UTS UNIVERSITY OF TECHNOLOGY SYDNEY

Knowledge Development, Technology and Quality of Experience in Collaborative Learning Environments

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Doctor of Philosophy

under the supervision of
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Certificate of Original Authorship

I, Abdulrahman Alyami, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

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List of Publications

The following research papers were published to provide some of the author's experiences and contributions during this Ph.D. journey. The main contribution of this study has been published in Quality and Quantity Journal classified as Q1 according to SCIMAGO. Therefore, the contribution contains a summary of our study findings based on the data analysis. Additionally, a part of the conducted literature review has been published at the PACIS 20 conference, ranked "A" according to CORE rankings. Lastly, two papers have been published in the International Conference on Education and New Learning Technologies (Edulearn 20 and 21). The former is a pilot study, and the latter is an example of aligning concepts between UML diagrams.

Main Contribution

- Alyami, A., Pileggi, S. F., & Hawryszkiewycz (2022). "***Knowledge development, technology and quality of experience in collaborative learning: a perspective from Saudi Arabia universities***". In the Quality & Quantity Journal, DOI**:** 10.1007/s11135-022-01476-9, *[Q1 – Source: Scimago, https://www.scimagojr.com]*.

Other Contributions

- Alyami, A., Pileggi, S. F., & Hawryszkiewycz, I. (2020). ***The Impact of New Technologies on Learning: A Literature review on Mobile Collaborative Learning***. In *Pacis Asia Conference on Information Systems*. [A-ranked conference, CORE], available at https://aisel.aisnet.org/pacis2020/213

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- Alyami, A., Pileggi, S. F., & Hawryszkiewycz, I. (2021). ***Enhancing and Consolidating Requirements Specification in Teaching System Design by Aligning Concepts from Heterogeneous Diagrams***. *Education*, *2021*. DOI: 10.21125/edulearn.2021.0061

Abstract

Collaborative learning approach is becoming more and more popular in practice, and technology is becoming more and relevant to assure learning outcomes. However, the quality of learning outcome depends on the levels of learning. This in turn leads to new ways to measure outcomes such as effectiveness, efficiency and enjoyment at the different levels to reflect academic performance and satisfaction. Rarely is the overall quality of the learning experience considered in many studies. At a more theoretical level, we identified differences between the different levels of learning, i.e., apply, analyse and eventually create, as in Bloom's taxonomy, and the process to develop and expand knowledge as in Nonaka's theory within collaborative learning environment.

In this thesis, we develop a conceptual framework for assessing the impact of collaborative technology on the process of knowledge development and the overall learning experience at different levels of learning. Learning has many levels ranging from developing an understanding of some area to creating innovative solutions. Each of these requires different ways of using collaborative technology and the kinds of technology used to achieve a common goal. Several recent studies have investigated the role of technology, as well as researchers have defined different metrics to assess learning outcomes and experience along the collaborative knowledge development process. More recently, technology has played a key role in facing the new challenges related to COVID-19, forcing the learning process to move to virtual or hybrid environments. The quality of learning experience is the measure used in this study, which defines a combination of effectiveness, efficiency, and enjoyment to assess overall academic performance and perceived satisfaction. Moreover, this study evaluates the impact on the quality of learning experience by looking at relationships among the fine-grained parameters proposed to reflect standard metrics for the overall learning experience.

From a methodological point of view, a conceptual framework has been proposed, and a quantitative study has been conducted among undergraduate and postgraduate students who are undertaking programs related to system design in Saudi Arabia universities. 152 responses have been collected through an online survey and analysed using SPSS for statistical analysis and SmartPLS for structural equation modelling.

Results show a positive impact of technology along the collaborative knowledge development process and a strong correlation among the different quality of learning experience parameters considered. This study reiterates the importance of technology in the establishment of flexibility and resilience in collaborative development environments. Collaborative learning and technology have a direct and indirect impact on the overall quality of learning experience at different levels of learning. Furthermore, technology and collaboration are driving factors in providing enjoyable learning environments that lead to better academic performance and perceived satisfaction. Indeed, despite some challenges, an integrated use of technology seems to properly support the most pressing needs in terms of quality experience, while the well-known social/educational issues related to the COVID-19 pandemic are not the object of this study. Those findings are expected to contribute to Saudi Arabia's vision 2030 and, more holistically, to the assessment of collaborative learning environments that extensively rely on technology as well as to support further exploration for researchers and academics in learning contexts.

Keywords: Collaborative Technology, Collaborative Learning, Knowledge Development, Knowledge Sharing

Main Research Terminology

Abbreviation	Definition
CL	Collaborative Learning refers to a learning process involving more than one student to achieve a common goal.
CT	Collaborative Technology is expected to support a collaborative learning process along the different phases for content sharing, task development and communication.
SD	System Design is commonly understood as a set of processes that aim to the specification of the different system elements and components that meet a given set of requirements.
TAM	Technology Acceptance Model is a well-known theory in the Information Systems field that models the acceptance of adopting technology among users.
Knowledge Development	Refers to the ability to employ data and information within groups to produce ideas by applying the target methods and techniques proposed.
Knowledge Sharing	The process to communicate, exchange and eventually enrich the developed knowledge.
QOLE	Quality of Learning Experience is a broad concept that is basically adopted to measure experience.
Effectiveness	Refers to the capability to deliver the requested outcome.
Efficiency	Indicates the capability to deliver an outcome with certain constraints, e.g., time.
Enjoyment	Enjoying the learning experience of adopting technology within collaborative learning environments.
AP	Academic Performance means assessing the learning outcome.
SS	Student Satisfaction refers to the student's perceived quality of experience.

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Chapter 1 - Introduction

This chapter is organised to provide a brief overview of our study. It begins with the research background highlighting the importance of education in our life and the strategies adopted to improve the quality of higher education around the world. Furthermore, it is then followed by the evolution of modern technology and its role in education before and during the Coronavirus pandemic. Overall, the current chapter demonstrates the position of this study toward adopting technology in the collaborative knowledge development process and the quality of learning experience. Thus, the purpose of conducting this study associated with research objectives and questions are reported. Additionally, the significance and scope of the study are presented to identify why this research is essential, along with subjects that have been addressed/unaddressed. Finally, the thesis structure is proposed.

1.1 Research Background

Education is an essential part of our life as it plays a significant role in building a mindful and responsible society by increasing social standing and awareness among people, as well as people's values, and opening to the World (Bhardwaj 2016). Education is seen as a lifelong process (Blossfeld & von Maurice 2011), which needs to be continuously developed in line with evolving personal and professional needs, including but not limited to determining reality, transferring values, and socializing learners so that they can contribute to their social development and knowledge advancement. Furthermore, education plays a significant role in sustainability, as it's a way to teach the new generations (Espinosa-Navarro et al. 2021). Sustainable development is central to university life's dimensions in developing the following aspects: curriculum design, scientific research, scholarships, operations, community communication, service, student opportunities, institutional missions, institutional structures, faculty members, staff as well as rewards (Corcoran, Calder & Clugston 2002). Additionally,

the investment in education is also seen as a critical factor contributing to the development of the process (Psacharopoulos & Woodhall 1993). The investment in the significance of education has been well recognised since the 1960s in either formal or informal education, including training. In addition, this investment can improve different aspects such as skills, knowledge, mindsets, and motivation for economic as well as social evolution. The World Bank has used loans to education organizations in different nations for over two decades. The bank has accumulated experience in forming educational policies and the design of particular projects. This experience not only highlights the need for educational investment but also indicates the difficulty of developing educational policies and investment methods that will contribute the most to a country's development effort.

On the other hand, many governments and educational organizations have been struggling to provide an effective learning environment. Such countries and educational organizations decided to improve many parts of their educational systems a few years ago by proposing visions as reported in (OCDE 2018). Some of these visions are now progressing with the hope of achieving particular goals in the upcoming years.

For instance, Saudi Arabia's vision 2030 (Government of Saudi Arabia 2020) is a strategic plan established in 2016 by Crown Prince Mohammed bin Salman. The main purpose of the vision is to overcome the dependence on oil by expanding its economy by developing public service sectors (i.e., education, health, infrastructure, tourism, and recreation). As a part of the Saudi Vision 2030, the Ministry of Education explicitly aims to improve the adoption of Information Communication Technologies (ICT (Mikre 2011)) and Electronic learning environments (E-Learning (Kumar Basak, Wotto & Bélanger 2018)), which are expected to become more effective in practice (Government of Saudi Arabia 2020; Hassan 2022). Additionally, vision 2030 intends to ensure at least five universities in Saudi Arabia become among the highest 200 Higher Education organizations across the world (Government of Saudi Arabia 2020). These

goals are in line with the National Centre for E-learning and distance education principles established by the Saudi Arabia Ministry of Education in 2007 (Alturki 2022). The Saudi Arabia Ministry of Education aims to merge the ICT into the educational system and ensure that students and instructors adopt e-learning within the academic environments (*National E-Learning Center* 2017). Thus, Saudi Arabia is considered a relevant example for this study because the education sector concentrates on improving the learning process by integrating ICT and E-learning into the educational system.

E-learning refers to the learning environment that is supported by modern technology and media (Kumar Basak, Wotto & Bélanger 2018). E-learning has emerged due to fast evolution of technology, and its advances are leading to a progressive enhancement of several aspects of life. Technology evolution has also affected education (Bonk 2009). Firstly, technology has made it simple for learners to access great amounts of information through the Web. Additionally, E-learning quickly emerged and continued to evolve over the years by defining new models for education. It empowered learning approaches different from the traditional ones (e.g., Cognitive Learning (Martins & Baptista Nunes 2016)).

On 11 February 2020, the World Health Organization announced a disease when communicating with the public: coronavirus (COVID-19) (WHO 2019). COVID-19 has forced the World to change and re-design many aspects of daily life, and significant restrictions have been enforced by Governments, such as closures of borders, social distancing, and lockdowns. Undoubtedly, Covid-19 has raised strong challenges also in education to maintain learning at the different levels (Adnan 2020). Educational organizations moved the facto from face-to-face to virtual learning environments, relying extensively on online resources (Qazi et al. 2021; Tawafak et al. 2021). The transformation of the learning environments forced by COVID-19 has benefited some parts of the visions introduced by countries and educational organizations in improving e-learning and the adoption of technology. The digital transformation in the light

of COVID-19 contributed to assessing the readiness of education organizations in the application of virtual environments, which is relatively not easy to achieve the change within a restricted time. According to the mentioned visions, the digital transformation application has been planned gradually for the long term. However, COVID-19 has quickly forced the digital transformation in a short time. Added to this, the digital transformation in educational contexts provides the opportunity to evaluate the quality of the learning experience when the learning environments largely rely on technology.

Accordingly and more specifically, this study focuses on the broad area of subjects related to system design (Hoffer, George & Valacich 2013), this research targets collaborative environments where students are requested to work collaboratively as a group to develop core tasks. Along the learning process, which also involves instructors who may provide feedback in different forms at key stages, students need to develop a common understanding of problems and goals that ultimately result in knowledge. Current technology contributes to establish a flexible and resilient collaborative learning environment to develop and share knowledge (Gokhale 1995; Pinheiro & Simões 2012; Recker, Mendling & Hahn 2013; Resta & Laferrière 2007)**.** The collaborative knowledge development process can be understood in multiple ways and in the context of this work, is seen as the ability to employ data and information within groups to produce ideas by applying the target methods and techniques proposed (Recker, Mendling & Hahn 2013). In general terms, knowledge sharing is considered the process to communicate, exchange and eventually enrich the developed knowledge (Baanqud et al. 2020)**.** Several studies have reported the effectiveness of adopting collaborative technology in knowledge development & sharing, and there are evidences of high performance within interactive environments (Flanagin, Sun Park & Seibold 2004; Ghavifekr 2020; Hidayanto & Setyady 2014; Lipponen & Lallimo 2004; Pinheiro & Simões 2012). However, the quality of learning experience is affected when the learning process largely relies on technology, as there

is a lack of assessment looking at the different dimensions or aspects. Rarely the overall quality of learning experience is considered as most analyses focus on specific aspects as well as the explicit assessment of the role of Collaborative Technology in education with a focus on recent challenges (COVID-19).

At a more theoretical level, there is a fundamental lack of studies that explicitly address the relationship between traditional learning models (for instance, modelled according to Bloom's taxonomy, which defines different levels of learning (Bloom 1984)), and the process of knowledge development and sharing (defined for example by the Nonaka's theory (Nonaka 1994)) in collaborative learning environments. The process to develop and share knowledge in collaborative learning presents in fact significant similarities and common challenges with a more generic organizational context (Baloian & Zurita 2012; Lee & Schottenfeld 2014).

1.2 Purpose and Research Questions

This study aims to assess the collaborative knowledge development process within environments that rely extensively on technology and the related overall quality of learning experience.

This study has an emphasis on achieving the following research objectives:

(i) Assess the impact of collaborative technology on the overall quality of learning experience at different levels of learning as per Bloom's taxonomy,
(ii) Investigate the process of knowledge development & sharing within collaborative environments which rely extensively on technology to gain flexibility and resilience,
(iii) Understand the relationship between academic performance and perceived satisfaction in such learning environments.

Additionally, the following questions have been raised to address the research gaps with the present study.

The main research question:

Q: *How does an extensive use of technology affect the development of the knowledge needed to apply, analyse and eventually create systems in collaborative learning environments?*

This main question is divided into three sub-questions to clarify the study context and provide a further understanding of the role of technology within collaborative knowledge process and the overall quality of learning experience.

Sub-questions:

Q1: *How is the process of knowledge developing and sharing influenced by collaborative technology?*

Q2: *How does technology support collaborative development to increase flexibility and resilience in the process of applying, analysing and eventually creating as per Bloom's taxonomy?*

Q3: *How does technology affect the relationship between academic performance and perceived satisfaction in collaborative learning environments?*

1.3 Significance and Scope of the Study

A Collaborative Learning approach is becoming more and more popular in practice, which supports the process of knowledge development and sharing, while collaborative technology is becoming more and more relevant to assure resilience and flexibility within collaborative learning environments.

The findings of this study are beneficial to (i) Saudi Arabia's vision 2030, as part of the Saudi vision aims at improving e-learning environments, which are expected to become more effective in practice, (ii) more holistically, to the assessment of collaborative learning environments which rely extensively on technology, and (iii) support further exploration for researchers and academics in learning contexts by looking at the theoretical and practical implications.

Additionally, the recent experience during the COVID-19 pandemic has further increased the potential relevance of the study (Hassounah, Raheel & Alhefzi 2020). The adoption of technology increased in the light of COVID-19 due to social distancing and other restrictions applied by governments. Thus, technology has become a more critical factor in the continuity of many sectors (for example, education (Adnan 2020; Pokhrel & Chhetri 2021)). Furthermore, technology has a significant role in unsustainability matters, such as pandemic crises and other unexpected issues (Espinosa-Navarro et al. 2021; Wang & Huang 2021). Integrating technology into the education system provides sustainable institutions that ensure learning flexibility and continuity (Ermenc & Niemczyk 2022).

This study identified a gap between learning dimensions/levels (e.g. Bloom's Taxonomy), and activities to develop and expand knowledge (e.g. Nonaka's theory) within collaborative learning environments. Therefore, we have combined into a unique analysis framework concepts from Bloom's and Nonaka's perspectives within a collaborative learning environment.

Given the large scope of the mentioned theories, this research only focuses on the aspects that are most relevant for the extent, and intent of the study conducted, i.e., socialization and externalization as in Nonaka's theory and understand, apply, analysis, evaluate and create as in Bloom's Taxonomy.

This study adopts a quantitative method conducted by an online survey as suggested in the literature presented in chapter two and justified in chapter three (section 3.1). The research is conducted among undergraduate and graduate students involved in programs addressing some kind of system design in Saudi Arabia universities as an experimental context. System design adopts in this study because it includes different levels of learning as in Bloom's taxonomy (Sharunova et al. 2022).

1.4 Thesis Structure

The thesis structure is divided into six chapters including the current chapter, i.e., introduction, literature review, methodology, conceptual model and hypotheses, data analysis, discussion and conclusions.

Chapter 1 presents a brief introduction related to the study, i.e., a background of the research context, the purpose of the study and its questions, the significance of conducting this study, the scope, and eventually the thesis structure.

Chapter 2 contains an extensive literature review regarding the current study. The chapter provides related work about the selected concepts from the literature, such as Collaborative Learning, Collaborative Technology, System Design, and Quality of Learning Experience. Then followed by a rich understanding of the existing theories framework involved in learning activities i.e., Bloom taxonomy, and knowledge creation i.e., Nonaka's theory, as well as specifying why these theories have been adopted in this study. Finally, the chapter identifies the gaps that have not been addressed in prior studies, followed by a chapter summary.

Chapter 3 clarifies the methodology adopted in this research. Firstly, it presents the research approach and process compared with the previous studies in the literature. Secondly, it describes the quantitative method, including designing an online survey and the instrument translation, pilot study, sample size, and data collection. In addition, the techniques and software tools utilised for the data analysis are identified, for instance, statistical analysis, measurement model analysis, and structural modelling. Lastly, a consideration of ethics is presented, followed by a chapter summary.

Chapter 4 presents the proposed conceptual model, related hypotheses, and supporting theoretical frameworks. Following the literature review introduced in Chapter 2, chapter 4 provides further explanations regarding the main concepts and fine-grained metrics represented in the conceptual model that demonstrates the study gaps. Finally, part of this chapter offers

justifications for the proposed hypotheses defined in the conceptual model, followed by a chapter summary.

Chapter 5 discusses the data analysis phase to measure the model and test the hypotheses. It begins by providing information about the profiles of the participants and performing screening of the data collected to ensure the data is reliable and valid for further analysis, followed by Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM). Ultimately, the importance-performance map analysis (IPMA) is reported, followed by a chapter summary.

Chapter 6 presents the discussion and conclusions. The chapter starts by reviewing the research objectives, questions, and hypotheses. Then it discusses the findings to answer the proposed questions along with the related hypotheses, followed by the study's contributions. Additionally, both the theoretical and practical implications are discussed. Last but not least, it concludes this research by highlighting the limitations and further work. Finally, references list, and appendices are presented. The thesis structure is displayed in Figure 1.

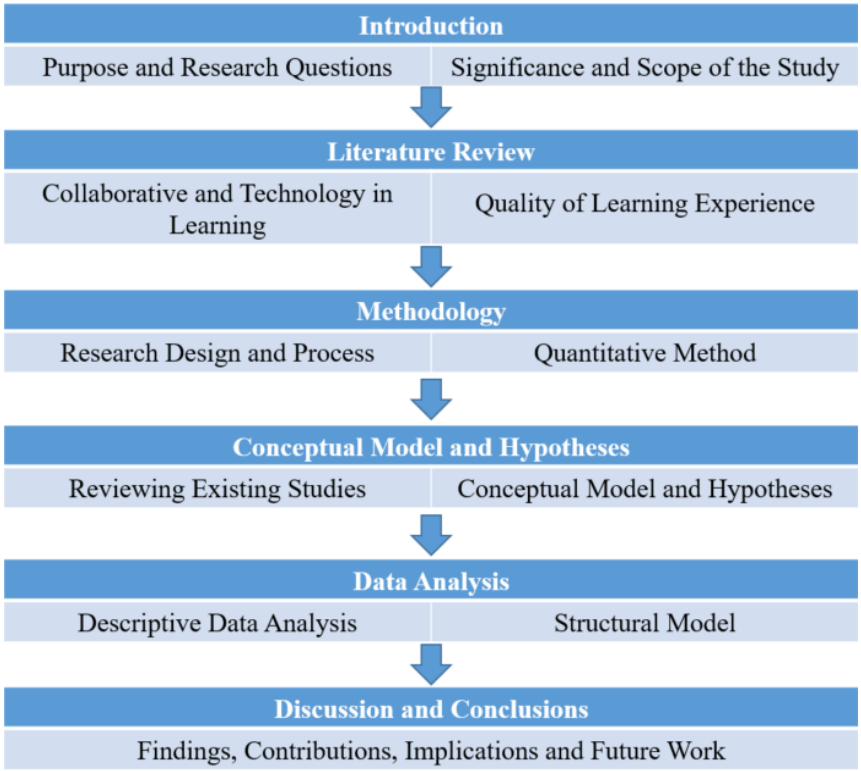


Figure 1 Thesis Structure

Chapter 2 - Literature Review

This chapter provides a comprehensive review of the literature focusing on related studies to the research constructs and the conceptual model discussed in chapter 4. This chapter begins with a review of existing studies in the context of knowledge developing and sharing within collaborative learning environments that rely largely on technology adoption. Additionally, this work defines system design as the experimental context (Hoffer, George & Valacich 2013; Sharunova et al. 2022) and identifies the most commonly accepted assessment metrics for the quality of experience, especially performance and satisfaction (Al-Rahmi, Othman & Musa 2014; Alalwan et al. 2019). Furthermore, we investigate and highlight other fine-grained metrics such as effectiveness (Lin, Huang & Ko 2020; Renner, Laumer & Weitzel 2014), efficiency (Renner, Laumer & Weitzel 2014), and enjoyment (Lin, Huang & Ko 2020) that further reflect the overall learning experience (Neumann, Finaly-Neumann & Reichel 1990). Further exploration of an overview of existing theoretical frameworks that describes the relationship between the traditional learning models (e.g., Bloom's taxonomy) and the process of knowledge development and sharing (e.g., Nonaka's theory) in collaborative learning environments. After reviewing the study context and the supporting theoretical frameworks, the chapter identifies the gaps in knowledge and opportunities to advance the field further. Finally, a chapter summary is presented.

2.1 Collaborative Learning

21st-century students are not appropriately educated by traditional educational strategies because of their early adoption of modern technology (Blair 2012). The pace of societal adoption of modern technology far outweighs the adoption of relevant educational technologies. Different eras have been marked by different learning processes, technologies, and methods. These education methods change from one style to another based on the available

resources, societal demand, and the search for better learning outcomes. For example, some of the earliest forms of education relied on memorization and explanation also known as traditional learning (Sulaiman & Shahrill 2015). Traditional learning depends on a teacher's personal effort since the teacher is the only source of education. As such, an alternative approach called collaborative learning has been recognized as a progressive approach that focuses on the realization of the mind, discussion, and thinking (Almajed et al. 2016; Sulaiman & Shahrill 2015). Additionally, effective practices and integration of available resources like technology can enhance the learning environment and practices. Practically, learning in groups has become more common in practice because evidence indicates that students working in a group perform better than their partners in different aspects (Neil Davidson 2014). Some of the outcome of group learning includes improvements in knowledge development, a high level of thinking, acquisition of social skills, and course satisfaction.

Collaborative learning was introduced in the 1970s by Britton (Neil Davidson 2014). It has been recognised as a unique learning approach for higher education students. Collaborative learning provides individuals with developmental, emotional, and social improvements through involvement and commitment to learning within the environment. According to the authors in (Neil Davidson 2014; Recker, Mendling & Hahn 2013), collaborative learning refers to two or more students working together to achieve a common goal. Collaborative learning is a process that places responsibility for group management and the final learning outcome on the students. Collaborative Learning approach is becoming more and more popular in practice (Kirschner 2001). However, this study focuses on collaborative learning approach due to its popularity in practice to achieve better learning outcomes. The study in (Johnson & Johnson 1989) reported five essential components for collaborative learning that help students work properly and proceed with the task completion, these components are listed as follows:

- Positive interdependence: team members have a common goal to complete a task.

- Individual responsibility: each member within the group is accountable for other members' success to avoid any delay in the progress.
- Promote interaction: strategies are adopted to encourage collaboration, increase trust among members and improve communication.
- Social skills activity: group members learn skills from each other to achieve the goal.
- Group processing: students proceed with tasks, obtain the experiences and commit to the goal achievement.

Furthermore, Mattessich and Monsey expanded on previous works highlighting the most factors cited in the literature that influence collaborative learning environments (Mattessich, Murray-Close & Monsey 2001). These factors include:

- Group open communication.
- Demonstrate understanding, respect, and trust.
- Suitable cross-sections among the team.
- Belief in the value of collaboration.
- Participate in each task equally.

Additionally, the formation of learning groups is an essential step that leads to the team's success, where the instructors usually act as a facilitator of the learning process. Nevertheless, the success of learning relies on the quality of student interaction and engagement within the learning activities to share knowledge and exchange experience (Scager et al. 2016). There are different group formations within collaborative learning environments, broadly these include formal, informal, and base groups (Johnson & Johnson 2009). The formal group usually contains 3 to 5 students working together to accomplish specific tasks for several weeks. The informal group lasts for a short time that involves, for example, classroom activities. The base group holds for longer terms, like a year or longer, these often apply to graduate programs. Many studies in the literature have argued and addressed different factors that affect group formations, these include group size, learner characteristics, homogeneous/heterogeneous

group type, and methods of selection of group members (Chen & Kuo 2019; Chen et al. 2015; Nhan & Nhan 2019; Odo, Masthoff & Beacham 2019; Zheng et al. 2018).

Given the need to develop and share knowledge among students, collaborative learning is quickly becoming an approach for knowledge building and achieving better learning outcomes (Razali et al. 2015). Collaborative learning is even considered a key factor in driving effective and efficient knowledge development (Bereiter 2005). More generally, knowledge is recognised as co-created and shared among peers, a single peer cannot own the knowledge unless acquiring it from previous experience. Thus, collaborative learning is an effective method that reflects positive advantages on students' learning, such as increasing academic performance, and satisfaction in the learning experience. Additionally, group work supports fostering creativity and obtaining skills such as critical thinking, communication, and solving problems. Therefore, many studies have applied different models in various contexts to determine the impact of engaging students in collaborative learning activities to build and share knowledge. For instance, some authors propose an approach in which knowledge acquisition collaboratively through participating and practicing in activities rather than individually (Paavola, Lipponen & Hakkarainen 2004). Additionally, Bereiter's approach to knowledge-building has been adopted broadly in educational organizations to provide students and instructors guidance for engaging in collaborative activities (Bereiter 2005). However, there are obvious challenges in adopting collaborative learning in practice, especially problems with information sharing to achieve specific tasks. Several works have focused on the quality of group interactions. For example, Caldeira focuses more on the quality of group cognition; he opines that students who participate in teams have the ability to develop knowledge and overcome the limitations of an individual mind (Caldeira 2008). Furthermore, in (Hmelo-Silver & Barrows 2008), the authors analysed how medical students can achieve knowledge building as a team supervised by an instructor in problem-based learning. The study in (Micari & Pazos

2021) addresses the social cognitive outputs among students organised in groups. In both mentioned cases (Hmelo-Silver & Barrows 2008; Micari & Pazos 2021), group work positively contributes to knowledge development & sharing. Besides, Winter and Neal studied the students' perceptions toward group work (Winter & Neal 1995); their findings showed the majority of the students produce more in group work, while a quarter of the students prefer working individually. Last but not least, the collaborative learning environments have become recently more and more popular in high education, which returns to the increase in online courses rather than traditional learning on campus (Razali et al. 2015).

2.2 Collaborative Technology

Technology adoption in collaborative learning environments has provided resilience and flexibility. At a theoretical level, technology is seen as effective and supportive in learning environments (Tamim et al. 2011). Collaborative technology refers to a set of online tools that are expected to support a collaborative learning processes among team members and foster interactions with instructors to achieve specific tasks (Alahmari 2019; Cheung & Vogel 2013). Collaborative technology can be also understood in the context of this work as an online tool that enables communication among peers via synchronous and asynchronous messages (Alavi, Dufner & Howard 2011). These messages can be delivered in the form of text, voice, and video or through online environments that support collaboration, brainstorming, sharing & working on documents, and remote learning (i.e., Social Media, Google Docs, Zoom, Learning Management Systems, etc.). According to (Hew & Cheung 2013), the most modern collaborative technology is recognised as Web2.0, which has become more prevalent in practice. Web2.0 tools have been adopted in a collaborative learning context that facilitates the process of developing and sharing information. Most especially, web 2.0 allows communication and interactions between users and educational platforms rather than reading the information from the website. Furthermore, Web 2.0 also allows individuals to customize

their space and share content and ideas collaboratively. Therefore, this study mainly focuses on the extensive adoption of modern technology within collaborative learning contexts that provides flexibility and resilience among students in achieving given tasks.

