USER EXPERIENCE AND CONTINUOUS ENROLMENT INTENTION IN THE MASSIVE OPEN ONLINE COURSES (MOOC): A CASE STUDY ON WORKING ADULTS IN MALAYSIA

By

CHONG SWIT YIE

Faculty Of Business And Finance
Universiti Tunku Abdul Rahman,
Master Of Philosophy
February 17th, 2025

DECLARATION

I hereby declare that the dissertation is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

CHONG SWIT YIE

10 December 2024

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

MOOC	Massive Open Online Courses
SRL	Self-Regulated Learning
SDT	Self-Determination Theory
CI	Continuous Intention
UX	User Experience
SLR	Systematic Literature Review

ABSTRACT

This study examines the relationship between intrinsic motivation and user experience (UX) in Massive Open Online Courses (MOOCs) among working adults, using Self-Regulated Learning (SRL) and Self-Determination Theory (SDT) as foundational frameworks. The study specifically adapts SDT's components—autonomy, relatedness, and competence—to assess intrinsic motivation factors like independence, communication skills, and job specificity. A quantitative, cross-sectional approach was employed, involving 200 working adults in Malaysia, sampled through online distribution. The questionnaire, validated by experts through Content Validity Index (CVI) analysis, and reliability-tested through pilot testing (Cronbach’s alpha), exhibited robust construct validity. Data were analyzed using PLS-SEM and SPSS to explore correlations and structural relationships, accounting for potential biases and demographic differences.

Findings reveal a significant relationship between intrinsic motivation and UX in MOOCs, suggesting that positive UX promotes continued interest (CI) in online learning among working adults. However, SRL showed only a partial moderation effect, impacting the factor of independence. The study's limitations include potential common method bias and limited ethnic diversity among respondents. This research contributes a validated instrument that future studies may adopt and highlights practical implications for MOOC providers and policymakers to tailor on-demand learning experiences suited to working professionals’ needs.

Keywords: MOOC, Self-Regulated Learning (SRL), Self-Determination Theory (SDT), Continuous Intention, User Experience, Working Adults

Subject Area: LC5201-6660.4 Education extension. Adult education. Continuing education

This page is intentionally left blank.

CHAPTER 1: INTRODUCTION

1.0 Introduction

The research background outlines the adoption of online learning impacted by the emerging technology trend. Besides that, this section includes the research problem highlighting adult learners' proactiveness towards online learning due to the direction of lifelong learning, as online learning is more flexible regarding location and time. This section is also extended to research questions, objectives, and significance of the study to understand the current gap in adult learners' continuous intention and user experience towards MOOC.

1.1 Research Background

The Malaysian Education System is governed by the Ministry of Education (MOE) (Musa, 2021). The Malaysian education system is categorised into preschool, primary, secondary, post-secondary, and tertiary education, split into public or private (Musa, 2021). Tertiary education is governed by the Malaysian Ministry of Education (MOE).

In the year 2020, Malaysia went through a change. The Education Ministry and Higher Education Ministry are separated due to the Cabinet lineup by Prime Minister Tan Muhyiddin Yassin, which ex-Prime Minister Tun Abdullah Ahmad Badawi once implemented in 2004.

Prime Minister Tan Sri Muhyiddin Yassin has revived the Higher Education Ministry. The current Education ministry was overloaded with monitoring education from preschool to higher learning (Nik Anis & Tan, 2020) to achieve 200,000 new international students (Kulasegaran, 2019). The Education sector applies the initiatives that have always been one of the country's gross domestic product (GDP) other than just education, where to date it has already accumulated RM31.5 billion from tuition fees and cost of living from the international student's expenditure to the Malaysian economy in 2018 (Rajaendram, 2020a).

Global technological growth has revolutionised the way learners receive an education. Traditional learning via face-to-face is being replaced with online education, supported by virtual platforms (Chin, 2020). Online education is gaining massive popularity (Trines, 2018; Schroeder, 2019; Chin, 2020), resulting in the rise of consumer needs towards Open Learning Platforms. Massive Online Open Courses (MOOC) became the most sought-after solution for global knowledge sharing and discussing a specific topic (Alyoussef, 2023).

The Malaysian Education Blueprint 2015-2025 is an effort by the MOE to develop the intellect of its nation by implementing its MOOC (Wan, Sirat, & Razak, 2018). According to Redrup (2018), Malaysians have invested at least $8.5 million to host Massive Open Online Courses (MOOC). The MOOC platform has garnered over 880 course development and 760,000 learner enrolments on OpenLearning (Growing from strength to strength, 2018; Jacobs, 2019).

Given the growing importance of providing education freedom to everyone and especially to equip the current and future workforce with relevant and current knowledge, the Malaysian Government has strategised MOOC as "Shift 9: Globalised Online Learning (GOL)" in the

Malaysia Education Blueprint 2015-2025 (Growing from strength to strength, 2018; Azizi, 2017). The GOL is the Government's initiative towards quality education where creative and engaging content is developed by subject matter experts to allow quality course delivery, which will be hosted by establishing a National e-Learning Centre. The Malaysian government needs to invest in education as it brings forth economic contribution and develops the future competent workforce that could be the long-term investment in developing the nation’s talent pipeline.

Traditional education has provided learners with sufficient facts and theories; however, it lacks application in the real world (Darling-Hammond et al., 2020). With the presence of MOOC courses that industry subject matter experts mainly develop, learners can connect to the real world with the theory and facts taught in class (The 50 Most Popular MOOCs of All Time, 2021).

Online learning has proven valuable during this COVID-19 pandemic, where learners and teachers could learn and share via online learning on MOOC. According to Li and Lalani (2020), online learning provides the convenience of information storage, which students can access anytime and anywhere, proven in this COVID-19 pandemic. It has made learning more feasible as teachers can upload any form of study material into the online learning platform, including documents, videos, e-books, or audio, which could foster students’ teamwork in learning (Fadiyah, 2020).

Other than that, the Malaysian Education Ministry has also implemented the 6-year plan, “The Way Forward for Private Higher Education Institutions (PHEIs): Education as an Industry (2020-2025)”, to ensure that the PHEIs are moving towards the target as a global education hub aiming for 200,00 worldwide students (Rajaendram, 2020b). Since the outbreak of the COVID-19 pandemic, there has been a delay in the 6-year plan, The Way Forward. However, it has caused an increase in e-learning as online learning and education is a necessity, as mentioned by Professor Dr Abdul Karim Alias, Director of Centre for Development of Academic Excellence (CDAE) at Universiti Sains Malaysia (USM) (COVID-19: Opportunities for e-Learning Industry, 2020).

The Malaysia MOE has ensured the quality of education by establishing the Malaysian Qualification Agency (MQA). Tertiary education in Malaysia is recognised nationwide when it complies with the MQA programme standards. The programme standards are as follows: duration, course, assessment, and subjects (Mazlan, 2019).

In recent events, over 1.37 billion students in 138 countries have been affected worldwide due to the COVID-19 pandemic, where over 193 countries have their schools closed by the end of March 2020 (David et al., 2020; Li & Lalani, 2020; UNESCO, 2020). Accordingly, the World Bank Edtech Team has geared up to explore how students worldwide can tune into their education. The team discovered many sources of online learning that are readily available in the national learning platforms, software and even on television and radio (World Bank, 2020). They categorised the availability of each online learning source by country that could be used to aid remote learning for different education categories. This effort keeps the learners busy besides upskilling and increasing their productivity during the control movement environment. It is proven that global online education surged during this COVID-19 pandemic. It recorded an increase of 425% enrollment and 55% course creation in the Udemy platform alone (Online Education Steps Up: What the World is Learning (from Home) 2020). Udemy is a technological platform that strives to achieve its mission of “helping anybody learn anything online,” which enables instructors to create courses and organisations that want to develop bite-sized specialised learning for their internal corporate learning (Lewis, 2020).

Adult learning education in Asia and the Pacific has risen from 2015 to 2018 by 49% (UNESCO: 4th Global Report on Adult Learning and Education, 2019). Lifelong learning has become a trend in this century. The term's meaning stems from the effort of continuous, voluntary, and self-motivation in developing knowledge or skills such as life skills, soft skills, and vocational skills for personal or professional courses (Ting, 2015). This knowledge and skills learnt will help learners integrate and stay abreast of the fast-paced world regarding social belonging, personal development, and self-sustainability (Dhawan, 2020). The convenient access to the internet has made lifelong learning a trend where everyone jumped into the idea of solving skills and knowledge at their fingertips.

The emerging trend of lifelong learning has affected a surge of demand and supply of short courses on online educational platforms (Global survey reveals growing interest in shorter programmes and lifelong learning, 2020; Head, Van Hoeck, & Garson, 2015). Online learning has become popular due to its flexibility, as it is accessible anytime and anywhere. Due to its flexibility, it has garnered a lot of attention from adult learners. Adult learners usually work and utilise them after working hours to learn (Ho & Lim, 2020). Hence, the an increasing trend of adult learners taking courses online.

Since 2018, there has been tremendous growth in Malaysian companies, wherein in 2013, it was 6.3 million to 8.1 million, which brings more job opportunities and the workforce. Many companies have realised e-learning could help reduce the cost of training and development and, at the same time, maximise the use of the workforce (Malaysia E-Learning Industry Revenue is Expected to Reach Over USD 2 Billion by 2023: Ken Research, 2019). Hence, with the ever-growing trend of lifelong learning, the demand of adult learners towards online learning increased as they can learn anytime. Their work is not hindered by training time or knowledge retention, and employees develop a growth mindset with constant learning and sharing (How and why E-learning will revolutionise the concept of company training, 2019).

Accordingly, there is a rise in market demand for short courses and professional certification on MOOC for workforces and professionals (Redrup, 2018; Lim et al., 2017). Spar and Dye (2018) reported higher employee retention, where at least 94% of employees are more loyal when the company focuses on learning and development. Hence, the statistics on MOOC courses' growth for adult learners have increased over the years, reaching 110 million people (Impey, 2020). Magnifying Malaysia, Muller (2021) reported internet usage in Malaysia in 2019. It was categorised by an activity where 83.5% of Malaysians primarily utilise the Internet to gather information and knowledge about goods and services. In addition, it was found that at least 39.9% of Malaysians use the Internet to consult learning websites for formal learning purposes 39.9% (top 14th), informal online courses at 9.5%, and lastly, doing a formal online course at 8.1%. The report by Muller (2021) showed that at least 50% of Malaysians use the internet to learn, whether formally or informally.

MOOC is known for its affordable education, where working adults can pursue their professional development (Çakiroğlu et al., 2023; Agarwala, 2013) and personal development and quickly improve their jobs (Loizzo et al., 2017; Dillahunt et al., 2016). Thus, MOOC is deemed to provide substantial opportunity for working adults to learn seamlessly, providing flexibility to perform their responsibilities in the learning process (Fieland, 2019).

1.2 Research Problem

Globally, MOOC dropout rates are known to be high, with completion rates often as low as 10% (Nesterowicz et al., 2022; Healy, 2017; Henderikx, Kreijns, & Kalz, 2017; Onah, Sinclair, & Boyatt, 2014; Reich, 2014). This trend reflects general challenges with MOOC engagement and retention, relevant to the Malaysian context as well (Amantha Kumar & Al-Samarraie, 2019). While specific statistics for Malaysia are somewhat scarce, there is relevant data from global trends that can be used to contextualize the issue. Research indicates that the average completion rate for MOOCs is around 7% for free courses, with higher completion rates observed for paid courses (about 59%) (WORLDMETRICS, 2024). However in a recent study by Chopra and Syazwani (2022) investigates dropout rates in MOOCs in Malaysia, focusing on the learner's perspective. It highlights that only 18% of Malaysian users complete the courses they start, while around 64% of the population has never participated in any MOOC platform. According to Aldowah, Al-Samarraie, and Alzahrani (2020), academic skills, capabilities, previous experience, instructional development, feedback, social appearance, and social aid influenced the dropouts of learners on MOOC. Dropout rates have been a concern, and some studies have been relating this issue towards learners' behaviour (Cong, 2020; Onah et al., 2014) and, hence, their intention to continue learning (Chen & Zhang, 2017; Hone & Said, 2016).

Self-Regulated Learning (SRL) is a process where learners are accountable for their learning (Demirören, Turan & Taşdelen, 2020; Yot-Domínguez & Marcelo, 2017). There has been a rise in studies on learners' autonomy towards MOOC, as seen in Table 1.1. There were lots of studies that mentioned dropout rates have been increasing. Hence, it heavily depends on the learner's initiative, perseverance, and adaptive skills (Albelbisi, 2019; Li, 2019; Milligan, Littlejohn & Hood, 2016). They utilise strategies such as setting learning goals to motivate themselves (Ding & Shen, 2019; Zhang, Chen, Miao, & Zhang, 2018). Hence, completion rates of learners on MOOC are highly dependent on their initiative as MOOC adopts a flexible learning model with no definite completion timeline.

Table 1.1 Findings of Learner's Autonomy towards MOOC

Author	Findings of Learner's Autonomy towards MOOC
Ginting, Djiwandono, Woods, & Lee (2021)	Better autonomy leads to better academic achievement as they are confident and motivated to learn from the materials provided.
Lan & Hew (2020)	Perceived competence and emotional engagement from Self-Determination theory correlated with MOOC completions.
Agonács & Matos (2019)	Elder learners are ready to learn on MOOC and are self-directed in their learning.
Ding & Shen (2019)	Learners demonstrated autonomy and practised motivation strategies.
Yang & Huo (2019)	Application of the MOOC's features and teaching model will encourage learners' autonomy.
Martin, Kelly, & Terry (2018)	MOOC engagement found as the findings show intrinsic motivation.

It was also found that MOOC platforms that offer quality content and valuable courses can retain users (Lu, Wang & Lu, 2019; Espada et al., 2014) because of their positive user experience—some familiar MOOC platforms such as Udemy, Coursera, edX and Udacity. Besides, courses that focus on more profound learning activities, such as in-depth interaction, also enhance user experience (OpenLearning Analytics: MOOCs in the New Academic Year 2018/2019, 2019). Therefore, improving learners' experience with MOOC can significantly impact the completion rate of the ongoing courses and future enrolment at MOOC (Lu et al., 2019; Alraimi, Zo, & Ciganek, 2015).

Fundamentally, User Experience (UX) measurement will be able to create brand loyalty, and user needs satisfaction by triggering a user's emotions and meeting the user's psychological needs and motivation to purchase (Zhao, 2022; Vermeeren, Roto, & Väänänen, 2016). UX has been mentioned many times in previous studies. Many researchers have emphasised the importance of studying UX for future studies. This has proven that UX significantly impacts MOOC usage (Li, Wang, Tan, 2018; Hone & Said, 2016). From the previous studies, UX focuses on phenomena such as the formation of experiences or what user experiences, experience expectation, or have experienced (Högberg, Hamari & Wästlund, 2019; Roto et al., 2011).

Several studies (Moreno-Marcos et al., 2020; Tawafak et al., 2019; Chacón-Beltrán, 2018; Ya et al., 2018; Joo, So, & Kim, 2018; Alexandron et al., 2017) have explored continuous intention (CI) towards MOOC, involving diverse respondent groups, such as young adults, university students, adults, and older adults. These studies primarily focused on analysing the influence of MOOC system features on CI. Conversely, Dai, Teo, and Rappa (2022) highlighted that working adults display greater motivation to learn when presented with improved features on MOOC. However, there has been limited research specifically dedicated to examining the motivation of working adults towards learning on MOOC, to the best of the author's knowledge.

Self-Determination Theory (SDT) has frequently examined learners' intrinsic motivation towards online learning (Lan & Hew, 2020; Loizzo et al., 2017). Furthermore, with the rise of MOOC as a significant learning platform, various studies have investigated learners' intrinsic motivation towards MOOC (Dong, Ji & Zhang, 2023; Nguyen & Chen, 2023; Zhu, Bonk & Berri, 2022). While some researchers have called for further exploration of motivation towards MOOC and its impact on learners' Continuous Improvement (CI) (Semenova, 2020), others have advocated for investigating learners' intrinsic motivation towards MOOC in future research (Joo et al., 2018). However, there is still a gap in understanding the sustainability of learners' motivation, mainly how intrinsic motivation influences their User Experience (UX) and Continuous Improvement (CI) in the context of MOOC. While there are studies that have separately addressed the positive impact of Intrinsic Motivation on learners' CI towards MOOC (Lei & Lin, 2022) and UX towards MOOC (Wang et al., 2023), the present study, in alignment with Self-Determination Theory (SDT), aims to investigate the intrinsic motivation of working adults concerning their MOOC User Experience (UX) and Continuous Improvement (CI).

The completion rate of MOOC depends on individual initiative, with a particular emphasis on self-regulated learning (SRL) (Ding & Shen, 2019; Li, 2019; Yot-Domínguez & Marcelo, 2017). Consequently, numerous studies have independently explored SRL and MOOC. However, there have been limited studies investigating the relationship between intrinsic motivation, SRL, and MOOC (Min & Nasir, 2020). Moreover, there is still a lack of research on how SRL moderates the connection between the intrinsic motivation of working adults, MOOC user experience (UX), and continuous improvement (CI). Therefore, this study aims to fill this gap by examining the role of SRL as a moderator in influencing the relationship between the intrinsic motivation of working adults on MOOC and their UX and CI.

1.3 Research Questions

1. How do working adults' intrinsic motivation factors affect their experience with MOOC?
2. How does SRL affect the relationship between working adults' UX and their intrinsic motivation factors?
3. What is the impact of MOOC's UX towards MOOC's CI among working adults?

1.4 Research Objectives

1. To examine the relationship between working adults' intrinsic motivation factors and their user experience with MOOC.
2. To measure the role of SRL in moderating the relationship between working adults' UX and their intrinsic motivation factors towards MOOC.
3. To determine the impact of MOOC's UX towards MOOC's CI among working adults.

1.5 Research Significance

This study highlights the target audience of adult learners, where many existing studies did not appropriately categorise their users. Loizzo et al. (2017) have mentioned an academic gap towards researching Adult Learners and their User Experience (UX) towards MOOC. Leris et al. (2017) have said the need to understand the satisfaction and dropout rates among learners by understanding the UX towards MOOC. Furthermore, Howarth et al. (2016) have added that researching the UX towards MOOC is essential in understanding course delivery and technological use. Loizzo and Ertmer (2016) added that researching UX and their background impacts the learning attitude and behaviour. A few more past studies have also shown a need to research further on the UX towards MOOC (Li, Wang, & Tan, 2018; Niu, 2018; Ya et al., 2018; Hone & Said, 2016).

Lifelong learning has become a trend, and this has caused many adults to adopt continuous learning. With the convenience of technology, adults embrace learning via online platforms as it is accessible anytime and anywhere with the UX that MOOC provides. With this study, adult learners can understand how other adult learners learn via MOOC, which could further help them adapt to learning.

It was found that many companies prefer to upskill their employees' development using online education as it is low cost and saves a lot of travelling time and money. With this study, employers would be able to find out how to ensure that their employees can follow through with the learning and development plan they had for their employees, which involves e-learning to provide a higher return on investment.

The Malaysian Ministry of Education (MOE) has the potential to create an enhanced strategy to incentivise local and private higher learning institutions, along with other providers, to attract and enrol a greater number of working adults into MOOC courses. By gaining insight into adult learning and minimising dropout rates, universities and course providers can devise more effective study plans. Consequently, key stakeholders can implement tailored strategies and techniques to engage the targeted audience.

In academics, this study will be able to close the gap between UX and SLR, as there were not many studies done on this relationship. Online platforms provide different system features, and many studies have on how user experience and system components influence learners' intention towards MOOC. However, this study highlights that learners with concrete SRL are not swayed by UX. The reason is that SRL enhances or provides the learner's initiative and motivation to learn via MOOC instead of being affected by UX. Learners will learn how to adapt and adopt the UX provided by different MOOC instead of being affected by it. Learners with high SRL are self-directed towards their own study goals. Hence, they will be least affected by the MOOC' UX.

With this study, SRL influences learners' intention towards MOOC. In addition, most MOOC encourages learners to create their study plans and pathways, which promotes the SRL among learners. MOOC stakeholders that can identify how SRL influences learners' intention towards MOOC platforms can organise and collaborate with content writers to retain learners. In the long run, continuous meanings of learners are generated when learners return for a different course.

1.6 Research Scope

This study focuses on the adult learner's User experience (UX) towards MOOC and what makes them continually choose MOOC where the theoretical considerations will be found in Chapter 2. Learners who have returned to MOOC to learn a new course are deemed to be satisfied with the platform they chose to learn, and it would be in the form of positive UX. This outlook is focused on addressing the Research Problem via quantitative data collection.

MOOC is used in this study because it represents all the online learning platforms that are available on the web. The word Massive Open Online Course (MOOC) has become a buzz, and a lot of research is slowly building into MOOC. This research focuses on UX as it represents the learner's determinants towards UX when they learn on MOOC.

This study is interested in understanding how adult learners perceive MOOC and what motivates them to learn from MOOC. Young adults in tertiary education mainly use MOOC as most universities already establish and implement blended learning. Hence, Adult learners, who are primarily working adults, are the target audience in the study where this study intends to understand what motivates their knowledge.

The theoretical concepts, Self-Determination Theory (SDT) and Self-Regulated Learning (SRL), have contributed to formulating the research's framework development. Both theories concern the self-motivation of learners towards learning. The application of theories has brought light to the factors affecting the UX of MOOC. The deduction from the UX and theories has shown that determinants such as Independence, Communication Skills, and Job requirements are essential predecessors of motivation towards MOOC.

1.7 Definition of Key Terms

This section lays down the key terms that are frequently used. Key terms are further defined in the context of this study. The study aims to examine the determinants of user experience (UX) in the context of Massive Open Online Courses (MOOC), with a particular focus on the impact of Self-Regulated Learning (SRL). Table 1.2 provides an overview of the key terms and definitions that will be used throughout the study.

Table 1.2: Key terms and Definition in this Study

Key Terms	**Operational Definitions**
Continuous Intention	Learners that continually uses MOOC for their learning
User Experience	Learner's User Experience towards MOOC where if its positive will influence their continuous learning to MOOC.
Working Adults	Adults aged between 25-60 who are within the working-age category that uses MOOC as a learning platform
Self-Determination Theory	Self-Determination Theory helps us understand the importance of intrinsic factors, such as autonomy, competence, and relatedness, in the context of MOOC.
Self-Regulated Learning	Self-Regulated Learning acts as the moderator in this study where it facilitates the intrinsic motivation of learners (SDT Theory) towards their learning experience on MOOC.

1.8 Summary

In conclusion, this chapter is fundamental in introducing the research by providing the context via background, research problem, questions, objectives, and significance of the study. With this information, readers will be able to move to the following chapters on potential hypotheses and the presented theoretical framework.

2.0 LITERATURE REVIEW

2.1 Introduction

This section intends to deliver a literature review that explains the underlying theories of Self-Determination Theory (SDT) and Self-Regulated Learning (SRL). Constructs from the theories are adapted to determine the study's research variables. The development of the framework and hypotheses are also discussed in this chapter.

2.2 Underlying Theories

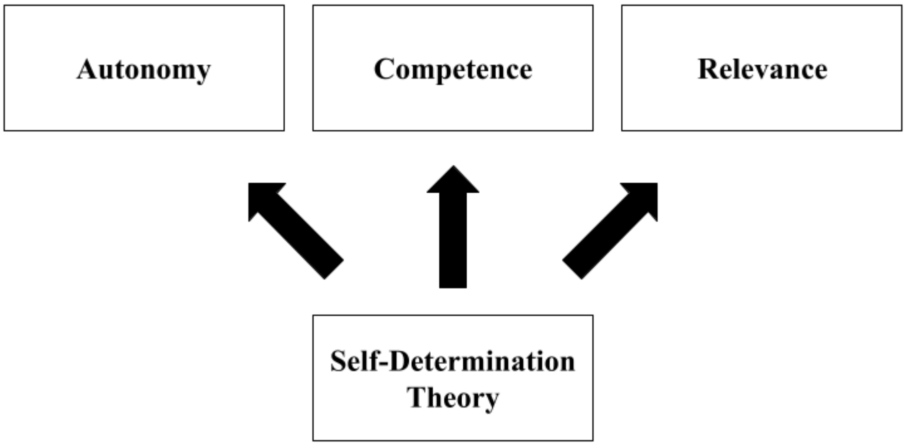
In this section, two theories are introduced: Self-Determination Theory (SDT) and Self-Regulated Learning (SRL). Briefly, SDT consists of 3 basic physiological needs known as autonomy, competence and relatedness that facilitate and motivate the growth of individuals. Meanwhile, SRL is a cyclic process comprising three phases: the forethought phase, the performance phase, and the evaluation phase, which guide individuals to reach their goals.

2.2.1 Self-Determination Theory

Self-determination theory (SDT) has gained widespread recognition through numerous research studies, explaining the ever-growing needs and motivation within a social context (Deci & Ryan, 2015; 2013; 2008; 2000). It has been extensively explored in the context of e-learning research (Lan & Hew, 2020; Loizzo et al., 2017; Durksen et al., 2016). In recent years, SDT has received significant attention in MOOC studies (Loizzo et al., 2016; Zhou, 2016). It is important to highlight that SDT is commonly integrated with other theories and models in these existing studies (See Table 2.1).

Figure 2.1 depicts the Self-Determination theory founded by Deci and Ryan (2000). According to Deci and Ryan (2015; 2000), motivation is developed within oneself, influenced by three basic psychological needs known as autonomy, competence and relatedness. Motivation is the satisfaction of psychological needs of autonomy, competence and relatedness that happens when learners are motivated to do something for the self-satisfaction of performing a particular activity (Deci & Ryan, 2015; 2000).

Figure 2.1: Self Determination Theory (SDT)



Source: Deci & Ryan (2000)

Autonomy is the motivation of individuals who participate in a particular activity with their willingness, volition and preference (Deci, Olafsen, & Ryan, 2017). Additionally, it is an innate behaviour of learners who want to be responsible for their own decisions, which could help them reach their desired goals (Filgona, Sakiyo, & Augustine. 2020; Deci & Ryan, 2008; Ryan & Deci, 2000). Learners can experience no task limitation, which means learners are not bound to complete a certain number of tasks, but instead, they have full autonomy to control their learning pace (Maddens et al., 2023; Martin, Kelly, & Terry, 2018).

Deci, Ryan and Guay (2013) mentioned that competence is a need of an individual to master their current situation and experience a feeling of competence. The feeling of competence is not limited to achievement but rather a “phenomenological” sense of experience. The ever-changing technology has pushed learners to master new skills and knowledge to stay competitive in the workplace (Hughes, 2021; Egloffstein & Ifenthaler, 2017).

Relatedness, known as Connection, is the sense of belonging and engagement with others as all of us need to connect to a certain degree (Deci & Ryan, 2008). Relatedness often motivates individuals to engage in something to feel connected to others, to feel cared for or care for others (Deci et al. 2013; Ryan & Deci 2000). Relatedness can be seen when learners are motivated to learn, interact, and connect on a topic to boost their psychological needs, such as confidence (Cook & Artino, 2016).

2.2.1.1 Summary of Past Studies on Self-Determination Theory (SDT)

In this study, past studies on MOOC using SDT were reviewed using the systematic literature review (SLR) technique. The followings were the inclusion criteria used in selecting the past studies for the SLR:

1. SDT + MOOC (Keywords)
2. Peer-reviewed journal
3. Last 5 years (2019-2023)

From this summary (Table 2.1), it could be concluded that many studies have combined SDT with other theories such as Social Motivation, Task Technology Fit Model, Technology Acceptance Model (Alami & El Idrissi, 2022; Alzaidi & Shehawy, 2022; Tawafak et al., 2020), Relationship Quality and Technology-user-environment framework (Gupta, 2019). Overall, past studies have used SDT alongside other theories to measure the learner’s behaviour towards MOOC. It implies that SDT could complement well with other theories and models.

Table 2.1 Summary of Studies on Self-Determination Theory (SDT)

Author	Research Area	Variables Investigated	Main Results
Cristea et al. (2023)	SDT as a measuring indicator for engagement on MOOCs	Engagement theories (Drive, Engagement, Process of Engagement) SDT (Autonomy, Relatedness, Competence)	Motivation is important in completion of MOOC.
Çakiroğlu et al. (2023)	Motivation towards professional Development Programmes via MOOC		It was found that Nature of Professional Development, Teaching Materials, evaluation, learning environ,ent and external factors motivates learners towards MOOC.
Bai, Hossain, Kumar, & Hossain (2022)	Effect of Perceived Fear, Quality, and Self-Determination on Learners' Retention Intention on MOOCs	IS Success Model (Service quality, Course quality, System Quality) SDT (External regulation, Identified Regulation, Integrated Reguation) Confirmation Retention Intention Perceived Fear Intention to Recommend	The results indicated that the quality of the course, as well as intrinsic and integrated motivation, have a notable impact on perceived usefulness and satisfaction, thereby enhancing the intention to continue participation. The results showed that integrated motivation and course quality emerged as the most crucial factors, despite receiving relatively little attention. Furthermore, the COVID-19 pandemic has heightened the importance of alternative learning methods and has made learners more aware of the often-overlooked benefits of MOOCs.
Hsu (2020)	Learners motivation towards MOOC	SDT (Autonomy, Relatedness, Competence)	Autonomy, Competence influences students engagement towards MOOC.
Moore & Wang (2021)	Learner's motivation towards MOOC Completion	Intrinsic Motivation Extrinsic Motivation	Students displaying intrinsic motivational tendencies outperformed those with extrinsic dispositions, and female students exhibited superior performance compared to their male

			counterparts.
Abdullatif & Velázquez-Iturbide (2020)	Relationship between motivation, personality traits towards the intention of learners in continuously using MOOC.	Internal and External Motivation Personality Traits (agreeableness, extraversion, and conscientiousness) Continuous Intention towards MOOC	It was found that internal motivation affects intention towards MOOC.
Lan & Hew (2020)	Engagement factors and SDT in completing courses on MOOC.	Behavioral Engagement Emotional Engagement Cognitive Engagement SDT (Autonomy, Relatedness, Competence)	Engagement factors (Behavioral, Emotional, Cognitive) and SDT (Autonomy, Competence, Relatedness) are correlated.
Fang, Tang, Yang, & Peng (2019)	SDT as a mediator for social interaction and learning engagement towards MOOC	Learning Engagement Social Interaction SDT (Autonomy, Relatedness, Competence)	The findings shows that competence
Gupta (2019)	Factors affecting the adoption of MOOC using the Technology-User-Environment (TUE)and SDT	Intrinsic Motivation Social Recognition Perceived Value Perceived Usefulness Personal Readiness Self-regulation Peer Influence	Learner's intention towards MOOC has a positive relationship by intrinsic motivation, social recognition, perceived value and perceived usefulness. Personal readiness, self-regulation and peer influence have no relationship
Hsu, Wang, & Levesque-Bristol (2019)	SDT in online learning	Learning Climate Autonomy Competence Relatedness Self-determination Index Perceived Knowledge Transfer Perceived Learning Gains	Satisfying Autonomy, Competence & Relatedness fosters learning outcomes in online learning

From Section 1.2, it was found that studies on the learner's initiative (Albelbisi; 2019; Li, 2019; Littlejohn et al., 2016) and their initiative to set learning goals to motivate themselves (Ding & Shen, 2019; Zhang et al., 2018) towards MOOC has increased. Hence, Self-Regulated Learning is a matching theory that learners motivate themselves with their initiative in setting learning goals and many more learning phases. The following subsection describes SRL in detail.

In recent years, there has been a growing focus on studying learner autonomy, which is associated with Self-Determination Theory (SDT), as evident in Tables 1.1 and 2.1. Additionally, there has been increasing attention towards learners' own initiatives, which are linked to constructs of Self-Regulated Learning (SRL), as shown in Table 2.2 in the next section, particularly in the context of MOOC. Although there is some overlap between learners' autonomy and their own initiatives, existing studies have tended to examine these similar constructs separately. Recognizing the increasing significance of both learners' autonomy and their own initiatives, and acknowledging their similarity, the current study aims to complement the utilization of SDT with the incorporation of SRL theory.

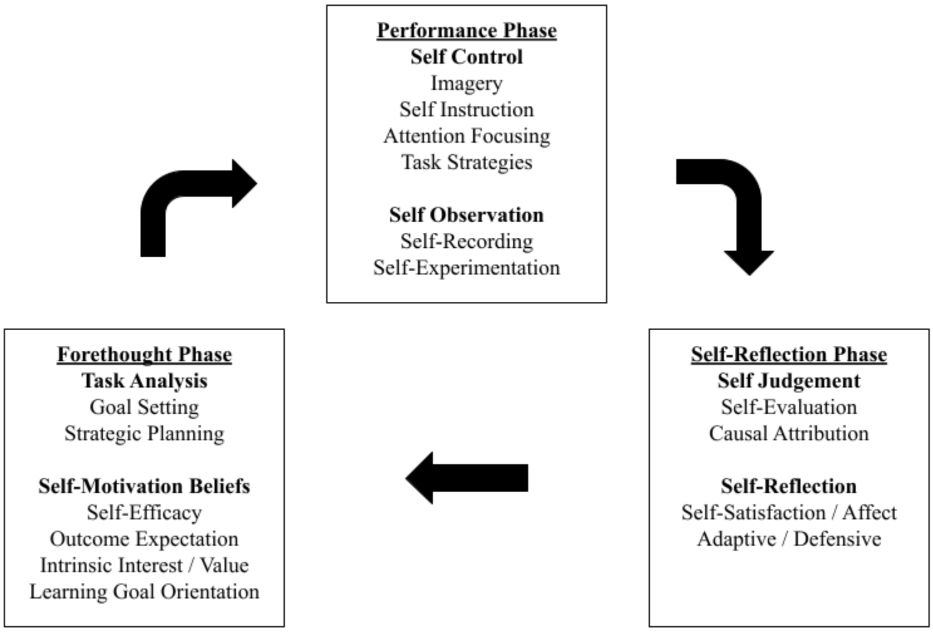
2.2.2 Self-Regulated Learning (SRL)

Some authors have highlighted that Self-Regulated Learning (SRL) is acquired through a combination of teacher instruction, guidance, and learners' observation (Harding et al., 2019). Alvi and Gillies (2020) and Lee et al. (2020) point out that SRL represents an ongoing challenge for both teachers and learners. Learners who engage in SRL continuously employ new learning strategies, monitoring their performance to achieve their goals (Araka et al., 2020; Kirk, 2020). Zumbrunn et al. (2011) emphasize that SRL is a process that can significantly contribute to academic success, particularly by enabling learners to adapt and improve their learning strategies based on an understanding of their weaknesses.

Meanwhile, it could also cause learners to fail when wrong learning strategies are applied (Panadero, 2017). According to Winne (2015), learners who intentionally choose to disregard studying are also a form of SRL as they are disengaging from learning. Such behavior is known as procrastination, where learners are highly aware of their work-avoidant nature of delaying their work till the last minute (Merett et al., 2020). Learners who procrastinate actively focus on distractive thoughts, emotions, feelings or situations (Palo, Monacis & Sinatra, 2019). Learners often fail to carry out follow-up learning, which causes failure to achieve their goals and mastery (Chou & Zou, 2020).

Figure 2.2 depicts the Cycle Model of Self-Regulated Learning by Zimmerman (1998). In this cyclic model, there are three phases in SRL: Forethought Phase, Performance Phase, and Self-Reflection Phase. The forethought is initiatives that include Task Analysis and Self-Motivational Beliefs; the Performance Phase includes Self-Control and Self-Observation, and the Self-Reflection Phase includes Self-Judgement and Self-Reaction.

Figure 2.2: A Cycle Model of Self-Regulated Learning



Source: Zimmerman (1998)

In the forethought phase, learners plan their learning strategies, including task analysis and underlying motivational learning beliefs, to be self-driven (Fauzi & Widjajanti, 2018). Task analysis includes the level of comprehension and action required to design the learning outcomes of the task (Jansen et al., 2020; Harding et al., 2018). Learners are in the mindset of self-motivation beliefs, including self-efficacy, outcome expectation, intrinsic interest, and learning goal orientation (Gan, Liu, & Nang, 2023). Self-efficacy is the learner's confidence in managing their motivation, behaviour and social environment (Cherry, 2023). Goal orientation concerns how people define and strive for success by setting goals and outcome expectations (Vandewalle, Nerstad & Dysvik, 2019). Learners with a high learning goal orientation strive towards mastery of a specific skill or task to enhance their competence by being attentive to their task analysis of goal setting and strategic planning (Park, 2018).

In the performance phase, learners usually go through self-control and self-observation. Learners deploy practical approaches and strategies established in a wayfinding solution to the forethought phase, such as enhancing time management (Zimmerman, Greenberg & Weinstein, 1994). This could show the better organisation of the learner's knowledge, meticulous self-judgments, and productive goal-setting to learn (Zimmerman & Bandura, 1994). Learners are likely to complete courses with suitable content, clear instructions, engaging teachers, and schedule flexibility (Oakley, Poole & Nestor, 2016).

Self-reflection is the last phase of the SRL cyclic phase. However, it does not end there as learners who implement SRL tend to learn from their previous experience, setting learning strategies, efforts, emotions and motivation to achieve their desired learning goal. Learners will evaluate their learning experience via self-judgement by comparing the performance and the initial goal set in the forethought phase. Learners usually observe and even gather feedback on their performance to carry out the self-assessment. In this phase, learners will assess their competence in task analysis, motivation strategies, self-control strategies, and other performance attributes influencing the outcome. This exercise will allow learners to understand whether their personal SRL cyclic model was effective or ineffective. Self-reaction is when learners are satisfied with their results and defend their current model. However, if they cannot achieve their learning goals, they will adopt new strategies to gain better learning strategies. Learners may alter their behaviours and even learning techniques to achieve their intended goal when they deem their current strategy unsuitable after monitoring their self-reflection at the last stage. As a result, those learners who practise SRL are good at independently creating and adjusting their learning strategies in a wayfinding solution to their learning goals. This gives greater satisfaction for their success (Md Zalli, Nordin, & Awang-Hashim, 2019).

