to consolidate previous TAM-related studies. UTAUT identifies four key factors (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderators (i.e., age, gender, experience, and voluntariness) to predict the behavioral intention of the use of technology and an actual technology used primarily in organizational contexts (Venkatesh et al. 2016). Unified Theory of Acceptance and Use of Technology (UTAUT) explained 77 percent of the variance in behavioral intention to use technology and 52 percent of the variance in technology use (Venkatesh et al. 2016).

3. Technological Evolution of E-Learning under Technology System Evaluation Theory (TSET)

The proliferation of information and communication technologies (ICTs) promotes the application of e-learning in the education area (Klašnja-Milićević et al. 2011), in which people can access online learning or teaching resources without a location limitation. As a result, e-learning plays a significant role in currently existing learning approaches. Featured of portability, it allows students to learn at any time and anywhere (Rodrigues et al. 2019). However, with increasingly accessible resources, the overwhelming amount of e-learning information brings difficulties for learners to search for appropriate information in fulfilling their needs (Ghauth and Abdullah 2010). Recommendation systems may create an effective method to solve the problem of information overload in the e-learning environment. Depending on students' dynamic preferences and interests (Ravi et al. 2019), these systems can recommend users with personalized online products or services (Lu et al. 2015), support users in locating relevant education contents (Khribi et al. 2015), make online resources more convenient (Tarus et al. 2017), and further to enhance personalized recommendations (Ravi et al. 2019).

Additionally, new technologies can also improve and evolve previous applications (Wang et al. 2020b). Automatic classifications of facial features create digital interlocutors that optimize the interactions between humans and machines (Fuentes-Hurtado et al. 2019). Machine-learning updates the quality and design of previous applications, making them more intelligent and flexible (Rachad and Idri 2020). Data mining algorithm contributes to evaluate e-learning courses about the validity of the ranking positions and their quantity and quality of contents (Kazanidis et al. 2020). The complementarity among techniques in the electronic learning system positively influences the whole systems' effectiveness (Navimipour and Soltani 2016).

After the outbreak of COVID-19, the technological factor is one of the critical factors to ensure the successful implementation of e-learning systems. Physical equipment, such as computers, servers, and communication networks, is necessary for the implementation of e-learning. Moreover, the availability of software applications and operating systems are also important (Almaiah et al. 2020). For instance, 5G services and Internet of Things (IoT) provide better indoor connectivity with small cell Next-generation Base Stations, in which students can stream online contents with low latency (Siriwardhana et al. 2020; Wu et al. 2020; Ye 2020). Changes in practices have enabled key industries of the information technology market or information system (Venkatesh et al. 2016) market to expand quickly to accommodate the surging demand for distance applications such as Zoom, WebEx, and Microsoft Teams (Dwivedi et al. 2020). In addition, attention to cybersecurity has been raised because hackers imitate a number of look-a-like free websites by hosting malicious codes during the COVID-19 period (Dwivedi et al. 2020).

4. Technological Adoption of E-Learning under Unified Theory of Acceptance and Use of Technology (UTAUT)

E-learning is not only a kind of virtual or distance education to deliver content in electronic ways also a real-time and simultaneous interaction between learners and instructors (Baporikar 2014). It is gradually playing an important role in education regarding its potential advantages: higher quality of learning, easier access to education, less cost, and more effective learning (Gilbert et al. 2007). To understand these advantages and further facilitate of adoption of online learning, this article expands the UTAUT model to compare factors promoting e-learning usage before and after the COVID-19 outbreak (see Figures 1 and 2).

4.1. E-Learning Adoption before COVID-19 Outbreak

4.1.1. Performance Expectancy

Performance Expectancy (Hurley and Dyke 2020) refers to the range of an individual's perception based on the usefulness of technology (Venkatesh et al. 2016). System quality and information quality including reliability, response time, content, and availability can determine the performance of information systems (Heo and Han 2003). Service quality and system use are added into the determinants of usefulness (Wang et al. 2007). Ease of use and system supportability should also be considered as the determinates of usefulness (Chen and Liu 2013). Because usefulness is hard to measure in a standard, many studies provided various methods to determine and test the relationship between PE and the acceptance and adoption of e-learning. Security, privacy, non-deception, fulfillment, and service recovery influences user satisfaction regarding e-learning (Elbeltagi and Agag 2016; Yang et al. 2019). Behavioral Intention has been considered as the level of commitment regarding an individual's engagement in a certain behavior the direct effect of PE on the Behavior Intention of using e-learning has been proved (Raza et al. 2020). The degrees of satisfaction and expectation confirmation have positive effects on whether users continue to use knowledge-sharing platforms (Pang et al. 2020).

