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Effect of Technology Self-Efficacy on The Relationship of Innovative Learning Skills and Learning Sustainability Among UAE Students

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Abstract

Amid the rapid adoption of Education 4.0 and the widespread shift to online learning in education, there is a critical concern about the readiness of high school students to navigate sustainable e-learning, prompting a study to investigate how Education 4.0's innovative learning skills affect their learning sustainability in the UAE and contribute valuable data for informed educational strategies. This research explores the inherent innovative learning skills of Education 4.0 and their influence on the sustainable acquisition of knowledge among high school students in the UAE. It examines the prevalent innovative learning skills, scrutinizes their impact on learning sustainability, and investigates the potential mediating role of technology self-efficacy in this dynamic. The study utilized a quantitative methodology, gathering data through distributed questionnaires among a selected group of 384 high school students in Abu Dhabi, UAE. The data was utilized to construct a mediation model exploring how Technology Self-Efficacy influences the relationship between Innovative Learning Skills and Learning Sustainability in UAE students. The analysis on the model found that the Technology Self-Efficacy has four partial mediation effects and one full mediation effect on the relationship between Innovative Learning Skills and Learning Sustainability among the five paths. The findings of this study contribute to the role of Education 4.0's innovative learning skills in improving high school students' learning sustainability in the UAE, providing actionable insights for educational policymakers and practitioners.

1. Introduction

Education stands out as a critical tool for teaching important human abilities that are in line with the economic, social, and technological transformations of the twenty-first century. The problems provided by Education 4.0 have increased the emphasis on education within the context of Industry Revolution 4.0 (IR4.0), emphasising the need to boost educational innovation. This emphasis originates from the growing relevance of nurturing innovative abilities through education, which is becoming increasingly important in the present digital ecosystem (Dewi et al., 2021; Ramrez-Montoya et al., 2021). Nonetheless, research on Education 4.0 learning abilities among UAE high school students remains minimal, emphasising the need to examine creative learning skills among high school students. This investigation aims to provide empirical data about the suitability of these abilities for high school students and their impact on students' learning sustainability.

Even though education 4.0 technology is expanding, there is reluctance in the education sector to adopt constantly changing education to assist the teaching-learning process (Oke et al., 2020). That is, the use of technology in teaching and learning has been primarily limited to a didactic approach wherein teaching is aided by the use of a personal computer and the availability of digital teaching resources. However, the technology skills of digital technology that underpin IR4.0 go beyond the use of computers and e-materials and must be compatible with the learner-centred method to improve students' learning experiences (Selamat et al., 2017). Therefore, investigating the students' innovative learning skills of Education 4.0 among high school students is needed to highlight their suitability for learning and their effectiveness in enhancing their skills and abilities to learn beyond the ability to use technological devices only.

Education 4.0 has been one of the domains which have been rapidly affected by the growth of technology in the present age, leading to the actual and possible development of digital technological abilities at all levels, including teaching. According to da Motta Reis et al. (2020), education 4.0 is crucial, and studies in this area are considered preliminary since many components need to be investigated, particularly students' learning skills. In their review, da Motta Reis et al. (2020) stated that there is a gap in the research about implementing Education 4.0 technology in the context of schools, including students' learning skills, such as critical thinking and problem-solving skills. According to Himmetoglu et al. (2020), learning skills of Education 4.0 requires more than using technological devices since learning became a need for other skills. The skills required for Education 4.0 have been classified in many studies as essential for learning sustainability, which includes critical thinking and problem solving, among others (Syakur et al., 2020; Oxenswärdh & Persson-Fischier, 2020; Mian et al., 2020). The studies of Motta Reis et al. (2020), Himmetoglu et al. (2020), Syakur et al. (2020), Oxenswärdh and Persson-Fischier (2020), and Mian et al. (2020) have highlighted the need to investigate learning skills related to Education 4.0, including critical thinking skills and problem-solving skills. As a response to the under investigation of Education 4.0 in schools, the current research will investigate the innovative learning skills of Education 4.0 among high school students in the UAE, especially since the constant advancement of technology in the education sector might leave a gap between technology advancement and students' learning skills.

Regarding collaborative learning skills, the education practices in the current open learning tools and modern learning environment have become essential innovative learning skills to foster equal opportunities for learning within the philosophy of life-long learning (Altınay, 2017). However, the outcomes of online collaborative learning through peer learning and online interaction among students are still questionable in terms of quality (Altınay, 2017). Based on the questionable outcomes of online collaborative learning, this research will investigate the effect of online collaborative learning as a critical skill of Education 4.0 about learning sustainability, which is also questionable among high school students.

In terms of self-regulated learning, it refers to the students' skills to be self-directed in their learning and in doing the study requirements depending on themselves (Hadwin et al., 2015). However, there are different issues related to self-regulate learning with online practices. One of the issues is related to the first experience of high school students with online learning with the sudden shift to online learning during the COVID-19 pandemic, which makes self-regulated learning among high school students need investigation. It is supported by Carter et al. (2020) that most of the studies on self-regulated learning were carried out among university students who aim to get a degree certificate, while this skill still needs investigation among high school students. Moreover, there is no clear evidence for any study investigating the relationship between self-regulated learning of Education 4.0 and learning sustainability among high school students, which supports the need to investigate this skill in the current research.

Technology self-efficacy has been investigated in different studies, which shows it is an essential skill of 4IR, and it positively influences students' online learning (Al-Rahmi et al., 2018). High school students are the new generation with skills in using technology in different forms, such as Tablets and iPads. However, using such technology self-efficacy among this age group to support the individuals learning at school and their life learning is still unclear. Even though high school students might have good technology self-efficacy, they might not use it positively to support their learning, which makes it worth investigating in this research.

In the context of the UAE, it is one of the first countries in the Middle East to shift the learning process to online learning. Also, the government remarkably supports the digitalization of education. However, there is no clear evidence for any study that has been carried out on students' learning skills of Education 4.0 among high school students. Technology is used in high schools, but there is a gap in the empirical studies on innovative learning skills of Education 4.0 among high school students.

To summarise, Education 4.0 is fast advancing, yet actual research demonstrating its impact on students' learning skills remain far behind. In the UAE, for example, most studies on online learning and Education 4.0 have concentrated on university students. Furthermore, there is no clear evidence for any study among high school students focused on Education 4.0 learning abilities about the student's learning sustainability as a life-long outcome. Because there is no clear evidence for a similar study in the historical literature, the primary gap that the current research attempts to overcome is examining innovative learning skills in relation to learning sustainability among high school students. As a result, the current study proposes an analytical model that can be used to improve the relationship between learning skills and learning sustainability using technology self-efficacy as a mediator, which adds to past research in the field of Education 4.0 and learning sustainability.

2. Literature Review

2.1 Innovative Learning Skills

In the Innovative learning skills domains there four groups namely technology skills; Online Collaborative Learning Skills;

2.1.1 Technology Skills

In response to the demand for innovative learning skills, educational institutions confronted the challenge of adapting to alternative teaching methods, particularly online learning. The closure of physical school infrastructure and the necessity for students to stay at home necessitated a swift transition from traditional classroom instruction to online learning. However, the abrupt shift limited the preparation time for both teachers and students to familiarize themselves with online learning tools and techniques. To ensure the effective utilization of online learning post-lockdown, it is crucial to assess learners' readiness and perspectives, employing an education approach centred on their needs. This assessment will significantly contribute to developing enhanced policies and practices for the comprehensive integration of online learning.