Therefore, self-regulated learning further emphasises the self-directive role of learners in outlining and planning their unique learning goals and strategies and considers their acumen and its impact on their learning task (Triquet, Peeters, & Lombaerts, 2017). In this manner, learners can stay centred on their initial intention of learning. By applying this cyclic SRL, learners can identify what learning process they adapted can satisfy their learning goals, which brings them to repeat the learning process. Additionally, learners with high SRL mainly achieve their learning goals (Jansen et al., 2020; Heidrun & Zeidner, 2019; Stoeger & Zeidner, 2019).

2.2.2.1 Summary of Past Studies on Self-Regulated Learning (SRL)

This study used the systematic literature review (SLR) technique to past studies on MOOC using SRL. The following were the inclusion criteria used in selecting the past studies for the SLR:

1. SDT + MOOC (Keywords)
2. Peer-reviewed journal
3. Last 5 years (2019-2023)

From this summary in Table 2.2, most studies retained the theory's original constructs, which are the forethought phase, performance phase, and self-reflection phase from the model introduced by Zimmerman (1998) (Jansen et al., 2020; Gafaro, 2019; Vilkova, 2019).

Some studies have used different terminology to represent the SRL phases. For instance, the

Forethought Phase is replaced with the Preparation Phase (Jansen et al., 2020) or Planning (Md Zalli et al., 2019); the Performance phase is replaced with the Action phase; and the Self-reflection phase is replaced with Reflection phase (Jansen et al., 2020).

However, many studies have researched the sub-processes of SRL known as Goal setting, Help-seeking, Time management, Self-evaluation, and Strategic Planning (Ceron et al., 2021; Vilkova, 2020; Md Zalli et al., 2019; Handoko et al., 2019). The past studies imply that SRL is flexible in adding and removing the constructs within the SRL model.

The current study removes SMB as it overlaps with the SDT's autonomy. Autonomy encourages learners to feel motivated towards learning (Mallipa & Papua, 2018), which is similarly found in SMB, where learners have a personal interest. Personal interest could be understood as the intention of an individual towards their benefit (Kenton, 2020). Similarly to SMB, learners' autonomy provides confidence to adapt to the ever-evolving society via their responsibility for learning and evaluation (Unjana et al., 2018). Confidence is an individual's beliefs of abilities and capabilities (Cherry, 2020), whereas the context of SMB means belief in their future capabilities to be successful (Sheldrake, 2016). A study done by Littlejohn et al. (2016) has stated that both learners who have high or low SRL have displayed confidence in achieving their learning goals in online learning, thus exhibiting their self-efficacy. Learners with high self-efficacy would have a high intrinsic interest in planning and setting their objectives for their learning expectations (Min & Nasir, 2020).

Table 2.2: Summary of Studies on Self-Regulated Learning (SRL)

Author	Research Area	Variables Investigated	Main Results
Jansen et al. (2020)	SRL intervention application on MOOC	Preparation Phase Action Phase Reflection Phase	SRL intervention is proven successful in supporting learner's SRL and course completion.
Vilkova (2019)	To analyse the relationship between SRL and MOOC	Forethought (Goal setting, self-efficacy, task value) Performance (task strategies, interest enhancement, help-seeking wayfinding solutions) Reflection (self-evaluation, self-satisfaction)	The SRL- Forethought phase (goal setting, self-efficacy, and task value) has shown signs in the regression towards MOOC completion.
Ceron et al. (2021)	Analyse the current state of the MOOC for learners to self-regulate their learning	Goal setting Help-Seeking Time management Self-evaluation Strategic planning	Identifying SRL helps MOOC facilitate learning for learners.
Md Zalli, Nordin, & Awang-hashim (2019)	SRL and learners satisfaction on MOOC	Planning (Task Strategy, environment structuring, goal setting) Time management Self-Evaluation Help-seeking	Help-seeking was found to not affect the learner's satisfaction on MOOC as it varies across different cultural contexts.
Handoko et al. (2019)	SRL on MOOC performance and learner's perception on subprocesses in SRL towards completion.	Goal setting Environmental structuring Time management Help-Seeking Task Strategies Self-Evaluation	Learner's goal-setting influences student performance and course completion on MOOC.
Albelbisi	To examine the relationship	Information quality	Providing support in terms of service quality factors

(2019)	between quality factors towards MOOC	Service Quality System Quality SRL	influences SRL positively on MOOC.
Gafaro (2019)	Relationship between the SRL processes and language learning on MOOC	Forethought (Task Analysis, Self-Motivation Beliefs) Performance (Self Control, Self-Observation) Reflection (Self Judgement, Self-Evaluation)	Student's SRL behaviour is essential in engaging with MOOC.
Wang & Zhu (2019)	Effectiveness of MOOC and traditional university education.	Students' participation MOOC-based flipped learning Student's Experience & Learning Experience	Learners find that Micro-lectures are helpful; meanwhile, online exercises lack detailed analysis of answers.
Vilkova & Shcheglova (2020)	SRL Skills	Goal setting Environmental structuring Time Management Help-Seeking Task Strategies Self-Evaluation	It was found that SRL strategies are dependent on external factors. Help-seeking is not relevant in a MOOC environment (ow communication between peers and instructors)
Lan et al. (2019)	SRL indicators in the students' performances that relate to learning patterns via navigation of content from clickstream data	Time Management Task Strategy Self-Instruction (Assessment Driven) Self-instruction of systematic learning Application	Motivation in attending MOOC and their learning behaviour (demographic and professional experience of learners) are found to have higher grades and completion rates.

2.2.3 Application of SRL and SDT in the Current Study

In subsection 2.2.1.1, previous research has demonstrated that Self-Determination Theory (SDT) can be effectively combined with other theories and models. Consequently, in the context of this study, SDT will complement Self-Regulated Learning (SRL). Furthermore, in subsection 2.2.2.1, it is explained that the concept of Self Motivational Beliefs (SMB) is excluded from the SRL model as it bears similarities to SDT's Autonomy. Previous studies have illustrated the inclusion and removal of original constructs within the SRL model, as evident in Table 2.2. As summarized in Table 2.3, both SRL and SDT theories will be applied to the MOOC context and working adults in the current study.

Table 2.3: Theory and Constructs Application in the Study

Theory	Constructs	Remarks	Application in the study
SDT	Autonomy	added SMB of SRL	Independence
	Competence	Competency would help them to meet their job specification	Job Specification
	Relatedness	Collaborative Learning (MOOC) could improve communication skills	Communication Skills
SRL	Forethought Phase (Task Analysis, Self-Motivational Beliefs) Performance Phase (Self-Control, Self-Observation) Self-Reflection Phase (Self-Judgement, Self-Reflection)	Remove SMB from forethought Phase because it is similar SDT’s Autonomy	Self-Regulated learning

Numerous studies have demonstrated that motivation plays a significant role in guiding learners' self-directed behaviours towards engaging with MOOC (Salikhova, Lynch, & Salikhova, 2020; Sun et al., 2019; Luik et al., 2017; deBarba et al., 2016; Milligan & Littlejohn, 2017). From the perspective of Self-Determination Theory (SDT), Dworkin (2015) has argued that autonomy is directly linked to learners' independence in pursuing their interests, indicating that their actions are not solely influenced by external factors. The Self-Motivational Beliefs (SMB) component includes self-efficacy, outcome expectation, intrinsic interest, and learning goal orientation (Wangida, 2020; Zimmerman, 1998). The similarities between SMB's self-efficacy and intrinsic interest align with SDT's concept of autonomy. This demonstrates a connection between SDT's autonomy and SMB, where Independence in Table 2.3 represents SMB, while Autonomy signifies learners' desire for full control over their learning (Martin, Kelly, & Terry, 2018).

MOOC offer learners complete autonomy to engage in flexible, self-paced learning without strict deadlines (Fieland, 2019). Drake and Rajaorko (2018) highlight that working adults prefer independent learning, benefiting from the ability to revisit videos, assignments, and materials to master their learning thoroughly. Consequently, learners are motivated as MOOC facilitate their independence in tailoring their learning journey at their own pace.

Individuals are driven by the desire for self-development to maintain competence and achieve mastery in their current job roles (Deci & Ryan, 2008). According to the management expert Covey (2006), competence is nurtured through capabilities (skills, knowledge, experience) and results (reputation, credibility, performance). This has led individuals to seek opportunities for learning and growth to adapt to the ever-changing demands of their industry (Li, 2022).

Online learning, particularly in the form of MOOC, has been instrumental in promoting competence among learners by facilitating continuous intention to learn. MOOC offer a range of bite-sized learning experiences, including theory, quizzes, video demonstrations, and assessments designed to foster learner competence (Ryan & Deci, 2017). The user experience of competency is further enhanced through features like progress bars and completion percentages, enabling learners to track their learning progress (Cheung & Ng, 2021; How do I gain 100% completion in a course? 2018).

Adult learners are particularly drawn to online learning because of the emphasis on competence, which motivates them to engage in evaluation and assessments (Diep et al., 2019). The desire to remain competent in the workplace and meet the job requirements to advance their careers is a powerful motivation for learners to continually return to online learning platforms.

Legault (2017) mentioned that individuals who seek relatedness tend to behave in a way agreeable to the group they value. Individuals are only delighted when relationships develop and return to fulfil the need for belonging to a group (Allen et al., 2021). MOOC courses also cover technical skills that are relevant to the industry, such as computer science, IT, cybersecurity, graphic design, coding and many more, which encourages continuous intention of adult learners towards MOOC (Massive Open Online Course (MOOC) Market: Growth, Trends, and Forecasts (2020 - 2025), 2020). Learners are encouraged to participate in discussion boards, video conferencing groups, peer-reviewing, and feedback which helps learners enhance their communication skills (Martin et al., 2018). These are communication skills relevant to SDT in relatedness, where learners want to fulfil the need to belong to a group (Allen et al., 2021). Furthermore, MOOC have offered many courses developed and designed by industry experts to help adult learners stay competent in their current job (Castaño-Muñoz & Rodrigues, 2021; The 50 Most Popular MOOCs of All Time, 2021).

The entire cyclical process of SRL, which is the forethought phase, performance phase, and self-evaluation phase without considering SMB, will be deemed to understand how learners are affected by SRL, which affects their intrinsic motivation towards MOOC's UX and hence CI. A study done by Littlejohn et al. (2016) has stated that both learners who have high or low SRL have displayed confidence in achieving their learning goals in online learning, thus exhibiting their self-efficacy. Learners with high self-efficacy would have a high intrinsic interest in planning and setting their objectives for earning expectations (Min & Nasir, 2020). Hence, it makes sense that learners begin with a strategic plan for learning to achieve their learning goals in the MOOC. By understanding their initial motivation beliefs towards learning, learners can relate their intention of learning which could drive their motivation and persistence towards achieving their goal. Learning in the MOOC space requires learners to manage their learning and participate in course activities to enhance their learning. As a result, the continuous intention of learners towards MOOC, resulting from the positive UX, is justified when learners can reflect on their purpose in learning and repeat the process of successful learning towards the next course.

2.2.3.1 User Experience and Continuous Intention in the current study

According to Vermeeren et al. (2016), it is crucial to measure user experience (UX) to improve brand loyalty and user satisfaction, thereby maintaining ongoing motivation for purchasing. Previous studies have also emphasised the significance of UX in the adoption of MOOC (Li, Wang, & Tan, 2018; Hone & El-Said, 2016). Additionally, UX serves as the initial touchpoint that shapes learners' experiences and expectations (Roto et al., 2011; Vermeeren et al., 2016).

Numerous studies have been conducted on the topic of continuous intention (CI) towards MOOC, including research by Moreno-Marcos et al. (2020), Tawafak et al. (2020), Chacón-Beltrán (2018), Ya et al. (2018), Joo et al. (2018), Alexandron et al. (2017), Howarth et al. (2016), and Chang, Hung, and Lin (2015). Mohamad et al. (2018) emphasized that the low completion rates of MOOC raise concerns about learners' willingness to use MOOC continuously. Studies by Bhattacherjee and Premkumar (2004) and Barnes (2011) shed light on the factors influencing CI on MOOC, contributing to its viability and sustainability (as cited in Mohamad et al., 2018). Additionally, Wang, Lin, and Su (2021) demonstrated a positive correlation between learner satisfaction and CI. Howarth et al. (2016) examined learners' motivation towards MOOC and its impact on CI and future enrollment in university courses. They suggested that future studies should investigate the influence of MOOC user experience (UX) on CI concerning course delivery and technology usage.

Two research studies have highlighted the positive influence of user experience (UX) on continuous intention (CI) towards MOOC. Lu, Wang, and Lu (2019) conducted an analysis based on the Expectation Confirmation Theory and found that UX significantly contributes to learners' CI to use MOOC. Similarly, Dai, Teo, and Rappa (2020) pointed out that past UX plays a vital role in determining learners' satisfaction and subsequently influences their CI towards MOOC.

2.3 Review of Variables

This section reviews the variables of this study on User Experience (UX), Learner's Intrinsic Motivation Factors (Independence, Communication Skills, Job Specification), Self-Regulated Learning (SRL) and Continuous Intention (CI). This section of the study reviews each variable in the context of its definitions and characteristics.

2.3.1 Learner's Intrinsic Motivation Factors

2.3.1.1 Independence

According to Grow (1991), a learner's autonomy is usually developed with the help of teachers. Teachers can encourage the growth of learners' autonomy when they develop teaching styles that could slowly ease them towards autonomy and self-directedness through the stages, as seen in Figure 2.3. The first stage is the learner's behaviour, where they are naturally dependent on their teachers for knowledge and skills, known as spoon-feeding their students. The next stage is where teachers develop the learner's curiosity and interest in the subject matter to get them more involved in the learning process, such as by giving them the flexibility to suggest their learning goals and outcomes. When learners are involved in their learning process, they will slowly become independent, take control of their own goals, and create self-directedness.

Confidence is mainly impacted by 4 factors which are performance (completion of the task or achieving their goal); vicarious experience (observing others succeed); persuasion (acknowledgements and affirmation from teachers and peers); and physiological states (physical and emotional reactions such as worry) (Bandura, 1977; 1997).

Figure 2.3: Stages of Self-Directedness

Source: Grow (1991)

After a thorough understanding of the self-directedness stages by Grow (1991), this study further examines the characteristics of an automated learner. Learning autonomy was first defined by Holec (1981) as "the ability to take charge of one's learning" where it involves the learner's characteristics such as the decision on learning objectives; determining learning contents and progress; control of teaching methodologies and techniques; monitoring of learning process; and lastly, evaluating their learning outcome.

Additionally, Mynard and Softlaten (2003), which were cited in El-Koumy (2019), have further compared the characteristics between the dependent learners and independent learners (Refer to Table 2.4). This finding has pointed out that independent learners, similar to self-efficacy, are most confident in making informed decisions. Besides that, learners take charge of and monitor their learning strategies.

Table 2.4: Characteristics of Dependent and Independent Learners

Dependent Learner	Independent Learner
Dependent on Teacher	Self-Supporting
Indecisive on their learning	Make literate decisions on their learning
Does not know own strengths and weaknesses	Knows own strengths and weaknesses
Does not apply what was taught in real-life	Apply what was taught in real-life
Dependent on teachers for their learning	Self-Supporting of their learning
Unaware of the best way to learn	Aware of the different strategies for learning
Does not set learning goals	Plan and set their learning goals
Extrinsically motivated by grades or rewards	Intrinsically motivated by learning progress
Do not reflect their learning	Reflect on learning process and progress

Source: Mynard and Sorflarten, 2003, p.35 as cited in El-Koumy, 2019

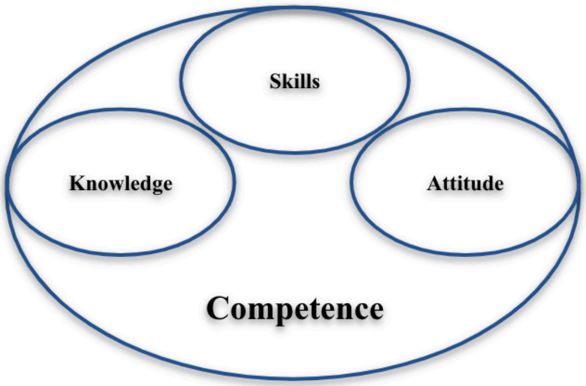
The typical traits of an independent learner include their initiative towards their learning (has time management skills and dedication in self-development) (Burroughs, 2019; Deslauriers et al., 2019); and responsibility towards their learning (self-motivated in planning their learning goals and strategies to achieve them) (Burroughs, 2019; Field, Duffy & Huggins, 2015). It could be said the same by Mullings (2019), states that independent learning happens when learners set goals, and monitor, and assess their performance over time to control their motivation in learning. That said, it is proven that independent learners are defined by Holec (1981), and their characteristics are further shown by Mynard and Sorflarten (2003).

The current study will analyse learners' independence with the attributes gathered by El-Koumy (2019) as, according to Table 2.4, independence is developed from SDT's autonomy and SMB. According to autonomy and SRL's SMB, learners are confident in learning and learning because of personal interest. It is said that independent learners will take full responsibility and complete control of their learning.

2.3.1.2 Job Specification

Competence is found to motivate learners to learn on MOOC. According to Nikolov, Shoikova, and Kovatcheva (2014), competence is evaluated by Knowledge, Skills and Attitude (KSA), which could help people achieve results and assess even performance at work demonstrated in Figure 2.4. Knowledge is the facts and information; skills are the capability, and attitude is the personal characteristics and behaviour.

Figure 2.4: Competency-based framework for curriculum development

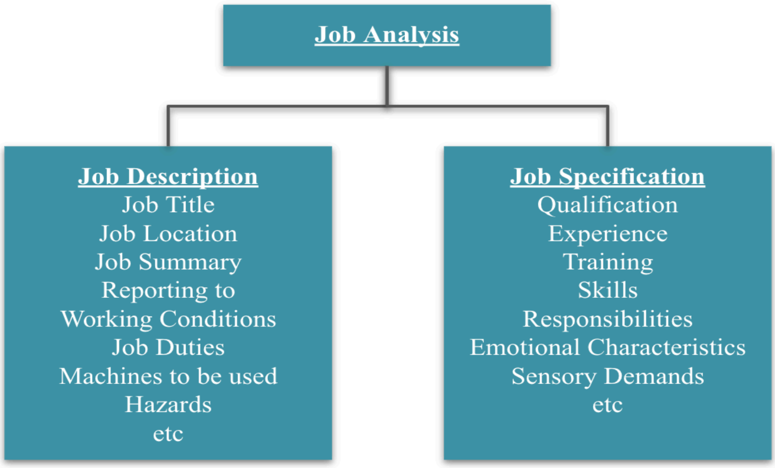


Source: Tumbas et al. (2019)

In Maslow's Hierarchy of Needs found in Figure 6, this study's context shows the importance of a learner's competence in the 4th level, known as esteem needs. Learners feel motivated when they are competent in their job, which can be seen when they are confident. In this level of need, learners desired achievement and prestige, and they could only achieve when they were competent in their job.

Udoh (2018) and Okunade (2015) states job descriptions and specifications stem from job analysis. As seen in Figure 2.5, job specification is the qualification (certification or education level), experience (working years), training, skills, responsibilities, emotional characteristics etc. Job specification shows an individual's KSA and the uniqueness that separates them from others.

Figure 2.5: The Breakdown of Job Analysis



Source: Udoh (2018) and Okunade (2015)

With the surge of talent, employers typically follow the trend of the current skills and knowledge needed to counter the ever-growing technological advancement. Hence, employers tend to focus on job specifications that provide job information, which assists in job performance evaluation, identifying the skills and knowledge gap; and outlining the employee's training needs (Prachi, 2019). A typical job description encompasses qualifications, qualities, abilities, capabilities, experience, skills, and knowledge (Job Description and Job Specification, 2021).

From our Management Guru, Covey (2008) highlighted that this has always been a dilemma where employers are afraid to invest in employees' learning and development because employees would not stay when they are competent: “What if we develop our employees and they leave?”. The other perspective would be: “What if we never develop them and they stay?”.

This study’s context seeks to understand how adult learners stay motivated in learning on MOOC. Adult learners are primarily workers who strive to remain competitive in their work and desire to achieve self-esteem, as seen in Maslow’s hierarchy of needs. To satisfy the desire for self-esteem, adult learners must ensure they qualify for their job specification with their current knowledge, skills and attitude (KSA), as Nikolov et al. (2014) mentioned. Udoh (2018) and Okunade (2015) notes that learners strive to stay competitive to build their resume and uniqueness in their job specification by continuous learning and attending training to stay updated and relevant with their KSA. In line with this study, Dai et al. (2022) also found that working adults pursue MOOC to develop their professional performance.

2.3.1.3 Communication Skills

From a study done by Crary (2016), 5 features of relatedness involve genuineness (congruence of verbal communication); acceptance (willingness to relate); empathy (sensible towards other feelings and messages); active listening (giving intentional attention); and presence (being there).

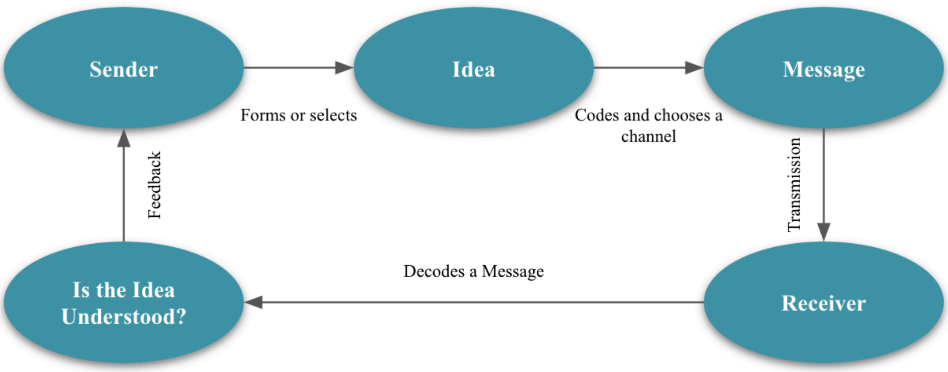
To understand the importance of learner's relatedness, Maslow's (1943) model on the hierarchy of needs in Figure 2.6 has shown 5 levels of conditions known as physiological needs, safety and security needs, social needs, esteem needs, and self-actualisation needs. The hierarchy of needs is shaped like a pyramid, and the lowest level must be fulfilled before moving to the next level. In this study context, relatedness is the social needs of Love and belonging. At this level, people seek to belong in a group and form relationships, whether to form a family or a group of friends.

Figure 2.6: Maslow's Hierarchy of Needs (Maslow, 1943)

Source: Maslow (1943)

According to Timanyuk et al. (2016), the Communication process, shown in Figure 2.7, starts with Sender giving the idea where they then choose the channel to pass the message to the receiver. Communication is only completed when the message is fully understood unless they need more clarification; receivers will ask for more clarification and give the sender feedback.

Figure 2.7: The Communication Process Model



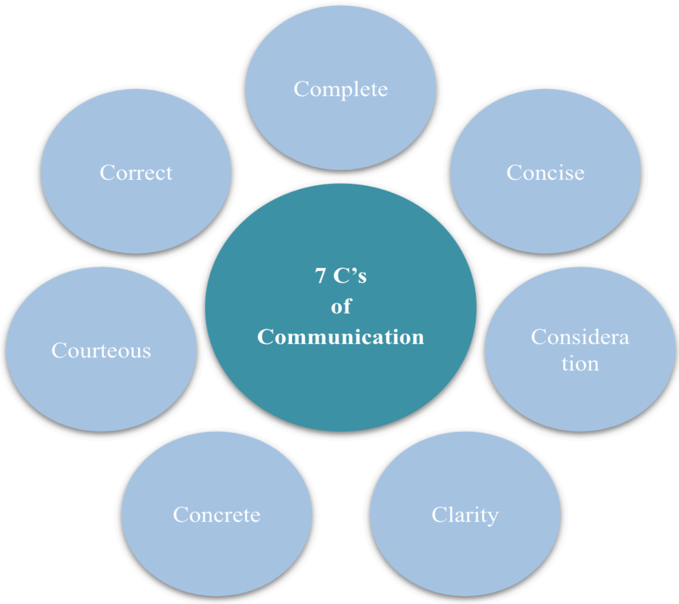
Source: Timanyuk et al. (2016)

Communication skills are relevant towards relatedness where learners want to fulfil the need to belong to a group (Allen et al., 2021; Bambaeeroo & Shokrpour, 2017) which is also similar to Maslow's Hierarchy of Needs, the third level known as social need. Communication skills are needed to participate fully in online learning platforms such as discussion boards, video conferencing groups, peer review, and feedback (Mohd Basar et al., 2021; Rawashdeh et al., 2021).

Communication skills have always been an essential check for employers where many hiring platforms, such as "indeed", even wrote an article for the top 10 communication skills. Those communication skills include active listening (engage, question, and rephrase); using the precise communication method; friendliness; confidence; feedback; volume and clarity; empathy; respect; non-verbal cues; and responsiveness (Communication Skills for Career Success, 2020). This has proven that communication skills are similar to relatedness in one way or another by comparing their similarities, such as active listening and empathy.

In the business world, Scott and Allen (1952) (Cutlip, Center, & Broom, 1985; as cited in Tyagi & Rathi, 2016) were the first ones who introduced the 7C's of Communication skills, as seen in Figure 2.8. Those 7C's of communication are completeness (listener must obtain all facts they need), conciseness (message should be short and easily understood), consideration (sender empathises with listeners), clarity (clear messages), concrete (specific to the point and not general), courtesy (respect that the sender sends to the listener), and lastly, correctness (no grammatical errors).

Figure 2.8: The 7C's of Communication



Source: Cutlip, Center, and Broom (1985); Scott and Allen (1952) (as cited in Tyagi & Rathi, 2016)

The traits of communication skills observed on MOOC would be learners' participation in discussion boards and forums and even helping their classmates when there are group projects and assignments. With the encouragement of communication on MOOC, learners can slowly develop their communication skills with the subject matter they learn. They can converse in their daily lives and feel relevant to their group. This fulfils the social needs of

Maslow’s Hierarchy of Needs (third level). Furthermore, communication skills can be found when learners on MOOC are confident in sharing information, giving feedback, listening actively and empathising (Crary, 2016).

In this study context, Scott and Allen (2016), who introduced the 7C’s of communication, are suitable for understanding learners' characteristics after learning from MOOC. The 7C’s show relevance towards relatedness and communication skills established by Crary (2016).

2.3.2 User Experience

According to Wereda and Grzybowska (2016), the market has presented where customers have rights and protection. Hence, businesses have constantly been improving customer relationships via their experiences. The customer experience (CX) is a process of exchange between an organisation and a customer within their relationship. CX typically goes through 4 stages: initial consideration, functional evaluation, purchase, and post-sales, where organisations would try to gain more data to customise their experiences. The exchange process includes awareness, discovery, cultivation, purchase, and endorsement, measurable via contact points.

Hausler (2017) mentioned that 7 characteristics of the modern customer change their expectation of Customer Experience (CX). Customers demand autonomy to oversee the experience where they can explore and share. They are always connected to their smartphones, which expect customised engagement. In addition, they are resourceful, which means they tend to research the products or services on multiple online platforms to find their preferred CX. Other than that, at least 70% of customers believe in online word-of-mouth rather than brand advertisements. 64% of Customers demand real-time service due to their mindset of “I Want It Now”. Lastly, they are highly opinionated, and if they love the brand, they would be their ambassador, and 3x more proactively recommend it. Hence, by understanding the latest characteristics of customers, organisations can customise the CX to provide a positive outlook of their brand towards their customers.

The CX value equation was introduced by Oracle Corporation (2012), where Acquisition (A), Retention (R), and Efficiency (E) is critical in business. A is the organisation’s capability to grow its customer base. R is the capability of an organisation to nurture and have a stronghold on its current customers. E is an organisation's capability to utilise fewer resources to create an impact for its customers. Hence, the CX Equation:

CX = A + R + E

In another blog written by Harper (2019), which was based on Dave Cherry’s 3 simple equations which create Customer Experience:

Content + Context = Connection

Ideation x Execution = Value

Insight + Intuition = Improved Decisions

Pine and Gilmore (1998) mentioned 4 dimensions known as 4Es in CX, which are aesthetics, entertainment, education and escapism. Aesthetics is the customer’s passive engagement in an experience where they are fully responsible for interpreting their physical environment. Entertainment is where customers develop passive involvement via events and performances, creating joy and amusement where most travelling industry thrives. Education is where customers actively engage and desire to learn and try something. Lastly, escapism requires active engagement with highly engrossed and absorbed customers.

There are similarities between customers' experiences and learners' experiences with their purpose, to begin with, a need and going through a process to satisfy their needs (Vuillaume, 2018; Hussain et al., 2017). The principles of consumerisation are similar to learning. Consumerisation is a trend that addresses innovations focused on consumer sectors (Ingalsbe et al., 2011; Cummings et al., 2009, as cited in Weiß & Leimeister, 2012). This could be proven mainly in on-demand services and the flexibility of learning anytime and anywhere, as technological advancement has shifted traditional learning to online learning.

Many researchers have emphasised the importance of studying UX for future studies. This has proven that UX has a significant impact on the usage of MOOC. It was found that there were several studies that UX is one of the variables affecting the use of MOOC (Li, Wang, Tan, 2018; Hone & El-Said, 2016). Many studies have implicated that there is an academic gap between UX and the usage of MOOC (Niu, 2019; Ya et al., 2018; Lerís et al., 2017; Loizzo & Ertner, 2017; Howarth, D'Alessandro, Johnson & White, 2016; Loizzo et al., 2016).

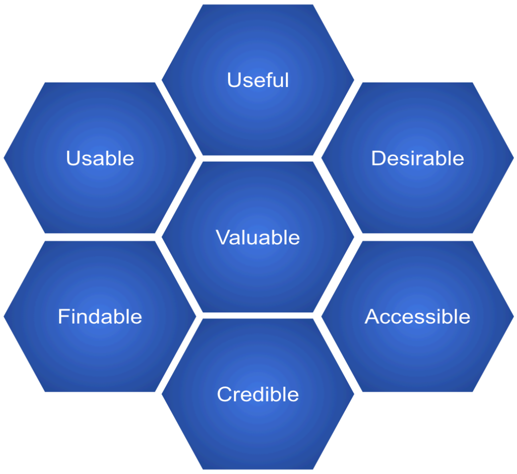
According to Zarour and Alharbi (2017), User Experience (UX) is context-dependent and subjectively defined. UX has been mentioned many times in previous studies. From the earlier studies, UX focuses on phenomena such as the formation of experiences or user experiences, experience expectation, or have experiences (Vermeeren, Roto, & Väänänen, 2016; Roto et al., 2011). Experience is the user's continuous reflection of events that change over time, where the period of user experience should be measured (Chen et al., 2020).

Overtime or Cumulative UX will be calculated via an outcome after a chain of usage and non-use. In the time/historical context of UX, the long-term UX study is preferable as industries rationalise overall product UX and create user attachments (Roto et al., 2011; Abro et al., 2015).

Folstad and Rolfsen (2006) mentioned that UX might have three “camps” with its connection to usability: UX encompasses usability, UX complements usability, and UX is part of the factors forming usability. It could be seen that usability seems to be one of the main elements of UX. Hence, usability should be one of the main characteristics of UX for this study.

Morville (2004; 2016) has designed a honeycomb UX with its 7 elements shown in Figure 2.9, known as applicable (question whether our products and systems are helpful and by using knowledge and innovation to create more valuable solutions); functional; desirable (image, identity, brand and emotional design); findable (create navigable websites and easily located products); accessible; credible (design elements that impact the trust of users); valuable (sites to give values to sponsors). They further mentioned that UX Honeycomb is an excellent tool for defining the priorities of our products and systems.

Figure 2.9: UX Honeycomb



Source: Morville (2004; 2016).

From the perspective of Martin's (2017, 2020) view, as seen in Figure 2.10, she outlines 10 characteristics of learner-centred experiences: personal, agency, inquiry, collaboration, authentic, critique and revision, productive struggle, goals, accountability models, and reflection.

Figure 2.10: 10 Characteristics of Learner-Centred Experiences

Source: Martin (2017; 2020)

Personal refers to the learner's autonomy in customising their learning with the flexibility and resources from learning platforms. Agency refers to the learner's capability to make decisions and be responsible for their behaviours within the learning process. Goals and accountability are the learner's responsibility towards achieving the goals set before their learning. Other than that, Inquiry refers to the learner's investment in understanding their learning by developing a questioning nature. Collaboration is where learners' effort reaches out to their networks and peers to gain diverse ideas. Authenticity happens when learners can experience learning by solving challenges in their context. Critique and revision are essential in a learning experience where learners can gain feedback from peers or teachers and evaluate their learning where they can look back and learn where they went wrong.

Besides that, productive struggle refers to an environment that could be customised towards learners who feel safe taking risks rather than one size fits to encourage more confidence in learning and growth. Models enable learners to benchmark and create a better outcome, such as presenting learners with a sample of study and based on the study, they are tasked to write something similar. Lastly, reflection is an essential element in the learning process, such as helping learners document their learning behaviour, progress, and feedback to look back and find a better way of learning next time.

UX will be the perspective as a field of study where it is focused on the research of phenomenon (such as the formation of experiences or what user experiences, experience expectation, or has experienced), designing systems that conform to specific UX, examining and generating UX design and assessment methods (Roto et al., 2011; Vermeeren et al., 2016). According to Chen et al. (2020), UX is affected by user needs, expectations and existing UX. This brings light to this study where UX in the context of study focuses on understanding how learners continuously use MOOC. In this study, Martin (2017; 2020) is the most suitable to study the Learner’s experience (UX) towards MOOC. This study could further analyse how learners' motivation affects the 10 characteristics of Learner’s experience (UX) towards MOOC, influencing the CI.

2.3.3 Continuous Intention

Theory of Planned Behaviour (TPB) is widely used to study behavioural intention (Ajzen, 1991). TPB defines that individuals control their behaviour in a manner where behaviours are either performed easily or require effort and resources. Behavioural intention is influenced by attitude, subjective norm, and perceived behavioural control (PBC).

Behavioural intention is generally the individual's likelihood of fulfilling a critical behaviour in forming actual conduct (Abdul Rashid, Jusoff & Kassim, 2009; Yi, Jackson, Park & Probst, 2006 cited in Hosseinikhah Choshaly & Tih, 2017). Alexandris, Dimitriadis and Markata (2002) have mentioned that an individual's behavioural intention is influenced by satisfaction with the products or services provided. When individuals are satisfied with the service or products, they become users who will form a relationship and stay loyal to the organisation providing the products or services (Kethan & Mahabub Basha, 2022). Hence, they will continuously support and form a positive behavioural intention when loyal to a brand and increase their continuous purpose (CI) as they are satisfied with the particular organisation.

Customer satisfaction brings customer loyalty. According to Keiningham et al. (2007), they analysed the behaviours of customer loyalty which are retention and recommendations. Loyal customers tend to recommend or become ambassadors of the brand or organisation. Jiang and Rosenbloom (2005) provided that higher customer retention influences the continuous intention of customers. Ranaweera and Prabhu (2003) added that customer retention is gained via customer satisfaction, reducing the switching of brands or organisations.

These studies show interdependence among customer retention, customer recommendation and continuous intention. Gerpott, Rams, and Schindler (2001) measured customer satisfaction, retention, and loyalty by the user's intent to repurchase and eagerness to recommend the product or service to others. Hence, the measurement of CI could be easily measured by the intention to repurchase and willingness to recommend to others.

In the context of CI of learning, CI is correlated to completion of the ongoing program and future enrolment and when learners complete the enrolled program and future enrolment (Rekha, Shetty, & Basri, 2022; Hone & Said, 2016; Alraimi et al., 2015).

Tsai et al. (2018) stated that there are 3 levels of learning interest where interest is the learner's need towards MOOC. Additionally, these 3 levels of learning interest form an intention that needs to be resolved, including the learning intention towards MOOC. The three levels are liking (preference of a learner), enjoyment (finding pleasure or benefit) and engagement (learners participate because they feel familiar with the MOOC). With these 3 levels of learning interest, learners can form a bond with MOOC and their CI towards MOOC increases.

In the current study, the typology of past literature reviewed in this section will be adapted in measuring the CI towards MOOC. The learner's CI towards MOOC would be calculated by working adults' intention to continue enrolling in other MOOC and recommend the MOOC to others besides showing their eagerness and engagement in completing the current MOOC.

2.3.4 Self-Regulated Learning (SRL)

SRL is where learners exercise control over themselves by implementing a cyclical process of forethought, performance, and self-reflection to achieve personal set learning goals. SRL consists of strategies that learners can apply, such as cognition, metacognition, and resource management, throughout the cyclical process of SRL.

Cognition strategy is a procedure required in knowing, encompassing perception and judgement. Cognition is the work of conscious and unconscious processes to gather knowledge (Britannica, 2021) via acquisition, storage and retrieval (Kizilcec et al., 2016). According to Barak, Hussein-Farraj, and Dori (2016), cognition is learning mastery. Learners ensure that the knowledge they have gathered is correctly understood by rethinking and processing learning which involves planning and critical thinking.

Metacognition refers to "thinking about thinking" (Flavell, 1979). In the context of SRL, metacognition refers to managing how we learn (Jaleel & Premachandran, 2016). According to Poth (2019), learners are more aware of learning experiences and activities during their learning goals. Hence, each of their actions towards learning is more purposeful.

In the context of SRL, resource management happens when learners take control of resources and strategies to maximise their learning environments (Zimmerman, 1986). The methods those learners have repeatedly used are time management and help-seeking, which were used in many previous studies known as a subprocess of SRL (Ceron et al., 2021; Vilkova & Shcheglova, 2020; Handoko et al., 2019; Md Zalli et al., 2019; Kizilcec et al., 2016).