4.1.2. Effort Expectancy

Effort Expectancy (EE) refers to the amount of effort that an individual receives from using e-learning (Raza et al. 2020). There is a debate about whether EE has positive or negative impacts on BI. It is significant to consider teachers' characteristics, teaching materials, and the design of learning contents when investigating the effort of e-learning (Lee et al. 2009). Meanwhile, from the perspective of student users, the differences in culture dimensions include masculinity/femininity, individualism/collectivism, power distance, and uncertainty avoidance (Tarhini et al. 2016). They all contribute to an individual's BI regarding the adoption of e-learning (HofstedeGeert and Minkov 2010). General research typically focuses on the impacts of sociodemographic factors while ignored potential interactive impacts on other relevant factors (Katharina et al. 2015). Research further explained that the sociodemographic characteristics represent both their membership in the sociality, their individual targets, motivations and the personal needs which directly related to their education and career pathway (Katharina et al. 2015).

4.1.3. Social Influence

Social Influence (SI) contains the external social environments related to an individual's Behavior Intention such as the reflection of peers, instructors and subjective social conditions (Venkatesh et al. 2016). There is a direct relationship of Social Influence on Behavior Intention regarding the implementation of e-learning (Raza et al. 2020). Besides those soft and indirect influences provided by peers, the governmental policies as enforcement tools are also important to determine an individual's Behavior Intention within different societies (Chen and Liu 2013). Generally, the major purpose of government policies is to achieve established administrative objectives. Governmental agencies play a meaningful role in affecting personal acceptance and adoption of innovations (Lynne et al. 1995). There was a strong and positive correlation between social pressure and competition with the implementation of e-learning (Law et al. 2010). Rewards can cause positive stimuli to decisions of daily behavior (Delgado et al. 2000). Learning combined with rewards is a way to stimulate personal motivation (Grant 1989). The research towards the willingness of employee participation in e-learning shows that it can be increased by providing incentives and rewards (Rosenberg and Foshay 2002). Rewards and praise stimulate are the most effective promotion (Law et al. 2010). Combining appropriate rewards and praise can be a primary driving force in learning (Jenkins 2001). In conclusion, governmental, affiliated organizational pressure and reward policies can have impacts on the acceptance and adaptation of e-learning.

4.1.4. Facilitating Conditions

Facilitating Conditions (FC) means the availability of adequate support and resources for the proper use of technology (Venkatesh et al. 2016). A fundamental component of e-learning acceptance and adoption has to rely on network infrastructures, and it is the essential element of e-learning (Baker 2013). However, the inequalities in access to education resulted from the issue of the "digital divide" is spreading internationally. The following Table 1 elicits the internet usage by world region. According to the data provided by Statista, it shows a clear emerging inequality between regions and elements of the population around the world. The online usage penetration of Europe achieved the highest at 97 percent while that of Africa was even below the global average of 57 percent, at only 42 percent.

Table 1. The Internet Usage by World Region.

World Region	Number of Internet Users 2020 (in Millions)	Penetration (% Population)
Asian	2525.03	54
Europe	727.85	97
North America	332.91	90
Latin America	467.82	72
Africa	566.14	42
Oceania/Australia	28.92	68

Note: Based on data extracted from <http://www.internetworldstats.com/stats.html>, accessed on 10 December 2020.

4.1.5. Effects of Technology Development

Technology development advances e-learning adoption. Specifically, a significant number of technologies of e-learning have contributed to performance expectancy and facilitating conditions. In term of performance expectancy, referred to as ease of use and user satisfaction, the information communication technologies relax the location restriction where people access online learning or teaching resources; machine-learning updates the quality and design of applications, realizing more intelligent and flexible ones; recommendation systems help users more easily find a needed class; data mining algorithm contributes to evaluate e-learning courses in term of the validity. All the technological complementarity promotes the effectiveness of e-learning systems and facilitating conditions.