Defining the term "e-readiness" within the research context is imperative. "E-readiness" encompasses two distinct meanings: first, the proficiency of learners with digital tools required for effective online learning, and second, the attitudes and experiences of learners regarding online learning. The technical preparedness and psychological readiness of learners are equally vital for the success of online learning. Some learners may exhibit reluctance despite evidence demonstrating the efficacy of online learning compared to traditional methods (Vivolo, 2016).

To fully harness the benefits of pervasive technology, a reform and alignment of the learning process are essential. Institutions should embrace methodologies involving new mobile devices and utilize open educational resources (OERs) distributed through various online practices. The transformative potential of online learning in the K-12 segment can be realized by establishing technology infrastructure, ensuring internet access and digital devices for students, providing student-centred professional development programs, and redesigning assessment methods (Patrick, 2011).

Online learners must demonstrate 21st-century learning skills such as critical thinking, creativity, collaboration, communication, and digital literacy to effectively navigate online learning resources. In the current digital environment, a learner-entered approach emphasizes the importance of developing these skills and acquiring subject-specific knowledge. Teachers, in turn, are expected to be proficient in both online and in-person instruction.

Teaching online differs significantly from traditional classroom settings, requiring fundamental concepts for enhancing student engagement. Establishing an online community, actively engaging students, and curating resources are crucial strategies. Research emphasizes the importance of social presence, direct instructions, learning content, and course design for learner satisfaction in online courses (Barbera et al., 2013). Additionally, flexibility, content, technology access, and communication are critical characteristics of high-quality online learning (Cashion and Palmieri, 2002).

Given the sudden shift to online education, labelled as "emergency remote teaching," concerns about potential negative perceptions persist. It is crucial to invest in understanding the practical use of online learning for individuals and organizations. The closure of traditional schooling infrastructure due to the COVID-19 pandemic has accelerated the exploration of alternative teaching methods, highlighting the need for investigation into the new features and implications of this transition to online learning (UNESCO, 2020).

In this context, the development of technology skills has become crucial, encompassing digital literacy, information literacy, media literacy, and digital citizenship. A learner-centred approach, coupled with the acquisition of digital literacy skills, ensures that online learning experiences are personalized and tailored to meet the unique needs of learners. Gathering feedback from learners is essential for continuous improvement and refinement of online learning strategies. Fostering technology skills empowers learners to thrive in the digital era of education, especially in the current landscape shaped by the COVID-19 pandemic.

2.1.2 Online Collaborative Skills

Education serves as a fundamental means to enhance an individual's quality and potential, especially in the context of globalization (Antony et al., 2015). The continuous improvement of people's quality and potential is crucial for developing high-quality human resources capable of realizing their full potential and addressing future challenges (Syakur et al., 2020). Within the domain of education, the use of instructional materials is a method employed to optimize classroom time. Online tools play a pivotal role in disseminating messages that engage students' minds, emotions, attention, and interest, thereby facilitating the learning process (Ananga, 2020). Media utilization in learning extends beyond the learning process itself; it aims to foster effective learning, particularly through collaborative learning approaches.

Collaborative learning, a student-centred learning (SCL) model, positions the learner at the core of the educational experience (Nasir & Aziz, 2020). This model involves active student engagement with peers to collectively construct knowledge, solve problems, and develop critical thinking and communication skills. Online collaborative learning utilizes digital technologies and platforms to facilitate collaboration, communication, and knowledge sharing among students, regardless of their physical locations. Online collaborative learning offers various benefits for students by promoting active participation, encouraging diverse perspectives, and enhancing social interaction and cooperation (Chung & Chen, 2020). It contributes to the development of crucial skills such as teamwork, communication, leadership, and negotiation, all highly valued in the digital age (Dillenbourg, 1999). Additionally, it fosters a sense of community and belonging, providing students with emotional support and a shared learning experience (Sun et al., 2008).

Engaging in online collaborative learning requires specific skills on the part of students, including effective communication, active listening, providing respectful and constructive feedback, negotiation and compromise, time management, and effective teamwork in diverse settings (Hernández et al., 2021). Digital literacy skills, encompassing online information evaluation and technological proficiency, are vital for successful online collaboration (Gikas & Grant, 2013). Educators play a crucial role in facilitating and supporting online collaborative learning. They are responsible for designing meaningful and challenging collaborative learning tasks aligned with learning objectives (Baepler et al., 2016). Educators also guide students in collaboration strategies, create a positive online learning environment, and facilitate reflection on the collaborative process (Hrastinski, 2008).

In essence, online collaborative learning stands as a student-centred approach fostering active engagement, knowledge construction, and the development of critical skills. Leveraging digital technologies, this model facilitates collaboration, communication, and knowledge sharing, enabling students to acquire essential skills for the digital age. The guidance and support of educators are pivotal in helping students thrive in a connected and collaborative online learning environment

2.1.3 Problem-Solving Skills

Problem-solving stands as a learning strategy employing context and motivation to assist students in resolving challenges (Argaw et al., 2017). The problem-solving process, delineated into stages by Chua et al. (2016) as problem-solving, problem analysis, discovery and reporting, and solution evaluation, is crucial in advancing students' skills and critical thinking (Han and Toh, 2019; Chua et al., 2016). Educators widely utilize problem-solving approaches to address challenges in science education (Hu et al., 2017). In the aspect of science, problem-solving contributes solutions to everyday issues, forming the basis for decision-making and future steps (Laurens et al., 2018). This aligns with Sukariasih et al.'s (2020) assertion that problem-solving in physics class's nurtures skills applicable to real-world problem-solving. Fitriani et al. (2020) highlight problem-solving as a cognitive and knowledge-forming process.

Evidence from three studies indicates enhancements in pupils' problem-solving abilities. Firstly, studies exploring problem-solving concepts and approaches from diverse perspectives (Retnowati et al., 2018). Secondly, specific subjects necessitate problem-solving skills (Schoenfeld, 2016), and it can be approached in a game-like manner (Barzilai & Blau, 2014). Thirdly, problem-solving has been employed to tackle scientific challenges, applying conceptual approaches to various physics issues (Carleo & Troyer, 2017). Consequently, the implementation of problem-based learning enhances students' learning skills (English & Kitsantas, 2013).

Problem-solving has evolved into a fundamental skill taught to meet students' needs (Franestian et al., 2020). Docktor and Heller (2009) identify five factors influencing problem-solving skills in science, including physics: 1) visualization/problem description; 2) science/physics approach; 3) unique application of science/physics concepts; 4) mathematical techniques; and 5) logical conclusions. Challenges such as students' limited experience with complex problems, educators' reluctance to facilitate instruction, and students' struggle to relate scientific learning to daily life influence science problem-solving skills (Wati et al., 2020). Importantly, problem-based learning surpasses non-problem-based learning in enhancing students' problem-solving abilities (Valdez & Bungihan, 2019).

2.1.4 Critical Thinking Skills

A person's capabilities in the 21st century can be categorized into three domains: (1) living and building a career, (2) learning and innovation, and (3) using information media and technology (Trilling & Fadel, 2009). The ability to learn, innovate, think critically, and solve problems is essential for individuals to thrive amid the increasing complexity of daily challenges (Putri et al., 2020). Critical thinking involves a deep exploration of logic and deliberation, wherein individuals avoid errors by questioning, analyzing assumptions, considering various perspectives, and systematically processing thoughts (Ennis, 2011). Problem-solving, as defined by Mayer, is a mental process or method for transitioning from a current situation to a desired outcome, while Gagne characterizes it as an activity where individuals apply existing knowledge to devise solutions in response to specific circumstances (Foshay & Kirkley, 2003).