Table 2.5 demonstrates a summary done by Clark (2012) on the characteristics and strategies of SRL. As seen in that table, each feature has been matched with a process that allows learners to practise SRL.

Table 2.5: Characteristics and Strategies of SRL

Characteristic	Strategy
Self-Assessment	Evaluating quality or progress
Retain records and manage to learn	Writing notes or errors down
Help-seeking	Ask for help from teachers
Modify and create learning strategies	Learning from experience
Goal setting	Setting goals
Shape the learning conditions	Setting conditions to ensure learning is easy
Time management	Managing time to reach the learning goal
Peer learning	Learning from peers
Persistent	Persevering to finish or accomplish learning goals
Self-rewarding	Celebrate every little progress to motivate themselves
Memorize	Rehearsing information recall
Self-aware	Non-judgmental towards weakness instead work on it

Source: Bandura (1986,1997), Zimmerman and Pons (1986), and Pintrich (1999,2004) (as cited in Clark, 2012)

In addition, learners with high SRL portray characteristics such as self-control and adaptation to alter their behaviours to suit their learning goals. Self-control is the ability to be rational and disciplined by resisting temptations, emotional impulses and gratification while being aware of long-term goals. Self-control is resisting distractions, managing time, and adhering to the strategies set (Zhu, Au, & Yates, 2016). With self-control, learners can complete the cycle process of SRL from the forethought phase, performance phase and self-evaluation phase, where they can resist distraction and achieve their learning goals. Adaptability is also characteristic that SRL learners should incorporate so that they can transform their behaviours to achieve learning goals. According to Md Zalli et al. (2019), learners adjust their learning strategies to adapt to their challenges during their performance stage and feedback from their self-evaluation stage. As explained in Table 2.3, the characteristics of SRL will be used for this study except for SMB, as it is similar to the SDT's autonomy which is adapted and reviewed in 2.3.1.1.

2.4 Proposed Research Framework

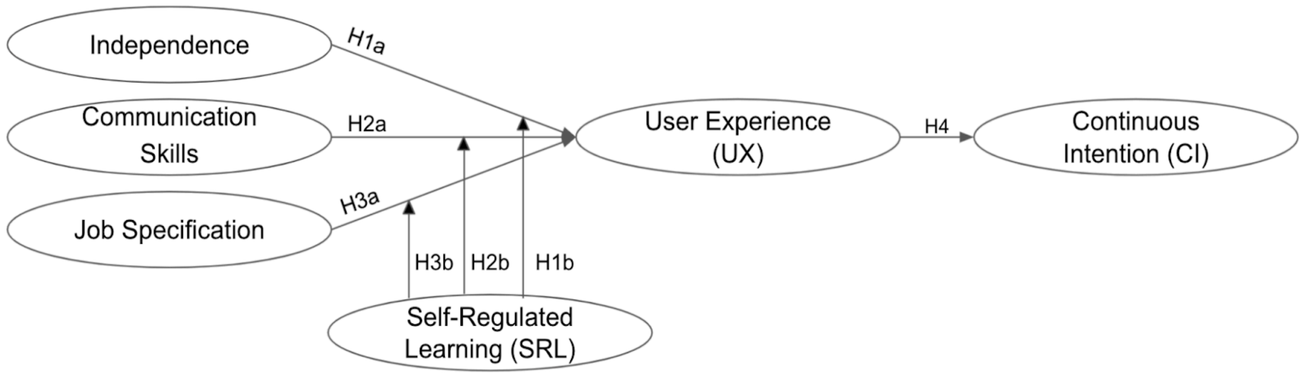
This study proposes a research framework, shown in Figure 9, that demonstrates the continuous intention of adult learners towards the UX of MOOC. The framework shows three phases:

1. To examine the relationship between working adults' intrinsic motivation factors and their user experience with MOOC.
2. To measure the role of SRL in facilitating the relationship between working adults' UX and their intrinsic motivation factors towards MOOC.
3. To determine the impact of MOOC's UX towards MOOC's CI among working adults.

SRL affects the learner's UX towards MOOC via the determinants of intrinsic motivation: independence, communication skills, and job requirement. Hence, SRL is the moderating factor between the Determinants of UX and CI. This study predicts continuous intention is the best outcome for measuring the learner's satisfaction with MOOC. With learners' satisfaction with UX on MOOC, learners tend to use MOOC in their learning continuously.

The framework (as seen in Figure 2.11) suggests that learners will have higher CI towards MOOC when they have positive UX. However, UX is not the only determinant of learner satisfaction. Hence, self-regulated learners with high SRL tend to be more motivated towards MOOC. The following sections discuss the relationship between the determinants of UX and UX and how SRL influences the relationship between the determinants of UX and UX.

Figure 2.11: Proposed Research Framework



2.5 Hypotheses Development

2.5.1 Relationship among Independence, User Experience, and SRL

Learners' independence motivates their learning and development. on MOOC, it could be facilitated where learners are asked to fill in their learning goals or expectations towards their courses, providing a positive UX (Barak et al., 2016). With positive UX towards MOOC facilitation of learner's independence, they will have more motivation to learn and be more involved in their learning progress, as Grow (1991) mentioned.

SDT has enabled autonomy for learners to decide their development (Ryan, 1993). On MOOC, the platform encourages learners to experience independence by learning at their own pace, time, and place (Raghavendra & Madhuri 2023). This has created a trend for learners to view learning as easily accessible with the UX provided by MOOC (Daniel, 2016). Independence allows learners to achieve their goals without disrupting their commitment and responsibilities in their daily lives (Yeo-eun et al., 2023). Due to the nature of flexibility in learning that MOOC's experience provides, most adult learners can learn without preceding their work commitments (Lan & Hew, 2020; Dillahunt et al., 2014).

Based on Reeve et al. (2008), have mentioned that autonomy stimulates SRL. It was found that online learning encourages and even establishes SRL strategies among learners as no teacher, tutor, or mentor is physically present (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). However, a study Kizilcec et al. (2017) mentioned that learners mainly challenge learners' independent need for explicit teacher guidance towards their learning. In addition, a similar conclusion was also found in a study by Layco, Parico, and Magno (2023), where Generation Y, who are proficient in ICT, need explicit guidance from teachers to use online learning. Another study done by Hendriks, De Jong, Admiraal, and Reinders (2020), stated that SRL prompts might be implemented by online learning platforms such as goal setting, monitoring and evaluating; however, even as learners have gained SRL knowledge, it is insufficient to maintain when it is not adequately supported. Reeve et al. (2008) mentioned that learners are encouraged to develop independence to continually apply the SRL skills and strategies in their learning.

According to Martin-Martin et al. (2018), learners' independence is best experienced when there are no restrictions on the learning duration provided by the MOOC. It is well known that online learning offers the experience of flexibility towards learners and encourages independence within learners. Hence, when learners experience deadlines, they tend to stray from their learning goal and try to complete within the stipulated time without learning or, worse still, give up halfway, finally; leading to course drop-off.

Learners' independence on MOOC can be reinforced when learners understand and apply the process of self-regulation, where they nurture their interest in learning (Jansen et al., 2020). Some studies found that MOOC that implement a pre-course survey for learners to plan to attempt and complete the course have resulted in higher completion rates (Davis et al., 2018; Yeomans & Reich, 2017). Accordingly, Cheng and Poon (2016) highlighted that platforms such as Duolingo and Codecademy had been supporting the independence of learners by helping learners to set learning goals and controlling their learning sessions.

From the studies shown, it is found that initiating SRL strategies in the forethought phase, where learners are encouraged to set learning goals and expectations, can instil independence within learners and could help in creating a positive user experience on MOOC (Cheng & Poon, 2016; Yeomans & Reich, 2017; Jansen et al., 2020). Hence, the following hypotheses are proposed:

H1a: There is a significant relationship between Independence and the User Experience on MOOC.

H1b: SRL moderates the relationship between Independence and the User Experience on MOOC.

2.5.2 Relationship among Communication Skills, User Experience, and SRL

Learners are often motivated to learn when more engagement is included, especially when learners can join discussions and conversations (Tang & Hew, 2022). When they can relate to one another through communication, it motivates them to learn more (Hurst, Wallace, & Nixon, 2013). Communication was found to reduce the amount of learners' dropout rates on MOOC as they feel connected when they discuss topics relevant to understanding better

(Kayaduman, 2020; Baek & Shore, 2016). Peer interaction is a factor in influencing learning achievement as they can exchange and help brainstorm ideas (Bingol, Kursun, & Kayaduman, 2020). Learners who can engage actively will have a positive user experience when learning on MOOC as they feel relevant and eager to communicate to help each other (Lan & Hew, 2020).

However, Lan and Hew (2020) stated that learners tend to stick to self-paced activities, which meant learning materials, videos, and completing quizzes. Hence, it was found that MOOC's user experience was not adequately maximised as there is no active participation in forums and peer assessments supported by Kizilcec et al. (2017). This has brought to attention that learners will have difficulty staying positive towards the user experience on MOOC as they do not feel related to the learners, instructors, course, and MOOC.

According to Cheng and Poon (2016), online learning platforms facilitate communication by connecting them to course advisors and peer-to-peer platforms to increase relatedness to create a positive user experience on MOOC. Similarly, Verstegen et al. (2018) stated that learners could collaborate via learning tasks without guidance. Hence, the UX provided by the MOOC is convenient for learners to navigate to communicate with other learners. This is further supported by the study by Cheng and Poon (2016), where MOOC connect learners to course advisors and peer-to-peer platforms to encourage more communication.

Learners with high SRL tend to communicate and seek help from their classmates (Vilkova & Shcheglova, 2021). Many studies have researched how learners communicate on MOOC where they use the subprocess of SRL known as help-seeking, which could be frequently seen in Table 2.1 (Handoko et al., 2019; Md Zalli et al., 2019; Vilkova, 2019; Vilkova, 2020; Ceron et al., 2021).

According to Oh, Chang and Park (2020), learners are encouraged to communicate by giving comments and feedback on group discussion boards of MOOC. Giving feedback, essential in two-way communication, motivates learners to engage more in learning (Tan et al., 2019). In the SRL, learners undergo the self-reflection phase to assess their learning. With the intervention of MOOC for communication, learners can relate more to the learning and knowledge that provides positive UX towards MOOC. Hence, the following hypotheses are proposed:

H2a: There is a significant relationship between Communication Skills and User Experience on MOOC.

H2b: SRL moderates the relationship between Communication Skills and the User Experience on MOOC.

2.5.3 Relationship among Job Specification, User Experience, and SRL

Ever since Lifelong learning has become a buzzword, many people have swarmed to learn how to use the internet to easily access information to improve knowledge, build new skills, and stay competent (Khan et al., 2022). Deci and Ryan (2008) mentioned that learners are keen to stay competent where they can feel satisfaction only when they desire achievement by gaining more knowledge and skills.

Adult learners are motivated to gain competence for job opportunities, promotions and higher salaries. However, they are more receptive to learning to achieve job satisfaction, confidence, and quality of life (Bellare et al., 2023). Adult learners appreciate online learning materials that emphasise real-world application, which could help them solve the current problem at their workplace to stay competent (Schwartz, n.d.; Lan & Hew, 2020).

The ever-competent market has also made employers aware that training and development are essential for employees (The importance of Training employees: 11 benefits, 2021; Launspach, 2022). Hence, employers have considered developing and training their employees to take on more significant responsibilities, improve organisational structure, increase morale, and create a better workplace environment. According to Gutierrez (2016), many employers have opted for online learning as it is more flexible and time-saving, as learners can learn at their pace and time without disrupting their duties. Dalporto (2020) added that e-learning contains job-ready skills they could learn quickly. The Return on Investment (ROI) is higher than in traditional classrooms as learners can use the new skills or knowledge quickly to complete a project.

To stay competitive in their job requirement, learners try to gain as much experience from MOOC (Alhazzani, 2020). Learners often turn to MOOC as they offer many industry-relevant contents developed by industry experts (Meet et al., 2022; Workplace learning report, 2020). Furthermore, many courses are often customisable to meet the job requirements of learners as it is developed by industry experts (Billionniere & Rahman, 2020). Hence, MOOC has become an option for many adult learners as it helps them stay competent in their job by ensuring their KSA qualifies for the job requirements.

MOOC have become more convenient and user-friendly, and many studies were done on User Interface (UI) and User Experience (UX) to understand the learning behaviour of learners (Liu et al., 2020; Miya & Govender, 2022). This has contributed to MOOC providing better features and UI for learners (Liu et al., 2020).

Many MOOC modules are now developed by Industry experts, enabling learners to learn directly from the expert's industrial experience (Meet et al., 2022; Workplace learning report, 2020).. In this manner, MOOC has provided learners to experience a self-reflection phase where they seek help and gain feedback directly from industry experts.

With the customised UX provided, learners can plan their learning goals (forethought phase - SRL) relevant to the competency of their job requirement. Furthermore, learners will have a higher intrinsic interest in their learning when they are given the flexibility to plan their learning strategically, which creates better performance and positive UX towards MOOC (Jansen et al., 2020). Hence, the following hypotheses are proposed:

H3a: There is a significant relationship between Job Requirements and User Experience on MOOC.

H3b: SRL moderates the relationship between Job Requirements and User Experience on MOOC.

2.5.4 Relationship between User Experience and Continuous Intention

The adoption of MOOC by learners or Malaysians is essential as the Malaysian Government has invested in and strategised MOOC as "Globalised Online Learning", which is itemised in the Shift Nine of the Malaysia Education Blueprint 2015-2025 (Higher Education) (Azizi, 2017, Growing from strength to strength, 2018). Many universities have jumped on the bandwagon to create MOOC courses and use MOOC as blended learning.

Nevertheless, the dropout rate has outweighed the completion rate of MOOC. As the MOOC completion rates are low, there has been an increasing need to study continuous intention towards MOOC (Wang et al., 203; Alraimi et al., 2015; Joo et al., 2018).

In addition, many studies have been done to understand UX by the formation of user experiences and user expectations (Vermeeren et al., 2016; Roto et al., 2011), which can positively affect continuous intention. There were many past studies highlighted in subsection 2.2.3.1 on UX towards MOOC and CI towards MOOC. Lu et al. (2019) and Wang et al. (2021) mentioned that learners with positive UX have higher CI towards MOOC.

It was found that MOOC lacks human factors such as engagement and interaction among learners and course instructors. Ibrahim and Rahim (2018) stated that interactive learning tools could improve learners' continuous intention towards MOOC. Learners were found to have such remarks based on their negative experiences with the MOOC platform. Therefore, there is a need to improve learners' learning experience at MOOC (Gamage, Perera & Fernando, 2020; Pilli & Admiraal, 2017) by addressing their concerns, particularly towards the MOOC platform. The completion rate of the ongoing courses and future enrolment at MOOC is expected to improve following the improvement in the learners' experience with MOOC (Lu et al., 2019; Alraimi, 2015), which could increase the rate of continuous intention towards MOOC. Hence, the following hypothesis is proposed:

H4: There is a significant relationship between User Experience and Continuous Intention towards MOOC.

2.6 Summary

In conclusion, this chapter has introduced the theories used in this study which is shown in the underlying theories and application of theories in this study. The variables of this study had also been demonstrated in a review of variables and determinants of variables. To make sense of the hypotheses, theories and variables were further organised into a framework to further explain the hypotheses development. The following chapter will use the research methodology to test the relationship between the discussed hypotheses.

3.0 Research Methodology

3.1 Introduction

Research methodology is the section in this study that establishes the research stays consistent and within the research objectives. This section examines the research philosophy, approach, sampling design, and data collection. The section on data collection covers the research instruments used, which are questionnaires and their distribution method.

3.2 Research Philosophy

Kuhn (1962) describes the research paradigm as the philosophical way of thinking, which was then further explained by Mackenzie and Knipe (2006) as the "researcher's worldview" in the context of educational research. As seen in Table 3.1, the research paradigm comprises epistemology, ontology, and methodology (Easterby-Smith et al., 2018). These elements help define the worldview on perspectives and shared beliefs when interpreting the research data.

Table 3.1 Components of Research Paradigm

Components of Research Paradigm	**Description**	**Questions We Ask**
Ontology	Philosophical beliefs of concepts (reality, existence)	What is reality?
Epistemology	Philosophical beliefs concerning knowledge (Nature, origin, rationality of belief)	How can I know reality?
Methodology	Methods that could be used to investigate a specified case	How do I find out?

Source: Easterby-Smith et al. (2018, p. 63)

According to the elements of the research paradigm demonstrated by Easterby-Smith et al. (2008), this study leans towards epistemology. Epistemology is the study of knowledge that comes from a Greek word: epistēmē ("knowledge") and logos ("reason") (Martinich & Stroll, 2021). While looking into Epistemology further, Mackenzie and Knipe (2006) discussed 4 paradigms in the educational research context where they covered Positivist / Positivism, Interpretivist/ Constructivist, Transformative, and Pragmatic, shown in Table 3.2 Components of the Research Paradigm which elaborates the methods and data collection tools used for each paradigm.

Table 3.2 Components of Research Paradigm

Paradigm	Methods	Data Collection Tools
Positivist/ Post Positivist	Quantitative	Experiments Quasi-experiments Tests Scales
Interpretivist/ Constructivist	Mainly qualitative methods But quantitative methods can be employed	Interviews Observations Document reviews Visual data analysis
Transformative	Mixed methods.	Any tools to avoid bias/discrimination such as sexism, racism, and homophobia
Pragmatic	Qualitative and/or quantitative methods. It is dependent on the research questions and research objectives.	Combination of tools from positivist and interpretivist paradigms such as interviews, observations, testing, and experiments.

Source: Mackenzie and Knipe (2006, p.6)

This study will be based on the Epistemology philosophy and Positivism worldview. Epistemology is chosen as the current study employs a broad set of assumptions where UX does not affect SRL but rather the other way around. This assumption is drawn as SRL is the learner's initiative towards MOOC instead of being affected by the UX. The current study also assumes that the SRL moderates the relationship between intrinsic motivation and UX, involving their continuous enrollment intention towards MOOC.

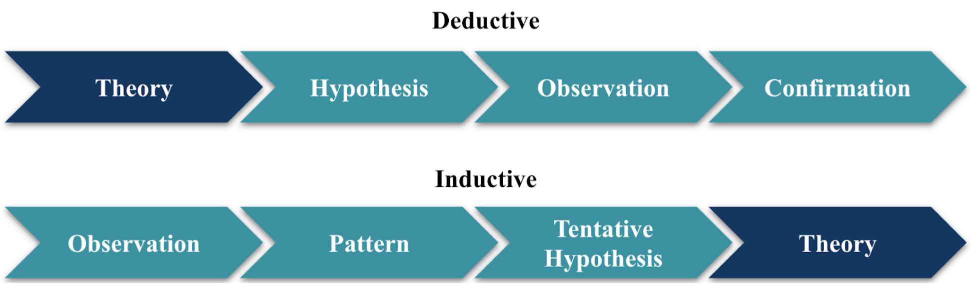
Positivism worldview studies the concerns regarding the experiences of the majority and then concludes the acceptable majority (Hammersley, 2019; Panhwar, Ansari, & Shah, 2017; Wildermuth, 1993). The current study focuses on analysing the learner's intrinsic motivation affecting the UX and then continuous enrolment intention towards MOOC. SRL will moderate the relationship between intrinsic motivation and UX. The current study will be carried out using the quantitative method, where a conclusion will be drawn from most of the target respondents.

3.3 Research Approach

This study will use the quantitative methodology to generalise the majority result obtained. Quantitative research can be further classified as descriptive and causal design. While causal research design is used to find cause and effect relationships between variables (Bloomfield & Fisher, 2019) and assess the effects of changes on current norms and processes (Dudovskiy, 2018), the descriptive research design is pursued mainly to understand the "what" instead of why and how something happened (Hutauruk & Puspita, 2020; Nassaji, 2015). In online learning, most past studies were found to have carried out quantitative approaches with descriptive design instead of causal design (Tsai et al., 2018; De Carvalho Junıor et al., 2019). This design is relevant to the current study as it seeks to understand the relationship between variables and what causes the variables to produce the intended results that are CI towards MOOC.

According to Burney and Saleem (2008) in Figure 3.1, the research reasoning types are divided into deductive and inductive methods. Hence, this study will use the deductive method to confirm the theory generated from the research questions on the Learner’s Continuous intention towards MOOC. The deductive method is applicable because this study’s framework is constructed concerning SDT and SRL's existing theories (Streefkerk, 2019).

Figure 3.1 Inductive and Deductive Research Approach



Source: Burney and Saleem (2008, p.6)

3.4 Sampling Design

This study aims to explore the UX of MOOC among working adults that are enrolled on MOOC, Malaysia. This section elaborates on the target population, which is working adults. In addition, a sampling technique that is judgemental sampling, is also chosen for the suitable amount of sample size for this study.

3.4.1 Target Population

According to Asiamah, Mensah, and Oteng-Abayie (2017), researchers typically gather data from respondents who belong to a specific research population sharing particular characteristics. In this study, the target population consists of working adults enrolled in Massive Open Online Learning in Malaysia. Notably, Shah (2020a) reported a significant rise in online learners on MOOC, reaching 180 million worldwide in 2020, attributed to the impact of the COVID-19 pandemic. This surge in online learners underscores the importance and relevance of this research, given the increasing demand for online learning. The overall population size of MOOC learners in Malaysia has not been specifically documented. However, a study by Ghazali, Nordin, Abdullah, and Ayub (2020) focused on university students and revealed that their efficacy in using MOOCs was positively linked to achieving meaningful learning outcomes.

Adult learners are the chosen target group as it was found that the learner's age category was not adequately defined from previous studies. According to Myers, Conte, and Rubenson (2014), adult learners are often categorised by age, educational level, or work experience. In addition, Kapur (2019) has highlighted that people engaged in careers and jobs are adult learners who should be below 65 years old. In Malaysia, the Minimum Retirement Age Act 2021 states that employees can retire at 60 in Section 4(1) (Chan, 2021). Another study by Kimmel, Gaylor and Hayes (2016) mentioned that adult learners are typically 25 and above.

Additionally, some studies showed most MOOC learners are adult learners aged between 25-44 (Ricart et al., 2020; Watson et al., 2017). Duffin (2020) also found that course designers and providers mainly offer suitable employment skills and knowledge-demand programs. Furthermore, Shah (2020b) found that the top 10 courses were career-focused and technology-focused subjects such as computer science, programming, business, management, and leadership.

The majority of MOOC learners aim to enhance their competence and relevance in the workplace. Hence, the present study focuses on a target population consisting of working adults aged between 25 and 60 years, specifically working adults in Malaysia. Previous studies also targeted adult learners, as evidenced in Table 3.3.

Table 3.3: Summary of Studies on Adult Learners and their key findings.

Author	Key Findings
de Barba et al. (2020)	It was found that session distribution and session activity are important to create engagement on MOOC.
Jung et al. (2019)	It was found that learners are motivated to learn on MOOC due to personal interests. However, grading does not impact a learner's academic path.
Wang, Guo & Sun (2019)	It was found that herding happens in online learning as learners are likely to follow other's recommendations .
Chacón-Beltrán (2018)	Value of teaching vocabulary learning strategies such as: memorising, learning meanings of words from the dictionary, and applying new words into sentences.
Damasceno (2018)	The usefulness and exchange of knowledge and strategies influence the participation and effectiveness among learners.
Davis, Chen, Hauff, & Houben (2018)	This study suggests contextualising findings and being detailed in analysing findings.
Torres & Beier (2018)	This study found that older adults are focused on lifestyle and healthy ageing for their preferred learning.
Kizilcec, Pérez-Sanagustín, & Mar Maldonado (2017)	Learners that portray high SRL skills has a drive to learn, longer time spent on MOOC courses, and experience with related courses.
Shapiro et al. (2017)	Learners are mostly motivated to learn online by knowledge acquisition, convenience, work-related or personal development. However, they are mostly facing a lack of time, followed by bad experiences, insufficient resources such as finance, or the internet.
Beigi, Wang, & Shirmohammadi (2015)	Discusses the positive impacts of vocational MOOC in academies.
Goldberg et al. (2015)	Non-university educated learners are as motivated as university-educated learners in completing a course and interacting in discussions.
Hood, Littlejohn, & Milligan (2015)	It was found that learning in a MOOC is impacted by learners' current knowledge, needs and roles.
Howarth, D'Alessandro, Johnson, &	Create awareness of the host university's MOOC courses via marketing to create more value for their

White (2016)	learning.
Loizzo, & Ertmer (2016)	Adult learners use different strategies to learn on MOOC, such as lurking, SDT, chat in discussion boards, and peer review.
Ulrich & Nedelcu (2015)	Faculty learners are avid on the educational system, HR development and assessment. Young learners emphasise personal development, interpersonal and societal problems.
Chacon-Beltran (2014)	Language learning is mainly affected by the usefulness perceived at different ages, experiences, and motivations.

3.4.2 Sampling Technique

There are two sampling techniques: probability sampling and non-probability sampling (McCombes, 2019). While the probability sampling technique enables the population to be selected as a sample, non-probability sampling means that there are selection criteria where not everyone has the opportunity to take part. Non-probability sampling techniques will be used in this study as the sampling frame (the name list of the entire target population) is not accessible by the researcher.

Judgemental sampling has been widely used for most MOOC studies (Bingol et al., 2020; Hendriks et al., 2020; GovindAarajan & Krishnan, 2019; Ghazali et al., 2018; Li et al., 2018). Trochim (2020) has further defined that judgement sampling, also known as purposive sampling, is a researcher who has a certain purpose and established set of criteria for the sample. Hence, for this study's context, judgemental sampling shall be used.

This study employs judgmental sampling to target specific MOOC learners, ensuring the inclusion of respondents with relevant experiences. The research aims to explore correlations between intrinsic motivation, user experience, and self-regulated learning (SRL) strategies. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study examines the relationship between these variables and their collective impact on learner outcomes.

Only respondents who meet the specified criteria will be considered qualified for participation. In the questionnaire design, respondents will need to indicate "Yes" to these criteria before proceeding to complete the full questionnaire. The proposed criteria for recruiting respondents are as follows:

1. Are you currently in any form of employment? (It implies that respondents are working adults)
2. The age range of 24-60 (working adult age in Malaysia)
3. Have you recently engaged in any MOOC courses? (It implies the respondent's current participation with the MOOC)
4. Have you completed any MOOC courses? (It implies the respondent's experience with the MOOC)

3.4.3 Sample size

Since online learning has become a trend in education, there were many subscribers on MOOC. According to Shah (2020b), learners had grown by over 60 million in 2020 due to the COVID-19 pandemic worldwide. Morris, Hotchkiss, and Swinnerton (2015) stated that most MOOC learners are primarily at least at a degree education level, and the average age from their sample size of 2,338 is 35 years old. Additionally, Bayeck (2016) has found that their sample size mainly consists of learners who are undergraduates at 55.6% of their sample size of 655 and 31.5% are postgraduates and professional bodies.

However, Guilford (1954), as cited by Memon et al. (2020), mentioned that Person Correlation analysis requires a minimum of 200 samples. Additionally, the sample size for SEM is a minimum of 200 observations (Kline, 2011). Similarly, Kurniawan (2014) stated that the minimum sample size in a structural equation could be based on the number of variables researched, shown in Table 3.4. Referring to Table 3.4, this study has 6 variables. Therefore a sample size of 200 is sufficient. Besides that, this study utilises SEM; therefore, a minimum sample size of 200 is feasible.

Table 3.4 Minimum Sample Size and Number of Variables

Number of Variables	Minimum Sample Size
3	200
5	200
10	200
15	360
20	630
23	975
30	1395

Source: Riduwan and Kuncoro (2008) as cited in Kurniawan (2014)

3.5 Data Collection

In that section of the study, data collection covered the questionnaire design that underwent a pre-test with sought-after experts, then was evaluated using the Content Validity Index (CVI). Ethical procedures were also featured to ensure that the research upheld the objectives of the study before pilot testing samples and the main survey. Main survey planning, such as the distribution method and location of target respondents, was also adequately justified.

3.5.1 Questionnaire Design

Pre-testing was deemed essential to ensure that respondents understood the questionnaire developed by the researcher and for researchers to measure the questionnaire's attributes (Hilton, 2017). The questionnaire was designed based on the concepts obtained from Section 2.3, Review of Variables.

The questionnaire content was adjusted to align with the research objectives and context of the study. It drew from previous research to formulate items for various variables:

- "Independence" items were based on the characteristics of independent learners (El-Koumy, 2019).
- "Job Specification" items were derived from a breakdown of Job Analysis (Udoh, 2018; Okunade, 2015).
- "Communication Skills" items were adapted from the "7C’s of communication" model (Cutlip, Center, and Broom, 1985; Scott and Allen, 1952, cited in Tyagi & Rathi, 2016).
- "UX" items were created based on the 10 characteristics of "Learner-Centred Experiences" (Martin, 2017, 2020).
- "CI" items were constructed using insights from past literature, indicating that working adults would continue enrolling in more MOOC courses, recommend them to others, and demonstrate eagerness and engagement in completing their current MOOC studies.

The questionnaire was divided into two sections: Sections A and B. In Section A, respondents could fill in their profiles, while Section B featured questions related to the research variables, which were adopted and adapted from past studies (refer to Table 3.5 and Appendix 1).

According to Nemoto and Beglar (2014), the Likert scale was employed to efficiently collect large quantities of data. This psychological measurement allowed respondents to demonstrate their emotions, views, or behaviour on a specific issue. The Likert scale had several benefits: data collection was fast, even with a large group of samples; it provided high reliability of individual's potential estimation; and yielded high validity of data analysis. The study's questionnaire used a five-point Likert scale, ranging from strongly disagree to strongly agree. The supervisor's insights were sought to refine the content during the questionnaire's development.

3.5.2 Pre-Test

Yan, Kreuter, and Tourangeau (2012) have mentioned that expert reviews are an established practice among researchers for questionnaire development. Furthermore, Ikart (2019) has mentioned that expert reviews are done voluntarily, where no fees are expected from researchers. This has encouraged most studies to use expert reviews as a form of pre-testing. In the context of this study, expert reviews are done by academic and industry experts. The experts reviewed the questionnaire and had determined the ease of understanding and relevance to this study. Experts were chosen with the following criteria:

1. Research experience in e-learning and associated fields; or
2. Involved in the design of MOOC content

Table 3.6 shows the recommended number of experts based on past studies. The minimum number of experts needed for a CV would be 6, but less than 10. This study involved at least 6 experts (a combination of those with research and content design experience).

Table 3.6: Recommended Number of Experts and Content Validity Index (CVI)

Author	Number of Experts	Content Validity Index (CVI)
Lynn (1986)	6-8	At least 0.83
Lynn (1986)	9	At least 0.78
Escobar-Pérez & Cuervo-Martínez (2008)	At Least 2	
Pedrosa et al. (2013)	2	
Sangoseni, Hellman, & Hill (2013)		At least 0.80
Masuwai, Mohd Tajudin, & Saad, (2016)	9	At least 0.80
Zamanzadeh et al. (2015) Rodrigues et al. (2017)		At least 0.79
Yusoff (2019)	At least 6; less than 10	
Shrotryia & Dhanda (2019)	Less than 5	1
Shrotryia & Dhanda (2019)	At least 6	At least 0.78

In this study, the experts were contacted earlier to brief the purpose and procedure of this study besides getting their consent to participate. Upon their consent, the pre-test questionnaires were emailed to them. In participating in the pre-test, experts were required to do the following:

1. Provide written evaluations or feedback on each variable containing the measurement items.

2. Evaluate the relevance of each item on a 4-point scale (1: not relevant, 2: somewhat relevant, 3: quite relevant, 4: highly relevant). Chang (1994) stated that a 4-point scale has higher reliability as more choices reduce measurement consistency. Furthermore, CVI is computed based on the total number of 3 and 4 collected for each item.

The ratings provided by the experts were utilised to calculate the Content Validity Index (CVI). In brief, a high CVI score indicated that participants easily understood the questionnaire and that it was relevant to the study's objectives. Two approaches were used to compute the CVI: Item CVI (I-CVI) and Scale CVI (S-CVI). I-CVI was employed to determine the relevance and clarity of each item, where the ratings of 3 or 4 per item were divided among the total number of experts. The I-CVI values ranged between 0 and 1, with the best value being greater than 0.79, qualifying the items as relevant. Items with a value below the best value were either amended or excluded (Rodrigues et al., 2017; Zamanzadeh et al., 2015).

On the other hand, S-CVI was used to assess the overall scale validity, and it was calculated using two methods: S-CVI Universal Agreement (UA) and S-CVI Average (AVE). S-CVI (UA) demonstrated the items rated 3 or 4 by experts, while S-CVI (AVE) was the average item quality based on the average I-CVI calculations. According to Shi, Mo, and Sun (2012), both S-CVI (UA) and S-CVI (AVE) values should be at least 0.8 and 0.9, respectively.

In this study, a minimum I-CVI value of at least 0.78 was adopted to ensure that the questionnaire items were relevant to the research objectives and provided clarity for the respondents. Simultaneously, both S-CVI (UA) and S-CVI (AVE) values were above 0.8 and 0.9, respectively.

3.5.3 Content Validity Index

Table 3.7 represents the CVI computed from the six experts' data. Based on the results shown, the current value of the I-CVI is 0.97, which indicates that all items in the instrument have a high level of content validity. Additionally, the current value of the S-CVI (UA) is 0.83, suggesting that the scale demonstrates a satisfactory level of content validity. Lastly, the current value of the S-CVI (AVE) is 0.97, suggesting a strong content validity for the entire scale. Based on these results, it can be concluded that the measurement instrument used in this study exhibits high content validity, as indicated by the high values of both I-CVI and S-CVI. This implies that the items in the instrument are considered relevant and appropriate by experts, and the scale as a whole effectively measures the intended construct.

Table 3.7: Content Validity Index from 6 Experts

Content Validity Index (CVI)	Current Value
I-CVI value of at least 0.78	0.97
S-CVI (UA) will be above 0.8	0.83
S-CVI (AVE) 0.9	0.97

The questionnaire content underwent review and finalisation based on feedback from experts before being administered to the participants. This study was conducted in accordance with the ethical guidelines outlined in the UTAR Ethical Clearance (U/SERC/214/2021) and the Personal Data Protection Act 2010 ("PDPA"). To reach the target respondents, who were online learners using MOOC, the questionnaires were distributed through Google Form links. These links were shared on MOOC forums/groups on Facebook. Before proceeding with the questionnaire, respondents were required to confirm their eligibility by checking a screening criteria box.

3.5.4 Ethical procedures

Ethical approval was deemed essential even before meeting the respondents, including the pilot study. Resnik (2020) mentioned that ethical procedures were crucial to uphold the research objectives, foster values of work collaboration (such as plagiarism or confidentiality issues), ensure researchers' accountability to the public (regarding misconduct in university or public regulations, conflicts of interest, and exploitation of test subjects), and develop moral and social values.

This study was conducted in accordance with the ethical principles set by UTAR Postgraduate Studies titled UTAR Ethical Clearance (U/SERC/214/2021) and in compliance with the Personal Data Protection Act 2010 (“PDPA”). All respondents were informed beforehand about the purpose of the study and that their responses were voluntary and confidential. They were assured that their details would not be shared with third parties and that the data would be used solely for educational purposes. To demonstrate their consent, respondents were required to "check" the consent box in the questionnaire via the distribution of Google Forms. With the specific consent obtained from the respondents regarding the ethical procedures, they felt comfortable providing their honest answers, sharing only voluntary personal details.

3.5.5 Pilot Study

According to In (2017), the pilot study helped researchers determine and enhance the quality and efficiency of the study. After finalizing the questionnaire, the pilot groups underwent a replicated process of formal data collection. Hertzog (2008) recommended that the sample size for the pilot study should be 10% of the initial sample size of the study. As a result, a total of 20 respondents participated in the pilot study. During this process, the questionnaire was distributed face to face to understand and observe the spoken and unspoken language, ensuring that respondents truly understood the questionnaire. Although the actual data collection was conducted online, with the Google Form link posted on MOOC forums and social media groups, the face-to-face distribution allowed for this crucial understanding.

The responses gathered from the pilot study were used to compute the Cronbach Alpha value for the study's research variables. This evaluation assesses the internal consistency and reliability of the measuring items (Bujang, Omar, & Bahanrum, 2018; Taber, 2018). According to Yuniwati et al. (2020), the Cronbach Alpha range is from 0 to 1.0. A value above 0.7 is considered "Acceptable," values below 0.7 are questionable, and values below 0.5 are unacceptable. Values above 0.8 are considered good, and those above 0.9 are excellent. This study adopted the interpretation of Cronbach Alpha's value by Yuniwati et al. (2020), where a Cronbach Alpha value of 0.7 was deemed acceptable.

3.5.6 Pilot-Test Reliability Analysis

Table 3.8 presents the results of a reliability analysis conducted on a pilot study to assess the internal consistency or reliability of the measurement scales used in the study. The analysis encompassed all constructs combined, consisting of 42 items, with a calculated Cronbach's alpha coefficient of 0.77. Cronbach's alpha is a measure of internal consistency, with values above 0.7 generally considered acceptable. In this case, the Cronbach's alpha of 0.77 suggests a moderate level of internal consistency for the entire set of items.

The independence construct comprised 9 items, and its Cronbach's alpha was calculated to be 0.792, indicating a good level of internal consistency for the items measuring independence. The communication skills construct consisted of 8 items, and it demonstrated a high level of internal consistency with a Cronbach's alpha of 0.905, suggesting that the items measuring communication skills were highly consistent in capturing the intended construct. Job specification, represented by 6 items, yielded a Cronbach's alpha of 0.932, indicating a very high level of internal consistency among the items measuring job specification.

