ENHANCING STUDENT KNOWLEDGE ACQUISITION IN ONLINE LEARNING: A DUAL PROCESSING AND SOCIAL CAPITAL PERSPECTIVE

ENHANCING STUDENT KNOWLEDGE ACQUISITION IN ONLINE LEARNING: A DUAL PROCESSING AND SOCIAL CAPITAL PERSPECTIVE

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Abstract

Social interaction in online learning can positively impact student learning outcomes, such as knowledge acquisition. As higher education increasingly transitions from traditional face-to-face learning to online platforms, understanding how to enhance student learning outcomes in online learning becomes essential. While social interaction differs in online and offline learning, the extant online learning literature mainly focuses on students' social interaction frequency or quantity in general, without delving into their use of technologies for social interaction (i.e., social features). To provide a richer process-oriented and social capital perspective, the overarching objective of this dissertation is to understand how the use of social features in online learning can enhance student learning outcomes through emotional and cognitive engagement. More specifically, three research questions are investigated: 1) How does students' use of social features in online learning affect their emotional and cognitive engagement experience with online learning? 2) How do multiple dimensions of social capital (i.e., structural capital, relational capital, and cognitive capital) moderate the relationship between students' use of social features in online learning and their emotional/cognitive engagement experience in online learning? 3) How do students' emotional/cognitive engagement experiences influence their knowledge acquisition in online learning?

Drawing on Dual Process and Social Capital theories, this research develops a research model to elucidate how students' use of online social features influences their knowledge acquisition through the dual processes of emotional and cognitive engagement in online learning, and the moderating role of social capital on the impact of students’ use of social features in online learning. Data for this study was collected through a survey of participants who had at least one semester of online learning experience in the past three years within a university program. Structural equation modeling was employed for data analysis. The findings indicate that students' use of social features in online learning positively influences both emotional and cognitive engagement, which, in turn, affects knowledge acquisition. Additionally, cognitive capital positively moderates the impact of social feature usage on emotional and cognitive engagement in online learning. Relational capital negatively moderates the impact on cognitive engagement, but not on emotional engagement in online learning. Structural capital positively moderates the impact on cognitive engagement but not on emotional engagement in online learning.

This dissertation contributes to the online learning literature by shedding light on how the utilization of social features can interact with students' social capital to influence their engagement, subsequently impacting their knowledge acquisition in online learning. The study advances the existing literature by exploring the intricate interplay between students’ social capital and their use of social features in online learning, elucidating the circumstances under which social resources enhance or impede the impact of such usage. From a practical standpoint, the insights gleaned from this study regarding students' online learning offer valuable guidance for distance educators and policymakers to enhance educational practices within online learning.

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Glossary of Terms

Term	Definition
Asynchronous Online Learning	Self-paced online learning experiences where students access course materials, lectures, and assignments at their own convenience, without the requirement to be online simultaneously with instructors or peers (Swan, 2001)
Average Variance Extracted (AVE)	A measure of construct validity which quantifies the extent to which the variance observed in a construct can be attributed to the construct itself rather than measurement error (Fornell, C., & Larcker, 1981)
Blended Learning	A combination of online and face-to-face instruction, where a portion of the course content and activities are delivered online, supplemented by in-person sessions (Chiu, 2021)
Cognitive Capital in Online Learning (CC)	Shared representations, interpretations, and systems of meaning among students in their online learning experiences (Nahapiet & Ghoshal, 1998)
Cognitive Engagement in Online Learning (CE)	Mental effort and active participation that students dedicate to the cognitive processes involved in their online learning experiences (Iqbal, Asghar, Ashraf, & Yi, 2022; Xiao & Hew, 2024)
Common method bias	A bias which often occurs when both the independent and dependent variables are measured within one survey, using the same (i.e., a common) response method (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003)
Emotional Engagement in Online Learning (EE)	Affective connection and investment that students develop in their online learning experiences (Gray & DiLoreto, 2016; Kahu, 2013; Lim, Choe, Zhang, & Noh, 2020)
Flipped Classroom	An instructional approach that involves delivering traditional lecture content online before class, thereby freeing up in-person class time for interactive activities, discussions, and problem-solving involving the use of that traditional lecture content (Du, Hew, & Li, 2023)
Homoscedasticity	Homoscedasticity assumes that the variances within different groups being compared are equal or similar (Dragan & Topolšek, 2014; Meyers et al., 2016).

Knowledge Acquisition in Online Learning (KA)	The extent to which students gain new information, understanding, or know-how in online learning context (Bates & Khasawneh, 2007; Bravo-Agapito et al., 2021; Xiao & Hew, 2024)
Online Learning	The process of acquiring knowledge, such as information, understanding, and know-how about a subject, through online tools (Panigrahi et al., 2018)
Relational Capital in Online Learning (RC)	Trust, obligations, respect and even friendship that arise from student relationships (Nahapiet & Ghoshal, 1998)
Social Capital	Support or assistance available from one's personal connections (Lu, Yang, & Yu, 2013)
Social Interactions (In Online Learning)	The process by which individuals act and react in relation to others in online learning (Lu, Yang, & Yu, 2013)
Social Features (In Online Learning)	Tools and functionalities that facilitate interaction among users in online learning (Panigrahi et al., 2018)
Social Learning	Students need to engage socially with their peers and instructors to become more engaged in the learning process (Weidlich & Bastiaens, 2019)
Social Presence	The feeling of being with another person and having access to their thoughts and emotions (Bharati, Zhang, & Chaudhury, 2015; Kirkwood & Price, 2005; Yousaf et al., 2023)
Structural Capital in Online Learning (SC)	Established social structures, like connections, roles that enable individuals to gain support and assistance from their connections (Nahapiet & Ghoshal, 1998)
Student Learning Outcomes	Consequences or results associated with student experiences (Prøitz, 2010)
Synchronous Online Learning	Acquiring knowledge through real-time interactions in online learning between instructors and students, typically facilitated through live video conferencing, chat rooms, or virtual classrooms (Dietrich et al., 2021; Panigrahi et al., 2018)
Use of Social Features in Online Learning (USF)	The integration and utilization of various interactive tools within an online learning context for social interaction and communication among students (Roque-Hernández, Díaz-Roldán, López-Mendoza, & Salazar-Hernández, 2023; Yousaf, Rehman, Ahmed, & Munawar, 2023). Note: this thesis does not differentiate social tools directed by the instructor or selected by students themselves.

Chapter 1. Introduction

Technology has unquestionably contributed to the creation of flexible educational opportunities that allow people to learn remotely. In recent years, there has been a surge in demand for online learning in higher education, offering courses through online channels rather than traditional face-to-face formats (Huber, Cortez, Kiili, Lindstedt, & Ninaus, 2023; Kent, Rechavi, & Rafaeli, 2019; Kim, Liu, & Bonk, 2005; Xiao & Hew, 2024). Universities or colleges have afforded students the opportunity to enroll in online learning which refers to the process of acquiring knowledge, such as information, understanding, and know-how about a subject, through online digital platforms and resources (Panigrahi et al., 2018) and blended learning programs which refer to a combination of online and face-to-face instruction, where a portion of the course content and activities are delivered online, supplemented by in-person sessions (Chiu, 2021). Especially impacted by the COVID-19 pandemic, universities worldwide had to pivot to online learning to minimize the disruption of educational experiences for students. Post-pandemic, online learning remains popular as universities seek to leverage its cost-saving and accessibility benefits (Adedoyin & Soykan, 2023; Huang & Wang, 2023; Yousaf et al., 2023).

Specifically, despite the weakened disruptive impact of the COVID-19 pandemic on face-to-face learning, the online learning market continues to demonstrate robust growth, with a global revenue (e.g., revenue generated from program fees paid by students) expected to reach US$185.20 billion by the end of 2024 (Statista, 2023). This growth trajectory is anticipated to persist, with a projected annual growth rate (compound annual growth rate 2024-2028) of 8.61%, resulting in a market revenue of US$257.70

billion by 2028 (Statista, 2023). Online learning in the higher education segment represents the largest market share, with a projected revenue of US$120.70 billion in 2024 (Statista, 2023). This growth is driven by factors such as increasing internet penetration, technological advancements in e-learning platforms, decreased cost of delivery, rising demand for flexible and accessible education options, and shifting preferences towards online learning (Aguilera-Hermida, 2020; Jackson & Serenko, 2023). As the demand for lifelong learning continues to rise, fueled by changing workforce dynamics and the need for enhancing domain knowledge, the online learning market is expected to experience sustained expansion in coming years.

In online learning, students face an array of challenges within these digital learning environments. Technical hurdles often loom large, as students grapple with issues stemming from unreliable internet connections, incompatible software or devices, and the daunting task of navigating complex online platforms (Adedoyin & Soykan, 2023). This technological shockwave becomes especially pronounced when students abruptly transition to online learning during crises like the COVID-19 pandemic, where the imperative for public health safety necessitates a swift shift to virtual study spaces (Adedoyin & Soykan, 2023).

Access and equity concerns further compound difficulties, as certain students encounter barriers hindering their ability to fully engage with online resources (Dhawan, 2020; Rizvi, Rienties, Rogaten, & Kizilcec, 2022; Zhao, Cao, Li, & Li, 2022). The lack of reliable internet access or appropriate technology exacerbates preexisting disparities in educational opportunities, particularly affecting those from economically disadvantaged backgrounds who lack sufficient financial support, thus widening the gap in educational equity (Adedoyin & Soykan, 2023; Hollister, Nair, Hill-Lindsay, & Chukoskie, 2022; Zhao et al., 2022).

Another formidable challenge is the absence of social connections and peer interactions inherent in traditional classroom settings, leaving students vulnerable to feelings of isolation and loneliness (Huang & Wang, 2023; Szopiński & Bachnik, 2022). Reports indicate that students often experience a sense of disconnection and isolation in online learning environments, potentially culminating in elevated dropout rates, as the absence of physical proximity and the perceived inferiority of the online learning experience can detract from engagement and motivation (Aguilera-Hermida, 2020; Jackson & Serenko, 2023).

Effective time management poses yet another hurdle, especially for students juggling multiple responsibilities or navigating self-paced courses (Pellas, 2014; Wei, Wang, & Klausner, 2012). For those with lower levels of self-regulation and self-control, distractions inherent in online learning platforms can prove particularly troublesome, requiring students to assume greater responsibility for their own learning—an adjustment that may be challenging for those accustomed to more structured, teacher-led instruction.

Moreover, maintaining motivation and sustained engagement presents a challenging task in the absence of the physical classroom environment and face-to-face interactions with instructors and peers (Chen & Jang, 2010; Xiao & Hew, 2024). Numerous studies (Gray & DiLoreto, 2016; Hollister et al., 2022; Huang & Wang, 2023) underscore the decline in student engagement and the subsequent attrition rates associated with online learning, as the absence of interpersonal connections and the monotony of the digital learning experience can diminish enthusiasm and commitment.

Communication hurdles also loom large in the online sphere, as effective interaction with instructors and peers becomes more challenging (Adedoyin & Soykan, 2023; Greenhow, Graham, & Koehler, 2022). Unlike in traditional settings where students can easily interact during breaks or after class, the mediated nature of online communication introduces barriers that impede deep connection and meaningful exchange of ideas (Kim, 2017; Panigrahi et al., 2018).

Due to the shifting trend from face-to-face learning to online learning in higher education and multiple challenges encountered by students, it is imperative to understand how to enhance student experiences in online learning. Addressing these multifaceted challenges demands proactive intervention from educators and institutions alike. This may involve providing robust technical support, cultivating opportunities for social interaction, furnishing resources for effective time management, and designing online courses that are both engaging and accessible. Given the complexity of the obstacles faced by students in online learning, it is pivotal to have a comprehensive theoretical understanding of the factors that promote successful student learning outcomes which refers to the consequences or results associated with instructional experiences (Prøitz, 2010)

1.1 Research Motivation

A key difference between face-to-face learning and online learning lies in the level of social interaction. The concept of social learning suggests that students need to engage socially with their peers and instructors to become more engaged in the learning process (Weidlich & Bastiaens, 2019). Prior literature (e.g., Costello, Restifo, & Hawdon, 2021; Jackson &

Serenko, 2023; Lu, Yang, & Yu, 2013; Yang, Head, & Lu, 2020) also highly recommends the importance of social capital in helping students to succeed in online learning. Through social interaction with peers or instructors, students are likely to overcome technical difficulties and social isolation feelings, and thus are more likely to continue participating and further succeed in online learning. Given the computer-mediated communication in online learning, it is important to understand students' use of online social features, which influence learner experiences.

While existing research has delved into students' utilization of social features in online learning, it has predominantly focused on the mechanism of social interaction and social presence on the student learning experience (Bharati, Zhang, & Chaudhury, 2015; Kirkwood & Price, 2005; Yousaf et al., 2023), neglecting other potentially important social factors. Since most learning and social activities in online learning are mediated through the use of social features which refers to the integration and utilization of various interactive tools (e.g., chatting, forums and discussions, video conferencing) within an online learning context for social interaction and communication among students (Roque-Hernández et al., 2023; Yousaf et al., 2023), it is important to understand how the use of these social features can impact student engagement and learning outcomes (Xiao & Hew, 2024). This alternative perspective enables a more comprehensive understanding of the ways in which the use of technology in online learning (i.e., use of social features) can shape online learning outcomes, thereby facilitating the design of online learning platforms with more effective social features.

Moreover, the exploration of moderators on the use of social features remains limited in the literature. Understanding these moderating effects can provide valuable insights into when and how the use of social features can benefit online learning engagement and outcomes. By optimizing the integration of social features within online learning, the overall online learning experience can be enhanced.

This research examines the moderating factor of social capital, as a key social resource from one's personal connections (Lu et al., 2013), which potentially impacts students' effectiveness of using social features in online learning. Social capital (Fleming & Waguespack, 2007; Inkpen, Tsang, & Inkpen, 2005) refers to the existence of social connections, and relational assets, such as norms and identity. As an intangible capital, the emergence and maintenance of social capital enable connected partners to enjoy privileged benefits, such as increased accessibility to information and support from network actors (Chang & Chuang, 2011; Kankanhalli, Tan, & Wei, 2005). Due to the richness of social capital conceptualization, we adopt a multi-dimensional view which consists of structural capital (i.e., network and connections with other students (Nahapiet & Ghoshal, 1998)), relational capital (i.e., qualities of student relationships, which can be expressed with trust, obligations, respect and even friendship (Nahapiet & Ghoshal, 1998)), and cognitive capital (i.e., shared representations, interpretations, and systems of meaning among students (Nahapiet & Ghoshal, 1998), which will be further explained in the theoretical section below.

Although previous studies have examined different types of interaction, including student-student interaction and student-instructor interaction in online learning in higher education (Phirangee & Malec, 2017; Sher, 2009), they mostly focused on the mere interactions among parties, without understanding student interaction's interplay with social capital a student gains through existing or previous networking activities.

Nonetheless, students' use of social features in online learning and their social capital can largely determine students' learning effectiveness. This research focuses on student-to-student interactions in higher education online learning, as prior studies indicate that peer interaction involves rich information flow (Phirangee & Malec, 2017) which may largely impact a student's social capital obtained in a specific educational course. Prior literature (e.g., Chiu, 2021; Eryilmaz, van der Pol, Ryan, Clark, & Mary, 2013) also identifies the importance of informal support and idea exchange among peers in learning. As such, this research focuses on social features used especially for peer interaction, as peers represent a large network of social resources and support for online students to leverage. Student peers may provide unique insights based on their expertise and personal experiences, and also provide more prompt support than instructors.

It is also important to note that prior literature has mostly focused on the overall student experience in online learning, such as satisfaction or overall engagement in various contexts (e.g., in higher education or in a massive open online course) (Richardson, Maeda, Lv, & Caskurlu, 2017). However, student experiences involve both utilitarian and hedonic aspects, as learning is considered a complex psychological process (Klock, Gasparini, & Pimenta, 2019; Symeonides & Childs, 2015). Thus, it is important to understand both systematic student experiences (i.e., cognitive engagement in online learning which refers to mental effort and active participation that students dedicate to the cognitive processes involved in their online learning experiences (Iqbal et al., 2022; Xiao & Hew, 2024)) and hedonic student experiences (i.e., emotional engagement in online learning which refers to affective connection and investment that students develop in their online learning experiences (Gray & DiLoreto, 2016; Kahu, 2013; Lim et al., 2020)) so that we may offer insight into how social features in online learning might influence student learning outcomes, such as knowledge acquisition, higher grades, satisfaction, through emotional and cognitive engagement. Given that higher education represents the largest revenue generator in the online learning domain, this dissertation focuses on social factors that can influence student learning outcomes within higher education contexts.

1.2 Research Objective and Questions

The overarching objective of this dissertation is to understand how the use of social features in online learning can enhance knowledge acquisition (a specific type of student learning outcome) through emotional and cognitive engagement. More specifically, the following three research questions are investigated:

RQ1: How does students' use of social features in online learning affect their emotional and cognitive engagement experience in online learning?

RQ2: How do multiple dimensions of social capital (i.e., structural capital, relational capital, and cognitive capital) moderate the relationship between students' use of social features in online learning and their emotional/cognitive engagement experience in online learning?

RQ3: How do students' emotional/cognitive engagement experiences influence their knowledge acquisition in online learning?

1.3 Thesis Outline

The structure of this thesis encompasses several chapters, each contributing to a comprehensive exploration of the research topic.

Chapter 1 serves as an introduction, elucidating the rationale, context, and impetus behind the research endeavor. It offers foundational definitions and background knowledge essential for understanding the components under investigation.

Chapter 2 provides a thorough Literature Review, synthesizing pertinent research on the study context and identifying key antecedents that impact student learning outcomes. This chapter critically examines existing scholarship to contextualize the current research within the broader academic discourse.

Chapter 3 lays the groundwork with a Theoretical Foundation, furnishing an overview of theories pertinent to the research inquiry.

Chapter 4 unveils the research model, delineating the definitions of constructs and rationale for the proposed hypotheses. This chapter provides the theoretical underpinnings guiding the empirical investigation.

Chapter 5 outlines the study's methodology, encompassing research design, sampling procedures, recruitment strategies, data collection methods, and techniques for data analysis. This chapter provides insights into the methodological approach employed to address the research questions.

Chapter 6 presents the Research Results and Data Analysis, synthesizing empirical findings derived from the collected data. This chapter offers a detailed examination and interpretation of the research findings, shedding light on the empirical implications of the study.

Chapter 7 constitutes the Discussion section, wherein the research findings are critically analyzed, interpreted, and discussed in light of the existing literature. Additionally, this chapter delves into the theoretical and practical contributions of the study, its limitations, avenues for future research, and summarizes overarching conclusions drawn from the research endeavor.

Chapter 2. Literature Review

In this chapter, a review of the literature pertaining to the major themes in this research is presented. It commences with an examination of the online learning context, within which this study is situated. The unique context of COVID-19 is described as it accelerated research scrutinizing online learning experiences and outcomes in universities or colleges over the past four years. Despite a diminishing public health risk from COVID-19, many post-secondary institutions continue to embrace online learning as a key component in their educational offerings. Additionally, various types of online learning are introduced to elucidate this mode of learning. Furthermore, a comprehensive review of prior studies on the antecedents of online learning outcomes is provided in order to highlight current gaps this dissertation seeks to fill.

2.1 Context of the Investigation

2.1.1 Online Learning Context

There are various types of online learning contexts. Firstly, fully online courses are entirely web-based where all learning activities, assessments, and interactions take place online without the need for any in-person attendance (Huber et al., 2023; Jackson & Serenko, 2023). Fully online courses offer various benefits and drawbacks. On the positive side, they provide students with flexibility in accessing course materials and completing assignments, accommodating diverse schedules and commitments (Panigrahi et al., 2018). Additionally, online courses remove geographical barriers, enabling students from different locations to access education conveniently and affordably. They often come with lower tuition fees and a wealth of personalized learning resources, including multimedia materials, fostering a customized learning experience (Belsky, 2019; Kim et al., 2005; Panigrahi et al., 2018). However, fully online courses often lack face-to-face interaction, potentially leading to feelings of isolation and limited collaborative opportunities (Hollister et al., 2022). Students must also exhibit strong self-discipline and motivation to succeed in a fully online learning environment, while technical challenges and limited hands-on learning opportunities can pose learning barriers (Pellas, 2014).

Secondly, blended learning is a combination of online and face-to-face instruction, where a portion of the course content and activities are delivered online, supplemented by in-person sessions (Chiu, 2021; Cocquyt, Diep, Zhu, De Greef, & Vanwing, 2017). On the positive side, blended learning provides flexibility for students to engage in both in-person and online activities, catering to diverse learning styles and preferences (Iqbal et al., 2022; Lin & Wang, 2012). This approach can enhance accessibility by reducing the need for physical attendance, allowing students to access course materials remotely. Additionally, blended learning offers opportunities for personalized instruction and individualized support through both virtual and in-person interactions (Chiu, 2021). However, challenges may arise from the need to balance the benefits of both modalities, potentially leading to logistical complexities and increased workload for instructors (Chiew, Tan, Wong, Yong, & Tiong, 2019; Lin & Wang, 2012). Moreover, the effectiveness of blended learning depends on the seamless integration of online and offline components, requiring careful planning and implementation. Additionally, students may face difficulties in managing their time and staying engaged across multiple learning environments, while technological issues or inconsistencies in instructional delivery may hinder the learning experience (Chiu, 2021).

A surging online learning mode is the flipped classroom, which is an instructional approach that involves delivering traditional lecture content online before class, thereby freeing up in-person class time for interactive activities, discussions, and problem-solving (Du, Hew, & Li, 2023). In this model, students engage with course materials independently outside of class, typically through pre-recorded videos, readings, or other multimedia resources. Classroom time is then utilized for collaborative and hands-on learning experiences, allowing students to apply and deepen their understanding of the concepts introduced in the pre-class materials (Dietrich et al., 2021). The flipped classroom approach promotes active engagement, fosters deeper learning through interactive exercises, and enables educators to provide targeted support and feedback to students during face-to-face sessions. Additionally, it encourages student-centered learning and facilitates the development of critical thinking and problem-solving know-how by shifting the focus from passive listening to active participation in the learning process.

Online learning can also be categorized by its level of synchronicity. Synchronous online learning involves real-time interactions between instructors and students, typically facilitated through live video conferencing, chat rooms, or virtual classrooms (Dietrich et al., 2021; Panigrahi et al., 2018). This approach enables immediate feedback, fosters active engagement, and promotes interaction among participants. In contrast, asynchronous online learning offers self-paced experiences where students access course materials, lectures, and assignments at their own convenience, without the requirement to be online simultaneously with instructors or peers (Alghamdi et al., 2020; Cheng, Huang, & Hebert, 2023; Kim, Merrill, Xu, & Kelly, 2022). This model provides flexibility for learners to manage their schedules and progress through the content at their own pace, accommodating diverse learning styles and commitments. However, asynchronous learning may lack the spontaneity and immediate interaction of synchronous methods, requiring learners to be self-motivated and disciplined in managing their time and staying on track with coursework.

This study centres on the fully online learning context with varying levels of synchronicity, which has seen a surge in popularity in recent years. While post-secondary institutions introduced numerous online courses during the pandemic, many have chosen to retain them even after the pandemic subsided. Unlike blended or flipped learning, this mode of learning lacks in-person contacts opportunities but offers high flexibility. Therefore, it is crucial to comprehend the social factors influencing student learning outcomes in online learning to enhance the effectiveness of this mode of instruction.

2.1.2 Sustained Online Learning Environment in Post-pandemic Periods

The COVID-19 pandemic significantly accelerated the adoption of online learning, a trend that continues to grow even in the post-pandemic period. During the pandemic, educational institutions worldwide were forced to rapidly transition to online platforms to maintain instructional continuity (Adedoyin & Soykan, 2023; Hollister et al., 2022). This shift highlighted the potential and flexibility of online learning, leading to its widespread acceptance in post-secondary institutions (Huang & Wang, 2023). Post-pandemic, many institutions recognize the benefits of online learning, such as increased accessibility, the ability to accommodate diverse learning styles, and the opportunity for students to balance education with other responsibilities. Online learning brings technological efficiencies to learning processes, as students can leverage various online tools including videoconferencing, online discussion forums, and social networking sites to acquire and exchange knowledge (Poondej & Lerdpornkulrat, 2020; Rapanta, Botturi, Goodyear, Guàrdia, & Koole, 2021). Online learning can also offer cost-savings benefits as post-secondary institutions may spend less on building maintenance and classroom accessories (Wu, Yu, Casale, & Gao, 2015). Accessibility is also greatly improved by online learning, since students in geographically diverse areas may take online courses together (Hollister et al., 2022; Li & Lalani, 2020). As a result, there has been a sustained emphasis on the importance of online learning. It is expected that post-pandemic higher education will continue to include online learning much more extensively than pre-pandemic norms (Rapanta et al., 2021).

This dissertation focuses on university students' experiences of online learning, as they are among the typical populations who became exposed to online learning in an unprecedented way. In addition, university students have been reported to experience more psychological stress compared to other students (e.g., K-12 students) (Barbayannis et al., 2022), and the elevated stress may adversely influence university students' online learning experience. Many university students feel increased anxiety as a result of changed delivery and uncertainty of university education (Huang & Wang, 2023; Irawan, Dwisona, & Lestari, 2020). Even in the post-pandemic periods, university students are reported to feel stressed due to academic workload, institutional regulation, lack of resources, and financial constraints (Akram, Bhutto, & Chughtai, 2022). Thus, this particular population of university students needs more attention regarding approaches to improve their online learning experience.

2.2 Antecedents of Student Learning Outcomes in Online Learning

Within this section, antecedents influencing student learning outcomes are examined based on the existing literature. Since student knowledge acquisition is an important aspect of student learning outcomes in online learning, the literature review section covers the broader domain knowledge regarding antecedents to student learning outcomes in online learning. These antecedents are classified into various categories, encompassing technological, cognitive, social, motivational, demographic, and course-related factors. While certain studies focus on singular types of antecedents (for example, Xiao & Hew, 2024; Du et al., 2023), several others explore multiple types concurrently in their investigations (for example, Cheng et al., 2023; Huber et al., 2023).

2.2.1 Student Knowledge Acquisition in Online Learning as a Specific Learning Outcome

Student learning outcomes are multi-faceted concepts encompassing various dimensions, including psychological, behavioural, and benefit outcomes (Detlor, Julien, La Rose, & Serenko, 2022; Detlor, Julien, Willson, Serenko, & Lavallee, 2011). Psychological learning outcomes involve changes in values and beliefs, reflecting a deeper cognitive and emotional engagement with online learning. Behavioural learning outcomes pertain to observable changes in actions and practices, such as continuance of online learning. Benefit outcomes, such as higher grades, improved knowledge acquisition, and better workforce preparation, highlight the effectiveness and efficiency gains resulting from online learning (Detlor et al., 2011).

This dissertation has a particular focus on student knowledge acquisition in online learning, which is a specific type of benefit outcome (Detlor et al., 2022). Stakeholders of post-secondary educations often prioritize gains such as knowledge acquisition because they are directly linked to student success and employability (Eryilmaz et al., 2013). Demonstrating significant benefit outcomes can enhance the reputation of educational institutions, attract more students, and secure funding and support from stakeholders who value utilitarian-based results (Kim et al., 2005). As such, the theoretical research model and empirical examination of this dissertation focus on antecedents to student knowledge acquisition in online learning.

The following subsections depict the broader domain knowledge of antecedents of student learning outcomes in online learning, which informs the theoretical development of antecedents to the specific outcome of knowledge acquisition in online learning. These antecedents are based on an umbrella framework comprising the learning environment, program components, and learner characteristics demonstrated to influence learning outcomes (Detlor et al., 2022). Each of these categories is further broken down to provide a more detailed understanding specific to online learning. For instance, technological antecedents fall under the umbrella of learning environments, while course-related antecedents are categorized under program components. Cognitive, social, motivational, and demographic factors are examined under the umbrella of learner characteristics. The literature review aims to provide comprehensive coverage of research regarding student learning outcomes in online learning, though it acknowledges the challenges of achieving absolute completeness due to the multidisciplinary nature of this field.

2.2.2 Technological Antecedents

Studies on online learning technological antecedents generally investigate how technological design or the use of online learning tools can influence student learning outcomes. The central concern of online learning has been how to leverage technology-mediated learning tools to improve knowledge acquisition (Panigrahi et al., 2018).

One stream of literature on technological antecedents compares the difference between online learning and traditional ways of learning. For instance, previous research suggests that digital learning content have a number of advantages compared to paper-based content but also have some disadvantages, such as access and navigation difficulty (Terpend, Gattiker, & Lowe, 2014). Moreover, working on an Internet-enabled device is always fraught with potential distractions, such as checking email and visiting non-task-related websites (Dietz & Henrich, 2014), which may have a negative impact on engagement and knowledge acquisition. However, through effective design of online learning, these disadvantages and distractions can be reduced.

Gamification design has been introduced and studied extensively as a means to increase the enjoyment and entertainment of online learning experiences (Klock et al., 2019; Moreno-Ger, Burgos, Martínez-Ortiz, Sierra, & Fernández-Manjón, 2008; Xiao & Hew, 2024). Games can be used as a support tool to online learning to improve the learning experience of the learners and increase engagement with online learning while also developing knowledge, such as following rules, adaptation, problem solving, interaction, critical thinking, creativity, teamwork, and good sportsmanship (Santhanam, Liu, & Shen, 2016). When games are introduced to online learning, students are found to be more motivated, curious, and inspired to learn (Huber et al., 2023; Poondej & Lerdpornkulrat, 2020). For example, a recent study (Xiao & Hew, 2024) suggests that tangible rewards such as points and badges can facilitate stronger engagement in online learning. In addition, social elements such as social comparison through leaderboard can also be integrated as a gamification design to promote online learning outcome.

Another body of research has focused on how social technological features can enhance students online learning through the experience of social presence (Leong, 2011;

Phirangee & Malec, 2017; Roque-Hernández et al., 2023). For instance, the addition of personal profiles and photographs can create connection among learners, which enhances students' online learning experience (Kear, Chetwynd, & Jefferis, 2014). When instructors present learning videos with the presence of an instructor in the video, students feel stronger connectedness and more engagement in their learning experiences (Andel et al., 2020). These research studies show that, when provided with additional social features to connect and interact, users are more likely to feel a greater sense of presence and learning engagement in the online learning.

More recently, the literature has examined Artificial Intelligence (AI)-enabled learning technology features, such as the use of AI instructors (Kim et al., 2022). Kim et al. (2022) suggest that students perceive AI instructors with a humanlike voice as more credible compared to those with a machinelike voice due to the enhanced perception of social presence of the AI instructor. Ultimately, the perceived credibility of an AI instructor positively impacts student intentions to enroll in future courses taught by AI instructors. Another study (Leong, 2011) tested 10 AI application storyboards to identify the phases and areas of learning in self-regulated online learning. The findings indicate that learners perceived AI applications as useful for supporting metacognitive, cognitive, and behavioural regulation, but not for regulating motivation.

2.2.3 Cognitive Antecedents

The early theoretical basis for online learning was cognitive based (Kirkwood & Price, 2005). This perspective suggests that knowledge independently exists, and learning is represented by knowledge transfer through information processing by the human brain (Tee & Karney, 2010). Influenced by this cognitive perspective, online learning tended to rely on a solo learner independently, rather than by any contextual or environmental factors.

Students' online learning experience is affected by their cognitive beliefs, including the perceived importance of online learning; online self-regulated learning goal setting; learning effort, self-efficacy, and cognitive thinking style (Chen & Jang, 2010; Graff, 2003; Hew, Huang, Du, & Jia, 2022; Pellas, 2014; Rabin, Kalman, & Kalz, 2019; Shen, Cho, Tsai, & Marra, 2013). For instance, when students perceive learning to be useful, they are more likely to achieve better utilitarian-based learning experiences (Rabin et al., 2019).

In addition, self-efficacy toward online learning plays an important role in students' online learning experience (Pellas, 2014). When students feel that they are capable of learning effectively, they are expected to achieve greater knowledge acquisition and engage more with online learning (Rabin et al., 2019; Shen et al., 2013). Students with better computer skills and self-control are also found to succeed in online learning (Wang, Xia, Guo, Xu, & Zhao, 2023).

Extant research also suggests a significant relationship between individual cognitive characteristics and online learning outcomes (El-Sabagh, 2021; Shahabadi & Uplane, 2015). Students have different cognitive learning preferences, and often use online learning features that match their own preferences to satisfy learning outcomes (El-Sabagh, 2021). For example, four dimensions of learning style are proposed in Kolb's learning style cycle which propose different learning styles (Morris, 2020), including accommodating (i.e., feel and do), converging (i.e., think and do), assimilating (i.e., think and watch), and diverging (i.e., feel and watch) (Morris, 2020). Students with assimilating and diverging learning styles prefer synchronous online activities, whereas students with assimilating and converging learning styles prefer asynchronous online activities (Shahabadi & Uplane, 2015).

2.2.4 Social Antecedents

Social constructivists emphasize the effects of social interactions on knowledge construction (Bapna, Benner, & Qiu, 2019; Kankanhalli et al., 2005). Social constructivists believe that students have better knowledge acquisition when learning with other students (He, 2013). According to these scholars, online learning should facilitate collaborative learning with the application of e-learning tools that promote students' interaction and knowledge exchange (Leong, 2011; Lu et al., 2013). Such a collaborative approach to online learning has gradually become prevalent, with students contributing to social interaction in online learning.

Increasingly, research has emphasized the impact of social interaction on students' learning experiences (Roque-Hernández et al., 2023; Symeonides & Childs, 2015; Yousaf et al., 2023). Previous studies (e.g., Bharati et al., 2015; Kirkwood & Price, 2005; Yousaf et al., 2023) suggest the need to provide shared learning spaces and tools for collaboration to gain effectiveness in learning. This constructivist learning perspective interprets knowledge as being constructed by learners through social interaction and mutual support (Pritchard & Woollard, 2013). Particularly with respect to online learning, there has been a pedagogical shift from direct instruction to facilitating collaborative social learning through peer-to-peer interactions (Chiu, 2021; Symeonides & Childs, 2015). Peer interaction can significantly impact student learning outcomes in online learning (Cheng et al., 2023). When students engage with their peers in discussions, collaborative projects, or group activities, these students have the opportunity to exchange ideas, receive feedback, and deepen their understanding of course materials in online learning (Yousaf et al., 2023).

Relationship quality between students is also positively related to emotional engagement which further influences behavioural engagement (Sun, Ni, Zhao, Shen, & Wang, 2019). Students' relationship quality can enhance their social involvement in the learning process, which increases their engagement.

The interaction between instructors and students also plays a pivotal role in determining student learning outcomes in online learning (Ong & Quek, 2023). Instructor's feedback may boost students' engagement by giving them timely and constructive advice (Eom, Wen, & Ashill, 2006; Ong & Quek, 2023). When instructors actively engage with students – such as by providing feedback, clarifying concepts, and facilitating discussions – it enhances students' understanding and retention of course material. Additionally, instructor-student interaction fosters a supportive learning environment, where students feel valued, motivated, and encouraged to participate actively in the learning process (Gopal, Singh, & Aggarwal, 2021). This personalized attention and support contributes to improved academic performance and overall satisfaction with the online learning experience.

2.2.5 Motivational Antecedents

Prior research discusses students' motivational experiences during individual learning activities which can influence their learning experience (Niculescu, Tempelaar, Dailey-Hebert, Segers, & Gijselaers, 2015). Anxiety, stress, and fatigue can demotivate individuals to engage in online learning (Bates & Khasawneh, 2007). Emotional reactions (e.g., anxiety, joyfulness) to using online learning tools can provide affective cues about the likelihood of success or failure that can be anticipated in engaging with online learning (Eryilmaz et al., 2013). When task demands associated with using an online learning system produce symptoms of stress and anxiety, students may interpret these to indicate they don't have the capability to complete the learning tasks successfully.

One important way to facilitate students' online learning when experiencing negative emotional states is through motivational support. Drawing from the self-determination theory which stresses the importance of autonomy, relatedness and competency, various studies also investigate these psychological factors and their positive influence on promoting student engagement and performance (Chiu, 2021; Huang & Wang, 2023). For example, when online learning supports students' autonomy, competence and relatedness needs, students become more motivated to engage in online learning. In addition, students who have strong motivational regulation capability can adjust their motivational state into a positive direction and thus achieve better learning outcome (Cheng et al., 2023).

2.2.6 Demographic and Course-related Antecedents

In online learning with diverse demographics, specific learning activities, such as discussions, may promote advancement for learners in certain contexts, like Anglo-Saxon, while hindering progress in others, such as South Asian (Rizvi et al., 2022). A recent study (Zhao et al., 2022) also confirmed the presence of a digital outcome divide between rural and urban students in China, which arise from their different levels cultural (i.e., e-learning self-efficacy) and social (i.e., parental and teacher support) capital. Online learning literature generally agrees upon the important role of demographic characteristics in online learning performance, while the specific findings are heterogeneous among studies using different sample participants. For example, females have been shown to display better academic performance than males due to better self-regulation capability in online learning, while age is a positive factor to student learning performance (Spencer & Temple, 2021). However, in another study (Paul & Jefferson, 2019), gender and student class rank (e.g., freshman or sophomore) are found to have no significant impacts on student performance.