Critical thinking skills are vital in today's dynamic world, enabling individuals to discern information credibility, question assumptions, analyse viewpoints, and approach problems systematically (Trilling & Fadel, 2009). Developing these skills equips individuals to navigate challenges, make informed decisions, and adapt to the rapidly changing environment. Four critical thinking competencies—reasoning effectively, using system thinking, making judgments and decisions, and solving problems—establish a link between critical thinking and problem-solving abilities (Trilling & Fadel, 2009). Basic problem-solving skills encompass selecting relevant data, determining the best problem-solving approach, comparing data in different forms, and deciding on the appropriate procedure to solve a problem (Butterworth & Thwaites, 2013).

Teaching critical thinking and problem-solving skills is imperative, as these skills are not acquired independently but through intentional instruction (Snyder & Snyder, 2008). Teachers play a crucial role in fostering thinking skills by guiding students on how to think rather than dictating what to think. In science education, students engage in exploratory or inquiry activities to gather data, concepts, and principles. Interactive encounters with real-life scientific challenges are crucial for honing critical thinking and problem-solving skills, making learning more engaging and relevant. Educational institutions play a pivotal role in cultivating critical thinking skills. By integrating teaching strategies that promote critical thinking, educators empower students to engage in open-ended discussions, analyse real-world problems, and appreciate diverse perspectives, fostering creativity and innovation. Cultivating critical thinking skills is essential for individuals to thrive in the 21st century and contribute positively to society.

2.2 Learning Sustainability

Despite the widespread use of the term "sustainability," our societal trajectory continues to exhibit severe unsustainability. While sustainability research and education have made notable analytical breakthroughs and generated new knowledge over the past two decades, these advancements have not instigated the required changes to address today's increasingly complex challenges (Wamsler et al., 2018). A critical examination reveals that most of the sustainability scholarship and education has focused on external factors such as ecosystems, larger socioeconomic structures, technology, and governance dynamics, neglecting a crucial dimension: people's internal aspects (Ives et al., 2019).

Education stands out as one of the most potent catalysts for sustainable development. Therefore, there is an urgent need for more comprehensive pedagogies to effectively address contemporary concerns. The United Nations' Sustainable Development Goals (SDGs), especially SDG4, highlight the dual role of education as both an end and a means to provide quality education and lifelong learning opportunities for all (United Nations, 2015). To achieve the SDGs, transformative pedagogies surpassing conventional methods are imperative.

Recently, there has been a growing recognition of the concept of inner or personal transformation in sustainability research and education to bridge existing gaps (Leichenko & Brien, 2019). Inner transformation involves changes in individuals' mindsets, encompassing values, beliefs, worldviews, and associated cognitive/emotional capacities like mindfulness, self-awareness, compassion, and empathy. These inner dimensions are central to many sustainability issues and can serve as powerful levers for change (Abson et al., 2017).

Mindfulness-based, contemplative teaching approaches are gaining popularity as innovative solutions to socio-ecological concerns and to foster a reflective, compassionate, just, and sustainable society (Frank et al., 2019). Mindfulness, defined as nonjudgmental awareness developed through consciously paying attention to subjective experiences with an open, welcoming, benevolent, and compassionate attitude, has gained traction in various societal domains, including education (Wamsler, 2020; van Dam et al., 2018). Research indicates that both teachers and students benefit in terms of health and well-being, emotional regulation, memory, attention, cognitive performance, interpersonal skills, prosocial behaviours, and ethical principles (Grossman, 2015; Luberto et al., 2018).

Despite the increased advocacy by influential entities like UNESCO for recognizing the cognitive and socio-emotional dimensions of learning in SDG-related education (UNESCO, 2017), knowledge in this area remains scarce and fragmented. The inner (or personal) sphere of transformation has yet to be systematically linked to sustainability education, indicating a critical gap in current research and educational approaches (Leichenko & Brien, 2019; Frank et al., 2019). There is a pressing need to explore the potential of inner transformation in education for sustainability, both as an end and as a means.

Hence, the quest for learning sustainability confronts the undeniable reality of persistent societal unsustainability despite the widespread use of the term. Transformative pedagogies, including interdisciplinary approaches, participatory learning, and critical thinking, are imperative to address the multifaceted challenges highlighted by the SDGs. Moreover, acknowledging and integrating the human dimension, fostering inner transformation, and exploring innovative teaching methods like mindfulness-based approaches are vital steps toward building a sustainable and equitable future.

2.3 Technology Self-Efficacy

Self-efficacy, as defined by Bandura (2005), is an individual's belief in their ability to successfully perform specific tasks. In the domain of technology, it signifies a person's confidence in effectively utilizing technological tools and platforms for learning. The assessment of technology learning self-efficacy provides insights into an individual's confidence in accomplishing learning tasks in an online setting (Revythi & Tselios, 2019). Technology learning self-efficacy serves as a crucial mediator in e-learning, enabling users to gauge their confidence in using e-learning technologies. In the context of e-learning, where students have the autonomy to learn based on personal preferences, possessing self-efficacy becomes essential for independent learning. Additionally, self-efficacy in technology relates to an individual's perception of their capacity to engage in online learning activities in their everyday life, encompassing activities such as using the internet, computers, and web-based educational materials. Those with strong self-efficacy in technology tend to view e-learning positively, while those with lower self-efficacy may harbor reservations (Revythi & Tselios, 2019).

The impact of self-efficacy in technology extends to student satisfaction with e-learning. Factors such as computer phobia, reflecting fear or anxiety related to using computers, can diminish student satisfaction, as students are less likely to embrace technology in the classroom if unhappy (Sun et al., 2008). Recognizing the significance of technology self-efficacy in e-learning, this study investigates into its role in regulating the relationship between perceived innovative factors influencing learning sustainability. Despite the recognition that self-efficacy may mediate students' abilities to use learning technologies, limited research has been conducted on the topic, emphasizing the importance of this study.

Promoting and nurturing technology self-efficacy in educational institutions can empower learners to engage more effectively in e-learning environments. Targeted interventions, such as technology training, support resources, and hands-on practice opportunities, can contribute to this goal. Additionally, pedagogical strategies that foster self-efficacy beliefs, including constructive feedback, peer collaboration, and skill-building experiences, can be employed by educators. Technology self-efficacy significantly impacts learners' success and satisfaction in e-learning. It is crucial for independent and meaningful engagement with online resources, emphasizing the need for educational institutions and instructors to cultivate and support students' technology self-efficacy. This support can unlock the full potential of e-learning tools and platforms. In the context of online learning, technology learning self-efficacy is pivotal in shaping students' confidence and motivation to engage with e-learning technologies (Revythi & Tselios, 2019). High levels of technology self-efficacy correlate with active participation in online learning activities, confident navigation of digital platforms, and effective use of technology tools.

Moreover, technology self-efficacy correlates with students' ability to engage in independent learning within an e-learning environment. Students with strong technology self-efficacy are more likely to take charge of their learning, make informed choices, and effectively use online resources (Revythi & Tselios, 2019). Their belief in their capabilities enables them to overcome technological challenges and adapt to new digital learning environments. Additionally, technology self-efficacy influences students' satisfaction with online learning experiences. Positive perceptions of technological abilities are linked to viewing e-learning as a valuable and effective learning concept (Sun et al., 2008). Conversely, students with lower technology self-efficacy may experience computer phobia or negative attitudes toward technology, hindering their engagement with online learning platforms.