The SRL construct, consisting of 7 items, had a Cronbach's alpha of 0.885, indicating a good level of internal consistency for the items related to self-regulated learning. User experience was measured by 6 items, with a Cronbach's alpha of 0.847, suggesting a good level of internal consistency among the items measuring user experience. Lastly, continuous intention, represented by 6 items, had a Cronbach's alpha of 0.898, indicating a good level of internal consistency among the items measuring continuous intention.

Table 3.8: Reliability Analysis of Pilot Study

Variables	Items	Cronbach's Alpha
Independence	9	0.792
Communication Skills	8	0.905
Job Specification	6	0.932
Self-Regulated Learning (SRL)	7	0.885
User Experience	6	0.847
Continuous Intention	6	0.898

Note. n = 20

Overall, the reliability analysis results suggest that the measurement scales used in the pilot study demonstrate acceptable to high levels of internal consistency. These findings provide evidence for the reliability of the measurement instruments and suggest that the items within each construct are consistent in measuring their respective constructs. However, it is important to note that these results are based on a small sample size (n=20), which may limit the generalizability of the findings.

3.5.7 Main Survey

The questionnaires were distributed in the form of Google Form links and were administered online due to the target respondents being online learners using MOOC. Consequently, the Google Form links were posted on MOOC forums/groups on Facebook. These specific groups were chosen because they only allowed participants who had taken part in their MOOC to join, fulfilling one of the judgmental sampling criteria for this study. Additionally, these groups provided a larger sample size with similar characteristics, as they consisted of individuals who were aware of MOOC and had completed at least one MOOC course.

The selected forum/groups on Facebook are

1. Coursera
2. MOOC - Massive Open Online Courses
3. Malaysia Online Tutor/ Online Learning / Online Classes Sharing Community
4. Free Udemy and Coursera Courses

During the fieldwork, judgmental sampling was implemented, and only qualified respondents were recorded. Respondents were required to "check" the criteria box before proceeding further, as mentioned in subsection 3.3.2, and all respondents met both criteria.

The data collection was targeted to last for 2 months, with the aim of obtaining 200 samples from the targeted respondents. Questionnaires were posted on the selected Facebook forum/group with a frequency of once a week to avoid spam postings and complaints from Facebook Groups.

The study employed judgmental sampling, therefore, the researcher gathered responses from both working adults within the researcher's company and university. Additionally, data were collected from social media groups and online learning platforms by approaching potential respondents to fill in the forms.

3.6 Proposed data analysis tool

In this section of the study, the data analysis was conducted using the proposed tools. Data screening procedures, which included addressing missing data, outliers, normality, multicollinearity, and common method bias (CMB), were implemented. Additionally, the Structural Equation Model (SEM) was analysed through Partial Least Squares Structural Equation Model analysis (PLS-SEM), where measurement models were evaluated.

3.6.1 Data Screening Procedures

As established by Hair et al. (2010), data screening procedures involved several methods, including addressing missing data, outliers, normality, multicollinearity, and standard method bias. The implementation of data screening procedures helped researchers in

1. Getting a clearer view of the interrelationships between the variables
2. Meeting the assumptions of multivariate data analysis

Hence, the following subsections mentions the data screening procedures.

3.6.1.1 Statistical Package for the Social Sciences (SPSS)

In this study, the researcher used the Statistical Package for the Social Sciences (SPSS), which the IBM Corporation develops. Social science students and academicians widely use SPSS as it helps analyse the comparison and correlational statistical tests (Habes, Ali, Pasah, 2021; Puteh, Azman Ong, & Mohd Hanafi, 2017). SPSS is used in this research to analyse the Multivariate Outlier Detection, Pearson's Correlation, and Cross Tabulation Analysis in both sections 4.3 and 4.4.

i) Missing data

According to Hair et al. (2006), it is common for missing data to occur during data collection. It is commonly found when respondents must complete a question or are left unattended. Data will influence the relationship between the variables and their key dimensions. Carter (2006) has suggested two ways in case the missing data analysis:

1. Deletion of Case: The researcher will delete the incomplete data from the data collection from the specific respondent.
2. Imputation: The researcher will place an estimated missing data value from the specific respondent.

In the context of this study, missing data and both the suggestions (deletion of case and Imputation) by Carter (2006) were easily solved as the Google Form feature allowed all questionnaire items to have a "Required" response before respondents could submit.

ii) Outliers

According to Cousineau and Chartier (2010), outliers were extreme values that deviated from a standard data set during data analysis. Outliers, such as their impact on mean and variability, could skew the results. There were two types of outliers: univariate data (one variable) and multivariate data (several variables). Since this study had more than two variables (multivariate data), Mahalanobis distance statistics were used. The Mahalanobis D2 value was calculated using linear regression in the statistical package for social sciences (SPSS), where values of P2 < 0.001 indicated potential multivariate outliers (Tabachnick & Fidell, 2013). Tabachnick and Fidell (2013) also suggested that removing values and using imputation could work on outliers if they comprised only about 0.10% of the data distribution. In this study, P2 < 0.001 was used to analyse the potential multivariate outliers.

iii) Normality

Normality was the general assumption before conducting SEM analysis. SEM programs were implemented to discover both univariate and multivariate normality. Normality, characterised by a bell-shaped curve where indicators are distributed with a mean of 0 and a standard deviation of 1, was assessed. Kurtosis and Skewness were also used to determine the distribution of the curve and identify non-normality. Kim (2013) had suggested that sample sizes over a certain threshold should consider Skewness values less than 2 and Kurtosis values less than 4 (as cited in Mishra et al., 2019). Hence, this study indicated the normality of the data distribution within the range of -4 to +4.

iv) Multicollinearity

Tabachnick and Fidell (2013) mentioned that multicollinearity occurred when two or more independent variables were correlated, leading to an increase in the standard error of coefficients. Therefore, multicollinearity could be avoided when outliers were removed. Pallant (2013) had established that assessing the Tolerance and Variance Inflation Factor (VIF) could indicate the existence of multicollinearity. The tolerance value evaluated whether independent variables were highly deciphered by other independent variables, and values below 0.1 indicated potential multicollinearity. Meanwhile, Hair et al. (2006) stated that VIF was the inverse value of Tolerance (VIF = 1/tolerance). Consequently, VIF values exceeding 10 indicated high collinearity. In this study, high collinearity was ensured by setting Tolerance > 0.1 and VIF > 10 as the criteria.

v) Common Method Bias (CMB)

Common Method Bias (CMB) was the non-covariance between independent and dependent variables. CMB was commonly found in cross-sectional studies as data for independent and dependent variables were gathered simultaneously using the same instrument or method (Podsakoff & Organ, 1986). Typically, method bias occurred when respondents used the same answers for all measuring items (Jordan & Troth, 2020). Podsakoff et al. (2003) indicated two aspects of solving the CMB: procedural and statistical solutions. Procedural solutions involved selecting independent and dependent variables from different sources and enhancing the instrument to ensure all measures were transparent and socially desirable (respondents did not feel pressured to answer according to social pressure).

According to Mackenzie and Podsakoff (2012), several conditions impacted the accuracy of respondents' responses, as shown in Table 3.9. Conditions that caused CMB included the absence of ability, inexperience towards the topic, hard or conceptual questions, item uncertainty, backdated questions, and oral presentation versus written presentation of the item (in either printed or online). The table provided potential remedies for each condition that caused CMB.

Table 3.9:Factors That Increase Method Bias by Decreasing the Ability to Respond Accurately

Conditions that cause method bias	**Potential remedies**
Absence of oral ability, education, or knowledge (Krosnick 1999; Krosnick & Alwin 1987; Schuman & Presser 1981 as cited in Mackenzie &Podsakoff, 2012)	Ensure that respondents are capable to understand the task by: Pre-testing to ensure that respondents could understand Presenting questions orally to supplement the written questions such as the use of audio computer aided self-administered interviewing (ACASI).
Inexperienced towards the topic (Fiske & Kinder, 1981; Schwarz, Hippler, & Noelle-Neumann, 1992, as cited in Mackenzie & Podsakoff, 2012).	Respondents should be selected based on prior experience or who show common interest in the topic. Be attentive when probing respondents about their motivations for their behaviour, impacts of environmental factors on their behaviour, or topics that touch on cognitive processes.
Hard or Conceptual Questions (Doty & Glick 1998; Krosnick 1991 as cited in Mackenzie & Podsakoff, 2012)	Avoid using unclear concepts or not providing examples. Instead, practice using simple terms and questions.
Item uncertainty (Krosnick 1991; Podsakoff et al. 2003; Tourangeau, Rips, & Rasinski, 2000 as cited in Mackenzie & Podsakoff, 2012)	Use simple terms and define technical terms.
Backdated questions (Krosnick 1991 as cited in Mackenzie & Podsakoff, 2012).	Do not ask questions that require respondents time to recall. Instead, ask questions that address the current state. Explain the importance of a questionnaire and their responses can influence the study.
Oral presentation versus written presentation of the item (in either printed or online)	Uses simple question terms and response choices. Use the written form or visual aids for complex questions that require long answers.

Source: Mackenzie and Podsakoff (2012, pg.5)

Meanwhile, Harman's one-factor test, using exploratory factor analysis (EFA), was one of the typical statistical solutions used to assess the presence of CMB. All the variables were put onto a single factor/component, and the total variance extracted was examined to ensure it was lower than 50 per cent (Podsakoff et al., 2003). Chang, Witteloostuijn, and Ede (2010) had mentioned that common method variance could mean that a single factor emerged, or one general factor represented the general covariance among the measures.

In the context of this study, procedural solutions were implemented as suggested in Table 3.7 (Mackenzie & Podsakoff, 2012). Meanwhile, Harman's one-factor test was employed as part of the statistical solution.

3.6.2 Partial Least Square SEM

Partial Least Squares Structural Equation Model analysis (PLS-SEM) was employed as a variance-based SEM approach widely used in social sciences disciplines (Sarstedt, Ringle, & Hair, 2017). It allowed for the estimation of complex models with multiple constructs and their relationship paths without imposing strict assumptions on the data (Hair et al., 2018). According to Henseler, Ringle, and Sarstedt (2015), PLS analysis was considered most suitable for measuring both the structural and measurement models.

In this study, SmartPLS 3.0 was used to evaluate all the paths simultaneously. As mentioned by Benitez et al. (2020), the analysis proceeded in two sequences: reliability assessment and measurement model validity, followed by the assessment of the structural model. The choice of PLS-SEM was appropriate as there were several correlated variables of user experience (UX) from working adults' continuous intention towards MOOC (Sawatsky, Clyde, & Meek, 2015).

The data was input into SmartPLS software (Hone & Said, 2016) to verify the reliability and validity of the gathered data (Munir, 2018) before assessing the studied paths. PLS-SEM provided path coefficients, T-values, and R^2 values (Nam, Kim, & Jin, 2018). Additionally, PLS-SEM was known to provide factor determinacy (latent construct scores), factor identification (flexible covariance structure), and robust prediction (asymmetric distribution and interdependent observations) (Chin, 1998a, 1998b; Wetzels, Odekerken-Schroder, & Van Oppen, 2009 as cited in Akter, Wamba, & Dewan, 2017). Hence, it was considered a suitable tool for conducting SEM in this exploratory study.

The current study implemented PLS-SEM as it fit the overview points provided by Hair et al. (2019):

- Research is focused on examining a theoretical framework from a perspective of prediction
- Research has complex constructs: The current study has 6 constructs
- Research objectives are implemented to analyse and understand theoretical extensions of established theories: The current study is examining on SDT fulfilment and SRL
- Path model contains more formatively measured constructs

3.6.2.1 Measurement Model

Measurement models were used to explore the latent variables before modelling the interrelationships in a structural model. The main goal of SEM was to design a model that could be justified by a theory. Therefore, each variable in the SEM model was a latent variable measured by convergent validity, discriminant validity, and unidimensionality.

i) Convergent Validity

Convergent validity was assessed to evaluate the relationship among the constructs. It was examined via Average Variance Extracted (AVE) and correlation. The value of AVE was required to be at least 0.5 to ensure that constructs covered at least 50% of the item's variance and reduce discrepancies, and the correlation value should be at least 0.70 (Hair et al., 2019). In this study, validity was considered achieved when all items from the measurement model had AVE > 0.50.

ii) Discriminant Validity

Discriminant validity was measured between two constructs, where unrelated constructs were not supposed to be correlated (Hair et al., 2019). Discriminant validity was primarily focused on evaluating the relationship among the latent variables. Henseler, Ringle, and Sarstedt (2015) introduced the Heterotrait-Monotrait (HTMT) ratio of correlations, which was applicable to marketing practitioners and social science disciplines. HTMT represented the average of heterotrait-heteromethod correlations (correlations of indicators across constructs) compared to Monotrait-heteromethod correlations (correlations of measurements of the same construct). According to Henseler et al. (2015), the threshold value of HTMT could be 0.85 when constructs are more different, which applied to the current study.

iii) Unidimensionality

Hair et al. (2006) had mentioned that unidimensionality was an essential estimate for calculating reliability and validity. Reliability was concerned with the consistency of the Cronbach Alpha values found across all variables (Ursachi, Horodnic, & Zait, 2015). Additionally, Bagozzi and Yi (1988) emphasized that the Composite Reliability (CR) should be at least 0.6, and the Average Variance Extracted (AVE) value should be at least 0.5. Hence, in this study, unidimensionality was verified by ensuring the Cronbach Alpha value was greater than 0.7, the CR value was at least 0.6, and the AVE value was at least 0.5 to ensure the data's reliability. Furthermore, the study also measured convergent and discriminant validity to ensure validity.

3.6.2.2 Structural Model

The structural model was essential in evaluating the relationship paths among the latent variables and determining their role in the model. PLS was able to handle large and complex structured models, allowing for the refinement of the measurement model. Therefore, the PLS analysis in this study confirmed the relationships among variables with robust statistical properties.

The study evaluated the direct path relationships and, subsequently, the indirect path of the moderating effect of the framework. Hair et al. (2011) had mentioned that path significance between the variables would be measured using the variance (R2), with the following values for PLS path models: R2 = 0.75 (significant); R2 = 0.50 (moderate); R2 = 0.25 (poor). T-statistics were considered more reliable when bootstrapping was involved. Hair et al. (2017) explained that the bootstrapping method required random observations from primarily collected data to create a PLS path model. This process was then repeated until subsamples reached 5000. The t-values, as stated by Hair et al. (2011), were as follows: 1.65 (significance level = 10 percent), 1.96 (significance level = 5 percent), and 2.58 (significance level = 1 percent). In this study's context, t-values of 1.96 were used to test the significance level. The effect size F2 was used to calculate the predictive relevance of exogenous variables on endogenous variables. Cohen (1988), as cited in Chin et al. (2013), stated that the value of F2 > 0.35 indicated a large effect size, F2 = 0.15 - 0.35 indicated an average effect size, F2 = 0.02 - 0.15 indicated a small effect size, and F2 < 0.02 indicated no effect size. Additionally, Q2 values were also used to evaluate predictive relevance, where values of Q2 > 0 indicated predictive relevance and Q2 < 0 indicated poor predictive relevance (Hair et al., 2014).

There were three options available for moderator analysis in PLS path modeling. Therefore, the two-stage method (Becker, Ringle & Sarstedt, 2019) was implemented in this study. This method involved using standardized indicator data, including reflective measurement models for the measurement of exogenous and moderator variables. Moderating analysis was carried out using bootstrapping to assess significance after the previous data analysis for all direct latent variables.

The critical values used in this study remained the same as discussed earlier, which was 1.96 (significance level = 5 percent). If the indicator weights were remarkable, sufficient verifiable support existed to retain the indicators. Additionally, each indicator's Variance Inflation Factor (VIF) was ensured to be <5.

3.7 Summary/ Conclusion

In conclusion, this chapter introduced the research methodologies, including the research paradigm, sampling design, data collection procedures, and proposed data analysis tool. The research paradigm helped determine the study method and data collection tools. The sampling design defined this study's target population, sampling technique, and sample size. The data collection section demonstrated the instrument used: a questionnaire design. Pre-test methods with expert reviews were conducted, followed by pilot testing, before launching the questionnaire to the public. The distribution of data collection and ethical procedures were properly elaborated. Lastly, the proposed data analysis tool covered the usage of SmartPLS and ensured the study’s reliability and validity.

4.0 Research Findings

4.1 Introduction

This chapter discusses the outcome of the data analysis and research discussion. The current study uses the techniques suggested in Subsection 3.5 to achieve this study's objectives. This section reports the analysis of data screening, measurement, and structural models.

4.2 Response Rate

All questionnaires in this current study were self-administered online. Furthermore, this method collected a 100% response rate from 200 samples. The researcher used two data collection steps to ensure that there was no missing data and that it was error-free.

The two steps are

1. Questionnaires are set compulsory to answer all the questions on Google Form
2. Only complete forms could be submitted

Since judgemental sampling was used, respondents are knowledgeable in the area of the research. Therefore, there were no errors, missing data or omission of data. The details of the responses are seen in Table 4.1 below.

Table 4.1: Response Rate

Questionnaires				Response rate (%)
Distributed	Received	Rejected	Usable	
200	200	0	200	**100**

4.3 Data Screening

Hair et al. (2010) mentioned that data screening would be done with several procedures to identify missing outliers, normality, multicollinearity, and common method bias (CMB). No missing data were found in this section of the study; no outliers were removed; data in this study are distributed normally; there is no multicollinearity and no significant CMB.

i) Missing data

The current study utilises Smart PLS software. This software replaces missing values with mean values, casewise and pairwise deletions (Hair et al., 2012). However, during the data collection, the researcher set the criteria where respondents could only submit complete answers via Google form. Therefore, there was no missing data.

ii) Outliers

As mentioned in Chapter 3.5.1, P2 < 0.001 will be used to analyse the potential multivariate outliers. Additionally, Mahalanobis D^2 was used to calculate multivariate outliers. As seen in Table 4.2, there were 7 cases found. However, the detected outliers are found to be reasonable. Hence, they are retained in this study as all P2 values are less than 0.001. Therefore, the outliers found could be more impactful as Partial Least Squares Regression (PLSR) tolerates all variations of outliers (Liebmann, Filzmoser & Varmuza, 2010).

Table 4.2: Multivariate Outlier Detection

Case	Mahalanobis D2	P-value
1	35.60327	0
2	32.71045	0
3	22.2839	0.00006
4	18.36019	0.00037
5	17.47577	0.00056
6	16.70487	0.00081
7	16.54411	0.00088

iii) Normality

This study investigates the descriptive statistics and normality of the dataset through skewness and kurtosis to assess both univariate and multivariate normality. Descriptive statistics are essential in summarizing the characteristics of the dataset and understanding the relationship between variables (Yellapu, 2018). Table 4.3 illustrates the descriptive statistics for 200 samples per item. The mean values of the variables range from 3.92 to 4.02, while the standard deviations fall between 0.65 and 0.72. Independence has the highest mean value of

4.02 with a standard deviation of 0.67, whereas Continuous Intention has the lowest mean value of 3.92 and a standard deviation of 0.72. These mean values suggest that, on average, respondents agree with the measurement items, as their scores are close to 4.00 on the 5-point Likert scale.

Although normality in self-reported data is often difficult to achieve, the results of this study demonstrate normality in the data, supported by skewness and kurtosis values within acceptable thresholds. This finding aligns with Ghasemi and Zahediasl (2012), who argue that normality is not a major concern when sample sizes are in the hundreds, as larger sample sizes mitigate potential non-normality issues.

Table 4.3: Summary of Descriptive Statistics

Constructs	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic
Independence	200	1.44	5	4.02	0.67
Communication Skills	200	1.63	5	4.01	0.65
Job Specification	200	1.83	5	4.01	0.7
Self-Regulated Learning	200	1.86	5	3.96	0.69
User Experience	200	1.83	5	3.94	0.7
Continuous Intention	200	1.67	5	3.92	0.72
Valid N (listwise)	200				

This study indicates the normality of the data distribution within the acceptable range of skewness and kurtosis values (-4 to +4), as outlined in subsection 3.5.1. Table 4.4 presents the skewness and kurtosis statistics for the study variables. As observed in the table, all variables fall within the normal range of -4 to +4, confirming that the dataset demonstrates acceptable levels of normality (Kim, 2013, as cited in Mishra et al., 2019).

PLS-SEM does not require data to be normally distributed, as it is a variance-based method that uses bootstrapping to test significance, making it robust to non-normal data (Hair et al., 2017). However, reporting normality through skewness and kurtosis tests provides valuable insights into the dataset and improves transparency. Although normality is not a strict requirement for PLS-SEM, understanding data characteristics helps ensure reliable and robust analyses.

Table 4.4: Skewness and kurtosis of the variables

Construct	Skewness	Kurtosis
Independence	-0.84	0.87
Communication Skills	-0.68	0.46
Job Specification	-0.63	0.1
Self-Regulated Learning	-0.65	0.17
User Experience	-0.57	-0.01
Continuous Intention	-0.46	-0.2
Valid N (listwise)	200	

iv) Common Method Bias (CMB)

Method bias occurs when respondents provide similar responses across survey items, potentially leading to biased results and inflated relationships between variables. In this study, common method bias (CMB) was evaluated using exploratory factor analysis (EFA) in SmartPLS, following the criterion proposed by Podsakoff et al. (2003), which states that CMB is a concern if the total variance explained by a single factor exceeds 50%. As shown in Table 4.5, Harman's single-factor test yielded a result of 50.809%, marginally exceeding the threshold. This finding initially indicates the presence of some degree of CMB. Podsakoff and

Organ (1986) highlighted that CMB often arises when data for all constructs—independent, dependent, mediating, and moderating—are collected through the same method, potentially inflating the relationships and distorting the results.

However, the study further examined CMB using the full collinearity approach, as recommended by Hair et al. (2017) and Kock (2015). All variance inflation factor (VIF) values were found to be below the threshold of 3.3, indicating that CMB is not a significant issue in the dataset. This finding suggests that while the Harman's single-factor test might indicate CMB, the VIF results validate the robustness of the model, confirming that the relationships among variables are not artificially inflated due to method bias.

Table 4.5: Common Method Bias (CMB)

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	21.34	50.809	50.809	21.34	50.809	50.809
2	2.378	5.662	56.471			
3	1.644	3.915	60.386			
4	1.41	3.357	63.743			
5	1.283	3.055	66.798			
6	1.091	2.597	69.395			
7	0.943	2.244	71.639			
8	0.846	2.014	73.653			
9	0.755	1.798	75.451			
10	0.706	1.681	77.132			
11	0.643	1.531	78.663			
12	0.628	1.495	80.158			
13	0.579	1.378	81.536			
14	0.55	1.31	82.846			
15	0.516	1.229	84.075			
16	0.494	1.177	85.252			
17	0.433	1.032	86.284			
18	0.412	0.981	87.265			
19	0.403	0.96	88.224			
20	0.386	0.92	89.144			

21	0.368	0.877	90.021
22	0.346	0.823	90.844
23	0.318	0.757	91.601
24	0.299	0.712	92.313
25	0.293	0.697	93.011
26	0.284	0.677	93.688
27	0.265	0.631	94.319
28	0.245	0.584	94.903
29	0.231	0.549	95.452
30	0.213	0.508	95.96
31	0.199	0.473	96.433
32	0.19	0.452	96.885
33	0.183	0.436	97.321
34	0.17	0.406	97.727
35	0.163	0.388	98.115
36	0.153	0.363	98.478
37	0.142	0.339	98.817
38	0.117	0.279	99.096
39	0.104	0.247	99.344
40	0.1	0.238	99.582
41	0.093	0.221	99.803
42	0.083	0.197	100

Extraction Method: Principal Component Analysis.

4.4 Survey Response Analysis

The section of this study analyses the survey responses in subsection 4.4.1, where the profile of respondents is demonstrated. Then, the following subsection, 4.4.2, explains cross-tabulation analysis between the respondent's demographic and Continuous Intention and User Experience. The cross-tabulation analysis is commonly used to examine nominal scale data (categorical demographic responses) to measure their relationships against the variables that reflect the research question, which are the dependent variables in this study (Jenkins-Smith et al., 2017).

4.4.1 Profile of the Respondents

At the same time, coding is needed for the researcher to prepare data, which is done by translating the raw data into purposeful categories (Allen, 2017). Table 4.6 demonstrates the coding for each response used to ease the data process and analysis using SPSS, done after the data coding. As seen in Table 4.6, the item “Gender” is given the response code “Female=1”, “Male = 2”, and “Other=3”. The age group’s response code is “24-29=1”, “30-36=2”, “37-42=3”, and so on. Next is the item “Highest Education Qualification” with the response codes “Secondary School Education=1” and “Certificate / Diploma=2”, and the following is seen in Table 4.6.

The respondents' background is shown in Table 4.6, collected from a sample of 200 respondents via judgmental sampling. The results show that the female and male respondents are close to equally distributed, with 44% and 56%. Most of the respondents were in the age group of 30-36 (40%) and followed by 24-29 (34.5%), while the least were from the age group of 55-60 (1%). According to Hirschmann (2022), there were at least 2.79 million respondents between the ages of 25 to 29 in the workforce, followed by the age group 30-34 at 2.34 million. The highest educational qualification of the respondents is mostly undergraduates (59%), which could be caused by the highest number of 25-34 age groups currently in Malaysia. After that, postgraduates amounted to 29.5%, and at the same time, there were no respondents with only Secondary School Education. In 2018, it was found that there was a 5% rise in the hiring of tertiary graduates, whereas a decline of a total of 6% for primary and secondary school leavers (Mahidin, 2019).

The monthly household income (RM) is equally distributed from RM2500 and below to RM6500. According to Salaries in Malaysia. Paylab. (2022), the salary range by age group 25-34 is RM2199 to RM5322. The working experience of respondents is mainly 5-10 years with 41%, followed by 5 years and below with 33%. Since most respondents were 24-34, their working experience will mostly be less than 5 or less than 10. Malaysian respondents make up about 95% of the sample size (190 out of 200), who are primarily Chinese (74.5%), followed by Malay (14%), Indian (7%), and others (4.5%).

Table 4.6: Demographic profiles of the respondents'

Item	Response	Code	Frequency	Percentage
Gender	Female	1	88	44.0
	Male	2	112	56.0
	Other	3	0	0
	Total		200	100
Age Group	24-29	1	69	34.5
	30-36	2	80	40.0
	37-42	3	30	15.0
	43-48	4	13	6.5
	49- 54	5	6	3.0
	55-60	6	2	1.0
	Total		200	100
Highest Education Qualification	Secondary School Education	1	0	0
	Certificate / Diploma	2	3	1.5
	Undergraduate	3	118	59.0
	Postgraduate	4	79	29.5
	Total		200	100
Monthly Household Income (RM)	2500 and Below	1	41	20.5
	2501 – 4500	2	52	26.0
	4501 – 6500	3	49	24.5
	6501 – 8500	4	35	17.5
	8501 – 10500	5	11	5.5
	10500 Above	6	12	6.0
	Total		200	100
Working Experience	5 years and below	1	66	33.0
	5 - 10 Years	2	82	41.0
	11 - 20 Years	3	37	18.5
	21 - 30 Years	4	12	6.0
	31 Years and above	5	3	1.5
	Total		200	100
Nationality	Malaysian	1	190	95.0
	Other	2	10	5.0
	Total		200	100
Race	Malay	1	28	14.0
	Chinese	2	149	74.5
	Indian	3	14	7.0
	Other	4	9	4.5
	Total		200	100

4.4.2 Cross Tabulation Result

The researcher used SPSS to analyse the Cross Tabulation. Crosstab is used to draw correlations and relationships within data. To demonstrate the relationship, two categorical variables are put together. In this study, the crosstab is seen in Table 4.7, which reflects the impact of demographic variables, which are Gender, Age Group, Highest Education Qualification, Monthly Income, Working Experience, Nationality and Race, on both the effect variables: User Experience and Continuous Intention. User Experience and Continuous Intention had been converted into categorical variables as the individual items are on the Likert scale of 1-5. Two studies categorised their scales into 5 categories: 0.5-1.44 (Strongly Disagree), 1.45-2.44 (Disagree), 2.45-3.44 (Neutral), 3.45-4.44 (Agree), and 4.45-5.0 (Strongly Agree) (Benard et al., 2021; Benard & Kebande, 2012). Therefore, this study concluded that the scale would be in 3 categories to simplify the results as seen:

Table 4.7: Conversion of Continuous Variable to Categorical Variable

Mean Value Scale	Previous Studies	Current Study
0.5-1.44	Strongly Disagree	Disagree
1.45-2.44	Disagree	
2.45-3.44	Neutral	Neutral
3.45-4.44	Agree	Agree
4.45-5.0	Strongly Agree	

The results of the crosstab analysis are shown in Table 4.8 with the categorical variables of the effect variables with the demographic variables. Table 4.8 showed no significant relationship between demographic and effect variables, as the p-values of their relationship do not meet the requirement (p-value < 0.05).

Even though there is no significant relationship between the demographic variables and the effect variables, it was found that the respondents mostly “Agree” irrespective of different demographic profiles. According to El Refae, Kaba and Eletter (2021), COVID-19 has changed traditional teaching in many educational institutes where they started implementing online learning. The finding from El Refae et al. (2021) correlates to this current study, where learners are now more susceptible to online learning, and it has become a norm in education. Hence, demographic profiles seem irrelevant to student behaviour and adult learners. This was further supported by Mohd Remali et al. (2013), who found that learners’ motivation stems from intrinsic and extrinsic motivation and self-efficacy. They found that gender and student’s background have no significance towards the learner’s behaviour and motivation towards learning.

Therefore, the cross relationships between the demographic, UX, and CI variables are not prominent overall. The cross-relationship result can be attractively presented if (1) the p-value score is less than 0.05 – the p-value also reflects the confidence level; (2) the distribution of data shown at the breakdown categories of the specific variables is exceptionally different from the compared variable.

Table 4.8: CrossTabulation Analysis

Demographic	Responses	User Experience (UX)			Total	Continuous Intention (CI)			Total	Chi-square		P-value < 0.05		df		Cramer's V		Relationship Significance	
		disagree	**neutral**	**agree**		**disagree**	**neutral**	**agree**		**UX**	**CI**	**UX**	**CI**	**UX**	**CI**	**UX**	**CI**	**UX**	**CI**
Gender	Female	3	22	63	88	3	24	61	88	**2.712**	**5.142**	**0.258**	**0.076**	**2**	**2**	**0.116**	**0.16**	**NO**	**NO**
	Male	2	19	91	112	3	26	83	112										
	Total	**5**	**41**	**154**	**200**	**6**	**50**	**144**	**200**										
Age Group	24-29	2	15	52	69	2	15	52	69	**5.646**	**6.516**	**0.844**	**0.77**	**10**	**10**	**0.119**	**0.128**	**NO**	**NO**
	30-36	1	14	65	80	2	20	58	80										
	37-42	1	7	22	30	1	7	22	30										
	43-48		2	11	13		4	9	13										
	49-54	1	2	3	6	1	2	3	6										
	55-60		1	1	2		2		2										
	Total	**5**	**41**	**154**	**200**	**6**	**50**	**144**	**200**										
Highest Education Qualification	Secondary School Education									**0.95**	**2.659**	**0.917**	**0.616**	**4**	**4**	**0.049**	**0.082**	**NO**	**NO**
	Certificate / Diploma	1	1	1	3	1		2	3										
	Undergraduate		19	99	118		31	87	118										
	Postgraduate	4	21	54	79	5	19	55	79										
	Total	**5**	**41**	**154**	**200**	**6**	**50**	**144**	**200**										
Monthly Household Income (RM)	2500 and Below	3	8	30	41	3	8	30	41	**4.931**	**4.462**	**0.896**	**0.924**	**10**	**10**	**0.111**	**0.106**	**NO**	**NO**
	2501 - 4500		11	41	52	1	12	39	52										
	4501 - 6500		10	39	49	1	11	37	49										
	6501 - 8500	1	8	26	35	1	11	23	35										
	8501 - 10500		2	9	11		3	8	11										
	10500 Above	1	2	9	12		5	7	12										
	Total	**5**	**41**	**154**	**200**	**6**	**50**	**144**	**200**										

Working Experience	5 years and below	2	13	51	66	2	13	51	66	**2.863**	**7.614**	**0.944**	**0.472**	**8**	**8**	**0.084**	**0.138**	**NO**	**NO**
	5 - 10 Years		14	68	82	1	20	61	82										
	11 - 20 Years	2	9	26	37	2	12	23	37										
	21 - 30 Years	1	3	8	12	3		9	12										
	31 Years and above		1	2	3	1	2		3										
	Total	**5**	**40**	**155**	**200**	**9**	**47**	**144**	**200**										
Nationality	Malaysian	4	38	148	190	5	46	139	190	**2.437**	**1.474**	**0.296**	**0.479**	**2**	**2**	**0.11**	**0.086**	**NO**	**NO**
	Other	1	3	6	10	1	4	5	10										
	Total	**11**	**85**	**319**	**200**	**6**	**50**	**144**	**200**										
Race	Malay	1	9	18	28		9	19	28	**6.548**	**3.986**	**0.365**	**0.679**	**6**	**6**	**0.128**	**0.1**	**NO**	**NO**
	Chinese	2	27	120	149	4	36	109	149										
	Indian	1	2	11	14	1	2	11	14										
	Other	1	3	5	9	1	3	5	9										
	Total	**5**	**41**	**154**	**200**	**6**	**50**	**144**	**200**										

4.5 Inferential Statistical Result

The Structural Equation Model (SEM) is used to analyse the network of relationships among variables (Suhr, 2006). SEM has two components: the measurement model and the structural model.

4.5.1 Measurement Models

The measurement model is analysed by 4 methods which are internal consistency (tested using Cronbach alpha and composite reliability); Construct validity (examined by convergent and discriminant validity); Convergent validity (tested based on item loadings and AVE); and Discriminant validity (analysed by Fornell and Laker method / HTMT) (Hair et al., 2021; Sujati et al., 2020).

These 4 methods could assess the validity and reliability of the construct (Hair et al., 2021). The measurement model includes 42 items shown in Table 4.9. It demonstrates the latent variables of Independence (9 items), Communication Skills (8 items), Job Specifications (6 items), Self-Regulated Learning as the moderator (7 items), User Experience (6 items), and Continuous Intention (6 items).

i) Reliability Assessment

Cronbach alpha and Composite Reliability are used to assess the internal consistency and unidimensionality. Cronbach alpha measures the reliability and consistency among variables where values should be >0.7 (Ursachi et al., 2015). Meanwhile, Composite Reliability measures the internal consistency of constructs' reliability where values should be >0.6 (Bagozzi & Yi, 1988). As demonstrated in Table 4.9, all the variables are >0.7 for Composite Reliability and Cronbach Alpha. The values of Cronbach's Alpha ranged from 0.919 to 0.931. Meanwhile, the values of Composite Reliability ranged from 0.931 to 0.943.

In order to evaluate the convergent validity, the study conducted an analysis of factor loadings and Average Variance Extracted (AVE). The criterion set for the factor loading values in this research was that they should be greater than 0.7, indicating a strong correlation between the indicators (Feng & Chen, 2020). Upon examining Table 4.9, it was observed that the majority of the factor loading values exceeded 0.7, signifying a satisfactory correlation between the indicators. However, two items, namely In2 (0.673) and CI6 (0.673), fell below the threshold of 0.7. As a result, these two items were deemed unsuitable and were subsequently removed from further analysis path analysis of the Measurement Model (Table 4.9) and also the Structural Model. This step was taken to ensure the validity of the measurement model and to improve the overall quality of the structural analysis.

The Average Variance Extracted (AVE) is used to validate constructs where the value should be at least 0.5 (Hair et al., 2019), as stipulated in subsection 3.5.2.1. AVE is generally used to analyse the amount of variance of the measurement error (Santos & Cirillo, 2021). As seen in Table 4.9, the values of all variables are above 0.5, demonstrating the validity of all items from the variables in the measurement model. The values of AVE ranged from 0.638 to 0.701.

Table 4.9: Results summary for reflective measurement models

Latent Variable	Item	Factor Loading	Composite Reliability	Cronbach's Alpha	Average Variance Extracted (AVE)
		> 0.70	**> 0.70**	**> 0.70**	**> 0.50**
Independence	In1	0.799	**0.931**	**0.931**	**0.676**
	In3	0.807			
	In4	0.781			
	In5	0.804			
	In6	0.8			
	In7	0.848			
	In8	0.877			
	In9	0.798			
Communication Skills	CS1	0.744	**0.934**	**0.919**	**0.638**
	CS2	0.817			
	CS3	0.811			
	CS4	0.779			
	CS5	0.827			
	CS6	0.806			
	CS7	0.823			
	CS8	0.781			
Job Specification	JS1	0.803	**0.932**	**0.913**	**0.696**
	JS2	0.844			
	JS3	0.865			
	JS4	0.829			
	JS5	0.832			
	JS6	0.832			
Self-Regulated Learning	SR1	0.759	**0.931**	**0.913**	**0.658**
	SR2	0.755			

	SR3	0.754			
	SR4	0.857			
	SR5	0.846			
	SR6	0.86			
	SR7	0.838			
User Experience	UX1	0.818	**0.934**	**0.915**	**0.701**
	UX2	0.848			
	UX3	0.866			
	UX4	0.843			
	UX5	0.821			
	UX6	0.825			
Continuous Intention	CI1	0.824	**0.940**	**0.920**	**0.758**
	CI2	0.876			
	CI3	0.872			
	CI4	0.88			
	CI5	0.868			

ii) Discriminant Validity: Heterotrait-Monotrait (HTMT)

This study used SmartPLS to measure the discriminant validity via the Heterotrait-Monotrait (HTMT) ratio that is set by Henseler et al. (2015). In addition, the HTMT value shall be < 0.90 to demonstrate the relatedness of two different constructs (Henseler et al., 2015). Table 4.10 shows the HTMT values ranged from 0.689 to 0.881 (less than the threshold of 0.90), which shows the validity of the constructs as unrelated constructs are not correlated to one another (Hair et al., 2019).