Many studies from the literature have reported the effects of adopting technology into the educational process in different contexts and situations (Alyami, Pileggi & Hawryszkiewycz 2020; Baanqud et al. 2020; Gupta et al. 2009; Habes et al. 2018; Recker, Mendling & Hahn 2013; Su et al. 2010; Wang 2009). According to the mentioned studies reported the extensive adoption of technology within learning environments may affect the quality of learning experience, including final outcomes. Indeed, a proper use of technology can facilitate students to effectively acquire skills, experience, and knowledge. For instance, the authors in (Recker, Mendling & Hahn 2013), conducted an empirical study that examined the impact of technology on cognitive group process through a collaborative environment to test students' experience of the collaboration and the outcomes of the accomplished task. Interestingly, their findings showed that collaborative technology supports the quality of the modelling process and knowledge development as well as provides flexibility and ease of use. The quality of learning outcome has been positively affected by technology adoption, which enables interactions and discussions among students to develop knowledge. In (Baanqud et al. 2020) investigates how technology like Cloud tools help postgraduate students involved in a collaborative discussion to construct knowledge focusing on cognitive engagement, cognitive presence, knowledge sharing, and reflective thinking. The results of this mentioned study indicate that technology adoption positively affects students' interaction, knowledge sharing, and reflective thinking in the process of knowledge development. Taken together, the effectiveness of building knowledge within collaborative learning environments cannot be overemphasized; additionally, technology adoption in group learning context facilitates and enhances the learning process to acquire knowledge. For instance, in (Wang 2009), the author designed a

technology-supported collaborative learning environment (i.e., an online file sharing tool (DriveHQ)) to write progress reports and develop product versions. Thus, strategies of friendship and meaningful learning tasks have been applied to encourage collaboration. The findings showed students within groups practice the adopted strategies positively, which promotes collaboration. However, the lack of features in the designed technology (DriveHQ) has led students to find their way by using different tools to support their communication, which is considered an essential factor in collaboration, as mentioned earlier in the previous section.

The authors in (Su et al., 2010) performed an experimental study that led to the design of a system that allows students to manage, share, and re-use individual and collaborative annotation. Su et al., attempted to understand the attitudes of individuals during technological adoption as well as investigate the relationship associated with the quality of sharing such annotations and the learning outcomes. They report better student satisfaction with using technology in collaborative environments, which helped individuals create and share annotations among peers. Furthermore, the learning achievement indicated an increase in group work, and the use of technology has an evident influence on learning outcomes and knowledge sharing. Conclusively, the establishment of a consolidated and agile technological environment is likely to make the whole learning experience more enjoyable for students (Ruiz et al. 2021). There are different possible practical effects of technological adoption in learning experience, for instance the study in (Schrader & Grassinger 2021) investigated the relationship between enjoyment and performance in attributional feedback. Additionally, the authors in (Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019) examined the impact of the interaction among teachers and students, emotional support among peers, and online tools within collaborative learning environments.

On the other side, according to (Ruiz et al. 2021), in the pre-COVID period, online resources provide flexibility and enable a more effective learning process which improves students' habits and facilitates the creation of skills through blended learning settings. Due to recent challenges – i.e., COVID-19 - Collaborative Technology plays a more and more important role in maintaining learning activities remotely (Adedoyin & Soykan 2020). It is expected to fully support students around the world by providing a scalable environment to interact and collaborate remotely (Alenazy, Mugahed Al-Rahmi & Khan 2019; Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019; Qazi et al. 2021; Tawafak et al. 2021). The study in (Qazi et al. 2021) evaluates the effectiveness of technology in distance learning and its role during the pandemic. The authors in the mentioned case reported that the students could adopt the technology in remote learning, enabling the sustainability of online education. Additionally, the challenges and experiences caused by the pandemic increasing the capability of educational organizations in terms of distance learning. Furthermore, the authors in (Tawafak et al. 2021)(Qazi et al. 2021)(Qazi et al. 2021) explored the effects of technology in light of teaching and negating technophobia among students to overcome the Covid-19 and avoid adding rough restrictions to education. The results show that modern technological features motivate and facilitate the intention of adopting e-learning. Added to this, the technology contributes effectively to maintaining learning remotely and preventing any consequences that may influence the students' learning in the future.

With the rapid development and the massive adoption of technology has defined new learning models (for instance, e-learning and m-learning). Therefore, we have reviewed the impact of technology on collaborative learning, focusing more on mobile applications (m-learning) (Alyami, Pileggi & Hawryszkiewycz 2020). M-learning aims to provide a more interactive learning environment assuming the active use of mobile devices (Gan & Balakrishnan 2017). In such a way, mobile technology will be a new layer added to education and teaching methods

(Ally J. 2014). M-learning has further contributed to facilitating distance learning and training without adherence to the political and geographical boundaries of the learners (Crane, Benachour & Coulton 2011). It assures higher flexibility for learners. Mobile learning relies on the always-connected principle (Ally et al. 2007). The benefits of adopting mobile technologies in learning have been discussed in several contributions (e.g. (Grønli et al. 2014; So 2016)). It is commonly assumed that m-learning can provide key features to establish and make effective collaboration within the learning environment (Mobile Collaborative Learning – MCL (Pasi Silander Jorma Tarhio 2004)). Additionally, according to the last social and technological trends, the combined use of mobile technology and online social networks intrinsically facilitates MCL environments in which mobile learners can easily collaborate and share knowledge and experiences, as well as they can effectively interact with each other (Grønli et al. 2014; Pasi Silander Jorma Tarhio 2004; So 2016). In this study, we conduct a literature review aimed to discuss the possible impact of MCL, looking at a number of typical parameters, such as user satisfaction (Information, March & Delone 2014), perceived ease-of-use (Davis 1989), perceived usefulness (Davis 1989), impact on affective and cognitive domain (Wikipedia 2019), and perceived enjoyment (Moon & Kim 2001).

2.2.1 Adoption of Technology

Recent statistics show an increasing adoption of mobile technology since 2000, when it was estimated less than 1 billion of mobile devices worldwide against more than 8 billion reached at the beginning of 2019 (ITU Union 2019). This clear trend is affecting, and it is expected to further affect the educational sector in which mobile technology is expected to be more and more relevant. The primary goal of MCL is to allow learners to increase their learning performance (Martin & Ertzberger 2013) and experience. MCL allows learners to collaborate regardless of their actual geographical location. In such a way, learning is customizable and flexible and it may be functional to specific and changing needs. MCL can be adopted in

practice in many different ways depending on the context to achieve different goals. A brief overview of applications in practice of MCL is proposed in Table 2.1.

Table 2.1 Mobile Collaborative Learning adoption in practice

Ref	Adoption of Mobile Collaboration Learning
(Liu & Chu 2010)	Using ubiquitous tools without using a textbook in the classroom.
(Chu, Hwang & Tsai 2010)	Using the ubiquitous environment to access digital resources while learning in real-world scenarios.
(Guerrero, Ochoa & Collazos 2010)	Using software tools for individual tasks or face to face group tasks in the classroom.
(Cavus 2011)	Using Learning Management System, e-mail, videoconference, and MMS through mobile devices.
(Holotescu & Grosseck 2011)	Using mobile multimedia and SMS messages in the classroom.
(Ryu & Parsons 2012)	Combined use of mobile and non-mobile learning. Individual learning supported by MCL.
(Mitroiu 2012)	Facebook app to share multimedia content
(Schaal, Matt & Grübmeyer 2012)	Outdoor mobile technology, e.g. Google Maps or other geo-located services.
(Furió et al. 2013)	Using augmented reality video game vs. traditional game.
(Fresno 2013)	Using mobile technology in and out classroom.
(Kim, Lee & Kim 2014)	Mobile Instant Messaging group vs. Personal Computer-based Instant Messaging group vs. Bulletin Board System group.
(Hyman, Moser & Segala 2014)	Using mobile devices in their course, such as an electronic reader, a tablet.
(Garcia-Cabot, De-Marcos & Garcia-Lopez 2015)	E-learning platform vs. m-learning.
(Reychav & Wu 2015)	Text vs. video
(Liaw & Huang 2015)	Interaction among teachers and students.
(Sabah 2016)	Incorporate mobile technology into their learning environment.
(Harley et al. 2016)	Augmented reality for a directed historical tour.
(Reychav, Ndicu & Wu 2016)	Using social media into mobile learning.
(Balakrishnan & Gan 2016)	Combined use of social networking and educational tools.
(Reychav & Wu 2016)	Non-interactive vs. interactive mobile learning application at an individual and group level.
(Fabian, Topping & Barron 2018)	Mathematic problems.
(Rejón-Guardia, Polo-Peña & Maraver-Tarifa 2019)	Personal Learning Environment.

Looking at MCL from a technological perspective (Figure 2), we found that MCL solutions are often part of Learning Management Systems (LMS), as well as they often offer

implementation as mobile apps. As expected, there is an extensive use of multimedia content and some novel future based on advanced technology (Augmented Reality). With some surprise, the direct use of Social Networks is relatively low.

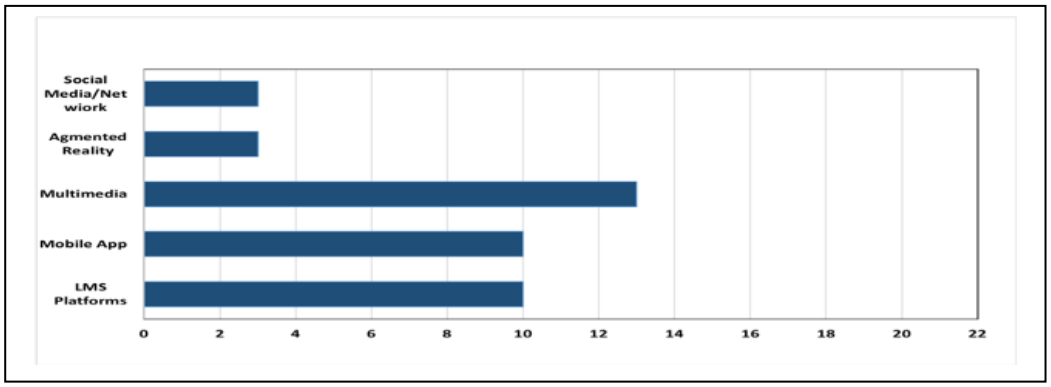


Figure 2 Technological perspective

2.2.2 Target Groups

In this context, a target group is defined as a group of learners who use some MCL-based solution along the learning process. This literature review found that MCL applications target both university-level (59%) and school (41%) students. More concretely, 18% of solutions are for postgraduate, 36% for undergraduate, 5% for college, 27% for primary school, and 14% for secondary school.

2.2.3 Selected Criteria in Existing Studies

We have investigated the use of our assessment criteria in the various contributions. Perceived usefulness (PU) and perceived ease-of-use (PEOU) are defined according to the Technology Acceptance Model (TAM) (Davis 1989). The former concept is associated with user perception in terms of value, while the latter is more related to usability. The third criterion, User satisfaction (US), reflects the quality of experience. The affective domain (AF) addresses feelings and, more in general, the emotional area. The impact on the cognitive domain (CO) considers mental skills, and it is indeed related to learning performance and motivation. Finally, perceived enjoyment (PE) aims at measuring the enjoyment of learning.

The use of the different selected criteria in the various contributions is reported in Table 2.2. Most contributions adopt at least one of the considered criteria. Only three selected papers (Furió et al. 2013; Liaw & Huang 2015; Rejón-Guardia, Polo-Peña & Maraver-Tarifa 2019) adopt all criteria, while other works adopt some of them. Overall, looking at the studies that adopted the first three parameters (US, PEOU, and PU), learners are satisfied in terms of outcomes and learning environments. Moreover, ease-of-use seems to have a direct positive influence on learning enjoyment, as it results in a less stressful user experience. Also, when learners perceive the usefulness of an additional learning value, the benefit is perceived at an affective level. It leads to increased motivation and cognitive performance.

We want to remark that users reported in general a very good quality of experience. However, such an experience becomes even better when ease-of-use and usefulness are recognized together (Balakrishnan & Gan 2016; Cavus 2011; Furió et al. 2013; Garcia-Cabot, De-Marcos & Garcia-Lopez 2015; Hyman, Moser & Segala 2014; Liaw & Huang 2015; Rejón-Guardia, Polo-Peña & Maraver-Tarifa 2019). Learners who use MCL in their learning show some increase in their cognitive performance (Balakrishnan & Gan 2016; Garcia-Cabot, De-Marcos & Garcia-Lopez 2015; Reychav & Wu 2015, 2016). MCL is personalized as a training tool (Garcia-Cabot, De-Marcos & Garcia-Lopez 2015). Text channel is effective in collaboration (Reychav & Wu 2015), as well as social media provides benefits and flexibility (Balakrishnan & Gan 2016). Finally, real-time interactions among learners are the key feature in (Reychav & Wu 2016). Last but not least, the affective state (especially enjoyment) drives motivation and has a clear impact on cognitive learning performance and may strongly influence future intentions (Balakrishnan & Gan 2016; Cavus 2011; Furió et al. 2013; Garcia-Cabot, De-Marcos & Garcia-Lopez 2015; Guerrero, Ochoa & Collazos 2010; Harley et al. 2016; Liaw & Huang 2015; Liu & Chu 2010; Rejón-Guardia, Polo-Peña & Maraver-Tarifa 2019; Reychav & Wu 2015).

Table 2.2 Mobile Collaborative Learning Assessment Based on Six Different Criteria

Reference	Assessment (✓= adopted ×= not adopted)					
	US	PEOU	PU	AF	CO	PE
(Liu & Chu 2010)	✓	×	×	✓	✓	✓
(Chu, Hwang & Tsai 2010)	×	×	×	×	✓	×
(Guerrero, Ochoa & Collazos 2010)	×	✓	×	✓	✓	✓
(Cavus 2011)	×	✓	✓	✓	✓	✓
(Holotescu & Grosseck 2011)	×	×	×	✓	✓	×
(Ryu & Parsons 2012)	×	×	×	×	✓	×
(Mitroiu 2012)	×	✓	×	×	✓	×
(Schaal, Matt & Grübmeyer 2012)	✓	×	✓	×	✓	×
(Furió et al. 2013)	✓	✓	✓	✓	✓	✓
(Fresno 2013)	×	×	✓	✓	✓	×
(Kim, Lee & Kim 2014)	✓	×	×	✓	✓	×
(Hyman, Moser & Segala 2014)	×	✓	✓	✓	×	✓
(Garcia-Cabot, De-Marcos & Garcia-Lopez 2015)	×	✓	✓	✓	✓	✓
(Reychav & Wu 2015)	✓	×	×	✓	✓	✓
(Liaw & Huang 2015)	✓	✓	✓	✓	✓	✓
(Sabah 2016)	×	✓	✓	×	×	×
(Harley et al. 2016)	×	✓	×	✓	✓	✓
(Reychav, Ndicu & Wu 2016)	×	✓	×	×	✓	✓
(Balakrishnan & Gan 2016)	×	✓	✓	✓	✓	✓
(Reychav & Wu 2016)	✓	✓	×	×	✓	×
(Fabian, Topping & Barron 2018)	✓	✓	✓	×	×	✓
(Rejón-Guardia, Polo-Peña & Maraver-Tarifa 2019)	✓	✓	✓	✓	✓	✓
User Satisfaction (US), Perceived Ease-of-Use (PEOU), Perceived Usefulness (PU), Affective Domain (AF), Cognitive Domain (CO) and Perceived Enjoyment (PE)						

2.3 System Design

System Design is an important field in computer science and information systems, it has become a core subject taught in the Information Systems (IS) curriculum for undergraduates as well as schools of business. System design is an approach established around the 1970s that addresses business needs and the technical issues related to software development (Siau et al. 2021). System Design is commonly understood as a set of processes that aim to the specification of the different system elements and components that meet a given set of

requirements (Hoffer, George & Valacich 2013). System design is typically recognized as a combination of analysis and design phases, involving a process and immersion in understanding the users' experience to design the target system. Thus, System analysis and design are considered two topics merged into one course in IS (Kohli & Gupta 2002). There is no precise method for teaching system design, which is quite challenging to understand the best practice and techniques (Siau et al. 2021). However, by definition, system design has a common goal. According to (Richmond, Seidmann & Whinston 1992), the common goal of system design is to involve students in practical group activities to achieve a given task. For instance (task analysis, solving problems, and designing a system). Additionally, colleges and universities are highly encouraged to engage students in such activities so as to incorporate their learning into real-life projects and learn how to collaborate effectively (Farwell et al. 1992). System design allows students to interact more with users to learn about their experience using a specific system (Haas 1988).

However, there are obvious challenges in adopting and incorporating system design; nevertheless, the importance and advantages outweigh the challenges (Harris et al. 2006); these benefits include but not limited to:

- Students learn different methods, techniques, and tools in developing the target system.
- Increases students' cognitive skills and problem-solving.
- Exposes students to learn the facts by collecting data from users' experiences.
- Allows to obtain collaboration skills among team members.
- Pre-requires for advanced courses related to programming development and database.
- Plays a key role in the development and implementation of IS.

Within the system design process, knowledge development and sharing have been recognized as critical factors for the success of the target design (Joshi, Sarker & Sarker 2007; Lowyck &

Pöysä 2001). Where members within a group have to develop and share the related knowledge to achieve a common goal in different phases (i.e., Planning, analysis, design and implementation (Hoffer, George & Valacich 2013)). Generally, there are two standard modelling approaches in system analysis and design: (i) the traditional method, known as the structured and (ii) the object-oriented (Harris et al. 2006)). The former consists of two phases, i.e., analysis of the system and then designing it by using a number of diagrams such as data flow diagrams and entity-relationship diagrams. The latter is commonly considered data-centric by using Uniform Modelling Language (UML), which is a set of entities, namely "classes" that encapsulate the data known as " attributes" as well as the processes "methods" related to every entity (Siau et al. 2021).

However, many studies have addressed the subject of system design looking at different aspects and approaches (Chen 2005; Dasgupta et al. 2007; Kohli & Gupta 2002). This study does not object to improving methodologies or techniques adopted in system design, as it is more about learning assessment considering system design as an experimental context. Therefore, this research targets collaborative environments where students are requested to work as a group to develop core tasks related to system design. System design is adopted in this study because it represents and includes different levels of learning as in Bloom's taxonomy. In other words, the adoption of system design as an experimental context in this study returns to the similarities of system design phases with the different classifications of learning in Bloom's taxonomy (Sharunova et al. 2022). More concretely, we put emphasis on the system design phases (Hoffer, George & Valacich 2013), where "Analysis" is related to the system requirements, "Design" is more about the recommended solutions, and "Development" is applying the components from previous stages together. These phases are known as the heart of the system design process that can be associated with analysis, creation, and application in Bloom's taxonomy (as described later in section 2.5.1).

2.4 Quality of Learning Experience

Quality of learning experience is a well-known concept that has been defined in (Neumann, Finaly-Neumann & Reichel 1990), which refers to the students' perspective toward direct and indirect inputs that have been given from educational organizations like universities. Many research has measured quality of learning experience to assess and explore related aspects of the learning experience in different contexts (Charkhabi, Abarghuei & Hayati 2013; Neumann & Finaly-Neumann 1989; Udo, Bagchi & Kirs 2011). Additionally, the most commonly accepted assessment metrics for the quality of experience are performance and satisfaction (Al-Rahmi et al. 2015; Al-Rahmi, Othman & Musa 2014; Al-Rahmi & Zeki 2017; Alalwan et al. 2019; Tullis & Albert 2013). While performance assesses the learning outcome, satisfaction refers to the student's perceived quality of experience. We focus on relevant studies in tandem with our objectives to understand how they measure and assess their learning experience. Mainly, we look into the studies with technology adoption within collaborative learning activities while evaluating different aspects of the learning experience.

Involving technology in collaborative learning has a tangible impact on academic performance (Resta & Laferrière 2007) by providing flexibility for engagement. Moreover, social media is seen as casual technology; it positively influences students' performance and supports learning environments. In study (Alalwan et al. 2019) reported that social media adoption in collaborative learning environments supports communication, enables knowledge sharing, and promotes learning activities. More specifically, the study integrated factors related to three theories (i.e., Constructivism theory, Communication theory, and Technology Acceptance Model (TAM)) to determine how social media affects peers' performance as well as its influence on providing effective and engageable collaborative learning environments. As we mentioned earlier, the most critical indicators for learning outcomes are satisfaction and performance, while academic achievement is typically associated with the extent of acceptance

and satisfaction of the learning environments. Consequently, the authors in (Al-Rahmi & Zeki 2017) observed a high level of satisfaction when students adopt the technology in collaborative learning activities, which increases learning performance.

The value of embracing modern technology in collaborative activities has been noticed as a way to enhance and promote different aspects of education, including the final learning outcomes. As reported in (Al-Rahmi, Othman & Musa 2014), adopting technology and social media in collaborative learning encourages interaction among students and instructors, enables knowledge sharing, and ultimately improves satisfaction and academic performance.

However, to assess an overall learning experience, it is important to consider fine-grained metrics, such as effectiveness (the capability to deliver the requested outcome) and efficiency (the capability to deliver an outcome with certain constraints, e.g., time) (Lin, Huang & Ko 2020; Renner, Laumer & Weitzel 2014). Rarely, effectiveness, efficiency, and enjoyment are simultaneously considered when assessing performance and satisfaction.

Table 2.3 summarizes how different previous studies from the literature assessed their learning experience that relies on technology adoption during collaborative learning activities.

Table 2.3 Assessment in previous studies

Ref	Research aim	Independent concept	Dependent concept
(Al-Rahmi et al. 2015)	Evaluates the impact of adopting social media within collaborative learning environments to improve academic performance.	• Social Media	• Collaborative learning • Academic performance
(Al-Rahmi, Othman & Musa 2014)	Observes a number of factors using social media collaboratively to enhance academic performance and satisfaction.	• Interactive with peers • Interactive with supervisor • Engagement • Perceived ease of use • Perceived usefulness	• Collaborative learning • Students' satisfaction • Students' academic performance
(Habes et al. 2018)	Tests the effect of adopting technology through a collaborative learning setting.	• Interactive with students • Interactive with teachers • Engagement • Behavioural intention	• Modern Media • Collaborative learning

(Qureshi et al. 2021)	Evaluates the impact of different social factors on students' learning performance, while collaborative learning and students' engagement are set as mediating variables.	• Interaction with peers • Interaction with instructors • Social presence • Social media • Collaborative learning "intervening" • Students' engagement "intervening"	• Learning performance
(Recker, Mendling & Hahn 2013)	Examines technology's impact on cognitive group process through a collaborative modelling process.	• Ease of collaborative technology • Ease of modelling through collaborative technology • Ease of validation using collaborative technology	• Perceived Semantic Quality • Perceived Usefulness • Satisfaction
(Rejón-Guardia, Polo-Peña & Maraver-Tarifa 2019)	Assesses the TAM model included subjective norms and social image to learn how to use a personal learning environment in Google apps to promote collaborative learning.	• Subjective norms • social image • Usefulness • Ease of use	• Use intention
(Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019)	Examines the impact of interaction factors that influence online collaborative learning.	• Interaction (i.e., teacher-student and student in groups), • Emotional support in a group • Online tools	• Collaborative learning
(Gomez, Wu & Passerini 2010)	Investigates the impact of involved computer-supported team-based learning as mediation in hybrid classrooms.	• Individual preparedness • Perceived team-member valuable contributions • Perceived motivation "intervening" • Perceived enjoyment "intervening"	• Perceived learning
(Baber 2021)	Examines the impact of social interaction among students through the effectiveness of online learning during (covid-19).	• Social interaction • Social distance "intervening"	• Effectiveness of online learning
(Baanqud et al. 2020)	Investigates how technology such as cloud tools help students	• Cognitive engagement • Cognitive presence	• Knowledge construction

	construct knowledge within collaborative environments.	• Knowledge sharing • Reflective thinking	
(Al-Rahmi & Zeki 2017)	Determines the influence of TAM using social media in a collaborative learning process.	• Perceived Usefulness • Perceived enjoyment • Perceived ease of use	• Social media • Collaborative learning • Students satisfaction • Learners' performance
(Alalwan et al. 2019)	Investigates the impact of the use of social media through collaboration and communication on students' academic performance.	• Perceived Usefulness • Perceived enjoyment • Perceived ease of use • Interaction • Engagement • Motivation • Ease of communication	• Collaborative learning • Intention to use social media • Online communication • Academic performance
(Alenazy, Mugahed Al-Rahmi & Khan 2019)	Evaluates the technology acceptance model (TAM) on using social media in collaborative learning to improve authoring among researchers.	• Perceived usefulness • Perceived enjoyment • Perceived ease of use • Social media use "intervening" • Collaborative learning "intervening"	• Collaborative authoring
(Liu, Zhong & Lim 2009)	Assesses how virtual learning environment characteristics can directly affect students' effectiveness on learning materials and communication that lead students to interact with each other and instructors within the system.	• Information Accessibility • Ease of Navigation • System Interactivity • System Support	• Self-controlled Learning • Communication • Skill Development • Subject-related Learning
(Lin, Huang & Ko 2020)	Evaluates different approaches to the blended learning environment and team-based learning to support course designing	• Perceived enjoyment • Knowledge sharing "intervening"	• Team effectiveness • Individual learning
(Devaraj, Easley & Michael Crant 2008)	Investigates the impact of personality factors on TAM and technology in collaborative settings	• Conscientiousness • Extraversion • Neuroticism • Openness • Agreeableness	• Perceived Usefulness • Perceived enjoyment • Perceived ease of use • Subjective norms

2.5 Supporting Theoretical Frameworks

The method of developing a conceptual model relies on understanding theories that are relevant to the study context (Jonassen 1997). From our readings list, we have identified a couple of theories involved in learning activities (e.g., Bloom's taxonomy) and knowledge creation (e.g., Nonaka's theory) as follows:

Why use Bloom's taxonomy:

Bloom's taxonomy is a framework that has been used to assess different levels of learning and has been applied in different contexts. As far as the author knows, there are very few works that address Bloom's taxonomy explicitly in collaborative learning environments (Gokhale 1995; Jyothi 2011; Karen Stokes Chapo 2021). Bloom's levels identify the activities followed in learning, and its structure can give us thoughts that lead to innovation, which is a compelling method to develop the needed knowledge in learning activities at different levels and dimensions.

In earlier research from Western Illinois University, Bloom's classification was adopted to design pre and post questionnaires for undergraduate students who work in small groups related to basic electronics subject (Gokhale 1995). The mentioned study aimed to determine the effectiveness of collaborative learning against individual learning to understand where critical thinking can be achieved between the experimental groups. At some universities and colleges, faculty members have been encouraged to use the different levels of Bloom's taxonomy as guides in designing and evaluating their courses. Western Michigan University has considered Bloom's Taxonomy a guideline for the faculty in Technology Center for courses design (Karen Stokes Chapo 2021). Where lecturers are requested to consider Bloom's classifications before adopting any technology in their courses by looking at what kind of knowledge students will learn as well as what teaching techniques will help accomplish the learning objectives. Virginia

Lee from the University of North Carolina stated that Bloom's Taxonomy is an effective tool to enhance critical thinking and describe the model of critical thinking (Kurfiss 1988). At the same time, Virginia Lee highlighted Bloom's Taxonomy explicit and measurable learning goals consistent with assessment procedures.

As mentioned in the following sub-section (2.5.1), Bloom's taxonomy has three dimensions, while this study focuses on the cognitive phase (i.e., the knowledge development process). We perceive a lack of analysis in depth of learning dimensions/levels of Bloom's Taxonomy and activities to develop and expand knowledge of Nonaka's theory in collaborative learning environments. More concretely, we put emphasis on the phases of analysis, design, and development in system design that can be associated respectively with analysis, creation, and application in Bloom's taxonomy. The adoption of system design as an experimental context because it includes different levels of learning as in Bloom's taxonomy (Sharunova et al. 2022).

Why use Nonaka's theory:

Knowledge management is essential in the field of education and academic environments. Knowledge management has substantial potential for the educational sector (Ni et al. 2018). Recently, Nonaka's theory has been extensively adopted as the theoretical framework for knowledge creation in an educational context (Baloian & Zurita 2012; Lee & Schottenfeld 2014; Lopez-Nicolas & Soto-Acosta 2010). Thus, knowledge generation and distribution amongst students and instructors is important. For instance, students who work in collaborative environments are required to develop and share relevant knowledge related to their tasks. Therefore, collaborative learning is becoming more popular in practice to foster knowledge development and sharing. Additionally, modern technology has the advantage of supporting the learning environments by providing flexibility and resilience for the development and sharing the needed knowledge among team members.

Nonaka's knowledge creation theory is a well known framework in an organizational context for knowledge management (Shuhuai et al. 2009). Furthermore, Nonaka's perspective focuses on the process of knowledge creation, which is similar to the educational principles that aim to build knowledge rather than acquire it. Accordingly, such a framework has been adopted within the educational context to redefine the learning objectives for knowledge development (Paavola, Lipponen & Hakkarainen 2004). Nonaka's theory describes innovation process and knowledge development among peers by engaging in four activities: socialization, externalization, combination, and internalization. The innovation process is converting the knowledge from tacit to explicit knowledge in which a person's experience is changed into collective and organizational knowledge.

Many studies have embraced Nonaka's theory of knowledge creation in collaborative learning environments. For instance, the study in (Lee & Schottenfeld 2014) assessed the university students' engagement through collaborative activities for knowledge development in the academic library by employing the theory of Nonaka of knowledge creation. The study analysed the activities conducted among group members based on the four dimensions of knowledge creation. Additionally, Nonaka's framework has been addressed in the field of ICT (Lopez-Nicolas & Soto-Acosta 2010). This study investigates the impact of integrating ICT into the process of creating and sharing knowledge through the different types of dimensions (i.e., Socialization, Externalization, Combination, and Internalization). While ICT plays a critical role in combining explicit knowledge in collaborative environments (Lopez-Nicolas & Soto-Acosta 2010). Furthermore, ubiquitous and modern technology like m-learning, has been recognised as critical in collaborative learning for knowledge construction processes. Baloian and Zurita designed a system that includes ubiquitous m-learning, which allows students to develop and share knowledge focussing on Nonaka's dimensions within collaborative learning environments without time and place constraints (Baloian & Zurita 2012).