Technology self-efficacy's significance extends to students' adoption and success in online learning environments. It empowers students to take ownership of their learning, utilize technology tools effectively, and view e-learning as a positive and valuable educational concept. Educators and institutions can support students' technology self-efficacy by providing training, resources, and support to build their confidence and competence in using technology for learning purposes. Research indicates that technology self-efficacy significantly influences attitudes, intentions, and behaviours related to technology use (Venkatesh et al., 2003). Higher levels of technology self-efficacy are associated with increased technology adoption and effective utilization in various contexts, including education, workplace, and everyday life (Compeau & Higgins, 1995; Venkatesh & Davis, 2000).

In the field of educational technology, technology self-efficacy is closely tied to higher levels of engagement, motivation, and persistence in online courses (Chen & Jang, 2010). It influences active participation in online discussions, seeking additional learning resources, and effective use of digital tools for collaborative learning (Teo, 2010). Furthermore, technology self-efficacy plays a critical role in the successful integration of technology in teaching and learning. Teachers with higher levels of technology self-efficacy are more willing to adopt and integrate technology into their instructional practices (Ertmer et al., 2012). They are more likely to use technology for lesson planning, content delivery, student assessment, and communication with students and parents (Wang et al., 2016).

Various studies have explored the factors influencing technology self-efficacy. Previous experience and training in using technology positively influence individuals' technology self-efficacy beliefs (Limayem et al., 2007). Social influence, such as peer support and encouragement, can also contribute to developing technology self-efficacy (Venkatesh et al., 2003). Importantly, technology self-efficacy is not a fixed trait but can be developed and enhanced through various interventions. Providing learners with hands-on experience, scaffolding support, and constructive feedback can boost their technology self-efficacy (Teo, 2011). Additionally, designing user-friendly interfaces, clear instructions, and accessible help resources can increase users' confidence in using technology (Park et al., 2019).

Thus, technology self-efficacy is a critical construct influencing individuals' beliefs, attitudes, and behaviours regarding technology use. It plays a significant role in online learning, technology integration in education, and various other contexts. Understanding the factors influencing technology self-efficacy and implementing strategies to enhance it can contribute to more effective and successful technology adoption and utilization

3. Conceptual Model

This study intended to develop a structural model showing the effect of technology self-efficacy as a mediator on the relationship of innovative learning skills and learning sustainability among UAE students. Based on the literature review on the above section, the conceptual model for this study is as figure 1.

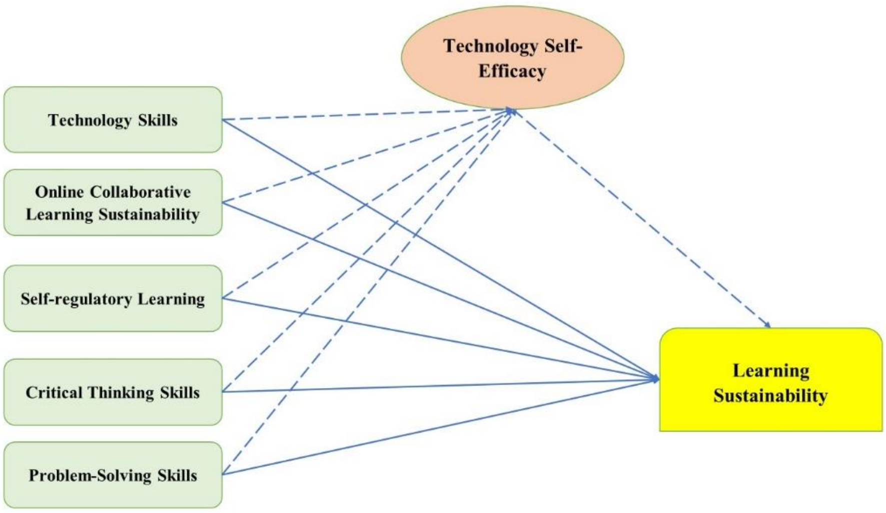

Fig. 1 *Conceptual model*

In Figure 1, the involved relationship of innovative learning skills is visually depicted, illustrating their direct impact on learning sustainability. These five distinct groups of skills function as independent variables or constructs, exerting a direct influence on the dependent variable which is learning sustainability. Notably, technology self-efficacy assumes the role of a mediator variable, mediating the relationship between the innovative learning skills and learning sustainability. Within this framework, the indirect relationships come into focus, explaining the paths through which the influence of innovative learning skills is channelled. These paths traverse the mediator, technology self-efficacy, before culminating in the ultimate outcome, the dependent variable. This mediation process underscores the distinction and dynamic nature of the relationships between the identified constructs, enriching our understanding of the intricate dynamics shaping learning sustainability.

4. Modelling

In recent advancements, there has been a significant uptick in the application of multivariate statistical analysis techniques, particularly focusing on Structural Equation Modelling (SEM). SEM, classified into covariance-based and variance-based types, encompasses the prominent second-generation variance-based method known as Partial Least Squares Structural Equation Modelling (PLS-SEM). This method proves instrumental in probing causal relationships among latent constructs in research studies. The current study employs PLS-SEM to explore the impact of Education 4.0's innovative learning skills on the learning sustainability of high school students in the United Arab Emirates (UAE). Furthermore, the research seeks to determine whether technology self-efficacy serves as a mediating factor in the relationship between Education 4.0's innovative learning skills and learning sustainability among high school students in the UAE.

The PLS-SEM evaluation process unfolds in two essential stages. The initial stage scrutinizes the measurement (outer) model, and the subsequent stage in the evaluation process delves into the structural (inner) model, probing the interdependence and interrelationships among the research constructs. Figure 2 illustrates the developed model after conducting the PLS Algorithm function in the SmartPLS software employed in this study.