Table 4.10: Heterotrait-Monotrait (HTMT)

	Communication Skills	Continuous Intention	Independence	Job Specification	Self-Regulated Learning	User Experience
Communication Skills						
Continuous Intention	**0.756**					
Independence	0.807	**0.689**				
Job Specification	0.721	0.767	**0.734**			
Self-Regulated Learning	0.779	0.788	0.713	**0.828**		
User Experience	0.764	0.856	0.739	0.818	**0.881**	

4.5.2 Structural Models

After assessing the Measurement Model, this section demonstrates via SmartPLS bootstrapping procedure as stipulated in subsection 3.6.2.2. Path coefficient and coefficient (R2) outputs will assess the structural model. The path coefficient assessment includes *T*-values, β-values, p-values and effect sizes (F2).

Hair et al. (2014) recommended using a bootstrapping procedure with a resample of 5000 to observe *R2*, corresponding T-values, and beta; besides effect sizes (*F2*) and predictive relevance, *Q2* needs to be reported for evaluating the structural model.

In this section, the researcher demonstrated the difference between the structural model with and without a moderator. This is to test the significant role of the moderator in the relationship between the variables.

4.5.2.1 Multicollinearity

The SmartPLS 3 PLS Algorithm deduces multicollinearity using the variance inflation factors (VIF). Hair et al. (2014) mentioned that VIF values of 5 show multicollinearity. Table 4.11 shows that the values are between 3.011 (lowest value) and 3.162 (highest value), which shows the absence of multicollinearity within independent variables. This result shows that the independent variables are not intercorrelated, which produces reliable statistical inferences and results. Hence, the independent variables of this study are reliable due to minor standard errors.

Table 4.11: PLS Algorithm calculating Variance Inflation Factors (VIF)

Constructs	User Experience	Continuous Intention
Independence	3.085	
Communication Skills	3.162	
Job Specification	3.011	
Self-Regulated Learning	3.031	
User Experience		1
Continuous Intention		

4.5.2.2 Model Measurements - R2, F2, Q2

In Table 4.12, both the R2 and Q2 of the structural model and the structural model without a moderator are presented. The R2 is calculated using the SmartPLS algorithm, while the Q2 is determined using the blindfolding method. According to Hair et al. (2014), a Q2 value greater than 0 indicates predictive relevance.

Specifically, the structural model yields R2 values of 0.623 for Continuous Intention and 0.74 for UX, indicating moderate significance. Moreover, Table 4.12 reveals that Continuous Intention and UX exhibit predictive relevance with values of 0.439 and 0.48, respectively. Additionally, the table provides effect sizes for these hypotheses:

1. H1a:

   Independence -> User Experience

   Independence -> Continuous Intention

2. H1b:

   Independence*SRL -> User Experience

   Independence*SRL -> Continuous Intention

3. H2a:

   Communication Skills -> User Experience

   Communication Skills -> Continuous Intention

4. H3a:

   Job Specifications -> User Experience

   Job Specifications -> Continuous Intention

5. H4:

   User Experience -> Continuous Intention

However, the largest effect size is observed in the relationship between UX (H4) and its value is indicated by F2 = 1.645. On the other hand, Hypotheses Independence (H1a), Moderating effect of Independence (H1b), Communication Skills (H2a), and Job Specification (H3a) exhibit small effect sizes, ranging from F2 = 0.02 to F2 = 0.15. Except for the Moderating effect of Communication Skills (H2b), all other hypotheses show the smallest effect size, with an F2 value of 0.031, which pertains to the relationship between job specification, SRL, and UX. Consequently, it can be concluded that SRL has limited practical application in moderating the relationship between the learner's intrinsic motivation (Independence, Communication Skills, and Job Specification) towards UX and CI.

The structural model without a moderator provides R2 of Continuous Intention, and UX demonstrated moderate significance with values of 0.63 and 0.641. Q2 > 0 shows predictive relevance with values 0.44 and 0.424. Compared to the structural model where the R2 and Q2 are analysed with moderators, there isn’t much change in the R2 and Q2 values. Furthermore, Table 4.14 shows that Independence (H1a), Communication Skills (H2a), Job Specification (H3a), and UX (H4) have effect sizes. UX (H4) has shown to have the largest effect size F2 > 0.35 (F2 = 1.661), whereas Job Specification (H3a) has an average effect size with a value of F2 = 0.276. Communication Skills (H2a) and Independence (H1a) show a small effect size with F2 = 0.084 and F2 = 0.039.

According to Albelbisi and Yusop (2019), System Quality (ease of use, ease of learning, UX, system features and integration) and Information Quality have little impact on learners' SRL. However, learners' Service Quality and Attitude impact learners' SRL toward MOOC. It was found that the results of information quality and service quality's R2 and Q2 of SRL are of moderate and medium predictive relevance. In addition, F2 of SRL also showed no to small effect size. Similarly, the current study found that the R2 and F2 of SRL and its role as moderators have a small effect size.

Table 4.12: R^2 and Q^2

Dependent Variables	**Structural Model**		**Structural Model without Moderator**	
	R2	***Q2***	***R2***	***Q2***
Continuous Intention	0.623	0.439	0.63	0.44
User Experience	0.74	0.48	0.641	0.424

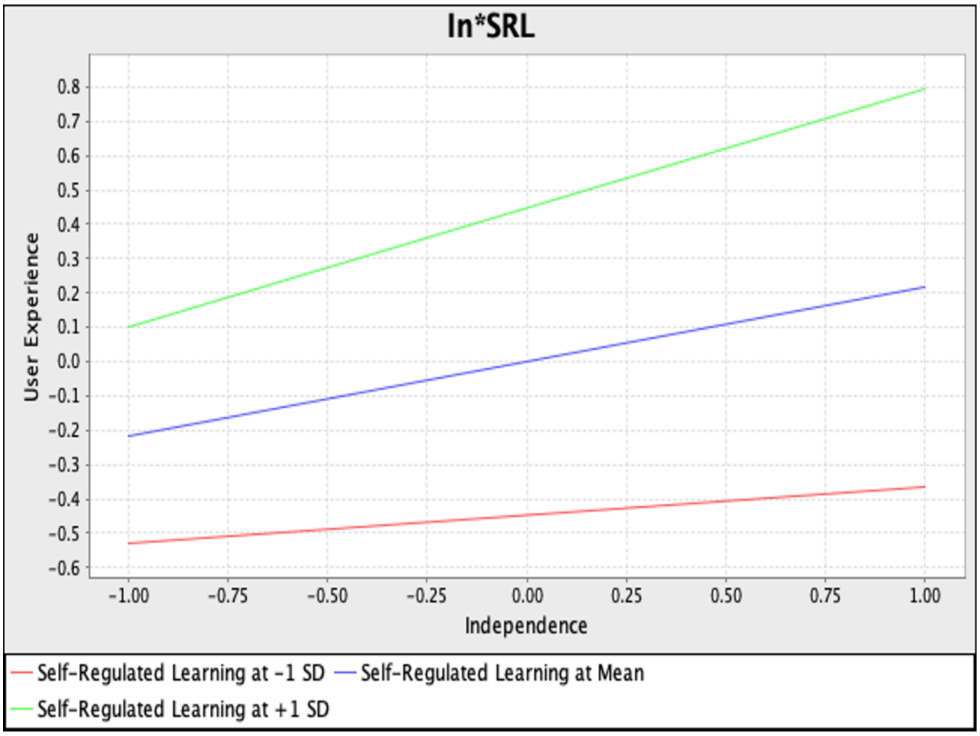
4.5.2.3 The Moderation Effects Created by SLR

i) SRL as a moderator in Independence and User Experience

Figure 4.1 shows SRL as a moderator in Independence and User experience. The slopes shown in the graph do not indicate any interaction, as they are all parallel. This shows no significant relationship between SRL, Independence and User Experience. Zhou (2020) highlighted that SRL's effectiveness as a moderator depends heavily on learners' prior self-regulation capacity. Learners lacking foundational SRL skills often struggle to benefit from SRL interventions, making its moderating role inconsistenterences. However, Sukowati, Sartono and Pradewi (2020) mentioned that SRL significantly relates to learners' independence.

Another study also said user experience encourages SRL (Safsouf, Mansouri & Poirier, 2020). Nicolas and Schoormans (2019) noted that autonomy enhances positive experiences. Hence, independence directly affects user experience, whereas SRL directly affects UX.

Figure 4.1: SRL as a moderator in Independence and User Experience

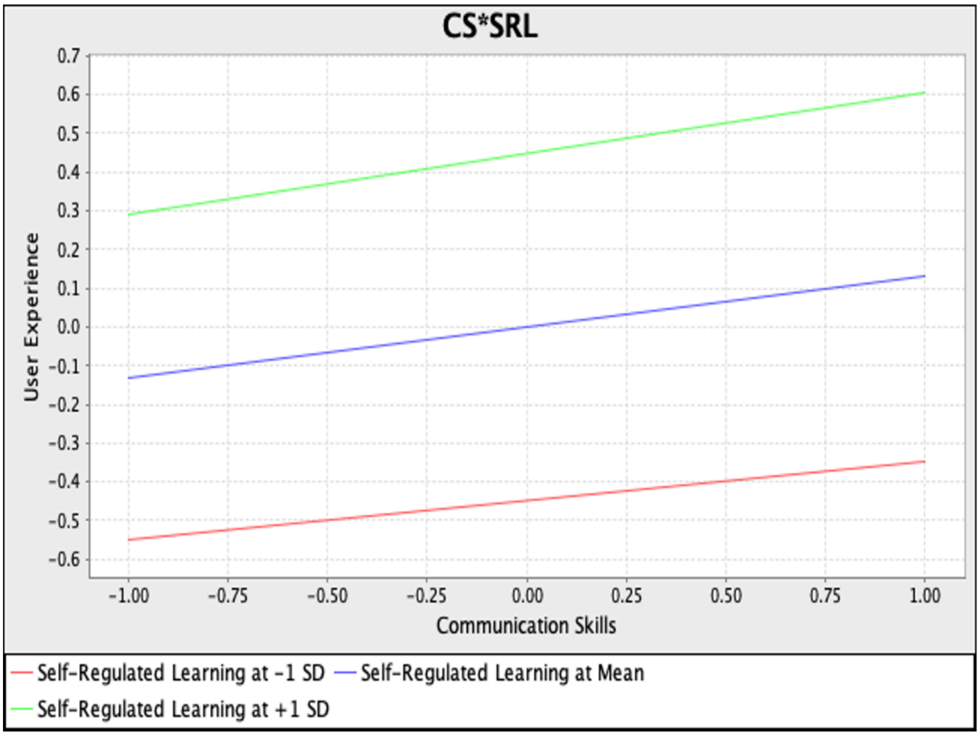


ii) SRL as a moderator in Communication Skills and User Experience

Figure 4.2 shows SRL as a moderator in Communication skills and User Experience. The slopes shown in the graph do not indicate any interaction, as they are all parallel. Therefore, there is no significant relationship between SRL, communication skills and User Experience. Kizilcec et al. (2017) found that while SRL strategies like time management and effort regulation improved persistence, their effectiveness was limited due to low help-seeking behavior, an essential predictor of success. In contexts where communication skills are essential for user experience, low help-seeking behavior (a component of SRL) could hinder collaboration and interaction, affecting the overall user experience. This emphasizes the need to tailor SRL interventions to address specific gaps like peer collaboration.

However, Thompson (2021) mentioned that improving SRL enhances communication in your workplace, where learners can listen actively and are better equipped to think before speaking or acting. Other than that, Zhao and Chen (2016) found that SRL was influenced by communication quality. They added that system and service quality influences SRL through communication quality and user satisfaction. In other words, SRL is set to impact communication skills where learners are motivated to learn. Hence, communication skills and SRL are interdependent on one another. However, SRL does not affect the relationship between communication skills and UX.

Figure 4.2: SRL as a moderator in Communication Skills and User Experience

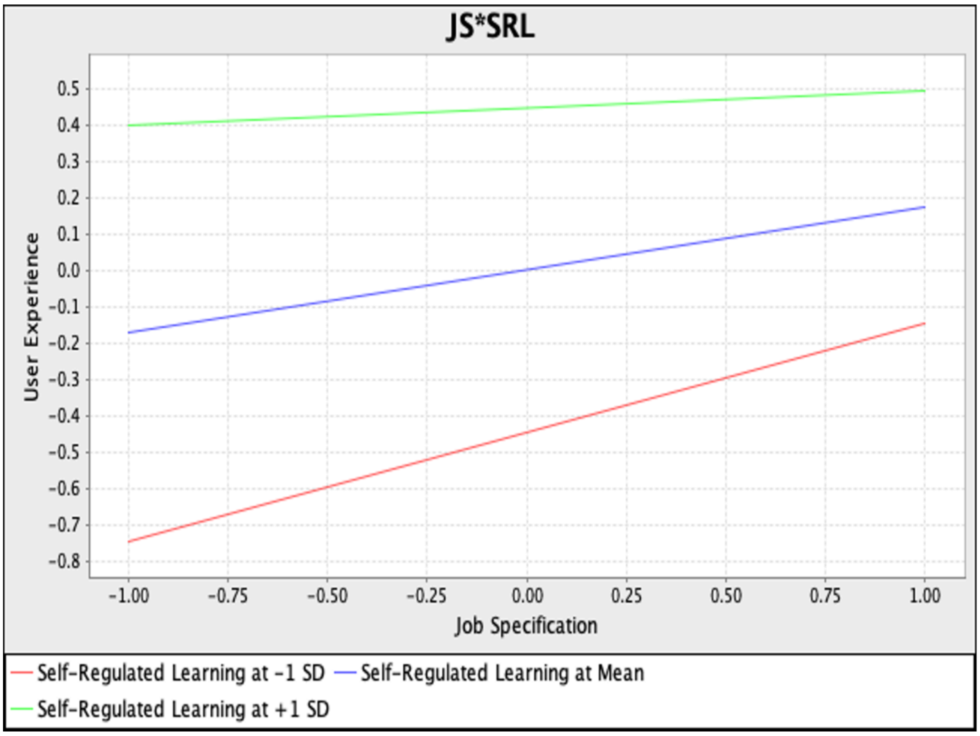


iii) SRL as a moderator in Job Specification and User Experience

Figure 4.3 shows SRL as a moderator in Job Specification and User Experience. The slopes shown in the graph do not indicate any interaction, as they are all parallel. Therefore, there is no significant relationship between the moderator and Job Specification. Hsu, Chen and Shin (2021) mentioned that young adults' perceived employability influenced SRL. Additionally, SRL and professional development come hand-in-hand, where learners are motivated to learn to be equipped for their professional needs (Ciga et al., 2015).

Research specifically exploring SRL as a moderator in the context of Job Specification and User Experience for MOOCs is limited. However, studies indicate that SRL strategies, such as goal-setting and self-monitoring, significantly enhance user satisfaction and performance in MOOCs. For example, Cao-Tuong and Hoang-Yen (2024) emphasized the role of SRL strategies in improving academic outcomes and satisfaction in MOOCs, suggesting indirect relevance to job-specific skills where structured learning is critical. In conclusion, job specification and SRL are interdependent on one another. SRL does not moderate the relationship between job specification and UX.

Figure 4.3: SRL as a moderator in Job Specification and User Experience



4.5.2.4 Confirmation of Hypotheses

i) Significant Path - with Moderator

As outlined by Hair et al. (2014), the inner model, also known as the structural model, serves as the framework for evaluating the significance and robustness of the relationships between variables, as indicated by the path coefficient and t-values, as illustrated in Table 4.13. It's important to note that for a 5% significance level, t-values exceeding 1.96 ($t > 1.96$) are required. In Table 4.13, the relationships demonstrating significance are H1a, H1b, H2a, H3a, and H4, as their respective t-values meet the criterion of $t > 1.96$.

Hypothesis H4 ($t=26.404$; $\beta = 0.789$; $p \leq 0.05$) demonstrates strong statistical significance, highlighting a substantial relationship between User Experience and Continuous Intention. Notably, this relationship boasts the highest level of significance, with a t-value of 26.404. Furthermore, the H4 ($t=26.404$; $\beta = 0.448$; $p \leq 0.05$) hypothesis is also substantiated due to its statistical significance.

In contrast, Hypotheses H1a ($t= 3.035$; $\beta = 0.028$; $p < 0.05$), H1b ($t= 1.965$; $\beta = 0.132$; $p \leq 0.05$), H2a ($t= 2.047$; $\beta = 0.13$; $p < 0.05$), and H3a ($t= 2.308$; $\beta = 0.174$; $p < 0.05$) exhibit statistical significance and receive support ($p \leq 0.05$). The t-values associated with these hypotheses underscore their significance, following the order of their respective hypothesis numbers: 3.035, 1.965, 2.047, and 2.308.

H2b ($t= 0.408$; $\beta = 0.216$; $p > 0.05$) does not exhibit significance and lacks support, as its t-value falls below the threshold of 1.96. Similarly, H3b ($t= 0.408$; $\beta = -0.127$; $p > 0.05$) faces a similar fate, as it is unsupported and statistically insignificant, with a t-value of 1.755.

The hypotheses examining the relationships among the independent, moderator, and dependent variables are as follows: H1b ($t= 1.965$; $\beta = 0.132$; $p \leq 0.05$), H2b ($t= 0.408$; $\beta = 0.216$; $p > 0.05$), and H3b ($t= 0.408$; $\beta = -0.127$; $p > 0.05$). Only H1b ($t= 1.965$; β

=0.132; p ≤ 0.05) received support and exhibited statistical significance. The relationships represented by H2b (t= 0.408; β =0.216; p > 0.05) and H3b (t= 0.408; β = -0.127; p > 0.05) are found to be statistically insignificant, as their t-values do not exceed the threshold of 1.96. This suggests a lack of significance despite the presence of relatively small effect sizes. Therefore, the moderator demonstrates significance only in the context of the relationship between Independence and UX (H1b). However, for SRL, UX, and CI, a significant effect size is observed solely in the relationship between SRL and UX.

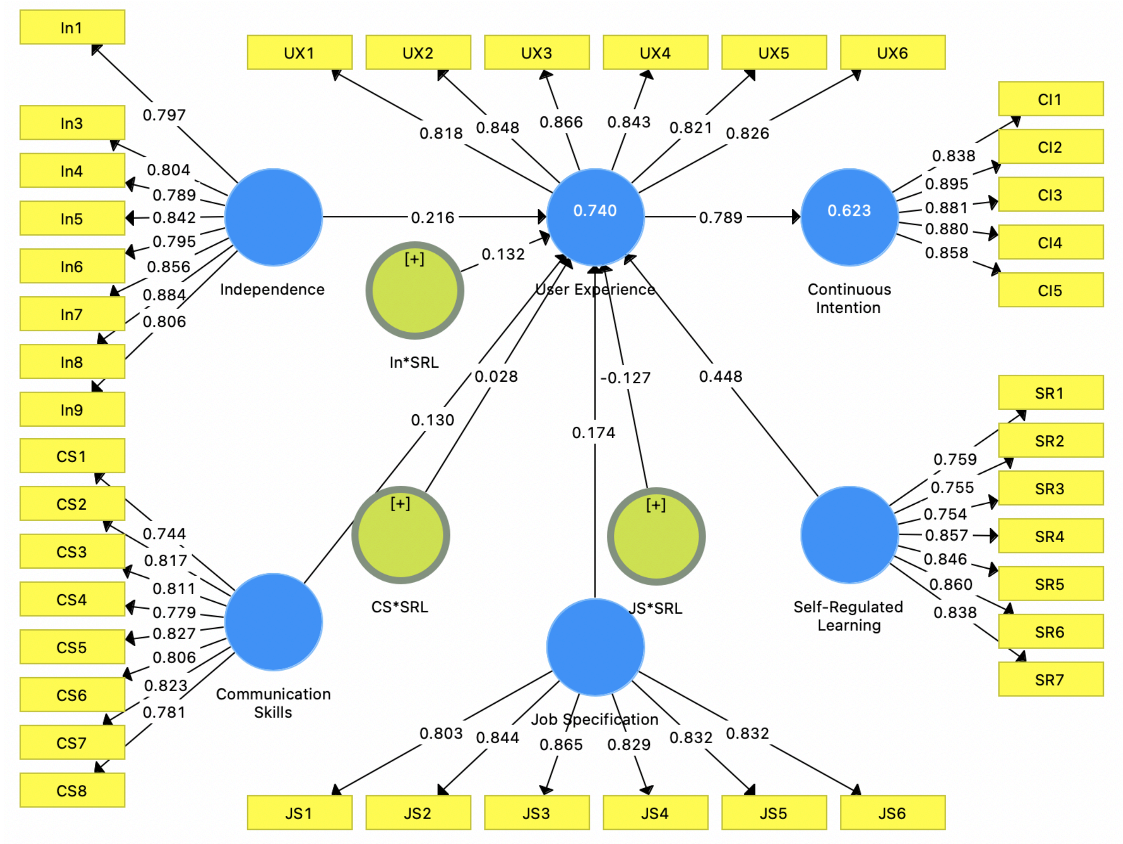
Table 4.13: Confirming the Hypotheses

	Hypothesis Relationship	Std. Beta	Std. Error	t-value > 1.96	p-value < 0.05	*F2* >0.02	Decision
H1a	Independence -> User Experience	0.216	0.071	3.035	0.003	0.06	Supported
	Independence -> Continuous Intention	0.171	0.056	3.075	0.002		Supported
H1b	In*SRL -> User Experience	0.132	0.067	1.965	0.05	0.031	Supported
	In*SRL -> Continuous Intention	0.104	0.053	1.968	0.05		Supported
H2a	Communication Skills -> User Experience	0.13	0.063	2.047	0.041	0.02	Supported
	Communication Skills -> Continuous Intention	0.102	0.05	2.027	0.043		Supported
H2b	CS*SRL -> User Experience	0.028	0.069	0.408	0.683	0.001	Not Supported
	CS*SRL -> Continuous Intention	0.022	0.055	0.406	0.685		Not Supported
H3a	Job Specification -> User Experience	0.174	0.075	2.308	0.021	0.039	Supported
	Job Specification -> Continuous Intention	0.137	0.06	2.276	0.023		Supported
H3b	JS*SRL -> User Experience	-0.127	0.072	1.755	0.08	0.031	Not Supported
	JS*SRL -> Continuous Intention	-0.1	0.056	1.772	0.077		Not Supported

H4	User Experience -> Continuous Intention	0.789	0.03	26.404	0	1.645	Supported

Figure 4.4 shows the structural model with a moderator, SRL, which is constructed via the SmartPLS. As seen from the figure, the variables are indicated with a round blue shape. Moderating effects as shown in round green shape, yellow boxes indicate the measuring items, and the arrows show the paths.

Figure 4.4: Structural Model with Moderator



In this study, it was postulated that Self-Regulated Learning (SRL) acts as a moderator in the connections between Independence, Communication Skills, and Job Specification. The following figures, specifically Figures 4.1, 4.2, and 4.3, present the outcomes of the moderation analysis involving SRL within the context of the relationships among three exogenous variables: User Experience and Continuous Intention, namely Independence, Communication Skills, and Job Specification.

ii) Significant Path - without Moderator

Table 4.14 displays the variables involved in hypothesis testing, excluding the moderator, SRL. In Table 4.14, it becomes evident that all hypotheses—H1a ($t= 2.273$; $\beta =0.187$; $p < 0.05$), H2a ($t= 2.939$; $\beta =0.267$; $p < 0.05$), H3a ($t= 5$; $\beta =0.447$; $p < 0.05$), and H4 ($t= 27.091$; $\beta =0.79$; $p < 0.05$)—gain support and demonstrate statistical significance. Notably, H4 ($t= 27.091$; $\beta =0.79$; $p < 0.05$) stands out as the most significant, boasting a t-value of 27.091. This underscores H4 ($t= 27.091$; $\beta =0.79$; $p < 0.05$) remarkable significance, indicating a substantial relationship between User Experience and Continuous Intention ($\beta =0.790$) with a p-value of 0.

Moving on to H3a ($t= 5$; $\beta =0.447$; $p < 0.05$), it was found to be the second most substantial significance, indicating a robust relationship between Job Specification and UX with a t-value of 5 and a p-value of 0 ($\beta =0.089$). Likewise, H2a ($t= 2.939$; $\beta =0.267$; $p < 0.05$) demonstrates a noteworthy association between Communication Skills and UX ($\beta =0.267$; $p \leq 0.05$) with a t-value of 2.939. Similarly, H1a ($t= 2.273$; $\beta =0.187$; $p < 0.05$)

establishes a significant connection between Independence and User Experience ($\beta = 0.187$; $p \leq 0.05$) with a t-value of 2.273.

Comparing these findings to those presented in Table 4.13, which encompassed relationships involving the moderator, we observe minimal variation. The hypotheses rejected in Table 4.13, namely H2b ($t= 0.408$; $\beta =0.216$; $p > 0.05$) and H3b ($t= 0.408$; $\beta = -0.127$; $p > 0.05$), which included the Moderator and SRL, remain unsupported. However, when these hypotheses are tested without the moderator, H2a ($t= 2.939$; $\beta =0.267$; $p < 0.05$), H3a ($t= 5$; $\beta =0.447$; $p < 0.05$), and H4 ($t= 27.091$; $\beta =0.79$; $p < 0.05$) exhibit a notable increase in their t-values, rising from 2.047, 2.308, and 26.404, respectively.

Table 4.14 Hypotheses Testing without Moderator

Hypothesis	Relationship	Std. Beta	Std. Error	t-value > 1.96	p-value < 0.05	*F2* >0.02	Decision
H1a	Independence -> User Experience	0.187	0.082	2.273	0.023	0.039	Supported
	Independence -> Continuous Intention	0.148	0.063	2.333	0.02		Supported
H2a	Communication Skills -> User Experience	0.267	0.091	2.939	0.003	0.084	Supported
	Communication Skills -> Continuous Intention	0.211	0.076	2.791	0.005		Supported
H3a	Job Specification -> User Experience	0.447	0.089	5	0	0.276	Supported
	Job Specification -> Continuous Intention	0.353	0.071	5.009	0		Supported
H4	User Experience -> Continuous Intention	0.79	0.029	27.091	0	1.661	Supported

Referring to Table 4.15, H2a ($t= 2.939$; $\beta =0.267$; $p < 0.05$), H3a ($t= 5$; $\beta =0.447$; $p < 0.05$), and H4 ($t= 27.091$; $\beta =0.79$; $p < 0.05$) show a more significant increase in terms of t-values when the moderator, SRL is removed in contrast to H2a (t= 2.047; β =0.13; $p < 0.05$), and H3a (t= 2.308; β =0.174; $p < 0.05$) and H4 (t=26.404; β =0.448; $p \leq 0.05$) when moderator was present during hypothesis testing. Its seen that the t-values rose:

1. H2a without moderator t = 2.939 > H2a with moderator t= 2.047
2. H3a without moderator t = 5 > H3a with moderator t= 2.308
3. H4 without moderator t = 27.091 > H4 with moderator t= 26.404

However, Table 4.15 shown that there is a decrease in the t-value for H1a (t= 2.273; β =0.187; $p < 0.05$) when tested without moderator against with moderator present H1a (t= 3.035; β =0.028; $p < 0.05$), which is 2.273 from 3.035. In addition, when SRL was removed, H3a (t= 2.308; β =0.174; $p < 0.05$) showed a significant relationship between Job Specification and UX with a p-value = 0; before SRL was removed, the p-value was 0.021. H4 (t= 27.091; β =0.79; $p < 0.05$) remains unchanged as the p-values before and after SRL removal are still p-value = 0.

This study addressed the intrinsic motivation factors such as independence, communication skills and job specification. It was found that learners with higher self-efficacy will likely have higher SRL (Bozpolat, 2016; Virtanen, Nevgi & Niemi, 2013; Zimmerman, 1990). In Zhao's (2016) research, it was observed that communication quality does not have a direct impact on promoting Self-Regulated Learning (SRL). Zhao also highlighted the constraint of online teacher-student communications, noting their limitations. Importantly, Zhao's study revealed a significant relationship between communication and User Experience (UX). Hence, higher communication increases UX towards MOOC. Lin et al. (2017) found that SRL does not moderate significantly between job demands and continual learning on MOOC. They mentioned that SRL has an indirect relationship between job demands and MOOC. On another note, Zhao (2016) said that positive and quality UX influences higher SRL towards learning on MOOC. Luo, Lin and Yang (2021) mentioned that intrinsic motivation relates to CI and SRL towards MOOC. Luo et al. (2021) mentioned that intrinsic motivation, SDT (Autonomy, Competence, and Relatedness), gives learners a sense of satisfaction towards learning.

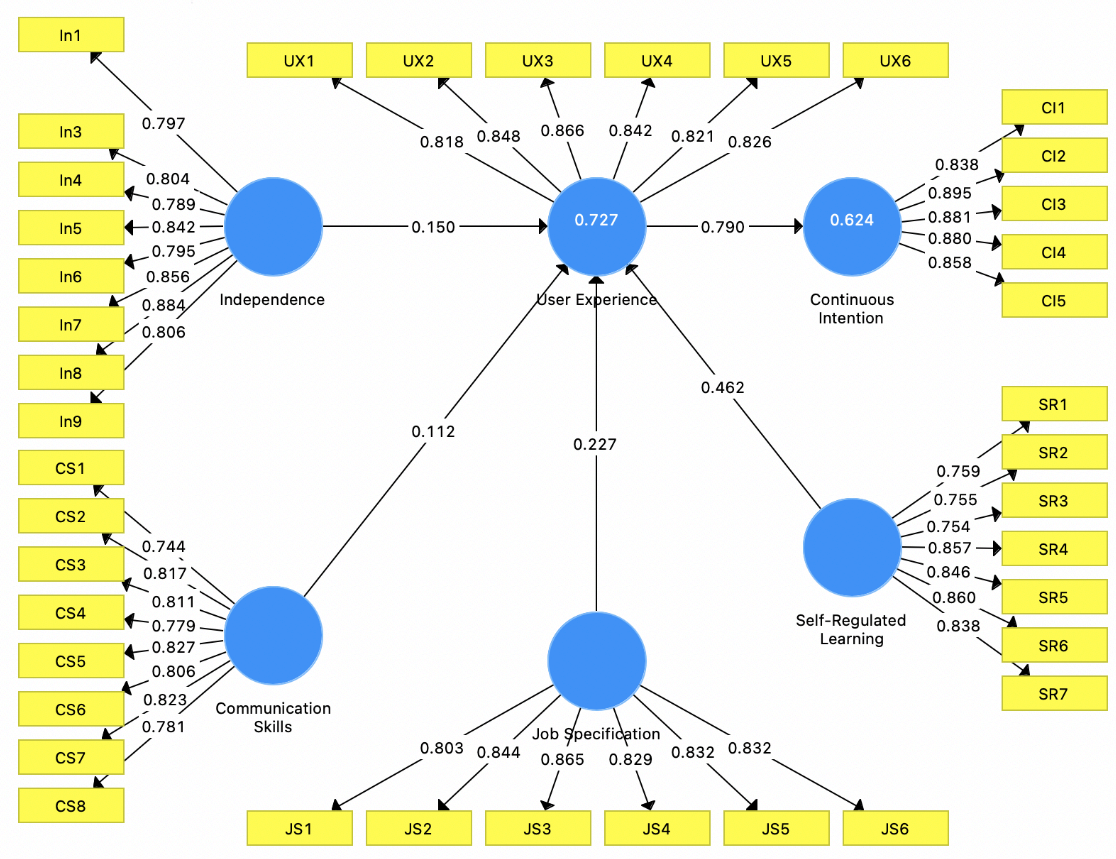
Self-efficacy in the current study refers to learners being independent in learning. Similarly, the current study has found no sign of SRL moderating the relationship between communication skills and UX and CI. Therefore, SRL moderating the relationship between independence and UX and CI is more significant than without SRL. Similarly, in the current study, SRL was found to have no significant moderating role between job specifications and UX and CI. Contrary to Albelbisi and Yusop (2019), this current study found that SRL shows a significant relationship with UX. Similarly, the current study found that SRL shows a significant relationship with CI.

Table 4.15: Comparison of the Structural Model with and without Moderator

	Hypothesis Relationship	With Moderator				Without Moderator			
		t-value > 1.96	**p-value < 0.05**	***F2* >0.02**	**Decision**	**t-value > 1.96**	**p-value < 0.05**	***F2* >0.02**	**Decision**
H1a	Independence -> User Experience	3.035	0.003	0.06	Supported	2.273	0.023	0.039	Supported
	Independence -> Continuous Intention	3.075	0.002		Supported	2.333	0.02		Supported
H1b	In*SRL -> User Experience	1.965	0.05	0.031	Supported				
	In*SRL -> Continuous Intention	1.968	0.05		Supported				
H2a	Communication Skills -> User Experience	2.047	0.041	0.02	Supported	2.939	0.003	0.084	Supported
	Communication Skills -> Continuous Intention	2.027	0.043		Supported	2.791	0.005		Supported
H2b	CS*SRL -> User Experience	0.408	0.683	0.001	Not Supported				
	CS*SRL -> Continuous Intention	0.406	0.685		Not Supported				
H3a	Job Specification -> User Experience	2.308	0.021	0.039	Supported	5	0	0.276	Supported
	Job Specification -> Continuous Intention	2.276	0.023		Supported	5.009	0		Supported
H3b	JS*SRL -> User Experience	1.755	0.08	0.031	Not Supported				
	JS*SRL -> Continuous Intention	1.772	0.077		Not Supported				
H4	User Experience -> Continuous Intention	26.404	0	1.645	Supported	27.091	0	1.661	Supported

Figure 4.5 shows the Model without the role of Moderator, Self-Regulated Learning (SRL). After removing the moderator, the path significance showed a difference from Figure 4.4, where there is an increase in H3a from 0.174 to 0.227 and H4 from 0.789 to 0.790. However, there is a decrease for H1a from 0.216 to 0.150 and H2a from 0.130 to 0.112.

Figure 4.5: Structural Model without Moderator



4.5.2.5 Model Fit

To analyse the Model Fit, Complete Bootstrap was done in PLS-SEM. Hair et al. (2021) mentioned that PLS-SEM uses model estimation and assessment, which is interpreted by theory and logic. Therefore, the estimated model is used. In the SmartPLS, Model fit in this study measures the Standardised root mean square residuals (SRMR) and Normed Fit Index (NFI).

SRMR computes the difference between the observed correlation and the model-implied correlation matrix, which could refrain from model misconception (Henseler et al., 2014). As seen in Table 4.16, the value shown by SRMR is 0.054, which shows there is no model misspecification (SRMR < 0.08) (Henseler et al., 2014; Ringle, Wende, & Becker, 2015). NFI, also known as Bentler and Bonett Index (1980), mentioned that values closer to 1 show a better fit. The NFI value shows 0.764.

a. Table 4.16: Model Fit Results

Model Fit	Saturated Model	Estimated Model
SRMR	0.054	0.063
NFI	0.767	0.764

4.5.2.6 Predictive Power of the Study's Model

Hair et al. (2021) mentioned that PLS-SEM uses model estimation and assessment which is analysed by theory and logic. Hence, the goodness of fit is not accurate for the PLS-SEM models. To assess the predictive power of this study, the "PLS Predict" option will be chosen in PLS-SEM.

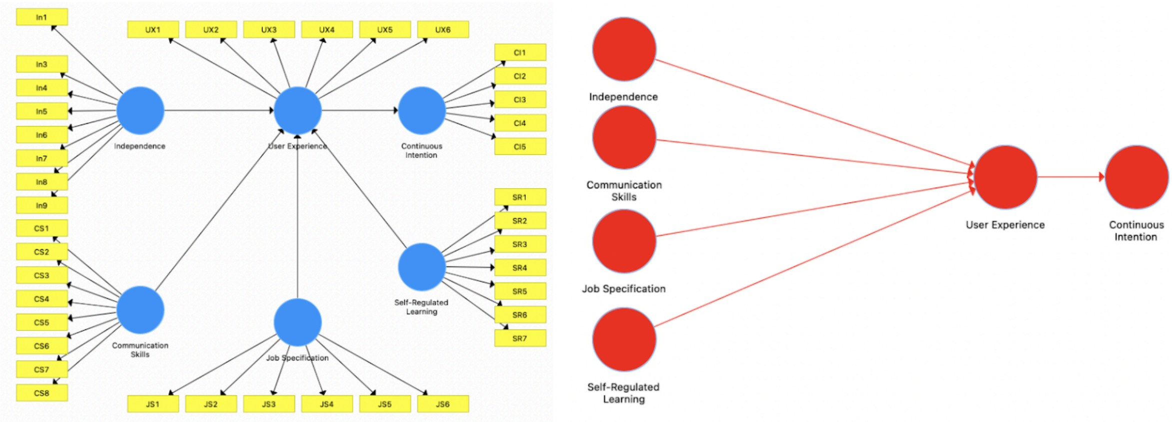
PLSpredict implements the k-fold cross-validation, which divides the dataset into equal k-sized subsets of data (Ringle et al., 2015). Shmueli et al. (2019) recommended the setting of k=10. This study will divide the data from 200 samples into 10 subsets, with 20 samples per subset.

The Linear Regression Model (LM) predicts the errors and summarises statistics without a specified PLS path Model, as seen in Figure 4.6. Hence, comparing PLS-SEM results against LM results will provide insight into whether the theoretical path model enhances the predictive outcome of indicator data against LM (Ringle et al., 2015).

Figure 4.6: Proposed PLS Model versus Linear Regression Model

Proposed PLS Model
Measurement Model and Structural Model

Linear Regression Model
No Measurement / Structural Model



PLSpredict forecasts the error statistics summaries such as root mean square error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) to evaluate the predictive results of their PLS path model for the manifest variables (MV or indicators) and the latent variables (LV or constructs) (Ringle et al., 2015).

