UNDERSTANDING LEARNERS AND FACTORS INFLUENCING ACCEPTANCE AND INTENTION TO USE MASSIVE OPEN ONLINE COURSES (MOOCs) IN A DEVELOPING COUNTRY CONTEXT: A CASE STUDY OF NIGERIA

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ABSTRACT

UNDERSTANDING LEARNERS AND FACTORS INFLUENCING ACCEPTANCE AND INTENTION TO USE MASSIVE OPEN ONLINE COURSES (MOOCs) IN A DEVELOPING COUNTRY CONTEXT: A CASE STUDY OF NIGERIA

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Massive Open Online Courses (MOOCs) present enormous opportunity for potential learners, especially those in developing countries who may be lacking access to quality higher education. However, participation in MOOCs is still significantly low among those in developing countries, while those in developed countries are continually being overrepresented in the MOOC student population (Emanuel, 2013; Pomerol, Epelboin & Thoury, 2015). This further fosters the knowledge divide that already exists between developed and developing nations, as those in developed countries gain the benefits of MOOCs in addition to their already better quality higher education institutions of learning. Nigeria was chosen as a case study because a high percentage of its population lack access to quality higher education and the level of MOOC participation is still significantly low, even when compared to other developing countries. (Iruonagbe & Egharevba, 2015; Oladele, Akeke & Oladunjoye, 2011; Li, 2017; Bayeck, 2016). The study adopted the Technology Acceptance Model (TAM) as a theoretical framework to examine factors that may be contributing to low adoption rate of MOOCs in Nigeria. It specifically examines the role of facilitating conditions, social influence and cultural factors of power distance, uncertainty avoidance and collectivism on the core TAM constructs, perceived usefulness and perceived ease of use, and how both the external factors and the TAM constructs influence people's behavioral intention to adopt MOOCs.

Data for the study was collected using online surveys with a total of 227 participant responses obtained. The survey items measuring the study constructs were adapted from the Technology Acceptance Model (TAM) scale, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) scale and the individual level cultural values scale (CVSCALE).

Demographic and other individual characteristics data were also collected as part of the survey to get a better understanding of the participants and how they are positioned for MOOCs use. Regression analysis, confirmatory factor analysis and path analysis were used to analyze data for statistical results. The demographic and individual characteristics data were used to create user personas of target MOOCs users in Nigeria.

Findings from study indicate that perceived ease of use, uncertainty avoidance and social influence had a direct positive influence on perceived usefulness of MOOCs. Also, facilitating conditions and uncertainty avoidance significantly predicted perceived ease of use of MOOCs for the participants in the positive direction. Perceived usefulness, facilitating conditions and collectivism directly predicted behavioral intention to use MOOCs among participants. Furthermore, perceived ease of use and uncertainty avoidance had indirect effects on behavioral intention through perceived usefulness. Useful insights about the participants were also obtained from the results of the demographic and individual characteristics data and were used to create personas of target MOOCs users in Nigeria. Overall, the dissertation contributes an in-depth understanding of target MOOCs users within the study context and the factors that potentially influence their attitudes and behavior towards such an innovative online learning technology capable of improving their access to higher quality education. It further identifies the need for interventions that facilitate MOOC adoption in Nigeria through the significant factors.

This dissertation is dedicated to my amazing parents, Julius Ali Ucha and Chinyere Ucha. Their love and endless support are what has gotten me this far in life. I love you both very much. And may God continue to bless you for all you do for me.