Regarding course design, the literature suggests that online learning courses should be specifically designed to fit the available online learning tools and student demands (Gopal et al., 2021). Trying to use a traditional in-person course design in an online course will hamper the course effectiveness and ultimately student engagement and performance. For instance, in online learning, course design following the self-regulation principle can facilitate students to learn independently and engage with online learning through the strategic processes of planning the study, performing the activities, and evaluating learning outcomes (Cocquyt et al., 2017; Lu et al., 2013; Venter, 2019).

2.3 Summary of Existing Literature on Student Learning Outcomes in Online Learning

Existing research on students' online learning experience has extensively investigated various factors including technological, cognitive, social, motivational, demographic, and course-related aspects. While these studies offer valuable insights into the determinants of positive online learning outcomes, there are notable limitations within this body of literature that warrant attention and further exploration.

Firstly, while the existing literature on technological antecedents has provided valuable insights into how design (such as gamification) can enhance student engagement and learning performance, insufficient attention has been paid to the utilization of social features within online learning platforms. In reality, a diverse array of social features, such as online discussion boards, brainstorming groups, messaging tools, and online video conferencing, are integrated into online learning tools (Andel et al., 2020). The recent COVID-19 pandemic has emphasized the challenge of students feeling disconnected from their peers, underscoring the importance of understanding students' use of social features in online learning and its potential impact on learning outcomes (Dhawan, 2020; Hollister et al., 2022).

Secondly, the existing literature predominantly explains the impact of social features on student learning outcomes through the concept of social presence or social interaction among students or with the instructor (Andel et al., 2020; Kear et al., 2014; Phirangee & Malec, 2017). While social presence represents students' sense of being socially connected in the online classroom, alternative explanations remain largely unexplored. Although social presence contributes to students feeling connected to the course, its direct association with student learning performance, such as knowledge acquisition or mastery, remains less clear. In addition, although social interaction represents an important networking source, there could be other social resources influencing students' learning experience, such as relational and shared language resources captured in social capital. Therefore, there is a need for further exploration to clarify the mechanisms through which social features influence student learning performance.

Thirdly, existing studies primarily focus on identifying antecedents to online learning performance, while overlooking contingent factors that may modify these relationships. For example, one potential moderating factor for the use of social features could be students' social resources, which may influence their effective utilization of social features. Social features (e.g., chatting, forum and discussion, video conferencing) may influence learners differently, thus understanding contingent factors that can moderate the impact of social features helps us to better understand their best use.

In summary, this research aims to address these gaps by examining the impact of the use of social features on students' learning performance and its underlying mechanisms. Additionally, it seeks to identify contingent factors that may modify the effects of social feature usage, such as students' social resources. By doing so, this study aims to provide a comprehensive understanding of the role of social features in online learning and their implications for student success.

A summary of the antecedents of student learning outcomes in online learning can be found in Appendix B. In the next chapter, theoretical background is discussed to inform the underlying mechanism and moderating factors for the relationship between use of social features in online learning and students' learning outcome of knowledge acquisition in online learning, and the moderating role of social capital.

Chapter 3. Theoretical Development

This dissertation integrates dual processing and social capital theories to understand how students' use of social features in online learning influence student knowledge acquisition in online learning through emotional and cognitive engagement.

Firstly, dual processing theory is highly relevant as it illuminates the dual processing of emotional and cognitive engagement experiences in relation to students' use of social features which is examined in research question 1 of this dissertation. Dual processing theory posits that human cognition operates through two systems: System 1, which is fast, automatic, and emotion-driven, and System 2, which is slow, deliberate, and logic-driven (Bago & De Neys, 2017; Evans & Stanovich, 2013; Wixted, 2007). This duality is crucial for understanding how students engage with social features in online learning. Social features often trigger emotional responses (System 1), such as feeling connected or motivated by peers, enhancing engagement and facilitating learning. Concurrently, these features support cognitive processes (System 2), such as critical thinking and problem-solving, by enabling discussions and collaborative activities. Therefore, dual processing theory provides a comprehensive framework for analyzing how social features impact student learning outcomes in online learning through emotional and cognitive engagement.

Additionally, social capital theory is highly relevant. Prior studies have highlighted the significant role of social capital in directly influencing student learning outcomes. (Kent et al., 2019; Lu et al., 2013; Venter, 2019). Alternatively, this dissertation draws on social capital theory to understand its moderating role in the impact of social features on students' emotional and cognitive engagement in online learning. This theory is pertinent because social resources have proven particularly relevant in online learning where face-to-face social cues are absent (Cocquyt et al., 2017; Venter, 2019). In online learning, students may rely more on their social capital for emotional and academic support (Andel et al., 2020). Social capital theory provides a framework to understand how these resources can motivate students, provide help with coursework, and offer support (Lu et al., 2013).

By integrating these theories, this dissertation aims to provide a nuanced understanding of how students' use of social features in online learning and multiple dimensions of social capital together influence student knowledge acquisition in online learning through emotional and cognitive engagement with online learning.

3.1 Dual Processing Theory

The dual processing theory, rooted in the foundations of psychological exploration, posits the simultaneous operation of two information processing systems: System 1 and System 2 (Bago & De Neys, 2017; Evans & Stanovich, 2013; Wixted, 2007). System 1 functions as an automatic and effortless information processing mechanism, drawing upon heuristics, intuition, and pattern recognition to swiftly generate responses (Moravec, Kim, & Dennis, 2020). Operating associatively and often outside conscious awareness, System 1 is deeply intertwined with hedonic emotions and intuitive judgments, frequently guided by well-established social-emotional norms. In contrast, System 2 engages in conscious, effortful, and controlled cognitive processing, requiring mental exertion and meticulous attention to detail (Bago & De Neys, 2017; Evans & Stanovich, 2013; Moravec et al., 2020). Dual processing theory asserts that both systems function concurrently, each fulfilling distinct roles in an individual's processing of stimuli, as shown in Figure 1.

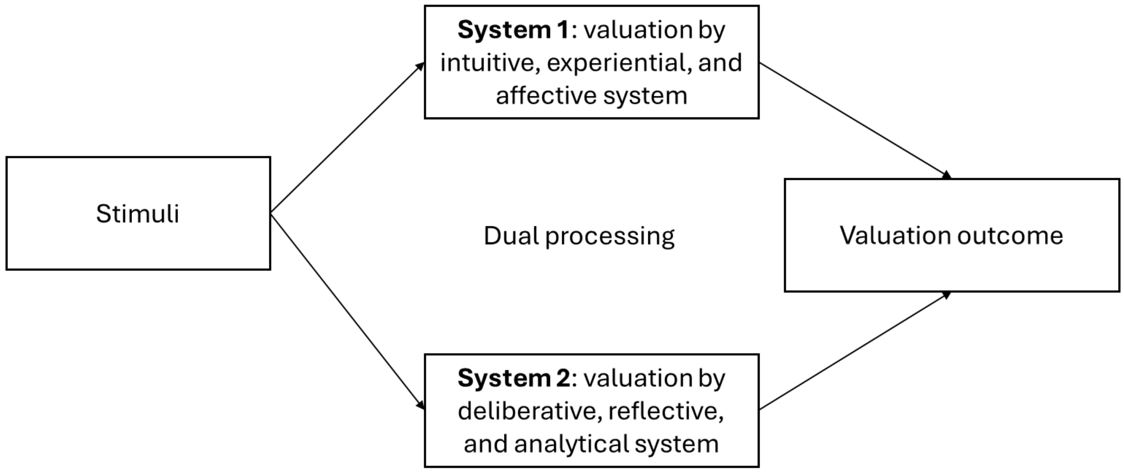

Figure 1. Dual Processing Framework

The dual processing theory has been applied in the educational learning context. For example, research by Tzur (2011) explores how students use System 1 for initial, quick understanding of new concepts and System 2 for deeper, more analytical learning. Effective study strategies, such as self-explanation (e.g., learners explaining the material to themselves as they study) and summarization (e.g., condensing larger pieces of information into concise summaries), engage System 2 to improve comprehension and retention. Studies on multimedia learning design (Mayer, 2019; Mayer & Moreno, 1998) show that integrating words and pictures helps manage cognitive load and engages both systems. For example, animations paired with narration can use System 1 for initial engagement and System 2 for deeper processing and understanding. While dual processing theory is proposed to be highly relevant for explaining information processing in the context of online learning (Mayer 2019), there is a notable absence of empirical studies that apply this theory in this specific domain.

This research adapts the dual processing theory in a similar way to the educational learning literature to inform students' dual engagement experience during online learning.

In line with the educational learning literature, it is important to separate System 1 and System 2 processes which provide unique values to student learning outcomes. For instance, in online learning, the use of social features may not only bring joyful experience to students in a heuristic way to sustain their interests in learning though System 1, but also stimulate deeper cognitive thinking through System 2 to gain in-depth understanding of the learning materials and facilitate knowledge acquisition (a positive learning outcome). As such, this dissertation proposes the potential benefits of both emotional and cognitive engagement in online learning for achieving knowledge acquisition.

Specifically, in this dissertation, the framework of dual processes is employed to investigate the intricate relationship between use of social features in online learning and knowledge acquisition. Emotional engagement in online learning is characterized as automatic, intuitive, and hedonic, mirroring the characteristics of System 1 processing (Chaiken & Ledgerwood, 2011; Moravec et al., 2020). Conversely, cognitive engagement in online learning is depicted as conscious, effortful, and deliberative, aligning with the attributes of System 2 processing (Evans & Stanovich, 2013; Wixted, 2007). The interaction among students through social features in online learning acts as stimuli capable of eliciting responses from both System 1 and System 2, thereby influencing knowledge acquisition.

Moreover, contextual factors play a pivotal role in moderating the activation of System 1 and System 2 processes. These factors encompass motivational influences, individual differences, and social contextual cues (Evans & Stanovich, 2013; Wixted, 2007). In particular, this research focuses on the use of social features in online learning, delving into the three dimensions of social capital that are likely to shape the impact of such features (Fulk & Yuan, 2013; de Zúñiga, Barnidge, & Scherman, 2017). Students may feel isolated in online learning, but social features such as discussion forums, group projects, and collaborative tools facilitate student interaction (Andel et al., 2020). These features can simulate the interactive nature of traditional classrooms, fostering engagement and positive learning outcomes, such as knowledge acquisition. Social features also support active learning via mechanisms such as discussions, debates, peer reviews, and collaborative problem-solving. These activities encourage students to construct their own understanding of the material, engage in critical thinking, and apply concepts in real-world contexts, leading to deeper learning and retention. By exploring these dimensions, the study endeavors to shed light on the interplay between social interaction, cognitive processing, and student knowledge acquisition in online learning.

3.2 Social Capital as a Moderator

Initially proposed by sociologist James Coleman, social capital theory explains the value and resources generated through social connections that facilitates the actions of individuals within that social structure (Coleman, 1990). Social capital is created when the interpersonal relationships among people facilitate their instrumental action or psychological needs (Best & Krueger, 2006; Coleman, 1990). In contrast to the physical capital embodied in tangible artifacts and the human capital possessed within an individual, social capital is used to describe the relational resources that are generated by multiple actors in a network through social communication and exchange (Nahapiet & Ghoshal, 1998).

Due to the richness of the social capital concept, three dimensions of social capital have been established in the literature, including structural, relational and cognitive capital

(Nahapiet & Ghoshal, 1998; Seibert, Kraimer, & Liden, 2001). The first dimension, cognitive social capital, refers to resources that promote shared understanding among connected individuals which allow them to engage in understandable communications (Chiu, Hsu, & Wang, 2006). It is a dimension of social capital that provides shared representations, interpretations, and systems of meaning among parties (Nahapiet & Ghoshal, 1998). This cognitive schemes and systems of meaning within the network can be exhibited in common vocabulary and narratives (Sun et al., 2012), which provide the foundation for communication and mutual understanding (Kwahk & Park, 2016). Cognitive social capital is often manifested in the use of shared language. For example, certain words within a social group may have specific meanings that can be understood by members within this social group but not by outsiders (Robert, Dennis, & Ahuja, 2008; Sun et al., 2012). Studies have shown that students who share a common language engage more effectively in peer interactions. For instance, prior study (Kim & Sax, 2009) found that language congruence among peers positively influenced academic engagement and performance. In other context such as work settings, prior research has found that cognitive social capital can facilitate shared vision and value such members can foster common understandings to facilitate knowledge acquisition in firms (Parra-Requena, Molina-Morales, & García-Villaverde, 2010). Another study (Tenzer & Pudelko, 2015) highlighted that language commonality reduces misunderstandings and fosters better teamwork, which parallels findings in educational settings.

The second dimension, relational social capital, represents the quality and maturity of social relationships between parties (Nahapiet & Ghoshal, 1998). It is a dimension of social capital that relates to the characteristics and qualities of personal relationships, which can be expressed with trust, obligations, respect and even friendship (Cullen-Lester, Maupin, & Carter, 2017; Mojdeh, Head, & El Shamy, 2018). The key expressions of the relational dimension of social capital are mutual trust, obligations and expectations, and identity and identification (Nahapiet & Ghoshal, 1998). The relational dimension of social capital is developed through a history of interaction (Carter, DeChurch, Braun, & Contractor, 2015) and is reflected in behavioural attributes such as trustworthiness, shared group norms, and reciprocity (Uhl-Bien & Maslyn, 2000). A prior study by Haythornthwaite (2008) explores how interaction and collaboration in online learning contribute to building relational social capital. It argues that strong relational ties enhance engagement by providing social support, fostering trust, and creating a sense of community. Similarly, other studies (e.g., Gu, Zhang, & Liu, 2014; Siu, Bakker, & Jiang, 2014) found that that strong relational social capital, characterized by trust and mutual respect, significantly enhances student engagement with online learning.

The third dimension, structural social capital, is concerned with the structural configuration of an individual's social relationships regarding who one reaches, how often one reaches, and what one communicates within their network (Singh, Tan, & Mookerjee, 2011). It relates to the properties of the social system and of the network of relations of an individual (Seibert et al., 2001). It mainly captures the configuration and pattern of connections between people and includes the roles, friendship, information, regulations that are expressions of this configuration. Structural social capital is tangible and can be more easily observed than the other dimensions of social capital (Goodarzi, Jiang, Head, & Lu, 2023; Lu et al., 2013; Lu, Jiang, Head, Kahai, & Yang, 2023). For instance, structural social capital can be captured by counting the number of social connections an individual has in their social media sites (Shmargad, 2014; Wasko, Teigland, & Faraj, 2009). By using information as expression of configuration, structural social capital can also be captured by formulating a network of communication (K.-Y. Huang, Chengalur-Smith, & Pinsonneault, 2019). Structural capital can be identified by the number of communications between the focal individual and others (Oppong-Tawiah, Bassellier, & Ramaprasad, 2016; Singh et al., 2011). Besides objective quantification of structural social capital, subjective quantification can also be achieved by asking individuals to self-evaluate (Sun et al., 2012), which provides a more holistic view of their structural capital through various means, including social media, face-to-face communication, etc.

A prior study by Doran, Doran, & Mazur (2011) explores how the structure of social networks within online learning influences student engagement. The study finds that well-structured social networks, characterized by frequent interactions and a high degree of connectivity, enhance student participation and collaboration. Similarly, utilizing learning analytics, a prior study by Ergün & Usluel (2016) analyzes the network structure of student interactions in online courses. That study finds that students who are centrally positioned in their social networks show higher levels of engagement and academic success. Another study by Glückler (2013) examines how structural social capital, defined by the density and connectivity of student networks, impacts engagement and academic performance. That study's findings suggest that students embedded in well-connected networks are more likely to engage in academic activities and perform better.

Social capital theory has been applied in studies reported in the online learning literature to show the impact of social support and resources on student knowledge acquisition in online learning (Kent et al., 2019; Liu & Yu, 2023; Mu, Bian, & Zhao, 2019;

Venter, 2019; Yang et al., 2020). For example, Lu et al. (2013) applied social capital theory in their study to propose a social constructivist view of online learning where learning relies on social exchanges and support among students. In general, these studies (e.g., Kent et al., 2019; Liu & Yu, 2023; Mu et al., 2019; Venter, 2019; Yang et al., 2020) suggest that social capital is a desirable resource to positively influence student knowledge acquisition in online learning. Social capital facilitates students to retrieve information normally not available to them and gain belongingness through enhanced relationships with other students in online learning (Cocquyt et al., 2017).

There are still opportunities to further apply the social capital lens to investigate online learning. Firstly, although prior studies have applied social capital theory to investigate online learning, they theorize social capital with a partial view. For instance, Cocquyt et al. (2017) only examines the structural social capital which is manifested in the structural social ties with other students in online learning. However, the quality of relationships and the language used as foundation of communication also play an important role in leveraging social capital for online learning (Mu et al., 2019; Venter, 2019; Yang et al., 2020). Thus, it is also important to consider a multi-dimensional perspective for social capital that incorporates both relational and cognitive capital to understand the impacts of social capital on online learning outcomes. Moreover, prior studies mainly examine the main effect of social capital on student learning outcomes, while this research focuses on its moderating role to adjust the impact of use of online social features on student knowledge acquisition in online learning. The reasons are twofold. Firstly, prior studies (e.g., Kent et al., 2019; Liu & Yu, 2023; Mu et al., 2019; Venter, 2019; Yang et al., 2020) have already highlighted the important role of social capital in facilitating student knowledge acquisition in online learning. By investigating the moderating role, the research contributes to a more comprehensive theoretical framework that integrates social capital theory with dual processing theory to explain student knowledge acquisition in online learning. Secondly, the dual processing theory suggests that social capital can serve as social contexts to adjust the System 1 and System 2 processing. When processing social features use, students are likely to draw on their social capital (such as the strength of relationships, shared language, etc.). As such, this research considers the three dimensions of social capital as moderating factors that affect the impact of the use of social features in online learning.

Chapter 4. Research Model and Hypotheses Development

This study proposes a theoretical model elucidating the interactive influence of students' use of social features in online learning and multiple dimensions of social capital on both emotional and cognitive engagement with online learning, subsequently shaping student knowledge acquisition in online learning. Given that knowledge acquisition is a pivotal determinant of online learning success (Bates & Khasawneh, 2007; Bravo-Agapito et al., 2021; Xiao & Hew, 2024), this research underscores its significance as the primary dependent variable. Furthermore, this dissertation delves into the moderating effects of cognitive, relational, and structural social capital, exploring their role in adjusting the relationship between the use of social features in online learning and emotional/cognitive engagement.

Drawing from dual processing theory, this research posits that students' interaction with social features in online learning can enhance student knowledge acquisition in online learning through two distinct mechanisms: emotional engagement (system 1) and cognitive engagement (system 2). Additionally, the integration of insights from social capital theory provides a complementary perspective, informing the three dimensions of social capital as moderators that influence the impact of students' use of social features in online learning. This multifaceted approach contributes to a comprehensive understanding of the dynamics between the use of social features, engagement, and knowledge acquisition in online learning. The proposed research model is presented in Figure 2, and the construct definition is shown in Table 1.

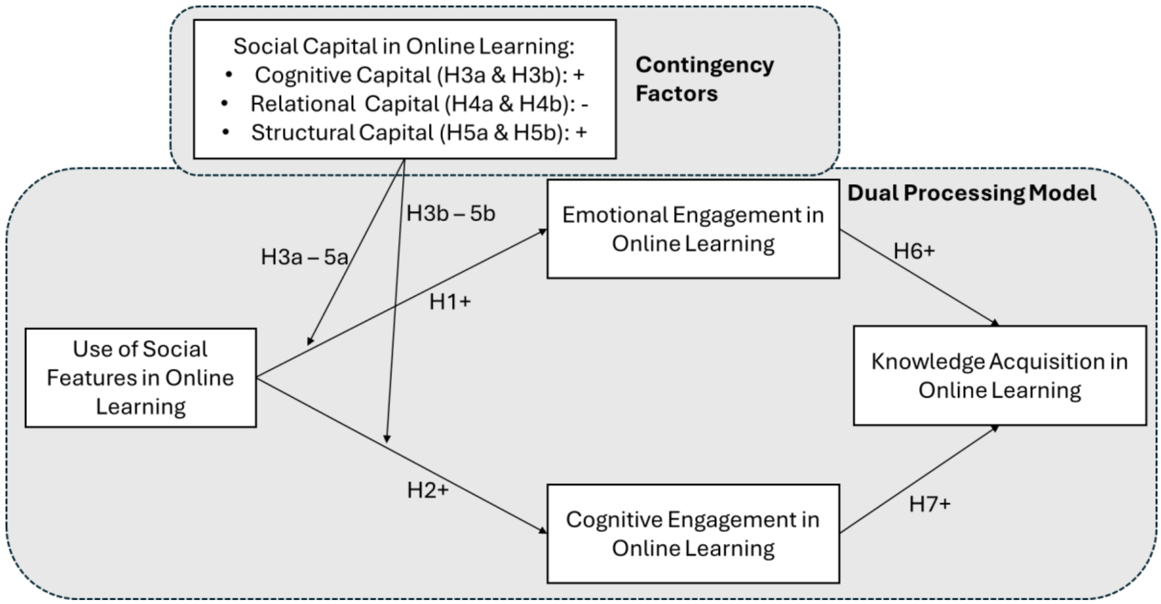

Figure 2. Research model

Table 1. Construct Definition

Construct	**Definition**
Use of Social Features in Online Learning	The integration and utilization of various interactive tools and platforms within an online learning context for social interaction and communication among students[1] (Roque-Hernández et al., 2023; Yousaf et al., 2023).
Emotional Engagement in Online Learning	Affective connection and investment that students develop in their online learning experiences (Gray & DiLoreto, 2016; Kahu, 2013; Lim et al., 2020).

[1] As stated in the literature review section, this research focuses on student-to-student interaction due to the richness of this communication type.

Cognitive Engagement in Online Learning	Mental effort and active participation that students dedicate to the cognitive processes involved in their online learning experiences (Iqbal et al., 2022; Xiao & Hew, 2024).
Cognitive Capital in Online Learning	Shared representations, interpretations, and systems of meaning among students (Nahapiet & Ghoshal, 1998)
Relational Capital in Online Learning	Qualities of student relationships, which can be expressed with trust, obligations, respect and even friendship (Nahapiet & Ghoshal, 1998)
Structural Capital in Online Learning	Network and connections with other students (Nahapiet & Ghoshal, 1998)
Knowledge Acquisition in Online Learning	The extent to which students gain new information, understanding and know-how in online learning context (Bates & Khasawneh, 2007; Bravo-Agapito et al., 2021; Xiao & Hew, 2024)

4.1 The Impact of the Use of Social Features in Online Learning on Students' Emotional and Cognitive Engagement

Previous studies (e.g., An et al., 2020; Andel et al., 2020; Kim et al., 2022) have extensively documented the various social features utilized by students in online learning, including group chatting, individual messaging, participation in discussion boards or forums, and engaging in video conference meetings. Among these features, several have been identified as particularly effective in fostering social bonds among students, thereby enhancing their senses of connection and belonging within their peer group (Phirangee & Malec, 2017; Pritchard & Woollard, 2013). For instance, students may utilize chat features to foster connections with fellow classmates through informal conversations. Additionally, they can leverage social networking features to stay updated on their peers' shared photos or experiences (De-Marcos, Domínguez, Saenz-De-Navarrete, & Pagés, 2014).

Prior research indicates that when students perceive a lack of connection with their peers in online learning settings, they may experience a sense of isolation and exclusion, leading to disengagement from the learning process (Adedoyin & Soykan, 2023; Dhawan, 2020). Conversely, when students actively utilize social features to connect with their peers and provide emotional support online, they are more likely to derive enjoyment from the online learning experience (Gray & DiLoreto, 2016). Through interactions with online social features in online learning, students can develop a sense of enjoyment and passion for their learning journey. Thus, we propose the following hypothesis:

H1. Students' use of social features in online learning is positively associated with their emotional engagement in online learning.

Students actively utilize online social features not only to cultivate social connections with their peers but also to foster critical thinking and broaden their understanding through knowledge exchange (Wei et al., 2012; Xiao & Hew, 2024). Research indicates that students can engage in dynamic case discussions, offering diverse perspectives and insights on online discussion boards (Kim, Lee, & Wang, 2020). Moreover, these platforms serve as catalysts for ideation sessions, where students collaboratively brainstorm ideas and develop innovative solutions within the online learning environment (Panigrahi et al., 2018). Furthermore, the interactive nature of online conference meetings facilitates lively exchanges, allowing students to explore a spectrum of viewpoints and engage in robust discourse (Greenhow et al., 2022; Kim et al., 2005).

Consequently, students can enhance their cognitive abilities by leveraging social features for information-seeking and knowledge exchange (Goes, Guo, & Lin, 2016; Kuang, Huang, Hong, & Yan, 2019). Through interactions with peers, students gain exposure to novel perspectives, fueling their intellectual curiosity and prompting analytical and deep thinking during online learning endeavors (Xiao & Hew, 2024). Thus, the utilization of social features in communication not only strengthens social bonds but may also enrich the cognitive engagement of students, facilitating a holistic learning experience in the digital landscape. Thus, the following hypothesis is proposed:

H2. Students' use of social features in online learning is positively associated with their cognitive engagement in online learning.

4.2 The Moderating Role of Social Capital in Online Learning

When students possess a high level of cognitive capital in online learning, they possess a shared language and demonstrate enhanced abilities to effectively communicate emotional support and social bonding messages (Fulk & Yuan, 2013; de Zúñiga et al., 2017). This shared linguistic framework enables them to establish deeper connections with their peers and fosters a sense of belonging within the online learning community (Lu et al., 2013). Conversely, when students encounter online interactions characterized by confusing expressions or cannot fully comprehend others' expressions, they may struggle to engage emotionally and meaningfully (Adedoyin & Soykan, 2023; Hollister et al., 2022). This lack of understanding can lead to feelings of isolation and detachment from the online learning group, ultimately resulting in a sense of disconnection (Huang & Wang, 2023; Szopiński & Bachnik, 2022). Therefore, we posit that students' cognitive capital serves as a crucial factor influencing the dynamics of online social interaction and emotional engagement with the learning process (Lu et al., 2013; Venter, 2019; Yang et al., 2020). Specifically, higher levels of cognitive capital can enhance students' ability to effectively utilize social features in online learning environments, thereby strengthening their emotional investment and sense of connection with the learning experience.

H3a: Students' cognitive capital will strengthen the association between their use of social features in online learning and emotional engagement in online learning.

Moreover, when students share a common language in online learning, they not only communicate effectively but also employ mutually understandable jargon, terminology, and conceptual frameworks in cognitive learning activities with their peers (Seibert et al., 2001). This shared language serves as a foundation for productive online discussions and brainstorming sessions, as it provides a cohesive cognitive framework for analyzing and understanding various perspectives (Nahapiet & Ghoshal, 1998). As such, students' cognitive capital enhances the effectiveness of their social features use in online learning platforms to promote cognitive engagement, as they can leverage their collective understanding to facilitate deeper discussion and understanding of diverse viewpoints (Chiu et al., 2006; Lu et al., 2013; Yang et al., 2020). Therefore, we propose that:

H3b: Students' cognitive capital will strengthen the association between their use of social features in online learning and cognitive engagement in online learning.

Relational capital encompasses the depth and quality of the social connections that students cultivate in online learning (Best & Krueger, 2006; Cameron & Webster, 2011). When students possess strong relational capital, they have developed meaningful relationships and networks within the online learning community, comprising friendships and support systems that may have evolved through prior interactions or shared experiences (Kent et al., 2019; Lu et al., 2013; Venter, 2019). However, research findings indicate that individuals who share strong bonds often lean towards offline communication methods, which afford them ample opportunities for informal conversation, shared experiences, and bonding activities (Kent et al., 2019; Lu et al., 2023). In online learning, students who have strong relational capital may find themselves longing for personal connections and face-to-face engagement with their peers (o'Flynn, 2015; Spencer & Temple, 2021). Despite their desire to connect in person, constraints such as public health restrictions, geographic disparity, or personal scheduling limitations may limit them to online interaction (Panigrahi et al., 2018; Wang et al., 2023). As such, students' strong relational capital which is associated with their desire for offline interactive learning may dampen the impact of online social feature usage on emotional engagement within the online learning environment. Thus, the following hypothesis is proposed:

H4a: Students' relational capital weakens the association between their use of social features in online learning and emotional engagement in online learning.

Furthermore, in online learning, students who possess strong relational capital may encounter fewer opportunities to gain novel insights from their peers, as per the weak tie perspective (Baer, 2010; Levin & Cross, 2004). This perspective posits that individuals tend to receive more diverse and unique information from acquaintances with whom they share weaker social connections (Granovetter, 1973; Kavanaugh, Reese, Carroll, & Rosson, 2003). Consequently, when students with strong relational capital in online learning engage in online social features use, such as debate, discussions, and brainstorming sessions, they may be less likely to encounter fresh perspectives from their peers (Tortoriello, Reagans, & McEvily, 2012). By contrast, when students with weaker ties engage in social features use with other students in online learning, their interaction is more likely to facilitate the exchange of information between distinct students and help to expedite the flow of ideas among students (Granovetter, 1973; Kavanaugh et al., 2003). This diminished exposure to new ideas associated with strong relational capital in online learning can result in students decreased cognitive involvement or engagement. As such, the following hypothesis is proposed:

H4b: Students' relational capital weakens the association between their use of social features in online learning and cognitive engagement in online learning.

In the landscape of online learning, students who have strong structural capital often possess the ability to forge extensive networks, establishing connections with a myriad of peers within online learning (Ali-Hassan, Nevo, & Wade, 2015; Lu et al., 2013; Singh et al., 2011; Wellman, Haase, Witte, & Hampton, 2001). This advantageous position empowers them to effectively utilize online social features, thereby facilitating their engagement with a broader spectrum of fellow learners (Lu et al., 2013; Yang et al., 2020). Consequently, students who have a substantial structural capital can expand their social circles through active participation in online social interactions, thereby fostering broader connections with a larger cohort of students within the online learning community.

As students cultivate relationships with an expanded network of peers through the utilization of social features, they are apt to experience a heightened sense of companionship in online learning (Greenhow et al., 2022; Lu et al., 2013; Panigrahi et al., 2018). Interacting with a diverse array of fellow students not only enriches their educational experience but also engenders a profound sense of unity and belonging (Panigrahi et al., 2018). This interconnectedness with a larger student body fosters a deeper sense of community and solidarity, thereby enhancing the overall emotional learning journey. Consequently, the structural capital of students in online learning environments serves as a catalyst in amplifying the impact of social feature utilization on their emotional engagement with the learning process. Thus, we propose the following hypothesis:

H5a: Students' structural capital strengthens the association between their use of social features in online learning and emotional engagement in online learning.

As previously discussed, students with strong structural capital are inclined to establish interactions with a diverse array of fellow learners within the online learning domain. This inherent advantage not only enables them to harness online social features for the exchange of ideas and experiences with a larger number of fellow students, thus facilitating access to a broader spectrum of perspectives and insights within their network. Consequently, students with strong structural capital are more likely to engage in intellectually stimulating knowledge exchange with their peers, thereby enriching their cognitive learning experience.

Moreover, many cognitive-enhancing learning opportunities within online environments entail voluntary collaborative endeavors such as group discussions, joint projects, and collective brainstorming sessions. By cultivating connections with a larger cohort of fellow students, individuals with significant structural capital enhance their prospects of participating in these cognitive-stimulating activities. This increased involvement in collaborative learning endeavors further augments their cognitive engagement in the online learning process.

Thus, the structural capital possessed by students serves as a facilitative mechanism, affording them a greater number of opportunities for knowledge exchange through interactions with a larger network of peers via online social features. Additionally, it enables students to partake in a myriad of cognitive activities alongside their fellow learners via social features in online learning. Consequently, we propose the following hypothesis:

H5b: Students' structural capital strengthens the association between their use of social features in online learning and cognitive engagement in online learning.

4.3 The Impact of Emotional and Cognitive Engagement on Knowledge Acquisition in Online Learning

When students experience a strong emotional connection to online learning, it often translates into heightened motivation and a genuine interest in the subject matter (Gray & DiLoreto, 2016; Huang & Wang, 2023; Xiao & Hew, 2024). Consequently, they demonstrate increased attentiveness and a deeper commitment to their online educational pursuits, leading to enhanced knowledge acquisition (Pellas, 2014; Yousaf et al., 2023).

Moreover, the emotional engagement of students towards online learning plays a crucial role in the retention and retrieval of information. When students are emotionally invested and passionate about their learning experiences, they are more inclined to encode newly acquired knowledge into their long-term memory (Cowan, 2008; Nielson & Powless, 2007; Park et al., 1996). This emotional resonance fosters stronger memory consolidation and facilitates easier recall of information when required.(McGaugh, 2018; Nielson & Powless, 2007; Osaka, Yaoi, Minamoto, & Osaka, 2013)

Furthermore, emotional engagement in online learning correlates positively with cognitive flexibility (Fredrickson, 2001; Raffaelli, Glynn, & Tushman, 2019). Students who are emotionally engaged exhibit a greater willingness and ability to apply the knowledge they have acquired in diverse contexts (Koch, Poljac, Muller, & Kiesel, 2018). This adaptability enhances their capacity to transfer learning from the online environment to real-world scenarios, thereby fostering deeper comprehension and practical application of the subject matter (Raffaelli et al., 2019). In summary, emotional engagement in online learning not only fuels motivation and interest but also enhances retention, retrieval, and application of knowledge across varied contexts, thereby enriching the overall learning experience and outcomes for students. Thus, the following hypothesis is proposed:

H6. Students' emotional engagement in online learning is positively associated with their knowledge acquisition in online learning.

In online learning, students' cognitive engagement plays a pivotal role in nurturing critical thinking, which are essential for effective learning and knowledge acquisition (Şendağ & Ferhan Odabaşi, 2009). Successful knowledge acquisition in online learning goes beyond mere passive reception of information; it entails active evaluation, analysis of the underlying rationale behind the information, and integration of interconnected concepts (Moravec et al., 2020). Through this process, students critically assess the flow of information in online learning, enabling them to attain a deeper understanding of the subject matter and internalize the knowledge for future application.

Furthermore, students' cognitive engagement in online learning facilitates exposure to diverse viewpoints and methodologies, thereby broadening the scope and depth of their knowledge (Hjertø, Paulsen, & Tihveräinen, 2014; Xiao & Hew, 2024). By actively engaging with varied perspectives, students are empowered to approach problems from multiple angles, fostering a more nuanced understanding of complex issues and enhancing their capacity for critical analysis and synthesis.

Moreover, cognitive engagement in online learning goes beyond simple memorization, often requiring the application of higher-order thinking capability such as knowledge categorization and self-reflection (Figl & Remus, 2023; B. Huang et al., 2019). Through these cognitive processes, students not only organize and categorize information effectively but also engage in introspection to identify areas for improvement within the online learning subject matter. By systematically categorizing knowledge, students can better allocate and retrieve pertinent information, enhancing their cognitive knowledge acquisition. Similarly, through self-reflection, students gain insights into their learning progress and areas that require further attention, enabling them to reinforce their understanding and ultimately improve their learning performance. As such, cognitive engagement in online learning not only cultivates critical thinking capability but also promotes deeper comprehension, mastery of subject matter, and exposure to diverse perspectives, thereby enriching students' overall learning experiences and facilitating more robust knowledge acquisition.

H7. Students' cognitive engagement in online learning is positively associated with their knowledge acquisition in online learning.

Chapter 5. Methodology

This dissertation adopts a positivist approach (Orlikowski & Baroudi, 1991), which is well-suited for testing theories to enhance our predictive understanding of phenomena related to knowledge acquisition in online learning. A positivist paradigm is characterized by the following elements, all of which are integral to this study. Firstly, the primary objective is to test established theories by applying them to specific constructs within the context of online learning. This involves examining the relationships between predefined variables to validate or refute theoretical predictions. Secondly, the study formulates explicit hypotheses derived from theoretical frameworks of the dual processing theory and the social capital theory. These hypotheses provide a clear, testable statement about expected relationships between variables. Thirdly, the research employs quantifiable measures for all variables, ensuring that data can be objectively analyzed using statistical techniques. This includes metrics for student engagement, knowledge acquisition, and dimensions of social capital. Fourthly, through rigorous hypothesis testing, the study assesses the validity of the proposed relationships between variables. This process involves collecting data, applying appropriate statistical methods, and determining whether the empirical evidence supports the hypotheses. Fifthly, the study aims to draw inferences about the broader population based on the sample data. This involves using statistical inference techniques to generalize findings, enhancing the study's external validity. An important objective is to ensure that the findings can be generalized beyond the specific sample used in the study. This involves selecting a representative sample and applying findings to a broader context, thus contributing to the field's theoretical and practical knowledge base in online learning context. By adhering to a positivist approach, this dissertation strives to contribute robust, empirical insights into the mechanisms of knowledge acquisition in online learning.