4.1.6. Behavioral Intention and Use Behavior

Behavioral Intention (Nabity-Grover et al. 2020) can be reflected by the level of commitment regarding an individual's engagement in a certain behavior (Ngai et al. 2007). Accordingly, students' Behavioral Intention towards e-learning can be assessed by the degree of students' commitment regarding the acceptance and adoption of e-learning to achieve their educational objectives. Users' experiences are the key factors for the test of Behavior Intention and Use Behavior because they can be used to qualify and provide a specific standard to the engagement of students' commitment (Ghasemaghahi and Hasanein 2016). Research shows that students with low engagement levels in e-learning usually feel boring, unengaging and easily misunderstanding (Kim et al. 2019). In contrast, students, who have a high level of engagement when they participate in e-learning proceedings, with high-level engagement of e-learning can overcome impediments both in space and time (McKnight 2004). E-learning is a helpful tool to enhance medical practice regarding its universal availability, asynchronous accessibility, interactivity, integration of implementation tools, and low cost for the users (Nicastro et al. 2015).

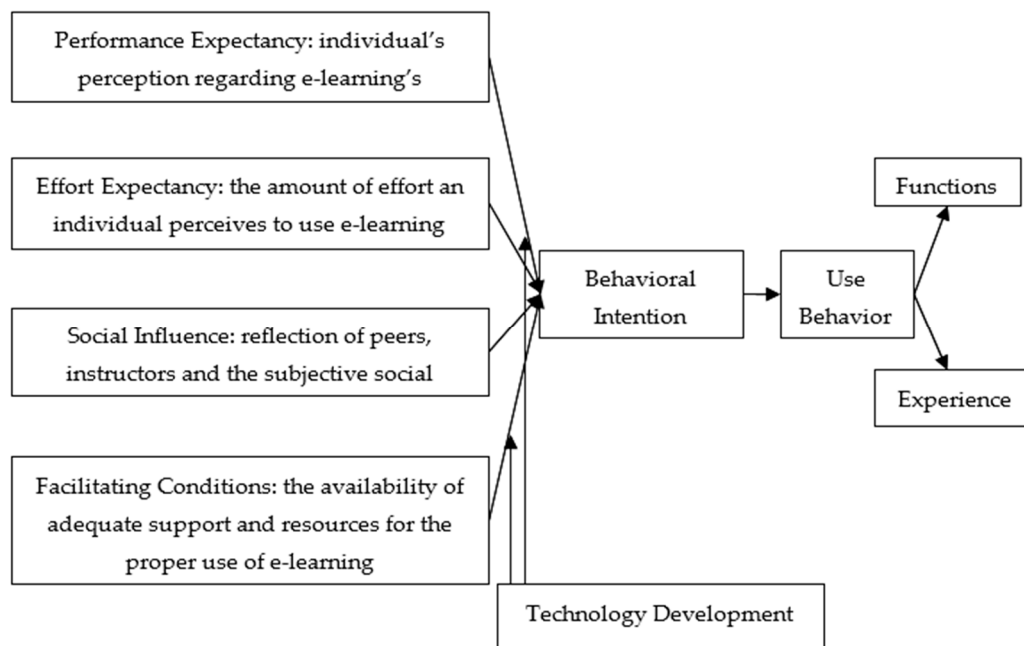


Figure 1. E-learning Adoption before the COVID-19 pandemic under UTAUT (Unified Theory of Acceptance and Use of Technology).