This study realized the vital role of modern technology in collaborative learning and its impact on developing and sharing the needed knowledge. Additionally, Nonaka's framework has been adopted in our study because of its popularity in collaborative learning environments and the importance of developing and sharing knowledge in group learning.

2.5.1 Bloom's Taxonomy

Bloom's Taxonomy is seen as a classification system in learning (Bloom 1984). This system classifies various priorities and skills that the teachers and educational system set for students. The taxonomy can be referred to the learning objectives for the students at different levels of learning. The Taxonomy was developed in 1956 under the guidance of educational psychologist Dr. Benjamin Bloom (Bloom 1984). The taxonomy aims to inspire advanced ways of thought in education, such as assessing and reviewing ideas, methods, practices, and values, instead of simply recalling realities "repetition". Those ways are the most commonly utilized in designing systems for schooling, preparation, and learning forms (Bloom 1972).

Explaining the concept further in-depth, Bloom's Taxonomy consists of three hierarchical models that are utilized to group the overall educational learning objectives into complexity hierarchy. These three hierarchical models address the learning objectives under the respective fields in cognitive, affective, and sensory domains. The reason for an instructor utilizing Bloom's taxonomy is to empower higher-level thinking in students by starting from lower-level cognitive skills. Conductive and cognitive learning results are assumed to feature how Bloom's taxonomy will be fused into large-scope educational guidelines. The concept of cognitive domains is the central to education and is now and then utilized to assemble educational programs and academic performance. Because of its importance, teachers are encouraged to be aware and realize these different learning levels for achieving better outcomes.

Dr. Benjamin likewise transformed the principal volume of the standard content, Taxonomy of Educational Objectives: the Classification of Educational Goals (Bloom 1984). Although named after Bloom, the distribution of Taxonomy of Educational Objectives followed a progression of meetings from 1949 to 1953, intended to improve the correspondence between instructors on the structure of educational plans and assessments (Horváth 2020). The primary edition of taxonomy, Handbook I: Cognitive was distributed in 1956 and in 1964 the second edition Handbook II: Affective was distributed. A reconsidered edition of taxonomy for the cognitive domain was made in 2001 (Anderson et al. 2015; Wilson 2016). The assembly expounded by Bloom and his colleagues encompassed six significant categories: Knowledge, Comprehension, Application, Analysis, Synthesis, and Evaluation. The classes after Knowledge were introduced as "skills and capacities," considering that knowledge was the important requirement for incorporating these skills. Although every class comprised subclasses, all focused sideways a spectrum from basic to mind-boggling, the taxonomy mainly agreed to these six principle classifications. Instructors have shown significant progress about how students learn, and how educators instruct. Eventually coming to the conclusion that instructing and learning incorporates something more than just deduction. Additionally, the state of mind and convictions of students and instructors are seen as the social and cultural condition of the class (by Patricia Armstrong, former Assistant Director 2016).

The original taxonomy was stated back in 1956 as mentioned before, introducing the six main categories/levels described with its verbs as follows (BouJaoude & Jurdak 2010; Center 2008);

- **Knowledge** includes recalling specific or general information (e.g., methods, processes, pattern, structure, and setting). Verbs related to this level: “choose, define, describe, find, identify, label, list, locate, match, name, recall, recite, recognize, record, relate, retrieve, say, select, show, sort, and tell”.

- **Comprehension** indicates a sort of comprehension or trepidation to such an extent that the individual understands what is being conveyed and can utilize the material or thought without essentially comparing it to other material. Verbs in this particular level: “clarify, classify, compare, conclude, construct, contrast, demonstrate, distinguish, explain, illustrate, interpret, match, paraphrase, predict, represent, reorganize, summarize, translate, and understand”.
- **Application** refers to the "utilization of abstraction in specific and solid circumstances." Verbs of this level: “apply, carry out, construct, develop, display, execute, illustrate, implement, model, solve, and use”.
- **Analysis** describes the “breakdown of the ideas into its constituent components or small parts that the overall order of arguments is clarified as well as the relations between thoughts communicated are made expressed". Verbs linked to this level: “analyse, ascertain, attribute, connect, deconstruct, determine, differentiate, discriminate, dissect, distinguish, divide, examine, experiment, focus, infer, inspect, integrate, investigate, organize, outline, reduce, solve (a problem), and test for".
- **Synthesis** includes the "assembling of components and parts together to frame an entirety." Verbs connected with this level: “adapt, build, compose, construct, create, design, develop, elaborate, extend, formulate, generate, hypothesize, invent, make, modify, plan, produce, originate, refine, and transform”.
- **Evaluation** makes the "decisions about the estimation of materials and adopted methods for particular purposes." Verbs connected with this level: “appraise, assess, award, check, conclude, convince, coordinate, criticize, critique, defend, detect, discriminate, evaluate, judge, justify, monitor, prioritize, rank, recommend, support, test, and value”.

This taxonomy is used as a tool that has information for designing educational programs as well as cognitive psychology programs. Moreover, the taxonomy has also been used as an evaluation method for learning programs, eventually becoming an icon for educational plans to set learning goals and structure classroom exercises. The taxonomy has also been adjusted for primary and secondary school use and extended to each discipline.

Most normally imagined the taxonomy as a pyramid. With the increasing essential cognitive exercises at the base, the first model revolved around static information and unique capacities. In any case, as the world advanced further, a gathering of cognitive intellectual, educational plan scholars, scientists, and evaluation masters, board of trustees distributed an amendment of Bloom's Taxonomy recognized three-domain of instructive learning:

- Cognitive: intellectual skills (knowledge).
- Affective: development in emotional areas (attitude or self).
- Psychomotor: manual skills (skills).

The knowledge dimension emphases on the content kinds of knowledge, which are categorized into four classes: Factual knowledge, Conceptual knowledge, Procedural knowledge, and Metacognitive knowledge (Krathwohl 2008). The dimension of cognitive processes focuses on how knowledge is used, which is categorized into remembering, understanding, applying, analysing, evaluating and creating as presented in figure 3. The taxonomy levels have been a source of contention among researchers and academics; however, the framework has been changed just a single time, a testament to the idea's solidness and reliability (Kress & Selander 2012).

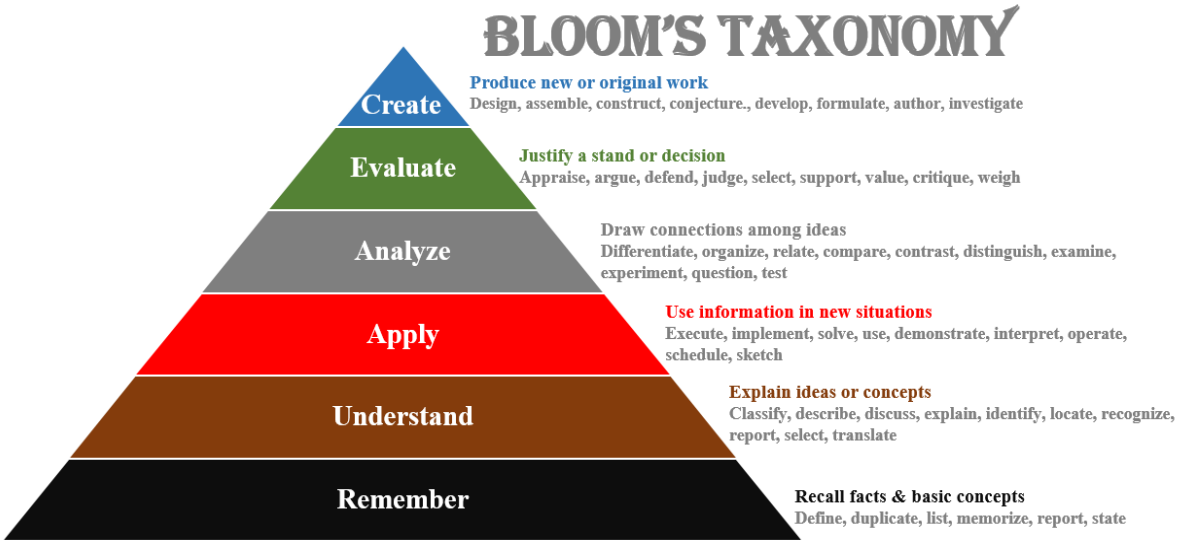


Figure 3 Major cognitive dimensions of Bloom's taxonomy (Wilson 2016)

Lorin Anderson (a previous student of Bloom) and David Krathwohl worked together to revise the cognitive domain of the original taxonomy and implement specific improvements (Krathwohl 2008; Wilson 2016). Table 2.4 shows the major changes made to the original taxonomy, which has changed all the names in the six levels from noun to verb forms in the revised version. Additionally, the last two levels in the original taxonomy have been reversed in the updated model by placing Create (Synthesis) as the last level.

Table 2.4 Original vs. Revised Taxonomy

Original Taxonomy in 1956	**Revised Taxonomy in 2001**
Knowledge	Remember
Comprehension	Understand
Application	Apply
Analysis	Analyse
Synthesis	Evaluate
Evaluation	Create

2.5.2 Nonaka's Theory

Nonaka's theory was established in 1994 (Nonaka 1994); it defines four models such as (socialization, externalization, internalization, and combination), known as the SECI model. Nonaka's theory is a well-known framework for accepting knowledge creation procedures in an organization context. Knowledge is the best way to present an essential direction for competitive advantage to any organization that seeks knowledge development. Nonaka's theory produces significant value to the organization by innovation and turning that knowledge across boundaries (Scalzo & Fariñas 2019).

The current society is moving toward knowledge creation and realizing the importance of expanding the existing knowledge by looking at different aspects. The gradual increase in the importance of knowledge has become very speedy, driving a shift in the Educational landscape. The knowledge has brought innovations and new technical things to the academic world. Technological and product innovations are also the results of an organization's knowledge. Thus, knowledge is a critical source for organizations to provide a competitive advantage that enables an organization to develop new products to support our life in different contexts (Jeong, Song & Hsiao 2018).

Nonaka has described knowledge as a dynamic, systematic, and ongoing procedure that occurs and emerges over time. Nonaka's knowledge model opines that most knowledge management processes focus on the evolutionary path. However, Nonaka has presented a well-established and relevant proposal focused on the knowledge management field. Nonaka has defined knowledge as a multifaceted concept, and the knowledge has never been explained well.

Nonaka describes the nature of knowledge and information, and defines the differences between organizational knowledge creations. Accordingly, there are two dimensions of knowledge creation (Nonaka & Yamaguchi 2022). These types of knowledge are tacit

knowledge and explicit knowledge. The author in (Yoon 2011) reported the complexity of the knowledge-sharing process as we only share 10% of our knowledge, and it is not easy to express all our knowledge. Additionally, explicit knowledge is a type of knowledge that can be transferred informally.

On the other hand, tacit knowledge is different from explicit. While tacit knowledge is the knowledge that we possess in our minds, it can not be described or transmitted to others. These are the personality qualities of a person. Therefore, these two types of knowledge can be very fruitful for organizations (Kahrens & Früauff 2018) as well as educational contexts (Baloian & Zurita 2012; Lee & Schottenfeld 2014; Lopez-Nicolas & Soto-Acosta 2010).

Nonaka has also opined that organizational knowledge can be created through ongoing social contact. The implicit and explicit knowledge include four models of knowledge conversion, as shown in figure 4. These models are socialization, externalization, internalization, and combination (Pandey et al. 2021).

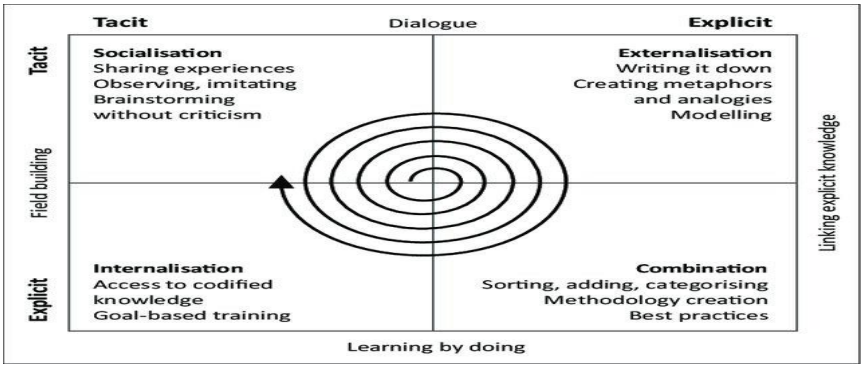


Figure 4 Nonaka's Models (Maluleka & Ngoepe 2018)

- **Socialization** is a procedure of sharing knowledge. The sharing of expertise includes imitations, observation, and practices. The apprentice would work with the educators and mentors to learn about the procedure, through observation, and imitation. Socialization is also described as capturing knowledge physically, whereas direct

contact is an assisted way to understand. The concept of socialization starts from sharing knowledge and experiences. When a person shares his experience with others at a workplace, it transmits that experience to the other people working there. The share of knowledge in this way is called socialization. Socialization is a fundamental way of communicating knowledge within an organization, such as among employees or learners (Pérez-Luño, Alegre & Valle-Cabrera 2019).

- **Externalization** is the process of explicitly developing tacit knowledge. The knowledge and information are crystalized and shared with others via external sources. Externalization includes the articulation and publication of the knowledge that will bring value to the organization (Ammirato, Linzalone & Felicetti 2021).
- **Internalization** defines the application and receiving of knowledge encapsulated by an individual and surrounded by learning through doing. Nonaka's model also focused on internalization. According to Nonaka, a single person absorbs internal knowledge and information; therefore, the knowledge could have consisted of the personal experiences connected with the individual. For instance, an instructor who is involved in the organization or group will share the knowledge with others, and those learners will realize that the training is not related to their experiences (Nonaka & Toyama 2015).
- **Combination** is defined as the integration and organization of knowledge, it involves the merging of the different types of explicit knowledge. The everyday use of the computer network and database exemplifies the combination model. The explicit knowledge is combined and gathered from inside and outside of the organization, the combined knowledge is then merged and transmitted for the organization's prosperity. After that, the newly created knowledge can be transferred among the organization's members and utilized for the wealth and development of the organization (Bachmaier & Seeber 2018).

2.6 Gaps Identification

Through our readings list, we identify gaps by looking at theoretical and practical perspectives, as shown below in Figure 5 (a) and (b). This study aims to assess the role of collaborative technology on the overall quality of experience. Additionally, it investigates the knowledge development and sharing process within collaborative learning environments, which rely extensively on technology. Furthermore, we intend to understand the relationship between academic performance and perceived satisfaction in such learning environments.

Within collaborative learning environments, knowledge development & sharing have been addressed in several studies (such as (Baanqud et al. 2020; Ghavifekr 2020; Hmelo-Silver & Barrows 2008; Recker, Mendling & Hahn 2013; Su et al. 2010; Wang 2009)); according to those contributions, group-work positively contributes to knowledge development & sharing. However, such studies do not fully address the impact on the overall quality of learning experience looking at different aspects. Additionally, we perceive a certain lack of analysis in depth of learning dimensions/levels (e.g., Bloom's Taxonomy (Bloom 1984)) and activities to develop and expand knowledge (e.g., Nonaka's theory (Nonaka 1994)).

Due to recent challenges – i.e., COVID-19, Collaborative Technology (Adedoyin & Soykan 2020; Al-Rahmi et al. 2015; Habes et al. 2018; Recker, Mendling & Hahn 2013) plays a more and more important role in maintaining learning activities remotely. Technology has to FULLY support students in reaching the materials, attending classes remotely, interacting, collaborating, and achieving the goals required to proceed with education (Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019; Qazi et al. 2021; Tawafak et al. 2021). However, despite the most modern technology it is supposed to be effective in education, its impact on the quality of learning experience across the different disciplines and activities is still to be fully assessed.

The most commonly accepted assessment metrics for the quality of experience are performance and satisfaction (Al-Rahmi & Zeki 2017; Alalwan et al. 2019; Tullis & Albert 2013). While performance assesses the learning outcome, satisfaction refers to the student's perceived quality of experience (e.g., feeling and thinking). However, such studies do not fully address the impact of the extensive adoption of collaborative technology on the different aspects of the overall quality of learning experience, such as effectiveness, efficiency, and enjoyment to assess the overall academic performance, and satisfaction. It is important to combine effectiveness (the capability to deliver the requested outcome) and efficiency (the capability to deliver an outcome with certain constraints, e.g., time) (Lin, Huang & Ko 2020; Renner, Laumer & Weitzel 2014). Effectiveness, efficiency, and enjoyment are rarely considered when evaluating performance and satisfaction. Broadly, there are different ways in the literature to adopt technology in education, for instance, individually or collaboratively. These learning methods have been applied in different environments and contexts, such as face-to-face, blending settings, or remote learning. Specifically, this study contributes to collaborative learning environments that rely largely on technology to develop and share knowledge as well as to assess the quality of learning experience by focusing on programs that include subjects related to System Design as an experimental context.

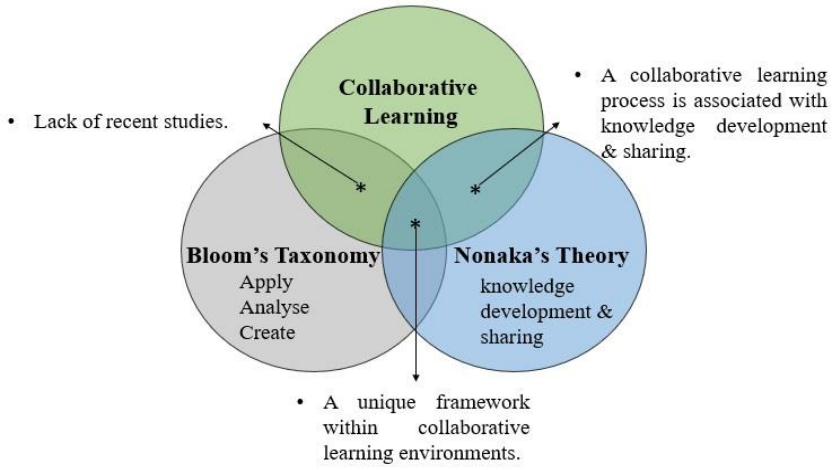


Figure 5 (a) Research Gaps

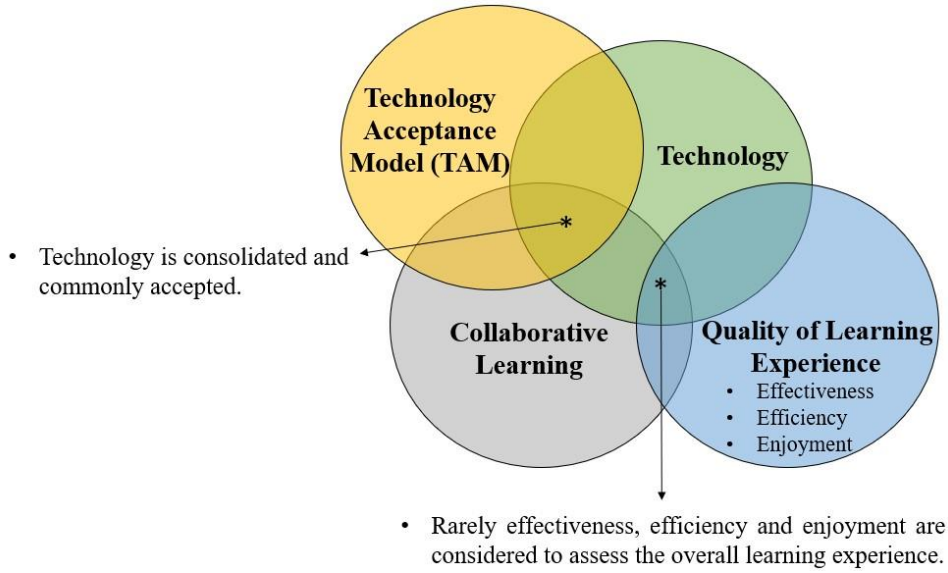


Figure 5 (b) Research Gaps

2.7 Chapter Summary

This thesis presents a concise literature review focusing on collaborative knowledge development when the learning environments primarily rely on technology adoption. The main point of this chapter is to discuss the adopted concepts and analyse other studies' perspectives to contribute to the existing literature. Furthermore, this chapter studies and identifies the most commonly accepted measures to assess the learning experience, including effectiveness, efficiency and enjoyment that reflect the overall performance and satisfaction. Such fine-grained metrics have not been investigated in previous studies at once to evaluate the overall learning experience. Additionally, the relationships among the adopted metrics are discussed based on the existing studies in the literature. On the theoretical level, this chapter identifies supporting theoretical frameworks: the different dimensions of learning as in Bloom's taxonomy and the knowledge creation as in Nonaka's theory. The integration of such frameworks hasn't been addressed in previous studies; therefore, further mapping of these theories is provided in detail in chapter four. Experimentally, System design considers the context for this study because it includes different levels of Bloom's taxonomy.

The next chapter (3) details the research methodology utilised to conduct the current study.

Chapter 3 - Methodology

This chapter aims to explain and justify the adopted methodology in this study. Firstly, it begins by defining and justifying the research paradigm. Secondly, the research design is presented to explain the overall research approach that has been utilised, i.e., quantitative method to answer the research questions by testing the hypotheses. Thirdly, the quantitative process is discussed, including the survey and instrument translation, pilot study, sample size, and data collection. Next, the data analysis procedures have been clarified by providing the steps and techniques adopted to analyse the collected data, such as statistical analysis, measurement model analysis, structural model, and further exploration by looking at the importance performance map analysis. Finally, the chapter concludes by viewing the consideration of ethics and a summary of the current chapter.

3.1 Research Paradigm

A research paradigm is a set of values and strategies communicated by the research community, in which the researcher must choose the appropriate and relevant methodology before conducting the study (Von Hellens, Beekhuyzen & Kerr 2006; Mingers 2003; Ozanne & Hudson 1989). The scientists and researchers should adopt a suitable method to answer the research questions and provide reasonable justification for their studies.

One guideline for such a choice is shown in Figure 6, known as the onion diagram (Mark Saunders, Philip Lewis 2016). The framework provides guidelines for the researchers to help them design their studies. The onion model has different layers that define the process for designing research, i.e., philosophy, approach, methodology, strategy, time horizon, techniques and procedures.

Our research is focused on the ways in which technology contributes to develop and share knowledge within collaborative learning environments. We measure this contribution by

looking at a combination of the quality of learning experience such as effectiveness, efficiency, enjoyment, and eventually assess the overall learning experience, including academic performance and satisfaction. Furthermore, this research evaluates the outcomes depending on the way that students use technology in the collaborative knowledge development process.

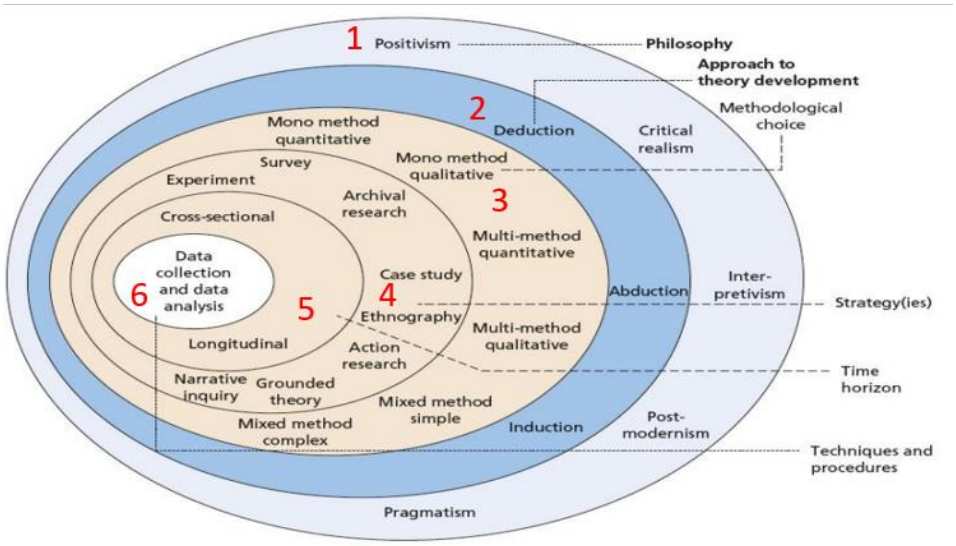


Figure 6 Onion diagram adopted from (Mark Saunders, Philip Lewis 2016)

According to (Ozanne & Hudson 1989), the positivism study supports explanations and provides predictions as well as relying on the assumption that researchers and scientists can come up with reliable and suitable knowledge by observing social life. Additionally, social attitudes influence external and internal factors, which can be seen as objects that contribute to changes in behaviour. Therefore, our research is consistent with the positivist approach as we measure how the extensive adoption of technology impacts upon the process of knowledge development and sharing in collaborative learning environments and the overall quality of learning experience.

Guided by the second layer, we use deductive reasoning because it allows testing hypotheses based on current theories by looking from general ideas to specific ones (Chen & Hirschheim 2004; Von Hellens, Beekhuyzen & Kerr 2006). Positivism and deductive reasoning are seen as

good choices to the current research because the study objectives demanded quantitative data to assess the relationships among the independent and dependent concepts as reported in (Mardiana 2020). The positivism approach leads to obtain quantifiable data, which allows for testing the hypotheses and a better understanding of the phenomena among the adopted factors.

According to the authors in (Von Hellens, Beekhuyzen & Kerr 2006), our study can be considered as positivism research. Firstly, a positivism study takes place when formal propositions are considered. Additionally, positivism focuses more on developing the hypothetic deductive method for theory testing (Chen & Hirschheim 2004; Von Hellens, Beekhuyzen & Kerr 2006). Positivism can also be seen as research hypotheses. At the same time, the positivism study is performed after conducting a literature review as well as integrating a theory that provides an understanding of the relationship between the research constructs and the phenomenon being investigated. The current study proposed a number of hypotheses after conducting a literature review related to the study objectives.

Secondly, a study can be recognised as positivism when the latent variables are measured in the form of quantitative data (Chen & Hirschheim 2004; Von Hellens, Beekhuyzen & Kerr 2006), which is an assumption of conducting the positivism project (Ozanne & Hudson 1989). Accordingly, this study adopts the measures quantitatively and all the scales used are valid and reliable for analysis, as discussed in chapter 5.

Thirdly, the positivism study includes testing hypotheses (Chen & Hirschheim 2004). During the process of hypotheses testing, researchers who conduct positivism studies have the capability to see things objectively and honestly. According to (Gupta 2020), positivism studies allow noticing the actions of individuals and organizations objectively. This observation can be reached by following specific data analysis techniques for each variable and associated hypotheses to determine the relationships among the concepts or variables.

The last principle of positivism research is that the findings of the studies should be generalised to the total target population. As reported in (Von Hellens, Beekhuyzen & Kerr 2006), positivists should follow precise protocols to acquire valid and reliable outcomes that can be more generic and applied to the target population.

However, Remenyi and Williams (1996) argued that the positivism studies are inappropriate in most circumstances (Remenyi & Williams 1996). Those researchers who refuse positivism studies claim that the facts are already created, and it is impossible to explain or understand the fact by pointing to the known truth. Also, the researchers who are critics of the type of positivism studies are more interested in meanings and interpretations, which are related to a qualitative approach that allows studying specific phenomena (Remenyi & Williams 1996).

Another research paradigm is understood as interpretivism, which refers to the reality being understood by a subjective interpretation as well as an intervention within the reality (Chen & Hirschheim 2004). The method of interpretivism is suitable for a study that adopts a qualitative approach (Mardiana 2020). Thus, an interpretivism paradigm supports subjective interpretation, which is not an appropriate paradigm to meet the purpose of the current study.

Therefore, the current study is considered a positivist research paradigm, as it aims to assess the impact of the extensive adoption of technology on the overall quality of experience as well as to investigate the process of knowledge development and sharing within collaborative learning environments. In similar cases, many studies in the literature adopted the positivism approach by conducting the hypothetical deductive method quantitatively (Al-Rahmi et al. 2015; Al-Rahmi & Zeki 2017; Alalwan et al. 2019; Baanqud et al. 2020; Ghavifekr 2020; Habes et al. 2018; Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019; Recker, Mendling & Hahn 2013). Additionally, prior discussions with the instructors who teach subjects related to system design have been considered to determine the best methodology to

address our research objectives. Accordingly, our research methodology has been determined based on pre-consultations and in line with previous studies in the literature.

3.2 Research Design

Research design is known as a process in which various research activities and related components are incorporated to ensure that the study is accomplished meaningfully and successfully addresses its objectives (J & A 2020). Research design allows the researchers to select the study strategies to collect relevant and unambiguous data for their specific research questions (Markham 2012). Consequently, the data is recommended to be appropriate for the study's purpose, i.e., questions and hypotheses that the researchers aim to address. As a result, a good study design is critical in ensuring that the research objectives are met convincingly. The research design links together several aspects of the research project, for instance, determining the sampling, the process of the data collecting, and eventually data analysis, in such a manner that the research runs smoothly and reasonably (Markham 2012). Ultimately, the research design process can be identified based on the study's problem and objectives.