5.1 Participant Recruitment

The target participants for this study were individuals with purely online learning experience in the past three years within a university setting. Given the variability in program designs across different geographical regions, the research specifically focused on students who had undergone online learning at universities in the United States or Canada. These selection criteria were deliberately integrated into the survey design to effectively filter and identify the desired participants. To determine the appropriate sample size for the study, the G* Power tool was utilized, adhering to established guidelines from prior research (Erdfelder et al., 1996). With an alpha level of 0.05 and a power of 0.95, the calculated sample size was estimated to be 119 participants. However, in order to ensure robust statistical power and to accommodate potential issues such as spoiled samples or missing data, the decision was made to collect data from a larger sample size of 330 participants. By expanding the sample size beyond the calculated minimum, the study aimed to enhance the reliability and generalizability of its findings. This approach allowed for a more comprehensive analysis of the research variables while providing a buffer against potential data limitations or outliers. Ultimately, the larger sample size contributed to the overall robustness and validity of the study's conclusions. The ethics clearance certificate is attached in Appendix A.

5.2 Data Collection

The data collection involved several stages to ensure the quality and effectiveness of survey questions. Among these stages were a pretest, pilot test, and main study, each serving distinct purposes in refining and validating the survey instrument. Throughout all stages of data collection, this research adhered rigorously to established guidelines and protocols of the McMaster Research Ethics Board. This commitment to ethical standards ensured the protection of participants' rights, confidentiality, and well-being throughout the research process.

5.2.1 Pretest

In the pretest phase, the survey questionnaire was distributed to three panel members renowned for their expertise in the Information Systems (IS) domain for meticulous review. These panel experts meticulously scrutinized the survey questionnaire, thoroughly examining each survey item to identify any potential ambiguities or confusions. Given that several survey items were adapted from previous studies to fit the online learning context, ensuring their seamless integration into this domain was paramount. The panel members, equipped with their deep understanding of IS concepts, meticulously assessed whether the adapted items effectively captured the essence of online learning experiences, addressing any potential mismatches or discrepancies that might arise during participant comprehension. Their invaluable feedback and insights provided critical guidance in refining the survey questionnaire, ensuring that each item resonated authentically within the online learning context.

5.2.2 Pilot Test

During the pilot test, the survey questionnaire was distributed to a cohort of 30 students with prior online learning experience at McMaster University. The proposed model underwent empirical validation utilizing a survey methodology facilitated by Qualtrics. Within the survey, participants were encouraged to express their perspectives and opinions regarding their online learning experiences. The outcomes derived from this pilot study played a pivotal role in refining the measurement scales utilized and in addressing any potential methodological biases or deficiencies within the survey design. Specifically, in the pilot study, participants expressed confusion about the online social features. Therefore, in the main study, explanations with specific examples were provided. Additionally, in the pilot study, participants were asked to report their use of social features in online learning during class time and outside of class time. However, participants indicated that there was significant overlap in their use of social features during and outside of class time, and some asynchronous learning sessions did not provide class time. As a result, the main study asked participants to report their use of social features in online learning overall, without distinguishing between inside and outside of class time. Furthermore, preliminary analysis of measurement item reliability tests was conducted utilizing the collected data from participants. This rigorous examination aimed to ensure the validity and consistency of the survey items before embarking on the main large-scale study.

5.2.3 Main Study

In the main study, data collection was conducted through Qualtrics, a specialized data marketing company known for recruiting qualified participants. Participants were selected based on specific criteria established for the study and recruited through the Qualtrics platform.

During the recruitment process, participants underwent screening questions embedded within the survey. Those who did not meet the predetermined criteria, such as lacking prior online learning experience in a university, were promptly directed away from the survey to prevent them from continuing further. To manage expectations and minimize participant frustration, the survey questionnaire included an upfront brief outlining the desired participant profile. This transparent approach ensured that individuals who did not qualify for the study would not invest unnecessary time in completing the survey.

Although screening was primarily based on participants' self-reported data, its validity was further bolstered through random cross-checks conducted by Qualtrics. This involved comparing participants' survey responses with background information available within the Qualtrics platform, ensuring alignment between reported learning experiences and educational backgrounds.

Additionally, to maintain data integrity, Qualtrics implemented measures to identify and remove potentially biased responses. Participants who completed the survey in an unreasonably short duration, suggestive of insufficient engagement, or took an unusually long time, indicative of distractions, had their responses excluded from the analysis.

Furthermore, a quality check question was incorporated into the survey design to verify participants' attentiveness and understanding. Only those who answered this question correctly had their data included in the main study dataset, further enhancing the reliability and validity of the collected data. The specific quality check question was "To indicate that you have read and answered the questions carefully and thoughtfully in this survey, please select 'somewhat agree' for this specific statement."

In order to encourage participants to provide genuine and reflective responses, they were prompted to recall their online learning experiences for one minute before proceeding with the survey. During this brief period, participants were asked to reflect on what they had learned and to recollect the technological tools they utilized to support their learning process. This recall exercise served (Camacho, Hassanein, & Head, 2018) as a cognitive priming mechanism, helping participants to reconnect with their past experiences and providing them with a contextual framework to inform their responses.

5.3 Measurements

Before delving into the specifics of each measurement, it is important to highlight that the constructs in this model were assessed using established scales that have been previously validated in educational or other relevant contexts. These scales were chosen for their demonstrated reliability and validity, ensuring that they accurately capture the constructs under investigation. By employing these well-validated measures, the study maintains a high standard of methodological rigour, allowing for more reliable and generalizable findings. The use of these established scales also facilitates the comparison of results with prior research, thereby contributing to a coherent and cumulative body of knowledge in the online learning context.

Use of Social Features in Online Learning (USF): Items for use of online social features in online learning were adapted from previous studies (Hsieh & Wang, 2007). Students' extent of use online social features can be determined by multiple factors, including the variety of features they use, the frequency of use, and their duration of use, and thus it is operationalized as a formative construct, as operationalized in social media context (Goodarzi et al., 2023). Three items were used for the collection of responses on a 7-point Likert scale ("strongly disagree" to "strongly agree").

Cognitive Capital (CC): Items of cognitive capital were adapted from existing studies (Chiu et al., 2006). This measure is reflective, and an example measurement is "My classmates and I used common terms or jargon in online learning." Three items were used for the collection of responses on a 7-point Likert scale ("strongly disagree" to "strongly agree").

Relational Capital (RC): Items of relational capital were adapted from existing studies (Chiu et al., 2006). This measure is reflective, and an example measurement is "The relationship was characterized by mutual respect between me and other students." Four items were used for the collection of responses on a 7-point Likert scale ("strongly disagree" to "strongly agree").

Structural Capital (SC): Items of structural capital were adapted from existing studies (Chiu et al., 2006). This measure is reflective, and an example measurement is "I developed interactive relationships with many other students in my program." Four items were used for the collection of responses on a 7-point Likert scale ("strongly disagree" to "strongly agree").

Emotional Engagement (EE): Items of emotional engagement were adapted from existing studies (Kahu, 2013). This measure is reflective, and an example measurement is "I really enjoyed my online learning." Three items were used for the collection of responses on a 7-point Likert scale ("strongly disagree" to "strongly agree").

Cognitive Engagement (CE): Items of cognitive engagement were adapted from existing studies (Iqbal et al., 2022). This measure is reflective, and an example measurement is "I related the lessons learned in online learning with a solution to the real-life problem." Three items were used for the collection of responses on a 7-point Likert scale ("strongly disagree" to "strongly agree").

Knowledge Acquisition (KA): Items of knowledge acquisition were adapted from existing studies (Eryilmaz et al., 2013). This measure is reflective, and an example measurement is "I have learned useful knowledge." Four items were used for the collection of responses on a 7-point Likert scale ("strongly disagree" to "strongly agree"). A summary of construct measurement is shown in Table 2.

Control variables: Control variables in this study encompass demographic variables, the details of which are outlined in Table 5 within the Results section. Additionally, other control variables include the synchronicity of online learning, prior knowledge of online learning, and prior knowledge of the study program. Specifically, the synchronicity of online learning can impact students' sense of presence in the online environment and may influence their perceptions of knowledge acquisition (Dahlstrom-Hakki, Alstad, & Banerjee, 2020; Saltarelli & Roseth, 2014). Synchronicity was assessed using a single-item measure: "My online learning experience was synchronous," with responses recorded on a 7-point Likert scale. Prior knowledge of online learning was gauged through a single-item measure: "I have extensive experience with online learning," with responses also recorded on a 7-point Likert scale. Similarly, prior knowledge of the course was evaluated with the single-item measure: "I have much prior knowledge about the study program," utilizing a 7-point Likert scale as the response format. Previous research has indicated that students' prior knowledge of online learning or the course can mitigate learning barriers and enhance familiarity with the study context, thereby facilitating learning outcomes (Panigrahi et al., 2018). The survey screenshots are attached in Appendix C.

Table 2. Survey Measurements

Construct	**Adapted Scale** (7-point Likert scale from "strongly disagree" to "strongly agree")
Use of Social Features in Online Learning (USF) (Hsieh & Wang, 2007)	USF1: I frequently used online social interaction features to support my online learning. USF2: I used a variety of online social interaction features to support my online learning. USF3: I used online social interaction features for

	extended periods to support my online learning outside the class time.
Cognitive Capital (CC) (Chiu et al., 2006)	CC1: My classmates and I used common terms or jargon in online learning. CC2: My classmates and I engaged in understandable communication in online learning. CC3: My classmates and I had shared language for communication in online learning.
Relational Capital (RC) (Chiu et al., 2006)	In my online learning: RC1: The relationship was characterized by mutual respect between me and other students. RC2: The relationship was characterized by personal friendship between me and other students. RC3: The relationship was characterized by mutual trust between me and other students. RC4: The relationship was characterized by high reciprocity between me and other students.
Structural Capital (SC) (Chiu et al., 2006)	In my online learning: SC 1: I developed interactive relationships with many other students in my program. SC2: I spent a lot of time interacting with other students in my program. SC3: I networked with many other students in my program. SC4: I had frequent communication with other students in my program.
Emotional Engagement (EE) (Kahu, 2013)	EE1: I really enjoyed my online learning. EE2: I was excited about my online learning. EE3: I was passionate about my online learning.
Cognitive Engagement (CE) (Iqbal et al., 2022)	CE1: I related the lessons learned in online learning with a solution to the real-life problem. CE2: I engaged myself in frequent debates and discussions about problems that arise in my online learning. CE3: I grasped every opportunity to learn in my online learning.
Knowledge	In my online learning:

Acquisition (KA) in Online Learning (Eryilmaz et al., 2013)	KA1: I have learned useful knowledge. KA2: I have gained new knowledge and insights. KA3: I have learned other students' personal experiences or expertise. KA4: I have learned practical knowledge.

5.4 Data Analysis

Collected data was analyzed using Smart PLS software. A two-stage approach to structural equation modelling (SEM) was used as recommended by Hair et al. (Hair, William, Barry, & Anderson, 2010). Firstly, the reliability and validity of the measures representing the constructs in the research model was confirmed. Specifically, item reliability was assessed through item loadings and construct reliability was assessed using the Cronbach's alpha and the composite reliability.

Discriminant validity and convergent validity were assessed by calculated the average variance extracted (AVE) with a threshold of 0.5 (Fornell, C., & Larcker, 1981). Secondly, measurement model for goodness of fit was assessed. Fit indices used to assess the measurement model include the root mean square error of approximation (RMSEA) and the goodness of fit index (GFI) (Chin, Marcolin, & Newsted, 2003). Path coefficients were calculated to test the proposed hypotheses. In the post-hoc analyses, common method bias was examined to ensure the robustness of the results, and mediation tests were performed to confirm the mediating role of emotional/cognitive engagement on the relationship between use of online social features in online learning and knowledge acquisition in online learning.

Chapter 6. Results

6.1 Data Screening

Outliers in data are observations that deviate significantly from the majority, potentially biasing analyses. Univariate outliers are extreme values on one variable, while multivariate outliers involve unusual combinations of values on multiple variables. Outliers can arise from issues like incorrect sample inclusion or data entry errors. To identify outliers, standardized Z-scores for univariate outliers and Mahalanobis D^2 values for multivariate outliers are used, leading to the exclusion of outliers to maintain data integrity. After removing outliers, the dataset is further assessed for normality, linearity, and homoscedasticity.

6.1.1 Outliers

Outliers in data refer to observations that significantly deviate from the majority of the dataset's values, potentially introducing bias and reducing the accuracy of analyses (Meyers, Gamst, & Guarino, 2016). A univariate outlier is a data point that consists of an extreme value on one variable. A multivariate outlier is a combination of unusual scores on at least two variables (Meyers et al., 2016). Outliers exist for several reasons. A reason for outliers can be failure to indicate codes for missing values in a dataset. Another possibility is that the case did not come from the intended sample. In this research, data entry is computerized through the Qualtrics platform and missing values are not allowed in order to proceed with the survey. As such, the most significant reason for outliers could be that the case did not come from the intended sample.

Both types of outliers suggest data anomalies and can influence the accuracy of outcome of statistical analyses. Although a single value may not qualify as a univariate outlier within its respective variable, its combination with other values across different variables may collectively indicate an anomaly in the dataset. Therefore, it's crucial to thoroughly examine both univariate and multivariate outliers to ensure the integrity of the data analysis process (Meyers et al., 2016).

To identify univariate outliers, a standard approach involves converting all variables into standardized Z-scores. Values exceeding a certain threshold, often set at 2.5 standard deviations from the mean, are flagged as outliers and removed from the dataset to prevent them from unduly influencing subsequent analyses (Pollet & van der Meij, 2017). For detecting multivariate outliers, more sophisticated methods are employed. Mahalanobis D^2 values are calculated to measure the distance of each case from the centroid of the dataset, considering the covariance structure of the variables. These D^2 values are then compared to a critical threshold derived from the chi-square distribution, typically set at an alpha level of 0.001 (Meyers et al., 2016). Cases with D^2 values (ranging from 12.15 to 20.25) equaling or exceeding this threshold are considered multivariate outliers and are excluded from further analysis to maintain the robustness of the dataset. Applying these two techniques, 24 cases were removed from the original sample dataset, resulting in a final sample of 306.

6.1.2 Multivariate Statistical Assumptions

After assessing sample outliers, the subsequent phase involves evaluating the overall data distribution characteristics in the sample data. In parametric multivariate statistical tests, three key dataset attributes are typically deemed significant: normality, linearity, and homoscedasticity (Dragan & Topolšek, 2014; Meyers et al., 2016).

Firstly, the Shapiro-Wilk's test and the Kolmogorov-Smirnov Test (KS Test) were performed to test the normality distribution of key constructs of interests proposed in the research model. The KS test is a non-parametric test used to determine whether a sample comes from a specific distribution, often the normal distribution (Hair et al., 2010; Meyers et al., 2016). It evaluates the maximum difference between the cumulative distribution function (CDF) of the sample data and the theoretical CDF of the specified distribution (e.g., normal distribution). It is suitable for large sample sizes and is relatively robust to outliers. The Shapiro-Wilk test is a parametric test used to assess the normality of a dataset (Meyers et al., 2016; Villasenor Alva & Estrada, 2009). It computes a test statistic based on the correlation between the sample data and the expected values under the assumption of normality. It performs well for small to moderate sample sizes and is generally more powerful than the KS test in such cases. The test results in Table 3 show that test statistics for both the KS test and the Shapiro-Wilk test were significant, thus rejecting the null hypothesis that the data was normally distributed. As such, non-normality was observed in these variables. In addition, histograms in Appendix E also confirm the non-normal distribution of these variables.

Table 3. Tests of Normality for All Constructs in the Research Model

Tests of Normality						
	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Knowledge Acquisition	0.120	306	0.000	0.927	306	0.000
Relational Capital	0.073	306	0.000	0.970	306	0.000
Structural Capital	0.061	306	0.008	0.967	306	0.000
Cognitive Capital	0.124	306	0.000	0.931	306	0.000
Cognitive Engagement	0.097	306	0.000	0.967	306	0.000
Emotional Engagement	0.086	306	0.000	0.966	306	0.000
Use of Social Features	0.094	306	0.000	0.954	306	0.000

Secondly, the linearity assumption necessitates a consistent relationship between two variables across their entire spectrum, resulting in a linear pattern when plotted together. Deviations from this pattern can lead to underestimation or failure to detect relationships by tools assuming linearity. To assess linearity, the normality of residuals of the regression standard residuals and the normal Predicted Probability (P-P) plot were examined (Meyers et al., 2016). As shown in Figure 3, the histogram of the regression standardized residual of the dependent variable followed a normal distribution in general. Figure 4 also shows the observed cumulative probability of regression standardized residual highly aligned with the expected cumulative probability. As such, the linearity assumption was satisfied. Further tests on each item's Q-Q plot and histogram are presented in Appendix D and E.

The last assumption to evaluate is the homoscedasticity of the dataset. Homoscedasticity indicates that the variability of dependent variables remains consistent across different levels of independent variables (Meyers et al., 2016). To assess homoscedasticity for linear regression analysis, a plot was generated between the residuals and their predicted values. Lastly, Figure 5 shows that there was a constant spread of data points across the zero line. Together, the homoscedasticity criterion was satisfied.

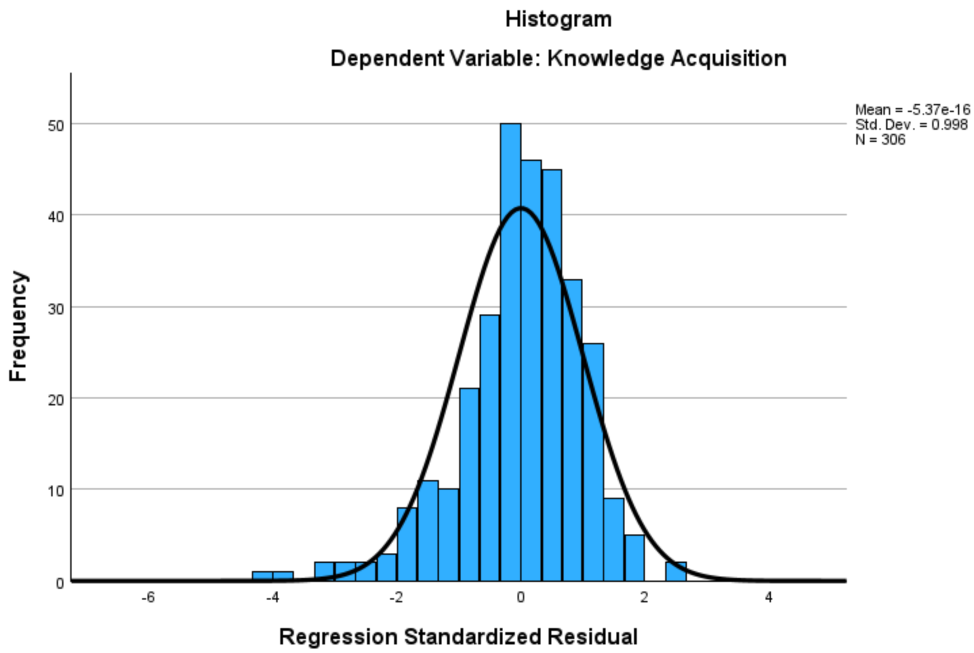

Figure 3. Histogram of Regression Standardized Residual

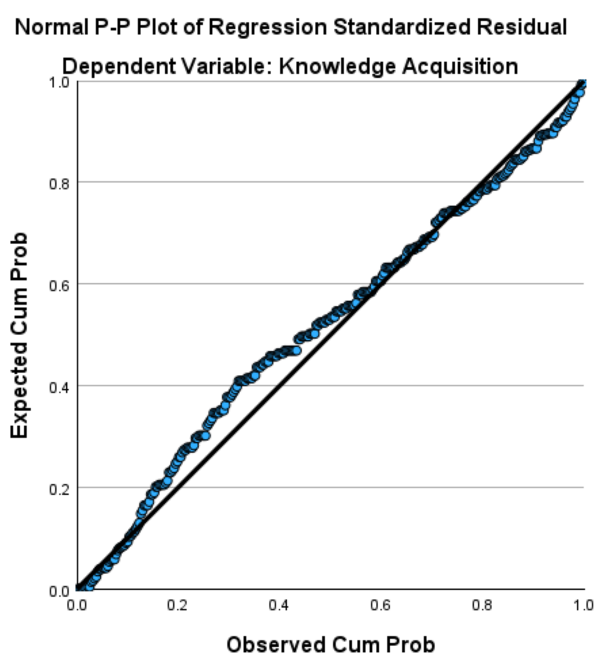

Figure 4. Normal P-P Plot of Regression Standardized Residual

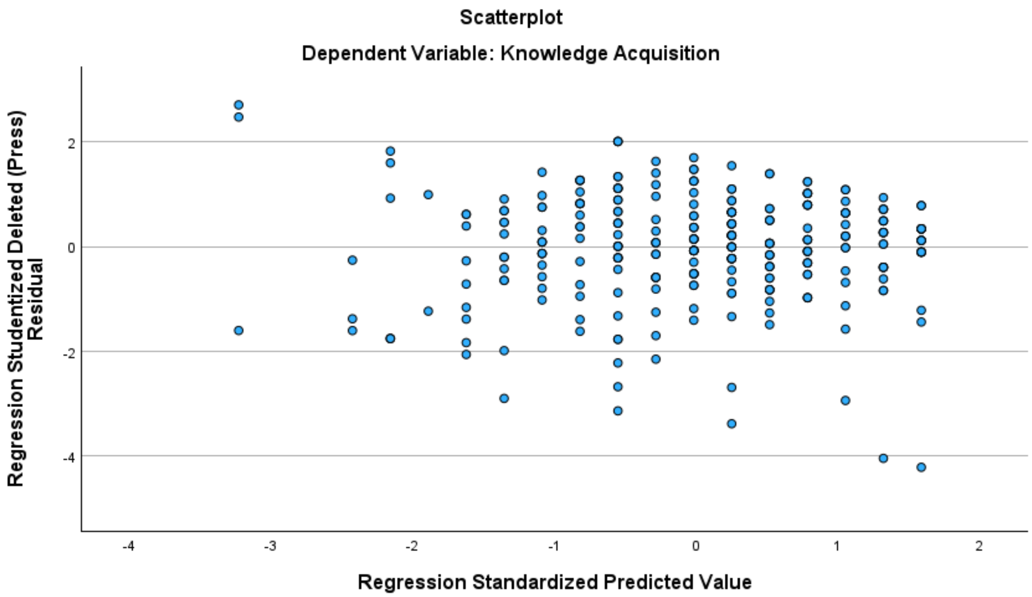

Figure 5. Scatterplot of Regression Standardized Residual

Given the data distribution in this sample, the selected analytical approach of partial least square structural equation modeling (PLS-SEM) well suited the empirical data. Since normal distribution of the data was not satisfied, parametric significance tests become inappropriate for determining the significance of coefficients like outer weights, outer loadings, and path coefficients. Instead, PLS-SEM relies on a nonparametric bootstrap procedure to assess the significance of estimated path coefficients (Chin, 2010; Henseler et al., 2014), and thus well suites the data in this dissertation with non-normal distribution. In bootstrapping, subsamples are generated by randomly selecting observations from the original dataset with replacement. These subsamples are then used to estimate the PLS path model.

6.2 Demographics of Participants

As demonstrated in Table 4, the majority of participants had at least one semester of online learning experience in a university within the past three years. Given the variation of the nature of post secondary education in various parts of the world, participants in this study were limited to students from North America, specifically Canada and the United States. Additionally, participants represent diverse areas of study, rendering the sample representative of students with varying expertise. The majority of participants underwent online learning during their undergraduate studies, reflecting the larger population of undergraduate students compared to those in master's or doctoral programs. Moreover, more than 90% of students experienced online learning in a course-based study mode, with a minority engaging in online courses during research-based programs. The sample exhibits a balanced distribution of female and male participants. Regarding age distribution, over half of the participants are over 35 years old, indicating a trend of individuals returning to university education after years of work experience (Li, 2022). The rise in popularity of online learning among middle-aged adults can be attributed to its flexibility (Panigrahi et al., 2018), allowing individuals to pursue further education while managing other commitments. This underscores the significance of online learning programs in facilitating career advancement for middle-aged adults.

Table 4. Sample Demographics of Participants (N=306)

Variable	Category	Frequency	Percentage
Length of online learning	More than one semester	197	64.4%
	One semester	70	22.9%
	Less than one semester	39	12.7%
Area of study	Business	61	19.9%
	Engineering	34	11.1%
	Health science	39	12.7%
	Natural science	35	11.4%
	Social science	27	8.8%
	Arts	42	13.7%
	Other	68	22.2%
Educational level	Undergraduate – 1st year	74	24.2%
	Undergraduate – 2nd year	47	15.4%
	Undergraduate – 3rd year	30	9.8%
	Undergraduate – 4th year	45	14.7%
	Master – 1st year	33	10.8%
	Master – 2nd year	19	6.2%
	PhD (any year)	10	3.3%
	Other	48	15.7%
Course type	Coursework	289	94.4%
	Research	11	3.6%
	Both coursework and research	6	2.0%
Gender	Male	148	48.4%
	Female	157	51.3%
	Other	1	0.3%
Age	18-20	9	2.9%
	21-23	35	11.4%
	24-26	22	7.2%
	27-29	18	5.9%
	30-32	23	7.5%
	33-35	18	5.9%
	35+	176	57.5%
Total		306	100

6.3 Descriptive Analysis and Measurement Model

To assess the reliability and validity of latent constructs[2], various criteria were employed. First, for construct reliability, the composite reliability coefficient, a robust measure of internal consistency, was assessed. As indicated in Table 5, all constructs exhibit Cronbach's alpha and compositive reliability values above 0.7, affirming their reliability (Hess, McNab, & Basoglu, 2014; Liu, Du, & Tsai, 2009). Next, indicator reliability was assessed based on established criteria. Each indicator's loading should ideally exceed 0.7, while loadings below 0.4 are typically excluded (Pereira & Tam, 2021). As such, the third item of cognitive engagement (i.e., CE3 in table 2) was excluded due to a loading below 0.4. In addition, the second item of relational capital (i.e., RC2 in table 3) was excluded due to a cross-loading above 0.6 on the structural capital. After excluding item RC2 and CE3, Table 8 confirms that all construct indicators exhibit loadings surpassing 0.7, underscoring strong indicator reliability.

Convergent validity was assessed using the Fornell and Henseler criteria. Specifically, the average variance extracted (AVE) of each construct should exceed 0.5, indicating that the latent variable explains over 50% of the variance observed in its indicators. In Table 5, all constructs demonstrate an AVE above 0.5, meeting the specified criterion. For discriminant validity, we employed the Fornell-Larcker criteria and cross-loadings. According to the Fornell-Larcker criterion, the square root of AVE for each construct should surpass the correlations between constructs. Additionally, each indicator's

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[2] For the formative construct use of social features in online learning (USF), the VIF value was used to evaluate its measurement quality, as done in previous research (Goodarzi et al., 2023). The VIF value of USF was 2.431, lower than the threshold of 3.3 adopted in previous IS research (Klein & Rai, 2009; Marett et al., 2013). Thus, the reliability of USF was confirmed.

loading should exceed all cross-loadings. As displayed in Table 6, the square roots of AVEs (on the diagonal) exceed the correlations between constructs (off-diagonal).

Table 7 confirms that all construct indicators exhibit loadings greater than cross-loadings, satisfying both criteria for the discriminant validity. In addition, as per (Gefen & Straub, 2005), "all the loadings of the measurement items on their assigned latent variables should be an order of magnitude larger than any other loading" (pp. 93), meaning that the difference should be at least 0.10 between the item loaded on the construct and the second highest loading of that item on another construct. Table 7 also confirms that the difference between the item loading on the construct and the second highest loading of that item on another construct is larger than 0.10 for all items. However, the difference of 0.10 between item loadings would have varied variance based on the size of the loading. Thus, Hair et al. (Hair, Black, Babib, & Anderson, 2019) argue that "to truly understand the impact of one loading compared to another, we should compare the differences in variance rather than just the difference in loading" (pp. 154). This allows for the more precise examination of the relative magnitude of the variance difference. As per Hair et al. (2019), ratios (i.e., computed by the item loading to its correspondent construct divided by the item loading to another construct) less than 1.5 are considered problematic cross-loadings and should be dropped from further analysis. Ratios between 1.5 and 2.0 are considered potential cross-loadings and should be examined more closely. In Table 7, item RC4 shows a potential cross-loading with the construct of structural capital, having a ratio of 1.95, while all other items have ratios larger than 2. Further examination of RC4 reveals that only the ratio with structural capital is 1.95, while its ratios with four other constructs are all above 2.0. Additionally, since relational capital and structural capital are different dimensions of the same overarching construct, social capital, a slight cross-loading is acceptable.

In summary, our assessment of construct reliability, indicator reliability, convergent validity, and discriminant validity demonstrates that our constructs are suitable for testing the conceptual model.

Table 5. Means, standard deviations, reliability and validity measures (CR, CA, AVE, VIF) of variables. (N=306)

Constructs	**Mean**	**SD**	**CR**	**CA**	**AVE**	**VIF**
USF	5.324	1.124	-	-	-	1.574
CC	5.710	0.996	0.785	0.780	0.543	1.617
RC	5.121	1.234	0.801	0.793	0.567	1.792
SC	3.769	2.667	0.922	0.911	0.773	2.907
EE	4.183	1.642	0.917	0.915	0.782	3.305
CE	4.825	1.497	0.890	0.888	0.799	2.767
KA	5.100	1.298	0.907	0.903	0.701	2.726

Note: 1) Construct abbreviations are shown here: Use of Social Features (USF), Cognitive Capital (CC), Relational Capital (RC), Structural Capital (SC), Emotional Engagement with Online Learning (EE), Cognitive Engagement with Online Learning (CE), and Knowledge Acquisition in Online Learning (KA). 2) Other abbreviations are shown here: Standard Deviation (SD), Composite Reliability (CR), Cronbach's Alpha (CA), Average Variance Extracted (AVE), and Variance Inflation Factor (VIF). 3) USF is a formative measure, and thus CR, CA and AVE are not applicable for USF.

Table 6. Correlations of Latent Variables (N=306)

Constructs	**CC**	**RC**	**SC**	**EE**	**CE**	**KA**	
1. CC	**0.737**						
2. RC	0.369	**0.753**					
3. SC	0.118	0.472	**0.850**				
4. EE	0.273	0.395	0.558	**0.885**			
5. CE	0.425	0.392	0.331	0.503	**0.894**		
6. KA	0.286	0.360	0.318	0.520	0.509	**0.837**	
7. USF	0.234	0.460	0.499	0.478	0.440	0.332	-

Note: 1) The square roots of AVE values are shown on the diagonal and printed in bold. 2) USF is a formative measure, and thus the AVE is not applicable for USF.

Table 7. Item Loadings of Latent Constructs

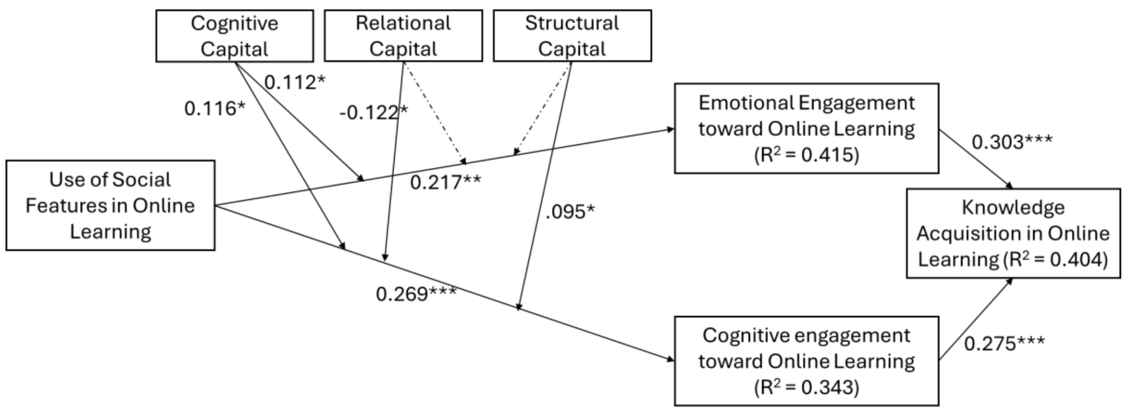
Constructs	Items	CC	RC	SC	EE	CE	KA
Cognitive capital (CC)	CC1	**0.803**	0.193	-0.061	0.017	0.113	0.110
	CC2	**0.801**	0.098	-0.007	0.165	0.123	0.063
	CC3	**0.809**	0.099	0.123	0.052	0.110	0.131
Relational Capital (RC)	RC1	0.206	**0.787**	-0.005	0.088	0.163	0.134
	RC2	*0.426*	*0.382*	*-0.135*	*0.121*	*0.096*	*0.211*
	RC3	0.151	**0.780**	0.311	0.101	0.033	0.148
	RC4	0.099	**0.740**	0.380	0.125	0.089	0.118
Structural Capital (SC)	SC1	0.074	0.188	**0.824**	0.268	0.028	0.075
	SC2	-0.029	0.159	**0.845**	0.222	0.075	0.120
	SC3	-0.007	0.108	**0.844**	0.093	0.064	0.084
	SC4	0.041	0.138	**0.837**	0.211	0.156	0.164
Emotional Engagement (EE)	EE1	0.147	0.079	0.243	**0.837**	0.150	0.242
	EE2	0.080	0.164	0.323	**0.783**	0.186	0.262
	EE3	0.087	0.116	0.292	**0.813**	0.135	0.244
Cognitive Engagement (CE)	CE1	0.250	0.171	0.168	0.197	**0.827**	0.238
	CE2	0.190	0.121	0.119	0.207	**0.839**	0.285
	CE3	*0.129*	*0.135*	*0.147*	*0.203*	*0.487*	*0.452*
Knowledge Acquisition (KA)	KA1	0.111	0.142	0.079	0.124	0.097	**0.837**
	KA2	0.072	0.080	0.101	0.190	0.271	**0.775**
	KA3	0.108	0.158	0.101	0.185	0.078	**0.857**
	KA4	0.097	0.056	0.166	0.185	0.129	**0.855**

Note: 1) USF is a formative measure, and items of USF are not supposed to be converged.
2) RC2 and CE3 were removed for further analysis due to its low loadings with its correspondent construct or high cross-loadings with other correspondent constructs.

6.4 Structural Model and Hypothesis Testing

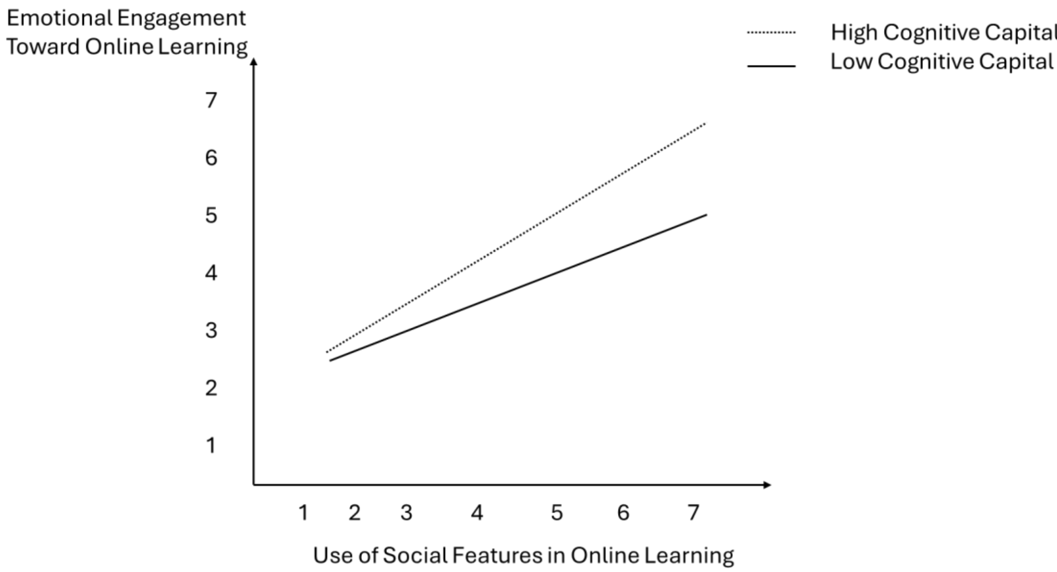
Model fit index was examined to ensure the goodness of fit for the research model. The square error of approximation (RMSEA) value was 0.04, satisfying the criterion that the RMSEA should be lower than 0.08 and thus confirmed the model fit (Xia & Yang, 2019). The goodness of fit index (GFI) value was 0.871, fulfilling the criterion that the GFI should be higher than 0.85 (Marsh & Balla, 1988; Someya et al., 2001), and thus also confirmed the model fit. To estimate the structural model, the explained variance (R^2) and the level of significance of the path coefficients were examined. The R^2 of dependent variables are 0.415, 0.343 and 0.404 for emotional engagement, cognitive engagement and knowledge acquisition, respectively, further confirming the goodness of fit for the empirical model. To assess the significance of the path coefficients, we used a bootstrapping procedure with 5000 iterations of resampling (Chin, 2010). Figure 6 shows the path coefficient results.