4.2. E-Learning Adoption after COVID-19 Outbreak

Performance Expectancy and Effort Expectancy

Self-efficacy is defined as the measurement of the degree or strength of an individual's belief in the ability to complete tasks and achieve goals. Whether students are motivated and feel confident in using e-learning systems is correlated to systems' successful adoption. There exists a strong relationship between self-efficacy and e-learning success. The role of learning engagement during the procedure of technology-mediated learning has demonstrated that students' behavior through remote learning was affected by self-efficacy (Hu and Hui 2012). Self-efficacy is correlated to abilities related to technology adoption, contributing to the engagement level during digital education (Wang and Newlin 2002). Students with a higher level of self-efficacy are prospected to earn a higher mark in the exam (Wang and Newlin 2002). Even during the COVID-19 pandemic, self-efficacy was continuing regarded as one of the factors influencing the usage of e-learning systems in some higher education institutions (Almaiah et al. 2020).

Performance Expectancy (Hurley and Dyke 2020) is the extent of an individual's perception regarding technology's utility and Effort Expectancy (EE) is regarded as how much effort an individual would like to invest in using technology (Dečman 2015). Both PE (Pang et al. 2020) and EE are psychological factors influencing an individual's adoption of technologies in the UTAUT model. EE is the antecedent to performance expectancy and effort expectancy (Brown et al. 2010). On the other hand, performance expectancy is positively influenced by self-efficacy. People with higher expectations towards technologies would therefore generate better task performance (Brown et al. 2010).

E-learning was used to be an auxiliary learning method due to its low cost and flexibility. Combining in-person learning and a remote approach helps students enhance their learning skills as well as awareness of life-long learning (Dhawan 2020). However, a series of government policies triggered by COVID-19 caused students to complete their studies in a quarantine manner. Many universities around the world have fully digitalized their operations. E-learning, therefore, became a necessity instead of an option in this circumstance (Dhawan 2020). Since e-learning has been more frequently and widely used during the post-COVID-19 period and has played an irreplaceable role in the education industry, the influence of self-efficacy on e-learning adoption should be paid more attention to.

4.3. Facilitating Condition

4.3.1. Financial Factor

The tertiary sector of Australia's education industry has been forced to rapidly respond to the outbreak of the novel coronavirus (COVID-19), which in turn has exposed it to new financial risks and its over-dependence on international markets (Thatcher et al. 2020). Australian universities in particular are now dealing with the prospect of losing up to \$19 billion in revenue by 2023 as a result of their reliance on tuition fees from international students, many of whom are currently unable to travel to Australia (Hurley and Dyke 2020). Both maintenance and operation of E-learning system and hiring IT experts need funding. Students' learning during the COVID-19 pandemic is completely dependent on the online system. As a result, the lack of funds to maintain the online system will affect the usage of e-learning. It has already been predicted by some higher education institutions (HEIs) that the economic recession resulted from COVID-19 would have an impact on international students and their families and cause unexpected university closure in short term and long term. To study the impact of COVID-19 on higher education institutions, the International Association of Universities (IAU) has conducted a Global Survey, collected around 600 responses from over a hundred universities across the world. According to the results, many respondents admitted that financial reduction is the most significant challenge that they are currently facing. Some of the interviewees agree that the long-term financial consequence is not optimistic.

The financial consequences of the current health crisis and the global economic recession may lead to a decline in student enrollment. More than 80% of interviewees believe that COVID-19 will have an impact on students enrolled in the new academic year, therefore having a direct negative influence on revenues. In this case, HEIs, especially those private education sectors, whose financial sources heavily rely on the enrollments would be severely affected (Marinoni et al. 2020). Some countries have already cut their education budgets to make space for the required spending on health and social protection. For those countries with average low- and medium-income levels, the expected spending on education which should have been increased is possible to be cut due to the pandemic in 2020 (Al-Samarrai et al. 2020). For example, universities have a limited budget to develop e-learning systems in Jordan (Al-Samarrai et al. 2020). Governments in developed countries such as UK and Australia did not quickly react to requirements from universities for additional funding in response to COVID-19. They prefer to allocate a budget to solve regional economic problems and employment problems, enhancing local economic recovery in priority (Brammer and Clark 2020). E-learning is challenged under COVID-19 in both developing and developed countries.

4.3.2. Technology Factor

Technology is a vital factor to ensure the implementation of the e-learning process. Poor Internet infrastructure, the acceptability of smartphones in education and the unfriendly digital classroom environment during the COVID-19 pandemic negatively influenced the expectation of e-learning (Zheng et al. 2020). While online teaching technology benefits students in e-learning, there are also many difficulties for students to adapt to the online system, such as login problems, installation and download problems. Students sometimes lose a sense of engagement because of those problems (Dhawan 2020).