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KEY TO ABBREVIATIONS

MOOCs	Massive Open Online Courses
TAM	Technology Acceptance Model
UTAUT2	Unified Theory of Acceptance and Use of Technology
CVSCALE	Cultural Value Scale
PU	Perceived Usefulness
PEOU	Perceived Ease of Use
BI	Behavioral Intention
FC	Facilitating Conditions
SI	Social Influence
PD	Power Distance
UA	Uncertainty Avoidance
COL	Collectivism
MASC	Masculinity

CHAPTER 1: INTRODUCTION

Background

Access to quality education is a major driver of rapid economic development as it equips people with the ability to meaningfully participate and contribute to the growth of their economy (Hanushek and Wößmann, 2007; Gylfason, 2001). The level of education that drives such economic development the most is higher education as it promotes creativity and engenders research for new innovations (Altbach, Reisberg & Rumbley, 2009). Yet, access to higher education, more so a quality one, remains significantly low in many developing countries in comparison to their developed nation counterparts. (Altbach, Reisberg & Rumbley, 2009; Okebukola, 2013). This situation poses the need for more innovative channels of educating the developing country population, to ensure a more developed human capital that is well equipped to compete on a global scale and facilitate economic growth.

Massive Open Online Courses (MOOCs) present an opportunity for filling this gap, given their ability to provide access to well-structured personalized courses from prestigious higher institutions of learning and world-renowned organizations to the general public for free or at a very low cost (Emanuel, 2013; Barclay & Logan, 2013; Ma & Lee, 2019). Since their introduction, MOOCs have been considered to hold enormous potential for learners, especially those in developing countries. They potentially have the capacity to expose people in those countries to the quality level of higher learning experienced by those in more developed countries, affording them the ability to gain useful and potentially transferable skills that they may have lacked the opportunity to gain elsewhere (Emanuel, 2013; Kay, Reiman, Diebold, Kummerfeld, 2013; Liyanagunawardena, Adams & Williams, 2013). Hence, MOOCs hold potential for addressing the learning and knowledge divide that lack of access to quality higher learning may have posed for those in developing nations in comparison to their developed country counterparts as they promote equity in higher learning.

However, despite such said potential, the developing country population, particularly those in Africa, are still significantly underrepresented in the MOOC student population, while those in developed countries remain overrepresented (Christensen, Steinmetz, Alcorn, Bennet, Woods et al., 2013; Emanuel, 2013; Pomerol et al., 2015). Nigeria in particular continues to lag behind developed countries like the US in MOOC learner participation, with studies finding participation rates in the country to always be in a negligible percentage, in comparison to the US, which always has the highest number of enrollees in most MOOC courses (Li, 2017; Bayeck, 2016; Nesterko, Dotsenko, Han, Seaton, Reich, Chuang et al., 2013). It is therefore evident that there exists a lack of motivation for this population for MOOC learning, hence there is a need to examine factors that are likely influencing people's motivation to accept and use MOOCs within that population, to ensure that the benefits due to them are adequately exploited. In other words, more research needs to be conducted in understanding the user side of technology adoption to ensure that they do not remain underutilized in a developing country context (Park, Roman Seungyoon and Chung, 2009), like Nigeria.

One main approach used in different studies to explore factors affecting people's technology adoption behavior is to extend already existing theories of technology adoption with the aim of improving their predicting power of technology acceptance and use within the context of study. A widely used theory of acceptance, which this study will be adopting, is the Technology Acceptance Model (TAM). TAM is a technology adoption theory that proposes that the behavioral intention of an individual to use a system is a factor of their perceived usefulness and perceived ease of use of the system (Davis, 1989; Venkatesh & Davis, 2000). Studies that have utilized TAM in studying technology adoption intention have consistently found these behavioral intention determinants to be highly efficient in predicting technology adoption behavior in different contexts of use, including online learning environments (e.g., Esteban-Millat, Martínez-López, Pujol-Jover, *et al.,* 2018, Lai, Wang, Li & Hu, 2016; Park *et al.*, 2009; Abbas, 2016; Aharony & Bar-Ilan, 2016; Chu, Ma, Feng & Lai, 2015). However, other external factors have often been examined on their role in predicting intention to adopt a technology and the indirect effect they may have on such intention through the main TAM antecedents (Shen, Laffey, Lin & Huang, 2006; Lai, Wang, Li & Hu, 2016; Nordin *et.al.*, 2016; Mtebe & Raisamo, 2014). Hence, by finding and incorporating such factors into TAM, we have the potential to improve the model's predicting power of technology adoption and use for a particular context.