Emotional engagement is explained through use of social features in online learning ($\beta = 0.217$; $p < 0.01$), which is positive and statistically significant. Therefore, hypothesis H1 is supported. Cognitive engagement is also explained through use of social features in online learning ($\beta = 0.269$; $p < 0.001$), which is positive and statistically significant. Therefore, hypothesis H2 is supported. The structural model also confirms the moderating impacts of social capital on the relationship between use of social features in online learning and emotional/cognitive engagement. Specifically, cognitive capital has a positive and significant moderating impact on the relationship between use of social features in online learning and emotional engagement ($\beta = 0.112$; $p < 0.05$). Thus, H3a is supported, suggesting that students' cognitive capital can strengthen the impact of use of social features in online learning on their emotional engagement with online learning. However, the moderating impacts of relational capital and structural capital are not significant for the relationship between use of social features in online learning and emotional engagement with online learning. Thus, H4a or H5a is not supported. In addition, the structural modeling results show that while cognitive capital ($\beta = 0.116$; $p < 0.05$) and structural capital ($\beta = 0.095$; $p < 0.05$) positively moderate the relationship between use of social features in online learning and cognitive engagement with online learning, relationship capital (β= -0.122; $p < 0.05$) negatively moderate this relationship. Thus, H3b, H4b, and H5b are all supported. Finally, the emotional engagement with online learning (β= 0.303; $p < 0.001$) and the cognitive engagement with online learning (β= 0.275; $p < .001$) are statistically significant in explaining the knowledge acquisition in online learning, thus supporting H6 and H7. The moderating impacts are plotted in Figures 7, 8, 9 and 10.



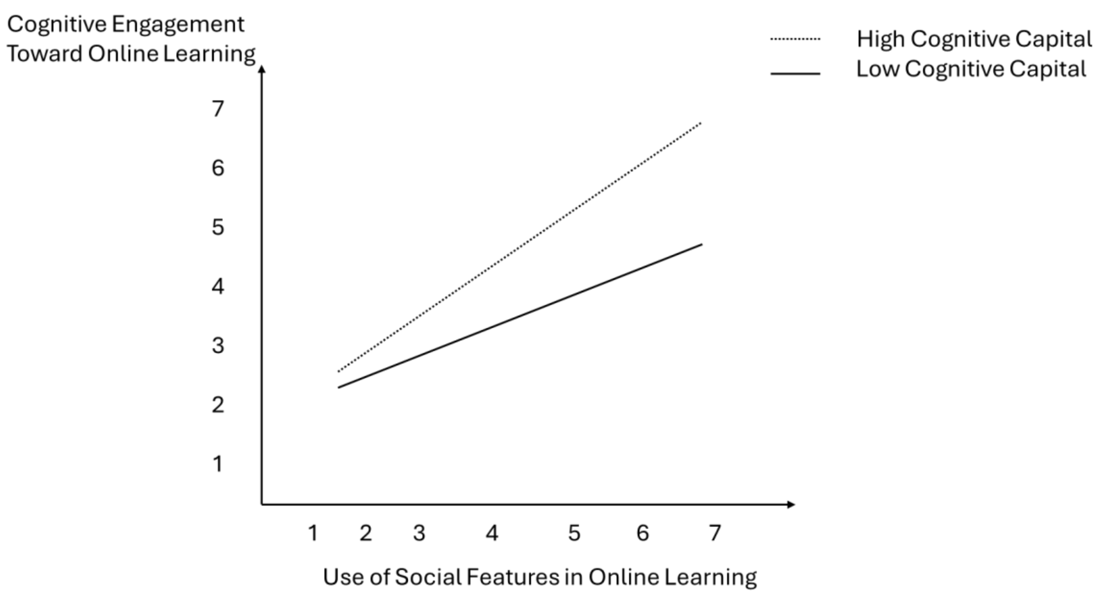
Note: 1) *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$. 2) Significant relationships are depicted with solid lines, whereas insignificant relationships are represented with dotted lines; 3) Insignificant relationships were also included in the structural equation modeling test. The coefficient for the insignificant moderating role of relational capital is -0.054 and the p value is 0.08. The coefficient for the insignificant moderating role of structural capital is 0.024 and the p value is 0.17.

Figure 6. Structural equation modeling results



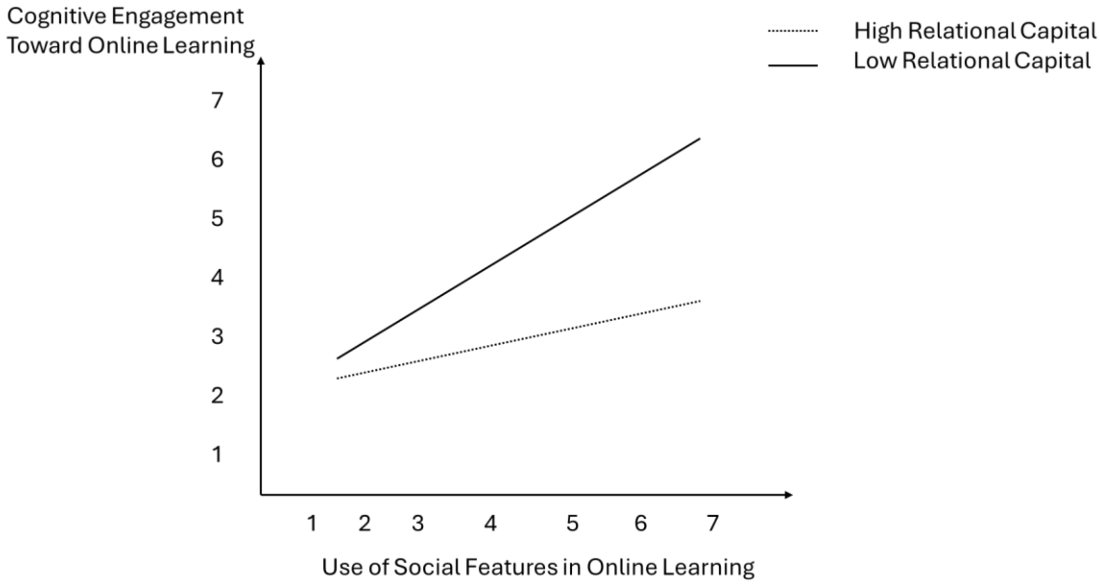
Note: Low and high cognitive capital is categorised by median-split approach.

Figure 7. The moderating impact of cognitive capital on the relationship between students' use of social features in online learning and emotional engagement in online learning



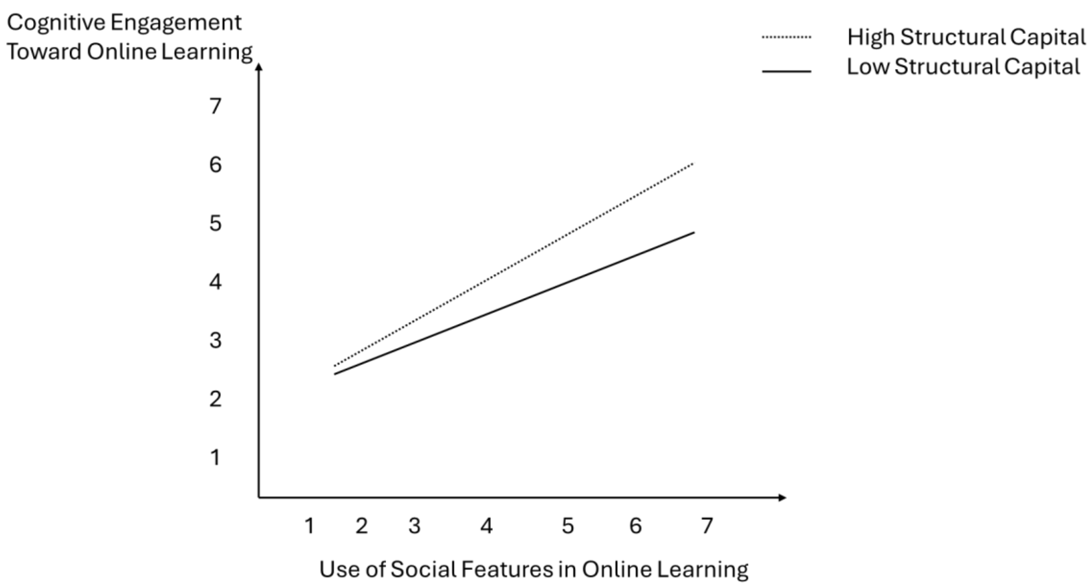
Note: Low and high cognitive capital is categorised by median-split approach.

Figure 8. The moderating impact of cognitive capital on the relationship between students' use of social features in online learning and cognitive engagement in online learning



Note: Low and high relational capital is categorised by median-split approach.

Figure 9. The moderating impact of relational capital on the relationship between students' use of social features in online learning and cognitive engagement in online learning



Note: Low and high structural capital is categorised by median-split approach.

Figure 10. The moderating impact of structural capital on the relationship between students' use of social features in online learning and cognitive engagement in online learning

6.5 Post-hoc Analysis

6.5.1 Common Method Bias

Common method bias (CMB) can be a potential concern for this research since self-reported data was collected via questionnaires. When CMB occurs, artificial covariance may exist between predictors and dependent variables since the same respondents provide the data. During data collection, two procedural measures were implemented (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003): (1) participants were briefed on the confidentiality of their data and encouraged to express their authentic opinions; and (2) diverse response formats, such as matrix questionnaires and sliding bar questionnaires, were employed to evaluate the various variables.

Harman's signal-factor analysis was performed to understand the statistical impact of CMB (Podsakoff et al., 2003). The first main factor was found to account for 37.96% of the variance, which was less than 50%, indicating that CMB was not a major concern. Second, we applied the marker variable method (Lindell & Whitney, 2001). Including additional independent variables that are likely to be affected by the CMB in the model estimation reduces the CMB, partly due to the rolling out of common method variance (Siemsen, Roth, & Oliveira, 2010). Since several control variables were included in the empirical structural model, CMB can be largely reduced. Variance inflation factors (VIFs) of all constructs (see Table 5) were lower than the threshold of 3.3 adopted in previous IS research (Klein & Rai, 2009; Marett, Otondo, & Taylor, 2013), providing further evidence that CMB does not contaminate the results of this research.

Finally, CMB is unlikely to be a concern for variables involved in interaction effects.

Previous study (Evans, 1985) showed using a Monte Carlo study that the existence of a correlated error among dependent and independent variables, something that would happen with CMB, makes artifactual interaction unlikely and attenuates true interactions. Since multiple interaction effects were observed in this research, CMB was not a significant concern.

6.5.2 Mediation Tests through PLS Indirect Effects Testing

Mediation effects were further examined to verify the mediating role of emotional and cognitive engagement. For this purpose, the procedure for testing mediation effects of a PLS model was applied, as in previous research (Gu, Deng, Zheng, Liang, & Wu, 2019; Rai, Patnayakuni, & Seth, 2006). First, a direct path was added between use of social features in online learning and knowledge acquisition in online learning. With the addition of this direct path, the R^2 of knowledge acquisition in the revised model (partial mediation) was 0.404, whereas the R^2 for knowledge acquisition in the original model (full mediation) was also 0.404. Following previous research (Gu et al., 2019; Rai et al., 2006), pseudo F-statistics[3] was computed to test if this difference is significant. The pseudo F-statistic is 0.000 with (299) degrees of freedom. The p value is not significant, suggesting that adding the direct effect does not improve the model fit. Moreover, the path coefficient of the direct effect is not significant, either. This suggests that emotional engagement and cognitive engagement in online learning fully mediate the effect of use of online features in online learning on knowledge acquisition in online learning.

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[3] The pseudo F statistic is computed using the formula f^2 * (n-k-1) with 1, (n-k) degrees of freedom where n is the sample size and k is the number of constructs in the model (Chin et al., 2003). The formula for computing f^2 is (R^2 partial mediation - R^2 full mediation)/(l- R^2 partial mediation).

Specific indirect relationships were further tested, as shown in Table 8. Specifically, use of social features and indirectly influence knowledge acquisition through both emotional (indirect coefficient: 0.066, p value = 0.007) and cognitive engagement (indirect coefficient: 0.074, p value = 0.003). However, all moderated mediation relationships (e.g., CC x USF -> EE -> KA) were non-significant. This suggests that although social capital can moderate the impact of USF on EE/CE, they cannot extend the moderating effect to the complete indirect relationship USF -> EE/CE -> KA.

Table 8. Indirect relationships

Indirect Relationships	Coefficient	Standard deviation (STDEV)	T statistics	P values
USF -> EE -> KA	0.066	0.027	2.453	**0.007**
USF -> CE -> KA	0.074	0.027	2.738	**0.003**
CC x USF -> EE -> KA	0.033	0.021	1.569	0.058
RC x USF -> EE -> KA	-0.01	0.016	0.623	0.267
SC x USF -> EE -> KA	0.005	0.016	0.346	0.365
CC x USF -> CE -> KA	0.031	0.021	1.475	0.070
RC x USF -> CE -> KA	-0.033	0.019	1.791	0.052
SC x USF -> CE -> KA	0.026	0.017	1.551	0.061

Note: 1) Construct abbreviations are shown here: Use of Social Features (USF), Cognitive Capital (CC), Relational Capital (RC), Structural Capital (SC), Emotional Engagement in Online Learning (EE), Cognitive Engagement in Online Learning (CE), and Knowledge Acquisition in Online Learning (KA).

6.5.3 Mediation Tests through Hayes' Process Approach

To confirm the robustness of the mediating test results, this research also followed Hayes' approach to examine the moderated mediation effects (Hayes, 2013, 2015, 2017). Model #4 was applied to test the simple mediation effect, as shown in figure 11. Model #7 was applied to test the moderated mediation effects with different moderators (i.e., cognitive, relational, and structural capital), as shown in figure 12, 13, and 14.

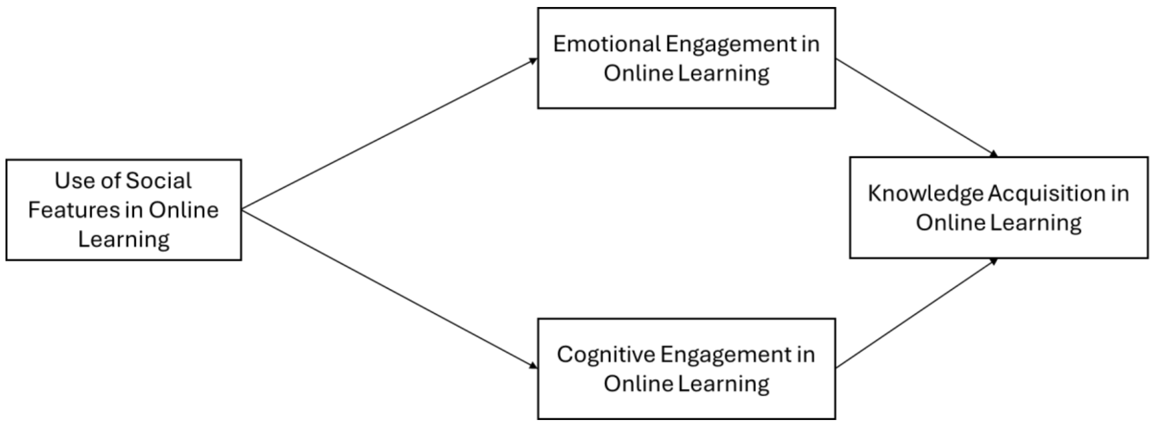

Figure 11. Process Model #4

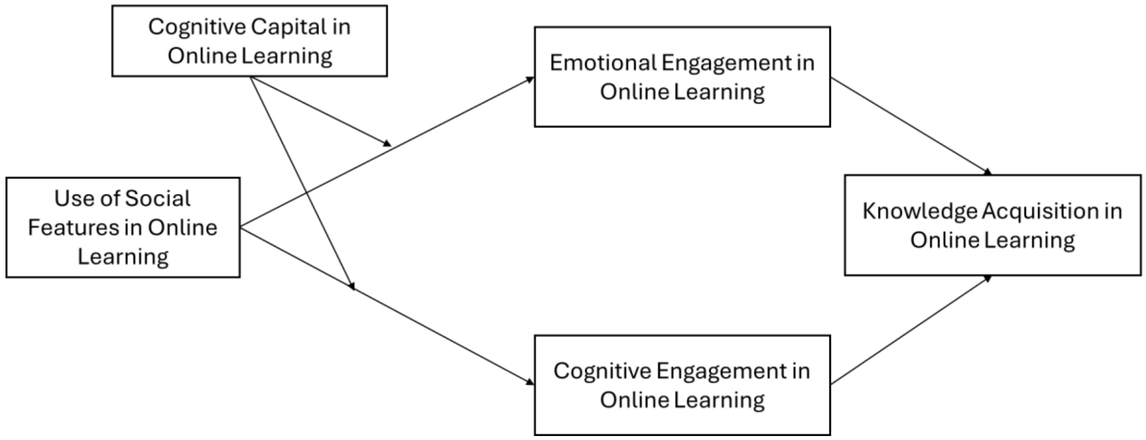

Figure 12. Process Model #7 (Moderator: Cognitive Capital in Online Learning)

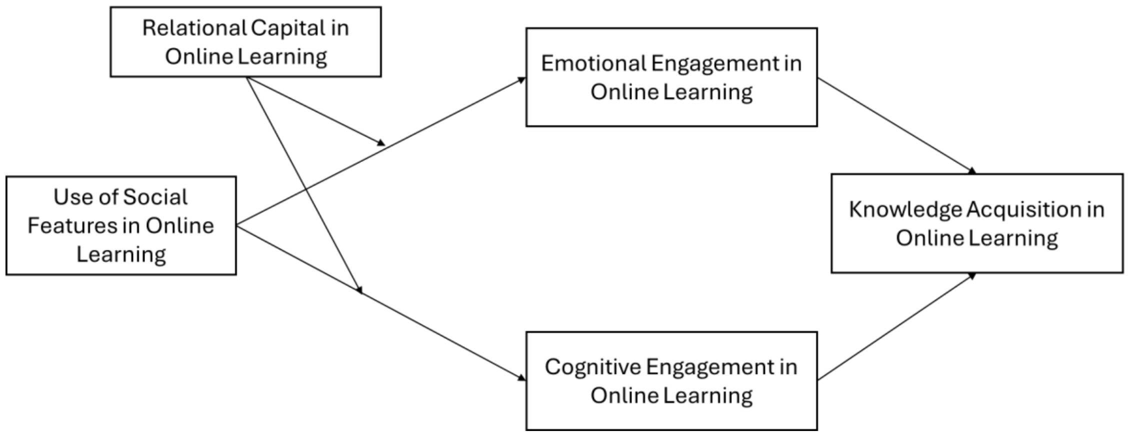

Figure 13. Process Model #7 (Moderator: Relational Capital in Online Learning)

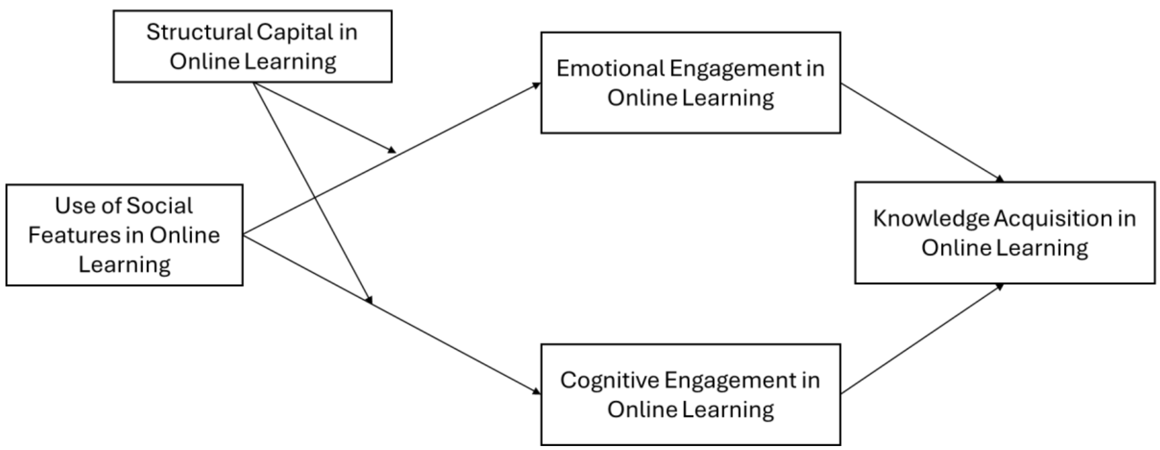

Figure 14. Process Model #7 (Moderator: Structural Capital in Online Learning)

Table 9 indicates the mediating effect of emotional and cognitive engagement in the relationship between use of social features in online learning and knowledge acquisition without adding conditional factors (i.e., cognitive, relational or structural capital). The results of running SPSS PROCESS Model #4 do not find supportive evidence of a direct effect. The significant indirect effect implies that use of social features' impact on knowledge acquisition in online learning is transmitted via emotional and cognitive engagement.

Table 9. Direct and indirect effects of use of social features in online learning on

knowledge acquisition mediated by emotional and cognitive engagement (PROCESS Model #4)

Type of effect	**Effect**	**SE**	**LLCI**	**ULCI**	**Zero include?**
Direct	.0258	.0573	-.0869	.1385	Yes
Indirect through emotional engagement	.0713*	.0248	.0283	.1248	No
Indirect through cognitive engagement	.0806*	.0291	.0309	.1448	No

Note. $^*p < 0.05$; SE = Standard Error; LLCI = Lower Limit Confidence Interval; ULCI = Upper Limit Confidence Interval

After setting the foundation of emotional engagement and cognitive engagement as mediators, a stepwise approach was performed to test the moderated mediation effects (see Table 10 and 11). The results of the moderated mediation tests (Table 10, Panel A) provided a non-significant and positive index for cognitive capital in online learning, which implies that the indirect mechanism (i.e., use of social features (USF) -> emotional engagement (EE) & cognitive engagement (CE) -> knowledge acquisition (KA)) does not differ in strength as a function of students' cognitive capital in online learning. The pattern of different levels of the moderator (i.e., cognitive capital) is presented in Table 11 (Panel A). Specifically, with an increase of cognitive capital from medium to high level, the indirect mechanism through emotional engagement in online learning remains to be positive and significant, and thus is not significantly moderated by students' cognitive capital. Similarly, with an increase of cognitive capital from low to high level, the indirect mechanism through cognitive engagement in online learning remains to be positive and significant, and thus is not significantly moderated by students' cognitive capital.

The results of the moderated mediation tests (Table 10, Panel B) provided a non-significant and positive index for relational capital in online learning, which implies that the indirect mechanism (i.e., use of social features (USF) -> emotional engagement (EE) & cognitive engagement (CE) -> knowledge acquisition (KA)) does not differ in strength as a function of students' relational capital in online learning. The pattern of different levels of the moderator (i.e., relational capital) is presented in Table 11 (Panel B). Specifically, with an increase of cognitive capital from low to high level, the indirect mechanism through emotional engagement in online learning remains to be positive and significant, and thus is not significantly moderated by students' cognitive capital. Similarly, with an increase of cognitive capital from medium to high level, the indirect mechanism through cognitive engagement in online learning remains to be positive and significant, and thus is not significantly moderated by students' cognitive capital.

In addition, the results of the moderated mediation tests (Table 10, Panel C) provided a non-significant and positive index for structural capital in online learning, which implies that the indirect mechanism (i.e., use of social features (USF) -> emotional engagement (EE) & cognitive engagement (CE) -> knowledge acquisition (KA)) does not differ in strength as a function of students' structural capital in online learning. The pattern of different levels of the moderator (i.e., structural capital) is presented in Table 11 (Panel C). Specifically, with an increase of structural capital from low to medium level, the indirect mechanism through emotional engagement in online learning remains to be positive and significant, and thus is not significantly moderated by students' cognitive capital. Similarly, with an increase of cognitive capital from low to high level, the indirect mechanism through cognitive engagement in online learning remains to be positive and significant, and thus is not significantly moderated by students' cognitive capital.

Collectively, the mediation test outcomes using Hayes' Process model align with those obtained from Smart PLS, affirming the robustness of the mediation findings. While the indirect effects are noteworthy via emotional and cognitive engagement, the more intricate moderated mediation effects are less pronounced.

Table 10. Index of moderated mediation for the cognitive capital

Panel A - Moderator: Cognitive capital (CC)					
Indirect mechanism	**Effect**	**SE**	**LLCI**	**ULCI**	**Zero include?**
USF->EE->KA	.0192	.0182	-.0128	.0600	Yes
USF->CE->KA	.0160	.0183	-.0171	.0549	Yes
Panel B - Moderator: Relational capital (RC)					
Indirect mechanism	**Effect**	**SE**	**LLCI**	**ULCI**	**Zero include?**
USF->EE->KA	-.0045	.0123	-.0310	.0191	Yes
USF->CE->KA	-.0197	.0154	-.0527	.0081	Yes
Panel C - Moderator: Structural capital (SC)					
Indirect mechanism	**Effect**	**SE**	**LLCI**	**ULCI**	**Zero include?**
USF->EE->KA	.0035	.0135	-.0222	.0310	Yes
USF->CE->KA	.0157	.0157	-.0131	.0483	Yes

Table 11. Conditional indirect effects at different levels of the moderating factors

Panel A - Moderator: Cognitive capital (CC)						
SPSS PROCESS Model ID	**Indirect mechanism**	**Level of CC**	**Effect**	**SE**	**LLCI**	**ULCI**
7	USF->EE->KA	Low	.0470	.0285	-.0043	.1092
		Mean	.0728*	.0260	.0285	.1316
		High	.0856*	.0324	.0312	.1568
	USF->CE->KA	Low	.0517*	.0288	.0032	.1152

		Mean	.0732*	.0282	.0242	.1351
		High	.0839*	.0350	.0252	.1595
Panel B - Moderator: Relational capital (RC)						
SPSS PROCESS Model ID	**Indirect mechanism**	**Level of RC**	**Effect**	**SE**	**LLCI**	**ULCI**
7	USF->EE->KA	Low	.0620*	.0263	.0200	.1204
		Mean	.0593*	.0234	.0200	.1103
		High	.0544*	.0258	.0085	.1104
	USF->CE->KA	Low	.0791*	.0310	.0269	.1444
		Mean	.0631*	.0255	.0201	.1178
		High	.0419	.0268	-.0034	.0996
Panel C - Moderator: Structural capital (SC)						
SPSS PROCESS Model ID	**Indirect mechanism**	**Level of SC**	**Effect**	**SE**	**LLCI**	**ULCI**
7	USF->EE->KA	Low	.0446*	.0216	.0085	.0924
		Mean	.0483*	.0220	.0111	.0988
		High	.0523	.0311	-.0004	.1224
	USF->CE->KA	Low	.0645*	.0281	.0169	.1234
		Mean	.0810*	.0286	.0324	.1424
		High	.0991*	.0384	.0338	.1834

Note. *p < 0.05; SE = Standard Error; LLCI = Lower Limit Confidence Interval; ULCI = Upper Limit Confidence Interval

6.5.4 Control Variable Analysis

Among the control variables, age, type of course, area of study, gender, length of online learning experience in the past three years, online learning synchronicity, and educational level did not have significant impacts on students' knowledge acquisition. However, both students' prior knowledge of the online course (β= 0.139; $p < 0.01$) and their prior knowledge about the online learning mode (β= 0.143; $p < 0.01$) have positive impacts on their knowledge acquisition.

Students who have prior exposure to the content covered in the online course—whether through previous study, related coursework, or relevant experience—are more likely to find it easier to grasp new concepts presented in the course (Yang, Lin, She, & Huang, 2015). Their familiarity with the subject matter can serve as a foundation upon which to build additional knowledge, enabling them to make connections more readily and comprehend new information more deeply (Panigrahi et al., 2018). Similarly, students who are already accustomed to the online learning environment tend to have a smoother transition into new online courses (Greenhow et al., 2022; Yang et al., 2015). They are familiar with the tools, platforms, and methods commonly used in online education, which can help reduce the learning curve associated with navigating the course materials and engaging with online activities. This prior knowledge of the online learning mode can contribute to a more efficient and effective learning experience.

6.6 Summary of Hypothesis Testing Results

The results of hypothesis testing are outlined in Table 12. While hypotheses H4a and H5a are not supported, the remaining hypotheses receive support. Further elaboration on the unsupported hypotheses is provided in the subsequent chapter. The predictors for knowledge acquisition collectively account for a variance of 0.404, indicating that these variables serve as significant predictors for the dependent variable, knowledge acquisition.

Table 12. Hypothesis Summary

Hypothesis Statement	**Results (coefficient and sig. level)**	**Supported or Not**
H1. Students' use of social features in online learning is positively associated with their emotional engagement in online learning.	0.217 (Sig. < 0.01)	Supported
H2. Students' use of social features in online learning is positively associated with their cognitive engagement in online learning.	0.269 (Sig. < 0.001)	Supported
H3a: Students' cognitive capital strengthens the association between their use of social features in online learning and emotional engagement in online learning.	0.112 (Sig. < 0.05)	Supported
H3b: Students' cognitive capital strengthens the association between their use of social features in online learning and cognitive engagement in online learning.	0.116 (Sig. < 0.05)	Supported
H4a: Students' relational capital weakens the relationship between students' use of social features in online learning and their emotional engagement in online learning.	-0.054 (Sig. > 0.08)	Not Supported

H4b: Students' relational capital weakens the relationship between students' use of social features in online learning and their cognitive engagement in online learning.	-0.122 (Sig. < 0.05)	Supported
H5a: Students' structural capital strengthens the relationship between students' use of social features in online learning and their emotional engagement in online learning.	0.024 (Sig. = 0.17)	Not Supported
H5b: Students' structural capital strengthens the relationship between students' use of social features in online learning and their cognitive engagement in online learning.	0.095 (Sig. < 0.05)	Supported
H6. Students' emotional engagement in online learning is positively associated with their knowledge acquisition in online learning.	0.303 (Sig. < 0.001)	Supported
H7. Students' cognitive engagement in online learning is positively associated with their knowledge acquisition in online learning.	0.275 (Sig. < 0.001)	Supported

Chapter 7. Discussion and Conclusion

This study explores the impact of students' use of social features in online learning on knowledge acquisition in online learning through emotional and cognitive engagement experiences. Furthermore, it delves into the moderating influence of social capital in online learning. Specifically, the research highlights three dimensions of social capital—cognitive, relational, and structural—and their moderating effects on the connections between students' use of social features and their emotional and cognitive engagement experiences in online learning. Data were gathered through a survey methodology to gauge students' perceptions of online learning, with structural equation modeling employed to analyze survey responses. Discussion on each hypothesis and its corresponding findings are detailed below.

7.1 Discussion of Findings

This research examined seven primary hypotheses, with two sub-hypotheses—H4a and H5a—not being supported, while the remaining hypotheses receiving support. Our first hypothesis was confirmed, indicating a positive correlation between students' utilization of social features in online learning and their emotional engagement in online learning. This aligns with the existing literature (e.g., Iqbal et al., 2022; Molinillo, Aguilar-Illescas, Anaya-Sánchez, & Vallespín-Arán, 2018), which posits that social interactions foster emotional connections and a sense of bonding among students in online learning. Our discovery further advances this understanding by demonstrating that interaction via social features in online learning similarly enhances students' emotional engagement.

The second hypothesis was similarly validated, indicating a positive association between students' utilization of social features in online learning and their cognitive engagement in online learning. This aligns with the existing literature (e.g., Molinillo et al., 2018; Xiao & Hew, 2024), which suggests that social interaction not only fosters networking but also provides informational benefits, thus enhancing students' cognitive engagement in online learning. This research reinforces this notion in online learning, where students' use of social features facilitates informational exchange through online channels, ultimately bolstering their cognitive engagement.

This study categorizes student engagement into cognitive and emotional engagement for a more nuanced understanding of how different factors influence these distinct aspects of engagement. Emotional engagement, which involves feelings of interest and enthusiasm, can be deeply affected by use of social features facilitating sense of belonging and connectedness. Cognitive engagement, on the other hand, relates to the intellectual investment in tasks and can be enhanced by collaborative social features that encourage deeper thinking and problem-solving. As such, use of social features plays a crucial role in both types of engagement through different mechanisms. This differentiation helps in designing targeted strategies to enhance overall engagement effectively.

The moderating influence of cognitive capital was also affirmed in H3a, indicating that students' cognitive capital enhances the link between their utilization of social features in online learning and their emotional engagement in online learning. This discovery aligns with existing literature on cognitive capital within online communities (Chang & Chuang, 2011; Chiu et al., 2006; Fulk & Yuan, 2013; Urzelai & Puig, 2019), which suggests that a shared language associated with cognitive capital fosters emotional exchange. Moreover, our finding extends understanding of the moderating role of cognitive capital in online learning by emphasizing its reinforcing effect on the relationship between students' use of social features in online learning and their emotional engagement.

The moderating role of students' cognitive capital is further confirmed in H3b, indicating its capacity to enhance the connection between students' use of social features in online learning and their cognitive engagement with the learning material. This finding aligns with previous perspectives that suggest a shared language associated with cognitive capital can facilitate knowledge and information exchange (e.g., Chiu et al., 2006; Wellman et al., 2001), consequently bolstering the impact of students' use of social features on their cognitive engagement.

However, the moderating role of relational capital on the relationship between students' use of social features in online learning and their emotional engagement with learning was not supported. Specifically, this moderating impact was non-significant. One potential reason could be that the study might have been conducted during a specific period influenced by external social factors, such as the COVID-19 pandemic. This global crisis could have altered the dynamics of online learning and interpersonal relationships, potentially affecting the moderating role of relational capital (Adedoyin & Soykan, 2023; Hollister et al., 2022). For instance, the pandemic might have restricted students' opportunities for offline interaction, leading them to rely more heavily on online social features for engagement (Dhawan, 2020; Huang & Wang, 2023). Consequently, even if students possessed strong relational quality and would prefer close networking through offline interaction, their reliance on online interactions during the pandemic might have diminished the salience of relational capital's moderating effect on the relationship between social feature usage and emotional engagement with learning.

The findings affirm hypothesis H4b, indicating that students' relational capital attenuates the association between their use of social features in online learning and their cognitive engagement in online learning. This discovery aligns with existing literature on weak ties, which posits that weak ties offer greater informational advantages compared to strong ties (Granovetter, 1973; Kavanaugh et al., 2003). Weak ties, characterized by weaker relational quality, are more apt to introduce novel information and perspectives (Levin & Cross, 2004). However, students' relational capital is characterized as a strong tie relationship, which hinders this influx of new information for enriching student interactions, and thereby impedes the connection between students' utilization of social features in online learning and their cognitive engagement with the learning material.

The findings do not support hypothesis H5a, which suggests that students' structural capital strengthens the relationship between their use of social features in online learning and their emotional engagement in online learning. One potential reason for this lack of support could be that having a large number of connections might lead to social overload (Lee, Son, & Kim, 2016), where students feel overwhelmed by the volume of interactions. This overload could detract from their ability to emotionally engage with the learning experience. Additionally, depending on fellow students' personal interests and goals, students may find it challenging to emotionally connect with content when their peers' interests diverge significantly from their own (Phirangee & Malec, 2017; Xie, Di Tosto, Lu, & Cho, 2018). For example, the wide age range in the gathered sample suggests that there may be varying interests among students in the context of online learning. Additionally, varying levels of online learning experience and different familiarity with the online learning subject can lead to diverse student learning interests. It is possible that students' heterogeneous backgrounds may make them feel less connected with each other, even if they interact often with each other.

Hypothesis H5b is supported, indicating that students' structural capital strengthens the relationship between their use of social features in online learning and their cognitive engagement in online learning. This finding is consistent with existing literature suggesting that a larger number of network connections can enrich the overall flow of information by providing opportunities to utilize online social features for connectivity (Cocosila & Igonor, 2015; Wellman et al., 2001; Xie et al., 2018). Consequently, students are more likely to be cognitively engaged due to the abundance of information and inputs available to them. Moreover, this finding reinforces prior literature which suggests that individuals may have numerous weak ties for informational exchange, while emotional exchange tends to occur within a smaller circle of close ties (Granovetter, 1973; Kavanaugh et al., 2003; Tortoriello et al., 2012). Therefore, while the positive moderating role of structural capital in H5b is upheld, the proposed moderating role in H5a is not supported.