A successful e-learning system should be designed to satisfy students' needs and be adopted easily (Almaiah et al. 2020). Except for these obstacles resulted from the e-learning system itself, distance learning through online channels remains a challenge in some developing countries due to the relatively low accessible rate of Internet services, devices and related technologies (Zheng et al. 2020). For example, e-learning for students in Pakistan has been negatively affected due to the lack of stable and affordable internet connections, the problem is particularly serious for those who come from rural areas. The limitation of the device also hinders the remote learning process. Students with no access to computers could only access online content through mobile phones. They can not take full

advantage of e-learning because a significant amount of content in an e-learning system is only available on the computer because of system compatibility (Adnan and Anwar 2020). Not only hardware and software should be taken into consideration, it was mentioned by experts that technology support helping users with solving technical problems is also essential (Almaiah et al. 2020).

4.4. Social Influence and Behavioral Intention: Social Isolation and COVID-19 Fear

UTAUT is a well-developed model which could explain more than 70% variation corresponding to factors influencing technology system adoption (Raza et al. 2020). UTAUT has been extended during the COVID-19 pandemic. Social isolation and COVID-19 fear are taken into consideration on the basis of the original UTAUT model. Social isolation is defined as the isolation caused due to lack of effective connections with others (De Jong Gierveld et al. 2006). To prevent the virus from spreading, policies such as lockdown and quarantine have reduced interactions among people, leading to the occurrence of social isolation. Social isolation is the additional factor improving behavior intention of e-learning usage. Students who are socially isolated are positively encouraged to study online through the e-learning system (De Jong Gierveld et al. 2006). COVID-19 fear is a situational response due to the threats of COVID-19 (Mertens et al. 2020). As Figure 2 shows, COVID-19 fear acts as the role of moderator factor adjusting the relationship between five factors in the UTAUT model and Behavioral Intention on adapting the e-learning system (Raza et al. 2020).

Social Isolation is significantly positively correlated to individuals' behavior intention on Learning Management System, therefore has a positive impact on consumer behavior in adopting E-learning system. Performance Expectancy (Pang et al. 2020), Social Influence (SI) and behavior Intention (Nabity-Grover et al. 2020) of e-learning systems can be moderated by COVID-19 fear. In other words, the presence of COVID-19 fear strengthens the link between PE, SI, and BI. The moderating effect of COVID-19 fear was statistically significant and had a negative impact on PE and a positive influence on SI, suggesting that the more COVID-19 fear a student experienced, users are less likely to adopt e-learning systems due to performance expectation while they are more likely to use the online tools after listening to insights from their peers, friends, instructors and classmates (Raza et al. 2020).