The current study adopts the quantitative approach, which has been recommended by (Trochim 2021), since the study aims to assess the relationships between various concepts related to technology adoption, collaborative learning, and the overall quality of learning experience. Furthermore, the quantitative method supports generalising the final research outcomes to the target population (Trochim 2021). Tierney argued that the most suitable method for the purpose of this study is to conduct a survey (Tierney 2002). The survey design is recommended since it allows the researcher to consider several factors simultaneously. Additionally, the author in (Leavy 2017) reported that by investigating a sample of the target population, the survey design gives a quantitative or numeric depiction of the population's perspectives and attitudes.

According to the discussion above and following the most common research design in the literature, we reiterate that the adopted process for this research is relevant and consistent with the previous studies as well as meeting the needs to achieve our research objectives.

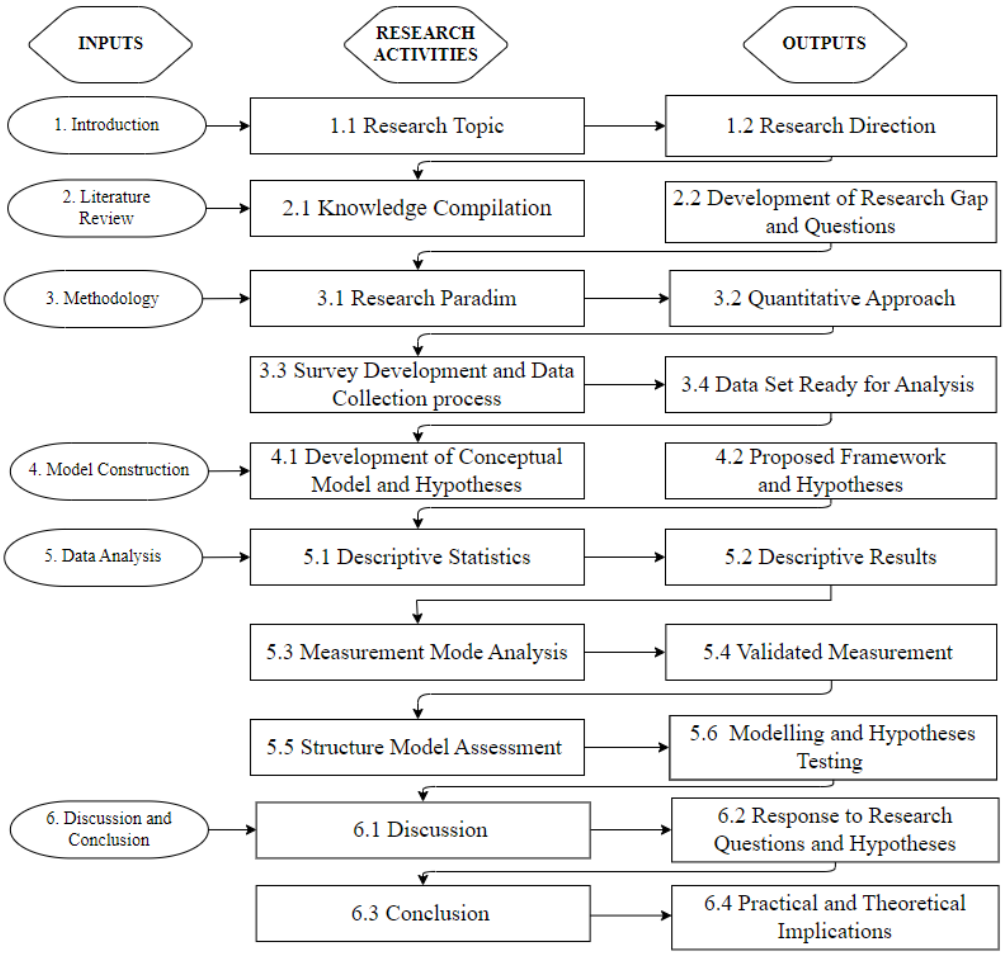


Figure 7 Research Process

Figure 7 displays the research design process and the main activities followed in conducting this study. The first step is to identify the study's topic and determine the research path and context, followed by performing an extensive literature review on the impact of technology adoption in collaborative learning environments to assess its influences on knowledge development and sharing as well as evaluate the overall quality of learning experience. The review process focused on identifying and stating the research gaps as well as the research questions. Following from that, the determination of the research approach based on the

previous studies reviewed in chapter two. Additionally, we developed the conceptual model, research hypotheses and the research questionnaire based on existing studies in the literature; some of the items have been modified to be more consistent with the research objectives. Moreover, efficiency items have been designed due to the lack of explicit assessment available in the literature. Added to this, the consideration of ethics has been obtained from the Ethics Committee at the University of Technology Sydney before proceeding with the survey distribution.

Then, we prepared for the data collection process by determining the software tool used to gather the data and collecting initial quantitative data from undergraduate and graduate students in subjects related to system design from Saudi Arabia universities. The main point of the initial data collection is to check the reliability of the research constructs, adopted indicators and refine the survey instruments before the final data collection (i.e., pilot study). Consequently, we have proceeded with the final collection after ensuring the adopted items are valid and reliable. Thus, data analysis including descriptive statistics, measurement model analysis, and structural equation model have been conducted to test the hypotheses and answer the research questions. The results for each hypothesis are discussed and interpreted based on the previous studies in the literature. Furthermore, the contributions, theoretical and practical implications, and limitations are reported. Finally, the conclusions of this study and the expected future work are discussed in detail.

3.3 Survey Development and Data Collection Process

This section contains the process of survey development and data collection. Firstly, it explains the process adopted to design the survey and the instrument translation. Secondly, the pilot study approach is considered to ensure the adopted and designed items are valid and reliable. Lastly, it highlights the target population along with the sample size.

The process adopted for the survey development and the data collection are discussed in the following subsections.

3.3.1 Survey Design and Instrument Translation

The nature of the quantitative study requires data quantitatively. This data can be obtained by conducting a survey, as reported in (Leavy 2017) and discussed also in (sections 3.1 and 3.2). This study developed and adopted survey items to meet the research objectives. The designed questionnaire aimed to measure the relationships among the research concepts proposed in Chapter 4. The main concepts considered in this study are Collaborative Technology, Collaborative Learning, and Quality of Learning Experience. Additionally, to assess the overall learning experience, it is important to consider fine-grained metrics, such as effectiveness, efficiency, and enjoyment that reflect academic performance and perceived satisfaction. Such a questionnaire is graded according to a five-point Likert scale, where 1 refers strongly disagree, and 5 indicates strongly agree (Allen & Seaman 2007).

The survey items for Collaborative Technology, Collaborative Learning, and Quality of Learning Experience, i.e., Effectiveness, Enjoyment, Academic Performance, and Perceived Satisfaction, have been adopted from existing studies in the literature (Alahmari 2019; Ioannou Nicolaou 2009). Efficiency items have been developed due to the lack of available scales in the literature. Once again, this study adopted system design as an experimental context and used Bloom's taxonomy and Nonaka's theory as supporting theoretical frameworks. Therefore, the items have been modified to meet the research objectives. The designed survey focused on assessing the role of collaborative technology in the development of the knowledge needed to "Apply", "Analyse" and eventually "Create" systems based on Bloom's taxonomy as well as the overall learning experience. Moreover, we adopted system design as an experimental context in this study because it includes many levels of Bloom's perspective.

The survey designed for this study is divided into four sections as follows:

- **Section 1**: Demographic information contains seven questions concerning the participants' profile in general and their experience of technology adoption in education.
- **Section 2**: Collaborative Learning has three questions that measure the perspective of collaborative learning among team members for the knowledge development process.
- **Section 3**: Collaborative Technology has three questions that measure the impact of the technology adoption among team members for communication and task development.
- **Section 4**: Quality of Learning Experience has thirteen questions that measure the fine-grained metrics such as Effectiveness, Efficiency, and Enjoyment to assess the overall academic performance and students' satisfaction.

Furthermore, academic experts and Ph.D. students at the University of Technology Sydney have been consulted regarding the survey questions before the final distribution. The main goal of prior consultation of the survey is to ensure that all the items are consistent with the research concepts and aimed to achieve the research objectives. Also, to ensure that we have addressed all the required criteria for designing the survey. The designed survey items are presented along with the research concepts/factors in Table 3.1 and reported in Appendix A.

Table 3.1 Measures Adoption

Factor	Item	Source
Collaborative Learning	**CL1:** Collaborative work helps the team members to improve their ways of thinking effectively	(Alahmari 2019; Ioannou Nicolaou 2009)
	CL2: I improved other members' contributions to my team and make sense of their ideas	

		CL3: I gained new skills and knowledge from other members of my team	
Collaborative Technology		**CT1:** Collaborative technologies make it possible for team members to collaborate	(Alahmari 2019; Ioannou Nicolaou 2009)
		CT2: Collaborative technologies help to work more effectively among team members	
		CT3: Collaborative technologies help team members to interact, communicate, share and combine diagrams faster and better than face-to-face collaboration	
Quality of Learning Experience	**Effectiveness**	**Effectiveness1:** Collaborative work helps the team to develop diagrams quickly and lead to better diagrams outcomes	(Alahmari 2019; Ioannou Nicolaou 2009)
		Effectiveness2: Collaborative technologies help to gather the data that is needed to develop the system model	
Quality of Learning Experience	**Efficiency**	**Efficiency1:** The team completed the tasks faster than I expected/planned	N/A
		Efficiency2: Individual tasks were still time-consuming	
		Efficiency3: Individual tasks were taking significant effort	
		Efficiency4: I found the ideation process within the team smooth and effective	

	Enjoyment	**Enjoyment1:** I enjoy working collaboratively instead of individually	(Alahmari 2019; Ioannou Nicolaou 2009)
		Enjoyment2: I enjoy using collaborative technologies with my team in learning more than face-to-face learning	
	Academic Performance	**AP1:** Overall, using technologies in collaborative activities with the team improves learning and leads to better system model outcomes	(Alahmari 2019; Ioannou Nicolaou 2009)
		AP2: Overall, I think adopting diagrams to support system design helped to create solutions	
	Students' Satisfaction	**SS1**: I was happy with the outcome of the system design	(Alahmari 2019; Ioannou Nicolaou 2009)
		SS2: It was relatively easy to make decisions within the team	

Instrument Translation:

Initially, the survey questions for this study were written in English as shown in Appendix A. Since the target population for this study are Arabic speakers (undergraduate and graduate students from Saudi Arabia universities), it was recommended in previous studies to translate the developed scales into Arabic to facilitate the students' understanding (Fincham 2008), as shown in Appendix B. The translation ensures the participants demonstrate a better

understanding of the questionnaire, which leads to precise responses (Sperber, Devellis & Boehlecke 1994).

Therefore, we conducted the forward translation process associated with a subjective evaluation as reported in (Sperber, Devellis & Boehlecke 1994). The adopted procedure ensures the translation from English to Arabic carries out the exact meaning and remains consistent. Academic experts and Ph.D. students who speak Arabic as a first language and English as a second have been consulted with respect to the Arabic version. This consultation ensures that the translation from Arabic to English delivers the same sense of meaning and readability.

Forward Translation & Subjective Evaluation process:

The researcher hired two certified translators to translate the questionnaire from English to Arabic. Each translated Arabic question in both versions was compared with its equivalent in English to ensure a high-quality translation without inconsistencies. Additionally, the researcher re-evaluated the final Arabic version to confirm the translation was done accurately and conveyed the same meaning and interpretation as the English version. During the evaluation process of the last version, the researcher worked in parallel with the translators to address any issues found in the translation before finalising the revised copy.

3.3.2 Pilot Study

The validation of the survey questionnaire has been frequently considered in previous studies. Typically, the pilot study considers a small sample of the target population (J & A 2020). Furthermore, a prior test of the survey items helps to identify issues associated with the questionnaire before proceeding with the final collection as reported in (Burn, A. C., & Bush 2006). Additionally, the pre-investigation of the survey provides an understanding of the quality of the translation and identifies problems, if any (J & A 2020).

Given the importance of prior validation of the survey, we have conducted a pilot study to check different aspects, such as the validity and reliability of the survey items, the quality of the instrument translation, and students' understanding of the questions. Thus, we proceeded with initial data (73 responses) from undergraduate and postgraduate students enrolled in subjects related to system design in Saudi Arabia universities. After analysing the initial data, the results were found to be statistically sound and confirmed that the developed survey is valid and reliable for moving on with the full-scale study.

3.3.3 Sampling and Data Collection

This study targets undergraduate and postgraduate students in Saudi Arabia universities. We focus only on students who have undertaken subjects related to system design within collaborative learning environments that rely extensively on technology adoption.

The sample size is seen as an important step during the process of conducting a study quantitatively, which determining the sample size contributes to acquiring precise results (ML Wolverton 2009). Existing studies on Structural Equation Modelling (SEM), determined different factors that can be adopted to identify suitable sample sizes. Hair et al, nominated five factors that can impact on the results of the structural modelling, including multivariate distributions, the adopted techniques for estimation, the level of the model complexity, missing data amount, and lastly the average error variance (Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014). Furthermore, many studies in the literature reported that the data collected from participants fell between 100 to 300 samples (Baanqud et al. 2020; Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019; Qureshi et al. 2021; Schaal, Matt & Grübmeyer 2012; Woods, Gomez & Arnold 2019), while the most recommended sample size is 300 (Habes et al. 2018; Lin, Huang & Ko 2020; Qureshi et al. 2021). However, a response rate higher than 50% of the target sample size is considered excellent in most circumstances, as reported in (Fincham 2008).

The completed online surveys for this study are 152 responses given by students who met the participation criteria and who volunteered to take the survey. The majority of statisticians agree that 100 samples must be included for any result to be considered meaningful (MacCallum et al. 1999), and collecting 10% of the target population is typically a suitable maximum sample size (Conroy 2021). Moreover, Hair et al, discussed the acceptance of at least 150 sample size in studies with seven or fewer constructs (Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014), which applies to our research. Accordingly, the completed responses have been considered for the data analysis, which is more than 50% of the recommended sample size as suggested in the literature as well as representing 10% of the target population. On the other hand, the current study received more than 152 responses, which were incomplete and have been excluded as recommended in (Marcoulides & Saunders 2006). The reason for receiving unfinished surveys is due to the study's stringent requirements, which required research targeted students with specific experience and skills in particular subjects related to system design.

Data Collection:

Due to Covid-19 and the restrictions enforced by governments and universities, such as remote learning and maintaining social distance. An online survey tool has been adopted to collect the relevant data for this study. The online survey was designed and distributed by the Qualtrics tool. The survey was conducted in the form of close-ended questions using a five-point Likert scale from 1 to 5, where 1 means strongly disagree, and 5 refers to strongly agree (Allen & Seaman 2007; Edwards, Thomas & Rosenfeld 1997). The application of the close-ended method elicits more complete answers by inquiries made of a limited number of mini responses (Edwards, Thomas & Rosenfeld 1997). Thus, the participants in our survey were required to choose from the limited responses instead of providing a written experience.

Additionally, we focused on providing a short description at the beginning of the questionnaire, such as the study aims and objectives, as well as the terminologies used in the questions. We also developed the survey so it could be answered in between 10 to 15 minutes. The techniques applied, such as the close-ended questions, Likert scales, and a brief explanation encouraged the participants to take and complete the survey. Sekaran has recommended these adopted strategies for designing a survey as it supports and increases the rate of participation in the questionnaire (Sekaran & Bougie 2013).

Three universities in Saudi Arabia have provided pre-consent for supporting this study during the data collection stage. These universities are Jouf University, Imam Abdulrahman Bin Faisal University, and Jubail University College. Most of the study data has been collected from the three mentioned universities. Additional responses have also been obtained from other universities in Saudi Arabia because the survey was distributed online and anonymously (the other universities reported in chapter 5, section 5.1.2). Accordingly, the researcher delivered the survey link (generated by the Qualtrics platform) and specified the target population to the instructors and vice presidencies for graduate studies and scientific research to distribute the survey link among undergraduate and postgraduate students undertaking programs related to System Design. The survey distribution occurred from December 2020 to February 2021 during the pandemic period of COVID-19, when universities were adopting remote learning.

3.4 Data Analysis Techniques

The data analysis process has been performed in three different stages, as suggested by (Sekaran & Bougie 2013). Firstly, to ensure the data collected is efficient and suitable for analysis. Secondly, check the reliability and validation of the data. Lastly, test the hypotheses and the relationships among the conceptual model constructs. The data has been analysed by using SPSS (George & Mallery 2018) and SmartPLS (Ringle, Da Silva & Bido 2014). The former has been used for statistical analysis to provide advanced descriptive analysis

capabilities, while the latter provides Measurement Model Analysis and Structural Equation Modelling to evaluate the measurement model's validity and test the associated hypotheses (Ringle, Da Silva & Bido 2014). Lastly, the IPMA has been performed to extend the results obtained from the PLS-SEM by considering the importance and performance of the research constructs. These analysis techniques are discussed in the following sub-sections.

3.4.1 Descriptive Data Analysis

The descriptive data analysis has been conducted using the SPSS software "version 26". Such analysis aims to prepare the data through specific processes and ensure the data suitability for further analysis techniques, i.e., measurement model analysis and structural modelling, as suggested by (Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014). The descriptive data procedures include the following (George & Mallery 2018):

- **Participants' profiles** to adequately represent the study population was determined by examining the respondents' profiles.
- **Missing data** can occur for many reasons, such as the participants may refuse and fail to respond to a survey question, or the data may be misplaced or incorrectly registered. Accordingly, the researcher should clean the missing data, while more than 10% leads the statistical analysis to be skewed.
- **Normality assessment** checks the distribution of the data measured by skewness and kurtosis to define the outliers or chi-square goodness of fit test.
- **Data screening** observes the outliers to be inconsistent with the other observations.
- **Means** refers to the average score in a variable's distribution of scores.
- **Standard deviations** provide a descriptive measure of how values depart, on average, from the mean of a distribution.

The results of descriptive data analysis are displayed in Chapter 5 and discussed in Chapter 6.

3.4.2 Measurement Model Analysis

According to Hulland, the Measurement Model Analysis can be conducted to assess the reliability and validity of the research constructs and their indicators/measures (Hulland 1999). More concretely, reliability and internal consistency (Cronbach 1951), and item-total correlations (LU 2007), as well as factor analysis techniques, including exploratory factor analysis (EFA) (Costello & Osborne 2005), and confirmatory factor analysis (CFA) (Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014), are used to perform the measurement model analysis. According to Hair et al., confirmatory factor analysis is recognised as an effective procedure to test a pre-determined "hypothesized" factor structure that fits the actual data (Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014).

Reliability is assessed by Cronbach's Alpha (CA), which measures the reliability of the construct indicators as well as internal consistency among scale items. Additionally, item-total correlations are conducted to evaluate how a specific item relates to its construct. The use of EFA is to identify a suitable set of variables as well as express the variables regarding its objectives. At the same time, CFA adopts to confirm the results and prepare for further model analysis, i.e., convergent reliability and discriminant validity (Ab Hamid, Sami & Mohmad Sidek 2017; Hair et al. 2012; Hair, Ringle & Sarstedt 2011; Hulland 1999). Convergent validity conducts if more measures are used for an individual construct. Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (CA) are used to measure Convergent Validity along with the loading of the measurements related to their corresponding constructs (Hulland 1999). Discriminant validity defines the extent to which measures of a given construct differ from different constructs' measurements in the same model (Campbell & Fiske 1959; Rönkkö & Cho 2022). There are different methods used to assess Discriminant Validity. In this study we adopt the Fornell and Larcker Criterion (Fornell & Larcker 1981),

the Heterotrait-Monotrait Ratio (HTMT) (Henseler, Ringle & Sarstedt 2015), and the Cross-Loading method (Ab Hamid, Sami & Mohmad Sidek 2017).

For further exploration, the importance-performance map analysis (IPMA) has been conducted to assess each construct's performance explicitly related to the conceptual model (Ringle & Sarstedt 2016). Both SPSS and SmartPLS have conducted the measurement model analysis. The results of the measurement model analysis are discussed in Chapter 5.

3.4.3 Structural Model

After assessing the validity of measurements, structural modelling can be conducted as an essential phase of SEM (Tenenhaus et al. 2005), which is known as the multivariate analysis method. The SEM is commonly used in existing studies to test the hypothesis and the relationships among the model constructs (Baber 2021; Qureshi et al. 2021). The SEM is considered a second-generation approach and is known as a regression that assesses relationships among multiple factors or variables (Flury, Murtagh & Heck 1988; Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014). In other words, it allows for evaluating different relationships between the independent and dependent concepts. Additionally, the SEM is recognized as covariance-based, where it employs the variance-covariance among testing variables to evaluate latent variables (Hair, Ringle & Sarstedt 2011). Therefore, the partial least squares SEM (PLS-SEM) is seen as a valuable approach to explaining the variance of the dependent concepts (Hair, Ringle & Sarstedt 2011). Thus, there are different kinds of software to conduct SEM analysis (Lisrel, Amos, and SmartPLS). This research uses (PLS-SEM) because of its capacity to assess multiple relationships among the independent and dependent contracts as well as its ability to test research hypotheses.

According to Hair et al., in (Hair, Ringle & Sarstedt 2011) stated that partial least squares structural equation modelling (PLS-SEM) uses to assess the causal relationships associated

with the conceptual model. More concretely, the SEM includes two different steps that deal respectively with the measurement of endogenous latent variable LV's Coefficient of Determination (R^2) and the evaluation of the path coefficients among LVs (Hair, Ringle & Sarstedt 2011; Sharma & Kim 2012). Furthermore, the SEM is considered an extension of the factor analysis mentioned in the previous section to confirm the results obtained from EFA through the CFA. Eventually, the SEM includes the factor analysis and the path testing/coefficients by confirming the measurement model analysis and the structural model. The results of the PLS-SEM are reported and discussed in Chapter 5.

3.4.4 Importance Performance Map Analysis (IPMA)

The IPMA is conducted after the structural modelling, which is a valuable analysis in PLS-SEM. It provides a further understanding of the constructs' performance and determines the critical factors within the model. Moreover, the IPMA adds a dimension for considering the average values of the latent variable to the standard results reporting of path coefficient estimates (Ringle & Sarstedt 2016). The IPMA contrasts the overall effects, which show the importance of the previous constructs in forming a specific target construct, with their average latent variable scores that indicate their performance (Ringle & Sarstedt 2016).

3.5 Ethics Consideration

The current study has considered the ethical requirements as the research participants are humans. The researcher has been eager to address the relevant criteria related to the ethical principles, such as participant's consent, anonymity, and the confidentiality of personal information. The researcher has also provided information related to the survey, for instance, (researcher information, research purpose, objectives, terminologies, and the estimated time to answer the questionnaire). Additionally, the participants have been informed that their contributions are voluntary, and they can withdraw at any time without detriment. Within the consent form, the participants have been informed that the questionnaire is considered an

anonymous survey, and no personal information is required to be disclosed. The prior consent intends to ensure that the participants understood the purpose of the study and had a clear picture of the survey before giving their approval. Finally, the researcher stated that the present study had obtained approval from the Ethics Committee at the University of Technology Sydney, Sydney, Australia. UTS HREC REF NO. (ETH20-5297).

3.6 Chapter Summary

This chapter discussed the research methodology employed to address the research questions proposed in chapter one and test the hypotheses suggested in the next chapter. The adopted research paradigm of the current study is described and selected from the previous studies that are consistent with our research objectives. The adopted research approach for this thesis is discussed using a quantitative method. The process and the techniques used in the quantitative approach are provided in this chapter, along with a justification for using it. 152 responses were collected from undergraduate and graduate students from Saudi Arabia universities through an online survey. The data collected were analysed using SPSS for statistical analysis and SmartPLS for structural equation modelling. The results of the data analysis are presented in chapter five. Finally, the consideration of ethics is also given.

The next chapter presents the research concepts associated with the conceptual model and the developed hypotheses.

Chapter 4 - Conceptual Model and Hypotheses

This chapter explains the theoretical and practical fundamentals of the proposed conceptual model to address the research gap and answer research questions posed by the suggested hypotheses. This research focuses on the studies related to the extensive adoption of technology within collaborative learning environments by looking at its impact on the knowledge development process and the overall quality of experience. Thus, based upon the literature review presented in Chapter 2, the current chapter explains the adopted independent and dependent concepts represented in the conceptual model. Firstly, it proposes an overview of the conceptual model, including the hypotheses and supporting theoretical frameworks. Secondly, it provides a rich understanding of the conceptual model's main blocks and fine-grained concepts. Lastly, the justifications and explanations of the relationships among research constructs and the developed hypotheses are discussed, followed by a summary of the current chapter.

4.1 Conceptual Model

The proposed conceptual model is depicted in Figure 8. The experimental context of the study focuses explicitly on System Design (Hoffer, George & Valacich 2013). We adopted system design as an experimental context because it includes many levels of Bloom's taxonomy. More concretely, we put emphasis on the phases of analysis, design, and development in system design that can be associated respectively with analysis, creation, and application in Bloom’s levels. Therefore, we assume the “analysis " phase in system design represents the "analysis" in Bloom's perspective, and the "design" phase of system design expresses the "design" in Bloom's taxonomy; eventually, the "development" phase in system design describes the "apply" in Bloom's framework as displayed in Table 4.1. As long as we have not hypothesized

any relationships in/out of the main System Design block, meaning this study does not contribute to any improvement related to the System Design phases.

Table 4.1 Mapping System Design phases with Bloom's Taxonomy levels

System Design		Bloom's Taxonomy
Analysis	→	Analyse
Design	→	Create
Development	→	Apply

Within the model, we distinguish among independent and dependent concepts, where an independent concept has the potential to influence the dependent concept (Stewart 1978). The main independent concepts are related to Collaborative Technology (Alahmari 2019), while those concepts related to Collaborative Learning (Recker, Mendling & Hahn 2013) and Quality of Learning Experience (Al-Rahmi, Othman & Musa 2014; Alalwan et al. 2019; Lin, Huang & Ko 2020; Renner, Laumer & Weitzel 2014) are understood as dependent concepts. Additionally, the framework assumes the process of collaborative learning associated with the knowledge development & sharing as in Nonaka's theory. Nonaka's conceptual approach addresses a set of principles for knowledge creation in a generic organizational context. Looking specifically at a collaborative environment in education, some principles and considerations may be reused in scope looking at the intrinsic need to develop knowledge in co-operation with others and to share it at different levels of learning.

Finally, the Technology Acceptance Model (TAM) is considered as an assumption, meaning we are assuming collaborative technology as a consolidated and commonly accepted asset within the target community. In other words, this study does not explicitly test the TAM during the data collection stage; however, we have adopted the TAM parameters in our literature review, and the review findings support our assumption.

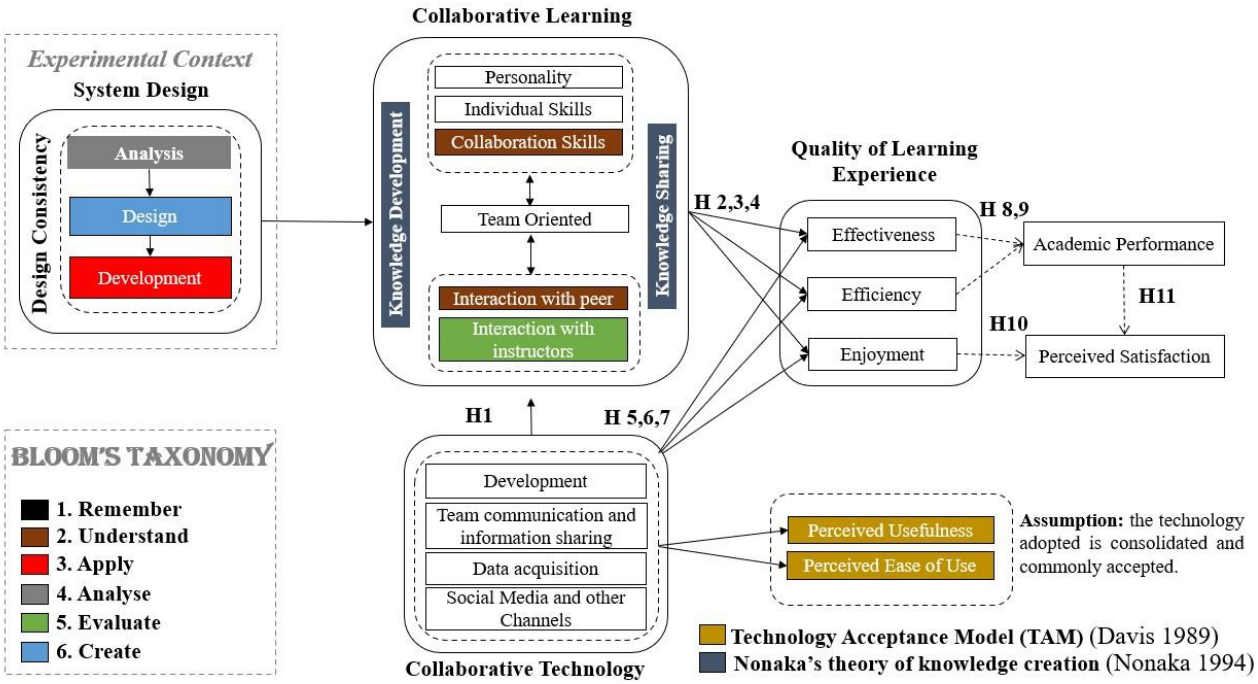


Figure 8 Conceptual Model

The next subsections describe more in detail the main blocks in the conceptual model.