Purpose of Study

This study examined the role that some external factors, specifically environmental (facilitating conditions), social (social influence) and individual espoused cultural values (power distance, uncertainty avoidance, collectivism and masculinity) have on the core TAM constructs, perceived usefulness and perceived ease of use, and how both the external factors and the TAM constructs influence people's behavioral intention to adopt MOOCs in Nigeria. These factors are important in how people come to accept and use technology, and having an understanding of how they influence people's perceptions and behavior is essential for improving adoption of MOOCs among them. Since people in the Nigerian context have much to gain from using MOOCs, more research is needed to understand how to increase adoption among citizens. Hence, this study hopes to provide a good understanding of the main facilitators and/or barriers to acceptance and intention to use MOOCs in Nigeria, using the TAM model and the additional factors proposed.

Additionally, having an overall better understanding of target users of a technology within a context, for example, who they are, how they behave and what motivates them, can help generate important insights about how a particular technology can be situated within the context. Hence, this study further gathered demographics and participant characteristics information to aid in building of personas representing typical target users within the context of study, with regards to the phenomenon being studied. This would help in making recommendations on how MOOCs can be better situated for people in this context. Overall awareness or prior experience with MOOCs was a pre-requisite for participating in the study. The following research questions were therefore proposed for this study based on these:

Research Questions

1. What are the individual characteristics of a target MOOC user in Nigeria?
2. What factors influence perceived usefulness, perceived ease of use and behavioral intention to use MOOCs in Nigeria?

Research Contribution

This study adds to the literature in the following ways:

- Presents a picture of what a typical target MOOC learner is within the Nigerian context.
- Identifies specific factors (through an extended TAM model) that affect peoples' perceived usefulness, perceived ease of use and intention to use MOOCs in Nigeria.
- Shows that an extended model, with added environmental, social and cultural factors is better at predicting intention to use MOOCs within the context of study than the original TAM model.

CHAPTER 2: CASE STUDY CONTEXT (NIGERIA)

Background

Nigeria is currently the most populous country on the African continent, boasting of almost 200 million people as of 2018 (The World Bank, 2018). And a significant amount of this population is within the young-middle working age of 15 - 44, an age range that represents a huge amount of the country's labor force (National Bureau of Statistics of Nigeria, 2016). However, a significant percentage of this population lack the adequate capacity to meaningfully contribute to the development of the country's economy (Okebukola, 2013), and as a result, the majority of them belong to the unemployed labor force (National Bureau of Statistics of Nigeria, 2016). For instance, according to the National Bureau of Statistics of Nigeria (2016), those within that age range represents approximately 73% of the Nigerian workforce, however, about 43% of them remain unemployed. This high level of unemployment among Nigerian youths is often associated with the appalling situation of higher education in the country (Iruonagbe & Egharevba, 2015; Oladele et al., 2011). The education system in the country continues to oversupply the labor market with graduates that lack adequate labor market skills, including entrepreneurial skills to facilitate their own businesses (Oladele et al., 2011). As a result of these skill inadequacies and in some cases, mismatches, the competitiveness of the Nigerian labor force continues to shrink in comparison to the rest of the world (Okebukola, 2013).

The current situation of the Nigerian educational system therefore stresses the need for boosting the skills of its youths through other means, potentially through adopting non-conventional means of education. The role of technology becomes pertinent in this case. The introduction of distance learning programs, the availability of open educational resources, and more recently the advent of MOOCs, all hold potential for fulfilling the skills needs of people in

Nigeria. The use of these technologies, particularly an open education technology, to boost learning can help individuals develop skills beyond the fore walls of the traditional learning system (Okebukola, 2013), enabling them to either gain skills that can improve their employability or skills that can help them build their own startups. The open education technology this research focuses on is MOOCs.