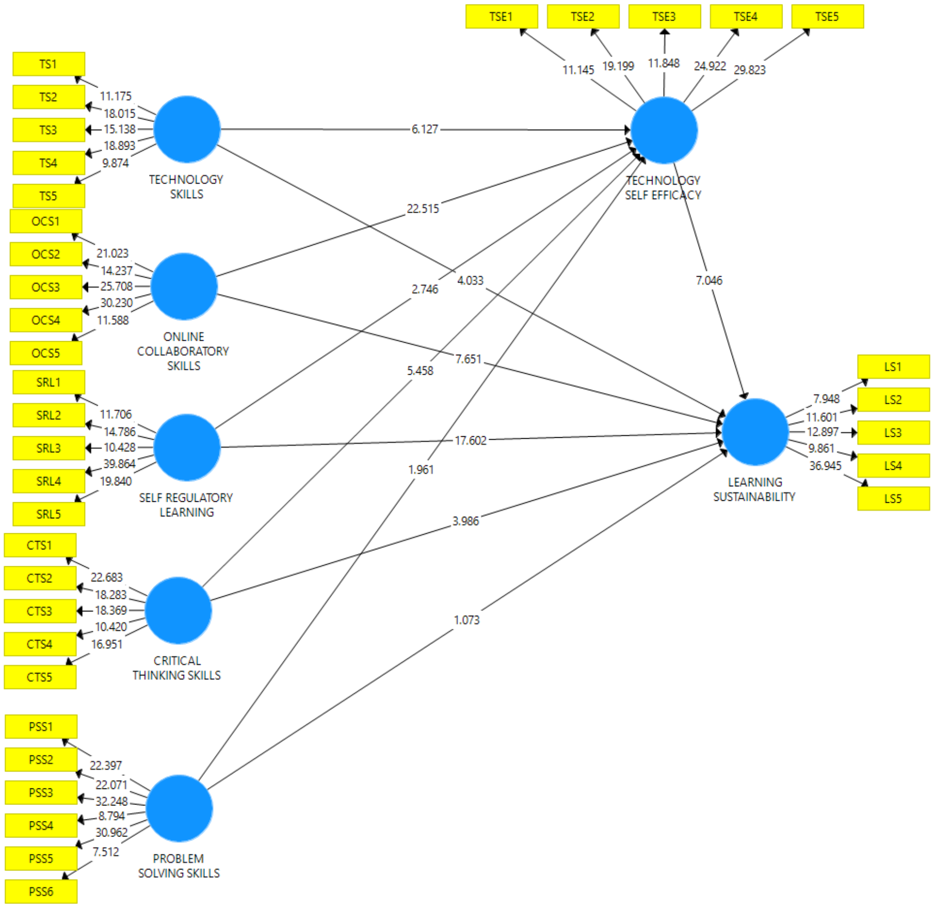

Fig. 2 *The developed model after conducting PLS Algorithm*

4.1 Evaluation of Measurement Component

The criteria for evaluating the measurement component of the model are reliability, convergent validity, and discriminant validity. Assessing the reliability is achieved through composite reliability, utilizing metrics such as Dillon-Goldstein's or Joreskog's rho to gauge the homogeneity of a block (Vinzi et al., 2010). The subsequent step in the measurement model evaluation entails a thorough examination of its validity, encompassing both convergent and discriminant aspects (Hair et al., 2014). Convergent validity is scrutinized by analysing the factor loadings of indicators and Average Variance Extracted (AVE). This examination highlights the model's proficiency in capturing the variance of the indicators, thereby affirming its validity (Wong, 2016). Discriminant validity is rigorously assessed through the Heterotrait-Monotrait (HTMT) criterion, Fornell and Larcker criterion, and cross-loading analysis within the outer models.

4.1.1 Reliability Assessment

Reliability, in the context of this study, pertains to the degree of consistency and stability exhibited by a scale in generating measures over time, particularly in relation to reflective items within the measurement model (Lowry & Gaskin, 2014). It signifies the extent to which a measurement scale is devoid of random error and measures the uniformity of responses across constructs (Pallant, 2011; Creswell, 2014). While Cronbach's alpha is commonly employed to assess reliability, PLS-SEM favours the use of composite reliability (Hair et al., 2011; Memon & Rahman, 2013; Wong, 2016).

In the context of PLS-SEM, a composite reliability of at least 0.7 is recommended for a measurement model to be deemed reliable (Wong, 2013). However, a threshold of 0.6 is also deemed acceptable, particularly for nascent scales (Chin, 1998; Hair et al., 2011; Bagozzi & Yi, 1988). The reliability metrics for the measurement models are outlined in Table 1.

Table 1 *Reliability of measurement models*

Code	Construct	Cronbach's Alpha	Rho_A	Composite Reliability
CTS	Critical thinking skills	0.836	0.840	0.883
LS	Learning sustainability	0.762	0.799	0.837
OCS	Online collaborative learning sustainability	0.836	0.843	0.884
PSS	Problem-solving skills	0.873	0.889	0.903
SRL	Self-regulatory learning	0.813	0.858	0.867
TSE	Technology self-efficacy	0.833	0.840	0.882
TS	Technology skills	0.770	0.773	0.842

Table 1 presents the outcomes of the reliability analysis for the measurement model. Internal consistency analysis, utilizing Cronbach's alpha, was conducted on the research constructs, and the findings are detailed below. Notably, all constructs demonstrated values surpassing the recommended minimum threshold of 0.7, signifying their reliability and internal consistency. Technology Skills (TS) exhibited the lowest Cronbach's alpha value at 0.770, albeit still exceeding the acceptable threshold of 0.7. Conversely, Technology Self Efficacy (TSE) displayed the highest Cronbach's alpha value at 0.833. Self-Regulatory Learning (SRL), Problem-Solving Skills (PSS), Online Collaborative Skills (OCS), Learning Sustainability (LS), and Critical Thinking Skills (CTS) all manifested Cronbach's alpha values of 0.833, 0.813, 0.873, 0.836, 0.762, and 0.836, respectively. These robust findings instill confidence in the study's outcomes, affirming the reliability and internal consistency of all research constructs.

4.1.2 Convergent Validity Assessment

Measurement models play a crucial role in explaining the variance of manifest items to achieve convergent validity, signifying the model's ability to accurately predict or explain the variance of these variables (Wong, 2016). Convergent validity gauges the degree to which a manifest variable is interconnected with other manifest variables within the same underlying construct (Hair, Hult, Ringle, & Sarstedt, 2014). The assessment of variance explanation for manifest variables involves evaluating the Average Variance Extracted (AVE), items' factor loadings, and their significance level (Lowry & Gaskin, 2014; Memon & Rahman, 2013; Wong, 2016).

For convergent validity, it is imperative that factor loadings for manifest variables are higher in their respective measurement model than in others, with a minimum requirement of 0.7 (Hair et al., 2014). In exploratory research, factor loadings within the range of 0.6 to 0.7 are considered acceptable (Hair, Ringle, & Sarstedt, 2011). Manifest variables with factor loadings below 0.4 should be eliminated from the measurement model, and items with lower loadings are also recommended for removal to enhance the Average Variance Extracted (AVE) (Hair et al., 2014). Additionally, factor loadings must be significant and converge within fewer than 300 iterations (Wong, 2016).

The Average Variance Extracted (AVE) represents the mean of the squared loadings of the measurement model's manifest variables, indicating the model's communality (Hair et al., 2014). AVE values for the measurement models are advised to exceed 0.5 (Hair et al., 2014; Hair et al., 2011; Lowry & Gaskin, 2014; V. E. Vinzi et al., 2010; Wong, 2016), denoting that at least 50 percent of the variance of the outer model is explained by the manifest variables (Memon & Rahman, 2013). The evaluation of convergent validity for the research measurement models, employing factor loadings and Average Variance Extracted (AVE), is detailed in Table 2.

Table 2 *Convergent validity result*

Code	Construct	Average Variance Extracted (AVE)
CTS	Critical thinking skills	0.850
LS	Learning sustainability	0.874
OCS	Online collaborative Skills	0.766

PSS	Problem-solving skills	0.844
SRL	Self-regulatory learning	0.821
TSE	Technology self-efficacy	0.803
TS	Technology skills	0.870

The outcomes of convergent validity are detailed in Table 4.9, demonstrating robust results. The AVE values for the CTS, LS, OCS, PSS, SRL, TSE, and TS measurement models are 0.850, 0.874, 0.766, 0.844, 0.821, 0.803, and 0.870, respectively. All these values surpass the recommended minimum threshold of 0.5, affirming their ability to explain at least 50% of the variance in the outer model. Additionally, every manifest variable exhibit factor loading exceeding 0.8, underscoring their significant contributions to the models. Consequently, all the measurement models have successfully met the criteria for convergent validity.

4.1.3 Discriminant Validity

Discriminant validity gauges the extent to which measurement models stand apart from other research constructs, assessing their uniqueness within the structural model (Memon & Rahman, 2013). Traditionally, two criteria—The Fornell and Larcker criterion and the Cross-loading criterion—have been employed for this evaluation. The Heterotrait-Monotrait (HTMT) criterion, a more recent addition, has gained theoretical and empirical support. The HTMT ratio averages heterotrait-heteromethod correlations relative to monotrait-heteromethod correlations (Henseler et al., 2015). Discriminant validity is confirmed if the HTMT ratio with other measurements is below 0.85 or, more liberally, below 0.9 (Henseler et al., 2015). Fornell and Larcker's (1981) criterion stipulates that the square root of the Average Variance Extracted (AVE) of each measurement model should surpass its correlation with any other model in the structural model. The cross-loading criterion, proposed by Chin (1998), demands that items load higher on their underlying constructs than on other constructs. Thus, for this study presents two discriminant validity assessment criteria were employed to affirm the distinctiveness of each measurement model, as detailed in Tables 3 and 4.