Lastly, the positive influence of emotional and cognitive engagement on student knowledge acquisition in online learning is affirmed in hypotheses H6 and H7, respectively. This result aligns with prior literature emphasizing the significance of student engagement in learning outcomes (Gray & DiLoreto, 2016; Jennings & Angelo, 2006; Xiao & Hew, 2024). By confirming the crucial role of both emotional and cognitive engagement, this study extends the existing literature on student engagement in online learning.

7.2 Contribution to Theory

This research significantly contributes to the advancement of theory in several key ways.

Firstly, it significantly enriches the online learning literature by examining the antecedent of knowledge acquisition in online learning and relevant mediators and moderators. With a particular emphasis on the interplay of students' use of social features and social capital in online learning, this study provides a comprehensive understanding of how students' use of social features influences the student knowledge acquisition in online learning. While the extant literature (Andel et al., 2020; Kear et al., 2014; Phirangee & Malec, 2017) mainly examines the impact of social features design on students' social presence and satisfaction perceptions in online learning, this dissertation extends the existing literature by shedding light on its influence on students' emotional and cognitive engagement and ultimately students' knowledge acquisition learning outcome. By shedding light on these complex dynamics, the research offers valuable insights into the effectiveness of online learning, thus addressing a crucial gap in the existing literature.

In addition, this research delves into the mechanism of student engagement, encompassing both emotional and cognitive dimensions, thus providing a nuanced understanding of the mechanism through which use of social features impacts students' knowledge acquisition in online learning. Unlike previous studies primarily focused on social presence as the mechanism driving the influence of social features on learning outcomes, this research extends our understanding by identifying additional emotional and cognitive engagement mechanisms in online learning. By shedding light on these alternative pathways through which social features in online learning affect students' knowledge acquisition, this study enriches the online learning literature, contributing to a more comprehensive understanding of the theoretical frameworks underlying the impact of social features on knowledge acquisition in online learning.

Furthermore, this research advances the utilization of dual processing theory within the realm of online learning, elucidating its relevance in understanding the dual processing nature inherent in the utilization of social features and social capital in online learning. Although prior research has advocated for the integration of dual processing theory within online learning frameworks, this study stands as a pioneering endeavor by empirically examining the applicability of this theory in such contexts. By undertaking empirical testing, this research not only substantiates the theoretical underpinnings of dual processing theory within online learning but also contributes to the refinement and validation of its application, thereby enhancing our understanding of the dual engagement mechanisms involved in utilizing social features in online educational settings.

Moreover, this study goes beyond mere exploration of use of social features and also identifies the moderating social capital that influence the use of social features in online learning on students' emotional and cognitive engagement. Through a nuanced examination of the three dimensions of social capital, the research uncovers how students' engagement with social features can yield varying effects on their emotional and cognitive involvement, contingent upon the composition of their social capital. This recognition of the dynamic interplay between social capital and online learning underscores the need for a more holistic understanding of the factors shaping educational experiences in the online learning realm.

Lastly, the research extends the application of social capital theory into the domain of online learning, thereby broadening our understanding of its relevance and implications in educational settings. By uncovering the diverse moderating effects associated with the three types of social capital, the study challenges conventional assumptions about the inherent benefits of possessing higher social capital. It highlights the potential drawbacks of overreliance on strong ties with strong relational quality, particularly when such connections fail to provide novel or diverse information. This nuanced perspective on the role of social capital prompts a reevaluation of traditional theories and calls for a more contextualized approach to understanding its influence in educational contexts.

Overall, this research makes significant contributions to theory by deepening our understanding of the dynamics underlying student knowledge acquisition in online learning, elucidating the nuanced impacts of social capital, and advocating for a more holistic and contextually sensitive approach to educational research and practice.

7.3 Contribution to Practice

From a practical standpoint, the insights gleaned from this study regarding student knowledge acquisition in online learning offer valuable guidance for distance educators and policymakers tasked with strategic planning, policy formulation, and the enhancement of educational practices in online learning. In particular, the study underscores the importance of leveraging social features in online learning that facilitate student interaction, thereby fostering enhanced knowledge acquisition.

Furthermore, this research also holds relevance for online learning providers, providing crucial considerations for optimizing the design of social features to promote students' emotional and cognitive engagement in online learning. Depending on students' available social capital, online learning providers should tailor features to facilitate shared language among students, encourage connections with a diverse array of peers to facilitate informational flow, while also mitigating the risk of social overload that could impede effective use of social features in online learning. Moreover, online learning providers should consider incorporating features that mimic close, small social circles to replicate the dynamics of offline interactions, particularly for students with strong relational ties.

Online learning educators can also leverage students' prior knowledge to design courses that build upon existing foundations. Understanding students' backgrounds allows for the creation of learning materials that are appropriately challenging yet accessible, facilitating deeper comprehension and engagement. By recognizing students' familiarity with the subject matter and online learning, instructors can offer personalized learning paths. This might include advanced assignments for students with prior exposure to the content or additional resources for those who need more support. This approach fosters active participation and encourages students to connect new information with what they already know.

The implications of the study's findings extend beyond the realm of online learning to encompass blended and face-to-face courses with an online component. While social features may be more limited in traditional classroom settings, the study underscores the pivotal role of student interaction, whether through digital platforms or in-person communication, in enhancing engagement and facilitating knowledge acquisition outcomes. Thus, educators across various educational modalities can benefit from prioritizing opportunities for meaningful student interaction to optimize learning experiences.

In summary, this research not only offers practical guidance for educators and online learning providers in but also underscores the broader relevance of fostering effective student interaction across diverse educational settings to promote optimal engagement and learning outcomes.

7.4 Limitations and Future Research

As with all research studies, there are limitations within this study that warrant exploration in future research endeavors. Firstly, a limitation of this dissertation is that it did not explore student learning outcomes beyond knowledge acquisition. Future research should address this gap by examining other types of student learning outcomes in online learning, such as psychological and behavioural outcomes, to provide a more comprehensive understanding of student learning outcomes in online learning.

Secondly, while this study examines the impact of students' use of social features on knowledge acquisition, it does not delve into the specific design aspects of these social features that may optimize and refine their effectiveness in promoting knowledge acquisition. Given the diversity of social features available in online learning platforms, further investigation into how to tailor and fine-tune their design is crucial for fully harnessing the potential of these platforms to enhance learning outcomes.

Thirdly, the data collection in this study was confined to North America, thus limiting the generalizability of the insights to this geographical region. As educational designs and online learning platforms vary across countries and cultures, future research should aim to replicate the research model in different cultural contexts to improve the external validity of the findings. By testing the research model in diverse cultural settings, a more comprehensive understanding of the factors influencing knowledge acquisition in online learning can be achieved.

Fourthly, this study relies on survey data as the primary source of information, which, while appropriate and suitable, has inherent limitations. To complement and enrich the findings, future studies could benefit from collecting feedback from students through qualitative methods such as interviews, focus groups, and observations of online learning activities, as well as conducting longitudinal investigations to provide a more comprehensive and nuanced understanding student learning outcomes in online learning. Future research could also incorporate secondary data sources, such as students' real usage activity or logs within online learning platforms, to analyze usage patterns and behaviours more accurately. Furthermore, future research can incorporate objective measures or alternative measures of learning outcomes other than perceived knowledge acquisition (e.g., academic performance).

Fifthly, the participants in this research were recruited through an online marketing research firm, encompassing university students from various regions and institutions. Despite efforts to control demographic variables such as age, gender, and major, there remains the possibility of unaccounted factors influencing the outcomes. To address this, future studies may consider conducting research within a single university program, where students share a common learning environment. This approach would minimize the potential influence of uncontrolled factors and enhance the internal validity of the findings.

Lastly, this research focuses on online learning in higher education, which may not be generalized to other types of online learning contexts (e.g., online learning for elementary or secondary education, and blended learning). Our research incorporates the COVID-19 context as a contextual background where online learning serves as a major portion of course delivery approach in higher education. Our research findings could be altered in contexts where social distancing requirements are not applicable and face-to-face interactions are the principal learning approach. For instance, blended learning is a combination of online and face-to-face instruction, where a portion of the course content and activities are delivered online, supplemented by in-person sessions (Chiu, 2021). The impact of students' use of social features on knowledge acquisition could be altered in blended learning where students can also interact with each other face-to-face. Future research may validate the impact of social capital on student online learning experience in these alternative contexts.

In summary, addressing these limitations through future research endeavors will not only deepen our understanding of the dynamics within online learning environments but also contribute to the development of more effective educational practices and policies tailored to diverse cultural contexts and student populations.

7.5 Conclusion

In conclusion, as post-secondary institutions increasingly adopt online learning, understanding how to enhance student learning outcomes in this context is imperative. This research addresses three main research questions pertaining to the influence of students' use of social features in online learning on their engagement experiences and learning outcome of knowledge acquisition in online learning, as well as the moderating role of various dimensions of social capital. Drawing upon dual process theory and social capital theory, a research model was developed to elucidate these relationships. Final survey data from 306 participants with online learning experience within a university program was analyzed using structural equation modeling. The findings reveal that students' use of social features positively impacts both emotional and cognitive engagement, subsequently affecting knowledge acquisition. Moreover, cognitive capital positively moderates the relationship between social feature usage and engagement, while relational capital negatively moderates the impact on cognitive engagement. Structural capital, on the other hand, positively moderates the impact on cognitive engagement but does not affect emotional engagement. This research contributes to the online learning literature by uncovering how social feature usage influences student knowledge acquisition in online learning through emotional and cognitive engagement experiences, and by identifying positive and negative moderating factors that further shape these relationships. Ultimately, these findings offer valuable insights for online learning providers and instructors in post-secondary institutions, informing the design of social features and use of social capital that promote students' emotional and cognitive engagement leading to greater knowledge acquisition in online learning.

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Appendix A. MREB Clearance Certificate

McMaster University | Research Ethics Board

McMaster University Research Ethics Board (MREB)
c/o Research Office for Administrative Development and Support
MREB Secretariat, GH-305
1280 Main St. W.
Hamilton, Ontario, L8W 4L8
email: ethicsoffice@mcmaster.ca
Phone: 905-525-9140 ext. 23142

CERTIFICATE OF ETHICS CLEARANCE TO INVOLVE HUMAN PARTICIPANTS IN RESEARCH

Today's Date: Oct/9/2020

Supervisor: Dr. Milena Head
Student Principal Investigator: Ms. Junyi Yang
Applicant: Junyi Yang
Project Title: Enhancing student experience in online learning: A social capital perspective
MREB#: 4967

Dear Researcher(s)

The ethics application and supporting documents for MREB# 4967 entitled "Enhancing student experience in online learning: A social capital perspective" have been reviewed and cleared by the MREB to ensure compliance with the Tri-Council Policy Statement and the McMaster Policies and Guidelines for Research Involving Human Participants.

The application protocol is cleared as revised without questions or requests for modification. The above named study is to be conducted in accordance with the most recent approved versions of the application and supporting documents.

If this project includes planned in-person contact with research participants, then procedures for addressing COVID-19 related risks must be addressed according to the current processes communicated by the Vice-President (Research) and your Associate Dean (Research). All necessary approvals must be secured before in-person contact with research participants can take place.

Ongoing clearance is contingent on completing the Annual Report in advance of the yearly anniversary of the original ethics clearance date: Oct/09/2021. If the Annual Report is not submitted, then ethics clearance will lapse on the expiry date and Research Finance will be notified that ethics clearance is no longer valid (TCPS, Art. 6.14).

An Amendment form must be submitted and cleared before any substantive alterations are made to the approved research protocol and documents (TCPS, Art. 6.16).

Researchers are required to report Adverse Events (i.e. an unanticipated negative consequence or result affecting participants) to the MREB secretariat and the MREB Chair as soon as possible, and no more than 3 days after the event occurs (TCPS, Art. 6.15). A privacy breach affecting participant information should also be reported to the MREB secretariat and the MREB Chair as soon as possible. The Reportable Events form is used to document adverse events, privacy breaches, protocol deviations and participant complaints.

Document Type	File Name	Date	Version
Secondary Use of Data	12.14 List of variables for secondary data	Jul/06/2020	v1
Response Documents	Summary of Revisions	Oct/08/2020	1.0
Recruiting Materials	10.6.7 Email Recruiting Script - Appendix 1 _Revised version	Oct/08/2020	v2
Test Instruments	11.14.7 Survey question _Revised	Oct/08/2020	v2
Consent Forms	16.6.7 survey preamble and consent_revised	Oct/08/2020	v2
Consent Forms	16.6.3 LOI_Revised	Oct/08/2020	v2

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Appendix B. Summary of Literature regarding Antecedents toward Student Learning Outcomes in Online Learning

Study	Student learning outcomes	Antecedents and their categories	Findings
(Xiao & Hew, 2024)	Emotional and cognitive engagement Learning performance	**Technological antecedents** Gamification design: tangible versus intangible rewards	Through a controlled experiment, this study found that tangible rewards in online learning facilitated students to experience stronger engagement and achieve better performance, as compared to intangible rewards.
(Cheng et al., 2023)	Achievement emotional profiles Environmental barriers	**Motivational, cognitive, and social antecedents** Time management Motivational regulation Academic procrastination Instructor immediacy Peer interaction Help-seeking	The Pure Positive Emotion profile correlated with improved time management and motivational regulation, as well as reduced academic procrastination. Text mining analysis of qualitative data revealed that students in the Blends of Negative Emotions and Nonemotional profiles encountered significant environmental barriers, including issues related to instructor immediacy, peer interaction, help-seeking, and technical difficulties.

		Technical difficulties	
(Du et al., 2023)	Student engagement	**Technological antecedents** Reminder function design: direct or indirect recommendations	When giving direct recommendations (e.g., specific steps or tasks to be completed) in online self-regulated learning, students are more engaged with the learning module, as compared to indirect recommendations (e.g., general reminder to complete all tasks).
(Huber et al., 2023)	Learning outcome Task engagement	**Technological and cognitive antecedents** Game elements Self-efficacy	Game elements affected both participant attrition and engagement. Participants with low self-efficacy were particularly prone to drop out in the non-game condition. Game elements also affected both learning efficacy and efficiency. Task attractivity partially mediates the effect of game elements on learning outcomes.
(Jackson & Serenko, 2023)	Affective stress response Coping toward stress	**Technological antecedent**	The study identified that the primary cause of student stress is the unreliability of technology, closely followed by academic challenges. The most common emotional

		Move to online learning under the COVID-19 lockdown	reaction observed is disaffection, characterized by passive disengagement, as well as feelings of distraction and lack of focus. In response to these challenges associated with online learning, students predominantly employ problem-focused coping strategies, with a strong emphasis on seeking university assistance and self-organization.
(Yousaf et al., 2023)	Student engagement	**Social antecedents** Interacting with other students	Student interaction can facilitate students to get more engaged with online learning.
(Ong & Quek, 2023)	Emotional, participatory, and performance engagement	**Social antecedents** Student teacher interaction	When students have effective interaction with teachers in online learning, their social needs can be fulfilled, and they are more likely to engage with their online learning.
(Huang & Wang, 2023)	Student engagement and academic performance	**Motivational antecedents**	Students' psychological needs of autonomy and competence promote optimal motivation, positive

		Psychological needs of autonomy, competency, relatedness	engagement and academic achievement in online learning
(Roque-Hernández et al., 2023)	Student engagement and satisfaction	**Technological antecedents** Use of interactive communication tools Instructor presence	Use of interactive communication tools in online learning can enhance instructor presence, which leads to more student engagement and satisfaction.
(Wang et al., 2023)	Student academic performance	**Cognitive and motivational antecedents** Online learning readiness Emotional competence	For college students, only online learning readiness (e.g., computer skills or self-control in an online learning environment) showed a significant positive relationship with online academic performance during COVID-19.
(Hollister et al., 2022)	Student engagement	**Social antecedents** Limitation of staying connected to peers and instructors	Students feel disconnected in online learning during COVID-19, which negatively influence their engagement. However, their feel more comfortable to

		Feeling more comfortable to ask and answer questions	ask and answer questions, which benefit them to get engaged during the online class.
(Hew et al., 2022)	Student engagement	**Cognitive antecedents** Perceived usefulness and ease of use of the chatbots in online learning tools	In the contest of using chatbots to set goals in online learning, students' perceived usefulness and ease of use of the chatbots in online learning can positively associate with their learning engagement.
(Kim et al., 2022)	Perceived credibility of online learning Retention in AI-enabled online learning	**Technological antecedents** AI voice: machinelike vs. humanlike AI expertise: novice vs. expert	The results suggest that students perceive AI instructors with a humanlike voice as more credible compared to those with a machinelike voice. Additionally, the study reveals that social presence acts as a mediator in the relationship between the voice of an AI instructor and their perceived credibility. Ultimately, the perceived credibility of an AI instructor positively impacts students' intentions to enroll in future courses taught by AI instructors.

(Rizvi et al., 2022)	Learner progress	**Course-related and demographic antecedents** Variation in course activities, such as articles, videos, discussions and quizzes predicted learner persistence	Specific learning activities, such as discussions, may promote advancement for learners in certain contexts, like Anglo-Saxon, while hindering progress in others, such as South Asia. This study provides fresh perspectives on the influence of cultural diversity on preferences in learning design.
(Szopiński & Bachnik, 2022)	Students' preference for online learning	**Cognitive antecedents** Cost of commuting to the university	Students' cognitive evaluation of the cost to commute to the university can influence their choice of online or offline class.
(Zhao et al., 2022)	Student performance	**Social, motivational and demographic antecedents** Geographic area: rural versus urban Intrinsic motivation to learn	The study confirmed the presence of a digital outcome divide between rural and urban students. Second, differences were observed between rural and urban students in habitus (i.e., intrinsic motivation) and various forms of capital, such as cultural (i.e., e-learning self-

		Capital including cultural, social capitals	efficacy) and social capital (i.e., parental and teacher support), which are identified as the primary factors contributing to the digital outcome divide.
(Dietrich et al., 2021)	Course performance Students' attitudes toward online learning Self-efficacy	**Technological antecedent** Individualized design of online learning tool	The personalized design intervention had a positive influence on students' attitudes and self-efficacy concerning inclusive education. However, it did not affect course performance, course-related self-efficacy, and task values.
(Gopal et al., 2021)	Students' satisfaction and performance	**Cognitive and course design antecedents** Quality of instructor Course design Instructor's prompt feedback Student expectations	Instructor effectiveness, appropriate design of online course, prompt feedback from instructors, and students' expectation which can be fulfilled through the online course delivery all contribute to higher students' satisfaction, which leads to better students' performance.

(Bravo-Agapito et al., 2021)	Student performance	**Technological and demographic antecedents** Access to student portal, questionnaire visits and attempts in student portal, task submission in student portal, and student age.	Age was identified as a negative predictor of the performance of students. In addition, cluster analysis found five groups of students and suggests that number of interactions with the student portal Moodle are closely related to performance of students.
(Chiu, 2021)	Engagement	**Technological antecedents** Digital support which refers to the design of technological learning environments to support students' innate needs.	Digital support enables students to satisfy their psychological needs, such as autonomy, relatedness, and competence, and thus can facilitate students' engagement in blended learning.
(Spencer & Temple, 2021)	Learning performance	**Demographic and cognitive antecedents**	Females display better academic performance than males, and minority students have lower performance

		Age, gender, race Academic performance level	than the majority students. Age, current academic performance have positive impact on students online learning performance.
(El-Sabagh, 2021)	Student engagement	**Technological and cognitive antecedents** Learning styles Adaptive learning environment	Adaptive online learning environment should be designed to match students' learning styles to achieve enhanced student engagement with the learning environment.
(Alenezi, 2020)	Student performance	**Technological antecedents** Use of e-learning materials and tools	The research revealed that increased utilization of e-learning materials and tools within an educational setting correlates with enhanced student performance and teaching efficiency.
(Alghamdi et al., 2020)	Academic performance	**Technological and demographic antecedents**	Multitasking in online classroom negative influences student academic performance, while this negative

		Multitasking of in online classroom Gender	impact is weaker for female students, than for male students, due to female students' better self regulation efficacy.
(Poondej & Lerdpornkulrat, 2020)	Engagement	**Technological antecedents** Gamified e-learning course	Gamified e-learning course was distributed to university students through online learning portal. Students were found to engage with the online learning tool more frequently with the gamified design.
(Aguilera-Hermida, 2020)	Cognitive engagement and academic performance	**Cognitive and motivational** Attitude, affect and motivation toward online learning; ease of use of technology and self-efficacy accessibility	The results suggest the positive and significant impact of attitude, motivation, self-efficacy, and technology utilization on students' cognitive engagement and academic performance.

(Wei & Chou, 2020)	Learning performance Students' satisfaction	**Cognitive and motivational antecedents** Self-efficacy (computer/Internet and online communication) Motivation for learning Learner control	Students' self-efficacy toward computer/Internet and motivation for learning have significant and positive impact on students' online discussion score and their satisfaction.
(Rabin et al., 2019)	Utilitarian based evaluation of the course	**Cognitive antecedents** Usability of online learning, goal-setting, learning effort	Learner satisfaction was significantly affected by: the importance of the MOOC's benefits; online self-regulated learning - goal setting; number of video lectures accessed; and, perceived course usability.
(Alqurashi, 2019)	Student satisfaction and perceived learning	**Cognitive and social antecedents** Online learning self-efficacy (OLSE), learner–	The study found that LCI was the strongest and most significant predictor of student satisfaction, while OLSE was the strongest and most significant predictor of

		content interaction (LCI), learner– instructor interaction (LII), and learner–learner interaction (LLI)	perceived learning. However, LLI was not predictive of student satisfaction and perceived learning.
(Huang, Hew, & Lo, 2019)	Behavioural and cognitive engagement	**Technological antecedents** Gamification-enhanced learning	Gamification-enhanced learning can promote undergraduate students' behavioural and cognitive engagement during flipped learning where students gain first exposure of class materials in online format.
(Klock et al., 2019)	Engagement	**Technological antecedents** User-centred gamification design	This study proposes a framework focused on the user-centred gamification in online learning, considering personal, functional, psychological, temporal, playful, implementable, and evaluative properties. The controlled experiment with 139 students revealed an increase in students' interaction, engagement, and satisfaction.

(Sun et al., 2019)	Emotional engagement and behavioural engagement	**Motivational antecedents** Intrinsic motivation	Fulfillment of three basic psychological needs for autonomy, competence and relatedness have significant positive effects on intrinsic motivation, which increases students' emotional engagement in online learning. Relationship quality between students is also positively related to emotional engagement which further influences behavioural engagement.
(Paul & Jefferson, 2019)	Student performance	**Demographic variable** Gender and class rank (i.e., freshman, sophomore, junior, senior)	No notable variance in student performance was observed between online learners and face-to-face (F2F) learners overall, nor in relation to gender or class rank.
(Niculescu et al., 2015)	Emotional engagement Exam outcome	**Motivational antecedents** Enjoyment of online learning	Enjoyment of online learning has a positive relationship with students' course performance, whereas hopelessness perception of online learning has a negative relationship with students' course performance.

(Terpend et al., 2014)	Course evaluation grades	**Technological antecedents** Adoption of e-textbook	Adoption of e-textbook is positively related to students' course evaluation grades.
(Kear et al., 2014)	Engagement	**Technological antecedents** Presence of personal profiles and photos in online learning	Personal profiles and photos help some online learners to feel in touch with each other and get more engaged with online learning.
(Pellas, 2014)	Emotional, behavioural and cognitive engagement	**Cognitive antecedents** Self-efficacy, self-regulation	Self-efficacy, meta-cognitive self-regulation, and self-esteem all positively impact emotional, cognitive, and behavioural engagement.
(Shen et al., 2013)	Engagement	**Cognitive antecedents** Self-efficacy	Self-efficacy toward online learning tools and interaction can influence students satisfaction toward online learning.
(Chen & Jang, 2010)	Cognitive engagement Learning achievement	**Motivational antecedents** Need for contextual support	This study finds a significant positive relationship between need satisfaction / contextual support and

		Need for satisfaction	learning outcomes. These students need will drive their engagement with the learning platform, which facilitate better learning outcomes.
(Moreno-Ger et al., 2008)	Engagement with learning	**Technological antecedents** e-adventure game	This study proposes a generic gameplay design that could support several pedagogical approaches, including features such as real-time adaptation to fit learner needs, in-game assessment and grading, and the integration with online education environments following the learning objects model. The adoption of game in online learning help improve students' engagement with learning.
(Bates & Khasawneh, 2007)	Cognitive engagement Knowledge mastery perception	**Emotional, social and cognitive antecedents** Anxiety toward learning	Students' anxiety toward using online learning is negatively related to students' knowledge mastery perception. However, previous success with online learning tools, training, and self-efficacy in using online

		Prior success and training with online learning Self-efficacy Instructors' feedback	learning tools have positive impacts on students' knowledge mastery perception. In addition, instructors' feedback has positive impacts on students' cognitive engagement with online learning.
(Peltier et al., 2007)	Emotional engagement The amount of learning	**Social antecedents** Student-student/instructor interaction	Both instructor-student interaction and student-student interaction have positive impacts on students' enjoyment in learning and their perceived amount of learning.
(Eom et al., 2006)	Emotional engagement Learning outcome	**Social, motivational, cognitive, and course design antecedents** Course structure, motivation, and feedback	Course structure, instructor feedback, self-motivation, learning style, interaction and instructor knowledge & facilitation all have positive impacts on students' emotional engagement with online learning. Instructor feedback, self-motivation, learning styles, and user satisfaction all have positive impacts on students' learning outcome.

Appendix C. Survey Screenshots

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Online learning survey for university students

This survey is administered by Dr. Milena Head and Ms. Junyi Yang (Ph.D. Candidate) at the DeGroote School of Business, McMaster University. The purpose of this study is to examine factors that may impact student experiences in online learning at the university/college. This survey should take approximately 10-15 minutes to complete.

Please answer the questions carefully. Respondent with low-quality answers will be removed from this study.

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LETTER OF INFORMATION

Research Sponsor: Natural Sciences and Engineering Research Council

Purpose of the Study: In this research project, we are hoping to learn how to enhance student's learning experience in online learning.

Procedures involved in the Research: You will be asked questions in the online survey that will take about 10 minutes. The questions involve multiple choice and open-ended questions regarding your perceptions in your online learning at your university. Upon completion of the survey and passing the quality check, you will get the reimbursement.

Potential Harms, Risks or Discomforts: The risks involved in participating in this study are minimal. The survey is totally anonymous and no identifiable information is required through the survey.

Potential Benefits: The research may not benefit you directly. We hope to learn more about student experience in online learning, which could provide insights for future design and delivery of courses through online learning.

Confidentiality: Every effort will be made to protect your confidentiality and privacy. The archive of the data will be maintained on a computer protected by a password.

Participation and Withdrawal: Your participation in this study is voluntary. It is your choice to be part of the study or not. You can withdraw the study during anytime when answering the survey questions. However, after completing the study, there is no way for withdrawal, as the survey data is anonymous.

Information about the Study Results: I expect to have this study completed by approximately winter 2023. If you would like a brief summary of the results, please let me know how you would like it sent to you.

Questions about the Study: If you have questions or need more information about the study itself, please contact me at: Yangj263@mcmaster.ca

This study has been reviewed by the McMaster University Research Ethics Board and received ethics clearance (protocol number: MREB 4967). If you have concerns or questions about your rights as a participant or about the way the study is conducted, please contact:

McMaster Research Ethics Secretariat
Telephone: (905) 525-9140 ext. 23142
C/o Research Office for Administrative Development and Support
E-mail: ethicsoffice@mcmaster.ca

→

I consent to participate in this study.

- ○ Yes
- ○ No

Have you ever engaged in online learning (i.e., learning courses online instead of in class) in a university/college in the past three years?

- ○ Yes, for more than 1 semester
- ○ Yes, for 1 semester
- ○ Yes, but less than 1 semester.
- ○ No

Where is your university/college located?

- ○ Canada
- ○ U.S.
- ○ Other

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Please recall your online learning experience in a university/college and provide the following details.

1) The time period of your online learning experience

2) The course topics

3) Your general feelings toward online learning

→

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Which Faculty were you in when engaging in the online learning?

- ○ Business
- ○ Engineering
- ○ Health sciences
- ○ Science
- ○ Humanities
- ○ Social science
- ○ Other

→

Which year were you in when engaging in the online learning?

- ◯ Undergraduate – 1st year
- ◯ Undergraduate – 2nd year
- ◯ Undergraduate – 3rd year
- ◯ Undergraduate – 4th year
- ◯ Master's – 1st year
- ◯ Master's – 2nd year
- ◯ PhD
- ◯ Other

Was your online learning course-based (i.e., taking online courses) or research-based (i.e., conducting research)?

- ◯ Taking online courses
- ◯ Conducting research
- ◯ Other

→

In this section, please answer the questions based on your online learning experience.

Please read the questions and answers carefully and express your true feelings.

→

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To communicate in online learning, students largely rely on online social interaction features, such as video conferencing, online discussion forums, social networking websites, online messaging/chatting, online whiteboards, etc. Please describe your use of these online social interaction features.

	Completely disagree	Moderately disagree	Somewhat disagree	Neutral	Somewhat agree	Moderately agree	Completely agree
I frequently used online social interaction features to support my online learning.	○	○	○	○	○	○	○
I used a variety of online social interaction features to support my online learning.	○	○	○	○	○	○	○
I used online social interaction features for extended periods to support my online learning outside the class time.	○	○	○	○	○	○	○
To indicate that you have read and answered the questions carefully and thoughtfully in this survey, please select 'somewhat agree' for this specific statement.	○	○	○	○	○	○	○

→

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When interacting with other students in my online courses ...

	Completely disagree	Moderately disagree	Somewhat disagree	Neutral	Somewhat agree	Moderately agree	Completely agree
My classmates and I used common terms or jargon in online learning.	○	○	○	○	○	○	○
My classmates and I engaged in understandable communication in online learning.	○	○	○	○	○	○	○
My classmates and I had shared language for communication in online learning.	○	○	○	○	○	○	○

→

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When describing my relationship with other students in my online courses ...

	Completely disagree	Moderately disagree	Somewhat disagree	Neutral	Somewhat agree	Moderately agree	Completely agree
The relationship is characterized by mutual respect between me and other students.	○	○	○	○	○	○	○
The relationship is characterized by personal friendships between me and other students.	○	○	○	○	○	○	○
The relationship is characterized by mutual trust between me and other students.	○	○	○	○	○	○	○
The relationship is characterized by high reciprocity between me and other students.	○	○	○	○	○	○	○

→

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When describing my interactions with other students in my online courses ...

	Completely disagree	Moderately disagree	Somewhat disagree	Neutral	Somewhat agree	Moderately agree	Completely agree
I developed interactive relationships with many other students in my program.	○	○	○	○	○	○	○
I spent a lot of time interacting with other students in my program.	○	○	○	○	○	○	○
I networked with many other students in my program.	○	○	○	○	○	○	○
I had frequent communication with other students in my program.	○	○	○	○	○	○	○

→

When describing my online learning experience at my program of study ...

Completely disagree	Moderately disagree	Somewhat disagree		Neutral		Somewhat agree	Moderately agree	Completely agree
1	2	3	4		4	5	6	7

I have learned useful knowledge.

I have gained new knowledge and insights.

I have learned other students' personal experiences or expertise.

I have learned practical knowledge.

Please indicate your agreement to the following statements.

Completely disagree	Moderately disagree	Somewhat disagree		Neutral		Somewhat agree	Moderately agree	Completely agree
1	2	3	4		4	5	6	7

I really enjoyed my online learning.

I was excited about my online learning.

I was passionate about my online learning.

Please answer the following statements.

	Completely disagree	Moderately disagree	Somewhat disagree	Neutral	Somewhat agree	Moderately agree	Completely agree
I related the lessons learned in online learning with a solution to the real-life problem.	○	○	○	○	○	○	○
I engaged myself in frequent debates and discussions about problems that arise in my online learning.	○	○	○	○	○	○	○
I grasped every opportunity to learn in my online learning.	○	○	○	○	○	○	○

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When describing my knowledge prior to my online learning ...

Completely disagree	Moderately disagree	Somewhat disagree		Neutral		Somewhat agree	Moderately agree	Completely agree
1	2	3	4		4	5	6	7

I have much prior knowledge about the study program

I have extensive experience with online learning

→

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Please indicate your agreement to the following statements ...