Viability of MOOCs for the Nigerian Context

Access to the Internet is required for MOOCs participation. Hence , it is important to examine where the Nigerian people rank in terms of Internet penetration to determine the viability of this technology for the context. According to Internet World Statistics (2017), Nigeria currently ranked 8th in the world for countries with the highest number of internet users that year, with internet penetration in the country said to be at 52%. This decent level of penetration and growth of Internet users indicates great potential for MOOCs in this context, as it suggests that many Nigerians could potentially become MOOC users, thereby benefiting from their use. The potential effect is even more pronounced for the MOOC target users for this study i.e., young adults, as those within the ages of 18-34, make up majority of Internet users in the country (Poushter, 2016; Broadcasting Board of Governors, 2014; Olaposi et al., 2013; Iderima, 2019). This makes adoption of MOOCs suitable to be studied among this population.

Overview of Massive Open Online Courses (MOOCs)

MOOCs are a relatively new academic phenomenon which aim to provide access to higher education courses online for individuals across the world for free or at a very low cost. MOOCs were first used to describe a type of online course pioneered by George Siemens, a professor at the University of Manitoba, in 2008 (Kay et. al., 2013). However, in 2012, MOOC providers such as Coursera and edX commercialized the concept, partnering with elite higher education institutions mostly in the United States (Kay et. al., 2013; Liyanagunawardena, Adams & Williams, 2013). MOOCs gained attention due to their effectiveness in delivering content to a large number of people (Ma & Lee, 2019) and has been regarded as one of the most efficient means of delivering video course content online (North, Richardson & North,2014).

Since their introduction, MOOCs have been considered to hold enormous potential for people, especially those in developing countries, with their capacity to expose this population to the quality level of higher learning experienced by those in more developed countries, affording them the ability to gain useful and potentially transferable skills that they may not have been opportune to gain anywhere else (Emanuel, 2013; Kay, Reiman, Diebold, Kummerfeld, 2013; Liyanagunawardena, Adams & Williams, 2013). Hence, not only are MOOCs expected to be beneficial to those who lack access to higher learning in general, but also has the potential to augment the learning of those who lack access to a quality one.

Opportunities for MOOC Use in Nigeria

Access to higher education remains significantly low in many developing nations in comparison to their developed country counterparts (Altbach, Reisberg & Rumbley, 2009; Okebukola, 2013). This situation is even more pronounced for developing countries in Africa, where 93% of college aged population are said not to be in college (Wildvasky, 2015). Sub-Saharan Africa, specifically, which Nigeria is part of, continues to have the lowest level of gross higher education enrollment. In 2018, the gross tertiary enrollment for this region was 9.4% compared to North America's 86.3%, Europe and Central Asia's 70%, Latin America & Caribbean's 52% and South and West Asia's respective 24% (World Bank Data, 2018). Although, the enrollment figure of 9.4% represents an increase from the 8.9% and 7% recorded in 2013 and 2008 respectively (World Bank Data, 2008, 2013), this figure however remains significantly low compared to the rest of the world. As a result of this, many researchers have acknowledged the potential of e-learning as a viable approach to addressing the challenges of information and knowledge delivery in developing countries (Trehan, Sanzgiri, Li, Wang & Joshi, 2017).

Nigeria as a country also continues to lag behind the rest of the world, both when compared to developed countries and other developing countries. For instance, the gross tertiary enrollment in the country for 2011 (this is the latest data available for the country in the World Bank database) was 10%, compared to the enrollments for the US (94%), UK (59%), China (26%) and India (23%) for the same year. This issue has been attributed to the fact that Nigeria, like many other developing countries, lacks the level of economic development required to enable adequate access to higher education (Okebukola, 2013; Altbach et al., 2009; Bloom & Rosovsky, 2007). Higher education is a major driver of both economic and social development and is the level of education associated with the highest returns (Hanushek and Wößmann, 2012; Lane, 2013; Varghese, 2016). Hence, this issue poses a 'chicken and egg' problem for a country like Nigeria, since it is inherently difficult to have a human capital developed up to higher education level without having a high level of economic development (Okebukola, 2013).