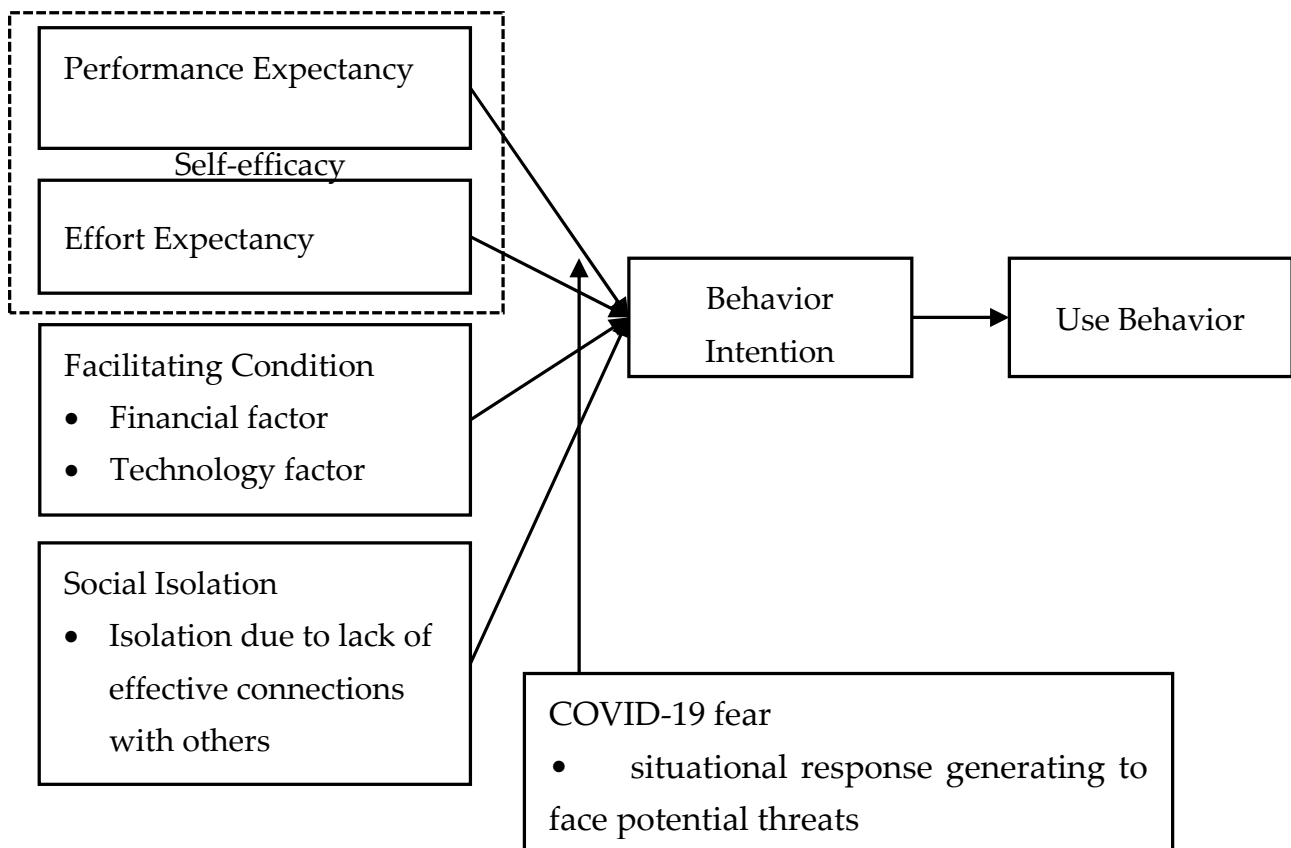


Figure 2. E-learning Adoption after the COVID-19 pandemic under UTAUT.

5. Discussion

5.1. Technological Evolution of Online Learning in the Two Stages

The function of e-learning is to promote the exchange of knowledge and interactions between teachers and students by digital devices, the internet and ICTs. Facing overloading information, users of e-learning started to apply recommendation systems to obtain personalized learning resources. Machine learning, automatic classifications, and data mining algorithm, continuously improved flexibility and dynamism. E-learning system has experienced evolutions of flexibility, dynamism, ideality, and micro-system transformation when it was equipped with fundamental functions under the harmonization of several sub-technical systems.

During the period of COVID-19, hardware and software are important elements for e-learning. IoT increased the possibility of the internet and 5G networking decreased latency. As a result, communicators can interact in a shorter response time, increasing the efficiency of information transfer and reaching ideality. The implement of IoT and 5G in e-learning ushered the dynamic evolution of the e-learning system.

5.2. Differences in E-Learning under Technology System Evaluation Theory (TEST) and Unified Theory of Acceptance and Use of Technology (UTAUT)

5.2.1. E-learning Became from Complementary to Necessity

There are obvious changes in e-learning by comparing it in pre-COVID 19 with that in post-COVID 19. Studies before COVID 19 emphasize the determinants which affect the acceptance and adoption of e-learning. They discuss whether use e-learning (Online Learning: A Panacea in the Time of COVID-19). At the early stage of e-learning study, researchers focus on its functional understanding and technical skills. The perspectives include user satisfaction and user motivation in terms of the quality of e-learning (Klasnic et al. 2008).