4.1.1 System Design

Referring to chapter two (section 2.3); System Design is commonly understood as a set of processes that aim to the specification of the different system elements and components that meet a given set of requirements. This study has considered System Design as an experiential context to achieve the research objectives. The fundamental phases of system design are understood as analysis, design, and development (Hoffer, George & Valacich 2013). The first step is the Analysis phase, which refers to the process of studying and structuring the target system requirements. The second phase is Design, which is recognised as an explanation of the suggested solutions that are transformed into logic, followed by physical system specifications. Lastly, the development phase is referred to as the process where the components/outcomes from the previous stages are applied together. Those phases are not explicit objects of this study for any improvements. Unless they have been considered to assess the learning environments, where students are requested to work collaboratively through these stages as a group to develop

core tasks related to system design at different levels of learning, as defined in Bloom's taxonomy.

4.1.2 Collaborative Learning (CL)

Collaborative Learning refers to a learning process involving more than one student to achieve a common goal (Recker, Mendling & Hahn 2013). There are very many factors, such as individual personality (Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019) and skills (Gomez, Wu & Passerini 2010), collaboration skills (Baber 2021), interaction among peers and instructors (Al-Rahmi, Othman & Musa 2014; Habes et al. 2018; Qureshi et al. 2021), that can potentially affect collaborative learning to develop knowledge properly. Those fine-grained concepts are not explicit objects of this study.

Collaborative learning environments have been the object of investigation in several studies (Baanqud et al. 2020; Ghavifekr 2020; Hmelo-Silver & Barrows 2008; Recker, Mendling & Hahn 2013; Su et al. 2010; Wang 2009); in general terms, group-work has normally a positive impact on the learning process and the consequent knowledge building within a given group. Knowledge can be defined in many different ways depending on the context. However, it is quite commonly associated with information, data, experience, expertise, fact, wisdom, and action (Akude 2014). Knowledge is the capability to use the information and data in practice (Applehans, Globe & Laugero 1999), while the authors in (Argyris 1992) define knowledge as the ability for effective practical actions.

The relationship between collaborative learning and knowledge building has been further investigated in (Recker, Mendling & Hahn 2013). It proposes an empirical study on post-graduate students to assess the impact of technology on the cognitive process within a group. Other studies (Baanqud et al. 2020; Su et al. 2010; Wang 2009) address more specific aspects.

In recent years, more and more works reiterate the relevance of knowledge development & sharing in education (Van Weert 2006) as well as collaboration is seen as a key factor to foster creativity and the consequent conversion of ideas into design. Collaborative activities improve student-learning outcomes in terms of satisfaction and performance and promote the knowledge development process via social interaction among peers. Last but not least, in (Ghavifekr 2020) the authors explicitly address the relationship between collaborative learning and academic performance. Besides, in (AL-Rahmi & Othman 2013), assessed student satisfaction in a collaborative environment by looking at indicators related to engagement.

As far as the author knows, there are very few studies that relate Bloom's taxonomy to collaborative learning environments, as mentioned earlier in chapter 2. The model proposed in this study assumes a partial mapping as in Figure 8 with a focus on aspects associated with collaboration. However, learning environments could in fact be more complex, for instance assuming instructors as an active part of the knowledge building process.

4.1.3 Collaborative Technology (CT)

Ideally, Collaborative Technology is expected to support a collaborative learning process along the different phases (Alahmari 2019). Technology plays a critical role in modern education (Nonaka 1994). The proposed conceptual model assumes collaborative technology mainly aimed to content sharing, task development (Recker, Mendling & Hahn 2013), communication (including Social Media (Al-Rahmi et al. 2015)) and data acquisition (Alahmari 2019; Habes et al. 2018). Those aspects have been proved to be key factors according to several studies. For instance (Recker, Mendling & Hahn 2013) puts emphasis on the relevance of technology in task development, as well as (Al-Rahmi et al. 2015; Habes et al. 2018) address social media, and (Krajcik et al. 1994; Marcu & Spiller 2020) deal with information sharing.

The adoption of social media is recognised as a valuable asset in learning activities (Alghizzawi et al. 2018). It provides the characteristics that are needed to support students in the education context. Social media leads students beyond ideas and supports further discovery through deepening (Al-Rahmi, Othman & Yusuf 2015), as well as facilitates skills development and provides a better learning experience (Al-Mohammadi & Derbel 2014). Additionally, social media supports the level of interaction among peers and the flexibility of use (AL-Rahmi & Othman 2013).

Several studies addressed the relationship between technology adoption in learning and collaboration (Gan, Menkhoff & Smith 2015), problem-solving (Unal & Cakir 2021), even within specific learning contexts (e.g. languages (Kern 2006)). In general terms, those studies have observed an acceptance of technology and, therefore, its effectiveness in learning (Raja & Nagasubramani 2018). Therefore, considering technology in collaborative learning activities has significant benefits, including but not limited to:

i. Facilitates student engagement and maintains following up the activities.
ii. Provides flexibility to engage at anytime & anywhere.
iii. Enhances the performance and supports deep understanding.
iv. Involves the student in the community that increases knowledge building and sharing as well as obtaining skills.

Technology Acceptance Model (TAM):

Technology Acceptance Model is a well-known theory in the Information Systems field that models the acceptance of adopting technology among users (Davis 1989). The theory defines Perceived usefulness (PU) and perceived ease-of-use (PEOU) as the main factors. The former concept is associated with user perception in terms of value, while the latter is more related to usability. Many studies have adopted the TAM to assess the technology acceptance within

collaborative learning environments focusing on different aspects (Al-Rahimi, Othman & Musa 2013; Alshurideh et al. 2023; Cheung & Vogel 2013; Granić 2022; Li & Yu 2020). Those contributions show positive learning outcomes along with the acceptance of technology adoption.

Usefulness in this study is more about the perceived value of using technology, as students believe that using different technology for various purposes would increase their overall performance (Davis 1989). The factors associated with TAM have been adopted by (Al-Rahimi, Othman & Musa 2013) to assess collaborative environments, as technology provides different opportunities for team communication, knowledge development and sharing. More recently, the authors evaluated the use of technology on academic performance in a study conducted during the Covid-19 pandemic (Alismaiel, Cifuentes-Faura & Al-Rahmi 2022).

On the other hand, *ease of use* is another factor of the TAM. Ease of use is defined as the system's usability (Davis 1989). The most critical post-adoption perceptions are usefulness and ease of use (Al-Rahmi & Zeki 2017). In the stated study, the authors examined the impact of social media within collaborative environments on overall performance and satisfaction using the TAM parameters. Additionally, TAM has been investigated to find out how modern technology, such as ubiquitous, impacts knowledge management at the organizational level (Gupta et al. 2022), as well as the influences of m-learning on knowledge sharing and development in the educational context (Al-Emran, Mezhuyev & Kamaludin 2021).

Last but not least, according to the results obtained from the literature review presented in Chapter 2, learners have the ability to adopt new technologies in order to engage, interact, and collaborate in an educational context (Alyami, Pileggi & Hawryszkiewycz 2020). These findings are a direct consequence of the massive presence of technology in most aspects of everyday life, which makes applying such technology straightforward.

Therefore, Technology Acceptance Model (TAM) in this study is considered an assumption, meaning the adoption of collaborative technology is a consolidated and commonly accepted asset within the target community based on both our literature review findings and previous studies in the same context.

4.1.4 Quality of Learning Experience

Quality of Learning Experience is a broad concept that is basically adopted to measure experience (Neumann, Finaly-Neumann & Reichel 1990). In the context of this study Quality of Learning Experience is associated with effectiveness (Lin, Huang & Ko 2020; Renner, Laumer & Weitzel 2014), efficiency (Renner, Laumer & Weitzel 2014), and enjoyment (Lin, Huang & Ko 2020). Those three factors can reflect standard metrics such as academic performance and satisfaction (Al-Rahmi, Othman & Musa 2014; Alalwan et al. 2019). Performance means assessing the learning outcome, while satisfaction refers to the student's perceived quality of experience. Effectiveness in this study refers to the capability to deliver the requested outcome. While Efficiency indicates the capability to deliver an outcome with certain constraints, e.g., time. Last is the enjoyment, which is basically enjoying the learning experience of adopting technology within collaborative learning environments.

The study in (Lin, Huang & Ko 2020) investigated the role of perceived enjoyment in a blended environment, where students, organised in teams, are expected to collaborate and engage in learning activities to increase their effectiveness. Additionally, the authors looked at students' overall quality of experience, with an explicit focus on their perception. Hsu and Lin (Hsu & Lin 2008) consider enjoyment as a key factor for engagement which is further empowered by social media adoption. (Renner, Laumer & Weitzel 2014) reiterated the relevance of effectiveness and efficiency as essential assessment metrics. Despite their relevance, effectiveness, efficiency and enjoyment are infrequently considered at once to assess overall performance and satisfaction. Students' performance and satisfaction are often the object of

study. Technology Acceptance Model (TAM), constructivism (L. S. Vygotsky 2020), and communication theories (Jensen 2020; Walther 1996) have been adopted to assess the effects of social media use on academic performance (Alalwan et al. 2019). In (Al-Rahmi, Othman & Musa 2014), the authors observed the influence of social media on different driver factors, such as interaction, engagement, ease of use, and usefulness.

4.2 Hypotheses

This study aims to assess the impact of adopting technology at different levels of learning within collaborative learning environments. More concretely, we put emphasis on assessing the knowledge development and sharing process as well as the overall quality of learning experience. The following hypotheses are associated with the underlying theory.

Relationship between Collaborative Technology and Collaborative Learning:

Technology can be seen in this study as a way that supports collaboration among team members and students' interaction with instructors to achieve the target design (for instance, technologies used for team communication, share and work on documents, data gathering, and task development). Examples of the technology are (Social Media, Google Docs, Zoom, Learning Management Systems, etc.). Collaborative Technology allows resilience and flexibility for team members to develop and share related knowledge for specific tasks. In the past, the technology did not address the issue of tacit knowledge, which is deemed critical to innovative activities in groups. As reported in (Gottfredson 2001; Kogut & Zander 2009; Nonaka, Toyama & Konno 2000), it is challenging to transfer knowledge without face-to-face interaction. However, many studies in the literature addressed the impact of the adoption of technology on the collaborative knowledge development process (Baanqud et al. 2020; Gupta et al. 2009; Recker, Mendling & Hahn 2013). These studies reported that modern technology has positively

contributed to facilitate the process of knowledge development and sharing. Additionally, the current technology enables knowledge building virtually without being co-located.

The following hypothesis has established that students within groups in collaborative activities are required to develop and share knowledge using technology. These activities include team communication, data acquisition, content sharing, and task development to transfer such information from tacit to explicit knowledge. The current technology has been stated as a key factor that supports students learning to obtain information during engagement in collaborative activities (Alahmari 2019; Habes et al. 2018). Social media and modern technology play a critical role in improving communication skills among team members (Al-Rahmi et al. 2015). Additionally, the authors in (Recker, Mendling & Hahn 2013), show the significant role of adopting technology in collaborative knowledge development and sharing. Ultimately, such factors have been reported positively when the technology is applied to collaborative learning environments. Therefore, the following hypothesis is developed:

H1: *Collaborative technology contributes to knowledge development and sharing.*

Relationship between Collaborative Learning and Quality of Learning Experience:

Within collaborative learning, many studies have investigated many aspects that can increase or affect collaborative activities and the learning experience (Al-Rahmi, Othman & Musa 2014; Baber 2021; Gomez, Wu & Passerini 2010; Habes et al. 2018; Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019; Qureshi et al. 2021). However, this study has focused on assessing the impact on the learning process and the consequent knowledge development within group learning. More specifically, we look at the students' effectiveness in the capability to achieve the required outcomes that rely on knowledge development and sharing within group. According to Pangil and Chan, the effectiveness depends on the ability to develop and share knowledge among team members (Pangil & Chan 2014). Moreover, the knowledge development process is noticed as a critical factor that leads to effectiveness and

increases the satisfaction of individuals (Systems & Dutta 1997). Last but not least, collaborative learning has been investigated and reported as supportive of the knowledge development process (Baanqud et al. 2020; Ghavifekr 2020; Hmelo-Silver & Barrows 2008; Recker, Mendling & Hahn 2013; Su et al. 2010; Wang 2009). Regarding the above discussion, the following hypothesis is proposed:

H2: *Collaborative learning contributes to effectiveness.*

Additionally, we assess the efficiency, which is the extent of the capability to achieve the outcomes within certain constraints i.e., Time. The authors in (Renner, Laumer & Weitzel 2014) mentioned the importance of considering efficiency along with effectiveness to assess learning environments. As far as the author knows, there is a lack of combining such metrics to assess the overall quality of learning experience. Therefore, the following hypothesis is suggested:

H3: *Collaborative learning contributes to efficiency.*

Furthermore, we put emphasis on measuring the level of students' enjoyment within collaborative learning environments, which is related to the experience of collaboration. According to (Lin, Huang & Ko 2020), when students perceive enjoyment, the process of knowledge building and sharing among groups is positively impacted. This insight refers to the collaborative activities as well as the impact of technology on enjoyment, which in turn influences the overall learning outcomes. Accordingly, the following hypothesis is proposed:

H4: *Collaborative learning contributes to enjoyment.*

Relationship between Collaborative Technology and Quality of Learning Experience:

The adoption of technology in collaborative learning environments is commonly assessed by looking at different aspects of metrics. The most popular learning experience measures are academic performance and satisfaction. This study considers effectiveness, efficiency, and enjoyment parameters to reflect the standard metrics to assess the learning experience, i.e.,

academic performance and satisfaction. Many studies reported the effectiveness of modern technology in supporting students learning and creating value, which reinforces educational expectations (Gonyea 2007; Livingstone 2012; Lopez-Nicolas & Soto-Acosta 2010). Furthermore, when the technology is applied to virtual teams, it positively affects their effectiveness (Wright 2013). These influences increased performance and satisfaction as well as enabled knowledge sharing and development to apply, analyse and eventually create the given task. Although efficiency is an essential metric in assessing the learning experience.

As far as the researcher knows, there is a lack of explicit assessment of efficiency. Thus, we investigated the extent to which the work teams achieved given tasks within specific constraints such as resources and time. Therefore, we developed the following hypotheses:

H5: *Collaborative technology contributes to effectiveness.*
H6: *Collaborative technology contributes to efficiency.*
H7: *Collaborative technology contributes to enjoyment.*

Relationship among Quality of Learning Experience:

The Quality of Learning Experience combines different metrics such as effectiveness, efficiency, and enjoyment to assess the overall learning experience, i.e., performance and satisfaction. It is essential to determine the correlation among these factors during the knowledge development process when collaborative learning environments rely largely on technology. Many studies from the literature have evaluated the learning experience by observing performance and/or satisfaction (Al-Rahmi et al. 2015; Al-Rahmi, Othman & Musa 2014; Al-Rahmi & Zeki 2017; Alalwan et al. 2019; Qureshi et al. 2021; Recker, Mendling & Hahn 2013). For example, the study in (Al-Rahmi, Othman & Musa 2014) assessed the relationship between the effectiveness of adopting technology on academic performance within a collaborative learning environment. Additionally, the authors have investigated the correlation between academic performance and satisfaction. Their study showed that

technology positively affects performance in terms of interaction and engagement, which significantly impacts on satisfaction. Academic performance and satisfaction strongly correlate and influence the overall learning experience (Al-Rahmi & Zeki 2017). Besides, when students are satisfied with the learning activities, their enjoyment level is positively increased, which results in better learning outcomes. According to Lin et al, enjoyment plays a key role in the level of satisfaction that leads to the success of the learning activities (Lin, Huang & Ko 2020). Due to a lack of assessment of efficiency, we investigated the relationship between academic performance and efficiency. Additionally, effectiveness, efficiency, and enjoyment are simultaneously considered to assess performance and satisfaction. Therefore, based on the findings, we develop the following hypotheses:

H8: *Academic performance depends on effectiveness.*
H9: *Academic performance depends on efficiency.*
H10: *Perceived satisfaction depends on enjoyment.*
H11: *Academic performance influences perceived satisfaction.*

4.3 Chapter Summary

The presented chapter discussed the developed conceptual model and the research hypotheses based on the studies discussed in the current chapter as well as chapter two, "Literature Review". Firstly, the chapter reviewed the theoretical and practical fundamentals associated with the conceptual model. Secondly, the relationships among the research constructs and the theoretical perspectives were described. Lastly, this chapter illustrated the proposed hypotheses to help the conducted research to answer the research questions.

The next chapter presents the data analysis method and justifies the results.

Chapter 5 - Data Analysis

This chapter demonstrates the data analysis process and the results obtained from the survey. Firstly, it displays the questionnaire survey, followed by the participants' demographic profile outcomes. Secondly, data preparation, including missing data, normality assessment, and outliers are reported to ensure the data collected is ready for further analysis. Thirdly, the measurement model analysis is presented and discussed to show the validity and reliability of the model along with the exploratory factor analysis (EFA). Fourthly, further analysis provides more assessment of the model measurement, namely confirmatory factor analysis (CFA) and structural modelling to check the relationship among research constructs and test the research hypotheses. Lastly, the important performance map analysis (IPMA) is performed to provide insights into the relationships among the research concepts within the model in terms of importance and performance.

5.1 Questionnaire Survey and Respondents' Profiles

Referring to Chapter 3, the current study adopts the quantitative approach and the related data for this study has been collected by an online survey using the Likert scale. The adopted methodology and research design process have been determined based on the previous studies suggested in the literature. A total of 18 items have been considered to obtain the relevant data to assess the impact of adopting technology on collaborative learning environments and the quality of learning experience. More conclusively, we put emphasis on evaluating the process of collaborative knowledge development and sharing. Additionally, we look at different parameters, i.e., effectiveness, efficiency, and enjoyment to assess the overall learning experience, including academic performance and satisfaction. Seven generic demographic information items are designed to reflect the participants' profiles.

The following subsections provide in-depth the data analysis process together with the results.

5.1.1 Questionnaire Survey

The survey was distributed among undergraduate and postgraduate students undertaking subjects related to system design from Saudi Arabia universities. After receiving the data, we considered the completed surveys for the analysis, which consisted of 152 responses. Furthermore, the incomplete surveys have been excluded, as discussed in Chapter 3.

5.1.2 Participants' Profiles

This section depicts the participants' demographic and contains general information, i.e., gender, age group, discipline, program, institution, and the experience of using technology in education. The following Table 5.1 reports the participants' profiles who participated in the current study.

Table 5.1 Demographic Characteristics of the participants

		Number of participants (n) =152	
		n	**%**
Gender	*Male*	72	47.4
	Female	80	52.6
Age Group	*18 – 20*	20	13.2
	21 – 23	83	54.6
	Over 24	49	32.2
Discipline	*Computer Science*	40	26.3
	Information Systems	85	55.9
	Computer Engineering and Networks	3	2
	Other	24	15.8
Program	*Undergraduate*	138	90.8
	Postgraduate	14	9.2
Institution	*Jouf University*	59	38.8
	Jubail University College	42	27.6
	Imam Abdulrahman Bin Faisal University	14	9.2
	Others	37	24.3
Previous experience with Collaborative Technology	*Less than a year*	14	9.2
	1-3 years	50	32.9
	4+ years	88	57.9

Gender:

In Table 5.1, there is a fundamental balance in terms of the gender as 52.6 % of participants (n=80) are females and 47.4% (n=72) are males. The following Figure 9 shows the graphical presentation of the gender distribution of participants.

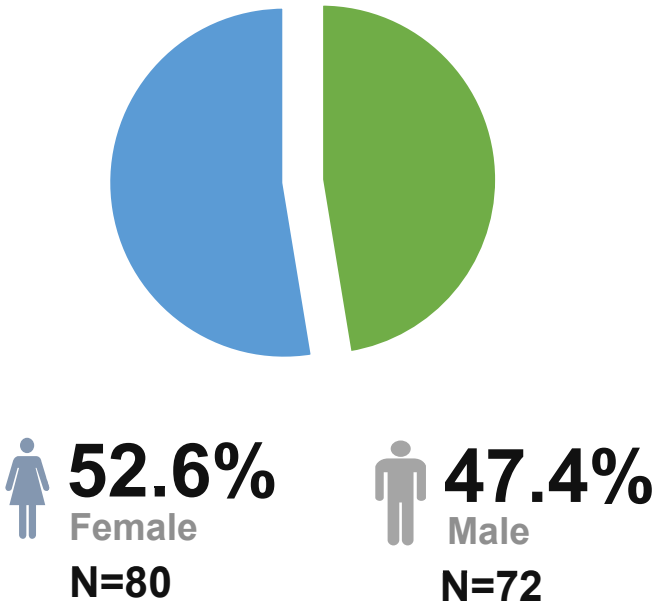


Figure 9 Gender distribution of participants (n=152)

Age Group:

Looking at the age factor, most participants (54.6%, n=83) are between 21 and 23 years old, while over 24 are significantly represented (32.2%, n=49) both with a minority under 21 (13.2%, n=20). Figure 10 depicts the graph presentation of age-wise distribution of participants.

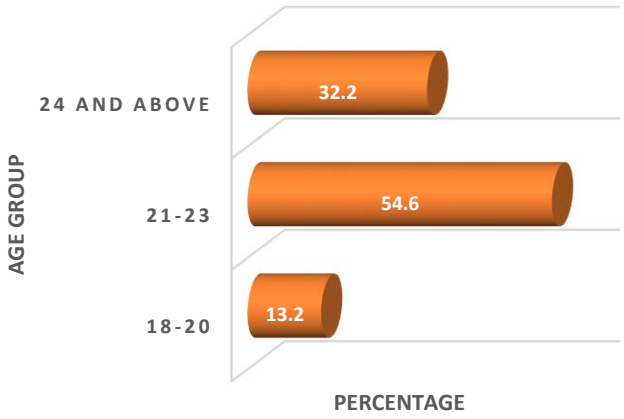


Figure 10 Age wise distribution of participants (n=152)

Discipline:

According to Table 5.1, the majority of participants (55.9%, n=85) are involved in the Information Systems discipline, with a significant contribution from students in Computer Science (26.3%, n=40); a minor participation (2%, n=3) is from Computer Engineering and Networks. Additionally, Figure 11 displays the chart of the major disciplines of the participants (n=152).

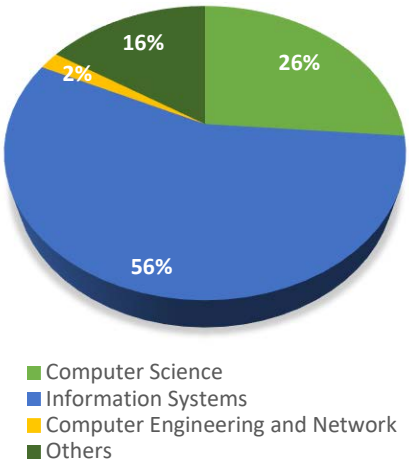


Figure 11 Major discipline of participants (n=152)

Program:

Refer to Table 5.1, 90.8% (n=138) of participants are undergraduate, while the remainder part (9.2%, n=14) are postgraduate. Figure 12 presents the graphical for the participants' program (n=152).

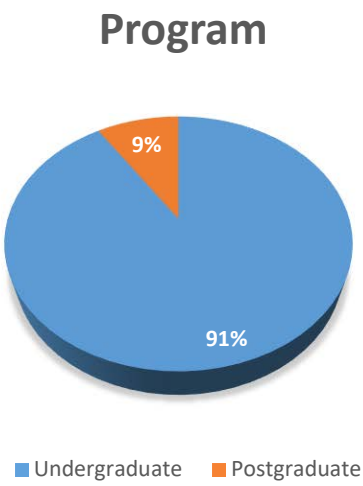


Figure 12 participants program (n=152)

Institution:

In Table 5.1, the majority of participants are from Jouf university (38.8%, n=59), followed by Jubail University College with (27.6%, n=42). A small number of participants (9.2%, n=14) are from Imam Abdulrahman Bin Faisal University, while the rest of the participants are from other universities (24.3%, n=37). Those universities are King Faisal University, King Abdulaziz University, Princess Nourah Bint Abdul Rahman University, Taibah University and Northern Border University. Figure 13 illustrates the graphic for the affiliation of participants.

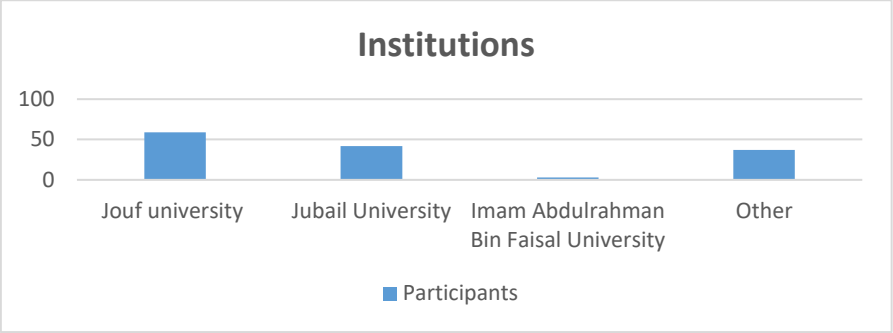


Figure 13 Affiliation of participants (n=152)

Previous experience with Collaborative Technology:

According to Table 5.1, the great majority of participants has reported a previous experience adopting collaborative technology in education. More concretely, (57.9%, n=88) of participants has declared more than four years of experience, while the (32.9%, n=50) has 1-3 years; only the (9.2%, n=14) has less than one year of experience. Figure 14 depicts the participants' experience of using technology in education.

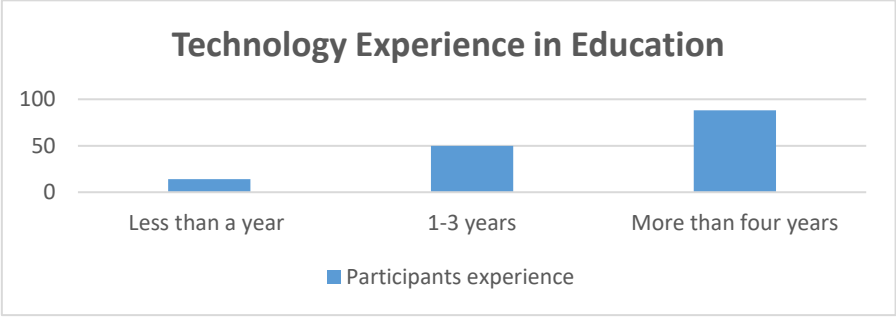


Figure 14 Technology Adoption (n=152)

5.2 Data Preparation

This section presents the outcomes in terms of the data preparation. The data preparation process allows decisions based on data analysis and extracting meaningful information from the data set. This extraction process includes the results of the adopted method for missing data analysis and the assessment of normality as well as the outliers screening. Additionally, the mean and standard deviations are also demonstrated.

5.2.1 Missing Data

At some point in the work, all researchers have run into the issue of missing quantitative data. Research informants may refuse or fail to respond to a survey query, or may be misplaced, or data may be incorrectly registered (Pigott 2010). Statistical analysis of missing data is traditionally performed under the presumption that all missing data is due to a missing completely at random operation (Little et al. 2014). Several forms of missing data can arise, which can affect how the researcher analyses the data gathered. Where there is a significant amount of missing data (more than 10%), the findings of subsequent statistical analysis may be skewed (Bennett 2001). Consequently, the incomplete surveys were removed, while the remaining 152 completed responses were taken for analysis purposes.

5.2.2 Normality Assessment

The breach of the normality principle does not trigger major problems with large enough sample sizes (> 30 or 40); which means we can use parametric procedures even though the data are not normally distributed (Ghasemi & Zahediasl 2012). Since the normality principle underpins most statistical experiments, a researcher is usually interested in how well the distribution can be approximated by the normal distribution. The presumption that data are sampled from a normal distribution is used in many data analysis approaches. The chi-square goodness of fit test, the Kolmogorov-Smirnov (K-S) test are the most common that evaluate the assumption of normality.

The Kolmogorov-Smirnov test, the Shapiro-Wilk test, the D'Agostino skewness test, the Anscombe-Glynn kurtosis test, and the D'Agostino Pearson omnibus test are all examples of statistical tests (Oztuna, Elhan & Tuccar 2006). Descriptive statistics can be used to examine skew and kurtosis. When using SEM, acceptable skewness values are between -3 and + 3, and acceptable kurtosis values are between -10 and + 10 (Brown 2006). For the construct items in this study, all values are within the acceptable value range as shown in Tables (5.2 to 5.8).