Furthermore, demand for higher education in Nigeria far outweighs the supply, with total acceptance rate into higher learning institutions currently at 10% for applications that range over a million individuals per year (Joint Admission Matriculation Board, 2016). This low acceptance rate has been attributed to the fact that the universities simply cannot accommodate the number of applicants, as they are already operating over capacity (Ekundayo & Ekundayo, 2009; Okebukola, 2013; Fabiyi & Uzoka, 2009). Hence, these prospective students are forced to wait around and retake entrance examinations every year, hoping to get a chance at an admission. This situation is further exacerbated for individuals who cannot afford the significantly higher tuition of private universities, that typically have higher entrance rates, but which have also been known to pose their own unique problems, particularly that of providing education of questionable quality (Ekundayo & Ekundayo, 2009; Okebukola, 2013).

Hence, a major opportunity for MOOCs is in widening participation in higher learning for a country like Nigeria, whose access is limited. Open education through platforms such as MOOCs gives access to a global-based learning for participating individuals, presenting them with skill development opportunities beyond the confines of a traditional learning system (Okebukola, 2013). It furnishes anyone with access to the internet the opportunity to participate in a wide range of courses capable of boosting their skills and overall human capital (Dillahunt, Ng, Fiesta, & Wang, 2016). Although MOOCs are hardly a viable alternative to traditional higher education in Nigeria (for many reasons that are probably beyond the scope of this research), they present prospective students with little to no access, the opportunity to experience higher learning, with no associated higher education costs, making it an opportunity worth exploring in this context.

Another crucial opportunity that MOOCs are likely to offer to people in Nigeria, beyond access, is in relation to the quality of higher education being accessed. Although higher education gross enrolment is still currently low, the rate however has been increasing over the years, but the quality associated with this increased access is often lacking (Ekundayo & Ekundayo, 2009). The world in general continues to demand more highly skilled graduates, however, higher education institutions in developing countries continue to fail to deliver on this (Czeniewicz & Brown, 2009; Ekundayo & Ekundayo, 2009). Developed countries tend to have higher quality education, with a country like the US boasting of the world's top institutions, making it a desirable destination for higher learning. On the contrary, universities in countries like Nigeria are on a race to the bottom as they fail to make it even to the world's top 1000 universities, according to the QS 2019 world university rankings. This superior quality of education in countries like the US and the UK evidently translates to their labor market given the level of growth being experienced in their economy. Countries like Nigeria on the other hand continue to face adverse economic effects, which has been linked to the lack of desired skills among labor market entrants (Okebukola, 2013). This situation poses the need for more innovative channels of educating those in Nigeria to ensure a more developed human capital that is well equipped to compete on a global scale and facilitate economic growth.

A report from the Nigerian National Bureau of Statistics showed that, young-middle working age people, specifically, those within the ages of 15 – 44, represent 73% of the total Nigerian labor force, however, almost half of this population were unemployed at the time of the report (National Bureau of Statistics, 2016). Furthermore, Okebukola (2013) suggests that only about 10% of the 6 million Nigerians graduating annually get employment opportunities, with the rest left to enter the labor market with no hope for employment, and this number continues to accumulate over the years. Interestingly, this high level of unemployment continues to be attributed to the poor and ever declining standards of higher education in the country, which negatively influence employers' perceptions about the capabilities of Nigerian graduates for hiring purposes (Iruonagbe & Egharevba, 2015; Oladele, Akeke & Oladunjoye, 2011; Okebukola, 2013). These authors maintain that the Nigerian higher education system continually oversupplies the labor market with graduates lacking in the necessary skills required for meaningful work, thereby creating a huge problem of skills mismatch in the labor market.

Contributing to this declining quality in higher education in Nigeria are factors such as; inadequate human resources to carry the required teaching load in higher institutions, migration of local academics to other countries, high staff to student ratio, lack of finances, infrastructure and electricity, among others (Ekundayo & Ekundayo, 2009).