On the other side, studies after the COVID-19 pandemic focus on the impact of applying e-learning with the improvement of e-learning's quality and effectiveness. E-learning became complementary to necessity. For instance, most face-to-face teachings were abolished by the Ministry of Education of the People's Republic of China (Wang et al. 2020a). It also denounced a policy called 'Disrupted classes, undisrupted learning' to provide online learning to over 270 million students. Most Chinese students, involving undergraduate medical students, attend formal online courses from their own homes regarding the research (Wang et al. 2020a). Simultaneously, K-12 (kindergarten to 12th grade) schools in the United States had to close due to the COVID-19 pandemic in the spring of 2020 to protect the well-being of society (Kaden 2020). They responded to the pandemic in various ways regarding location, infrastructure, financial resources, socioeconomics, and community needs (Kaden 2020). This unplanned and unprecedented disruption to society and education caused the schooling to migrate to an online environment (Kaden 2020). This trend seems to represent the changing of most countries when they reacted to COVID-19.

5.2.2. The Changes on Determinates Regarding the Facilitating Condition

E-learning is restricted by facilitating conditions. Before the COVID-19 pandemic, studies pay more attention to governmental pressure and reward policies relating to the implementation of e-learning. Due to the COVID-19 pandemic, Even the performance of the market and stocks are quite different, most stock market indexes decreased after the COVID-19 pandemic (Wójcik and Ioannou 2020). The health care sector which heavily depended on governmental support lost 10 percent globally, while the energy sector lost the most at 33 percent (Figure 3).

Sector	19 February to 9 April
Health care	-10%
Consumer staples	-11%
Utilities	-16%
Communication services	-17%
Information technology	-18%
Materials	-18%
Consumer discretionary	-21%
Real estate	-22%
Industrials	-24%
Financials	-27%
Energy	-33%

Figure 3. Changes in Global Stock Market Index. Note: based on data of S&P Global indices by sector from S&P Global Intelligence database.

Regarding those negative financial impacts, studies after the COVID-19 pandemic focus more on the financial support issues which are highly related to the implementation of e-learning, because most educational institutions have a limited budget to develop e-learning systems. Meanwhile, government, in most circumstances, represents an essential financial source for those institutions during the pandemic. On the other side, there are some methods to improve the wideness and deepness of e-learning. For the wideness, it means how to help more learners access to e-learning system. For the deepness, it means more e-learning functions are provided to users. Financial support issues, external distraction, family interruption, and management issues all became the major concerns after the COVID-19 pandemic.

5.2.3. New Problems Caused by Social Isolation

Even the governmental policies regarding Social Isolation are different in countries, they all experienced new challenges. Considering COVID-19 fear caused by COVID-19, public education in most countries decided to change from in-person to online. Teachers had to deal with huge changes in education contents and conditions in unfamiliar ways, for example, a lack of technical knowledge, negative attitude, course integration with technology and a lack of motivation. Even though some types of technology are not brand new, it became a challenge when education depends on e-learning during COVID-19.

5.2.4. The Mediating Effect of COVID-19 Fear after COVID-19

The role of psychological factors has changed after the COVID-19 pandemic. Most studies in pre-COVID-19 elicited psychological factors as dependent variables to investigate how it impacts the acceptance and adaptation of e-learning, while those factors switched to represent as a mediator to explain the relationship between Performance Expectancy, Social influence and Behavioral Intention. Before the COVID-19 pandemic, people were interested in the satisfaction of e-learning. Many studies after the pandemic also concern about the impact caused by COVID-19 fears which occurred psychological stress, anxiety and negative attitudes on both learners and providers.

5.3. Theoretical Implication

This study theoretically investigates how the COVID-19 pandemic influences technology evolution and technology adoption from the perspective of e-learning. The results contribute to relevant research on e-learning, TEST, UTAUT and crisis effect from three aspects.

First, this study finds that the efficiency of e-learning should be realized through the establishment of infrastructure by expanding the TEST theory. Previous studies have discussed the effectiveness of e-learning to encourage more users to accept e-learning and to satisfy users by improving its functions. Recently technology development of e-learning became the essential foundation of education because it was the only way to continue education after quarantine orders of COVID-19. The increasing population of e-learning accelerated research into relative infrastructure including 5G and IoT.