5.2.3 Outlier Screening

Experiment results also contain entries that are either inconsistent with current models' expectations or stand out from the rest of the results to the point that they can be classified as outliers (Barbato et al. 2011). As part of the investigation, the researcher should search the data to identify an outlier. An outlier is an observation that "appears" to be inconsistent with the data set's other observations (Walfish 2007). The data set has been inspected and confirmed in this study to have an acceptable normal distribution and be free of extreme outliers.

5.2.4 Mean and Standard Deviations (SD)

The mean is the average score in a variable's distribution of scores, which is computed by adding up the scores for each participant in a sample on a certain variable and dividing the total by the sample size (George & Mallery 2018). The mean is the most generally used measure of the 'typical' value for a variable in a distribution, and it is one of several measures of central tendency. The most commonly used measure of variability is the standard deviation, which provides a descriptive measure of how values depart, on average, from the mean of a distribution. The mean and standard deviation of the constructs are shown in Tables 5.2 to 5.8.

5.3 Preliminary Data Analysis

This section presents the data analysis results for the descriptive statistics analysis defined in the earlier sub-sections, as well as shown below in Tables (5.2 to 5.8). The outcomes are represented according to the three main concepts assessed in the current study. These concepts are Collaborative Technology, Collaborative Learning, and the Quality of Learning Experience by looking explicitly into the fine-grained metrics, i.e., Effectiveness, Efficiency, Enjoyment, Academic performance, and students satisfaction.

5.3.1 Collaborative Technology Factors

Table 5.2 presents the descriptive statistics analysis for Collaborative Technology. We measure the items using the Likert scale from 1 to 5. The items are focused on content sharing, task development, communication (including Social Media), and data acquisition. Additionally, the results show the data screening and prove there are no outliers as well as both kurtosis and skewness values are within the suggested range. Therefore, the provided results demonstrate the data is normally distributed.

Table 5.2 Descriptive Statistics of Collaborative Technology

Constructs					**SD**	**D**	**N**	**A**	**SA**
	Skewness	**Kurtosis**	**Mean**	**Std D**	**N (%)**	**N (%)**	**N (%)**	**N (%)**	**N (%)**
Collaborative Technology									
CT1: Enabling collaboration	-2.202	5.321	4.50	0.854	3(2.0)	4(2.6)	6(3.9)	40(26.3)	99(65.1)
CT2: Effective collaboration	-1.807	3.362	4.49	0.838	2(1.3)	2(1.3)	16(10.5)	32(21.1)	100(65.8)
CT3: Engagement, communication and knowledge development	-1.765	2.811	4.36	0.994	5(3.3)	4(2.6)	15(9.9)	35(23.0)	93(61.2)
Note: Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), Strongly Agree (SA)									

5.3.2 Collaborative Learning Factors

Table 5.3 shows the descriptive statistics analysis for Collaborative Learning. We measure the items using the Likert scale from 1 to 5. The items mainly focus on the knowledge development process among group members. Moreover, the results show the data screening and prove there are no outliers, as well as both kurtosis and skewness values are within the suggested range. Therefore, the provided results demonstrate the data is normally distributed.

Table 5.3 Descriptive Statistics of Collaborative Learning

Constructs					**SD**	**D**	**N**	**A**	**SA**
	Skewness	**Kurtosis**	**Mean**	**Std D**	**N (%)**	**N (%)**	**N (%)**	**N (%)**	**N (%)**
Collaborative Learning									
CL1: Knowledge development	-2.303	6.127	4.48	0.876	5(3.3)	0	9(5.9)	41(27.0)	97(63.8)
CL2: Brainstorming	-1.564	3.215	4.36	0.841	3(2.0)	0	18(11.8)	50(32.9)	81(53.3)
CL3: Group thinking	-1.849	4.074	4.42	0.850	3(2.0)	2(1.3)	12(7.9)	46(30.3)	89(58.6)
Note: Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), Strongly Agree (SA)									

5.3.3 Quality of Learning Experience Factors

Tables 5.4 to 5.8 show the descriptive statistics analysis for the Quality of Learning Experience Factors. The associated factors are effectiveness, efficiency, and enjoyment. Those three factors reflect the standard metrics for the overall quality of experience, which are academic performance and satisfaction. We measure the items using the Likert scale from 1 to 5. The items mainly focus on different aspects related to each metric. Effectiveness refers to the capability to deliver the requested outcome, while efficiency is seen as the capability to deliver an outcome with certain constraints and enjoyment related to the learning experience. Overall, the performance assesses the learning outcome, and satisfaction refers to the student's perceived quality of experience. Additionally, the results show the data screening and prove there are no outliers, as well as both kurtosis and skewness values are within the suggested range. Therefore, the provided results demonstrate the data is normally distributed.

Table 5.4 Descriptive Statistics of Effectiveness

Constructs					SD	D	N	A	SA
	Skewness	Kurtosis	Mean	Std D	N (%)	N (%)	N (%)	N (%)	N (%)
Effectiveness									
Effectiveness 1: Develop and document expected outcomes	-2.189	5.377	4.49	0.869	4(2.6)	1(0.7)	11(7.2)	36(23.7)	100(65.8)
Effectiveness 2: Data model and gathering	-2.001	5.391	4.47	0.797	3(2)	0	11(7.2)	47(30.9)	91(59.9)
Note: Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), Strongly Agree (SA)									

Table 5.5 Descriptive Statistics of Efficiency

Constructs					SD	D	N	A	SA
	Skewness	Kurtosis	Mean	Std D	N (%)	N (%)	N (%)	N (%)	N (%)
Efficiency									
Efficiency 1: Time constraints (group)	-1.265	1.446	4.28	0.895	2(1.3)	4(2.6)	21(13.8)	47(30.9)	78(51.3)
Efficiency 2: Individual vs group tasks	-1.292	1.547	4.22	0.913	2(1.3)	8(5.3)	14(9.2)	59(38.8)	69(45.4)
Efficiency 3: Difficulty of Individual tasks	-1.966	4.687	4.45	0.836	3(2.0)	2(1.3)	10(6.6)	46(30.3)	91(59.9)
Efficiency 4: Ideation & brainstorming	-1.636	4.060	4.40	0.766	2(1.3)	1(0.7)	11(7.2)	58(38.2)	80(52.6)
Note: Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), Strongly Agree (SA)									

Table 5.6 Descriptive Statistics of Enjoyment

Constructs					SD	D	N	A	SA
	Skewness	Kurtosis	Mean	Std D	N (%)	N (%)	N (%)	N (%)	N (%)
Enjoyment									
Enjoyment 1: Collaborative vs individual work	-2.053	3.710	4.44	1.015	6(3.9)	4(2.6)	11(7.2)	27(17.8)	104(68.4)
Enjoyment 2: Use of technology	-1.427	1.304	4.28	1.043	4(2.6)	8(5.3)	19(12.5)	32(21.1)	89(58.6)
Note: Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), Strongly Agree (SA)									

Table 5.7 Descriptive Statistics of Academic Performance

Constructs					SD	D	N	A	SA
	Skewness	**Kurtosis**	**Mean**	**Std D**	**N (%)**	**N (%)**	**N (%)**	**N (%)**	**N (%)**
Academic Performance									
SP1: Learning effectiveness	-1.842	4.022	4.47	0.805	2(1.3)	2(1.3)	12(7.9)	42(27.6)	94(61.8)
SP2: Quality of learning	-1.970	4.907	4.51	0.772	2(1.3)	1(0.7)	11(7.2)	41(27.0)	97(63.8)
Note: Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), Strongly Agree (SA)									

Table 5.8 Descriptive Statistics of Perceived Satisfaction

Constructs					SD	D	N	A	SA
	Skewness	**Kurtosis**	**Mean**	**Std D**	**N (%)**	**N (%)**	**N (%)**	**N (%)**	**N (%)**
Perceived Satisfaction									
PS 1: Outcome	-1.523	3.425	4.47	0.709	1(0.7)	1(0.7)	10(6.6)	54(35.5)	86(56.6)
PS 2: Decision making within a group	-1.026	0.469	4.14	0.938	1(0.7)	11(7.2)	18(11.8)	57(37.5)	65(42.8)
Note: Strongly Disagree (SD), Disagree (D), Neutral (N), Agree (A), Strongly Agree (SA)									

5.4 Measurement Model Analysis

The measurement model analysis takes place after the data screening. It aims to assess the reliability and validity of the model constructs and the associated indicators. More concretely, scale reliability such as internal consistency and item-total correlations, as well as factor analysis techniques, including exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), are used to perform the measurement model analysis. Additionally, there are different process to assess the CFA, i.e., indicator reliability, convergent reliability, discriminant validity, and eventually model fit. The following sub-sections discuss in detail the process adopted for Measurement Model Analysis with the results.

5.4.1 Scale Reliability

Internal consistency and item-total correlations have been employed to assess the scale reliability of the main constructs, i.e., collaborative technology, collaborative learning and

quality of learning experience. Quality of learning experience includes the fine-grained metrics such as effectiveness, efficiency, and enjoyment to evaluate the overall academic performance and satisfaction. Each evaluation method (internal consistency and item-total correlations) and its results are presented in the sub-sections below.

5.4.2 Internal consistency

The coefficient alpha, also known as Cronbach's alpha after Cronbach's influential 1951 paper, which is the most popular method of measuring internal consistency in the social sciences (Thomas J. Dunn 2014). Cronbach's alpha coefficient (Cronbach 1951) is commonly used as a reliability metric for a questionnaire intended to test a single build. Cronbach's alpha is a statistic that writers frequently use to demonstrate the appropriateness of tests and scales designed or used for research initiatives. According to (Hair Black, W.C., Babin, B.J., Anderson, R.E. & Tatham, R.L. 2006), values of 0.60 to 0.70 are the minimum baseline of acceptability as a measurement method. The Cronbach's alpha coefficient of the build measurement scales used in the current study is shown in (Tables 5.9 to 5.15). The alpha values for all scales ranged from 0.639 to 0.924.

5.4.3 Item-total Correlations

The item-total correlation is the sum of all the variables that show the construct's correlation (LU 2007). The construct is determined by describing the correct items and deleting the unnecessary ones in item-total correlation analysis (Churchill JR 1979). When the corrected item-total correlation value is less than 0.30, it means the item is measuring something different from the others (Pallant 2007). As a result, a value of less than 0.30 for item-total correlation is not recommended. The build item-total correlations for each factor are greater than 0.30, as shown in (Tables 5.9 to 5.15).

Table 5.9 Cronbach Alpha for Collaborative Technology

	Construct	Corrected Item-Total Correlation	Cronbach's α
SL#	**Collaborative Technology**		
1	Collaborative technologies make it possible for team members to collaborate	**0.762**	**0.823**
2	Collaborative technologies help to work more effectively among team members	**0.778**	**0.812**
3	Collaborative technologies help team members to interact, communicate, share and combine diagrams faster and better than face-to-face collaboration	**0.755**	**0.839**

Table 5.10 Cronbach Alpha for Collaborative Learning

	Construct	Corrected Item-Total Correlation	Cronbach's α
SL#	**Collaborative Learning**		
1	Collaborative work helps the team members to improve their ways of thinking effectively	**0.760**	**0.888**
2	I improved other members' contributions to my team and make sense of their ideas	**0.832**	**0.827**
3	I gained new skills and knowledge from other members of my team	**0.806**	**0.848**

Table 5.11 Cronbach Alpha for Effectiveness

	Construct	Corrected Item-Total Correlation	Cronbach's α
SL#	**Effectiveness**		
1	Collaborative work helps the team to develop diagrams quickly and lead to better diagrams outcomes	**0.829**	**0.920**
2	Collaborative technologies help to gather the data that is needed to develop the system model	**0.836**	**0.919**

Table 5.12 Cronbach Alpha for Efficiency

	Construct	Corrected Item-Total Correlation	Cronbach's α
SL #	**Efficiency**		
1	The team completed the tasks faster than I expected/planned	**0.742**	**0.857**
2	Individual tasks were still time-consuming	**0.603**	**0.881**
3	Individual tasks were taking significant effort	**0.732**	**0.859**
4	I found the ideation process within the team smooth and effective	**0.698**	**0.866**

Table 5.13 Cronbach Alpha for Enjoyment

	Construct	Corrected Item-Total Correlation	Cronbach's α
SL #	**Enjoyment**		
1	I enjoy working collaboratively instead of individually	**0.624**	**0.639**
2	I enjoy using collaborative technologies with my team in learning more than face-to-face learning	**0.589**	**0.688**

Table 5.14 Cronbach Alpha for Academic Performance

	Construct	Corrected Item-Total Correlation	Cronbach's α
SL #	**Academic Performance**		
1	Overall, using technologies in collaborative activities with the team improves learning and leads to better system model outcomes	**0.807**	**0.924**
2	Overall, I think adopting diagrams to support system design helped to create solutions	**0.705**	**0.865**

Table 5.15 Cronbach Alpha for Perceived Satisfaction

	Construct	Corrected Item-Total Correlation	Cronbach's α
SL#	**Perceived Satisfaction**		
1	I was happy with the outcome of the system design	**0.607**	**0.697**
2	It was relatively easy to make decisions within the team	**0.725**	**0.861**

5.4.4 Exploratory Factor Analysis (EFA)

In the social sciences, exploratory factor analysis (EFA) is a frequently used and widely implemented statistical methodology (Costello & Osborne 2005). More conclusively, if the sample size is small, the number of factors is relatively large, or the structure is unclear. There might be a lot of uncertainty regarding population parameters (Robert R. Shinji Yamagata, John E Kurtz Terracciano 2010).

EFA entails a set of phases that can be approached in various ways (Urbano Lorenzo-Seva 2006). As a result, researchers use EFA to find a set of unobserved, i.e., latent components that rebuild the complexity of visible data in an essential form (Matsunaga 2010). SPSS has been used to perform the EFA analyses and establish the acceptability of the data for factor analysis. Bartlett's Test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy are used (Field 2009). KMO and Bartlett's test must be at least 0.60, with a p-value (significant threshold) of 0.05 to suggest sufficient correlations among measurement items (Field 2009; Pallant 2007). Table 5.16 shows that the overall inter correlations assumptions are met using the KMO and Bartlett's measures.

Table 5.16 Exploratory Factor Analysis, KMO and Bartlett's test of Sphericity

Constructs		***Bartlett's test of Sphericity***		
	KMO	***Approx. Chi-Square***	***df***	***Sig.***
Collaborative Technology	0.743	236.075	3	0.000
Collaborative Learning	0.741	281.579	3	0.000
Effectiveness	0.500	99.892	1	0.000
Efficiency	0.786	227.406	6	0.000
Enjoyment	0.500	50.349	1	0.000
Academic Performance	0.500	97.894	1	0.000
Perceived Satisfaction	0.500	83.740	1	0.000
* Kaiser-Meyer-Olkin Measure of Sampling Adequacy Degree of Freedom (df), Significance (Sig)				

5.4.5 Confirmatory Factor Analysis (CFA)

CFA adopts to confirm the results and prepare for further model analysis, i.e., convergent reliability, discriminant validity. The former represents the convergent validity if more measures are used for an individual construct, while the latter defines the extent to which measures of a given construct differ from different constructs' measurements in the same model (Ab Hamid, Sami & Mohmad Sidek 2017; Hair et al. 2012; Hair, Ringle & Sarstedt 2011; Hulland 1999). Additionally, confirmatory factor analysis is recognised as an effective procedure to test a pre-determined "hypothesized" factor structure that fits the actual data (Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014).

PLS estimates parameters for both the ties between measurements and constructs, i.e., loadings, and the connections between various constructs, i.e., path coefficients (Ringle, Da Silva & Bido 2014). At the same time, a PLS model is usually studied and understood in two stages: (1) the measurement model's reliability and validity, and (2) the structural model's reliability and validity (Ringle, Da Silva & Bido 2014).

Indicator reliability, and the convergent validity of measures connected with individual constructs, as well as discriminant validity can all be used to evaluate the measurement model's suitability (Hulland 1999).

Indicator Reliability:

Individual item dependability is evaluated in PLS by looking at the loadings (or simple correlations) of the measurements with their corresponding constructs. The rule of thumb of accepting items with loadings of 0.7 or higher indicates that the construct and its measure have more shared variance than error variance (Ab Hamid, Sami & Mohmad Sidek 2017; Hulland 1999; Nunnally 1978). Table 5.17 reveals that all items' loadings on their constructs are more than 0.7, specifying indicator reliability.

Convergent Reliability:

When using multiple measures to investigate a single construct, the researcher should consider not just the reliability of individual assessment items, but also the degree to which the measures have convergent validity (Hulland 1999).

The values associated with the different metrics adopted in the study are reported in Table 5.17. More concretely, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (CA) are used to measure Convergent Validity along with the loading of the measurements related to their corresponding constructs (Hulland 1999). AVE refers to the average variance shared between a construct and its related measures, which indicates convergent validity; CR evaluates the internal consistency among scale items, and CA measures the reliability of the construct indicators (Hulland 1999).

The selected metrics have different thresholds to ensure that the obtained measures are reliable and valid for further analysis as reported in (Hair et al. 2012; Hair, Ringle & Sarstedt 2011; Hulland 1999). Typically, a value for AVE that is 0.5 or higher is assumed to be appropriate.

For CR and CA values are in the range 0-1. The typical accepted values are in the range 0.7-0.9 and should not be lower than 0.6.

Table 5.17 Item loadings, (AVE), (CR) and (CA)

Construct	Item	Loading	AVE	CR	CA
Collaborative Technology (CT)	**CT1:** Enabling collaboration	0.899	0.805	0.925	0.881
	CT2: Effective collaboration	0.907			
	CT3: Engagement, communication and knowledge development	0.917			
Collaborative Learning (CL)	**CL1:** Knowledge development	0.888	0.832	0.937	0.900
	CL2: Brainstorming	0.930			
	CL3: Group thinking	0.917			
Effectiveness	**Effectiveness 1:** Develop and document expected outcomes	0.922	0.849	0.918	0.822
	Effectiveness 2: Data model and gathering	0.921			
Efficiency	**Efficiency 1:** Time constraints (group)	0.839	0.660	0.885	0.842
	Efficiency 2: Individual vs group tasks	0.752			
	Efficiency 3: Difficulty of Individual tasks	0.855			
	Efficiency 4: Ideation & brainstorming	0.799			
Enjoyment	**Enjoyment 1:** Collaborative vs individual work	0.882	0.767	0.868	0.698
	Enjoyment 2: Use of technology	0.870			
Academic Performance (SP)	**SP1:** Learning effectiveness	0.919	0.847	0.917	0.819
	SP2: Quality of learning	0.921			
Perceived Satisfaction (PS)	**PS 1:** Outcome	0.892	0.826	0.905	0.809
	PS 2: Decision making within a group	0.926			

Measured values in Table 5.17, show that all loadings are higher than the target threshold (0.7). On the other side, AVE measures fall in the range 0.660-0.849, while CR values range from 0.868 to 0.937 and CA measures are above 0.69.

Discriminant Validity:

Discriminant validity is the typical methodological counterpart to convergent validity, and it examines how different measures of one concept are from assessments of other components in the same model. In other words, discriminant validity defines the extent to which measures of a given construct differ from different constructs' measurements in the same model (Ab Hamid, Sami & Mohmad Sidek 2017; Hair et al. 2012; Hair, Ringle & Sarstedt 2011; Hulland 1999).

There are different methods to assess discriminant validity (Campbell & Fiske 1959; Rönkkö & Cho 2022). In this study, we adopt the Fornell and Larcker Criterion (Fornell & Larcker 1981), the Heterotrait-Monotrait Ratio (HTMT) (Henseler, Ringle & Sarstedt 2015), and the Cross-Loading method (Ab Hamid, Sami & Mohmad Sidek 2017).

According to the Fornell and Larcker Criterion (reported in Table 5.18), in order to have valid measurements, the diagonal elements in the relevant rows and columns should be much larger than the off-diagonal elements (Fornell & Larcker 1981; Hulland 1999).

Table 5.18 Fornell and Larcker Criterion

	Academic Performance	Collaborative Learning	Collaborative Technology	Effectiveness	Efficiency	Enjoyment	Perceived Satisfaction
Academic Performance	**0.920**						
Collaborative Learning	0.687	**0.912**					
Collaborative Technology	0.811	0.733	**0.897**				
Effectiveness	0.797	0.833	0.813	**0.921**			
Efficiency	0.747	0.567	0.693	0.666	**0.812**		
Enjoyment	0.758	0.735	0.823	0.817	0.683	**0.876**	
Perceived Satisfaction	0.760	0.574	0.685	0.627	0.812	0.659	**0.909**

Heterotrait-Monotrait Ratio (HTMT) is seen as an alternative method with proven high-performance to determine discriminant validity (Henseler, Ringle & Sarstedt 2015). Typical acceptance thresholds for HTMT are between 0.85 (Clark & Watson 1995; Tabri & Elliott 2012) and 0.90 (Gold, Malhotra & Segars 2001; Teo, Srivastava & Jiang 2008). Table 5.19

reports the measured values that fall within the recommended thresholds. A value higher than the threshold indicates a lack of discriminant validity.

Table 5.19 Discriminant Validity Heterotrait-Monotrait Ratio (HTMT)

	Academic Performance	***Collaborative Learning***	***Collaborative Technology***	***Effectiveness***	***Efficiency***	***Enjoyment***	***Perceived Satisfaction***
Academic Performance							
Collaborative Learning	0.800						
Collaborative Technology	0.865	0.822					
Effectiveness	0.812	0.762	0.835				
Efficiency	0.886	0.712	0.791	0.793			
Enjoyment	0.841	0.895	0.675	0.652	0.884		
Perceived Satisfaction	0.557	0.676	0.818	0.769	0.756	0.888	

Cross-loading assessment is often considered as an item-level discriminant validity (Ab Hamid, Sami & Mohmad Sidek 2017) as the loading indicators on the target factor have to be more significant than on the other constructs. The acceptance threshold is normally 0.70 (Ab Hamid, Sami & Mohmad Sidek 2017). Table 5.20 shows the measured Cross-Loading.

Table 5.20 Assessment of Cross-Loading

	Academic Performance	***Collaborative Learning***	***Collaborative Technology***	***Effectiveness***	***Efficiency***	***Enjoyment***	***Perceived Satisfaction***
AP 2	**0.919**	0.572	0.632	0.662	0.721	0.612	0.726
AP1	**0.921**	0.691	0.86	0.804	0.654	0.781	0.673
CL 1	0.608	**0.888**	0.646	0.724	0.544	0.599	0.552
CL 2	0.654	**0.930**	0.693	0.758	0.512	0.73	0.511
CL 3	0.615	**0.917**	0.666	0.797	0.497	0.678	0.511
CT 1	0.758	0.708	**0.899**	0.76	0.65	0.683	0.615
CT 2	0.734	0.674	**0.907**	0.772	0.654	0.746	0.624
CT 3	0.69	0.585	**0.886**	0.649	0.557	0.792	0.603
Effectiveness 1	0.703	0.842	0.725	**0.922**	0.765	0.772	0.563
Effectiveness 2	0.766	0.694	0.773	**0.921**	0.721	0.734	0.593
Efficiency 1	0.646	0.561	0.654	0.754	**0.839**	0.631	0.731
Efficiency 2	0.492	0.347	0.447	0.762	**0.752**	0.524	0.549
Efficiency 3	0.514	0.394	0.492	0.731	**0.855**	0.452	0.589
Efficiency 4	0.721	0.493	0.610	0.728	**0.799**	0.582	0.722
Enjoyment 1	0.692	0.756	0.699	0.799	0.637	**0.882**	0.583
Enjoyment 2	0.635	0.527	0.744	0.63	0.559	**0.870**	0.573
PS 1	0.76	0.578	0.649	0.645	0.742	0.608	**0.926**
PS 2	0.61	0.457	0.593	0.483	0.735	0.591	**0.892**

Model Fit:

The standardised root mean square residual (SRMR) is calculated by translating both the sample and projected covariance residuals into correlation matrices. Additionally, the root mean square residual (RMSR) is a measure of the mean absolute value of the covariance residual (SmartPLS). The most sensitive index to models is SRMR, which has a cutoff value near to 0.08 (Henseler, Ringle & Sarstedt 2014; Hu & Bentler 1999).

The Bentler-Bonett index, often known as the normed fit index (NFI), is another helpful approximate model fit criterion (P. M.Bentler & G.Bonett 1980). According to (Lohmöller 1989), Bentler-Bonett index is attributed with suggesting the use of the NFI in conjunction with PLS path modelling. NFI values greater than 0.90 are deemed acceptable for factor models (Hu & Bentler 1999). As a result, Hu and Bentler, recommend a cut-off value of 0.08 for PLS path models, which appears to be more appropriate PLS path modelling in new technology research (Henseler, Hubona & Ray 2016). On the other hand, Hair et al, recommended that the researchers be cautious in reporting the model fit analysis using PLS-SEM (Hair et al. 2017). The concern is that the critical threshold values are still not being straightforward, as well as the threshold values are in the early stage and require more studies. Although this study reported the result of the model fit, where we agree with Hair and other researchers, the threshold values are still not optimal, and further investigation is recommended. Table 5.21 shows the result of model fit.

Table 5.21 Model Fit

	Saturated Model	***Estimated Model***
SRMR	0.080	0.096
d_ULS	1.105	1.572
d_G	0.961	1.110
Chi-Square	839.664	872.373
NFI	0.684	0.672

5.5 Structural Model Assessment

The structural modelling can be examined after assessing the validity of measurements to check the relationship among research constructs. Furthermore, the structural modelling can be conducted as an essential phase of SEM (Tenenhaus et al. 2005). The process of the structural modelling allows measuring the Coefficient of Determination (R^2) of each endogenous latent variable (LV) as well as evaluating the path coefficients among LVs to test the hypotheses (Hair, Ringle & Sarstedt 2011; Loehlin & Beaujean 2016; Sharma & Kim 2012; Tenenhaus et al. 2005).

Looking at R^2 three possible levels are normally considered: substantial level refers to values around .670, while average level indicates values around .333, and values below .190 are considered to be weak (Chin 1998). The values of R^2 are recommended to be sufficiently high to ensure that the model has a minimal degree of explanatory power (Sharma & Kim 2012).

Figure 15 summarises path analysis, and the measured values for R^2 are reported. According to such measures, Effectiveness (0.782), Enjoyment (0.716), and Academic Performance (0.719) are well over the substantial level. Collaborative Learning (0.537), Efficiency (0.488) and Perceived Satisfaction (0.594) present values close to the substantial threshold.

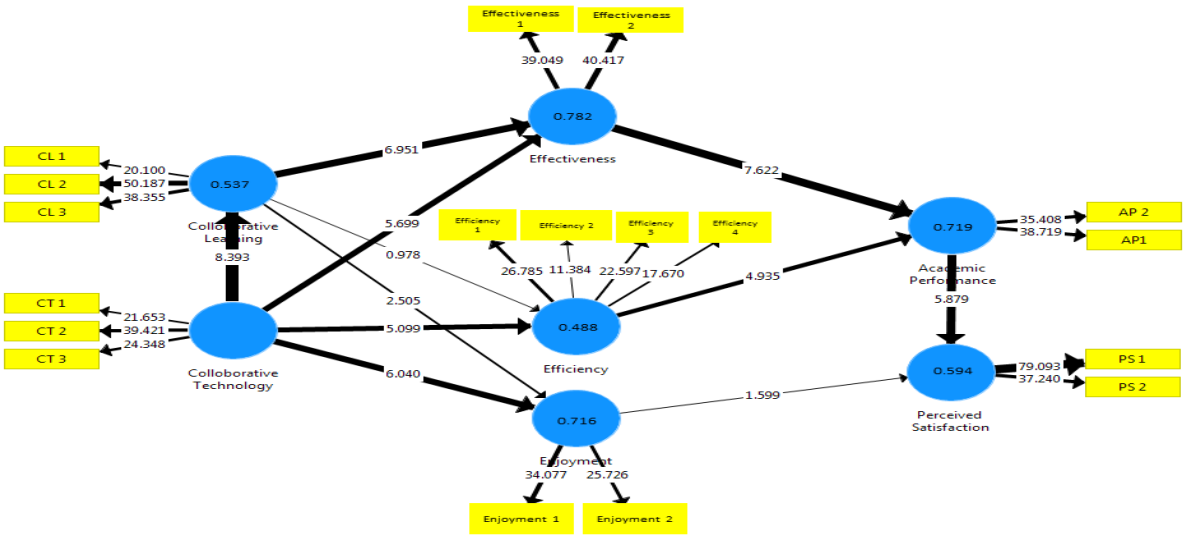


Figure 15 Path Analysis

The Path-Coefficient is a standardised regression coefficient (ß) in PLS-SEM to test the structural model and hypothesis by highlighting the direct effect among the constructs (Hair, Ringle & Sarstedt 2011). The bootstrap approach in PLS path analysis tests the relevance of path coefficients associated with the standard error of the path and t-value (Hair, Ringle & Sarstedt 2011). Thus, a total of 5000 bootstrap sub-samples have been applied to examine the path coefficients and make the hypotheses assessment.