The comparison outcome is seen in Table 4.17, where PLS-SEM should show lower prediction error in RMSE and MAE compared to LM. The prediction error of LM is only shown in manifest variables (Ringle et al., 2015). Table 4.17 shows the Predictive Performance of the PLS Model versus the Benchmark Linear Regression Model (LM). However, as seen in Table 4.17, 2 values of MAE from the PLS predict higher than LM Predict, indicators CI5 and UX2. Since most of the values of PLS Predict are lower than the LM Predict, it shows a medium predictive power (Shmueli et al., 2019).

Table 4.17: Predictive Performance of the PLS Model versus Benchmark Linear Regression Model.

Composite	Indicator	PLS Predict		LM Predict	
		RMSE	MAE	RMSE	MAE
Continuous Intention	CI1	0.681	0.561	0.75	0.585
	CI2	0.602	0.499	0.65	0.517
	CI3	0.646	0.528	0.727	0.572
	CI4	0.622	0.512	0.671	0.536
	CI5	0.644	0.539	0.671	0.531
User Experience	UX1	0.618	0.496	0.656	0.496
	UX2	0.578	0.477	0.582	0.472
	UX3	0.562	0.462	0.59	0.472
	UX4	0.611	0.506	0.657	0.542
	UX5	0.611	0.493	0.656	0.528
	UX6	0.578	0.472	0.63	0.505

Other than that, the predictive results of the PLS path model can also be compared with the Q^2 value. The Q^2 values will be compared from PLS Predict and the simple mean prediction. Table 4.18 compares Q^2 and Q^2 Predict, found from the latent variables. The Q^2 results are positive, and the outcomes are smaller than Q^2 Predict. This shows that PLS-SEM models offer better predictive performance (Ringle et al., 2015).

Table 4.18: Q2 for Latent Variables

Latent Variables	Q^2	Q^2 Predict
Continuous Intention	0.44	0.601
User Experience	0.424	0.703

4.6 Summary

This chapter demonstrated the analysis of data by Statistical Package for Social Sciences (SPSS) and Partial Least Squares (PLS). Using SPSS, this study identified no missing data, reasonable outliers, distributed data distribution normally, and there is bias found via CMB analysis. Furthermore, survey response analysis was done where relationships between demographic profiles were done against UX and CI via crosstab analysis. It was found that there was no significant relationship between demographic profiles and UX and CI. Moving to the analysis of the measurement model done by PLS, internal consistency, construct validity, convergent validity, and discriminant validity were done. Lastly, the structural model was analysed to determine the multicollinearity, model measurements using $\boldsymbol{R^2}$, ***F2***, $\boldsymbol{Q^2}$, moderation analysis, the model fit and predictive power of the study's model. In the next chapter, a discussion of the findings will be done.

5.0 Discussion and Implication

5.1 Introduction

This chapter summarises key findings and research implications derived from the study findings. This chapter summarises vital findings, theoretical and practical implications, limitations and recommendations for future researchers. The current study aimed to explore the relationship between intrinsic motivation and UX and CI towards MOOC with a moderating effect of SRL. Furthermore, the study also discussed that SDT's Intrinsic Motivation (Autonomy, Competence, and Relatedness) are closely related to Independence, Job Specification, and Communication Skills. In addition, Independence is similar to SRL's SMB (self-efficacy), as learners are satisfied to learn and achieve milestones by themselves.

5.2 Discussion of Key Findings

5.2.1 Intrinsic Motivation and User Experience on MOOC for Working Adults

It was found that intrinsic motivation does play a significant role in the relationship of working adult's UX on MOOC. As seen on Subsection 4.5.2.4, Table 4.15, the hypothesis relationships between Intrinsic Motivation Factors (Independence, Communication Skills and Job Specification) and UX on MOOC among working adults are supported with and without moderator:

H1a : There is a significant relationship between Independence and the User Experience on MOOC. (Supported)

H2a : There is a significant relationship between Communication Skills and User Experience on MOOC. (Supported)

H3a : There is a significant relationship between Job Requirements and User Experience on MOOC. (Supported)

This suggests that intrinsic motivation factors (Independence, Communication Skills and Job Specification) plays a significant role in the UX of MOOC among Working Adults. These findings are corroborating to the study's Research Question No.1 : How do working adults' intrinsic motivation factors affect their experience with MOOC?.

Luo et al. (2021) mentioned that intrinsic motivation, SDT (Autonomy, Competence, and Relatedness), gives learners a sense of satisfaction towards learning. Previous studies have claimed that motivation towards MOOC stems from SDT (Khan et al., 2018; Zhou, 2016). Therefore, solidifying the relationship between learners' intrinsic motivation towards MOOC. Furthermore, Kopolovich (2020) said that user-friendly MOOC motivates learners as it is considered a part of edutainment. Communication between learners and teachers is one factor that encases edutainment (Ferraz-Caetano & Dias, 2021).

In this study, Independence, as mentioned by Mynard and Sorflarten, 2003 as cited in El-Koumy (2019) had 9 characteristics (self-reliant, Able to make informed decisions on their learning, Aware of own strengths and weaknesses, Connecting classroom learning with the real world, Take responsibility for their learning, Aware of the different strategies for learning, Plan their learning and set goals, Intrinsically motivated by learning progress, and, Reflect on the learning process and progress). Therefore, learners with greater autonomy in their learning experience are more likely to be motivated to learn, persist in their learning efforts, and achieve better learning outcomes. This is because learners who feel in control of their learning are more likely to be engaged, interested, and invested in the learning process, which can lead to higher levels of intrinsic motivation. on MOOC, autonomy can be supported by providing learners with various learning resources and activities that allow them to choose how they want to learn. This may include offering multiple pathways for learning, providing a range of multimedia resources, and allowing learners to set their own learning goals.

Zhao (2016) also found the relationship between communication and UX is significant. Communication can play an essential role in supporting the relationship of MOOC, particularly the intrinsic motivation factor of relatedness. Relatedness refers to the social aspects of learning, such as feeling connected to others who are also learning the same material. on MOOC, communication can help foster a sense of community and collaboration among learners, enhancing their motivation and engagement with the course material (Zhang et al., 2016). This can be particularly important for learners who may be studying in isolation, without access to the social support they typically receive in a traditional classroom setting. There are many ways that communication can support the relationship of MOOC, giving it a better UX, such as discussion forums, peer assessments, webinars, social media and many more.

Many MOOC are designed to provide learners with job-relevant skills and knowledge and may be tailored to specific industries or professions (Castaño-Muñoz & Rodrigues, 2021). In addition, by aligning their learning goals with job specifications, learners can also enhance their motivation and engagement with the course material. When learners can see a clear connection between their learning and their career goals, they are more likely to be motivated to complete the course and apply what they have learned in their job. Consistent with the findings of this study, Dai et al. (2022) similarly discovered that working adults engage on MOOC to enhance their professional performance.

5.2.2 Indirect role of SRL towards Intrinsic Motivation and User Experience towards MOOC for Working Adults.

In subsection 4.5.2.4, the relationship between intrinsic factors and UX towards MOOC, with and without the moderating role of SRL, was analysed. The analyses discovered that the moderating effect of SRL towards the relationship between the two specific intrinsic factors (namely Communication Skills and Job Specification) and UX was not substantiated. Nevertheless, the SRL facilitates the relationship between independence and UX significantly as seen:

H1b : SRL moderates the relationship between Independence and the User Experience on MOOC. (Supported)

H2b : SRL moderates the relationship between Communication Skills and the User Experience on MOOC. (Not Supported)

H3b : SRL moderates the relationship between Job Requirements and User Experience on MOOC. (Not Supported)

Furthermore, the moderation effect in subsection 4.5.2.3 reveals no interaction (as the Figure 4.1, Figure 4.2, and Figure 4.3) is found to be parallel and does not intersect between the intrinsic factors and UX towards MOOC.

It suggests that the SRL plays a partial and indirect role in the relationship between Intrinsic Motivation factors and UX towards MOOC. These findings are corroborating to the study's Research Question No.2 : How does SRL affect the relationship between working adult's UX and their intrinsic motivation factors?).

It was found that learners with higher self-efficacy will likely have higher SRL (Ömer & Akçayoğlu, 2021; Lee at al., 2019; Bozpolat, 2016; Zimmerman, 1990). A study said user experience encourages SRL (Safsouf, Mansouri & Poirier, 2020). Nicolas and Schoormans (2019) noted that autonomy enhances positive experiences. Hence, independence directly affects user experience, whereas SRL directly affects UX.

Thompson (2021) mentioned that improving SRL enhances communication in your workplace, where learners can listen actively and are better equipped to think before speaking or acting. Other than that, Zhao and Li (2016) found that SRL was influenced by communication quality. They added that system and service quality influences SRL through communication quality and user satisfaction. In other words, SRL is set to impact communication skills where learners are motivated to learn. Hence, communication skills and SRL are interdependent on one another. However, SRL does not affect the relationship between communication skills and UX. Zhao (2016) noted that communication quality does not promote SRL. Hsu, Chen and Shin (2021) mentioned that young adults' perceived employability influenced SRL.

Additionally, SRL and professional development come hand-in-hand, where learners are motivated to learn to be equipped for their professional needs (Ciga et al., 2015). In conclusion, job specification and SRL are interdependent on one another. However, SRL does not moderate the relationship between job specification and UX. Lin et al. (2017) found that SRL does not mediate significantly between job demands and continual learning on MOOC. They mentioned that SRL has an indirect relationship between job demands and MOOC.

5.2.3 The impact of MOOC's UX on MOOC's CI among the working adults.

Previous studies (mentioned in subsection 1.5) have shown that positive UX will have a higher possibility of CI towards MOOC. With this study, the findings further confirmed the understanding. In subsection 4.5.2.4, table 4.15 it was found that UX and CI has a significant relationship as both with and without moderator was found to have p-value =0 and largest t-values. Therefore:

H4 : There is a significant relationship between User Experience and Continuous Intention towards MOOC. (Supported)

These findings suggest that UX and CI has a significant relationship. These findings are corroborating to the study's Research Question No.3 : What is the impact of MOOC's UX towards MOOC's CI among working adults?

Other than that, the cross-tabulation analysis showed no relationship between the dependent variables UX and CI. The cross-tabulation analysis demonstrates the respondent's profile measured against the dependent variables. Therefore, it shows that demographic affects the UX and CI little.

The user experience on a MOOC (Massive Open Online Course) can significantly impact learners' continuous intention to participate as it has demonstrated the usefulness and confirmed user expectations (Rekha, Shetty, & Basr, 2023; Gu, Xu, & Sun, 2021). User experience can affect the CI of MOOC by providing satisfaction by meeting the expectation or goals of learners and social interaction such as collaboration between learners (Martin, 2017). By providing learners with a positive and engaging experience, MOOC providers can increase satisfaction to foster a sense of community and collaboration that encourages learners to continue participating.

5.3 Implications

In this section, the study elaborates on the involvement of intrinsic motivation, user experience and continuous intention on MOOC for working adults towards the theoretical, practitioners and policymakers. Additionally, it has also come to the attention that there is a rise in studies of MOOC and learners' behaviour and motivation. This was caused by the COVID-19 pandemic, where education has evolved with the efficient use of technology. Table 5.1 summarises the implication of each Research Objective of this study.

Table 5.1: Summary of Implications for each Research Objective.

RO	Description	Variables	Theoretical	Practitioners	Policy Makers
RO1	To examine the relationship between working adults' intrinsic motivation factors and their user experience with MOOC.		This study found that intrinsic motivation factors contribute to the learner's UX towards MOOC. With previous studies (mentioned in chapter 1), this study confirmed the relationship between intrinsic factors and their UX towards MOOC. Therefore, future researchers could refer to the detailed breakdown of the intrinsic factors towards MOOC.	This study targets working adults, enabling practitioners to fully understand how they are affected in their learning on MOOC. In addition, it will contribute to the initiation of MOOC research towards a specific group, such as working adults, as they are one of the primary learners of MOOC.	HEIs to work with MOOC Web Developers to create a more user-friendly (UX) interface to support learning independence. (non-complicated UI)
		Independence	Future researchers could refer to the findings and cite that independence affects their UX towards MOOC.		
		Communication Skills	Future researchers could use this study's findings further to research the relationship between Communication skills and UX.	At the same time, practitioners could look into improving communication courses relevant to the current	HEIs to collaborate with working adults to develop courses that are industry related that could benefit worldwide learners.

		Job Specification	Future researchers could use this study's findings to research further the relationship between Jobs Specification towards UX	industry as technology has changed how communication works.	
RO2	To measure the role of SRL in moderating the relationship between working adults'UX and their intrinsic motivation factors towards MOOC.		Previous studies found that SRL plays a role in moderating intrinsic motivation factors; however, this study found it to have an indirect effect. Future researchers could use the findings of this study to further theorise SRL as a moderating effect between intrinsic motivating factors and UX.	MOOC course providers could also understand the learner's motivation toward MOOC. This could lead to MOOC course providers developing programme learning outlines that could aid in motivating learners to learn quickly (Zhu, 2022). Hence, this study aids MOOC course providers in understanding the motivation of learners that could help them in designing the course.	COVID-19 pandemic has changed the way traditional education functions, where distance learning has been positively accepted, and learners have been at an all-time high (Mishra, Gupta, & Shree, 2020). This study will provide insights into higher education institutions (HEIs) in understanding adult learners' motivation in learning. This, in turn, aids in providing certificate or professional courses online where working adults can learn quickly anywhere and anytime.

Independence	With this study, future researchers would be able to see the connection between autonomy and UX; and SRL towards UX. Therefore, it was found that autonomy and SRL affect UX separately.		HEIs to refer to the findings of this study to create a better learning matrix so that learners would feel motivated to learn independently.
Communication Skills	With the findings of this study, future researchers could refer to and further investigate the role of SRL in moderating the relationship between intrinsic factors and UX.	With this study, practitioners would understand that MOOC is limited by chance to communicate among peers. However, practitioners shall include on-demand skills and knowledge that could get working adults to feel smart or knowledgeable when they communicate at work. This would enhance their learning experiences and causes CI towards MOOC.	

		Job Specification		With this study, practitioners could better understand their learning behaviour towards MOOC and help them in their lifelong learning process. Therefore, they could create courses or modules to benefit their work life and create on-demand skills and knowledge.	Some HEIs, like Harvard University, provide more than 600 free online courses, University Sains Malaysia is starting Master of Business Administration Online, and Universiti Tunku Abdul Rahman has its MOOC that offers micro-credentials of accredited programmes that is on demand for the job market.
RO3	To determine the impact of MOOC’s UX on MOOC’s CI among working adults.		Hence, future researchers could use this framework when designing UX and CI research. Furthermore, future researchers could refer to the current funding and look into understanding the learning behaviour among working adults.	MOOC developers can identify the learner's behaviour to create a better interface. Therefore, increasing the CI when UX is positive.	HEIs to collaborate with MOOC developers and course developers towards creating an ecosystem of working adult learning.

5.3.1 Theoretical Implications

This study found that intrinsic motivation factors contribute to the learner's UX towards MOOC. With previous studies (mentioned in Chapter 1), this study confirmed the relationship between intrinsic factors and their UX towards MOOC. Therefore, future researchers could refer to the detailed breakdown of the intrinsic factors towards MOOC.

Furthermore, this study provided a questionnaire template for future researchers to study MOOC and learner motivation. This would give researchers a sample for in-depth learning on the specific constructs, which could help them solidify and further research its characteristics. Furthermore, this study demonstrated that the constructs are reliable and valid for the study of MOOC.

This study targeted respondents from Malaysia working adults. Therefore the findings of this study should not be generalised for worldwide learners. However, the findings of this study provide an understanding of Malaysia Working Adults that future researchers could refer to for future studies or consider when strategising the conceptual framework and make a comparison when they work on generalised learners.

Previous studies found that SRL plays a role in moderating intrinsic motivation factors; however, this study found it to have an indirect effect. Future researchers could use the findings of this study to further theorise SRL as a moderating effect between intrinsic motivating factors and UX. With this study, future researchers could see the connection between autonomy and UX; and SRL towards UX. Therefore, it was found that autonomy and SRL affect UX separately. With the findings of this study, future researchers could refer to and further investigate the role of SRL in moderating the relationship between intrinsic factors and UX.

5.3.2 Practitioners

This study targets working adults, enabling practitioners to fully understand how they are affected in their learning on MOOC. In addition, it will contribute to the initiation of MOOC research towards a specific group, such as working adults, as they are one of the primary learners of MOOC. At the same time, practitioners could look into improving communication courses relevant to the current industry as technology has changed communication.

MOOC course providers could also understand the learner’s motivation toward MOOC. This could lead to MOOC course providers developing programme learning outlines that could aid in motivating learners to learn quickly (Zhu, 2022). Hence, this study aids MOOC course providers in understanding the motivation of learners that could help them in designing the course. With this study, practitioners would understand that MOOC is limited by chance to communicate among peers. However, practitioners shall include on-demand skills and knowledge that could make working adults feel competent or knowledgeable when they communicate at work. This would enhance their learning experiences and causes CI towards MOOC.

This study targets working adults, enabling practitioners to fully understand how they are involved in their learning on MOOC. With this study, practitioners could better understand their learning behaviour towards MOOC and help them in their lifelong learning process. Therefore, they could create courses or modules to benefit their work life and create on-demand skills and knowledge. MOOC developers can identify the learner's behaviour to create a better interface. Therefore, increasing the CI when UX is positive.

5.3.3 Policy Makers

HEIs to work with MOOC Web Developers to create a more user-friendly (UX) interface that could support learning independence—HEIs to collaborate with working adults to develop courses that are industry related that could benefit worldwide learners. MOOC developers will become more well-known and sought-after, and there will be more subscriptions. Therefore, MOOC developers will have more meaningful feedback from learners to create quality learning. HEIs to collaborate with working adults to develop systems that are industry related that could benefit worldwide learners. There will be more communication and job-relevant skills courses that could fit everyone's needs.

The COVID-19 pandemic has changed how traditional education functions, where distance learning has been positively accepted, and learners have been at an all-time high (Mishra, Gupta, & Shree, 2020). This study will provide insights into higher education institutions (HEIs) in understanding adult learners' motivation in learning. This, in turn, aids in providing a certificate or professional courses online where working adults can learn quickly anywhere and anytime. HEIs refer to the findings of this study to create a better learning matrix so that learners would feel motivated to learn independently. Some HEIs, like Harvard University, provide more than 600 free online courses, University Sains Malaysia is starting Master of Business Administration Online, and Universiti Tunku Abdul Rahman has its MOOC that offers micro-credentials of accredited programmes that is on demand for the job market. HEIs to collaborate with MOOC developers and course developers towards creating an ecosystem of working adult learning.

The overrepresentation of Chinese respondents in MOOC studies in Malaysia could indicate a greater awareness or engagement among this demographic, possibly influenced by cultural, educational, or socioeconomic factors. This highlights the need for targeted outreach to underrepresented groups, ensuring equitable participation and a comprehensive understanding of the MOOC landscape. It suggests policy implications for MOOC providers and education policymakers to design inclusive strategies to address this disparity.

With this study, employers could motivate and develop their employees' competency by understanding learning motivation. They can then use this information to select or design

MOOC that address these specific training needs and provide their employees with opportunities to enhance their skills and knowledge.

5.4 Limitations and Recommendations for Future Researches

Future researchers could use a different methodology to gather a wider variety of responses. The methodology used was judgemental sampling which is the least time-consuming. Moss (2020) mentioned that although judgmental sampling helps locate the particular niche of population interest (in order words, the right target respondents, it may create unnecessary bias and judgement to researchers. Therefore, future researchers could use a different type of methodology for sampling to gather the least biassed data.

Furthermore, the investigation revealed that the predominant demographic among the target respondents was of Chinese ethnicity. Despite the crosstab analysis indicating a lack of significant correlation between the demographics and the variables of the present study, caution must be exercised when extrapolating these results. It is important to note that these findings are confined to the specific context of working adults in Malaysia. Consequently, in future research endeavours, a recommended approach could involve determining a proportionate representation of respondent ethnicity. This suggestion takes into account the utilization of judgmental sampling, a method that affords researchers the freedom to select respondents based on their discretion.

Other than that, it was found that this study contains biasness which is generally common among social science studies. This is easily caused by respondents that are not subject matter experts and could not differentiate the questions. However, the questionnaire of this study had been verified as comprehensive by external subject matter experts via content validity index (CVI). Therefore, it is recommended that future researchers to conduct a mixed methodology that involves qualitative and quantitative to ensure validity and reliability of the study.

This study specifically targets working adults who would enable practitioners to fully understand how they are affected in their learning on MOOC. In addition, it will contribute to the initiation of MOOC research towards a specific group, such as working adults, as they are one of the primary learners of MOOC. It could help in understanding their learning behaviour towards MOOC.

Future researchers could refer to the findings and cite that independence affects their UX towards MOOC. Future researchers could further use this study's findings to research the relationship between Communication skills and UX. Future researchers could use this study's findings further to research the relationship between Jobs Specification and UX.

Hence, future researchers could use this framework when designing UX and CI research. Furthermore, future researchers could refer to the current funding and look into understanding the learning behaviour among working adults.

5.5 Summary

Based on the most recent Systematic Literature Review (SLR) conducted for this study, it is evident that there is insufficient prior research addressing the intersection of the combined keywords of "Working Adults," "MOOCs," "Self-Determination Theory (SDT)," and "Self-Regulated Learning (SRL)." This study aligns with the prevailing trend in the field, focusing on the shifts in education triggered by the pandemic and the subsequent rise of online learning, particularly Massive Open Online Courses (MOOCs). Moreover, this research uniquely targets a relatively underrepresented demographic in the existing literature, namely, working adults and adult learners.

Additionally, this study combines aspects of SDT, specifically autonomy, with SRL's self-motivational beliefs (SMB), recognizing their inherent similarities. Furthermore, this research adapts the intrinsic factors of SDT, including autonomy, competence, and relatedness, into the constructs of independence, communication skills, and job specification, adding to its distinctiveness.

Other than that, it was found that there is limited attention given to SRL as a moderator in the context of MOOC-based learning. However, the research outcomes of this study indicated that each construct studied directly influences learners' motivation concerning MOOCs, with the exception of SRL.

This study carries significant implications for theory development, practical applications, and policymaking, particularly concerning the engagement of working adults, SRL, User Experience (UX), Continuous Intention (CI), and Intrinsic Motivation within MOOC. By understanding these dynamics, it becomes possible to motivate and support learners effectively, ultimately reducing dropout rates in MOOCs.

It's important to acknowledge that perfection and conclusive findings are elusive, given the continuous evolution of both human behaviour and technology. Therefore, this study acknowledges its limitations and provides recommendations for future research to further enrich our understanding in this dynamic field.

References

Abdullatif, H. & Velázquez-Iturbide, J.Á., (2020). Relationship between motivations, personality traits and intention to continue using MOOCs. Educ Inf Technol 25, 4417–4435. https://doi.org/10.1007/s10639-020-10161-z

Abro, Ahsanullah & Sulaiman, Suziah & Mahmood, Ahmad Kamil & Khan, Muzafar. (2015). Understanding factors influencing User Experience of interactive systems: A literature review. 10. 18175-18185.

Agarwala, (2013, March 7). A Research Summary on MOOC Completion Rate [Web log post]. Retrieved October 27, 2020, from https://edlab.tc.columbia.edu/blog/8990-A-Research-Summary-on-MOOC-Completion-Rates

Agonács, N., & Matos, J. (2019). Self-directed learning readiness of Language MOOC learners. EMOOCs-WIP.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human decision Processes,50, 179–211.

Akter S., Wamba S. F., & Dewan S., (2017). Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality, Production Planning & Control, 28:11-12, 1011-1021, DOI: 10.1080/09537287.2016.1267411

Alami, Youssef & El Idrissi, Issam. (2022). Students' adoption of e-learning: evidence from a Moroccan business school in the COVID-19 era. Arab Gulf Journal of Scientific Research. 40. 54-78. 10.1108/AGJSR-05-2022-0052.

Albelbisi, (2019). The role of quality factors in supporting self-regulated learning (SRL) skills in MOOC environment. Educ Inf Technol 24, 1681–1698. https://doi.org/10.1007/s10639-018-09855-2

Albelbisi, Nour & Yusop, Farrah. (2019). Factors Influencing Learners' Self –Regulated Learning Skills in a Massive Open Online Course (MOOC) Environment. Turkish Online Journal of Distance Education. 20. 1-16. 10.17718/tojde.598191.

Aldowah, Al-Samarraie & Alzahrani, A.I. et al. (2020). Factors affecting student dropout in MOOCs: a cause and effect decision-making model. J Comput High Educ 32, 429–454. https://doi.org/10.1007/s12528-019-09241-y

Alexandris, K., Dimitriadis, N., & Markata, D. (2002). Can perceptions of service quality predict behavioral intentions? An exploratory study in the hotel sector in Greece.Managing Service Quality, 12 (4), 224-231.

Alhazzani, N. (2020). MOOC's impact on higher education. Social Sciences & Humanities Open, 2(1), 1–6. https://doi.org/10.1016/j.ssaho.2020.100030

Alexandron, Ruipérez-Valiente, Chen, & Merino, & Pritchard, (2017). Copying@Scale: Using Harvesting Accounts for Collecting Correct Answers in a MOOC. Computers & Education. 108. 10.1016/j.compedu.2017.01.015.

Allen, M. (2017). The sage encyclopedia of communication research methods (Vols. 1-4). Thousand Oaks, CA: SAGE Publications, Inc doi: 10.4135/9781483381411

Allen, K. A., Kern, M. L., Rozek, C. S., McInereney, D., & Slavich, G. M. (2021). Belonging: A Review of Conceptual Issues, an Integrative Framework, and Directions for Future Research. Australian journal of psychology, 73(1), 87–102. https://doi.org/10.1080/00049530.2021.1883409

Alraimi, Zo, & Ciganek, (2015). Understanding the MOOCs continuance: The role of openness and reputation. Computers & Education, 80, 28-38. https://doi.org/10.1016/j.compedu.2014.08.006

Alyoussef, I. Y. (2023). The Impact of Massive Open Online Courses (MOOCs) on Knowledge Management Using Integrated Innovation Diffusion Theory and the Technology Acceptance Model. Education Sciences, 13(6), 531. MDPI AG. Retrieved from http://dx.doi.org/10.3390/educsci13060531

Alvi & Gillies, (2020). Teachers and the teaching of self-regulated learning (SRL): the emergence of an integrative, ecological model of SRL-in-context. Education Sciences 10 (4) 98 98. https://doi.org/10.3390/educsci10040098

Alzaidi, M.S. & Shehawy, Y.M. (2022), "Cross-national differences in mobile learning adoption during COVID-19", Education + Training, Vol. 64 No. 3, pp. 305-328. https://doi.org/10.1108/ET-05-2021-0179

Amantha Kumar, & Al-Samarraie, H. (2019). Challenges faced by Malaysian students in MOOCs: Language proficiency and course engagement. International Research Journal of Engineering and Technology, 7(3), 5315-5320. Retrieved from https://www.irjet.net

Araka, E., Maina, E., & Gitonga, R. et al. (2020). Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—systematic review (2008–2018). RPTEL 15, 6. https://doi.org/10.1186/s41039-020-00129-5

Asiamah, N., Mensah, H. K., & Oteng-Abayie, E. (2017). General, Target, and Accessible Population: Demystifying the Concepts for Effective Sampling. The Qualitative Report,22(6), 1607-1621. Retrieved from http://nsuworks.nova.edu/tqr/vol22/iss6/9

Azizi, N. A. (2017, September 26). Malaysia at the forefront of e-Learning. Retrieved April 10, 2020, from https://www.nst.com.my/news/nation/2017/09/284259/malaysia-forefront-e-learning

Baek, J., & Shore, J. (2016). Promoting student engagement in MOOCs. In Proceedings of the third ACM conference on learning @ scale, (pp. 293–296). New York: ACM. https://doi.org/10.1145/2876034.2893437.

Bagozzi RP & Yi Y. On the evaluation of structural equation models. J Acad Mark Sci. 1988;16:74–92. doi: 10.1007/BF02723327.

Bai X, Hossain MN, Kumar N, & Hossain MY., (2022). Effect of Perceived Fear, Quality, and Self-Determination on Learners' Retention Intention on MOOCs. Psychol Res Behav Manag. 2022 Oct 4;15:2843-2857. doi: 10.2147/PRBM.S379378. PMID: 36217377; PMCID: PMC9547593.

Bambaeeroo, F., & Shokrpour, N. (2017). The impact of the teachers' non-verbal communication on success in teaching. Journal of advances in medical education & professionalism, 5(2), 51–59.

Bandura, (1977). Self-efficacy: toward a unifying theory of behavioral change Psychological Review, 84 (2) (1977), pp. 191-215, 10.1037/0033-295X.84.2.191

Bandura, (1997). Self-efficacy: the exercise of control Freeman, New York (1997)

Barak, M., Hussein-Farraj, R. & Dori, Y.J, (2016). On-campus or online: examining self-regulation and cognitive transfer skills in different learning settings. Int J Educ Technol High Educ 13, 35. https://doi.org/10.1186/s41239-016-0035-9

Bayeck (2016). Exploratory study of MOOC learners' demographics and motivation: The case of students involved in groups. Open Praxis, 8(3), pp. 223–233.

Becker, Ringle & Sarstedt, (2018). ESTIMATING MODERATING EFFECTS IN PLS-SEM AND PLSc-SEM: INTERACTION TERM GENERATION*DATA TREATMENT. Journal of Applied Structural Equation Modeling: 2(2),1-21.

Bellare, Y., Smith, A., Cochran, K., & Lopez, S. G. (2023). Motivations and barriers for adult learner achievement: Recommendations for institutions of higher education. Adult learning, 34(1), 30-39.

Benard, Masese Chuma & Kebande, Victor. (2012). SWOT analysis of growth of women entrepreneurs in Dar Es Salaam. Acad. Res. Int.. 4. 50-58.

Benard, Masese Chuma & Charles, Masoud & Charo, Joel & Mgala, Mvurya. (2021). Cyber-Crimes Issues on Social Media Usage Among Higher Learning Institutions Students in Dar ES Salaam Region, Tanzania. International Journal of Scientific Research in Science, Engineering and Technology. 138-148. 10.32628/IJSRSET218418.

Benitez, Jose & Henseler, Jörg & Castillo, Ana & Schuberth, Florian. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. Information & Management. 57. 103168. 10.1016/j.im.2019.05.003.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88(3), 588–606. https://doi.org/10.1037/0033-2909.88.3.588

Billionniere, E., & Rahman, F. (2020, April). Redesigning learning spaces and credentials for 21st-century emerging tech careers. In Society for Information Technology & Teacher Education International Conference (pp. 1001-1006). Association for the Advancement of Computing in Education (AACE).

Bingol, I., Kursun, E., & Kayaduman, H. (2020). Factors for Success and Course Completion in Massive Open Online Courses through the Lens of Participant Types. Open Praxis, 12(2), 223-239. doi:http://dx.doi.org/10.5944/openpraxis.12.2.1067

Bloomfield, J., & Fisher, M. J. (2019). Quantitative research design. Journal of the Australasian Rehabilitation Nurses Association, 22(2), 27-30

Bozpolat, E. (2016). Investigation of the self-regulated learning strategies of students from the faculty of education using ordinal logistic regression analysis. Educational Sciences: Theory & Practice, 16, 301-318. http://dx.doi.org/10.12738/estp.2016.1.0281

Britannica, T. Editors of Encyclopaedia (2021, March 2). Cognition. Encyclopedia Britannica. https://www.britannica.com/topic/cognition-thought-process

Bujang, Omar, & Bahanrum (2018). A review on sample size determination for Cronbach's alpha test: a simple guide for researchers. Malays J Med Sci. 25(6):85–99. https://doi.org/10. 21315/mjms2018.25.6.9

Burney,S.M.A & Saleem, H., (2008), "Inductive & Deductive Research Approach", Lecture delivered on 06-03-2008 at Auditorium of Faculty of Arts and Science, University of Karachi, Karachi, Pakistan

Burroughs, C. (2019, July 11). How to become an independent learner. Retrieved March 11, 2021, from https://chloeburroughs.com/become-independent-learner/

Çakiroğlu, Ü., Özkan, A., Çevik, İ. et al. (2023). What motivate learners to continue a professional development program through Massive Open Online Courses (MOOCs)?: A lens of self-determination theory. Educ Inf Technol (2023). https://doi.org/10.1007/s10639-023-12087-8

Cao-Tuong, D., & Hoang-Yen, P. (2024). Examining student characteristics, self-regulated learning strategies, and their perceived effects on satisfaction and academic performance in MOOCs. Electronic Journal of e-Learning, 22(8), 41–59.

Carter, R.L. (2006). Solutions for Missing Data in Structural Equation Modeling. Research & Practice in Assessment, 1(1), 1-6.

Castaño-Muñoz, J., & Rodrigues, M. (2021). Open to MOOCs? Evidence of their impact on labour market outcomes. Computers & education, 173, 104289. https://doi.org/10.1016/j.compedu.2021.104289

Cerón et al., (2021). "Self-Regulated Learning in Massive Online Open Courses: A State-of-the-Art Review," in IEEE Access, 9(511-528). Doi: 10.1109/ACCESS.2020.3045913.

Chacón-Beltrán, (2018). Vocabulary learning strategies outside the classroom context: what adults learn in a technology-based learner-centred environment. Language Learning Journal, 46(5), 583-593.

Chan, J. (2021, January 12). 8 Things To Know About The Minimum Retirement Age In Malaysia - Employment and HR - Malaysia. Welcome to Mondaq. https://www.mondaq.com/retirement-superannuation-pensions/1024990/8-things-to-know-about-the-minimum-retirement-age-in-malaysia#:~:text=The%20minimum%20retirement%20age%20of,Minimum%20Retirement%20Age%20Act%202012.

Chang, Ray I., Hung, Yu Hsin, & Lin, Chun Fu, (2015). Survey of learning experiences and influence of learning style preferences on user intentions regarding MOOCs. British Journal of Educational Technology, 46 (3), 528-541.

Chang, SJ., van Witteloostuijn, A. & Eden, L., (2010). From the Editors: Common method variance in international business research. J Int Bus Stud 41, 178–184. https://doi.org/10.1057/jibs.2009.88

Charlotte Emma Hilton (2017) The importance of pretesting questionnaires: a field research example of cognitive pretesting the Exercise referral Quality of Life Scale (ER-QLS), International Journal of Social Research Methodology, 20:1, 21-34, DOI: 10.1080/13645579.2015.1091640

Cheng, R. & Poon, I. (2016). UX of e-Learning: A Look at How Two Online Learning Platforms Support Self-Regulated Learning. User Experience Magazine, 16(2). Retrieved from https://uxpamagazine.org/ux-of-e-learning/

Chen T, Peng L, Jing B, Wu C, Yang J, & Cong G. (2020). The Impact of the COVID-19 Pandemic on User Experience with Online Education Platforms in China. Sustainability. 12(18):7329. https://doi.org/10.3390/su12187329

Chen Y. & Zhang M., (2017). MOOC student dropout: pattern and prevention. In Proceedings of the ACM Turing 50th Celebration Conference - China (ACM TUR-C '17). Association for Computing Machinery, New York, NY, USA, Article 4, 1–6. DOI:https://doi.org/10.1145/3063955.3063959

Cherry, K. (2020, July 22). How self efficacy helps you achieve your goals. Retrieved March 11, 2021, from https://www.verywellmind.com/what-is-self-efficacy-2795954

Cherry, K. (2023, February 27). *How self efficacy helps you achieve your goals*. Verywell Mind. https://www.verywellmind.com/what-is-self-efficacy-2795954

Cheung, Siu & Ng, Kai. (2021). Application of the Educational Game to Enhance Student Learning. Frontiers in Education. 6. 10.3389/feduc.2021.623793.

Chin, C. (2020, March 29). Learning mustn't stop with Covid-19. Retrieved April 2, 2020, fromhttps://www.thestar.com.my/news/education/2020/03/29/learning-mustnt-stop-with-covid-19

Chopra, A., & Syazwani, A. (2022). Investigating the common factor of drop-out based on learner's perspective and dropout rate in MOOCs in Malaysia. Academia.edu. Retrieved from https://www.academia.edu/72978749

Chou, CY. & Zou, NB. (2020). An analysis of internal and external feedback in self-regulated learning activities mediated by self-regulated learning tools and open learner models. Int J Educ Technol High Educ 17, 55. https://doi.org/10.1186/s41239-020-00233-y

Ciga, E., García, E., Rueda, M.I., Tillema, H., & Sánchez, E. (2015). Self-Regulated Learning and Professional Development. In: Tillema, H., Westhuizen, G.J.v.d., Smith, K. (eds) Mentoring for Learning. SensePublishers, Rotterdam. https://doi.org/10.1007/978-94-6300-058-1_12

Clark, Ian. (2012). Formative Assessment: Assessment Is for Self-regulated Learning. Educational Psychology Review. 24. 10.1007/s10648-011-9191-6.

Communication skills for career success. (2020, December 30). Retrieved March 11, 2021, from https://www.indeed.com/career-advice/resumes-cover-letters/communication-skills

Cook DA & Artino AR Jr. (2016). Motivation to learn: an overview of contemporary theories. Med Educ. 50(10):997-1014. doi: 10.1111/medu.13074. PMID: 27628718; PMCID: PMC5113774.

Cong Jin (2020) MOOC student dropout prediction model based on learning behavior features and parameter optimization, Interactive Learning Environments, DOI: 10.1080/10494820.2020.1802300

Cousineau, Denis & Chartier, Sylvain. (2010). Outliers detection and treatment: A review. International Journal of Psychological Research. 3. 10.21500/20112084.844.

Covey, S. M. R. (2008). The speed of trust. Simon & Schuster.

COVID-19: Opportunities for e-Learning Industry. (2020, November 6). Retrieved November 08, 2020, from https://www.mida.gov.my/home/covid-19:-opportunities-for-e-learning-industry/posts/

Crary, Pamela. (2016). Relatedness Matters. Holistic Nursing Practice. 30. 345-350. 10.1097/HNP.0000000000000177.