	Completely disagree	Moderately disagree	Somewhat disagree	Neutral	Somewhat agree	Moderately agree	Completely agree
My online learning experience was synchronous	○	○	○	○	○	○	○

→

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Your gender

- ○ Male
- ○ Female
- ○ Other

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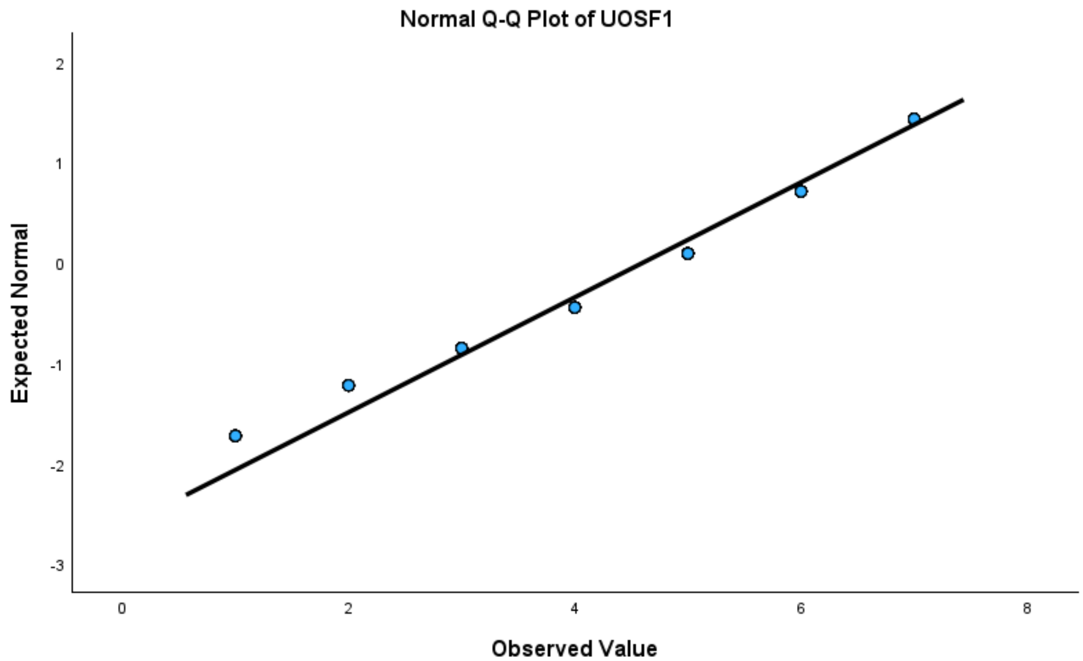
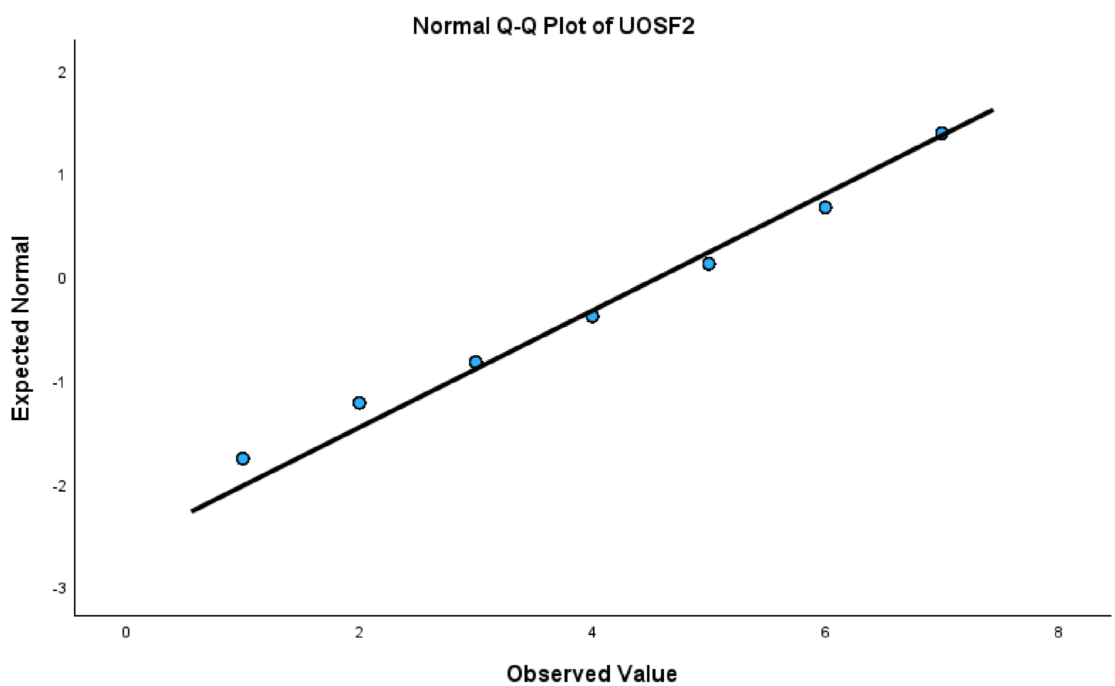
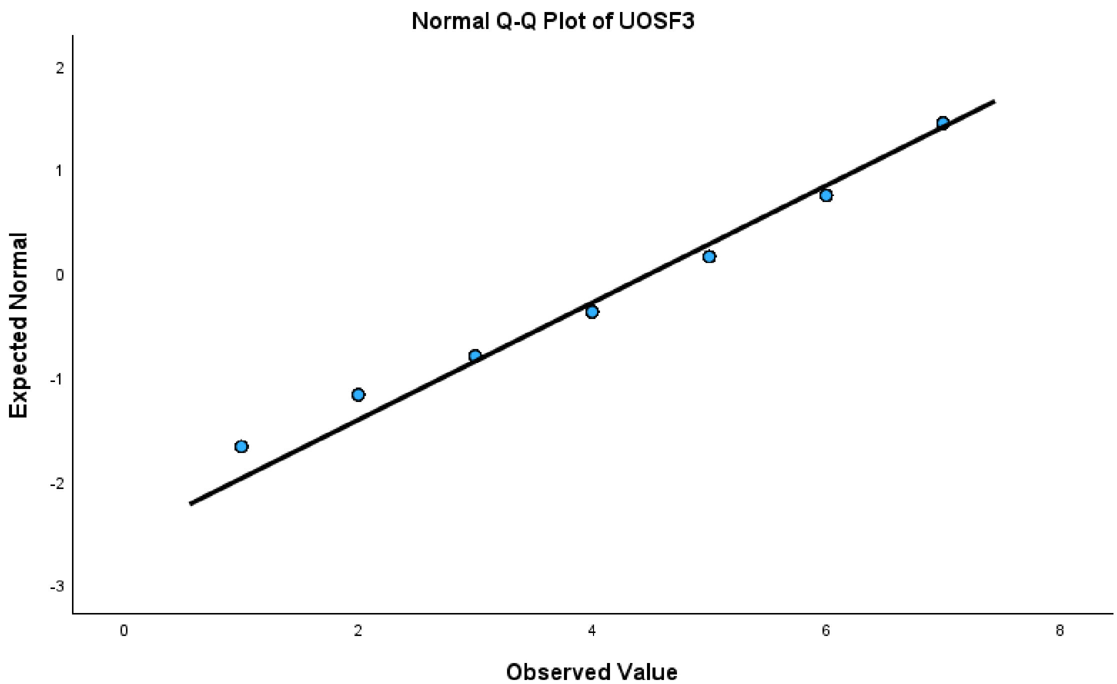
Your age

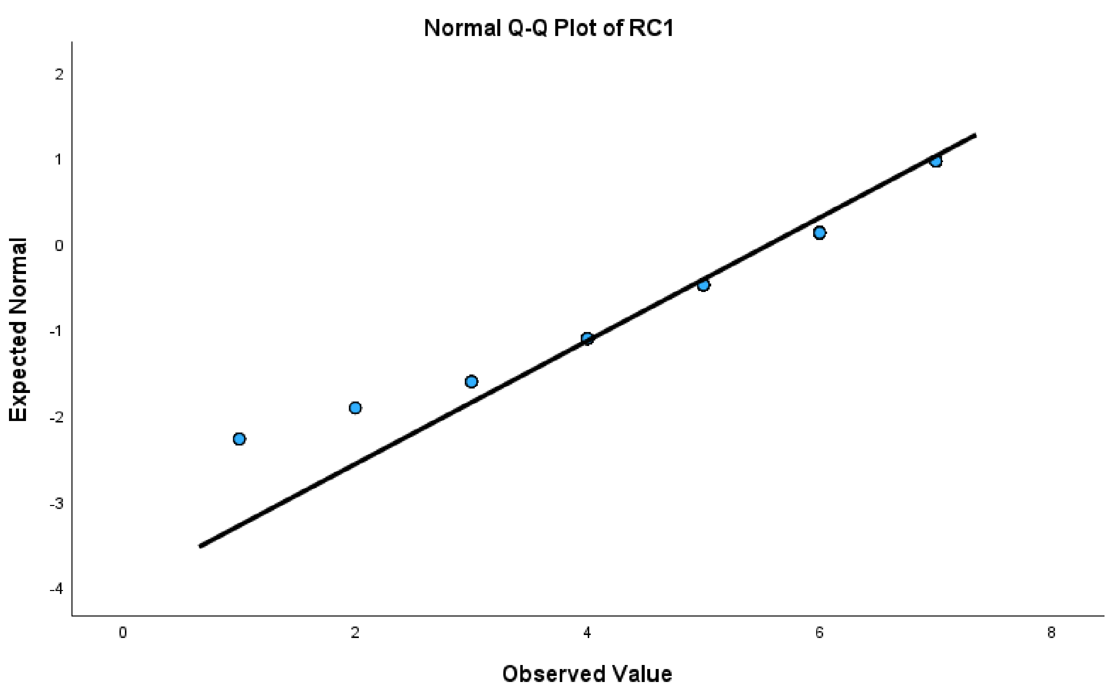
- ○ 18-20
- ○ 21-23
- ○ 24-26
- ○ 27-29
- ○ 30-32
- ○ 33-35
- ○ 35+

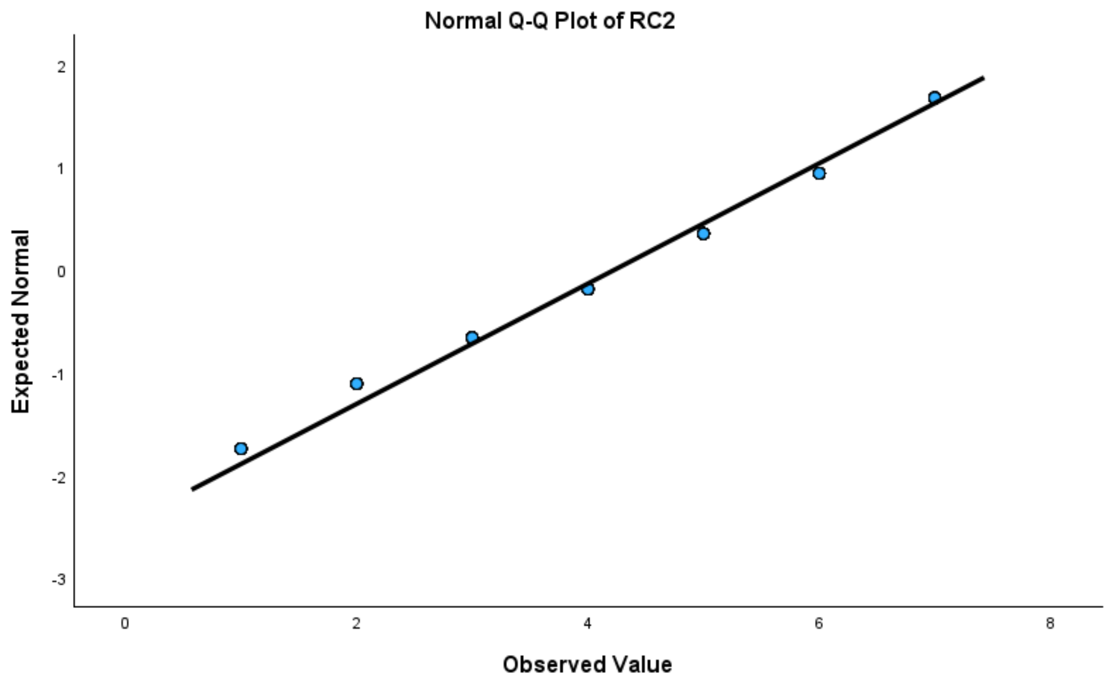
Appendix D. Q-Q Plots of Measurement Items

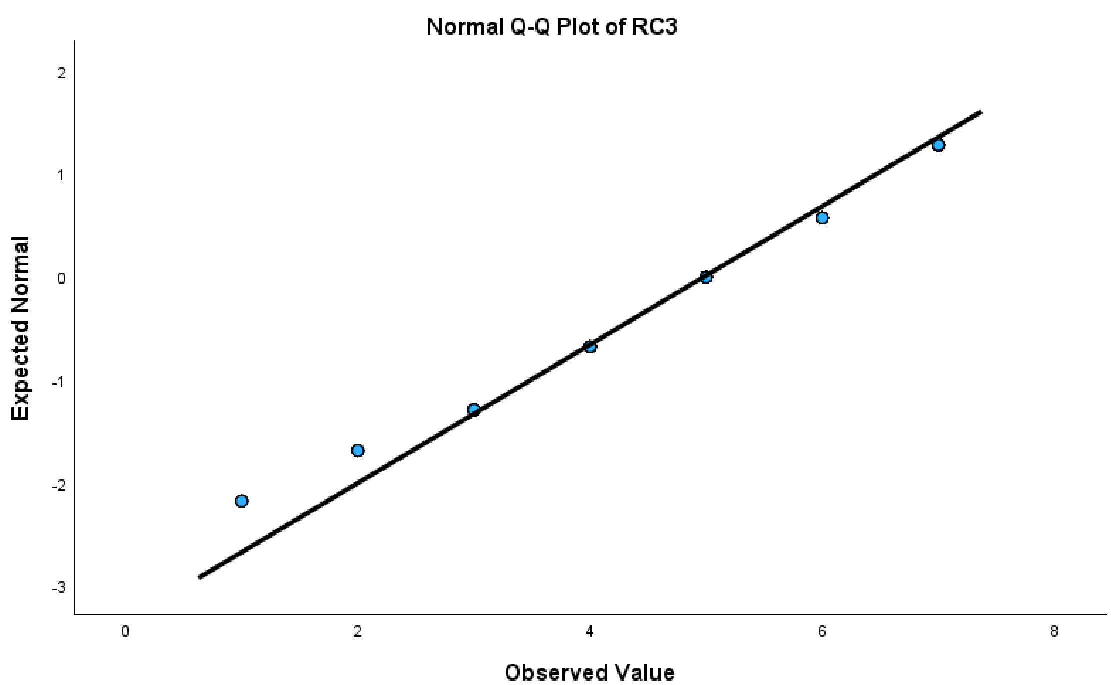


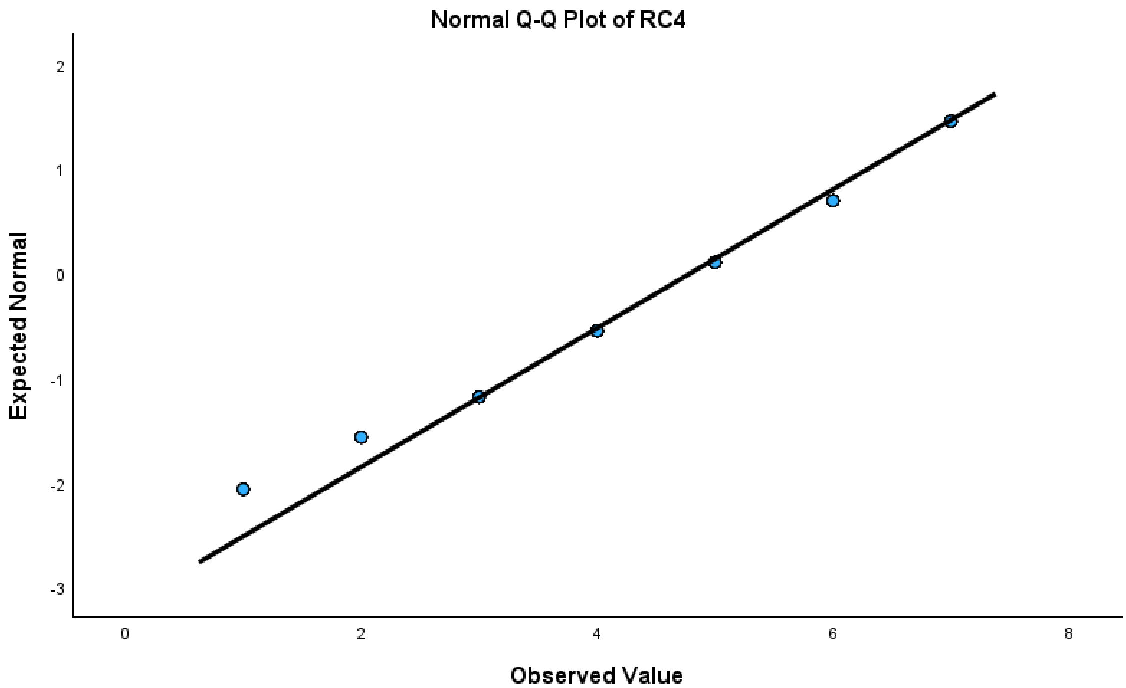


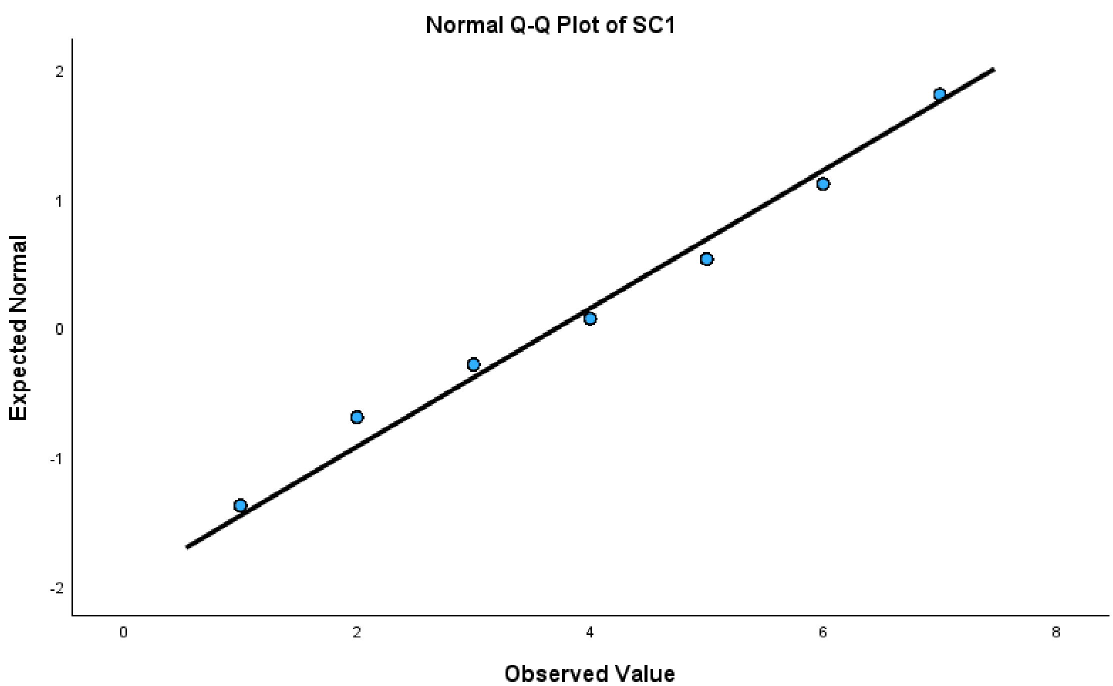

Normal Q-Q Plot of UOSF3
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

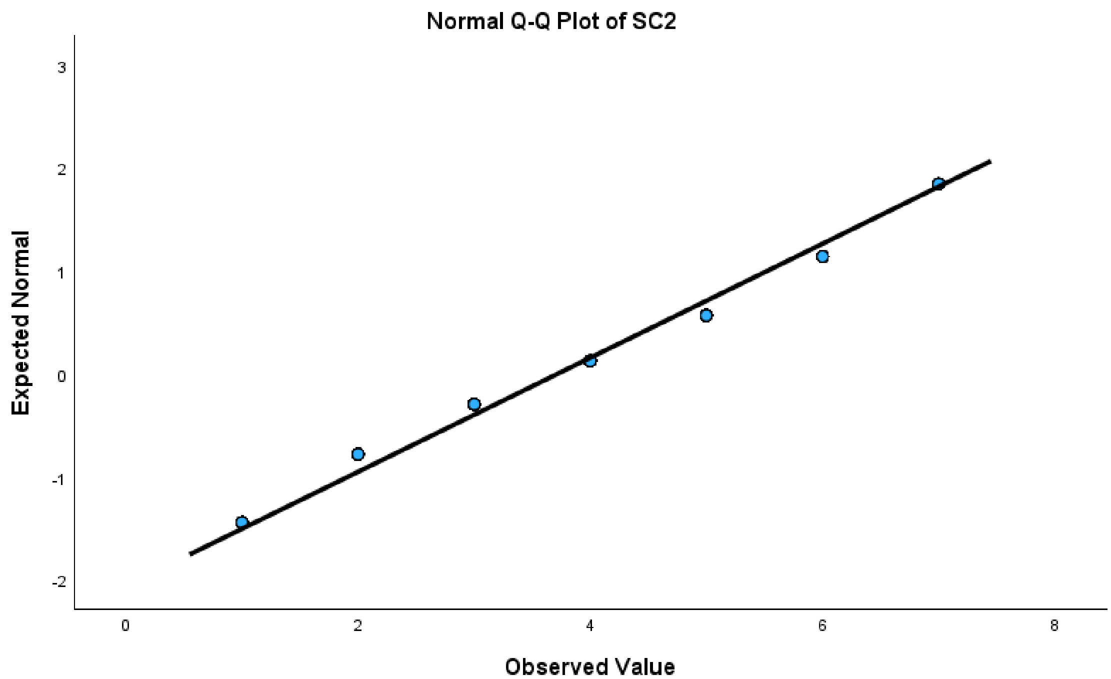

Normal Q-Q Plot of RC1
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
2
4
6
8