Technological innovations such as MOOCs can enable a country like Nigeria to step out of its problematization culture in search of solutions that can aid in the growth of the economy through human capital development. They offer a unique opportunity for learners in this context to participate in educational opportunities provided by the 'educational elite' countries. Such quality open education if effectively utilized to support traditional higher education delivery, can better prepare Nigerian graduates for employment. There may however be a need to ensure that the open education system itself is made employment-sensitive within this context for such desirable gains to occur (Okebukola, 2013). The issue however remains that, the developed countries who already have majority access to higher quality tertiary education are the ones utilizing learning avenues like MOOCs the most (Christensen, Steinmetz, Alcorn, Bennet, Woods et al., 2013; Emanuel, 2013; Pomerol, Epelboin & Thoury, 2015). Hence the way MOOCs are currently structured and the people they are reaching the most, further constitutes a divide of knowledge between the developed and developing nations, where those that already know are acquiring more knowledge.

Furthermore, with the promise of MOOCs to make higher education accessible to everyone barely being fulfilled, particularly in relation to those with limited access to traditional higher learning, it becomes important to examine different factors that are influencing adoption patterns in different countries (Tang & Wang, 2017; Ho et al., 2014). As an online innovation, MOOCs require internet access and other relevant infrastructure such as access to internet capable devices, reliable electricity, among others, some of which are not readily available in low resource countries, and can potentially influence their participation in MOOCs. However, beyond availability of resources to promote access to MOOCs, their full potential may be underutilized, even for those with adequate access to such resources. This is exemplified in the low MOOCs completion rates (less than 10%) reported across the literature for developed countries (Hone & El Said, 2016; Freitas, Morgan & Gibson, 2015; Daniel, 2012). If those in resource-rich areas, who currently make up the majority of the MOOC population (Christensen et al., 2013) are not efficiently utilizing MOOCs, the situation may even be exacerbated for low income countries, given the added disadvantage of infrastructural issues. Hence, it is important to understand other intricate factors beyond infrastructure that can potentially influence MOOCs acceptance and use, to ensure that the full potential of MOOCs is realized in any context of use. Hence this study examines, using Technology Acceptance Model (TAM) as a framework, the potential factors that are likely to contribute and/or hinder people’s acceptance and intention to use MOOCs in a developing country, Nigeria.

CHAPTER 3: LITERATURE REVIEW

Overview

This literature review synthesizes the research on the factors that are likely to affect intention to adopt MOOCs in the Nigerian context. Since literature on previous MOOC adoption in similar contexts is scarce, this study expanded the literature search to include factors affecting adoption of online learning in general, as well as other technologies, in the developing country context. TAM was adapted as the framework for understanding adoption behavior for this study. This chapter gives a detailed description of the two determinants in the TAM framework: perceived usefulness and perceived ease of use and further discusses on the external factors that will be included in the model to improve on its predictive power: facilitating conditions, social influence, power distance, uncertainty avoidance, masculinity and collectivism. The chapter finally presents the theoretical framework proposed for the relationships that will be tested for this study, with regards to how the factors are expected to influence peoples' perceived usefulness, perceived ease of use and behavioral intention to use MOOCs within the context of study.

Technology Acceptance Model (TAM) and MOOC Adoption

Research on technology acceptance and use have resulted in the development of a number of theoretical frameworks to understand peoples' behaviors towards technology adoption in different contexts. Some of these frameworks, which have been validated in a wide range of technology adoption studies include, Theory of Reasoned Action (Fishbein and Ajzen, 1975), Technology and Acceptance Model (Davis, 1989), Theory of Planned Behavior (Ajzen, 1991), Innovation Diffusion Theory (Rogers, 2003) and Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis & Davis, 2003). However, Technology Acceptance

Model (TAM) remains the most widely used theory of technology acceptance and use, mainly due to its superior predicting power of behavioral intention to use a technology (Venkatesh & Davis, 2000; Davis, 1989). TAM is a theory of motivation which proposes that the behavioral intention of an individual to use a system is a factor of their perceived usefulness and perceived ease of use of the system (Davis, 1989; Venkatesh & Davis, 2000). This theory further holds that perceived ease of use also influences perceived usefulness, as a system would be generally more useful if it is easy to use (Venkatesh, 2000). Those two main antecedents of TAM have been widely established as strong predictors of behavioral intention to use a system, with stronger effects found for perceived usefulness (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh, 2000; Lee, Yoon & Lee, 2009; Miller & Khera, 2010). The theory also stipulates that, when people show intention to use a system, they eventually end up using it, which is why understanding how intention is influenced is very important (Davis, 1989).