Table 3 *Discriminant validity using HTMT ratio criterion*

Constructs	CTS	LS	OCS	PSS	SRL	TSE	TS
CTS							
LS	0.932						
OCS	0.786	0.981					
PSS	0.820	0.868	0.633				
SRL	0.962	1.203	0.833	0.890			
TSE	0.780	0.931	1.147	0.637	0.853		
TS	1.184	0.955	0.876	0.774	0.969	0.934	

Using the HTMT criterion, Table 3 reports the discriminant validity results. The highest HTMT ratio, 0.969 between TS and SRL, remains below the liberal threshold of 1.0 (Henseler et al., 2015). Additionally, the HTMT ratio between TS and LS, at 0.955, is below the liberal threshold. All other HTMT ratios fall below the recommended conservative maximum of 0.969 (Henseler et al., 2015). Consequently, the measurement models meet the discriminant validity requirement based on the HTMT criterion.

Table 4 *Discriminant validity using Fornell and Larcker criterion*

Constructs	CTS	LS	OCS	PSS	SRL	TSE	TS
CTS	**0.776**						
LS	0.714	0.741					
OCS	0.671	0.778	0. 826				
PSS	0.737	0.704	0.583	0.782			
SRL	0.797	0. 754	0.732	0.755	0. 937		
TSE	0.663	0.775	0.7970	0.583	0.751	0.970	
TS	0.720	0.750	0.731	0.653	0.784	0.782	0.916

Table 4 presents the assessment of discriminant validity using the Fornell and Larcker criterion. The diagonally italicized and bolded values signify the square roots of the Average Variance Extracted (AVE) for each measurement model, while the values below the diagonal depict the correlations between the measurement models. The findings reveal that none of the measurement models show correlations surpassing the square root of their AVE with any other measurement model. Therefore, the measurement models have effectively met the discriminant validity criteria according to the Fornell and Larcker criterion.

4.2 Evaluation of Structural Model

The second phase of PLS-SEM evaluation involves scrutinizing the structural (inner) model, responsible for establishing the cause-and-effect relationships between the measurement models to address research questions and test hypotheses (Hair et al., 2014). This model seeks to predict endogenous constructs by exploring the relationships between these constructs and the exogenous ones (Hair et al., 2014). The assessment of the structural model encompasses various criteria, such as examining path coefficients and their significance through a bootstrapping procedure, evaluating the coefficients of determination (R2) for endogenous constructs, gauging the effect sizes of the exogenous measurement model via Cohen's f2, assessing the model's predictive relevance using cross-validated redundancy (Q2), and scrutinizing the global goodness of fit of the model (GoF) (Goh et al., 2014; Hair et al., 2011; Lowry & Gaskin, 2014; Memon & Rahman, 2013; Vinzi et al., 2010; Wong, 2016).

Path coefficients and their significance are crucial for comprehending the strength and direction of relationships between constructs. Utilizing a bootstrapping procedure ensures reliable results by obtaining estimates of standard errors and bias-corrected confidence intervals for path coefficients (Hair et al., 2014). Coefficients of determination (R2) gauge the amount of variance in endogenous constructs explained by exogenous constructs, with a higher R2 indicating a more substantial impact of exogenous constructs on endogenous constructs. Effect sizes of the exogenous measurement model, measured by Cohen's f2, signify the strength of relationships between exogenous constructs and their associated manifest variables (Hair et al., 2014).

Predictive relevance is assessed through cross-validated redundancy (Q2), indicating the model's ability to accurately predict new data. A higher Q2 signifies a more robust model (Hair et al., 2014). Lastly, the global goodness of fit of the model (GoF) is examined, considering the collective performance of both measurement and structural models (Hair et al., 2014).

4.2.1 Path Coefficients Evaluation

The primary aim of PLS-SEM is to predict the causal relationships between exogenous and endogenous constructs in research, typically formulated as hypotheses. After executing the model, hypotheses are tested by scrutinizing the path coefficients (Hair et al., 2014b). Path coefficients quantify the strength of relationships between constructs in the structural model, where values closer to 1 indicate a robust positive relationship (Hair et al., 2014).

The significance of the paths is assessed using p-values or t-statistics obtained through bootstrapping (Kock, 2014). The path coefficients, along with their significance levels, offer insights into the internal quality of the model (Hair et al., 2011). To ensure the inner model's quality, it is imperative that path coefficients be statistically significant (Wong, 2016). The path coefficients for this study are outlined in Table 5.

Table 5 *Path coefficients*

Constructs	Path	Path coefficient / strength	P Values	Path significant result
IV -> DV	CTS -> LS	-0.426	0.000	Significant
	OCS -> LS	0.970	0.000	Significant
	PSS -> LS	0.037	0.284	Not Significant
	SRL -> LS	0.938	0.000	Significant
	TS -> LS	0.368	0.000	Significant
M -> DV	TSE -> LS	-0.884	0.000	Significant
IV -> M	CTS -> TSE	-0.465	0.000	Significant
	OCS -> TSE	0.835	0.000	Significant
	PSS -> TSE	0.049	0.050	Not Significant
	SRL -> TSE	0.076	0.006	Significant
	TS -> TSE	0.505	0.000	Significant
IV -> M -> DC	CTS -> TSE -> LS	0.386	0.000	Significant
	OCS -> TSE -> LS	-0.743	0.000	Significant
	PSS -> TSE -> LS	-0.064	0.001	Significant

TS -> TSE -> LS	-0.446	0.000	Significant
SRL -> TSE -> LS	0.061	0.007	Significant

 # IV- independent variables; DV-dependent variable; M-mediator

Table 5 illustrates both direct and indirect relationships. The table encompasses 11 direct relationships and 5 indirect relationships. All paths are statistically significant, except for the PSS -> LS and PSS -> TSE relationships, which lack significance. It is crucial to note that insignificant paths should not be considered for their coefficients.

Among the direct relationships, the most robust path is OCS -> LS, boasting a coefficient value of 0.970. On the other end of the spectrum, the weakest direct relationship is SRL -> TSE, registering a coefficient value of 0.076.

Regarding indirect relationships, the most influential path is OCS -> TSE -> LS, showcasing a coefficient value of -0.743. It is important to emphasize that the positive or negative sign merely denotes the direction. Conversely, the weakest indirect relationship is SRL -> TSE_-> LS, exhibiting a coefficient value of 0.061.

4.2.2 Coefficient of Determination (R^2) Assessment

The structural model's effectiveness can be gauged through R^2, which measures how well the model elucidates the variance. R^2, also known as the coefficient of determination, signifies the collective impact of exogenous constructs on predicting or elucidating the variance of the endogenous construct within the structural model. A higher R^2 value denotes a superior model quality in terms of variance explanation, whereas a lower value suggests diminished quality (Hair et al., 2014; Hair et al., 2011; Memon & Rahman, 2013; Wong, 2016).