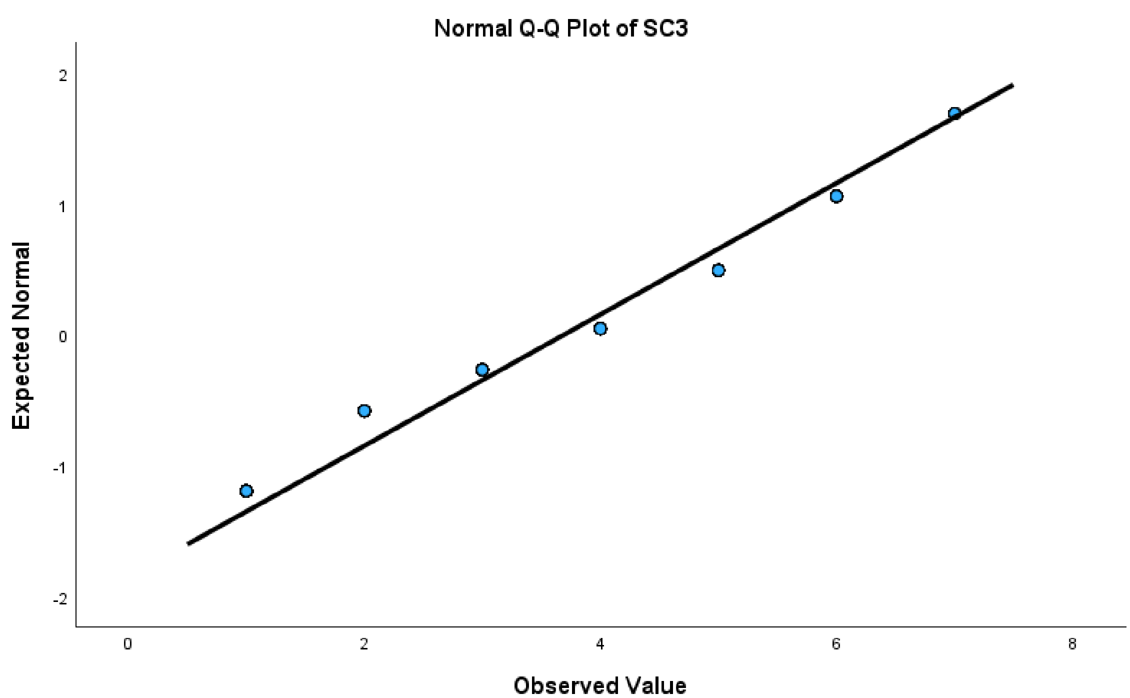

Normal Q-Q Plot of RC2
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

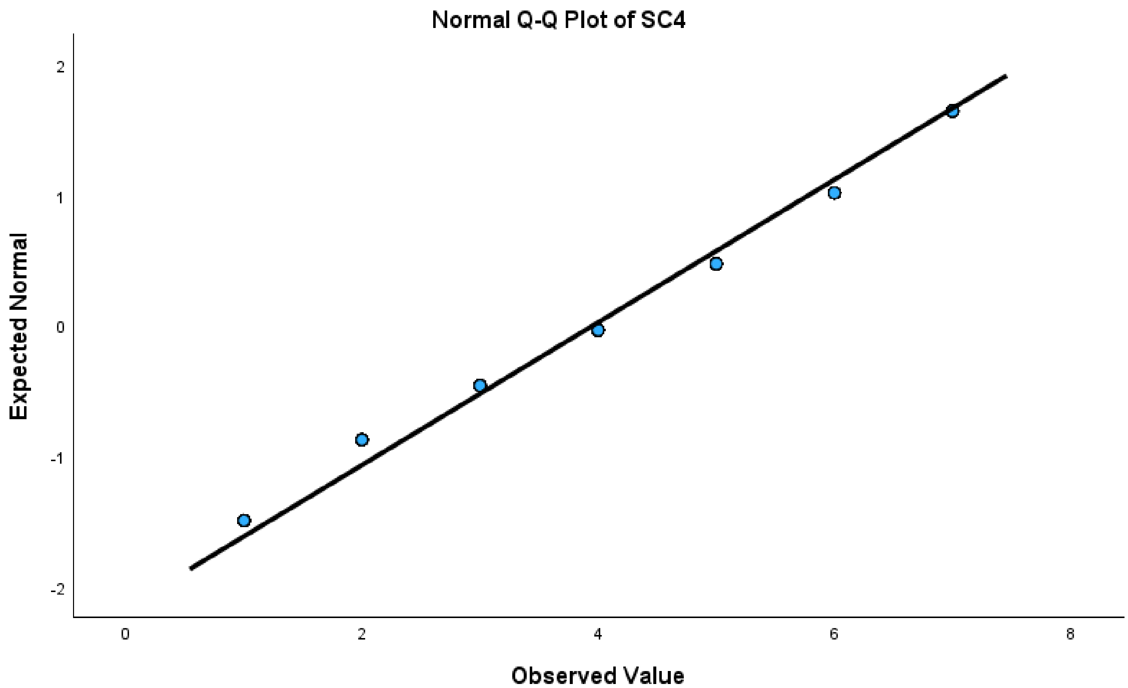

Normal Q-Q Plot of RC3
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

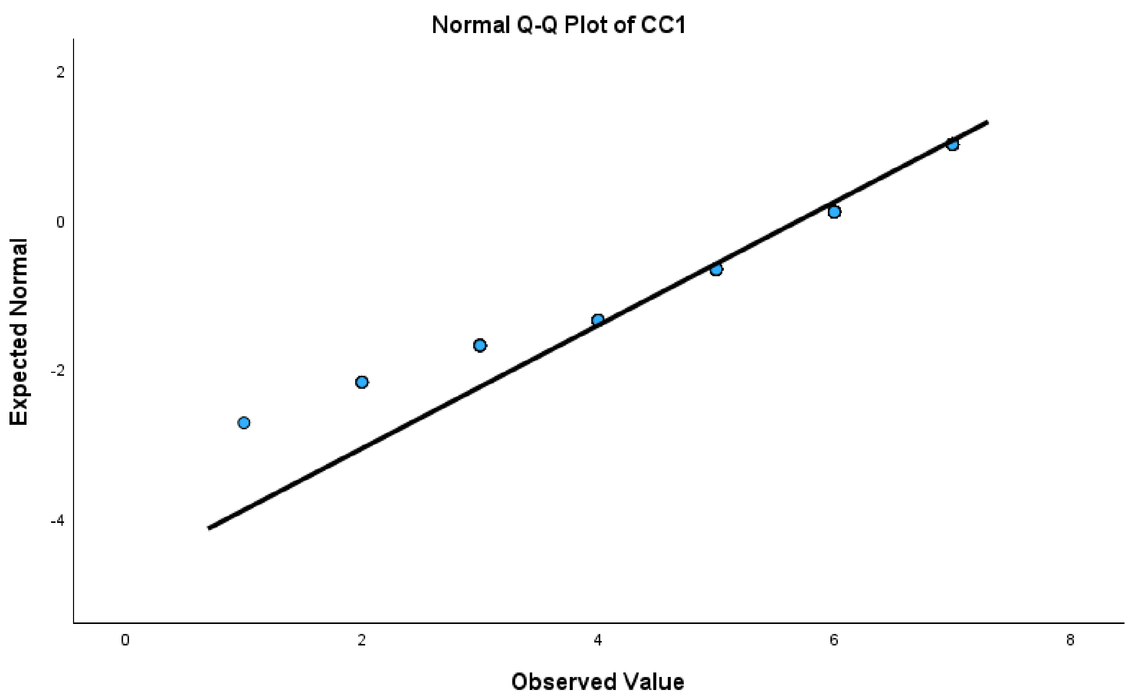

Normal Q-Q Plot of RC4
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

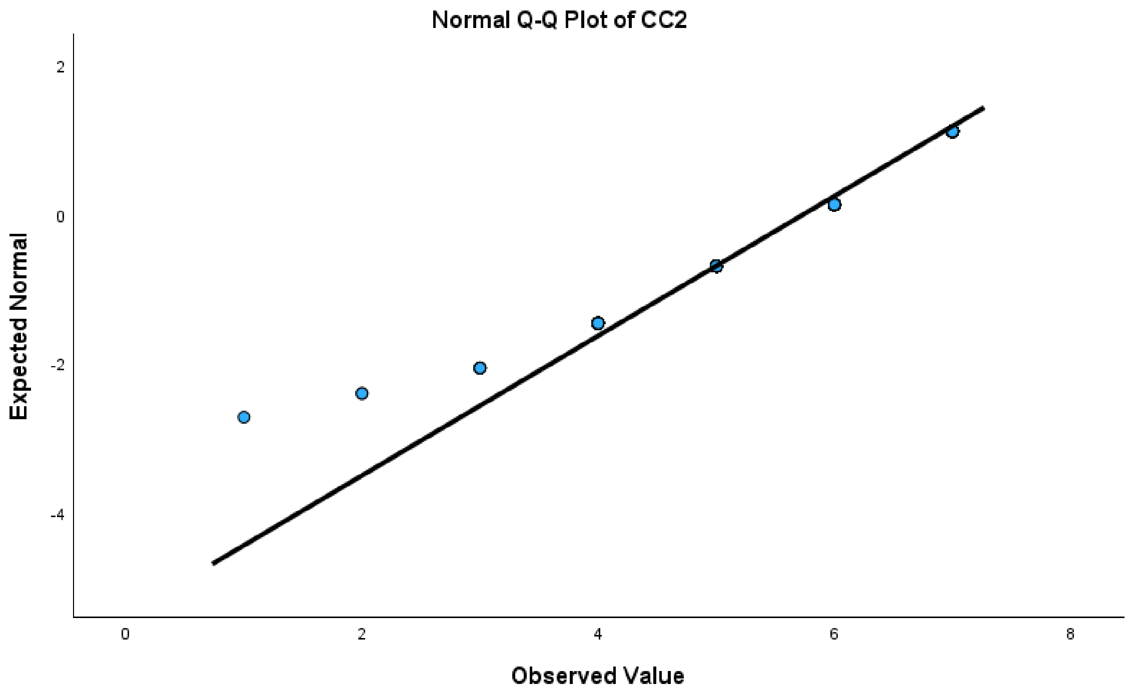

Normal Q-Q Plot of SC1
Expected Normal
Observed Value
2
1
0
-1
-2
0
2
4
6
8

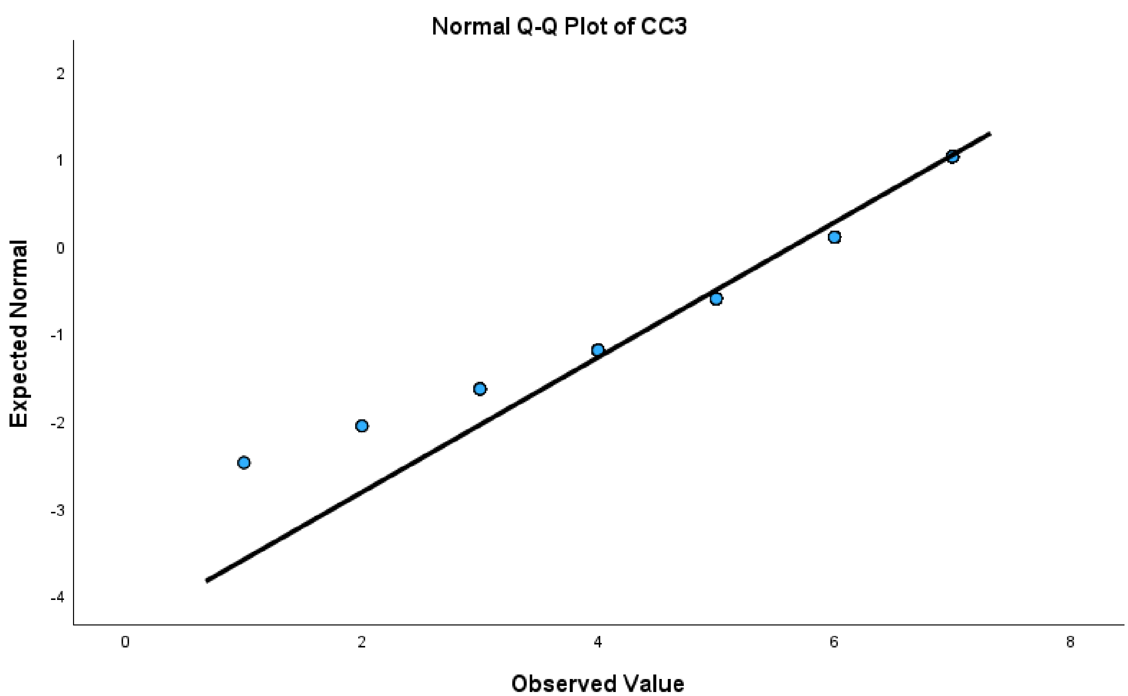

Normal Q-Q Plot of SC2
Expected Normal
Observed Value
3
2
1
0
-1
-2
0
2
4
6
8

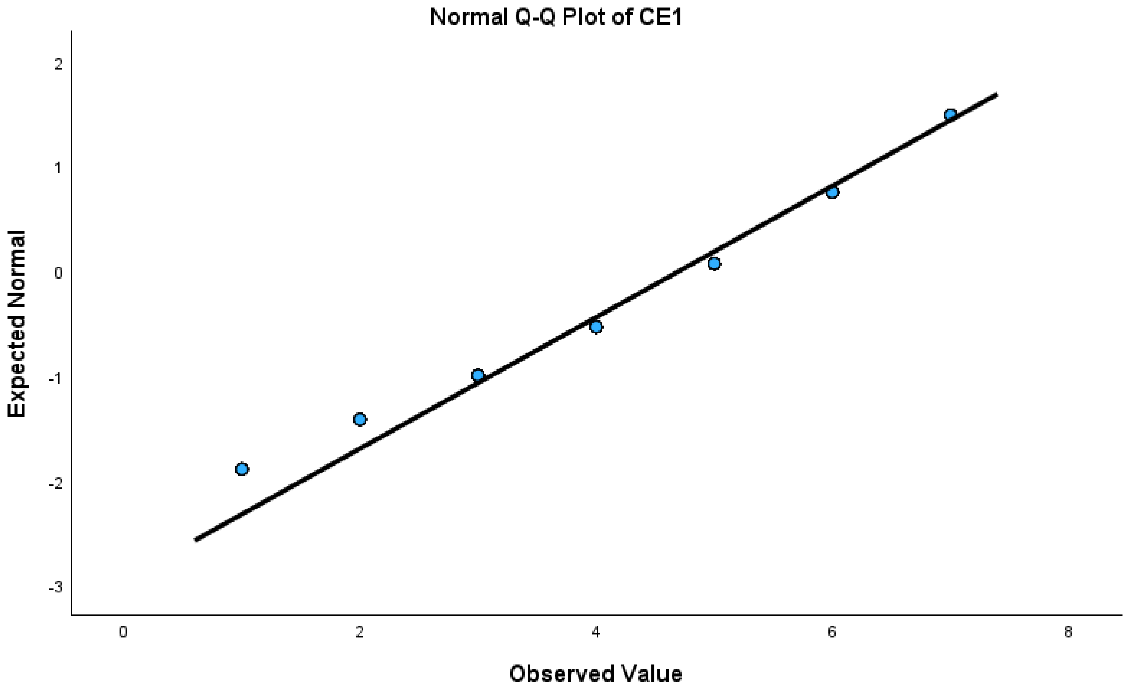

Normal Q-Q Plot of SC3
Expected Normal
Observed Value
2
1
0
-1
-2
0
2
4
6
8

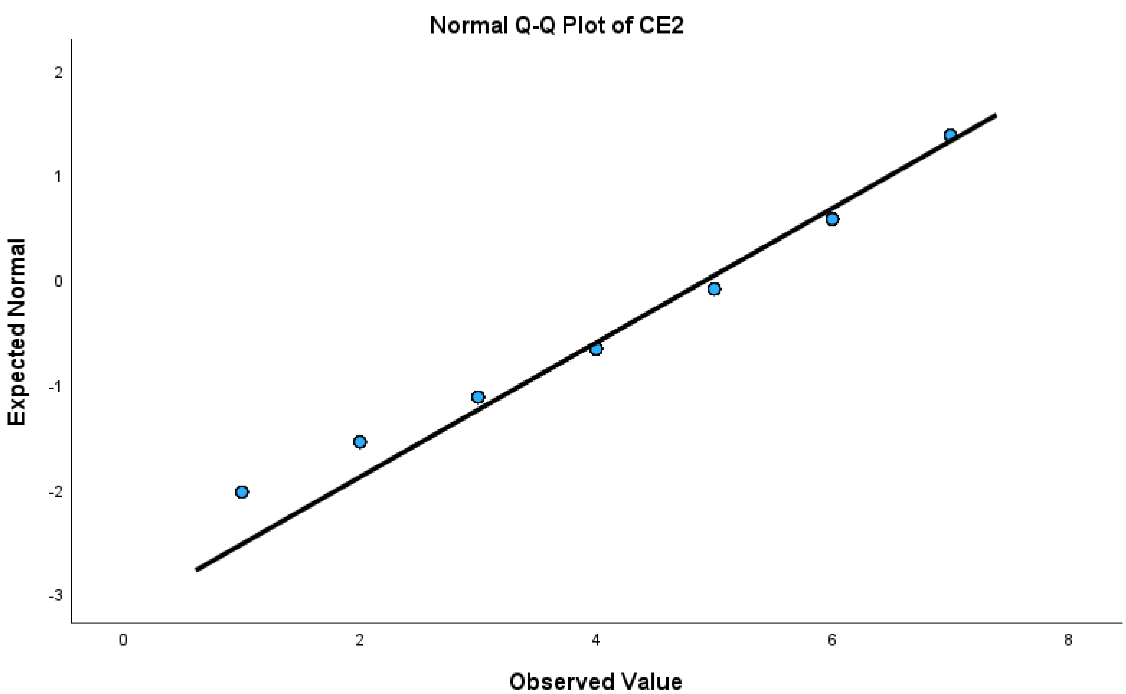

Normal Q-Q Plot of SC4
Expected Normal
Observed Value
2
1
0
-1
-2
0
2
4
6
8

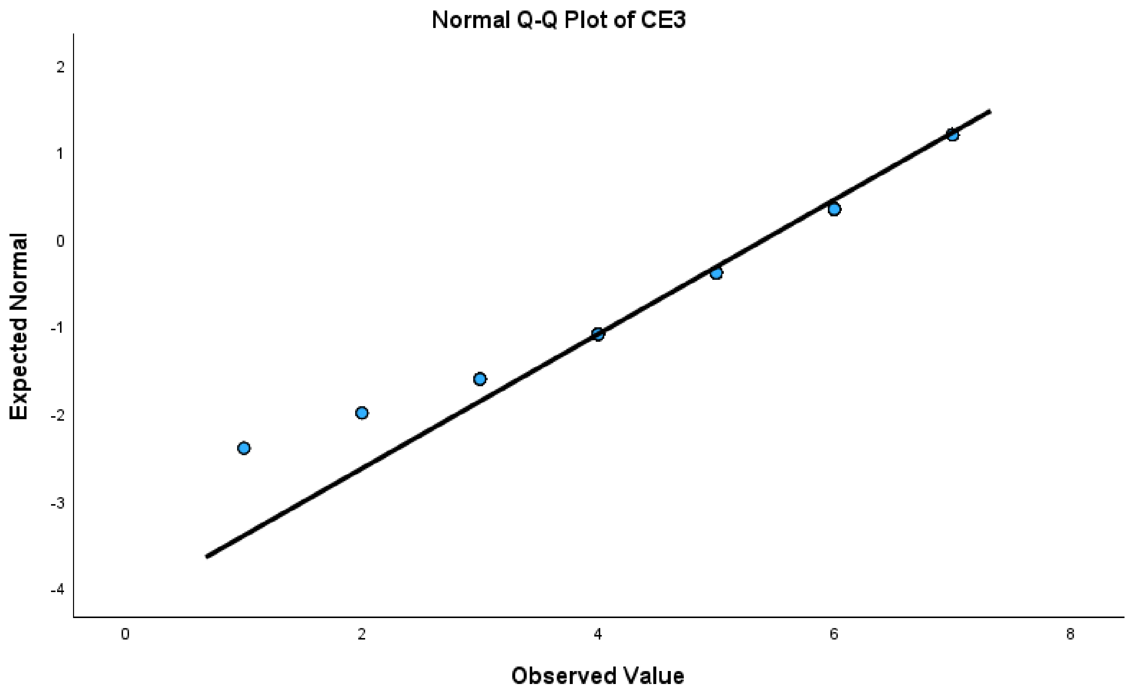

Normal Q-Q Plot of CC1
Expected Normal
Observed Value
2
0
-2
-4
0
2
4
6
8

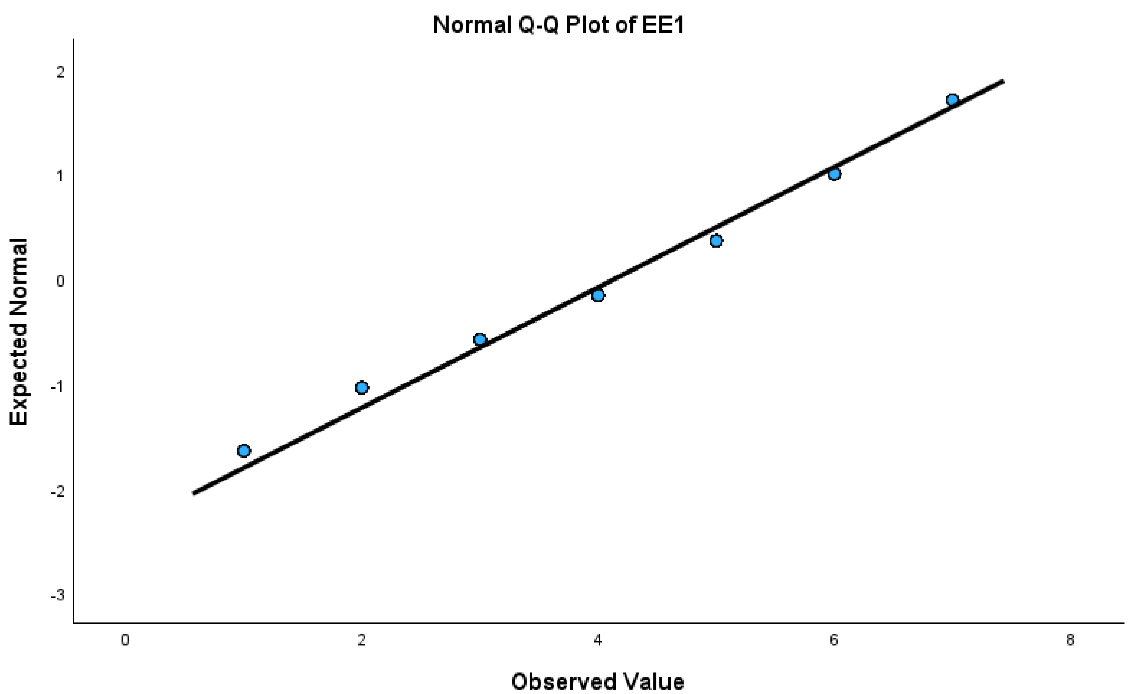

Normal Q-Q Plot of CC2
Expected Normal
Observed Value
2
0
-2
-4
0
2
4
6
8

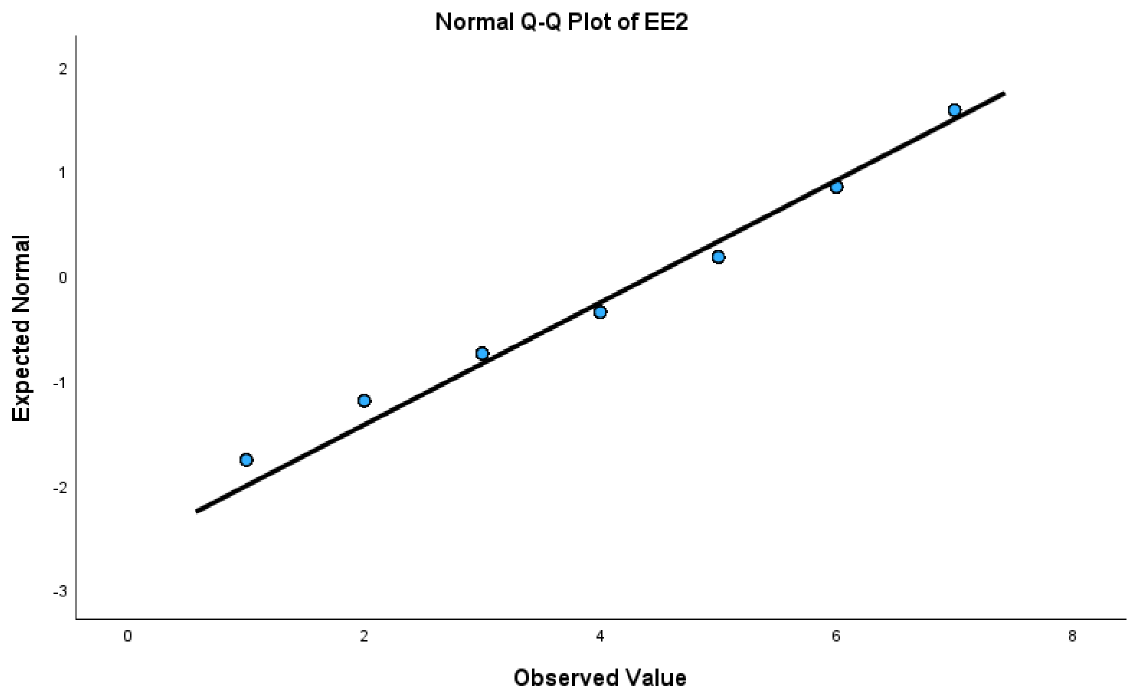

Normal Q-Q Plot of CC3
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
2
4
6
8

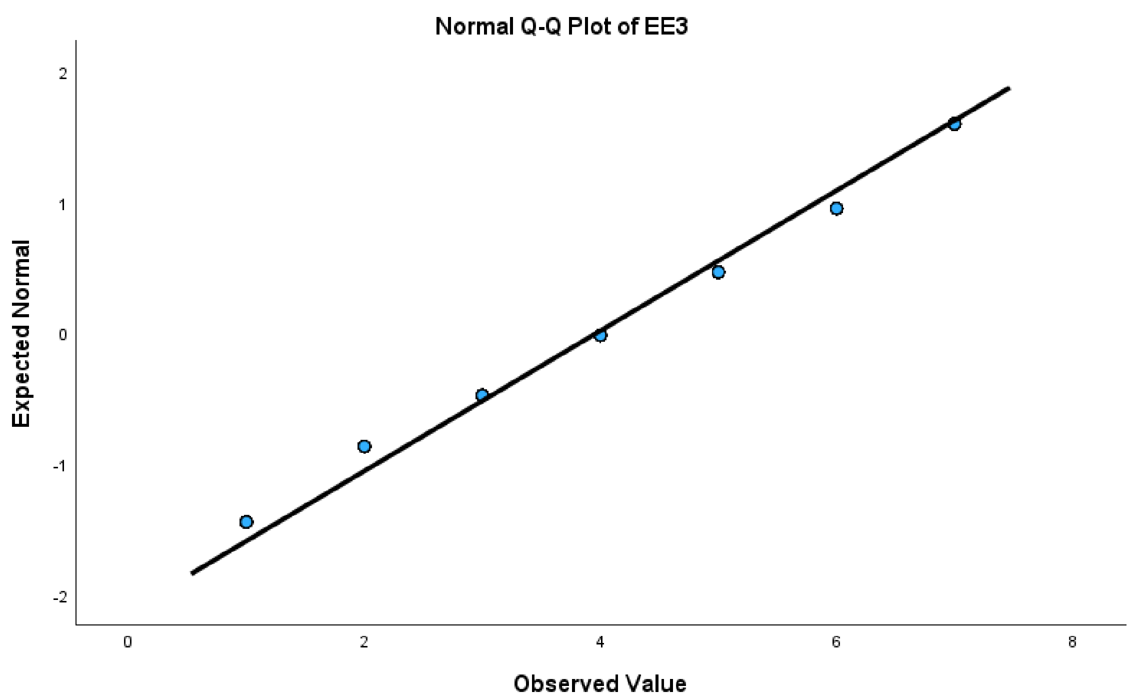

Normal Q-Q Plot of CE1
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

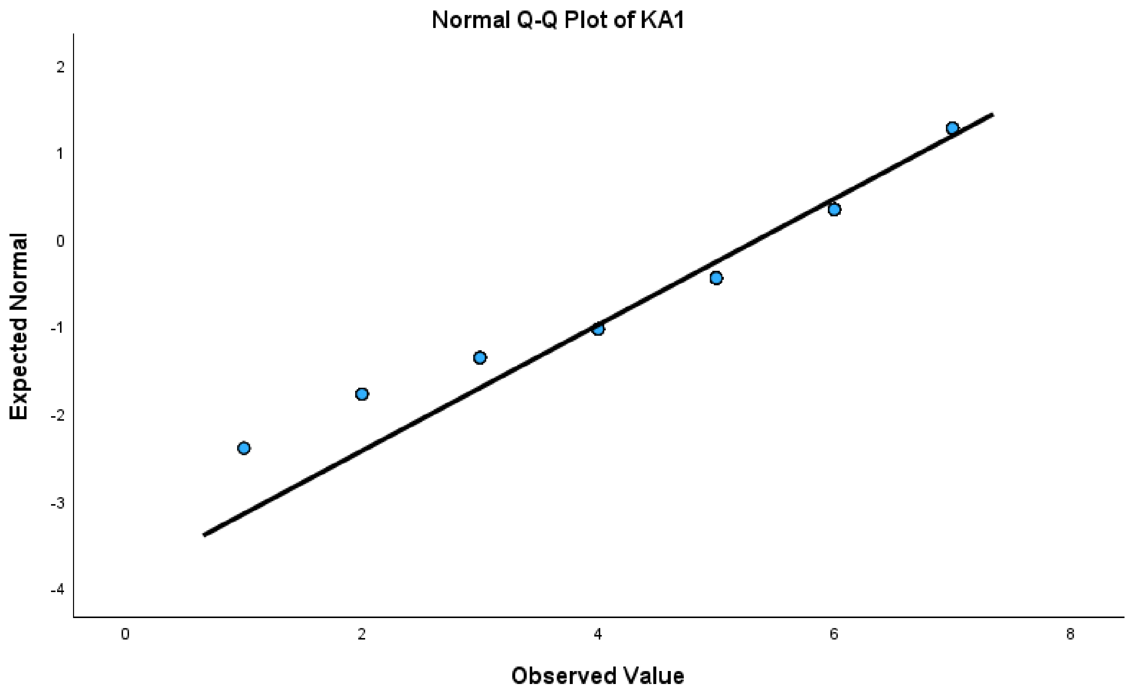

Normal Q-Q Plot of CE2
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

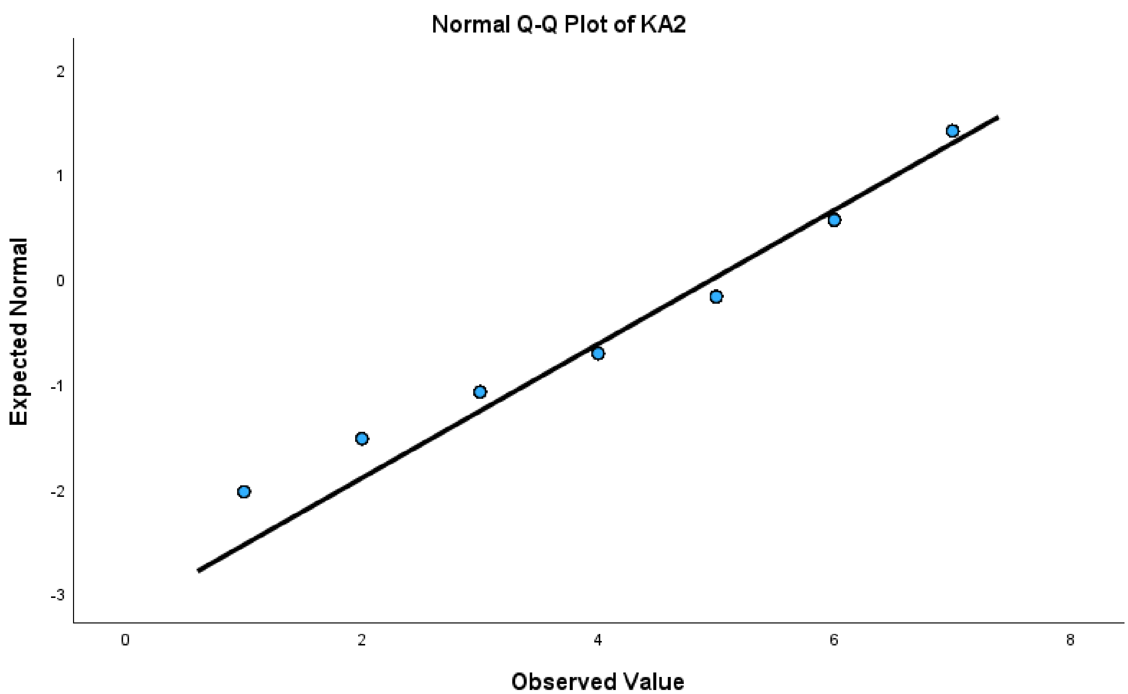

Normal Q-Q Plot of CE3
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
2
4
6
8

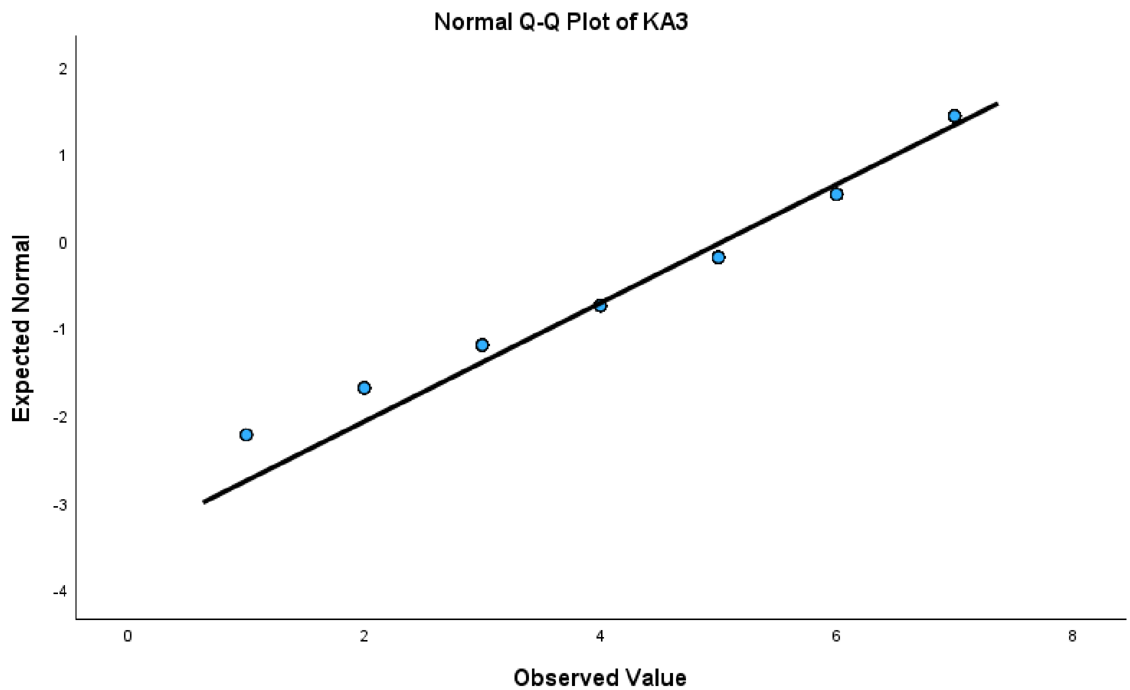

Normal Q-Q Plot of EE1
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

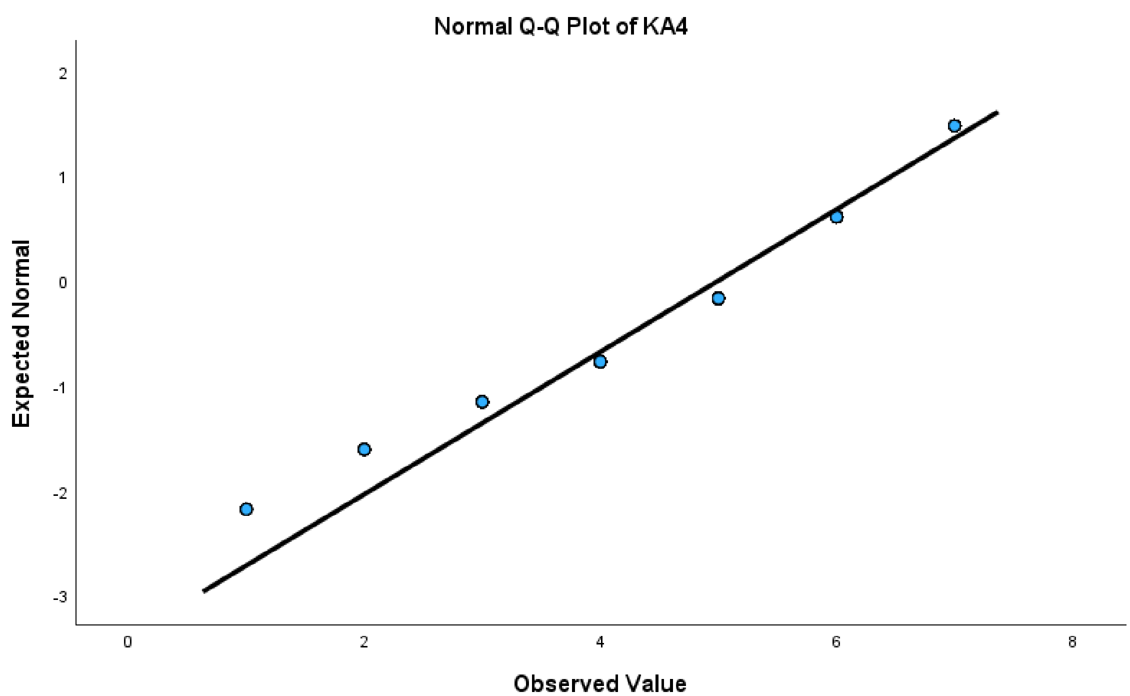

Normal Q-Q Plot of EE2
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8


Normal Q-Q Plot of EE3
Expected Normal
Observed Value
2
1
0
-1
-2
0
2
4
6
8

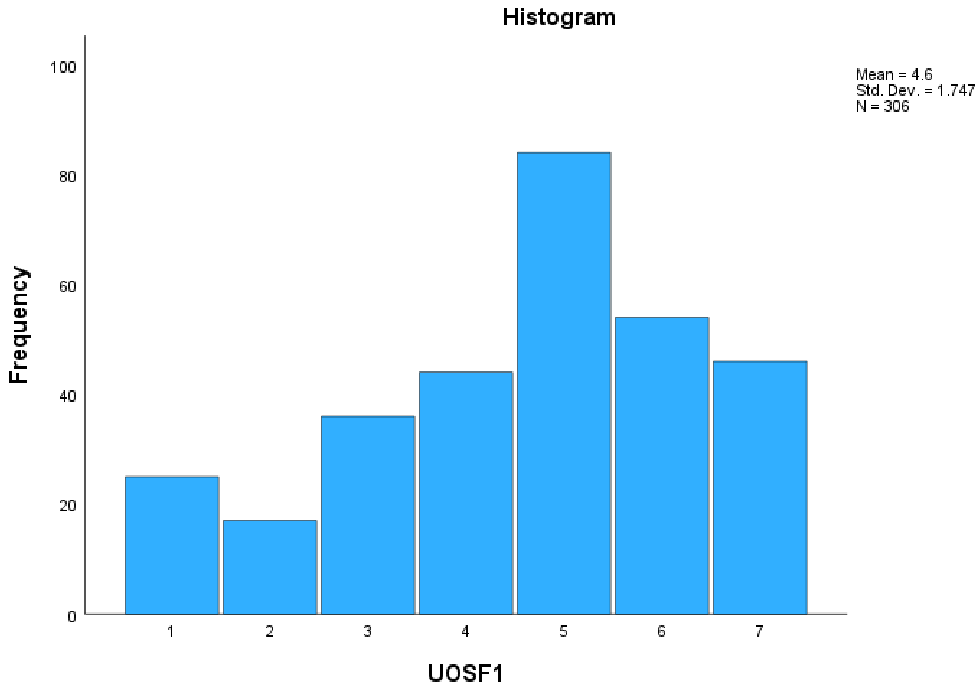

Normal Q-Q Plot of KA1
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
2
4
6
8

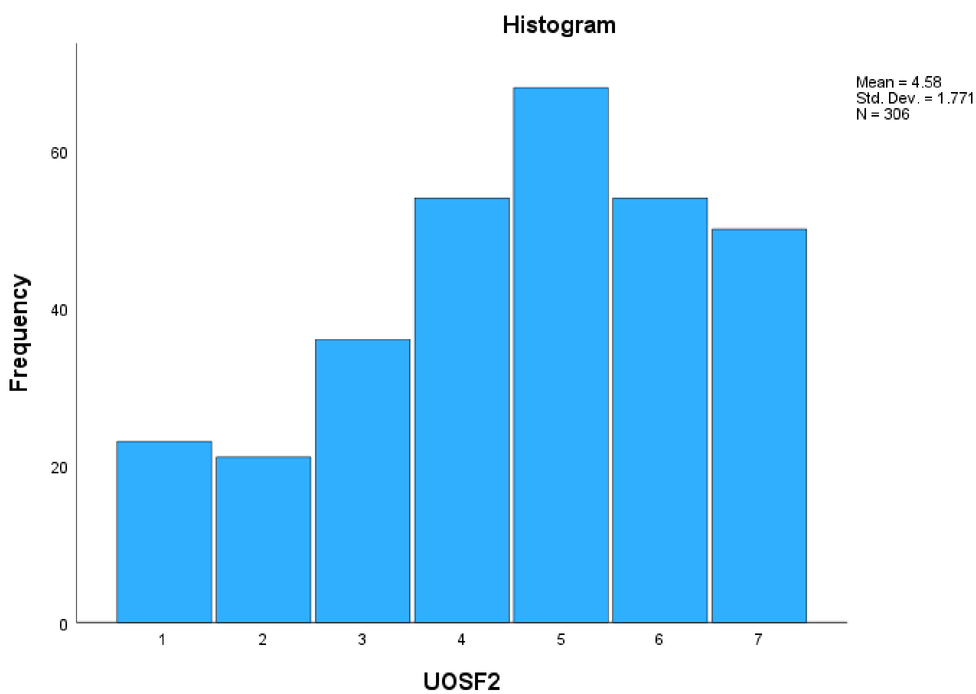

Normal Q-Q Plot of KA2
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

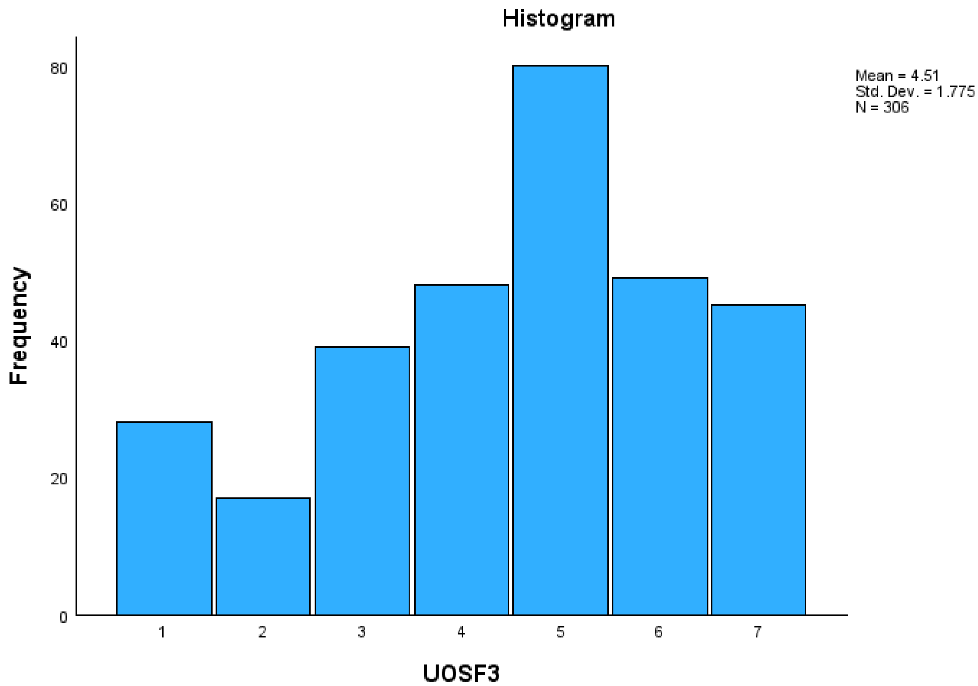

Normal Q-Q Plot of KA3
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
2
4
6
8

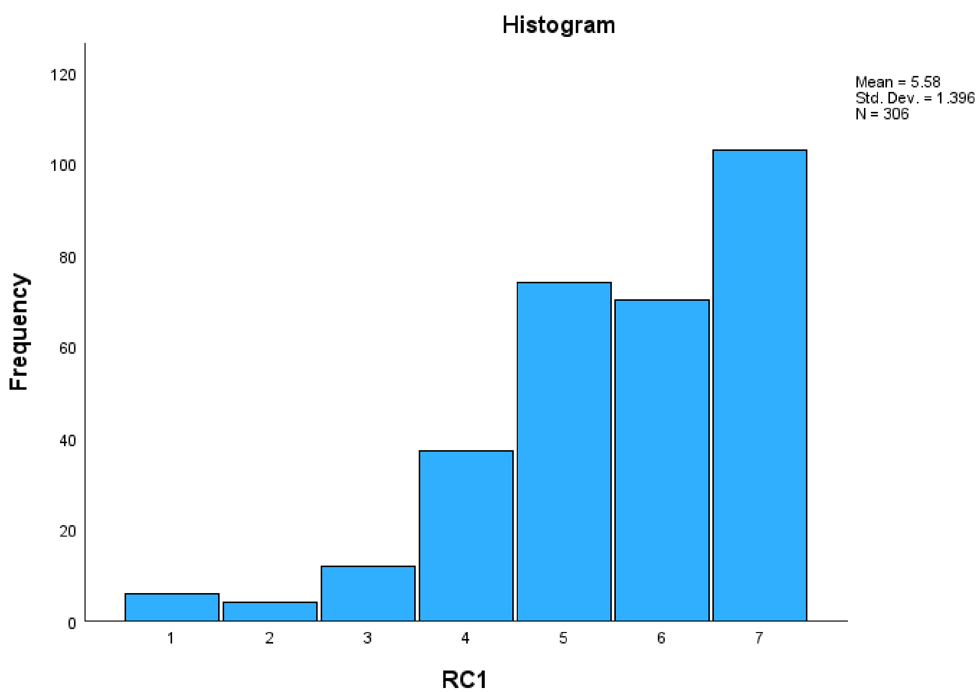

Normal Q-Q Plot of KA4
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
2
4
6
8

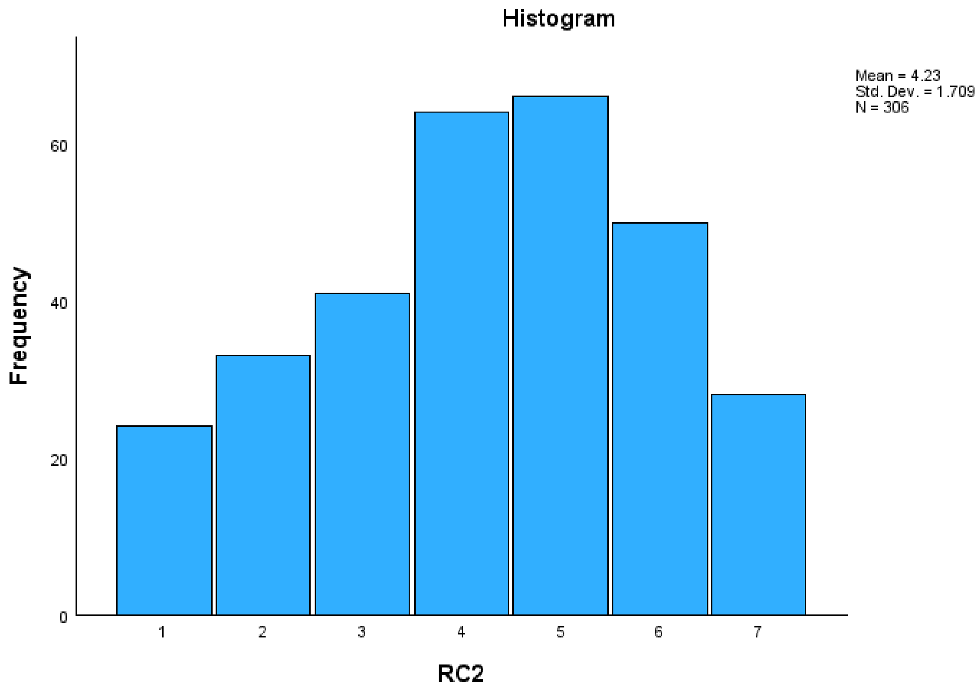
Appendix E. Histograms of Measurement Items

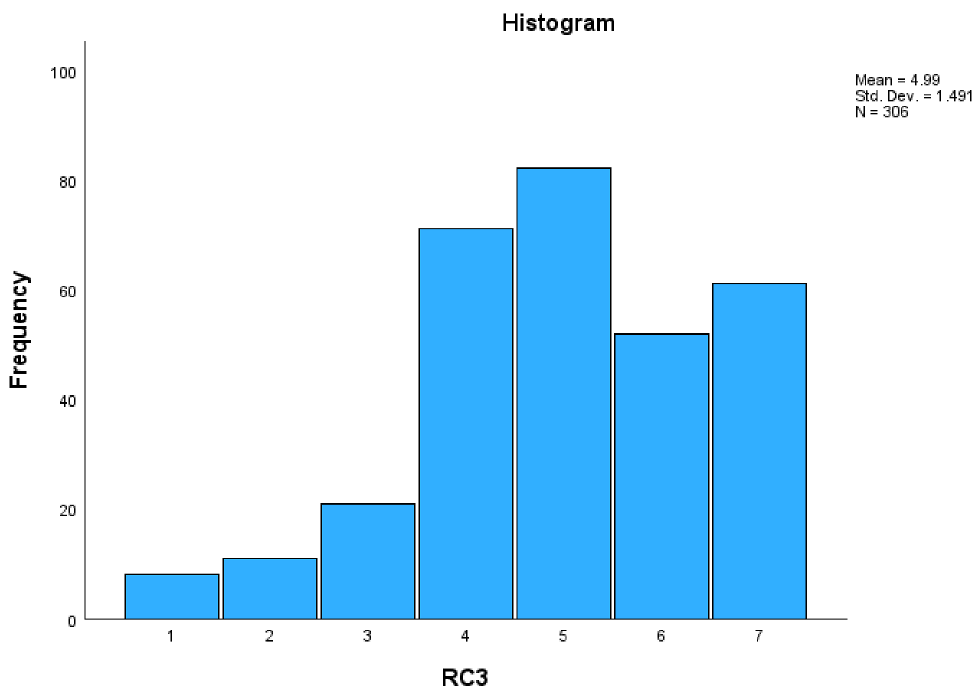


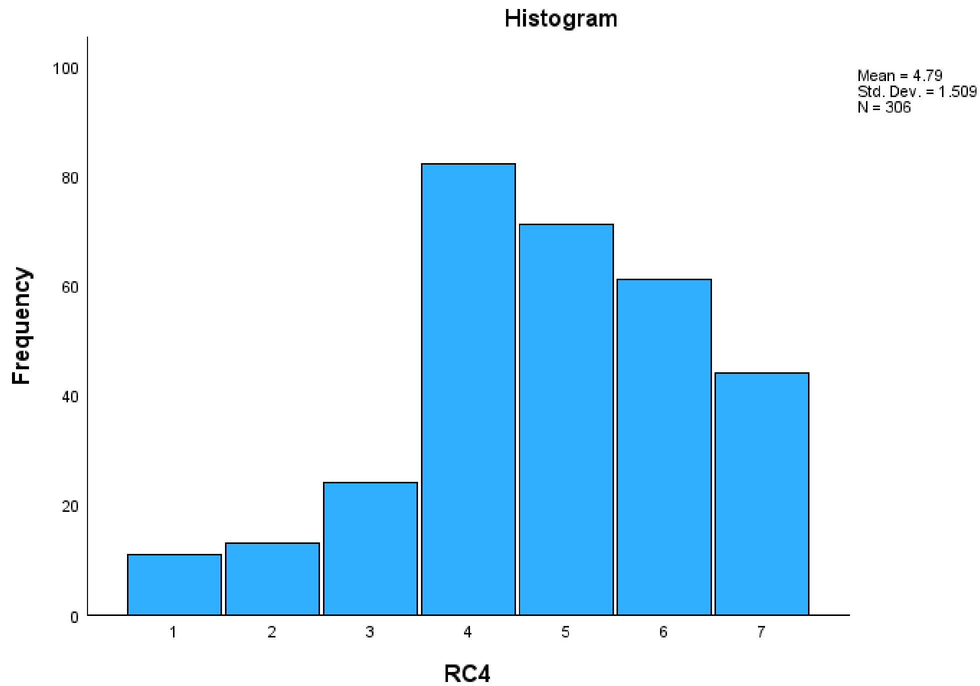


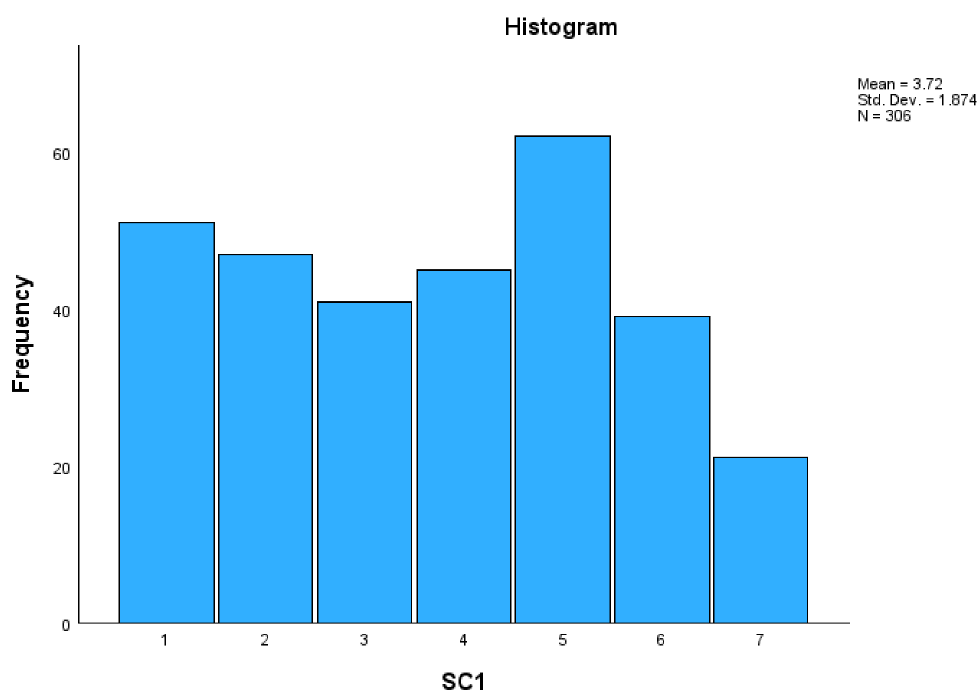

Histogram
Mean = 4.51
Std. Dev. = 1.775
N = 306
Frequency
0
20
40
60
80
1
2
3
4
5
6
7
UOSF3