Cristea, A.I., Alamri, A. & Alshehri, M. et al. (2023). The engage taxonomy: SDT-based measurable engagement indicators for MOOCs and their evaluation. User Model User-Adap Inter. https://doi.org/10.1007/s11257-023-09374-x

Cutlip, S. M., Center, A. H., & Broom, G. M. (1985). Effective public relations. Englewood Cliffs, N.J: Prentice-Hall.

Dai, Hai Min & Teo, Timothy & Rappa, Natasha. (2020). Understanding continuance intention among MOOC participants: The role of habit and MOOC performance. Computers in Human Behavior. 112. 106455. 10.1016/j.chb.2020.106455.

Dai, Hai Min & Teo, Timothy & Rappa, Natasha. (2022). The role of gender and employment status in MOOC learning: An exploratory study. Journal of Computer Assisted Learning. 38. n/a-n/a. 10.1111/jcal.12681. https://onlinelibrary.wiley.com/doi/full/10.1111/jcal.12681

Dalporto, G. (2020, April 14). Council post: Online LEARNING: Choosing the right program as an employer or student. Retrieved March 29, 2021, from https://www.forbes.com/sites/forbesbusinessdevelopmentcouncil/2020/04/14/online-learning-choosing-the-right-program-as-an-employer-or-student/?sh=1e3fa8e54a83

Daniel, J. (2016, January). Making sense of flexibility as a defining element of online learning. Teach Online. Retrieved January 18, 2022, from https://teachonline.ca/tools-trends/exploring-future-education/making-sense-flexibility-defining-element-online-learning

David, R., Pellini, A., Jordan, K., & Phillips, T. (2020, April). Education during the COVID-19 crisis: Opportunities and constraints of using EdTech in low-income countries. Retrieved June 07, 2020, from https://edtechhub.org/coronavirus/edtech-low-income-countries/

Davis, D., Triglianos, V., Hauff, C., & Houben, G-J. (2018). SRLx: A Personalized Learner Interface for MOOCs. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), Lifelong Technology-Enhanced Learning: 13th European Conference on Technology Enhanced Learning, EC-TEL 2018 (pp. 122-135). (Lecture Notes in Computer Science; Vol. 11082). Springer. https://doi.org/10.1007/978-3-319-98572-5_10

de Barba, Paula & Malekian, Donia & Oliveira, Eduardo & Bailey, James & Ryan, Tracii & Kennedy, Gregor. (2020). The importance and meaning of session behaviour in a massive open online course. Computers & Education. 146. 103772. 10.1016/j.compedu.2019.103772.

De Carvalho Junıor, G , Robles, D , De La Serna, M , & Rıvas, M . (2019). Comparative Study SPOC vs. MOOC for Socio-Technical Contents from Usability and User Satisfaction. Turkish Online Journal of Distance Education, 20 (2), 4-20. DOI: 10.17718/tojde.557726

Deci, E. L., & Ryan, R. M.(2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macrotheory of human motivation, development, and health. Canadian Psychology/Psychologie canadienne, 49(3), 182–185. https://doi.org/10.1037/a0012801

Deci, E. L., & Ryan, R. M. (2015). Self-Determination Theory. International Encyclopedia of the Social & Behavioral Sciences. 10.1016/B978-0-08-097086-8.26036-4.

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-Determination Theory in Work Organizations: The State of a Science. Annual Review of Organizational Psychology and Organizational Behavior, 4(1), 19–43. doi:10.1146/annurev-orgpsych-032516-113108

Deci, E. L., Ryan, R. M., & Guay, F. (2013). Self-determination theory and actualization of human potentials. In D. M. McInerney, H. W. Marsh, R. G. Craven, F. Guay, & D. M. McInerney (Eds.), Theory driving research: New wave perspectives on self-processes and human development (pp. 109–133). Charlotte: Information Age Publishing.

Demirören, M., Turan, S., & Taşdelen Teker, G. (2020). Determinants of self-regulated learning skills: the roles of tutors and students. Advances in physiology education, 44(1), 93-98

Deslauriers, L., McCarty, L. S., Miller, K., Callaghan, K., & Kestin, G. (2019). Measuring actual learning versus feeling of learning in response to being actively engaged in the classroom. Proceedings of the National Academy of Sciences of the United States of America, 116(39), 19251–19257. https://doi.org/10.1073/pnas.1821936116

Dhawan, S. (2020). Online Learning: A Panacea in the Time of COVID-19 Crisis. Journal of Educational Technology Systems, 49(1), 5–22. https://doi.org/10.1177/0047239520934018

Diep, Anh & Zhu, Chang & Cocquyt, Celine & Greef, Maurice & Vo, Minh Hien & Vanwing, Tom. (2019). Adult learners' needs in online and blended learning viewed through the lens of existence, relatedness and growth (ERG) theory. Australian Journal of Adult Learning. 59. 224-255.

Dillahunt, T. R., Wang, B. Z., & Teasley, S. (2014). Democratizing higher education: Exploring MOOC use among those who cannot afford a formal education. International Review of Research in Open and Distance Learning, 15(5), 177–196 Retrieved from http://www.irrodl.org/index.php/irrodl/article/view/1841.

Dillahunt T.R., Ng s., Fiesta M., & Wang Z. (2016). Do Massive Open Online Course Platforms Support Employability?. In Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16). ACM, New York, NY, USA, 233-244. DOI: https://doi.org/10.1145/2818048.2819924

Ding Y. & Shen H. (2019) Delving into learner autonomy in an EFL MOOC in China: a case study, Computer Assisted Language Learning, DOI: 10.1080/09588221.2019.1681464

Dong, L., Ji, T., & Zhang, J. (2023). Motivational Understanding of MOOC Learning: The Impacts of Technology Fit and Subjective Norms. Behavioral Sciences, 13(2), 98. MDPI AG. Retrieved from http://dx.doi.org/10.3390/bs13020098

Drake, M., & Rajaorko, P. (2018, June 27). MOOCs in the continuing vocational training – what motivates employees in MOOCs? Retrieved February 15, 2021, from https://uasjournal.fi/in-english/moocs-in-continuing-vocational-training/

Dudovskiy, J. (2018, January). Causal research (explanatory research) - research-methodology. Retrieved April 27, 2021, from https://research-methodology.net/causal-research/

Duffin, E. (2020). Leading distance learning institutions in the United States in 2018, by number of students taking at least one distance learning course. https://www.statista.com/statistics/944274/us-distance-learning-institutions-by-enrollment-students/

Durksen, T.L., Chu, MW., & Ahmad, Z.F. et al. (2016). Motivation in a MOOC: a probabilistic analysis of online learners' basic psychological needs. Soc Psychol Educ 19, 241–260. https://doi.org/10.1007/s11218-015-9331-9

Easterby-Smith M, Thorpe R, Jacson, P, & Jespersen L, (2018). Management & Business Research. 6th ed. Los Angeles, London, New Delhi, Singapore, Washington, Melbourne DC: SAGE Publications; 2018. 434 p. ISBN 978-1-5264-2479-2 ISBN 978-1-5264-2480-8 (pbk) ISBN 978-1-5264-4695-4 (pbk & interactive ebk (IEB))

Egloffstein, M. & Ifenthaler, D. (2017). Employee Perspectives on MOOCs for Workplace Learning. TechTrends 61, 65–70. https://doi.org/10.1007/s11528-016-0127-3

El-Koumy & Abdel Salam. (2019). A Multifaceted Framework for EFL Curriculum Development to Prepare Students for Building a 21st Century Egypt.

El Refae, G., Kaba, A., & Eletter, S. (2021). The the impact of demographic characteristics on academic performance: Face-to-face learning versus distance learning implemented to prevent the spread of covid-19. The International Review of Research in Open and Distributed Learning, 22(1), 91–110. https://doi.org/10.19173/irrodl.v22i1.5031

Escobar-Pérez J. & Cuervo-Martínez A. (2008). Validez de contenido y juicio de expertos: Una aproximación a su utilización. Av. Med. 6:27–36.

Espada J., Rodríguez C. C., Díaz V. C., & Crespo R.G. (2014). Method for analysing the user experience in MOOC platforms. 2014 International Symposium on Computers in Education, SIIE 2014. 10.1109/SIIE.2014.7017722.

Fadiyah, S. (2020, April 03). 5 Benefits of ERP for Home Based-Learning during Covid-19 Pandemic. Retrieved June 22, 2020, from https://www.hashmicro.com/blog/5-benefits-of-erp-for-home-based-learning-during-covid-19-pandemic/

Fang, Jiaming & Tang, Lufen & Yang, Jingjing & Peng, Min. (2019). Social Interaction in MOOCs: The Mediating Effects of Immersive Experience and Psychological Needs Satisfaction. Telematics and Informatics. 39. 10.1016/j.tele.2019.01.006.

Fauzi, A & Widjajanti, Djamilah. (2018). Self-regulated learning: the effect on student's mathematics achievement. Journal of Physics: Conference Series. 1097. 012139. 10.1088/1742-6596/1097/1/012139.

Feng, B., & Chen, M. (2020). The impact of entrepreneurial passion on psychology and behavior of entrepreneurs. Frontiers in Psychology, 11, 1733.

Ferraz-Caetano, J., & Dias, D. (2021). Chemistry Edutainment: A Storytelling Activity for Middle-School Children. In Handbook of Research on Contemporary Storytelling Methods Across New Media and Disciplines (pp. 364-391). IGI Global.

Fieland, M. (2019, March 04). How do MOOCs Work? Everything About Massive Open Online Courses. Retrieved July 25, 2020, from https://www.accreditedschoolsonline.org/resources/moocs/

Field, Rachael & Duffy, James & Huggins, Anna. (2015). Teaching independent learning skills in the first year: A positive psychology strategy for promoting law student well-being. Journal of Learning Design. 8. 1. 10.5204/jld.v8i2.238.

Filgona, Jacob & Sakiyo, John & Okoronka, Augustine. (2020). Motivation in Learning. Asian Journal of Education and Social Studies. 10. 16-37. 10.9734/AJESS/2020/v10i430273.

Flavell, J. (1979). Metacognition and Cognitive Monitoring: A New Area of Cognitive-Developmental Inquiry. American Psychologist, 34, 906-911.

Folstad & Rolfsen, (2006). "Measuring the effect of User Experience design changes in e-Commerce web sites: A case on customer guidance," User Exp. Towar. a unified view, pp. 10–15.

Gafaro, B.C. (2019). Exploring Self-Regulated Language Learning with MOOCs Journal Item.

Gamage, D., Perera, I., & Fernando, S. (2020). MOOCs lack interactivity and collaborativeness: evaluating MOOC platforms. Int. J. Eng. Pedagog., 10(2), 94-111.

Gan Z, Liu F, & Nang H. (2023). The Role of Self-Efficacy, Task Value, and Intrinsic and Extrinsic Motivations in Students' Feedback Engagement in English Learning. Behavioral Sciences, 13(5):428. https://doi.org/10.3390/bs13050428

Ghazali, N., Nordin, N., Abdullah, A., & Ayub, E. (2020). The Relationship between Students' MOOC-efficacy and Meaningful Learning. Asian Journal of University Education. 16. 89. 10.24191/ajue.v16i3.11071.

Gerpott, T. J., Rams, W., & Schindler, A. (2001). Customer retention, loyalty, and satisfaction in the German mobile cellular telecommunications market. Telecommunications Policy, 25(4), 249–269. doi:10.1016/s0308-5961(00)00097-5

Ghazali, N., Sahari Nordin, M., Hashim, S., & Hussein, S. (2018). Measuring content Validity: STUDENTS SELF-EFFICACY and meaningful learning in massive open online Course (MOOC) Scale. Proceedings of the International Conference on Education in Muslim Society (ICEMS 2017). doi:10.2991/icems-17.2018.25

Ginting, Daniel & Djiwandono, Patrisius & Woods, Ross & Lee, Debra. (2021). Is Autonomous Learning Possible For Asian Students? The Story Of A Mooc From Indonesia. 20. 60-79.

Global survey reveals growing interest in shorter programmes and lifelong learning. (2020, March 23). Retrieved December 11, 2020, from https://monitor.icef.com/2019/10/global-survey-reveals-growing-interest-in-shorter-programmes-and-lifelong-learning/

Goldberg, L. R., Bell, E., King, C., O'Mara, C., McInerney, F., Robinson, A., & Vickers, J., (2015). Relationship between participants' level of education and engagement in their completion of the Understanding Dementia Massive Open Online Course Approaches to teaching and learning. 15(1), 2020.

GovindAarajan, P. B., & Krishnan, A. R. (2019). A study on influence of web quality and self efficacy on massive open online courses (moocs) technology adoption by extending the utaut model with reference to student mooc users. Shanlax International Journal of Management, 7(2), 47-53. doi:10.34293/management.v7i2.820

Grow, G. (1991). Teaching learners to be self-directed. Adult Education Quarterly, 41, 125–149.

Growing from strength to strength. (2018, September 2). Retrieved from https://www.thestar.com.my/news/education/2018/09/02/growing-from-strength-to-strengt

Gu, Wei & Xu, Ying & Sun, Zengjun. (2021). Does MOOC Quality Affect Users' Continuance Intention? Based on an Integrated Model. Sustainability. 13. 12536. 10.3390/su132212536.

Gupta, K.P. (2019), "Investigating the adoption of MOOCs in a developing country: Application of technology-user-environment framework and self-determination theory", Interactive Technology and Smart Education, Vol. 17 No. 4, pp. 355-375. https://doi.org/10.1108/ITSE-06-2019-0033

Gutierrez, K. (2016, April 7). Facts and stats that reveal the power of elearning [infographic]. Retrieved March 29, 2021, from https://www.shiftelearning.com/blog/bid/301248/15-facts-and-stats-that-reveal-the-power-of-elearning

Habes, M., Ali, S., & Pasha, S. A. (2021). Statistical package for social sciences acceptance in quantitative research: From the technology acceptance model's perspective. FWU Journal of Social Sciences, 15(4), 34-46.

Hair, J.F., Anderson, R.E., Tatham, R.L., & Black, W.C. (2006). Multivariate Data Analysis (5th ed.). Upper Sadle River: NJ, PearsonEducation Incorporation.

Hair, Joe F.; Ringle, Christian M.; Sarstedt, Marko (2011). PLS-SEM: Indeed a Silver Bullet. The Journal of Marketing Theory and Practice, 19(2), 139–152. doi:10.2753/mtp1069-6679190202

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2012). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3rd Ed., Sage: Thousand Oaks.

Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sartedt, M. (2014). A primer on partial least squares structural equation modeling. Thousand Oaks, CA: Sage.

Hair, & Risher, Jeff & Sarstedt, Marko & Ringle, Christian. (2018). When to use and how to report the results of PLS-SEM. European Business Review. 31. 10.1108/EBR-11-2018-0203.

Hair Jr, Sarstedt, Hopkins, & Kuppelwieser, V. (2014), "Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research", European Business Review, Vol. 26 No. 2, pp. 106-121. https://doi.org/10.1108/EBR-10-2013-0128

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). Multivariate Data Analysis (8th ed.).United Kingdom: Cengage Learning.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S. (2021). An Introduction to Structural Equation Modeling. In: Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. Classroom Companion: Business. Springer, Cham. https://doi.org/10.1007/978-3-030-80519-7_1

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S. (2021). Evaluation of Reflective Measurement Models. In: Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. Classroom Companion: Business. Springer, Cham. https://doi.org/10.1007/978-3-030-80519-7_4

Haba, H. F., & Dastane, O., (2019). Massive open online courses (MOOCs) - Understanding online learners' preferences and experiences. International Journal of Learning, Teaching and Educational Research. 18 (8), 227- 242.

Hamed, T. (2016). Sampling Methods in research Methodology; How to Choose a Sampling Technique for Research. International Journal of Academic Research in Management (IJARM), 5(2), 18–27. http://dx.doi.org/10.2139/ssrn.3205035

Hamid, M & Sami, Waqas & Sidek, M. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. Journal of Physics: Conference Series. 890. 012163. 10.1088/1742-6596/890/1/012163.

Hammersley, Martyn. (2019). From Positivism to Post-Positivism: Progress or Digression?. Teoria Polityki. 3. 175-188. 10.4467/25440845TP.19.009.10292.

Handoko, E., Gronseth, S. L., McNeil, S. G., Bonk, C. J., & Robin, B. R. (2019). Goal Setting and MOOC Completion: A Study on the Role of Self-Regulated Learning in Student Performance in Massive Open Online Courses. The International Review of Research in Open and Distributed Learning, 20(3). https://doi.org/10.19173/irrodl.v20i4.4270

Harding, S.-M., English, N., Nibali, N., Griffin, P., Graham, L., Alom, B., & Zhang, Z. (2019). Self-regulated learning as a predictor of mathematics and reading performance: A picture of students in Grades 5 to 8. Australian Journal of Education, 63(1), 74–97. https://doi.org/10.1177/0004944119830153

Harding., S., Nibali., N., English., N., Griffin., P., Graham., L., Alom, BM., & Zhang., Z. (2018). Self-regulated learning in the classroom: Realising the potential for Australia’s high capacity students. Assessment Research Centre, Melbourne Graduate School of Education.

Harper, S. (2019, October 14). 3 customer Experience Equations --Math you'll actually Use: Innovative Leadership Institute. Retrieved March 07, 2021, from https://www.innovativeleadershipinstitute.com/3-customer-experience-equations-math-youll-actually-use/

Hausler, S. (2017, September 27). 7 characteristics of the modern customer. Retrieved March 08, 2021, from https://smartercx.com/7-characteristics-modern-customer/

Head, Van Hoeck, & Garson, (2015). Lifelong learning in the digital age: A content analysis of recent research on participation. First Monday, 20 (2 - 2). https://firstmonday.org/ojs/index.php/fm/article/download/5857/4210 doi: http://dx.doi.org/10.5210/fm.v20i2.5857

Healy, P. A. (2017). Georgetown's First Six MOOCs: Completion, Intention, and Gender Achievement Gaps. Undergraduate Economic Review, 14(1), 1.

Heidrun Stoeger & Moshe Zeidner (2019) Self-regulated learning in gifted, talented, and high-achieving learners, High bility Studies, 30:1-2, 1-8, DOI: 10.1080/13598139.2019.1601326

Henderikx, M., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in massive open online courses based on the intention–behavior gap. Distance Education, 38, 353 - 368.

Hendriks, R. A., De Jong, P. G., Admiraal, W. F., & Reinders, M. E. (2020). Uncovering motivation and Self-regulated learning skills in integrated medical Mooc Learning: A mixed methods research protocol. BMJ Open, 10(10). doi:10.1136/bmjopen-2020-038235 https://bmjopen.bmj.com/content/10/10/e038235

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Hertzog, M. (2008). Considerations in determining sample size for pilot studies. Research in nursing & health, 31 2, 180-91.

Hirschmann, R. (2022, June 22). Malaysia: Labor Force by age 2021. Statista. Retrieved August 3, 2022, from https://www.statista.com/statistics/862634/malaysia-labor-force-by-age/.

Högberg, J., Hamari, J., & Wästlund, E. (2019). Gameful Experience Questionnaire (GAMEFULQUEST): an instrument for measuring the perceived gamefulness of system use. User Modeling and User-Adapted Interaction, 29(3), 619-660.

Holec, H. (1981). Autonomy and Foreign Language Learning. Oxford/New York: Pergamon Press. (First Published 1979, Council of Europe).

Hone, K. S., & Said, G. R. E. (2016). Exploring the factors affecting MOOC retention: A survey study. Computers & Education, 98, 157–168. doi: 10.1016/j.compedu.2016.03.016

Hosseinikhah Choshaly, Sahar & Tih, Siohong. (2017). The Factors Associated with the Behavioural Intention of Ecolabelled Products. Pertanika Journal of Social Sciences and Humanities. 25.

How and why E-learning will revolutionise the concept of company training. (2019, July 15). Retrieved November 08, 2020, from https://www.whappy.it/en/e-learning-for-company-training/

Howarth, J. P., D'Alessandro, S., Johnson, L., & White, L., (2016). Learner motivation for MOOC registration and the role of MOOCs as a university 'taster'. International Journal of Lifelong Education. 35(1), 74-85.

How do I gain 100% completion in a course? (2018, July 02). Retrieved January 28, 2021, from https://help.openlearning.com/t/x15w10/how-do-i-gain-100-completion-in-a-course

Ho Y.Y., Lim W.Y.R. (2020) Educating Adult Learners: Bridging Learners' Characteristics and the Learning Sciences. In: Sanger C., Gleason N. (eds) Diversity and Inclusion in Global Higher Education. Palgrave Macmillan, Singapore. https://doi.org/10.1007/978-981-15-1628-3_4

Hsu, L. (2020). Learning tourism and hospitality subjects with massive open online courses (MOOCs): A cross-sectional and longitudinal study. Journal of Hospitality Leisure Sport & Tourism Education, 100276.

Hsu, A. J., Chen, M. Y. C., & Shin, N. F. (2021). From academic achievement to career development: does self-regulated learning matter?. International Journal for Educational and Vocational Guidance, 1-21..

Hughes, C. (2021). The Changing Learning Technological Landscape for Trainers in the Wake of COVID-19. Advances in Developing Human Resources, 23(1), 66–74. https://doi.org/10.1177/1523422320972108

Hurst, B., Wallace, R., & Nixon, S. B. (2013). The Impact of Social Interaction on Student Learning. Reading Horizons: A Journal of Literacy and Language Arts, 52 (4). Retrieved from https://scholarworks.wmich.edu/reading_horizons/vol52/iss4/5

Hussain, Emmanuel, Mkpojiogu, Ja'afaru Musa, & Salah Mortada, (2017). "A user experience evaluation of Amazon Kindle mobile application", AIP Conference Proceedings 1891, 020060 https://doi.org/10.1063/1.5005393

Hutauruk, M., & Puspita, D. (2020). A metapragmatic analysis: a study of pragmatic failure found in indonesian efl students. Linguistics and Literature Journal, 1(2), 62-69.

Ibrahim, M.M., & Rahim, M., (2018). MOOCs continuance intention in Malaysia: the role of interactivity and enjoyment. Journal of Global Business and Social Entrepreneurship (GBSE), 4(11), 56-63.

Ikart, Emmanuel. (2019). Survey Questionnaire Survey Pretesting Method: An Evaluation of Survey Questionnaire via Expert Reviews Technique. Asian Journal of Social Science Studies. 4. 1. 10.20849/ajsss.v4i2.565.

Impey, C. (2020, September 06). Massive online open courses see exponential growth during COVID-19 pandemic. Retrieved December 25, 2020, from https://theconversation.com/massive-online-open-courses-see-exponential-growth-during-covid-19-pandemic-141859

In J. (2017). Introduction of a pilot study. Korean Journal of anesthesiology, 70(6), 601–605. https://doi.org/10.4097/kjae.2017.70.6.601

Jacobs, J. (2019, Feb 24). Education: A free MOOC on cloud computing. Retrieved April 10, 2020, from https://www.theedgemarkets.com/article/education-free-mooc-cloud-computing

Jaleel, S., & Premachandran, P. (2016). A Study on the Metacognitive Awareness of Secondary School Students. Universal Journal of Educational Research, 4, 165-172.

Jansen, R. S., van Leeuwen, A., Janssen, J., Conijn, R., & Kester, L. (2020). Supporting learners' self-regulated learning in massive open online courses. Computers & Education, 146, 103771.

Jansen, Renée S.; van Leeuwen, Anouschka; Janssen, Jeroen; Conijn, Rianne; Kester, Liesbeth

Jenkins-Smith, H.C., Ripberger, J.T., Copeland, G.W., Nowlin, M.C., Hughes, T., Fister, A.L., & Wehde, W. (2017). Quantitative Research Methods for Political Science, Public Policy and Public Administration (With Applications in R): 3rd Edition.

Jiang, P., & Rosenbloom, B. (2005). Customer intention to return online: price perception, attribute-level performance, and satisfaction unfolding over time. European Journal of Marketing, 39(1/2), 150–174. doi:10.1108/03090560510572061

Job Description and Job Specification. (2021). Retrieved March 12, 2021, from https://www.managementstudyguide.com/job-description-specification.htm

Joo, Young & So, Hyo-Jeong & Kim, Nam. (2018). Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. Computers & Education. 122. 10.1016/j.compedu.2018.01.003.

Jordan, P. J., & Troth, A. C. (2020). Common method bias in applied settings: The dilemma of researching in organizations. Australian Journal of Management, 45(1), 3–14. https://doi.org/10.1177/0312896219871976

Kapur, Radhika. (2019). The Adult Learner - Meaning and Significance.

Kayaduman, H. (2020). Student interactions in a flipped classroom-based undergraduate engineering statistics course. Computer Applications in Engineering Education. https://doi.org/10.1002/cae.22239

Keiningham, T. L., Cooil, B., Aksoy, L., Andreassen, T. W., & Weiner, J. (2007). The value of different customer satisfaction and loyalty metrics in predicting customer retention, recommendation, and share-of-wallet. Managing Service Quality: An International Journal, 17(4), 361–384. doi:10.1108/09604520710760526

Kenton, W. (2020, December 14). What is Self-Interest? Retrieved March 11, 2021, from https://www.investopedia.com/terms/s/self-interest.asp

Kethan, M. & Mahabub Basha S. (2022). Relationship of Ethical Sales Behaviour with Customer Loyalty, Trust and Commitment: A Study with Special Reference to Retail Store in Mysore City. East Asian Journal of Multidisciplinary Research, 1(7), 1365–1376. https://doi.org/10.55927/eajmr.v1i7.874

Khan, Z. Hameed, Y. Yu, T. Islam, Z. Sheikh, & S. U. Khan, (2018). "Predicting the acceptance of MOOCs in a developing country: Application of task-technology fit model, social motivation, and self-determination theory," Telematics Informat., 35(4), pp. 964–978. https://doi.org/10.1016/j.tele.2017.09.009

Khan, N., Sarwar, A., Chen, T. B., & Khan, S. (2022). Connecting Digital Literacy in Higher Education to the 21st Century Workforce. Knowledge Management & E-Learning, 14(1), 46-61.

Kimmel, Sara & Gaylor, Kristena & Hayes, J.. (2016). Age Differences among Adult Learners: Motivations and Barriers to Higher Education. Academy of Business Research Journal. IV. 32-58.

Kirk, K. (2020, September 04). Develop Self-Regulated Learners: Choosing and Using the Best Strategies for the Task. Retrieved January 13, 2021, from https://serc.carleton.edu/sage2yc/self_regulated/index.html

Kizilcec, R. F., et al. (2021). The role of self-regulated learning strategies in MOOCs. Retrieved from https://www.researchgate.net/publication/308957955_Self-regulated_learning_strategies_predict_learner_behavior_and_goal_attainment_in_Massive_Open_Online_Courses_In_press

Kizilcec, R.F., Pérez-Sanagustín, M., & Maldonado, J. (2016). Recommending Self-Regulated Learning Strategies Does Not Improve Performance in a MOOC. Proceedings of the Third (2016) ACM Conference on Learning @ Scale.

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. Computers & Education, 104, 18–33.

Kline, R. B. (2011). Principles and practice of structural equation modeling. New York, NY: Guilford.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kopolovich, O. (2020). Learning soft skills in the digital age: Challenges and insights from development and teaching'Negotiation Management'MOOC. Online Journal of Applied Knowledge Management (OJAKM), 8(2), 91-106.

Kuhn, T. S. (1962). The structure of scientific revolutions. (1st Edn). Chicago, IL: University of Chicago Press.

Kulasegaran, P. (2019, November 30). Muhyiddin: Govt plans to attract 200,000 international students by 2020. The Star Online. https://www.thestar.com.my/news/nation/2011/09/13/muhyiddin-govt-plans-to-attract-200000-international-students-by-2020/.

Kurniawan, Shelvy. (2014). The Influence of Green Marketing on Green Satisfaction Mediated By Perceived Quality and Its Impact to Green Trust in Injection Motorcycle. The Winners. 15. 85. 10.21512/tw.v15i2.622.

Lan, M., Hew, K.F. (2020). Examining learning engagement in MOOCs: a self-determination theoretical perspective using mixed method. Int J Educ Technol High Educ 17, 7. https://doi.org/10.1186/s41239-020-0179-5

Lan, Min & Hou, Xiangyu & Qi, Xinyu & Mattheos, Nikos. (2019). Self-Regulated Learning Strategies in world's first MOOC in Implant Dentistry. European Journal of Dental Education. 23. 10.1111/eje.12428.

Launspach, T. (2022). Crazy Busy: Keeping Sane in a Stressful World. John Wiley & Sons.

Layco, E. P., Parico, A. D., & Magno, J. C. (2022). Probing Teachers'competencies In Using Online Assessment Tools: Basis For A Capacity Building Program. International Journal of Early Childhood Special Education, 14(3).

Lee, S.S., Samarasekera, D.D., Sim, J.H. et al. (2020). Exploring the Cultivation of Self-Regulated Learning (SRL) Strategies Among Pre-Clinical Medical Students in Two Medical Schools. Med.Sci.Educ. 30, 271–280. https://doi.org/10.1007/s40670-019-00894-z

Legault, Lisa. (2017). Self-Determination Theory. Encyclopedia of Personality and Individual Differences. 10.1007/978-3-319-28099-8_1162-1.

Lei, J., & Lin, T. (2022). Emergency Online Learning: The Effects of Interactional, Motivational, Self-Regulatory, and Situational Factors on Learning Outcomes and Continuation Intentions. The International Review of Research in Open and Distributed Learning, 23(3), 43–60. https://doi.org/10.19173/irrodl.v23i3.6078

Leris, Dolores & Sein-Echaluce, María & Hernández, Miguel & García, Concepción. (2016). Validation of indicators for implementing an adaptive platform for MOOCs. Computers in Human Behavior. 72. 10.1016/j.chb.2016.07.054.

Lewis, M. (2020, July 20). Michael Lewis. Retrieved December 11, 2020, from https://www.moneycrashers.com/udemy-review-online-courses/

Li, C., & Lalani, F. (2020, April 29). The COVID-19 pandemic has changed education forever. This is how. Retrieved June 07, 2020, from https://www.weforum.org/agenda/2020/04/coronavirus-education-global-covid19-online-digital-learning/

Li, K. (2019). MOOC learners' demographics, self-regulated learning strategy, perceived learning and satisfaction: A structural equation modeling approach. Computers & Education, 132(1), 16-30. Elsevier Ltd. Retrieved December 11, 2020 from https://www.learntechlib.org/p/200789/.

Li, L. (2022). Reskilling and Upskilling the Future-ready Workforce for Industry 4.0 and Beyond. Inf Syst Front. https://doi.org/10.1007/s10796-022-10308-y

Li B., Wang X., & Tan S.C., (2018). What makes MOOC users persist in completing MOOCs? A perspective from network externalities and human factors. Computers in Human Behavior. 85, 385-395.

Liebmann, Bettina & Filzmoser, Peter & Varmuza, Kurt. (2010). Robust and classical PLS regression compared. Journal of Chemometrics - J CHEMOMETR. 24. 10.1002/cem.1279.

Lim, V., Wee, L., Teo, J., & Ng, S. (2017). Massive Open and Online Courses and Open Education Resources in Singapore.

Lin, Xiao-Fan & Liang, Jyh-Chong & Tsai, Chin-Chung & Hu, Qintai. (2017). The moderating role of self-regulated learning in job characteristics and attitudes towards web-based continuing learning in the airlines workplace. Australasian Journal of Educational Technology. 34. 10.14742/ajet.3198.

Linda Darling-Hammond, Lisa Flook, Channa Cook-Harvey, Brigid Barron & David Osher (2020) Implications for educational practice of the science of learning and development, Applied Developmental Science, 24:2, 97-140, DOI: 10.1080/10888691.2018.1537791

Liu, S., Liang, T., Shao, S., & Kong, J. (2020). Evaluating Localized MOOCs: The Role of Culture on Interface Design and User Experience. IEEE Access, 8, 107927-107940.

Loizzo, J., & Ertmer, P. A., (2016). MOOCocracy: the learning culture of massive open online courses. Educational Technology Research and Development. 64(6), 1013-1032.

Loizzo, J., Ertmer, P., Watson, W., & Watson, S. (2017). Adult MOOC Learners as Self-Directed: Perceptions of Motivation, Success, and Completion. Retrieved October 27, 2020, from https://olj.onlinelearningconsortium.org/index.php/olj/article/view/889

Lu F., Wang B., & Lu Y. (2019). Understanding Key Drivers Of Mooc Satisfaction And Continuance Intention To Use. Journal of Electronic Commerce Research, 20 (2), 105-117.

Luik, P., Suviste, R., Lepp, M., Palts, T., Tõnisson, E., Säde, M., & Papli, K. (2017). What motivates enrolment in programming MOOCs? British Journal of Educational Technology, 50(1), 153-165. doi:10.1111/bjet.12600

Luo, Y., Lin, J. & Yang, Y., (2021). Students' motivation and continued intention with online self-regulated learning: A self-determination theory perspective. Z Erziehungswiss 24, 1379–1399. https://doi.org/10.1007/s11618-021-01042-3

Lynn MR (1986) Determination and quantification of content validity. Nursing Research, 35(6), 382-386.

Mackenzie, N. & Knipe, S. (2006). Research dilemmas: paradigms, methods and methodology. Issues In Educational Research, 16, 1-15.

MacKenzie & Podsakoff, (2012). Common Method Bias in Marketing: Causes, Mechanisms, and Procedural Remedies. Journal of Retailing 88, 542–555. versity. http://dx.doi.org/10.1016/j.jretai.2012.08.001

Maddens, L., Depaepe, F., Raes, A. et al. Fostering students' motivation towards learning research skills: the role of autonomy, competence and relatedness support. Instr Sci 51, 165–199 (2023). https://doi.org/10.1007/s11251-022-09606-4

Mahidin, M. U. (2019, April 30). Labour Force Survey Report, Malaysia, 2018 . Department of Statistics Malaysia Official Portal. Retrieved August 4, 2022, from https://www.dosm.gov.my/v1/index.php?r=column%2FcthemeByCat&cat=126&bul_id=ekU0SG1yQk1wcExKUDhvN2RHTlhjZz09&menu_id=U3VPMldoYUxzVzFaYmNkWXZteGduZz09

Malaysia E-Learning Industry Revenue is Expected to Reach Over USD 2 Billion by 2023: Ken Research. (2019, September 10). Retrieved November 08, 2020, from https://www.prnewswire.com/news-releases/malaysia-e-learning-industry-revenue-is-expected-to-reach-over-usd-2-billion-by-2023-ken-research-300914849.html

Mallipa, Imelda & Papua, Universitas. (2018). Motivating Students To Be Autonomous Learners Through Portfolio In Learning English. 10.13140/RG.2.2.27855.59041.

Martin, K. (2017, October 07). 10 characteristics of Learner CENTERED EXPERIENCES: Katie Martin. Retrieved March 08, 2021, from https://katielmartin.com/2017/10/07/10-characteristics-of-learner-centered-experiences/

Martin, K. (2020, May 02). 10 characteristics of learner-centered experiences for REMOTE Learning: Katie Martin. Retrieved March 08, 2021, from https://katielmartin.com/2020/05/02/10-characteristics-of-learner-centered-experiences-for-remote-learning/

Martin, N., Kelly, N., & Terry, P. (2018). A framework for self-determination in massive open online courses: Design for autonomy, competence, and relatedness. Australasian Journal of Educational Technology, 34(2). https://doi.org/10.14742/ajet.3722

Martinich, A. & Stroll, Avrum (2021, February 11). Epistemology. Encyclopedia Britannica. https://www.britannica.com/topic/epistemology

Martín-Martín, Orduna-Malea, Thelwall, & López-Cózar, (2018). Google Scholar, Web of Science, and Scopus: A systematic comparison of citations in 252 subject categories. Journal of Informetrics. 12, 1160-1177. 10.1016/j.joi.2018.09.002.

Martin, Neil & Kelly, Nick & Terry, Peter. (2018). A framework for self-determination in massive open online courses: Design for autonomy, competence, and relatedness. Australasian Journal of Educational Technology. 34. 10.14742/ajet.3722.