While there are no universally defined benchmarks for an acceptable R2 level, researchers propose various recommendations that can differ across disciplines. As a general guideline, a value of 0.25 is considered weak, 0.50 is seen as moderate, and 0.75 is deemed substantial (Hair et al., 2014; Wong, 2016). However, Hair et al. (2014) argued that in the field of consumer behaviour, an R^2 value of 0.2 is considered high. These benchmarks were applied to evaluate the R^2 levels in this study, and the R^2 values of the final model are presented in Table 6

Table 6 *R^2 values of the model*

Endogenous constructs	R Square
LS	0.968
TSE	0.968

Table 6 showcases the coefficient of determination (R^2) values for the structural model in this research, revealing the proportion of variance in the endogenous construct explained by the exogenous constructs. Both Learning Sustainability (LS) and Technology Self-Efficacy (TSE) variables boast R^2 values of 0.968. With a general guideline deeming an R^2 value of 0.75 as substantial, the research's R^2 value of 0.968 is deemed highly substantial.

All R^2 values for the endogenous constructs in the model surpass 0.5, signalling excellent predictive accuracy (Hair et al., 2014). This suggests that the exogenous constructs significantly contribute to the variation in the endogenous constructs, underscoring the model's robust explanatory power. In summary, the elevated R^2 values affirm that the structural model aligns well and offers valuable insights into the interrelationships among the investigated constructs.

4.2.3 Effect Size (f2) Evaluation

Relying solely on the R^2 value is insufficient for understanding the individual impact of each exogenous construct. While R^2 provides a comprehensive measure of the combined contribution of all exogenous constructs in predicting variance, and path coefficients reveal the individual effects of each path in the structural model, they do not uncover the specific exogenous construct's relative contribution to R^2. To gain a better understanding of this contribution, the effect size (f^2) becomes relevant (Hair et al., 2011).

According to Chin (1998), the effect size assesses the relative influence of exogenous constructs on the endogenous construct(s) by estimating changes in R-squared. Cohen's f^2 is employed to determine the effect size of each construct in the structural model, involving the removal of a specific construct from the model and observing the resulting alterations in R^2 (Hair et al., 2014b).

Cohen (1988) stated that effect size can identify which predictors make a substantial difference in explaining the variance in the dependent variable. Larger f^2 values suggest a more substantial impact of a particular predictor on the outcome, enhancing the understanding of the practical significance of individual predictors in a statistical model.

$$\text{Effect Sizes, } f^2 = \frac{R^2 incl - R^2 excl}{1 - R^2 incl} \quad (1)$$

Where,

f^2 is an effect size

R^2 incl. is R^2 included (R^2 with a particular construct included in the model)

R^2 excl. is R^2 excluded (R^2 with a particular construct excluded from the model)

1 is a constant

Cohen (1988) proposed a set of standards to evaluate the effect sizes, which define a small effect size as f^2 of 0.02, a medium effect size as f^2 of 0.15, and a large effect size as f^2 of 0.35. To evaluate the effect sizes of the constructs in this research, the above criteria were employed and are presented in Table 7.

Table 7 *Effect sizes (f^2)*

Exogenous construct	**Endogenous constructs**	
	Dependent	**Mediator**
	LS	**TSE**
CTS	0.334	0.638
OCS	1.241	8.897
PSS	0.015	0.027
SRL	6.737	0.046
TSE	0.799	-NA-
TS	0.246	0.827

Table 7 illustrates the effect sizes (f^2) of each construct on Learning Sustainability. Critical thinking skills (CTS), online collaborative skills (OCS), problem-solving skills (PSS), self-regulatory learning (SRL), and technology skills (TS) exhibit a medium effect size on Learning Sustainability, as evidenced by their f^2 values of 0.334, 1.241, 0.015, 6.737, and 0.246, respectively. These values suggest a moderate contribution of these constructs to the prediction of Learning Sustainability. Notably, the construct of training (TSE) demonstrates a large effect size on Learning Sustainability, indicated by its f^2 value of 0.799. This highlights the substantial and significant impact of training on Learning Sustainability.

4.3 Hypothesis Testing

Bootstrapping is a statistical method used for hypothesis testing. It works by repeatedly sampling data from the observed dataset, creating multiple simulated samples. This helps estimate the variability of a statistic and provides more reliable confidence intervals. In hypothesis testing, bootstrapping allows researchers to assess the distribution of test statistics and calculate confidence intervals without strict assumptions about the population. It is especially valuable for small sample sizes or non-normally distributed data, improving the reliability of statistical inferences when traditional assumptions may not apply. Figure 3 show the model after conducting bootstrapping process in SmartPLS software.

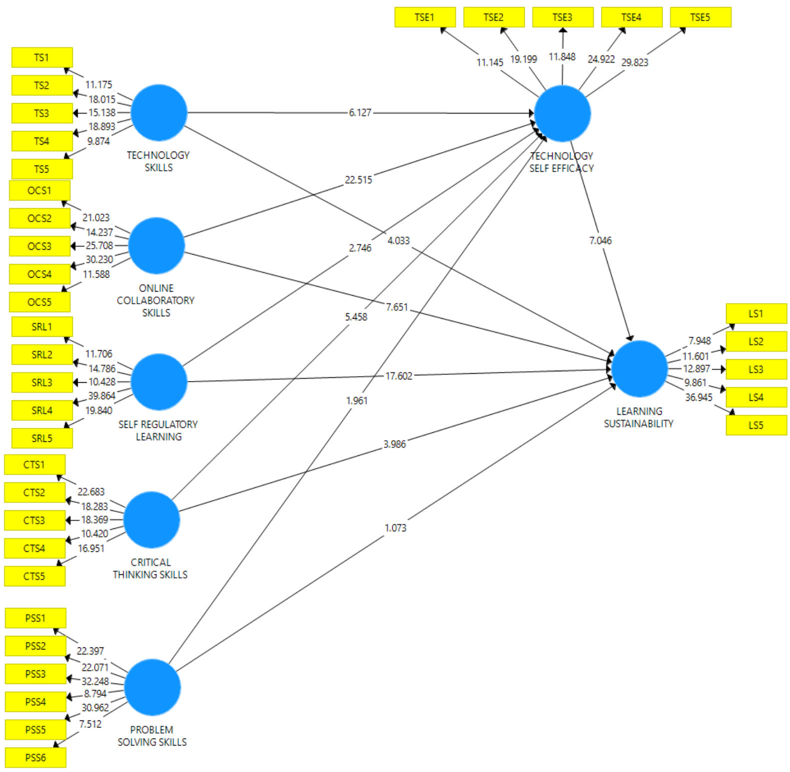

Fig. 3 *Structural model after bootstrapping*

The model in the study comprised five constructs of innovative learning skills within Education 4.0: critical thinking skills (CTS), online collaborative learning sustainability (OCS), problem-solving skills (PSS), self-regulatory learning (SRL), and technology skills (TS), and serving as independent factors. Learning sustainability (LS) functioned as the dependent construct, with technology self-efficacy (TSE) acting as the mediator. Table 8 displays the hypotheses, facilitating a straightforward comparison and interpretation of results. Through an examination of the path coefficients and their significance, then it can assess whether the data aligns with the hypothesized relationships between constructs, providing essential insights for drawing meaningful conclusions and advancing theoretical understanding in the field.