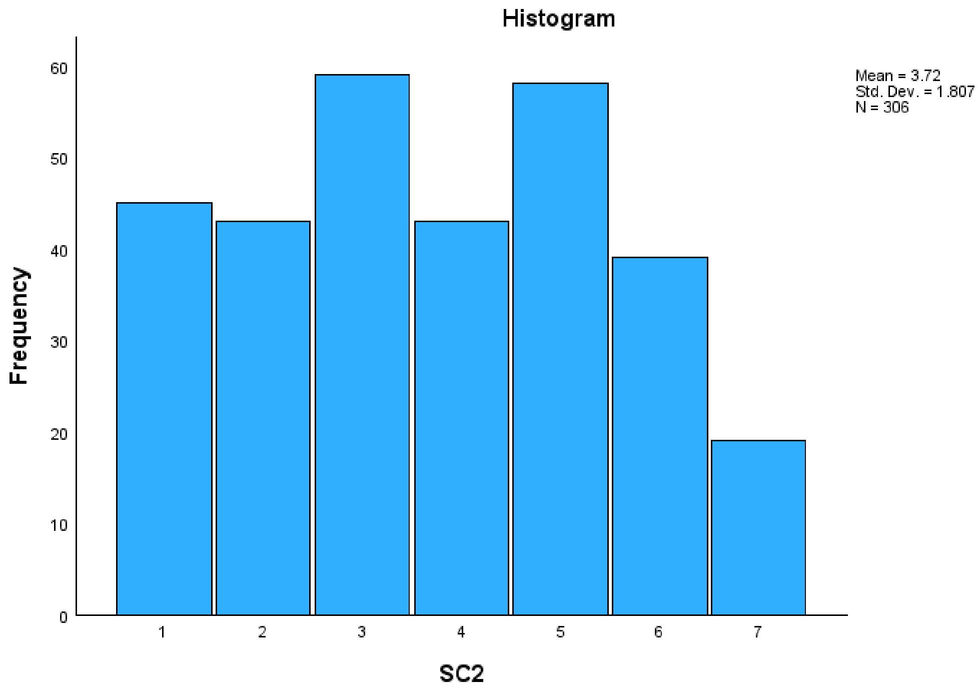

Histogram
Mean = 5.58
Std. Dev. = 1.396
N = 306
Frequency
0
20
40
60
80
100
120
1
2
3
4
5
6
7
RC1

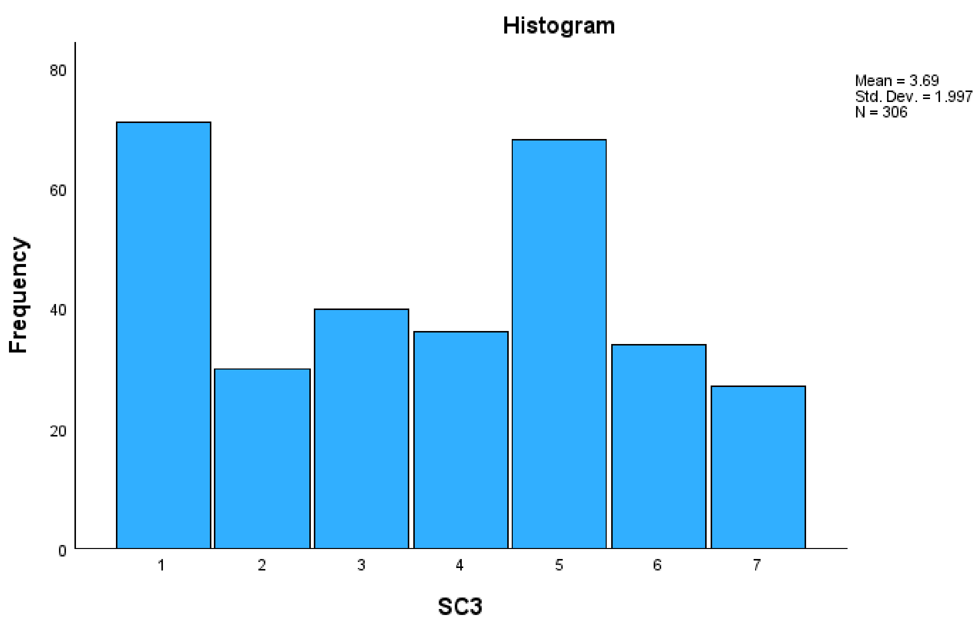

Histogram
Mean = 4.23
Std. Dev. = 1.709
N = 306
Frequency
60
40
20
0
1
2
3
4
5
6
7
RC2

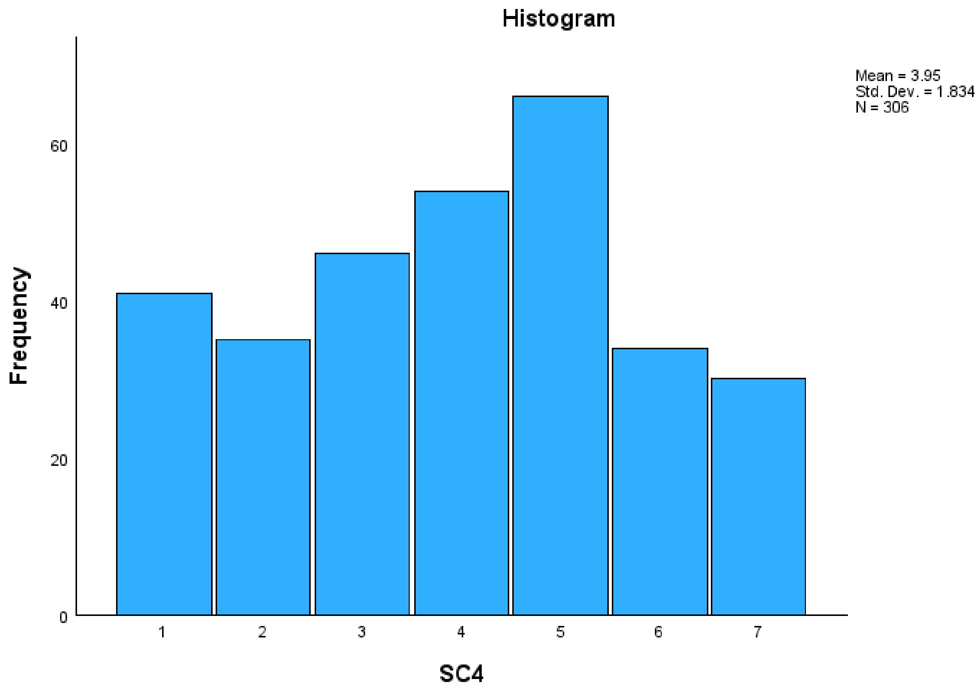

Histogram
Mean = 4.99
Std. Dev. = 1.491
N = 306
Frequency
100
80
60
40
20
0
1
2
3
4
5
6
7
RC3

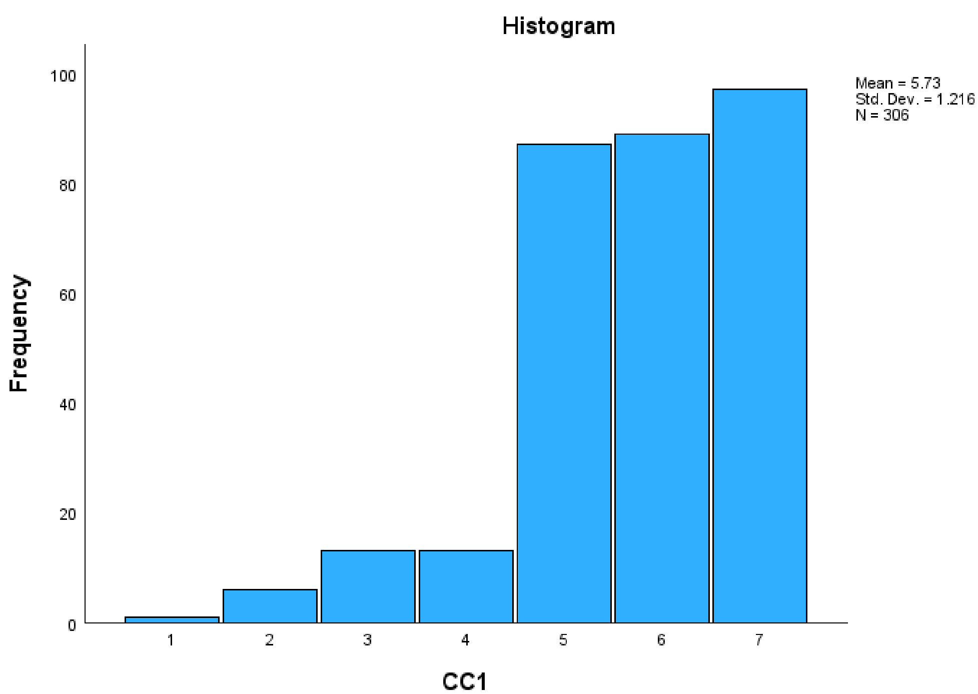

Histogram
Mean = 4.79
Std. Dev. = 1.509
N = 306
Frequency
0
20
40
60
80
100
1
2
3
4
5
6
7
RC4

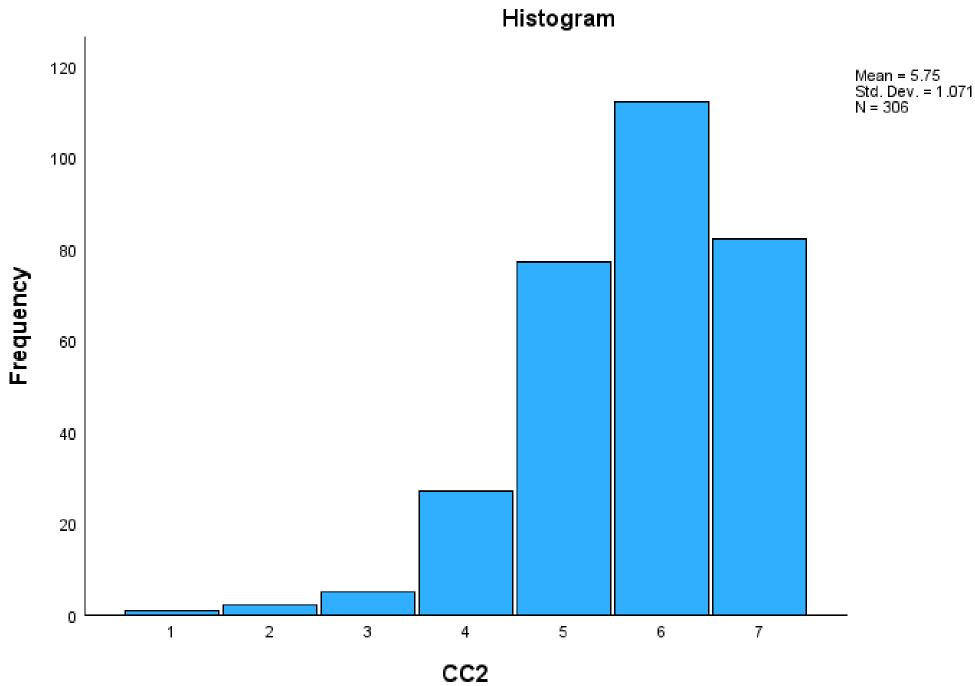

Histogram
Mean = 3.72
Std. Dev. = 1.874
N = 306
Frequency
0
20
40
60
1
2
3
4
5
6
7
SC1

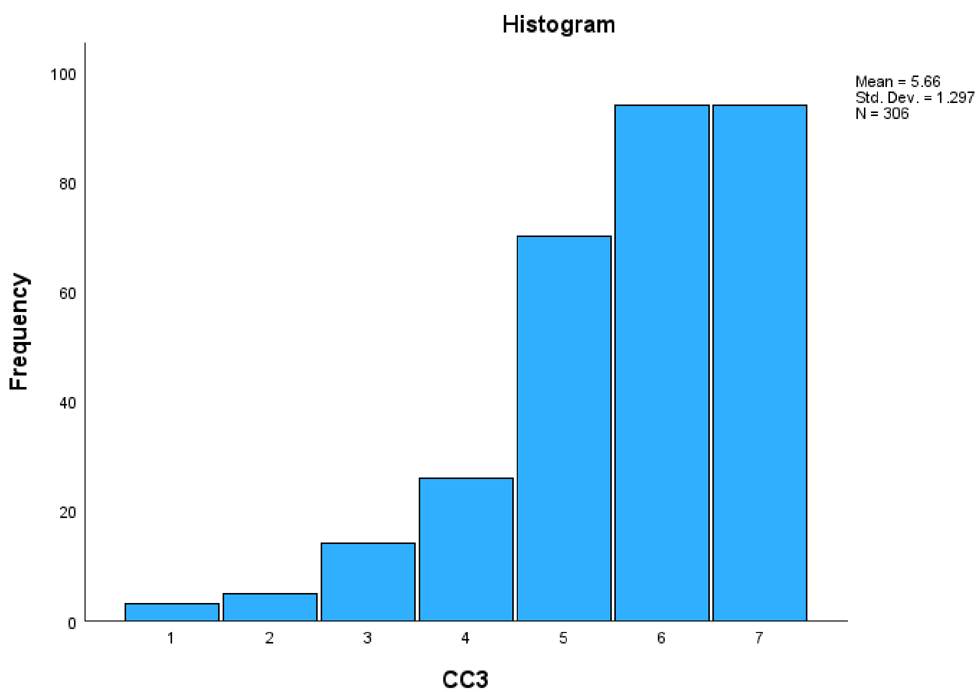

Histogram
Mean = 3.72
Std. Dev. = 1.807
N = 306
Frequency
60
50
40
30
20
10
0
1
2
3
4
5
6
7
SC2

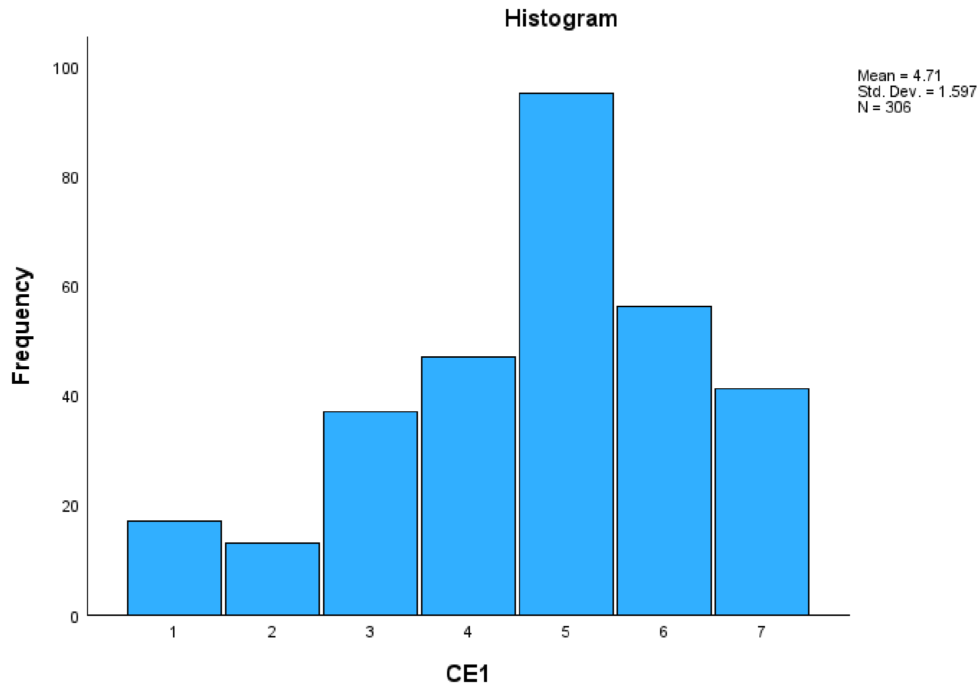

Histogram
Mean = 3.69
Std. Dev. = 1.997
N = 306
Frequency
80
60
40
20
0
1
2
3
4
5
6
7
SC3

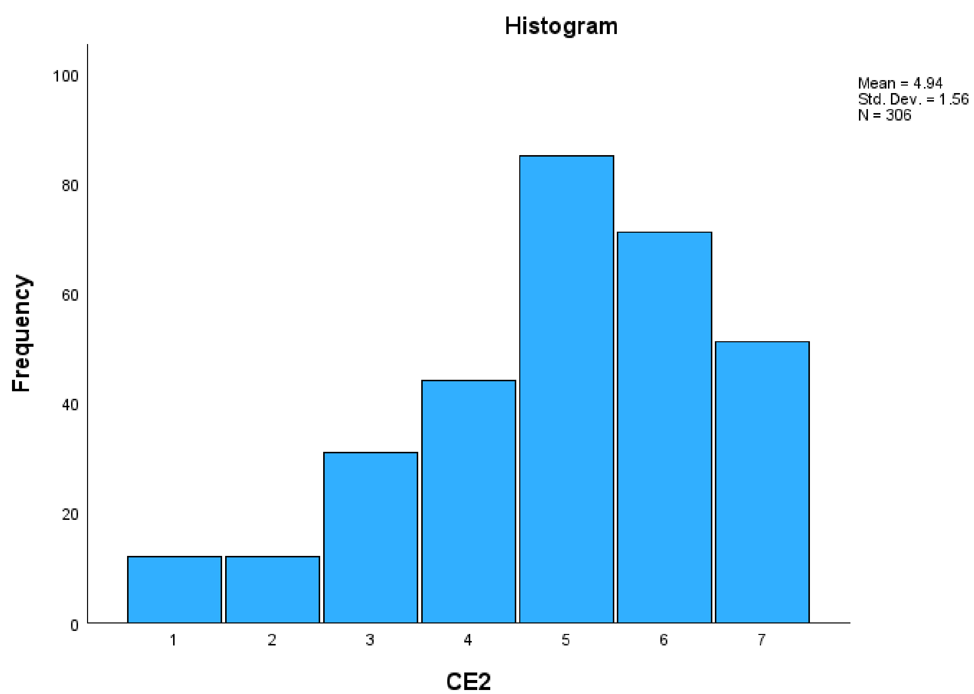

Histogram
Mean = 3.95
Std. Dev. = 1.834
N = 306
Frequency
0
20
40
60
1
2
3
4
5
6
7
SC4

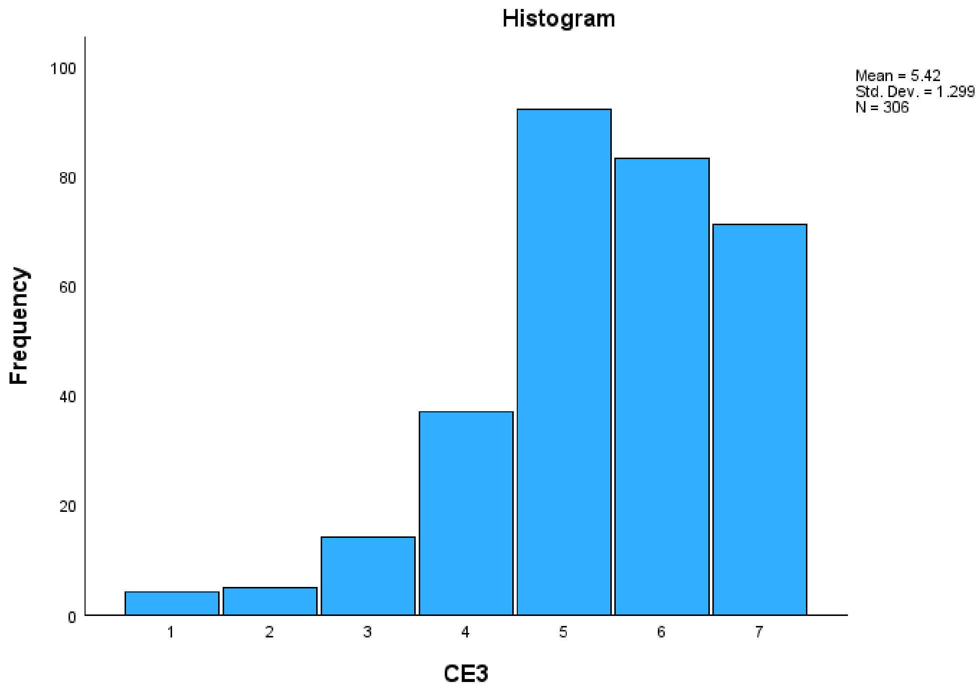

Histogram
Mean = 5.73
Std. Dev. = 1.216
N = 306
Frequency
0
20
40
60
80
100
1
2
3
4
5
6
7
CC1

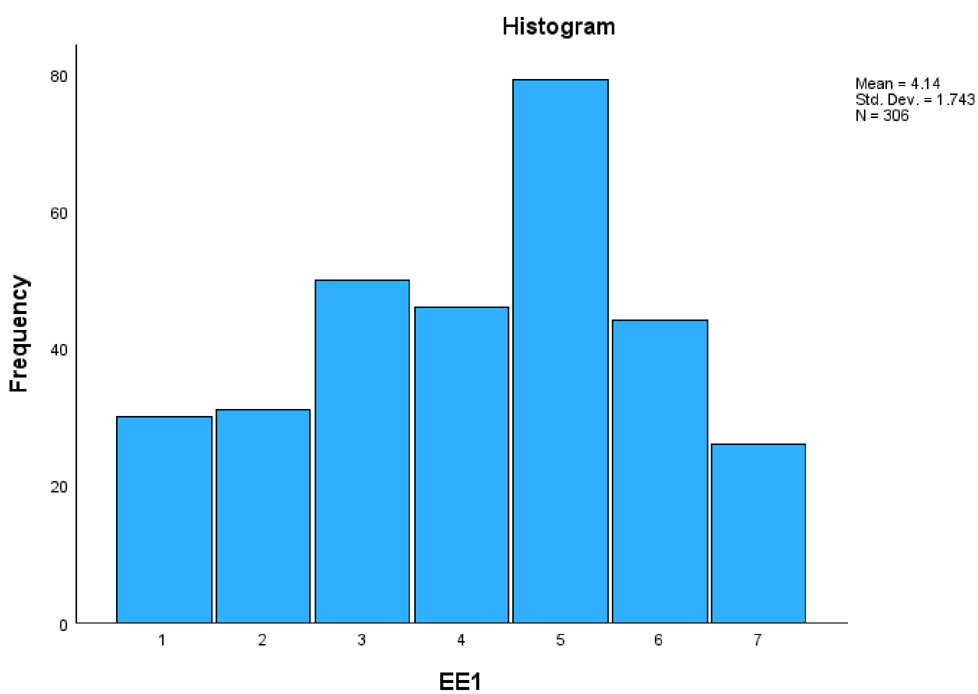

Histogram
Mean = 5.75
Std. Dev. = 1.071
N = 306
Frequency
120
100
80
60
40
20
0
1
2
3
4
5
6
7
CC2

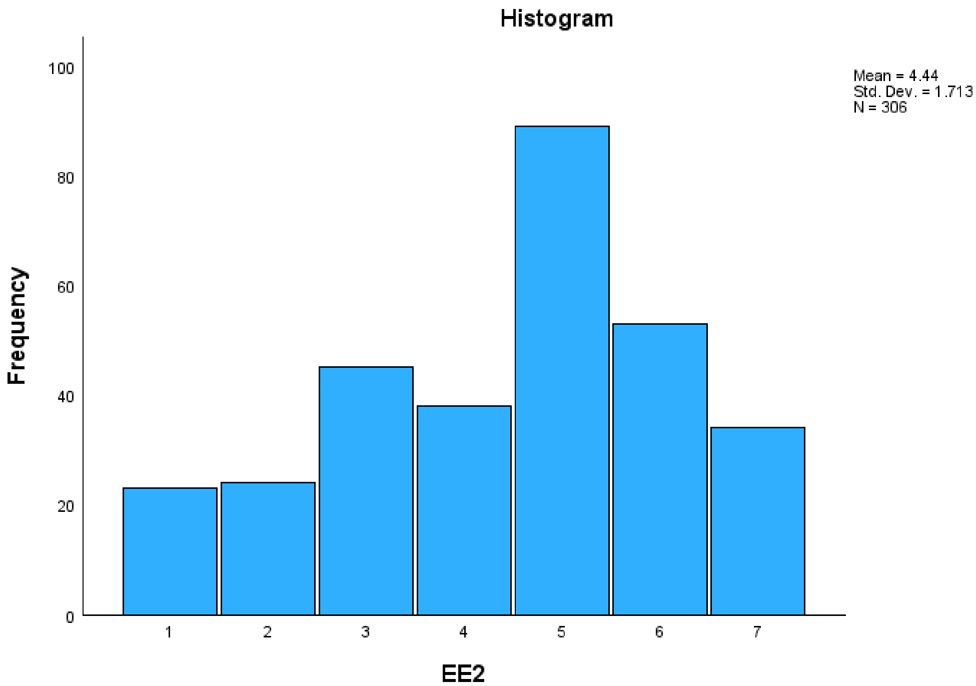

Histogram
Mean = 5.66
Std. Dev. = 1.297
N = 306
Frequency
100
80
60
40
20
0
1
2
3
4
5
6
7
CC3

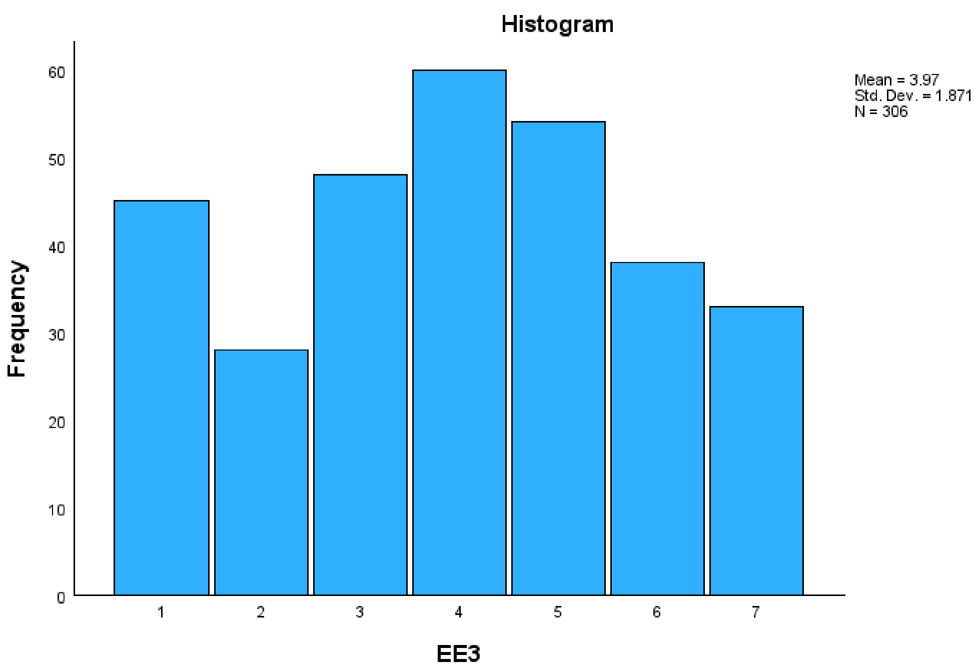

Histogram
Mean = 4.71
Std. Dev. = 1.597
N = 306
Frequency
0
20
40
60
80
100
1
2
3
4
5
6
7
CE1

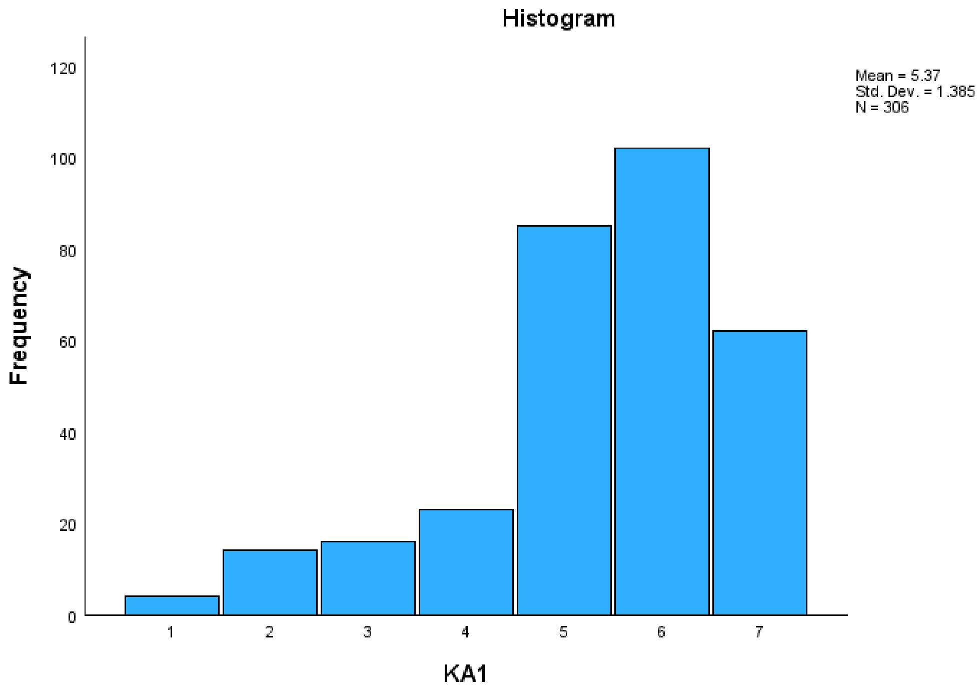

Histogram
Mean = 4.94
Std. Dev. = 1.56
N = 306
Frequency
0
20
40
60
80
100
1
2
3
4
5
6
7
CE2

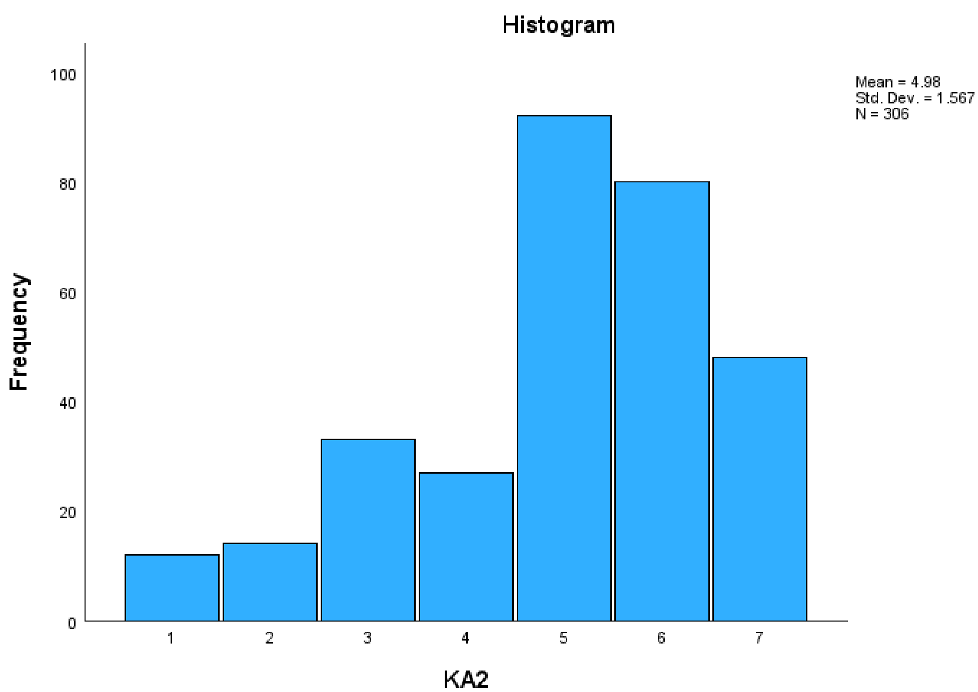

Histogram
Mean = 5.42
Std. Dev. = 1.299
N = 306
Frequency
100
80
60
40
20
0
1
2
3
4
5
6
7
CE3

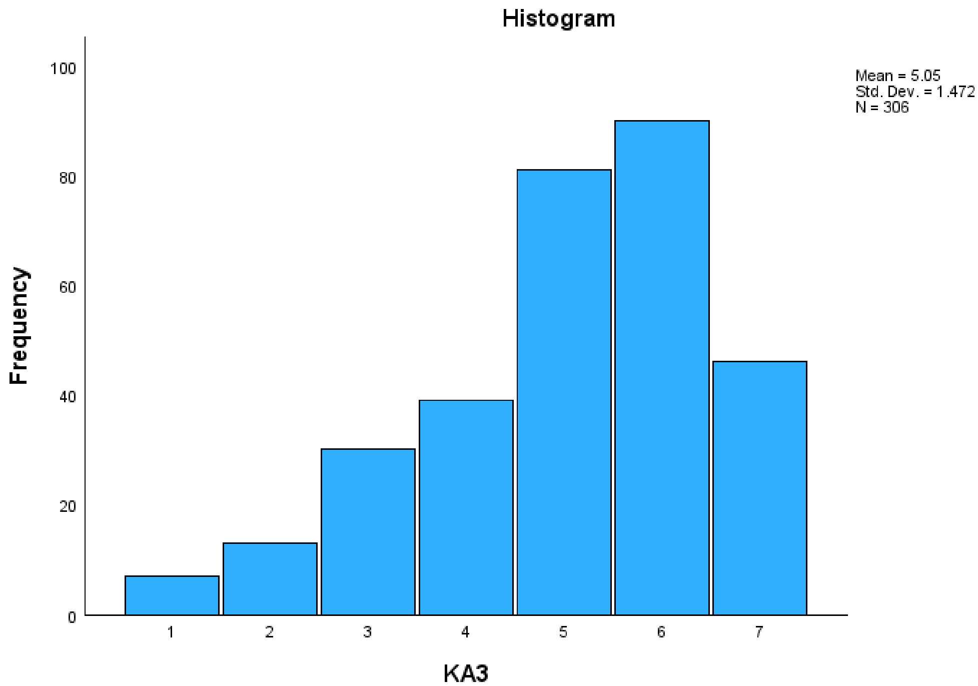

Histogram
Mean = 4.14
Std. Dev. = 1.743
N = 306
Frequency
80
60
40
20
0
1
2
3
4
5
6
7
EE1

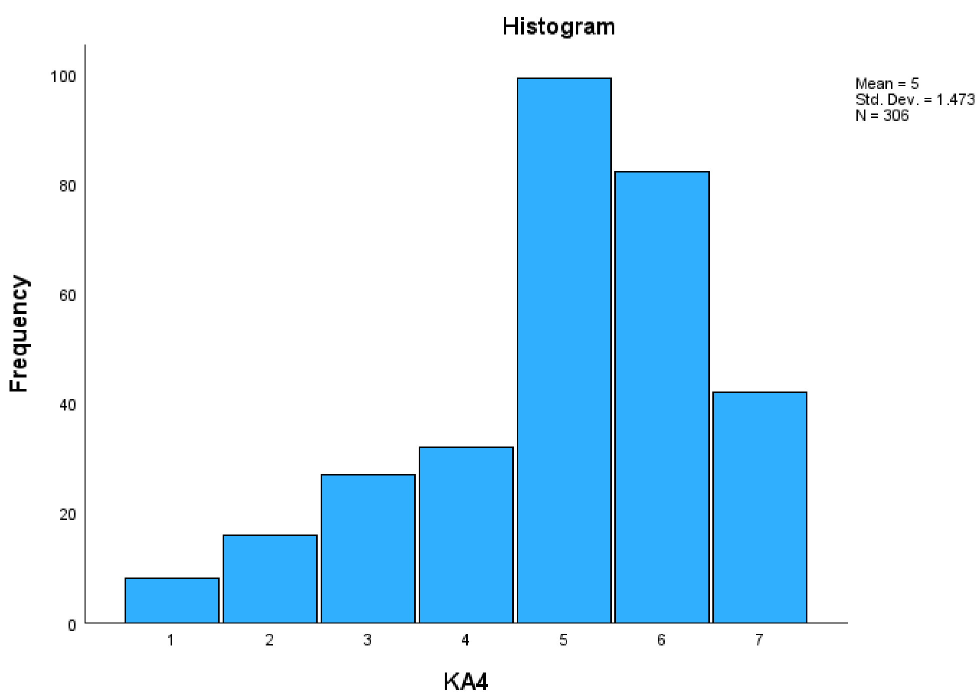

Histogram
Mean = 4.44
Std. Dev. = 1.713
N = 306
Frequency
100
80
60
40
20
0
1
2
3
4
5
6
7
EE2


Histogram
Mean = 3.97
Std. Dev. = 1.871
N = 306
Frequency
60
50
40
30
20
10
0
1
2
3
4
5
6
7
EE3


Histogram
Mean = 5.37
Std. Dev. = 1.385
N = 306
Frequency
120
100
80
60
40
20
0
1
2
3
4
5
6
7
KA1


Histogram
Mean = 4.98
Std. Dev. = 1.567
N = 306
Frequency
100
80
60
40
20
0
1
2
3
4
5
6
7
KA2


Histogram
Mean = 5.05
Std. Dev. = 1.472
N = 306
Frequency
100
80
60
40
20
0
1
2
3
4
5
6
7
KA3


Histogram
Mean = 5
Std. Dev. = 1.473
N = 306
Frequency
100
80
60
40
20
0
1
2
3
4
5
6
7
KA4