Maslow, A. H. (1943). A theory of human motivation. Psychological Review, 50(4), 370-96.
Massive Open Online Course (MOOC) Market: Growth, Trends, and Forecasts (2020 - 2025). (2020). Retrieved January 24, 2021, from https://www.mordorintelligence.com/industry-reports/massive-open-online-course-mooc-market
Masuwai, Azwani & Mohd Tajudin, Nor'ain & Saad, Noor. (2016). Evaluating the face and content validity of a Teaching and Learning Guiding Principles Instrument (TLGPI): A perspective study of Malaysian teacher educators. GEOGRAFIA OnlineTM Malaysian Journal of Society and Space. 12. 11-21.
Mazlan, M. (2019, April 23). What Is MQA Accreditation and Do You Need It? https://eduadvisor.my/articles/what-is-mqa-accreditation-do-you-need-it/.
McCombes, S. (2019, February 25). Sampling methods: Types and techniques explained. Retrieved April 02, 2021, from https://www.scribbr.com/methodology/sampling-methods/
Md Zalli, Mohd Muslim & Nordin, Hasniza & AWANG-HASHIM, ROSNA. (2019). The role of self-regulated learning Strategies on learners' satisfaction in Massive Open Online Course (MOOC) Evidence from Malaysia MOOC. 8. 2286-2290. 10.35940/ijitee.J1138.0881019.
Meet, R. K., Kala, D., & Al-Adwan, A. S. (2022). Exploring factors affecting the adoption of MOOC in Generation Z using extended UTAUT2 model. Education and Information Technologies, 27(7), 10261-10283.
Memon, Mumtaz & Ting, Hiram & Hwa, Cheah & Ramayah, T. & Chuah, Francis & Cham, Tat Huei. (2020). Sample Size for Survey Research: Review and Recommendations. 4. i-xx. 10.47263/JASEM.4(2)01.
Merett, Francielle Nascimento, Bzuneck, José Aloyseo, Oliveira, Katya Luciane De, & Rufini, Sueli Édi. (2020). University students profiles of self-regulated learning and motivation. Estudos de Psicologia (Campinas), 37, e180126. Epub March 13, 2020.https://dx.doi.org/10.1590/1982-0275202037e180126
Milligan, C., Littlejohn, A., & Hood, N. (2016). Learning in MOOCs: A comparison study. In Proceedings of the European Stakeholder Summit on Experiences and Best Practices in and around MOOCs (EMOOCS 2016) (pp. 15-26). Books on Demand.
Milligan & Littlejohn (2017). Why Study on a MOOC? The Motives of Students and Professionals. International Review of Research in Open and Distributed Learning, 18 (2), 99-102.
Min, H., & Nasir, M. K. M. (2020). Self-Regulated Learning in A Massive Open Online Course: A Review of Literature. European Journal of Interactive Multimedia and Education, 1(2), e02007. https://doi.org/10.30935/ejimed/8403
Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. Annals of cardiac anaesthesia, 22(1), 67–72. https://doi.org/10.4103/aca.ACA_157_18
Miya, T. K., & Govender, I. (2022). UX/UI design of online learning platforms and their impact on learning: A review. International Journal of Research in Business and Social Science (2147-4478), 11(10), 316-327.
Mohamad, Mawaddah & Ibrahim[1], Amlus & Abdul Rahim, Mohd kamarul Irwan. (2018). MOOCs Continuance Intention In Malaysia: The Role Of Interactivity And Enjoyment.
Mohd Basar, Zulaikha & Mansor, Azlin & Jamaludin, Khairul & Alias, Bity. (2021). The Effectiveness and Challenges of Online Learning for Secondary School Students -A Case Study. Asian Journal of University Education. 17. 119-129. 10.24191/ajue.v17i3.14514.
Mohd Remali, Azrinawati & Ghazali, Mohamad & Kamaruddin, Mohammad & Kee, Tan. (2013). Understanding Academic Performance Based On Demographic Factors, Motivation Factors & Learning Styles. Asian Social Science. 3. 1938-1951.

Moore, R.L. & Wang, C. (2021). Influence of learner motivational dispositions on MOOC completion. J Comput High Educ 33, 121–134 (2021). https://doi.org/10.1007/s12528-020-09258-8

Moreno-Marcos, P. M., Munoz-Merino, P. J., Maldonado-Mahauad, J., Perez-Sanagustin, M., Alario-Hoyos, C., & Kloos D. C., (2020). Temporal analysis for dropout prediction using self-regulated learning strategies in self-paced MOOCs. Computers and Education. 145.

Morris, Neil & Hotchkiss, Stephanie & Swinnerton, Bronwen. (2015). Can demographic information predict MOOC learner outcomes?.

Morville, P. (2004, June 21). User experience design. Retrieved March 18, 2021, from http://semanticstudios.com/user_experience_design/

Morville, P. (2016, October 12). User experience honeycomb. Retrieved March 18, 2021, from https://intertwingled.org/user-experience-honeycomb/

Moss, A. (2020, August 10). Pros & cons of different sampling methodsew. Pros and Cons of Different Sampling Methods. Retrieved February 22, 2023, from https://www.cloudresearch.com/resources/guides/sampling/pros-cons-of-different-sampling-methods/#:~:text=By%20exercising%20judgment%20in%20who,the%20researcher%2C%20leading%20to%20bias.

Müller, J. (2021, April 07). Malaysia: Share of individuals using internet by activity 2019. Retrieved April 14, 2021, from https://www.statista.com/statistics/873940/share-of-individuals-using-internet-by-activity-in-malaysia/

Mullings, C. (2019, January 7). Developing independent learning skills that improve outcomes. Retrieved March 11, 2021, from https://blog.irisconnect.com/uk/blog/9-tips-for-encouraging-students-to-become-independent-learners/

Munir, F.F. (2018). Reliability and Validity Analysis on the Relationship between Learning Space, Student's Satisfaction and Perceived Performance Using SMART-PLS. The International Journal of Academic Research in Business and Social Sciences, 8, 775-783.

Musa, N. binti. (2021, July 26). *Education system*. MOE. https://www.moe.gov.my/en/dasarmenu/sistem-pendidikan

Myers, K., Conte, N., & Rubenson, K. (2014). Adult Learning Typology. Retrieved August 28, 2019 from http://www.srdc.org/media/199755/adult-learning-typology.pdf

Nam, Kim & Jin, (2018). A Comparison Analysis among Structural Equation Modeling (AMOS, LISREL and PLS) Using the Same Data. Journal of the Korea Institute of Information and Communication Engineering, 22 (7), 978-984. http://doi.org/10.6109/jkiice.2018.22.7.978

Nassaji, Hossein. (2015). Qualitative and descriptive research: Data type versus data analysis. Language Teaching Research. 19. 129-132. 10.1177/1362168815572747.

Nemoto, T., & Beglar, D. (2014). Developing Likert-scale questionnaires. In N. Sonda & A. Krause (Eds.), JALT2013 Conference Proceedings. Tokyo: JALT.

Nesterowicz, K., Bayramova, U., Fereshtehnejad, S., Scarlat, A., Ash, A., Augustyn, A. M., & Szádeczky, T. (2022). Gamification Increases Completion Rates in Massive Open Online Courses. International Journal of Information and Communication Technology Education (IJICTE), 18(1), 1-12. http://doi.org/10.4018/IJICTE.294447

Nicolas, J. C. O., & Schoormans, J. (2019). The Experience of Autonomy with Durable Products. Proceedings of the Design Society: International Conference on Engineering Design, 1(1), 4009–4018. https://doi.org/10.1017/DSI.2019.408

Nik Anis, N. M., & Tan, T. (2020, March 10). PM: A Cabinet to serve the people. The Star Online. https://www.thestar.com.my/news/nation/2020/03/10/pm-a-cabinet-to-serve-the-people.

Nikolov, Shoikova, & Kovatcheva, (2014). “Competence based framework for curriculum development”. [Online]. Available: https://unesco.unibit.bg/sites/default/files/CBFramework_TEMPUS-PICTET_Nikolov_Shoikova_Kovatcheva.pdf.

Niu Lung-Guang, (2018). Decision-making determinants of students participating in MOOCs: Merging the theory of planned behavior and self-regulated learning model. Computers and Education. 134, 50-62. https://doi.org/10.1016/j.compedu.2019.02.004

Nguyen, V., Chen, HL (2023).Examining impacts of information system success and perceived stress on students’ self-regulated learning mediated by intrinsic motivation in online learning environments: second-order structural equation modelling analyses. Educ Inf Technol (2023). https://doi.org/10.1007/s10639-023-11685-w

Oakley, B., Poole, D., & Nestor, M. (2016). Creating a sticky MOOC. Online Learning, 20(1), 1-12.

Oh, E.G., Chang, Y. & Park, S.W. (2020). Design review of MOOCs: application of e-learning design principles. J Comput High Educ 32, 455–475. https://doi.org/10.1007/s12528-019-09243-w

Okunade, B. (2015). Personnel and Industrial Relations in Education EME 312. Distance Learning Centre, University of Ibadan, Ibadan.

Ömer, Ö. Z. E. R., & Akçayoğlu, D. İ. (2021). Examining the roles of self-efficacy beliefs, self-regulated learning and foreign language anxiety in the academic achievement of tertiary EFL learners. Participatory Educational Research, 8(2), 357-372.

Onah, Daniel F. O., Sinclair, Jane & Boyatt, Russell, (2014). Dropout rates of massive open online courses: behavioural patterns. In: 6th International Conference on Education and New Learning Technologies, Barcelona, Spain, 7-9 Jul 2014. Published in: EDULEARN14 Proceedings pp. 5825-5834. ISBN 9788461705573. ISSN 2340-1117.

Online Education Steps Up: What the World is Learning (from Home). (2020, July 28). Retrieved October 27, 2020, from https://research.udemy.com/research_report/online-education-steps-up-what-the-world-is-learning-from-home/

OpenLearning Analytics: MOOCs in the New Academic Year 2018/2019. (2019, February 21). Retrieved from https://learninghub.openlearning.com/2018/11/01/openlearning-analytics-01/.

Oracle Corporation, (2012). ‘Customer Experience (CX) Metrics and Key Performance Indicators’, online leaflet.

Pallant, J. (2013). SPSS survival manual. McGraw-Hill Education (UK).

Palo, V.D., Monacis, L., & Sinatra, M. (2019). How self-regulated learning strategies interfere between metacognitions and decisional procrastination.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. Frontiers in Psychology, 8, Article 422. https://doi.org/10.3389/fpsyg.2017.00422

Panhwar, Dr Abdul Hameed & Ansari, Dr & Shah, Asif. (2017). Post-positivism: An Effective Paradigm for Social and Educational Research. International Research Journal Arts & Humanities (IRJAH). 45. 253-260.

Park, S.W. (2018). Motivation Theories and Instructional Design.

Pedrosa I., Suárez-Álvarez J., García-Cueto E. Evidencias Sobre La Validez De Contenido: Avances Teóricos Y Métodos Para Su Estimación/Content Validity Evidences: Theoretical Advances and Estimation Methods. Acción Psicol. 2013;10:3–18. doi: 10.5944/ap.10.2.11820.

Pilli, Olga & Admiraal, Wilfried. (2017). Students' Learning Outcomes in Massive Open Online Courses (MOOCs): Some Suggestions for Course Design. Yuksekogretim Dergisi. 7. 46-71. 10.2399/yod.17.001.

Pine, B., & Gilmore, J. H. (1998). Welcome to the experience economy. Harvard Business Review, July-August, 97–105.

Podsakoff, PM, & Organ, DW (1986) Self-reports in organizational research: Problems and prospects. Journal of Management 12: 531–544.

Poth, R. (2019, October 14). Metacognition and why it matters in education. Retrieved March 13, 2021, from https://www.gettingsmart.com/2019/10/metacognition-and-why-it-matters-in-education/

Prachi, M. (2019, January 02). Job description vs job specification - difference and comparison. Retrieved March 12, 2021, from https://theinvestorsbook.com/job-description-vs-job-specification.html

Puteh, Fadilah & Azman Ong, Mohd Hanafi. (2017). Quantitative Data Analysis: Choosing Between SPSS, PLS and AMOS in Social Science Research. 3.

Raghavendra, C.K. & Madhuri, M. (2023). ICT Tools for Efficient Implementation of Blended and Flipped Learning Models. In Redefining Virtual Teaching Learning Pedagogy (eds R. Bansal, R. Singh, A. Singh, K. Chaudhary & T. Rasul). https://doi.org/10.1002/9781119867647.ch20

Rajaendram, R. (2020a, April 26). Road to success. The Star. Retrieved November 8, 2020, from https://www.thestar.com.my/news/education/2020/04/26/road-to-success

Rajaendram, R. (2020b, April 26). Paving the Way Forward. The Star. Retrieved November 7, 2020, from https://www.thestar.com.my/news/education/2020/04/26/paving-the-wayforward

Ranaweera, C., & Prabhu, J. (2003). The influence of satisfaction, trust and switching barriers on customer retention in a continuous purchasing setting. International Journal of Service Industry Management, 14(4), 374–395. doi:10.1108/09564230310489231

Rawashdeh, Alaa & Youssef, Enaam & Alarab, Asma & Alarab, Mahmoud & Al-Rawashdeh, Butheyna. (2021). Advantages and Disadvantages of Using e-Learning in University Education: Analyzing Students' Perspectives. Electronic Journal of e-Learning. 19. 107-117. 10.34190/ejel.19.3.2168.

Redrup, Y. (2018, June 11). OpenLearning raises $8.5 million from Malaysian investors. Retrieved April 2, 2020, from https://www.afr.com/technology/openlearning-raises-85-million-from-malaysian-investors-20180606-h1119l

Reeve J, Ryan R, Deci EL, et al. (2008). Understanding and promoting autonomous self-regulation: A self-determination theory perspective. In: Schunk DH, Zimmerman BJ, eds. Motivation and self-regulated learning: theory, research, and applications. Lawrence Erlbaum Associates Publishers, 2008: 223–44.

Reich, J. (2014) MOOC completion and retention in the context of student intent // EDUCAUSE Review Online. Retrieved from: https://er.educause.edu/articles/2014/12/mooc–completion–and–retention–in–the–context–of–student–intent.

Rekha, I. S., Shetty, J., & Basri, S. (2023). Students' continuance intention to use MOOCs: empirical evidence from India. Education and information technologies, 28(4), 4265–4286. https://doi.org/10.1007/s10639-022-11308-w

Resnik, D. (2020, December 23). What is ethics in research & Why is it important? Retrieved April 29, 2021, from https://www.niehs.nih.gov/research/resources/bioethics/whatis/index.cfm

Ricart, S., Villar-Navascués, R. A., Gil-Guirado, S., Hernández-Hernández, M., Rico-Amorós, A. M., & Olcina-Cantos, J. (2020). Could MOOC-TAKERS' Behavior discuss the meaning of Success-dropout Rate? Players, auditors, and spectators in a Geographical analysis course about Natural risks. Sustainability, 12(12), 4878. doi:10.3390/su12124878

Ringle, Christian M., Wende, Sven, & Becker, Jan-Michael. (2015). SmartPLS 3. Boenningstedt: SmartPLS. Retrieved from https://www.smartpls.com

Rodrigues, I.B., Adachi, J.D., Beattie, K.A. et al. (2017). Development and validation of a new tool to measure the facilitators, barriers and preferences to exercise in people with osteoporosis. BMC Musculoskelet Disord 18, 540. https://doi.org/10.1186/s12891-017-1914-5

Roto, V., Law, E., Vermeeren, A., & Hoonhout, J. (2011). User experience white paper; Bringing clarity to the concept of user experience. Retrieved from http://www.allaboutux.org/files/UX-WhitePaper.pdf

Safsouf, Yassine & Mansouri, Khalifa & Poirier, Franck. (2020). Development Of A Measurement Tool To Evaluate The Learning Experience In An E-Learning System. International Conference e-Learning 2020, 101-107.

Salaries in Malaysia. Paylab. (2022). Retrieved August 4, 2022, from https://www.paylab.com/my/salaries-in-country

Salikhova, N. R., Lynch, M. F., & Salikhova, A. B. (2020). Psychological Aspects of Digital Learning: A Self-Determination Theory Perspective. Contemporary Educational Technology, 12(2), ep280. https://doi.org/10.30935/cedtech/8584

Sangoseni O, Hellman M, & Hill C (2013). Development and Validation of a Questionnaire to Assess the Effect of Online Learning on Behaviors, Attitudes, and Clinical Practices of Physical Therapists in the United States Regarding Evidence-based Clinical Practice. The Internet Journal of Allied Health Sciences and Practice 11(2), 1-13.

Santos, Patricia & Cirillo, Marcelo. (2021). Construction of the average variance extracted index for construct validation in structural equation models with adaptive regressions. Communications in Statistics - Simulation and Computation. 1-13. 10.1080/03610918.2021.1888122.

Sawatsky, M. L., Clyde, M., & Meek, F. (2015). Partial least squares regression in the social sciences. The Quantitative Methods for Psychology, 11 (2), 52-62.

Schroeder, B. (2019, August 14). Disrupting Education. The Rise Of K-12 Online And The Entrepreneurial Opportunities. Retrieved April 2, 2020, from https://www.forbes.com/sites/bernhardschroeder/2019/08/14/disrupting-education-the-rise-of-k-12-online-and-the-entrepreneurial-opportunities/#368c427848a2

Schwartz, M. (n.d.). Engaging Adult Learners. Retrieved March 23, 2021, from https://www.ryerson.ca/content/dam/learning-teaching/teaching-resources/teach-a-course/engaging-adult-learners.pdf

Shah, D. (2020, August 16). By the numbers: Moocs during the pandemic - class central. Retrieved April 16, 2021, from https://www.classcentral.com/report/mooc-stats-pandemic/

Shah, D. (2020, December 08). By the Numbers: MOOCs in 2020 - Class Central. Retrieved April 14, 2021, from https://www.classcentral.com/report/mooc-stats-2020/

Sheldrake, Richard. (2016). Confidence as motivational expressions of interest, utility, and other influences: Exploring under-confidence and over-confidence in science students at secondary school. International Journal of Educational Research. 76. 50-65. 10.1016/j.ijer.2015.12.001.

Shi, J., Mo, X., & Sun, Z. (2012). Zhong nan da xue xue bao. Yi xue ban = Journal of Central South University. Medical sciences, 37(2), 152–155. https://doi.org/10.3969/j.issn.1672-7347.2012.02.007

Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.-H., Ting, H., Vaithilingam, S. and Ringle, C.M. (2019), “Predictive model assessment in PLS-SEM: guidelines for using PLSpredict”,Working Paper.

Shrotryia, V. K., & Dhanda, U. (2019). Content Validity of Assessment Instrument for Employee Engagement. SAGE Open. https://doi.org/10.1177/2158244018821751

Sarstedt, Marko & Ringle, Christian & Hair, Joe. (2017). Partial Least Squares Structural Equation Modeling. 10.1007/978-3-319-05542-8_15-1.

Spar, B., & Dye, C. (2018). *LinkedIn's 2018 workplace learning report*. Workplace Learning & Development Report 2018 | LinkedIn Learning. https://learning.linkedin.com/resources/workplace-learning-report-2018

Streefkerk, R. (2019, November 11). Inductive vs. deductive research approach (with examples). Retrieved April 14, 2021, from https://www.scribbr.com/methodology/inductive-deductive-reasoning/

Suhr, D.D. (2006). The Basics of Structural Equation Modeling.

Sujati, Heronemus & Sajidan, Mr & Akhyar, Muhammad & Gunarhadi, Gunarhadi. (2020). Testing the Construct Validity and Reliability of Curiosity Scale Using Confirmatory Factor Analysis. Journal of Educational and Social Research. 10. 229. 10.36941/jesr-2020-0080.

Sukowati, Sukowati & Sartono, Kus & Pradewi, Gunarti. (2020). The effect of self regulated learning strategies on the primary school students' independent learning skill. Psychology, Evaluation, and Technology in Educational Research. 2. 10.33292/petier.v2i2.44.

Sun, Y., Ni, L., Zhao, Y., Shen, X-L., & Wang, N. (2019). Understanding students' engagement in MOOCs: An integration of self-determination theory and theory of relationship quality. British Journal of Educational Technology, 50(6), 3156-3174. https://doi.org/10.1111/bjet.12724

Tawafak, Ragad M., Romli, Awanis B.T., Arshah, Ruzaini bin Abdullah, & Malik, Sohail Iqbal, (2019). Framework design of university communication model (UCOM) to enhance continuous intentions in teaching and e-learning process. Education and Information Technologies, 2020.

Tabachnick, B. G., & Fidell, L. S. (2013). Using Multivariate Statistics, 6th ed. Boston: Allyn and Bacon

Taber, K.S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. Res Sci Educ 48, 1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Tan, Fiona & Whipp, Peter & Gagné, Marylène & Van Quaquebeke, Niels. (2019). Students' perception of teachers' two-way feedback interactions that impact learning. Social Psychology of Education. 22. 10.1007/s11218-018-9473-7.

Tang, Y., & Hew, K. F. (2022). Effects of using mobile instant messaging on student behavioral, emotional, and cognitive engagement: a quasi-experimental study. International Journal of Educational Technology in Higher Education, 19, 1-22.

Tawafak, R.M., Romli, A.B.T., Arshah, R.b.A. et al., (2020). Framework design of university communication model (UCOM) to enhance continuous intentions in teaching and e-learning process. Educ Inf Technol 25, 817–843 (2020). https://doi.org/10.1007/s10639-019-09984-2

The 50 Most Popular MOOCs of All Time (Updated For 2021). (2021). Retrieved April 22, 2021, from https://www.onlinecoursereport.com/the-50-most-popular-moocs-of-all-time/

The importance of Training employees: 11 benefits. (2021, February 23). Retrieved March 29, 2021, from https://www.indeed.com/career-advice/career-development/importance-of-training

Thompson, H. (2021, September 9). What are self-regulations skills? (and how to improve them). What Are Self-Regulations Skills? (And How To Improve Them). Retrieved June 25, 2022, from https://www.indeed.com/career-advice/career-development/self-regulation-skills

Timanyuk, Iryna & M., Mnushko & V., Sofronova & Aliekperova, Nataliia & Pestun, Iryna. (2016). Management And Marketing In Pharmacy Part I Management in Pharmacy.

Ting, Su-Hie. (2015). Lifelong Learning for Personal and Professional Development in Malaysia.

Trines, S. (2018, December 18). Educating the Masses: The Rise of Online Education in Sub-Saharan Africa and South Asia. Retrieved April 2, 2020, from https://wenr.wes.org/2018/08/educating-the-masses-the-rise-of-online-education

Triquet, K., Peeters, J., & Lombaerts, K. (2017). Self-Regulated Learning Online: Benefits, Empirical Foundations, Multi-level, and Multi-modal Promotion & Evaluation thereof for Teacher Professional Development. Contributing SRL Part to Teach-UP. A policy experimentation co-funded by Erasmus+. Deliverable D1.1: Gaps in ITE and CPD provision report. Department of Educational Sciences, Vrije Universiteit Brussel.

Trochim, P. (2020, March 10). Nonprobability sampling. Retrieved April 15, 2021, from https://conjointly.com/kb/nonprobability-sampling/

Tsai, Y. H., Lin, C. H., Hong, J. C., & Tai, K. H. (2018). The effects of metacognition on online learning interest and continuance to learn with MOOCs. Computers & Education, 121, 18–29. https://doi.org/10.1016/j.compedu.2018.02.011.

Tumbas, Pere & Sakal, Marton & Pavlićević, Veselin & Raković, Lazar. (2019). Digital Competencies in Business Informatics Curriculum Innovation. 9655-9664. 10.21125/inted.2019.2400.

Tyagi & Rathi, (2016) Effectiveness of "7Cs of communication" in the teaching of mathematics at elementary school level. International Journal of Applied Research, 1(13): 377-382.

Udoh, Udeme. (2018). Job Analysis and Design.

UNESCO: 4th Global Report On Adult Learning and Education, (2019). Retrieved December 25, 2020, from https://uil.unesco.org/system/files/grale_4_final.pdf

UNESCO. (2020, June 04). Education: From disruption to recovery. Retrieved June 07, 2020, from https://en.unesco.org/covid19/educationresponse

Unjana, Suphandee & Sunan, Sripai & Jamloong, Woonprasert & Sirisak, Ardwichai & Terdsak, Suphandee. (2018). Indicators of characteristics of Learners Autonomy in English Language of Primary 6 students in the Northeast of Thailand. Educational Research and Reviews. 13. 590-597. 10.5897/ERR2018.3562.

Ursachi, Horodnic, & Zait, (2015). How reliable are measurement scales? External factors with indirect influence on reliability estimators. 7th International Conference on Globalization and Higher Education in Economics and Business Administration, GEBA 2013. Procedia Economics and Finance 20, 679 – 686.

Vandewalle D., Nerstad C., Dysvik A. (2019). Goal orientation: a review of the miles travelled and the miles to go. Annu. Rev. Organ. Psychol. Organ. Behav. 6 115–144. 10.1146/annurev-orgpsych-041015-062547

Vermeeren, A. P. O. S., Roto, V., & Väänänen, K. (2016). Design-inclusive UX research: design as a part of doing user experience research. Behaviour and Information Technology, 35(1), 21-37. https://doi.org/10.1080/0144929X.2015.1081292

Verstegen, D., Dailey-Hebert, A., Fonteijn, H., Clarebout, G., & Spruijt, A. (2018). How do virtual teams collaborate in online learning tasks in a MOOC?. International Review of Research in Open and Distributed Learning, 19(4).

Vilkova, K. (2019). Self-regulated learning and successful MOOC completion. EMOOCs-WIP.

Vilkova K & Shcheglova I. (2020) Deconstructing self-regulated learning in MOOCs: In search of help-seeking mechanisms. Education and Information Technologies. 2020 Jun:1-17. DOI: 10.1007/s10639-020-10244-x.

Virtanen, P., Nevgi, A., & Niemi, H. (2013). Self-regulation in higher education: students' motivational, regulational and learning strategies, and their relationshıps to study success. Studies for the Learning Society, 3(1–2), 21–36.

Vuillaume, S. (2018, December 19). What can the customer experience tell us about the learner experience? Retrieved March 08, 2021, from

https://www.global-learning-development.com/2018/06/14/what-can-the-customer-experience-tell-us-about-the-learner-experience/
Wan, C.D., Sirat, M.B., & Razak, D.B. (2018). Education in Malaysia Towards a Developed Nation.
Wang, Kai & Zhu, Chang. (2019). MOOC-based flipped learning in higher education: students' participation, experience and learning performance. International Journal of Educational Technology in Higher Education. 16. 10.1186/s41239-019-0163-0.
Wang, T.; Lin, C.-L.; Su, Y.-S. (2021). Continuance Intention of University Students and Online Learning during the COVID-19 Pandemic: A Modified Expectation Confirmation Model Perspective. Sustainability, 13, 4586. https:// doi.org/10.3390/su13084586
Wang, W., Zhao, Y., Wu, Y.J. & Goh, M. (2023), "Factors of dropout from MOOCs: a bibliometric review", Library Hi Tech, Vol. 41 No. 2, pp. 432-453. https://doi.org/10.1108/LHT-06-2022-0306
Watson, S.L.; Watson, W.R.; Yu, J.H.; Alamri, H. & Mueller, C. (2017). Learner profiles of attitudinal learning in a MOOC: An explanatory sequential mixed-methods study. Comput. Educ. 114, 274–285
Wangida, M.N. (2020). The Importance of Self-Motivation in the Forethought Phase of Self-Regulated Learning.
Weiß, Frank & Leimeister, Jan Marco. (2012). Consumerization. Business & Information Systems Engineering. 4. 363-366. 10.1007/s12599-012-0234-4.
Wereda, Wioletta & GRZYBOWSKA, Monika. (2016). CUSTOMER EXPERIENCE – DOES IT MATTER?. Modern Management Review. XXI. 10.7862/rz.2016.mmr.35.
Wildermuth B. (1993) Post-Positivist Research: Two Examples of Methodological Pluralism. Library Quarterly 63(4), pp. 450-468.
Winne P.H., (2015). Self-Regulated Learning. International Encyclopedia of the Social & Behavioral Sciences (2), 535-540. https://doi.org/10.1016/B978-0-08-097086-8.25091-5
Workplace learning report 2020: LinkedIn Learning. (2020). Retrieved March 29, 2021, from https://learning.linkedin.com/resources/workplace-learning-report-2020
World Bank, (2020, March 26). Remote Learning, Distance Education and Online Learning During the COVID19 Pandemic: A Resource List by the World Bank's Edtech Team. Retrieved June 07, 2020, from http://documents.worldbank.org/curated/en/964121585254860581/Remote-Learning-Distance-Education-and-Online-Learning-During-the-COVID19-Pandemic-A-Resource-List-by-the-World-Banks-Edtech-Team
WORLDMETRICS. (2024). MOOC completion rates: A global perspective. Retrieved from https://www.worldmetrics.com
Ya H.T., Chien H.L., Jon C.H., & Kai H.T., (2018). The effects of metacognition on online learning interest and continuance to learn with MOOCs. Computers and Education, 121, 18-29.
Yan, T., Kreuter, F., & Tourangeau. (2012). Evaluating Survey Questions: A Comparison of Methods. Journal of Official Statistics, 28 (4), 503-529.
Yang Xiao & Huo Ran (2019). Effects of Online Teaching on Student Autonomous Learning with U-MOOCS: A Case Study of Business English and Communication Journal of Literature and Art Studies, 10(4), 307-312. doi: 10.17265/2159-5836/2020.04.006
Yellapu, Vikas. (2018). Descriptive statistics. International Journal of Academic Medicine. 4. 60. 10.4103/IJAM.IJAM_7_18.
Yeomans M. & Reich J., (2017). Planning prompts increase and forecast course completion in massive open online courses. In Proceedings of the Seventh International Learning Analytics & Knowledge Conference (LAK '17). Association for Computing Machinery, New York, NY, USA, 464–473. DOI:https://doi.org/10.1145/3027385.3027416

Yot-Domínguez, C. & Marcelo, C, (2017). University students' self-regulated learning using digital technologies. Int J Educ Technol High Educ 14, 38. https://doi.org/10.1186/s41239-017-0076-8
Yuniwati et al (2020) J. Phys.: Conf. Ser. 1567 022102
Yusoff MSB. (2019). ABC of content validation and content validity index calculation. Education in Medicine Journal. 11(2):49–54. https://doi.org/10.21315/eimj2019.11.2.6
Zamanzadeh V, Ghahramanian A, Rassouli M, Abbaszadeh A, Alavi- H. (2015). Design and implementation content validity Study: development of an instrument for measuring patient-centred communication. J Caring Sci. 4(5):165–78.
Zarour, M., & Alharbi, M. (2017). User experience framework that combines aspects, dimensions, and measurement methods. Cogent Engineering, 4.
Zhang, Qing & Peck, Kyle & Hristova, Adelina & Jablokow, Kathryn & Hoffman, Vicki & Park, Eunsung & Bayek, Rebecca. (2016). Exploring the communication preferences of MOOC learners and the value of preference-based groups: Is grouping enough?. Educational Technology Research and Development. 64. 10.1007/s11423-016-9439-4.
Zhang, M., Zhu, J., Wang, Z., & Chen Y. (2018). Providing personalized learning guidance in MOOCs by multi-source data analysis, 22(3), 1189–1219.
Zhang, Y., Chen, J., Miao, D., & Zhang, C. (2018). Design and Analysis of an Interactive MOOC Teaching System Based on Virtual Reality. iJET, 13, 111-123.
Zhao, H. (2016). Factors inuencing self-regulation in e-learning 2.0: Conrmatory factor model. Canadian Journal of Learning and Technology, 42(2), n2.
Zhao Jibing, (2022). "Strategies That Improve UX (User Experience) Design Through Product Innovation". Walden Dissertations and Doctoral Studies. 12902. https://scholarworks.waldenu.edu/dissertations/12902
Zhao, Hong & Chen, Li. (2016). How Can Self-regulated Learning Be Supported in E-learning 2.0 Environment: a Comparative Study. Journal of Educational Technology Development and Exchange. 9. 10.18785/jetde.0902.01.
Zhou & Mi., (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. Computers and Education. 92-93, 194-203.
Zhou, M. (2020). A study of self-regulation and MOOC outcomes. Online Learning Journal, 24(3), 45-67.
Zhu Y., Au W., & Yates G., (2016). University students' self-control and self-regulated learning in a blended course. The Internet and Higher Education, 30, 54-62. https://doi.org/10.1016/j.iheduc.2016.04.001
Zhu, M., Bonk, C. J., Berri, S. (2022). Fostering self-directed learning in MOOCs: Motivation, learning strategies, and instruction. Online Learning, 26(1), 153-173. DOI: 10.24059/olj.v26i1.2629
Zimmerman, B. J. (1986). Becoming a self-regulated learner: Which are the key subprocesses? Contemporary Educational Psychology, 11(4), 307-313. http://dx.doi.org/10.1016/0361-476X(86)90027-5
Zimmerman, B. J. (1998). Developing self-fulfilling cycles of academic regulation: An analysis of exemplary instructional models. In D. H. Schunk, & B. J. Zimmerman (Eds.), Self-regulated learning. From teaching to self-reflective practice, (pp. 1–19). New York: The Guilford Press.
Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. Educational Psychologist, 25(1), 3–7.
Zimmerman, B. J. (2009). Theories of self-regulated learning and academic achievement: An overview and analysis. In B. J. Zimmerman, & D. H. Schunk (Eds.), Self-regulated learning and academic achievement, Theoretical Perspectives (pp. 1–38). New York: Routledge.

Zimmerman, B. J., & Bandura, A. (1994). Impact of self-regulatory influences on writing course attainment. American Educational Research Journal, 31(4), 845–862. https://doi.org/10.2307/1163397

Zimmerman, Barry. (2015). Self-Regulated Learning: Theories, Measures, and Outcomes. International Encyclopedia of the Social & Behavioral Sciences. 10.1016/B978-0-08-097086-8.26060-1.

Zimmerman, B. J., Greenberg, D., & Weinstein, C. E. (1994). Self-regulating academic study time: A strategy approach. In D. H. Schunk & B. J. Zimmerman (Eds.), Self-regulation of learning and performance: Issues and educational applications (pp. 181–199). Lawrence Erlbaum Associates, Inc.

Zimmerman, B. J., & Moylan, A. R. (2009). Self-regulation: Where metacognition and motivation intersect. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), Handbook of Metacognition in education, (pp. 299–315). New York: Routledge.

Zumbrunn, S., Tadlock, J., & Roberts, E. D. (2011). Encouraging self-regulated learning in the classroom: A review of the literature. Metropolitan Educational Research Consortium (MERC).

Appendix 1

Table 3.5 Sample Statements / Questions derived from the characteristics of Variables

Key Dimensions	Characteristics	Citations	Sample Statements / Questions
Independence	Self-Reliant	Mynard and Sorflarten, 2003, p.35 as cited in El-Koumy, 2019	I usually search for more information when I don't understand a subject.
	Able to make informed decisions on their learning		I usually look at the ratings and feedback for each course before I enrol.
	Aware of own strengths and weaknesses		I am aware of my study capabilities.
			I am aware that I am easily distracted / last-minute when I am learning but I try to fix that.
	Connect classroom learning with the real world		I would like to use the things I learn at my current job.
	Take responsibility for their learning		I understand that online learning requires more responsibility.
	Aware of the different strategies for learning		I know that there are different learning strategies that I can use to learn. (mind mapping/ writing notes/ etc etc)
	Plan their learning and set goals		I plan my learning goals.
	Intrinsically motivated by learning progress		I take initiative to learn proactively.
	Reflect on learning process and progress		I monitor my learning progress.
Communication Skills	Completeness	Scott and Allen (1952)	I became more attentive towards others as I practice active listening while I am learning.
	Conciseness		I learned that structuring messages that includes all information and facts are easily understood by listeners as I was learning from MOOC.
	Consideration		I can empathise with my peers / my course instructor when I give any feedback.
	Clarity		I can share information easily with others as I am more equipped with knowledge and skills after learning in MOOC.
	Concrete		I am able to structure my thoughts and communicate more easily as I have to give feedback to the course / peers.

	Courtesy		I became more courteous / respectful during communication as I have to practice giving feedback for the course or my peers during learning.
	Correctness		I tend to pay more attention towards the correctness of my communication with others.
			I double check my communication to make sure that what I say is relevant all the time.
Job Specification	Qualification	Okunade (2015) (as cited in Udoh, 2018)	I enroll in MOOC to stay competent at my current job.
			I enroll in MOOC to stay relevant at my current job.
	Experience		I enroll in MOOC to gain more insights and experience from others.
	Training		I enroll in MOOC to gain new knowledge and skills.
	Skills		I enroll in MOOC to make sure that my knowledge and skills are up to the current trends.
	Responsibilities		I enroll in MOOC because I need additional Knowledge and skills to perform a current project / job.
	Emotional Characteristics		I enroll in MOOC to enhance my emotional intelligence.
	Sensory Demands		I enroll in MOOC to enhance my sensory demands.
User Experience	Personal	Martin (2017; 2020)	I prefer learning flexibility and using the resources available
	Agency		I am responsible in making my own decisions for learning
	Inquiry		I am curious which makes me think and ask questions
	Collaboration		I reach out to others to understand more of a topic or problem I faced
	Authentic		I apply what I have learnt and tried using it in my daily life or work.
	Critique + Revision		I check my learning progress to find feedbacks and evaluations from peers or course instructor
	Productive Struggle		I am confident in applying what I learned at work or daily life
	Goals + Accountability		I am responsible towards my own achievement and goal setting
	Models		I benchmark from sample studies in order to perform better

	Reflection		I check my learning progress and find out how I can do better in the future
Continuous Intention	Intent to repurchase	Gerpott et al. (2001) Tsai et al. (2018)	I intend to continuously use MOOC
	Eagerness to recommend to others		I would likely recommend the course I learnt to others
			I would likely recommend the MOOC platform to others
	Liking		I am satisfied with the MOOC of my choice so far
	Enjoyment		I find that learning from MOOC benefits me
	Engagement		I don't mind participating in giving opinions on the course I learnt
			I don't mind giving opinions towards the MOOC platform I used
Self-Regulated Learning	Self-evaluate	Bandura (1986,1997), Zimmerman and Pons (1986), and Pintrich (1999,2004) (as cited in Clark, 2012)	I reflect on the learning goals and my current progress.
	Keep records and monitor learning		I set a learning schedule and a due date to monitor my progress.
	Seek help from adults		I enter forums or seek help from peers when I face difficulties when I am learning in MOOC.
	Adapt and invents new learning strategies		I enroll in MOOC because I can repeat and rewind the course over and over again.
	Set goals and plan learning progression		I go over the MOOC Course structure and I set my own goal so that I can plan my learning progress.
	Structure the learning environment		Learning anytime.
			Learning anywhere.
	Manage time		I enroll in MOOC because I can organise my own schedule.
			I keep myself motivated by planning my schedule to learn.
	Engage in peer learning		I believe that participating with others in learning activities improves my learning
	Use non-classroom resources		I search for more information online or check online forums when I face difficulties in understanding the course.
	Are persistent and complete what they started		I feel satisfied when I complete an online course.
			I feel satisfied when I earn the certification or credential.
	Regulate progress by using self-consequences		I feel guilty if I missed out on the learning that I scheduled.

			I do more the next day if I miss my learning schedule.
			I change my schedule or rearrange my daily activities so that I can learn on time.
	Memorize and rehearse information		I memorise and rehearse information by sharing my knowledge and skills with others after I learn.
	Are self-aware		I became more responsive after I learned in MOOC as I have to complete assignments or even provide feedback when I was learning.