Table 8 *Model's hypothesis testing*

Constructs	Path relationship	Original Sample (O)	T Statistics (|O/STDEV|)	P Values	Path significant result
	CTS -> LS	-0.426	3.986	0.000	Significant
	OCS -> LS	0.970	7.651	0.000	Significant
IV -> DV	PSS -> LS	0.037	1.073	0.284	Not Significant
	SRL -> LS	0.938	17.602	0.000	Significant
	TS -> LS	0.368	4.033	0.000	Significant
M -> DV	TSE -> LS	-0.884	7.046	0.000	Significant
	CTS -> TSE	-0.465	5.458	0.000	Significant
	OCS -> TSE	0.835	22.515	0.000	Significant
IV -> M	PSS -> TSE	0.049	1.961	0.050	Not Significant
	SRL -> TSE	0.076	2.746	0.006	Significant
	TS -> TSE	0.505	6.127	0.000	Significant
	CTS -> TSE -> LS	0.386	5.713	0.000	Significant
	OCS -> TSE -> LS	-0.743	7.895	0.000	Significant
IV -> M -> DC	PSS -> TSE -> LS	-0.064	3.216	0.001	Significant
	TS -> TSE -> LS	-0.446	6.050	0.000	Significant
	SRL -> TSE -> LS	0.061	2.729	0.007	Significant

 # IV- independent variables; DV-dependent variable; M-mediator

Based on the results in table 8, the model indicates that specific innovative learning skills of Education 4.0 positively impact learning sustainability. In the direct relationship between innovative learning skills and learning sustainability, it was found that technological skills were found to positively affect learning sustainability with a path coefficient of 0.368, a t-statistic value of 4.033, and a p-value of 0.000. Additionally, online collaborative learning skills positively impact learning sustainability with a path coefficient of 0.970, a t-statistic value of 7.651, and a p-value of 0.000. Self-regulated learning skills were also found to positively impact learning sustainability, with a path coefficient of 0.076, a t-statistic value of 2.746, and a p-value of 0.006. Even though critical thinking skills did show significant effects but negatively to the learning sustainability, as evidenced by its path coefficients of -0.426, t-statistic values of 3.986, and p-values of 0.000. On the other hand, problem-solving skills did not show significant effects on learning sustainability, as evidenced by it path coefficient of 0.037, t-statistic values of 1.073, and p-values of 0.284.

In the direct relationship between innovative learning skills and technology self-efficacy, it was found that there is a significant causal relationship between critical thinking skills and technology self-efficacy, with a path coefficient of -0.465, a t-statistics value of 5.458, and a p-value of 0.000. There is also a positive relationship between online collaborative learning skills and technology self-efficacy, with a path coefficient of 0.835, a t-statistics value of 22.515, and a p-value of 0.000. However, problem-solving skills have an insignificant relationship with technology self-efficacy with path coefficients of 0.050, t-statistics values of 1.961, and p-values of 0.050.

For indirect relationship between innovative learning skills, technology self-efficacy, and learning sustainability, it was found that there is a significant positive relationship between self-regulatory learning, learning sustainability, and technology self-efficacy, with path coefficients of 0.938 and 0.076, t-statistics values of 17.602 and 0.076, and p-values of 0.000 and 0.006, respectively. Also, it was found that there is a significant but negative relationship between technology skills and learning sustainability and technology self-efficacy, with a path coefficient of -0.446, a t-statistics value of 6.050, and a p-value of 0.000. Additionally, it was discovered that online collaborative learning with technology self-efficacy and learning sustainability has significant but negative relationship, with a path coefficient of -0.743, a t-statistics value of 7.895, and a p-value of 0.000. Moreover, the relationship of problem-solving skills; technology self-efficacy and learning sustainability negatively significant, with a path coefficient of -0.064, a t-statistics value of 3.216, and a p-value of 0.001. Similarly, relationship of self-regulatory learning; technology self-efficacy and learning sustainability positively significant, with a path coefficient of 0.061, a t-statistics value of 2.729, and a p-value of 0.007. Additionally, relationship of technology skills; technology self-efficacy and learning sustainability positively significant, with a path coefficient of -0.446, a t-statistics value of 6.050, and a p-value of 0.000. Furthermore, the relationship critical thinking skills; technology self-efficacy and learning sustainability positively significant, with a path coefficient of 0.386, a t-statistics value of 5.713, and a p-value of 0.000.

5. Deciding Mediating Effect of Technology Self-Efficacy

The study's model consisted of five construct of innovative learning skills of Education 4.0 which are critical thinking skills; online collaborative learning sustainability; problem-solving skills; self-regulatory learning; and technology skills serve as independent construct. While, learning sustainability serve as dependent construct and technology self-efficacy as mediator construct. Based on the results of hypothesis testing on the model, it needs to decide the mediation effect of the technology self-efficacy construct. According to Ghasemy et al. (2020), mediation effects manifest in various forms: full, partial, and no mediations. Full mediation occurs when the direct relationship is not significant, but the indirect relationship is. In contrast, partial mediation occurs when both the direct and indirect relationships are significant. Lastly, no mediation is observed when the direct relationship is significant, but the indirect relationship is not, or when both the direct and indirect relationships are not significant. Derived from the hypothesis testing outcomes presented in Table 8, the significant levels of each direct and indirect relationship within the paths are illustrated in Table 9.

Tale 9 *Mediation effect of Technology Self-Efficacy (TSE)*

Direct relationship	Path significant result	Indirect relationship	Path significant result	Mediation Effect
CTS -> LS	Significant	CTS -> TSE -> LS	Significant	Partial
OCS -> LS	Significant	OCS -> TSE -> LS	Significant	Partial
PSS -> LS	Not Significant	PSS -> TSE -> LS	Significant	Full
TS -> LS	Significant	TS -> TSE -> LS	Significant	Partial
SRL -> LS	Significant	SRL -> TSE -> LS	Significant	Partial

Table 9 depicts five paths with direct and indirect linkages with mediation effects. As a result, the Technology Self-Efficacy has four partial mediation effects and one full mediation effect on the relationship between

Innovative Learning Skills and Learning Sustainability among the five paths. The full mediation effects is the relationship of Problem-solving skills (PSS) -> Technology Self-Efficacy (TSE) -> Learning Sustainability (LS).

6. Conclusion

The importance of education in the twenty-first century, which is distinguished by economic, social, and technical developments, emphasises the need for new learning capabilities, particularly in the context of Education 4.0. Despite the emphasis on improving educational innovation, there is a significant gap in the investigation of Education 4.0 learning skills among UAE high school students. The purpose of this study is to give empirical data about the applicability of these skills for high school pupils, as well as their impact on learning sustainability. While Education 4.0 technology is expanding, there is reluctance to adopt dynamic educational techniques, limiting technology's usage in teaching to a didactic approach. The current study fills this need by investigating unique learning skills among high school students that go beyond the usage of electronic devices. The rapid advancement of technology in education, particularly in the realm of Education 4.0, needs a more in-depth study of students' learning abilities, including critical thinking and problem-solving abilities.

This research explores the inherent innovative learning skills of Education 4.0 and their influence on the sustainable acquisition of knowledge among high school students in the UAE. It examines the prevalent innovative learning skills, scrutinizes their impact on learning sustainability, and investigates the potential mediating role of technology self-efficacy in this dynamic. The study utilized a quantitative methodology, gathering data through distributed questionnaires among a selected group of 384 high school students in Abu Dhabi, UAE. The data was utilized to construct a mediation model exploring how Technology Self-Efficacy influences the relationship between Innovative Learning Skills and Learning Sustainability in UAE students. The analysis on the model found that the Technology Self-Efficacy has four partial mediation effects and one full mediation effect on the relationship between Innovative Learning Skills and Learning Sustainability among the five paths. The full mediation effects is the relationship of Problem-solving skills (PSS) -> Technology Self-Efficacy (TSE) -> Learning Sustainability (LS). The findings of this study contribute to the role of Education 4.0's innovative learning skills in improving high school students' learning sustainability in the UAE, providing actionable insights for educational policymakers and practitioners.

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