P-value is adopted to assess the consistency (Hair, Ringle & Sarstedt 2011; Kazár 2014). Path coefficients are considered to be significant if the p-value is lower than 0.05 and not significant if higher than 0.05 (Hair, Ringle & Sarstedt 2011; Kazár 2014).

Table 5.22 provides an overview of conducted measures. According to p-value measurement, H3 and H10 are insignificant (reject the hypotheses with p-value > 0.05), while all others fall within the significant range (accept the hypotheses with p-value < 0.05).

Table 5.22 Hypotheses testing result

Hypothesis	Relationship	Std. Beta	Std. Error	T-value	Decision	P-value	F^2	Q^2	95% CI LL	95% CI UL
H 1	Collaborative Technology → Collaborative Learning	0.726	0.084	8.720	Supported	0.000**	1.1598	0.7794	0.560	0.864
H 2	Collaborative Learning → Effectiveness	0.515	0.077	6.698	Supported	0.000**	0.5550	0.2548	0.356	0.657
H 3	**Collaborative Learning → Efficiency**	**0.138**	**0.136**	**0.935**	**Not Supported**	**0.350ns**	0.0176	0.0071	-0.115	0.442
H 4	Collaborative Learning → Enjoyment	0.281	0.111	2.560	Supported	0.011*	0.1232	0.0275	0.038	0.456
H 5	Collaborative Technology → Effectiveness	0.435	0.079	5.499	Supported	0.000**	0.3853	0.1753	0.278	0.589
H 6	Collaborative Technology → Efficiency	0.592	0.114	5.273	Supported	0.000**	0.3242	0.1581	0.327	0.772
H 7	Collaborative Technology → Enjoyment	0.620	0.098	6.271	Supported	0.000**	0.5669	0.2606	0.450	0.836
H 8	Effectiveness → Academic Performance	0.534	0.072	7.449	Supported	0.000**	0.5658	0.2807	0.393	0.684
H 9	Efficiency → Academic Performance	0.392	0.080	4.847	Supported	0.000**	0.2883	0.1462	0.220	0.533
H 10	**Enjoyment → Perceived Satisfaction**	**0.195**	**0.121**	**1.630**	**Not Supported**	**0.104ns**	0.0369	0.0190	-0.031	0.439
H 11	Academic Performance → Perceived Satisfaction	0.612	0.105	5.839	Supported	0.000**	0.3916	0.2372	0.415	0.819

H1 is definitely significant according to measured values (ß =0.726, t=8.720, p< 0.01), as well as H2 (ß =0.515, t=6.698, p< 0.01), H4 (ß =0.281, t=2.560, p< 0.05), H5 (ß =0.435, t=5.499,

p< 0.01), H6 (ß =0.592, t=5.273, p< 0.01), H7 (ß =0.620, t=6.271, p< 0.01), H8 (ß =0.534, t=7.449, p< 0.01) H9 (ß =0.392, t=4.847, p< 0.01), H11 (ß =0.612, t=5.839, p< 0.01). As mentioned before, H3 and H10 are not supported by empirical measurements according to the analysis thresholds.

Another feature of the structural model is to assess its predictive power. The most popular measure of predictive relevance is the Stone–Geisser Q^2 (Geisser 1974; Stone 1974), which stipulates that the model must be able to reliably foresee each endogenous latent construct's indicators (Hair, Ringle & Sarstedt 2011). The Q^2 is determined using the blindfolding method. Greater than zero Q^2 values imply that the observed values have been well reconstructed and the model is predictively meaningful (Q^2 values less than zero indicate that the model is not predictively relevant) (Henseler, Ringle & Sinkovics 2009). Table 5.22 shows that the values of predictive relevance Q^2 are not less than zero, indicating that the predictive relevance is acceptable.

Additionally, Cohen's F^2 is used to calculate the size effect of each path in the structural equation model (Cohen 1992). The effect size determines whether or not an independent LV significantly impacts a dependent LV. The size effect is determined as the proportion of unexplained variance in the LV to which the path is connected multiplied by the rise in R^2 of the LV (Chin W 1998). The values of F^2 are reported in Table 5.22; the value of (0.35) seems large, while (0.15) is medium, and (0.02) is small (Chin W 1998).

A confidence interval (CI) measures how fit your sample represents the study target population (Berry 1989). Therefore, the values of upper and low confidence intervals should fall between -1.96 and +1.96 (McLeod 2019). Table 5.22 shows the low and upper confidence interval (CI LL and CI UL) are within the acceptable range.

5.6 Important Performance Map Analysis (IPMA)

The importance-performance map analysis (IPMA; also known as importance-performance matrix, impact-performance map, or priority map analysis). The IPMA is considered a useful analysis approach in PLS-SEM. The IPMA adds a dimension for considering the average values of the latent variable to the standard results reporting of path coefficient estimates (Ringle & Sarstedt 2016).

The IPMA contrasts the overall effects, which show the importance of the previous constructs in forming a specific target construct, with their average latent variable scores that indicate their performance (Ringle & Sarstedt 2016). Each construct's performance is graded on a scale of 0 to 100; the closer the value is to 100, the better the variable's performance. The IPMA analysis are reported in the following Tables (5.23 to 5.28) and Figures (16 to 21):

Collaborative Learning:

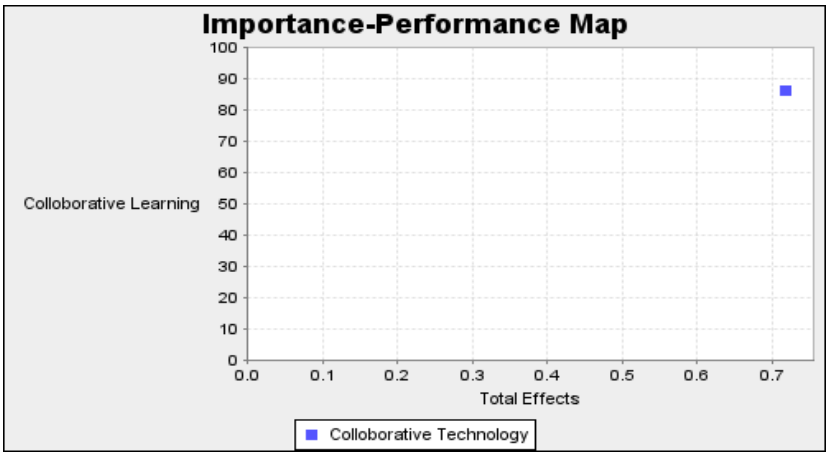


Figure 16 Important Performance Map Analysis of Collaborative Learning

Table 5.23 (IPMA) result of Collaborative Learning

Construct	Importance (Total Effect)	Performances
Collaborative Technology	0.718	86.409

The IPMA analysis for “Collaborative Learning” is reported in Figure 16 and Table 5.23. The result indicates that Collaborative Learning would increase by a value of 0.718 of “Collaborative Technology”.

Effectiveness:

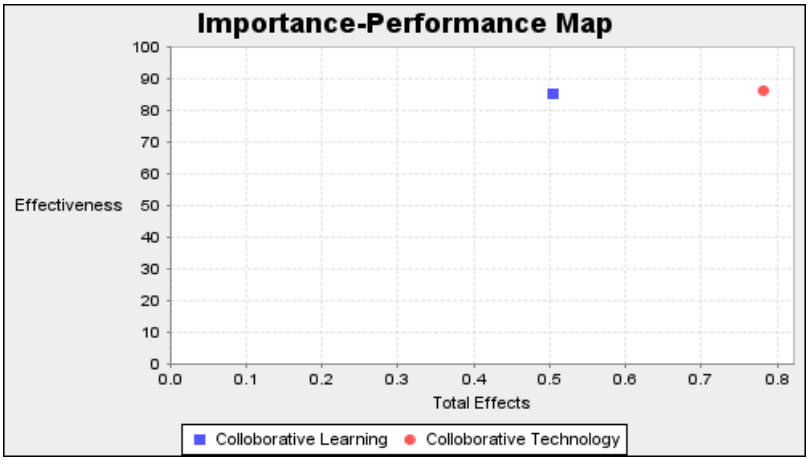


Figure 17 Important Performance Map Analysis of Effectiveness

Table 5.24 (IPMA) result of Effectiveness

Construct	Importance (Total Effect)	Performances
Collaborative Learning	0.505	85.413
Collaborative Technology	0.782	86.409

The IPMA analysis for “Effectiveness” is shown in Figure 17 and Table 5.24. The results of the analysis demonstrate that the highest performance construct for effectiveness is “Collaborative Technology” followed by “Collaborative Learning”. The “Effectiveness” would increase by a value of 0.782 of “Collaborative Technology”, and 0.505 value of “Collaborative Learning”.

Efficiency:

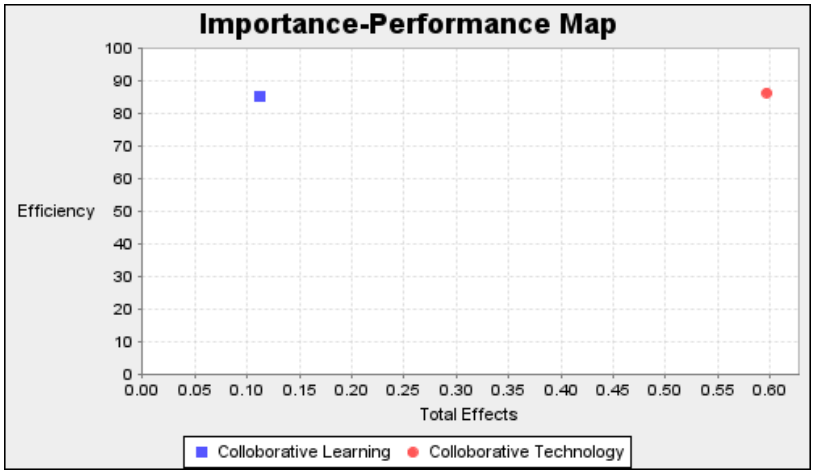


Figure 18 Important Performance Map Analysis of Efficiency

Table 5.25 (IPMA) result of Efficiency

Construct	Importance (Total Effect)	Performances
Collaborative Learning	0.112	85.413
Collaborative Technology	0.597	86.409

The IPMA analysis for "Efficiency" is presented in Figure 18 and Table 5.25. The results of the analysis show that the highest performance construct is "collaborative technology" followed by "Collaborative Learning". The "Efficiency" would increase by a value of 0.597 of "Collaborative Technology", and 0.112 value of "Collaborative Learning".

Enjoyment:

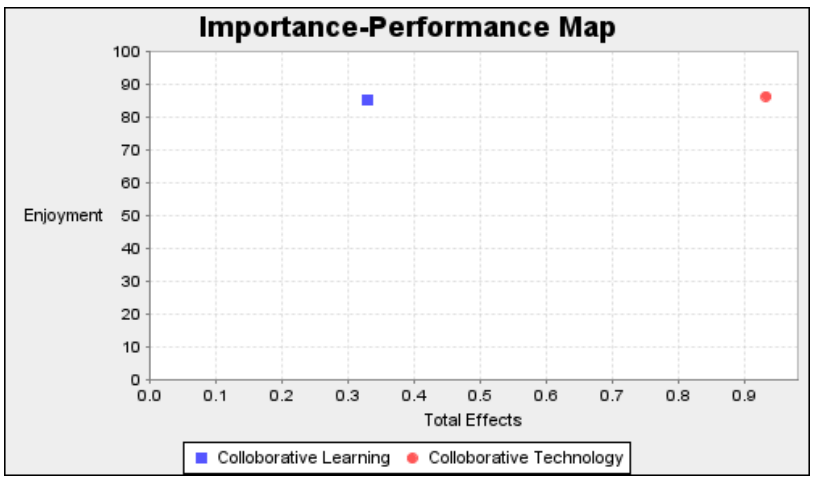


Figure 19 Important Performance Map Analysis of Enjoyment

Table 5.26 (IPMA) result of Enjoyment

Construct	Importance (Total Effect)	Performances
Collaborative Learning	0.329	85.413
Collaborative Technology	0.932	86.409

The IPMA analysis for "Enjoyment" is presented in Figure 19, and Table 5.26. The results of the analysis show that the highest performance construct is "Collaborative Technology" followed by "Collaborative Learning". The "Enjoyment" would increase by a value of 0.932 of "Collaborative Technology", and 0.329 value of "Collaborative Learning".

Academic Performance:

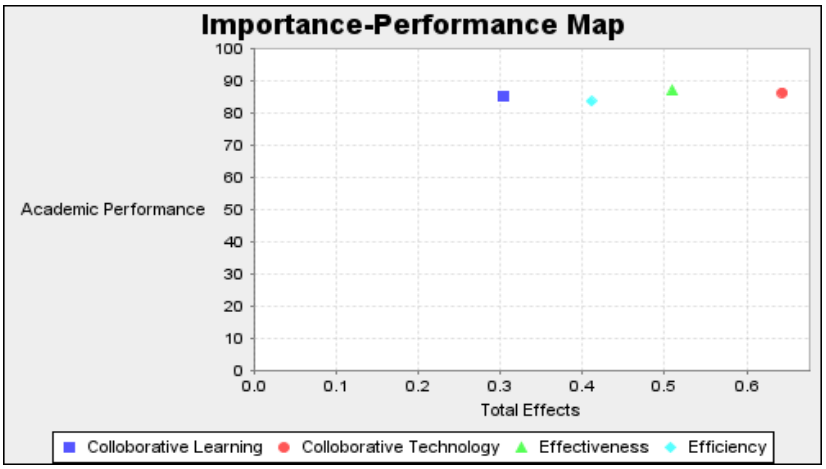


Figure 20 Important Performance Map Analysis of Academic Performance

Table 5.27 (IPMA) result of Academic Performance

Construct	Importance (Total Effect)	Performances
Collaborative Learning	0.303	85.413
Collaborative Technology	0.643	86.409
Effectiveness	0.510	86.993
Efficiency	0.411	83.622

The IPMA analysis for "Academic Performance" is presented in Figure 20 and Table 5.27. The results show that the highest performance construct is "Effectiveness" followed by "Collaborative Technology". The "Academic performance" would increase by a value of 0.510 of "Effectiveness" and 0.643 value of "Collaborative Technology".

Perceived Satisfaction:

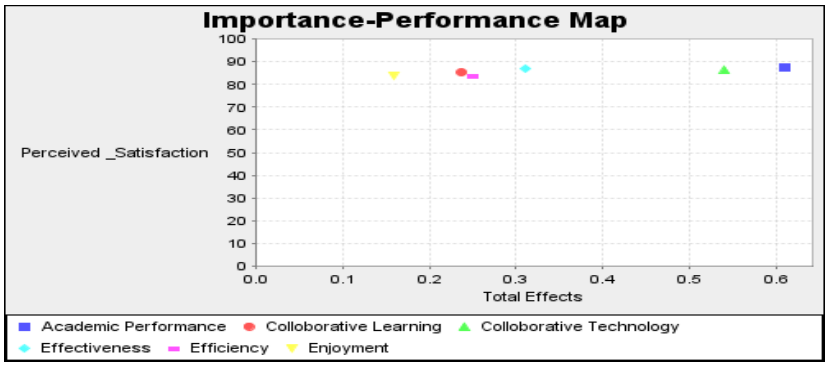


Figure 21 Important Performance Map Analysis of Perceived Satisfaction

Table 5.28 (IPMA) result of Perceived Satisfaction

Construct	Importance (Total Effect)	Performances
Academic Performance	0.611	87.344
Collaborative Learning	0.237	85.413
Collaborative Technology	0.541	86.409
Effectiveness	0.311	86.993
Efficiency	0.251	83.622
Enjoyment	0.159	84.037

The IPMA analysis for "Perceived Satisfaction" is reported in Figure 21, and Table 5.28. The results of the analysis display that the highest performance construct is "Academic Performance" followed by "Effectiveness. The "Perceived Satisfaction" would increase by a value of 0.611 of "Academic Performance", and 0.311 value of "Effectiveness".

5.7 Chapter Summary

This chapter presented the data analysis process along with the results. Descriptive data analysis was performed to understand the characteristics of the data gathered through the questionnaire survey. Then, the data set was scrutinised for outliers and normal distribution. The data set was examined and found to have an appropriate normal distribution without extreme outliers. A measurement model analysis was performed to assess the scale dependability for model constructs. The build measuring scales used in this study had

Cronbach's alpha coefficients ranging from 0.639 to 0.924. Each factor's build item-total correlations are greater than 0.30. The number of factors was then determined using exploratory Factor Analysis (EFA) for model constructs. The KMO and Bartlett's measurements are used to meet the overall inter correlations assumptions. SmartPLS 3.0 results for Partial Least Squares PLS-SEM. All of the assumptions are met in the measurement model structural model (path analysis). The test demonstrated that all items have loadings greater than 0.7 on their constructions, indicating indicator reliability. The average variance extracted (AVE) estimated ranges from 0.660 to 0.849, while the composite reliability values ranges from 0.868 to 0.937. Cross-loading analysis, also known as "item-level discriminant validity," is a popular method for establishing discriminant validity. All item cross-loadings are more than 0.70, with HTMT values falling under the 0.90 threshold. The R^2 Values of LV's Collaborative Learning is 0.537; Effectiveness is 0.782; Efficiency 0.488; and Enjoyment 0.716; Academic Performance 0.719; Perceived Satisfaction 0.594 respectively, and the values of predictive relevance R^2 are not less than zero, showing that the predictive relevance is acceptable. For hypotheses H3 and H10, the results confirmed that the association are not significant ($P>0.05$). While H1, H2, H4, H5, H6, H7, H8, H9, and H11 are all significant positive effects. The average values of the latent variable are also used in the typical results reporting of path coefficient estimates in importance-performance map analysis (IPMA). The IPMA results reiterated that collaborative technology contributes to increasing the performance of collaborative learning, effectiveness, efficiency, and enjoyment. Additionally, collaborative technology positively impacts academic performance, but this impact increases when students perceive the effectiveness and become more productive. Consequently, perceived satisfaction is ultimately increased positively when perceived academic performance and effectiveness.

The next chapter discusses the findings based on the data analysis outcome, followed by the conclusions and future work.

Chapter 6 - Discussion and Conclusions

In the previous chapter, we have presented the results of the data analysis. The analysed data was collected from undergraduate and postgraduate students in Saudi Arabia universities. The techniques adopted for the analysis started with statistical analysis, measurement model analysis, and then structural modelling. The IPMA analysis has been conducted to extend the results by considering each construct's performance and importance.

The current chapter discusses the fundamental findings related to the present study. It begins by providing an overview of the study conducted in terms of the research purpose, questions, and hypotheses. Then, the study's findings are illustrated based on the previous studies in the literature to provide proper interpretations of the outcomes and to elaborate on how to answer the research questions by reference to the hypotheses' results. The explanation and discussion provided in this chapter are valuable to show how the current study is addressed compared to existing research in the literature. Additionally, the study's contributions, limitations and both the theoretical and practical implications are discussed. Finally, the conclusions of this study and further work have been reported.

Review of research purpose, questions, and related hypotheses:

The main goal of the current study was to assess the impact of the extensive adoption of technology within collaborative learning environments. More concretely, the study assessed the impact of collaborative technology on knowledge development and sharing. Additionally, this study evaluated the impact on the overall quality of learning experience by looking at relationships among the fine-grained parameters. These factors are effectiveness, efficiency, and enjoyment to reflect standard metrics for the overall academic performance and perceived satisfaction.

At a more theoretical level, this study addressed the relationships between traditional learning models, i.e., Bloom's taxonomy and Nonaka's theory. The former defines different levels of learning, and the latter describes the process to develop and expand knowledge. Bloom's framework has been widely adopted in various contexts of education to assess and design different levels of learning. Nonaka's theory is a well-known framework in an organizational context, while the process to develop and share knowledge in collaborative learning presents in fact significant similarities and common challenges with a more generic organizational context. Once more, this research is conducted among undergraduate and postgraduate students involved in programs related to system design in Saudi Arabia universities as an experimental context. System design has been adopted as an experimental context because it includes different levels of Bloom's taxonomy.

Thus, chapter two has highlighted and reviewed the existing studies that are relevant to our research concepts and context. It identified different gaps in particular: (i) previous studies in Collaborative Learning environments do not fully address the impact on the overall quality of learning experience parameters considered, (ii) the impact of Technology on the quality of learning experience across the different disciplines and activities is still to be fully assessed, and (iii) rarely effectiveness, efficiency, and enjoyment are simultaneously considered to assess performance and satisfaction. Focussing on the identified gaps in the literature review, the current study proposed the research questions (reported in Chapter one, section 1.2) and the related hypotheses (reported in Chapter four, section 4.2). This main question is divided into sub-questions to clarify the study context and provide a further understanding of the role of technology within collaborative knowledge process and the overall quality of learning experience.

To test the hypotheses and answer the research questions, we conducted a quantitative study through an online survey as recommended in previous studies from the literature. The

completed surveys provided 152 responses, which have been considered for the data analysis as reported in Chapters three and five. The following section briefly explains how the present study has addressed the research questions and hypotheses.

6.1 Addressing Research Questions and Hypotheses

According to the quantitative analysis conducted, nine out of eleven hypotheses have been accepted. There is no contradiction or significant inconsistency with results obtained in other studies as in the literature. For instance, in (Alalwan et al. 2019; Alenazy, Mugahed Al-Rahmi & Khan 2019; Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019), the impact of technology within collaborative learning environments is overall assessed positively, as well as the influence of collaborative technology has resulted in an increased academic performance and perceived satisfaction in (Al-Rahmi, Othman & Musa 2014; Al-Rahmi & Zeki 2017). Our research conducted in a specific context has reiterated the importance of technology on the establishment of effective collaborative learning environments. Most part of the underlying theory is in line with the analysis of collected data. Assuming the intrinsic complexity of the knowledge building process within collaborative learning environments, the study has pointed out once again the critical role of technology in general terms and its clear impact on the overall quality of experience.

More specifically, to answer Q1: *How is the process of knowledge developing and sharing influenced by collaborative technology?* The related hypothesis for such question is (H1). Thus, collaborative technology plays a positive role in the process of knowledge development and sharing. Adopting technology within a collaborative learning environment contributes to building the knowledge needed at different levels of learning and enables knowledge sharing among students. Therefore, the finding of (H1) is supported and consistent with other existing studies as in the literature. The authors in studies (Baanqud et al. 2020; Rejón-Guardia, Polo-

Peña & Maraver-Tarifa 2019), found a positive impact of the use of technology within group work that contributes to support the knowledge development as well as sharing.

To answer Q2: *How does technology support collaborative development to increase flexibility and resilience in the process of applying, analysing and eventually creating as per Bloom's taxonomy?* The related hypotheses are from H2 to H7. Looking at (H2), collaborative learning contributes to effectiveness, where students have the capability to deliver the requested outcome. Thus, the final decision for (H2) is supported as it has been tested positively in previous research. The following studies (Alenazy, Mugahed Al-Rahmi & Khan 2019; Lin, Huang & Ko 2020) have found a positive impact of involving students in group work to achieve specific outcomes effectively as they could analyse the given resources, i.e. materials and apply them to a new situation to create their task.

On the other hand, the study doesn't demonstrate a direct relationship between Collaborative Learning and efficiency as in (H3). That is in a way surprising although largely understandable in the context proposed where collaboration among students presents some challenges and it's not always perceived by students as a value but rather like some additional effort that not necessarily leads to efficiency in developing tasks.

Additionally, this study found collaborative learning contributes to enjoyment as in (H4). This hypothesis was tested positively, where team members perceived enjoyment in collaborative activities. The finding of H4 is consistent with previous studies as revealed in the literature as the authors in (Gomez, Wu & Passerini 2010) reported the positive effect on students' enjoyment during collaborative learning process. Furthermore, group work provides an enjoyable learning environment that helps to increase learning achievement by sharing knowledge and working together for better learning outcomes (Lage, Platt & Treglia 2000).

We also assessed the direct impact of collaborative technology on effectiveness, efficiency, and enjoyment as in (H5, 6, and 7). These hypotheses aimed to test the impact of collaborative technology adoption in terms of task development, communication, data acquisition, and the use of social media. These proposed hypotheses associated with the direct impact of collaborative technology have been tested positive. Previous studies do not fully address the impact of the extensive adoption of collaborative technology on the different aspects of the overall quality of learning experience, such as effectiveness, efficiency, and enjoyment. However, existing studies in the literature are partially consistent with our results for (H5 and 7) (Alalwan et al. 2019; Alenazy, Mugahed Al-Rahmi & Khan 2019; Baber 2021; Gomez, Wu & Passerini 2010; Lin, Huang & Ko 2020; Liu, Zhong & Lim 2009). While efficiency has not been explicitly assessed in previous studies. Nevertheless, the relationship between collaborative technology and efficiency in this study has been tested positively as in (H6).

Technology has been widely adopted within collaborative learning environments to provide flexibility and resilience among team members as it supports the task development phases. More specifically, Technology facilitates using the collected information in new scenarios, enables connections among notions, and eventually creates /produces the given task. More recently, technology plays a key role to face the new challenges related to COVID-19, which forced the move mostly to remote learning. This study was conducted in the early stage of COVID-19, when universities were forced to adopt remote learning. We focused on assessing the impact of technology on the collaborative knowledge development process and the overall quality of learning experience. Thus, our results are in line with the previous studies conducted during the restrictions caused by covid-19, where the technology provides resilience and flexibility and supports the process of collaborative knowledge development and sharing (Adedoyin & Soykan 2020; Elumalai et al. 2019; Qazi et al. 2021; Tawafak et al. 2021).

Given the importance of the relationships among quality of learning experience metrics have been evaluated as mentioned above in (H8, 9, 10, and 11), which are related to answering Q3: *How does technology affect the relationship between academic performance and perceived satisfaction in collaborative learning environments?* The final outcome for (H8, 9, and 11) has been tested positively. Thus, the hypotheses proved that academic performance depends on effectiveness and efficiency as well as academic performance influences perceived satisfaction. Seldom, Effectiveness, efficiency, and enjoyment are explicitly taken into account to assess performance and satisfaction. However, the relationship between performance and satisfaction is commonly tested in previous studies in the literature. As mentioned in studies (Al-Rahmi, Othman & Musa 2014; Al-Rahmi & Zeki 2017), the authors found clear links between performance and satisfaction. These findings are consistent with our result in H11.

We reiterate the lack of direct relationship between enjoyment and perceived satisfaction, which is rather related to performance. In other words, students are still primarily concerned about their final results. However, technology seems to impact positively on enjoyment. Additionally, we measured the enjoyment by considering two items that might prevent the relationship between enjoyment and satisfaction from being positive. Although, researchers who conduct PLS-SEM discussed the acceptance of a single item for each construct (Asyraf & Afthanorhan 2013; Cheah et al. 2018). Furthermore, we measured other parameters by two items, such as effectiveness, academic performance, and satisfaction, which resulted in positive relationships.

In summary, Table 6.1 shows the previous studies' findings in the literature, where technology has been addressed within collaborative learning environments to determine its impact on different aspects.

Table 6.1 Summary of previous studies' findings

Ref	Research aims	Research Findings
(Al-Rahmi et al. 2015)	Evaluates the impact of adopting social media within collaborative learning environments to improve academic performance.	• Social media plays a key role in improving academic performance, while collaborative learning is recognized as a mediator. • Social media has a significant impact on academic performance within collaborative learning activities.
(Al-Rahmi, Othman & Musa 2014)	Observes a number of factors, i.e., interactions, engagement, ease of use, and usefulness, through social media collaboratively to enhance academic performance and satisfaction.	• Academic performance has a positive relationship along the interaction with peers and teachers, as well as engagement. • Collaborative learning positively affects satisfaction and academic performance.
(Habes et al. 2018)	Tests the effect of adopting technology on, i.e., interaction with students and teachers, engagement, and behavioural intention, through a collaborative learning setting.	• The tested factors are influenced positively by applying modern technology, which leads to accepting the collaborative learning environment.
(Qureshi et al. 2021)	Evaluates the impact of different social factors, i.e., interactions, social media use, and social presence, on students' learning performance, while collaborative learning and students' engagement are set as mediating variables.	• Collaborative learning and engagement have been influenced positively by the observed social factors, which improve learning activities and performance.
(Recker, Mendling & Hahn 2013)	Examines technology's impact on cognitive group process through a collaborative modelling process.	• Collaborative technology supports the process of modelling and collaboration as collaborative technology helps expand knowledge and task accomplishment. • Perceived usefulness and satisfaction depend on the given tasks.
(Rejón-Guardia, Polo-Peña & Maraver-Tarifa 2019)	Assesses the TAM modal included subjective norms and social image to learn how to use a personal learning environment in Google apps to promote collaborative learning.	• Overall, students collaborate using technology when they perceive the value of engagement; it leads to increase usefulness. • Technology allows peers to develop and share knowledge collaboratively in solving problems and contributing new content.
(Hernández-Sellés, Pablo-César Muñoz-Carril & González-Sanmamed 2019)	Examines the impact of interaction factors that influence online collaborative learning.	• The results point out collaborative process enables the interaction between teachers and students. • Technology facilitates the communication process and supports sustained emotion within group work.