Second, this study finds the changes in factors of the UTAUT model that affect e-learning adoption when facing the crisis accordingly. This finding reveals the particularity and heterogeneity of the UTAUT model by analyzing different application scenarios of the model. After the COVID-19 outbreak, financial support and social isolation are the new factors that influence technology adoption. The decrease of financial support during COVID-19 slowed down the maintenance and operation of e-learning, resulting in the decrease of behavior intention of using e-learning technologies and tools. Social isolation offered more opportunities for e-learning due to lockdown. The unexpected changed of switching from in-person class to online, on the other hand, brought many hardware and software issues. Additionally, the COVID-19 fear is added as a new moderator. COVID-19 fear has two-sided affection on the use and acceptance of e-learning. On one hand, a study online released the stress of unnecessary COVID-19 exposure in classrooms. On the other hand, the pandemic anxiety distracted people from their study and work plan; e-learning users are less likely to only focus on online education. Our findings reveal that the measurable results of technology adoption partially depend on financial supports, social distance and the users' invisible emotions in the crisis circumstance.

Last but not least, our study proposes and validates the interaction of technology evolution and technology adoption. Technology evolution as input and technology adoption as output is not isolated. This connection promotes a combination of TEST theory with the UTAUT model, expanding the research boundary of these two theories as well as suggesting the significance of the practice.

5.4. Practical Implication

The findings in our study provide some implemental insights for technology developers and technology promoters. To promote new technology, technology developers are recommended to reevaluate the external factors and find out new determinators that will affect the implementation of new technology. Technology developers should also pay attention to the emotions and feelings of the users because those invisible factors can be the changing point when promoting new technologies. The findings also reveal that although social influence can cause unexpected results in technology development, the decrease of financial support will directly weaken the implementation of new technology. Governments are suggested to provide sufficient funds and policy support when promoting new technologies.

5.5. Limitations and Future Research Directions

This paper offers a theoretical perspective for strategic decision-makers to foresee the interaction between technology development and user adoption when launching a new technology. In terms of technological evolution, few studies talked about the uneven development of subsystems and the increase in complexity from simplicity by integration. Future research can take these two principles into account to improve the relevant technology of online education. Moreover, problems related to network security during the crisis period can be addressed in the future. It is also a way to promote e-learning technologies. With regards to research methods, future studies can implement quantitative methods to test our research conclusions.

6. Conclusions

This article respectively expands Technology System Evaluation Theory (TEST) and Unified Theory of Acceptance and Use of Technology (UTAUT), considering COVID-19. It also creatively combines those two theories to analyze the changes in e-learning before and after the COVID-19 pandemic.

Our review of e-learning evaluation literature under Technology System Evaluation Theory (TEST) finds out that studies after the COVID-19 pandemic paid more attention to technology efficiency rather than effectiveness. Prior technology development of e-learning was a promotion to encourage potential users to accept and use e-learning. However, recent technology development of e-learning was the essential foundation of education because it became the only way to continue education after quarantine orders of COVID-19.

One of our objectives of this article is to find out the interaction of e-learning development and user adoption because the evolution of new technology and how people use and accept it are not isolated. That is the reason that we combine the Technology System Evaluation Theory (TEST) and Unified Theory of Acceptance and Use of Technology (UTAUT). We set the technology evolution of e-learning (TEST model) as the moderate factor in the UTAUT model. The modified UTAUT model with TSET moderator explains that the higher Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Condition, the quicker users will adapt to e-learning.

Finally, we introduce COVID-19 fear, as the unique determinant in this case to expand UTAUT. COVID-19 fear negatively affected user's psychology and then their behavioral intention. A budget cut of education due to COVID-19 weakened user's acceptance and use of e-learning. Their behavior intention was limited by insufficient financial support because without the financial limitation, e-learning can reach out to more users and achieve more functions. The conclusion of how social isolation affects e-learning given COVID-19 fear has not yet been addressed. Social isolation benefited the interactions of online classes, which increased the behavior intention of e-learning users. On the other hand, unexpected social isolation pushed students and teachers to online immediately when they were not yet technically nor mentally ready. The negative emotion decreased the behavior intention to continue using e-learning technologies and tools.

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