(Gomez, Wu & Passerini 2010)	Investigates the impact of computer-supported team-based learning as mediation in hybrid classrooms by looking at motivation and enjoyment.	• Motivation contributes to interactions and perceived learning. • Enjoyment is impacted by motivation and group contributions. • Students who are motivated and engaged in team activities lead to enjoy the learning and achieve better outcomes.
(Baber 2021)	Examines the impact of social interaction among students through the effectiveness of online learning during (Covid-19)	• Students' interaction in online learning positively affects their learning effectiveness, where students continue learning online and maintain social distance to reduce the risk of the virus.
(Baanqud et al. 2020)	Investigates how technology such as cloud tools helps students construct knowledge within collaborative environments.	• Technology positively correlates with cognitive engagement, knowledge sharing, and reflective thinking in knowledge development.
(Al-Rahmi & Zeki 2017)	Determines the influence of TAM by adopting social media in a collaborative learning process.	• Technology strongly affects satisfaction, improving the collaborative learning process and providing better outcomes.
(Alalwan et al. 2019)	Investigates the impact of the use of social media in collaboration and communication in terms of academic performance.	• Social media improves the way of collaboration and communication. • Social media supports knowledge sharing and engagement in learning activities. • Overall, adopting technology within the collaborative learning process has positively affected academic performance.
(Alenazy, Mugahed Al-Rahmi & Khan 2019)	Evaluates the technology acceptance model (TAM) when researchers adopt social media within collaborative learning to improve authoring.	• Adopting social media in collaborative activities has contributed positively to researchers authoring.
(Liu, Zhong & Lim 2009)	Assesses how virtual learning environment characteristics can directly affect students' effectiveness on learning materials and communication that lead students to interact with each other and instructors within the system.	• Technology in learning has become an essential factor in learning where the way of designing the tools should be more effective. • The virtual learning settings should be more consistent with pedagogical methods to come up with efficient and effective online environments.
(Lin, Huang & Ko 2020)	Evaluates a collaborative blended learning environment in terms of knowledge share and enjoyment.	• Students enjoy the blended learning environments, which facilitate the knowledge-sharing process among team members.
(Devaraj, Easley & Michael Crant 2008)	Investigates the impact of personality (e.g., big five factors) on TAM and technology in collaborative learning environments.	• Personality factors play a critical role in students' attitudes, beliefs, and the relationships between intention to use and the system used; thus, it is essential to consider these factors when designing tools.

6.2 Contributions, Implications and limitations

The contributions of present study aimed to assess the impact of knowledge development and sharing as well as to evaluate the overall quality of experience within collaborative environments that extensively rely on technology. Firstly, the findings of this study are expected to contribute to Saudi Arabia's vision 2030, as part of the Saudi Vision aims to improve e-learning environments, which are expected to become more effective in practice. Secondly, this study contributes more holistically to the assessment of collaborative learning environments that rely extensively on technology. Lastly, this study also contributes to support further exploration for researchers and academics in learning contexts by looking at the theoretical and practical findings.

Theoretical implication:

At a more theoretical perspective, we have combined into unique analysis framework concepts from Bloom's taxonomy and Nonaka's theory to assess the role of collaborative technology in the development of the knowledge needed to "Apply", "Analyse" and eventually "Create" systems based on Bloom's taxonomy.

Bloom's taxonomy focuses mostly on learning objectives in educational settings, while Nonaka's theory addresses knowledge creation within organizational contexts. The process to develop and share knowledge in collaborative learning presents in fact significant similarities and common challenges with a more generic organizational context (Baloian & Zurita 2012; Lee & Schottenfeld 2014).

Additionally, the socialization dimension from Nonaka's perspective focuses more on knowledge sharing and experience among the target community, i.e., tacit knowledge (Muhisn et al. 2019). While the externalization dimension from Nonaka supports converting tacit knowledge to explicit knowledge (Yi 2006). However, Bloom's classifications and related

verbs represent the needed process of developing tacit knowledge and combining explicit knowledge, as reported in (Babin, Sena & Garven 2017).

More specifically, this study focuses on different levels of learning as per Bloom's Taxonomy, such as (understand, apply, analyse, evaluate and create), and two knowledge dimensions as per Nonaka's theory (socialization and externalization).

Refer to Figure 22, each level from Bloom has specific verbs. Those verbs in understand, apply and analyse can support the process of tacit knowledge development in the socialization dimension as per Nonaka's model. At the same time, the verbs that represent evaluate and create from Bloom support the externalization process in Nonaka's perspective to combine explicit knowledge.

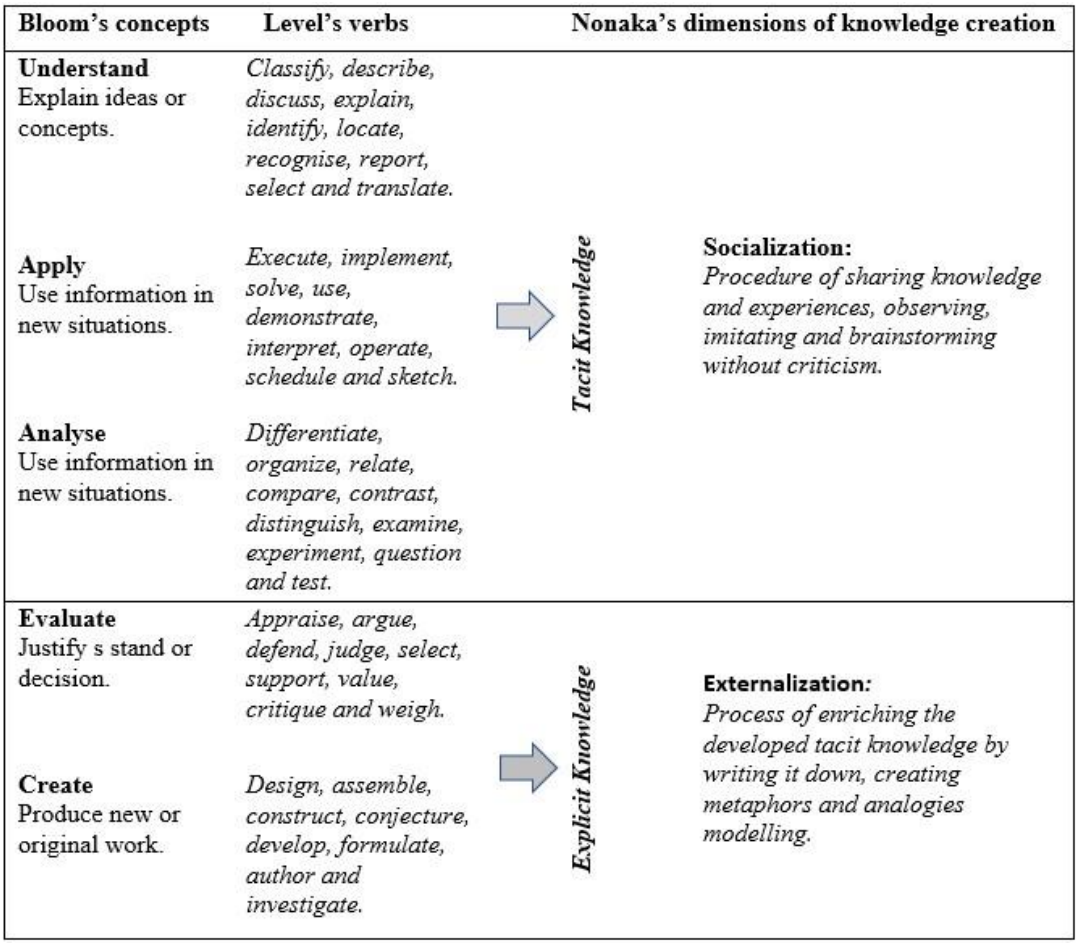


Figure 22 Combining frameworks of Bloom's Taxonomy and Nonaka's Theory

On the other hand, our research chose system design as the experimental context because it represents Bloom's levels as suggested in (Sharunova et al. 2022). However, this study defined System design as three main phases, i.e., analysis, design and development; while these phases can express the analyse, creation and application as per Bloom's taxonomy.

Practical implication:

From a more practical perspective, this research aims to better understand collaborative learning environments that rely extensively on technology and to assess the overall quality of experience in such a context. System design is not an easy task at an educational level, considering this specific task may have affected the study, meaning we do not necessarily expect the same outcome looking at contexts different from system design.

Furthermore, this study points out that there is a positive trade-off between, on one side, flexibility and resilience fostered by technology and, on the other side, the quality of learning experience, meaning we can achieve environments that are more flexible and resilient while keeping the same quality of experience. Once again, this study was conducted during Covid-19; thus, from a practical perspective, this study reveals that students could collaborate in knowledge development and sharing remotely as well as enjoy the experience.

Limitations:

Any study being conducted has limitations, which are expected due to constraints related to the adopted research design, methodology, resources, and other reasons reported in (Connelly 2013). In this study, we have identified a number of limitations. Firstly, as the experiment took place in Saudi Arabia universities looking specifically at programs that address some aspect of system design, considering a variety of contexts and different countries could further consolidate the main findings of the research and generalise the results.

Secondly, the sample size is an essential step in any quantitative study, as it plays a significant role in terms of the quality of data analysis outcomes (ML Wolverton 2009). This study targets a specific population, where the survey has been distributed among undergraduate and postgraduate students enrolled in subjects related to system design in three Saudi Arabia universities. The survey focused on students with particular experience and skills in a specific context. Therefore, this study is considered only the completed surveys for data analysis, which amounted to 152 responses, while more responses might consolidate the current research findings. This study received more than 152 responses but some were excluded from the data analysis based on recommendations in the literature (Marcoulides & Saunders 2006). However, Hair et al. in (Hair, Joseph F. , Black, Jr, William C. Babin, Barry J. & Anderson 2014) discussed the acceptance of at least 150 sample size for studies with seven or fewer constructs, which applies to our research. Statistically, our descriptive analysis, measurement model analysis, and SEM analysis showed that the research constructs and the adopted measures or indicators are valid and reliable, which resulted in acceptable outcomes. Moreover, the best practices adopted to determine the sample size for conducting structural equation modelling (SEM) is reported in (Finch & French 2018). The authors in the above-mentioned case discussed that; each survey's response should have at least five times the number of variables for the structural equation modelling analysis. Therefore, following the recommendation, this study targets a sample size >= 90, estimated as 5*18, where (n =18) refers to the total number of questions in the questionnaire. As a result, the collected data exceeded approximately 75% of the recommended sample size. In (Fincham 2008), the author discussed that a response rate higher than 50% of the target sample size is considered excellent in most circumstances. Upon the recommended sample size in the literature, the completed response rate for this study is more than 50%. Ultimately, most statisticians agree that 100 samples are enough to provide meaningful results, as reported in (MacCallum et al. 1999), and collecting 10% of the target

population is typically seen as a maximum sample size unless it exceeds 1000 (Conroy 2021). For example, if the target population is 1000 students, thus 100 samples out of the total population are considered the maximum.

Lastly, some of the quality of learning experience metrics have been measured by two items. This can be seen as a limitation in some cases, especially when a study has reflective constructs and intend to conduct Structural Equation Modelling (Dash & Paul 2021). The recommendation in the literature suggests at least three items for a single construct to perform structural modelling, as reported in (Asyraf & Afthanorhan 2013; Chau 1997). However, SmartPLS has overcome this limitation by conducting Partial Least Squares based Structural Equation Modelling (Asyraf & Afthanorhan 2013). Also, the study in (Cheah et al. 2018) discussed the acceptance of conducting PLS-SEM by using a single item for each construct.

6.3 Conclusions and Future Work

This study addressed the impact of collaborative technology on the overall quality of experience at different levels of learning. The main focus is on the relationship between knowledge development and quality of experience understood as academic performance and perceived satisfaction within collaborative learning environments that extensively rely on technology.

The analysis conducted on the collected data is in line with suggested hypotheses with two relevant exceptions. These exceptions are discussed in the previous section (6.1). In summary, the study has clearly pointed out a direct impact of technology on the collaborative knowledge building process, as well as directly and indirectly on the overall quality of learning experience. Accordingly, collaborative technology contributes to knowledge development and sharing as well as leads to effectiveness, efficiency and enjoyment.

Additionally, results show a positive impact of technology along the collaborative knowledge development process and a strong correlation among the different quality of learning experience parameters considered. Thus, collaborative knowledge development contributes to effectiveness and enjoyment but does not contribute to efficiency. As mentioned earlier, students do not always perceive it as a value; however, it seems the extra effort undertaken by students to develop the required task does not necessarily lead to greater efficiency.

Academic performance depends on effectiveness and efficiency, which influences perceived satisfaction, while perceived satisfaction does not depend on enjoyment directly. This is because students are still concerned about their learning outcomes. However, technology positively increases the level of enjoyment. Eventually, technology and collaboration are driving factors in providing enjoyable learning environments that lead to better academic performance and perceived satisfaction.

Despite the evident impact of technology on learning performance and experience, we also reiterate the relevance of other aspects related to a human approach to education. It is currently an object of research, but it is outside the scope of this present study.

Furthermore, the study has indirectly tested the Technology Acceptance Model (TAM), which is under the key assumption that the technology adoption is consolidated and largely accepted. It could be an object of further research. Moreover, this study was conducted in the early stage of COVID-19, when remote learning took place. Post-pandemic assessments could be considered for future work.

We chose system design as an experimental context in our research, as it includes most of Bloom's learning levels. Bloom’s taxonomy is a well-known framework for learning assessment and design. It has been widely adopted in previous studies looking at different contexts. Nonaka's theory is commonly addressed within organizational contexts for

knowledge creation. Several studies have been adopted utilising the theory in collaborative learning environments. This is because there is a common goal between educational and organizational contexts toward knowledge development and sharing. Nonaka's framework has four dimensions (socialization, externalization, combination, and internalization). As a result, the current study has combined different levels of Bloom's taxonomy, such as (understanding, applying, analysing, evaluating and creating), and socialization and externalization dimensions from Nonaka's theory into a unique analysis framework within collaborative learning environments. More concretely, the related verbs for the mentioned learning levels as per Bloom's framework, reflect the process of developing tacit and explicit knowledge in socialization and externalization dimensions proposed in Nonaka's theory.

Therefore, this study has not addressed all the dimensions of analysis provided by Nonaka's framework; it could be an object of future work. Additionally, this study has addressed most of Bloom's classifications, except remember level; however, it could also be an object for further exploration.

Finally, the case study was chosen in the context of Saudi Arabia universities; an assessment of generalising the case study could be an object of further investigation.

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Appendix A: English Survey Questionnaire

Survey Questionnaire

Creating Seamless Platforms for Virtual Teams for Collaborative Learning:

Supporting learning in innovation and creativity

Dear participant

I invite you to participate in a study; the purpose of this study is to assess the impact of collaborative technology on the overall quality of learning experience at different levels of learning. We focused more on how students develop and share knowledge using technology that impacts the overall quality of experience in collaborative learning environments which fully supported by technology.

You have been selected because you are in the category targeted by this study (undergraduate or postgraduate students); it takes to participate in this approximately about 15 minutes. Participating in this questionnaire is voluntary, as you can withdraw any time without any consequences. The study is conducted by **Abdulrahman Alyami**, which has been approved by the Ethics Committee at the University of Technology Sydney, Sydney, Australia. UTS HREC REF NO. (ETH20-5297).

For more information about this study, click on the following link:

Information Sheet and Consent Form for Online Surveys

Thank you in advance for your time and cooperation.

Yours Sincerely,

Abdulrahman Alyami
PhD Student
School of Information, Systems, and Modeling
Faculty of Engineering and IT
University of Technology Sydney, Australia

○ Yes, I consent to participate, please read carefully the research terminology.
○ No, I do not consent to participate.

Basic Research Terminology

System analysis is studying a system or its parts to build a model that is composed of diagrams showing all relationships in the system.

Collaboration is when two or more individuals are working together to complete tasks and achieve common objectives using the system models; it requires the integration of many kinds of activities, including expert evaluations by the individual, combining captured data as well as brainstorming for developing a system model, ideas, and solutions.

A system is made of a number of parts.

A system model is a description of the system, and the system model is made up of a number of aligned diagrams.

A diagram describes parts of the system, for example, data flow diagram, and use- case diagram, etc. Each diagram can include all or some system parts.

Collaborative technologies make learning easier and possible for students to share and work on documents together (e.g. Blackboard, Microsoft teams, G suite, Zoom, etc.).

Synchronous means when two members of the team or more exchange information in real-time.

Asynchronous means when two members of the team exchange information without the requirement of responding immediately.

Software tool enables graphical representation by developing a diagram or a system model.

Section One: Demographic Information

1. **Gender?**
   - ○ Male
   - ○ Female
2. **What is your age group?**
   - ○ 18-20
   - ○ 21-23
   - ○ 24 and above
3. **What is your major?**
   - ○ Computer Science
   - ○ Information Systems
   - ○ Computer Engineering and Network
   - ○ Others, Please specify ……
4. **Are you an undergraduate or postgraduate student?**
   - ○ Undergraduate student
   - ○ Postgraduate student
5. **What is your institution's name?**
   - ○ Jouf University
   - ○ Imam Abdulrahman Bin Faisal University
   - ○ Jubail University College
   - ○ Others, Please specify ……
6. **What kind of project did you work with your team in the current semester?**
   - ○ Graduation Project
   - ○ Course Project
   - If your answer is **Course Project**, please specify the name of the course: ……
7. **How long have you been using collaborative technologies in education?**
   - ○ Less than a year
   - ○ 1-3 years
   - ○ More than four years

Section Two: Collaborative Learning Perspective:

This section has three questions that measure the perspective of the collaborative work among team members for knowledge development.

In Questions 1 - 3, please answer these questions according to the scale given below:

	Factors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Collaborative work helps the team members to improve their ways of thinking effectively	○	○	○	○	○
2	I improved other members' contributions to my team and make sense of their ideas	○	○	○	○	○
3	I gained new skills and knowledge from other members of my team	○	○	○	○	○

❖ **Please provide any comments regarding your experience in collaborative learning:**

……

Section Three : Collaborative Technology Perspective:

This section has three questions that measure the perspective of the use of collaborative technology among team members for knowledge development and sharing.

In Questions 1 - 3, please answer these questions according to the scale given below:

	Factors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Collaborative technologies make it possible for team members to collaborate	○	○	○	○	○
2	Collaborative technologies help to work more effectively among team members	○	○	○	○	○
3	Collaborative technologies help team members to interact, communicate, share and combine diagrams faster and better than face-to-face collaboration	○	○	○	○	○

❖ **Please provide any comments regarding your experience in collaborative technology:**

……

Section Four : Quality of Learning Experience:

This section has thirteen questions that measure quality of learning experience as Effectiveness, Efficiency, and Enjoyment to assess the overall academic performance and students' satisfaction.

Please answer the following questions according to the scale given below:

	Factors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Effectiveness:					
1	Collaborative work helps the team to develop diagrams quickly and lead to better diagrams outcomes	○	○	○	○	○
2	Collaborative technologies help to gather the data that is needed to develop the system model	○	○	○	○	○
	Efficiency:					
1	The team completed the tasks faster than I expected/planned	○	○	○	○	○
2	Individual tasks were still time-consuming	○	○	○	○	○
3	Individual tasks were taking significant effort	○	○	○	○	○
4	I found the ideation process within the team smooth and effective	○	○	○	○	○
	Enjoyment:					
1	I enjoy working collaboratively instead of individually	○	○	○	○	○
2	I enjoy using collaborative technologies with my team in learning more than face-to-face learning	○	○	○	○	○
	Academic Performance:					
1	Overall, using technologies in collaborative activities with the team improves learning and leads to better system model outcomes	○	○	○	○	○
2	Overall, I think adopting diagrams to support system design helped to create solutions	○	○	○	○	○

Perceived Satisfaction:

1	I was happy with the outcome of the system design	○	○	○	○	○
2	It was relatively easy to make decisions within the team	○	○	○	○	○

❖ **Please provide any comments regarding your experience in Quality of Learning Experience:**

……

Thanks for your participation…

Appendix B: Arabic Survey Questionnaire

استبيان

إنشاء منصات سلسة للفرق الافتراضية للتعلم التعاوني:

دعم التعلم في الابتكار والإبداع

عزيزي المشارك

أدعوك للمشاركة في هذه الدراسة؛ تهدف الدراسة إلى تقييم تأثير التكنولوجيا التعاونية على الجودة الشاملة لتجربة التعلم على مستويات مختلفة من التعلم. ركزنا أكثر على كيفية تطوير الطلاب للمعرفة ومشاركتها باستخدام التكنولوجيا التي تؤثر على الجودة الشاملة للخبرة في بيئات التعلم التعاوني التي تدعمها التكنولوجيا بالكامل..

وقع الاختيار عليك للمشاركة كونك من الفئة المستهدفة بهذه الدراسة التي تستهدف طلاب المرحلة الجامعية أو طلاب الدراسات العليا. تستغرق المشاركة في هذا الاستبيان حوالي 15 دقيقة. وتعد المشاركة في هذه الدراسة اختيارية، حيث يمكنك الانسحاب في أي وقت دون أي تبعات تترتب على انسحابك.

يجري هذه الدراسة الباحث عبد الرحمن اليامي، وقد أجيزت من قبل لجنة الأخلاقيات بجامعة سيدني للتكنولوجيا، سيدني، أستراليا، رقم المرجع (ETH20-5297).

لمزيد من المعلومات حول هذه الدراسة، يرجى الدخول على الرابط التالي:

ورقة المعلومات واستمارة الموافقة على الاستبيان عبر الإنترنت

شكرا لك مقدما على وقتك وتعاونك.

وتفضلوا بقبول فائق الاحترام.

عبدالرحمن اليامي
طالب دكتوراه
قسم نظم المعلومات والنمذجة
كلية الهندسة وتقنية المعلومات
جامعة سيدني للتكنولوجيا ، أستراليا

○ **أوافق على المشاركة، يرجى قراءة مصطلحات البحث بعناية.**

○ **لا أوافق على المشاركة.**

مصطلحات البحث الأساسية

تحليل النظام (System Analysis) هو دراسة نظام أو أجزائه لبناء نموذج يتكون من مخططات توضح جميع العلاقات في النظام.

التعاون (Collaboration) أن يعمل شخصان أو أكثر معًا لإكمال المهام وتحقيق الأهداف المشتركة باستخدام نماذج النظام، حيث يتطلب العديد من الأنشطة، بما في ذلك تقييمات الخبراء من قبل الفرد, وجمع البيانات بالإضافة إلى العصف الذهني لتطوير نموذج النظام والأفكار والحلول.

النظام (System) يتكون النظام من عدد من الاجزاء.

نموذج النظام (System Model) هو وصف للنظام، ويتكون نموذج النظام من عدد من المخططات المحاذية لبعضها البعض (متوافقة).

الرسم التخطيطي/ مخطط (Diagram) يصف أجزاء من النظام. على سبيل المثال، مخطط تدفق البيانات DFD، ومخطط حالة الاستخدام Use-Case ، إلخ. ويمكن أن يحتوي كل مخطط على جميع أجزاء النظام أو بعض من أجزاء النظام.

التقنيات التعاونية (Collaborative Technologies) تجعل التعلم أسهل وتمكن الطلاب من مشاركة المستندات والعمل عليها في الوقت نفسه (على سبيل المثال، Blackboard، Microsoft Team، G Suite، Zoom وما إلى ذلك).

التزامن (Synchronous) يعني أن يتبادل عضوان فأكثر من الفريق المعلومات في الوقت الفعلي.

غير متزامن (Asynchronous) يعني عندما يتبادل عضوان من الفريق المعلومات دون الحاجة إلى الاستجابة على الفور.

الأداة البرمجية (Software Tool) تتيح التمثيل الرسومي عن طريق تطوير رسم تخطيطي أو نموذج نظام.

القسم الأول: المعلومات الديموغرافية

1. **الجنس؟**

○ ذكر

○ أنثى

2. **ما هي الفئة العمرية؟**

○ 18-20

○ 21-23

○ 24 فأكثر

3. **ما تخصصك؟**

○ علوم الحاسب

○ نظم المعلومات

○ هندسة الحاسب والشبكات

○ أخرى ، يرجى التحديد .....

4. **هل أنت طالب بكالوريوس أو ماجستير؟**

○ طالب بكالوريوس

○ طالب ماجستير

5. **ما هو أسم مؤسستك؟**

○ جامعة الجوف

○ جامعة الإمام عبدالرحمن بن فيصل

○ كلية الجبيل الجامعية

○ أخرى ، يرجى التحديد .....

6. **ما نوع المشروع الذي عملت به مع فريقك في الفصل الدراسي الحالي؟**

○ مشروع التخرج

○ مشروع مقرر

- إذا كانت إجابتك هي **مشروع مقرر**، فيرجى تحديد اسم المقرر: .....

7. **منذ متى تستخدم التقنيات التعاونية في التعليم؟**

○ اقل من سنة

○ 1-3 سنوات

○ أكثر من أربع سنوات

القسم الثاني: منظور العمل التعاوني:

يحتوي هذا القسم على ثلاثة أسئلة تقيس منظور العمل التعاوني بين أعضاء الفريق لتنمية المعرفة

في الأسئلة التالية من 1 إلى 3 ، يرجى الإجابة على هذه الأسئلة وفقًا للمقياس الموضح أدناه:

	العوامل	لا أوافق بشدة	لا أوافق	محايد	موافق	موافق بشدة
1	يساعد العمل التعاوني أعضاء الفريق على تحسين طرق تفكيرهم بشكل فعال	○	○	○	○	○
2	قمت بتحسين مساهمات الأعضاء الآخرين في فريقي وفهمت أفكارهم	○	○	○	○	○
3	اكتسبت مهارات ومعرفة جديدة من أعضاء فريقي	○	○	○	○	○

❖ **يرجى تزويدنا بأي تعليقات بخصوص تجربتك في الأعمال التعاونية:**

.....

القسم الثالث: منظور التقنيات التعاونية

يحتوي هذا القسم على ثلاثة أسئلة تقيس منظور استخدام التكنولوجيا التعاونية بين أعضاء الفريق لتطوير المعرفة ومشاركتها.

في الأسئلة التالية من 1 إلى 3 ، يرجى الإجابة على هذه الأسئلة وفقًا للمقياس الموضح أدناه:

	العوامل	لا أوافق بشدة	لا أوافق	محايد	موافق	موافق بشدة
1	تتيح التقنيات التعاونية لأعضاء الفريق إمكانية التعاون	○	○	○	○	○
2	تساعد التقنيات التعاونية على العمل بشكل أكثر فعالية بين أعضاء الفريق	○	○	○	○	○
3	تساعد التقنيات التعاونية أعضاء الفريق على التفاعل والتواصل والمشاركة والجمع بين المخططات بشكل أسرع وأفضل من التعاون وجهًا لوجه	○	○	○	○	○

❖ **يرجى تزويدنا بأي تعليقات بخصوص تجربتك في التقنيات التعاونية:**

.....

القسم الرابع: جودة تجربة التعلم:

يحتوي هذا القسم على ثلاثة عشر سؤالاً تقيس جودة تجربة التعلم مثل الفعالية والكفاءة والمتعة لتقييم الأداء الأكاديمي ورضا الطلاب.

يرجى الإجابة على هذه الأسئلة التالية وفقًا للمقياس الموضح أدناه:

	العوامل	لا أوافق بشدة	لا أوافق	محايد	موافق	موافق بشدة
	الفعالية:					
1	يساعد العمل التعاوني الفريق على تطوير المخططات بسرعة ويؤدي إلى نتائج أفضل للمخططات	○	○	○	○	○
2	تساعد التقنيات التعاونية في جمع البيانات اللازمة لتطوير نموذج النظام	○	○	○	○	○
	الكفاءة:					
1	أكمل الفريق المهام بشكل أسرع مما توقعت / خططت	○	○	○	○	○
2	كانت المهام الفردية تستغرق وقتاً طويلاً	○	○	○	○	○
3	كانت المهام الفردية تبذل جهداً كبيراً	○	○	○	○	○
4	لقد وجدت أن عملية التفكير داخل الفريق سلسة وفعالة	○	○	○	○	○
	المتعة:					
1	أنا أستمتع بالعمل التعاوني بدلاً من العمل الفردي	○	○	○	○	○
2	أستمتع باستخدام التقنيات التعاونية مع فريقي في التعلم أكثر من التعلم وجهًا لوجه	○	○	○	○	○
	الأداء الأكاديمي:					
1	بشكل عام، يؤدي استخدام التقنيات في الأنشطة التعاونية مع الفريق إلى تحسين التعلم ويؤدي إلى نتائج أفضل لنموذج النظام	○	○	○	○	○
2	بشكل عام ، أعتقد أن اعتماد المخططات لدعم تصميم النظام ساعد في إيجاد حلول	○	○	○	○	○

رضا الطلاب:

1 كنت سعيدًا بنتائجة تصميم النظام	○	○	○	○	○
2 كان من السهل نسبيًا اتخاذ القرارات داخل الفريق	○	○	○	○	○

❖ **يرجى تزويدنا بأي تعليقات بخصوص تجربتك في جودة تجربة التعلم:**

.....

شكرا لمشاركتكم...