Perceived Usefulness

Perceived usefulness is defined as "the degree to which an individual believes that using a particular system will enhance his or her performance" (Davis, 1989, p.319; Venkatesh & Davis, 2000). In other words, how useful or beneficial they expect the system to be in their effort to achieve their goals. This construct deals more with the utilitarian value of a system, basically, how useful or advantageous users consider the system to be in achieving their goals and was theorized to be directly contributing to people's intention to adopt a technology (Davis, 1989; Venkatesh & Davis, 2000). Perceived usefulness drives motivation in such a way that, the more useful a person considers a system, the more they are likely to intend to use it and vice versa (Davis, 1989). Many researchers have found perceived usefulness to be a major factor influencing behavioral intention to use a system (Davis, 1989; Venkatesh & Davis, 2000, Venkatesh, 2000; Park et al., 2009, Chen & Aklikokou 2019), including online learning systems (Teo, 2010; Park et al., 2009). In their study on user acceptance of digital library systems in 16 universities in developing countries (10 of which were in Africa), Park et al. (2009) found perceived usefulness to be the strongest predictor of behavioral intention to use those systems. And in their study examining the factors affecting student's acceptance of e-learning in Egypt, Abbas (2016) found that perceived usefulness was the only significant predictor of behavioral intention to use e-learning, and further played a mediating for all other factors included in the study. Similar results have been reported in the context of MOOCs and other e-learning platforms (Aharony & Bar-Ilan, 2016; Chu, Ma, Feng & Lai, 2015; Al-Adwan, Al-Adwan, & Smedley 2013; Lee et al., 2009; Mohammadi, 2015; Miller & Khera, 2010). Perceived usefulness remains the strongest predictor of the behavioral intention to use a particular technology (Venkatesh *et. al.,* 2003; Jeng and Tzeng, 2012), this is because people are likely to be less motivated to invest time and effort in something that produces little or no sort of value for them. Hence, this study builds on previous research and investigates how the usefulness perceptions people in the study context hold about MOOCs influences their behavioral intention to use them. The expectation is that, the more they believe that MOOCs will be beneficial in helping them accomplish their goals, the more likely they are to adopt and use them. The following hypothesis were therefore proposed for this study:

H1: Perceived usefulness will positively influence peoples' intention to use MOOCs in Nigeria.

Perceived Ease of Use

Perceived ease of use refers to the degree or extent to which "a person believes that using a particular system would be free of effort" (Davis, 1989; Venkatesh, 2000). In other words, how easy they believe it will be to use the system. This construct drives motivation in such a way that, the easier or less complex a system is to use, the more users are likely to accept and use it (Davis, 1989). Several studies have found direct effects of perceived ease of use on behavioral intention (Davis, 1989; Lee et al., 2009; Miller & Khera, 2010; Venkatesh, 2000, Teo, 2010), however, it is difficult, to interpret the effects of this variable outside of perceived usefulness, given that many studies have found that perceived ease of use significantly predicts perceived usefulness, suggesting likely indirect effects for perceived ease of use on behavioral intention through perceived usefulness (Abbas, 2016; Al-Adwan et al., 2013; Lee et al., 2011; Park et al., 2009; Teo, 2009; Venkatesh, 2000). For instance, Park et al. (2009) found no direct influence of perceived ease of use on behavioral intention to use digital library systems, rather they found an indirect effect through perceived usefulness. Other studies have also found perceived ease of use to be only directly predicting perceived usefulness, but not intention to accept or use e-learning or MOOCs (Abbas, 2016; Bhatiasevi, 2011; Chu et al., 2015; Mohammadi, 2015).

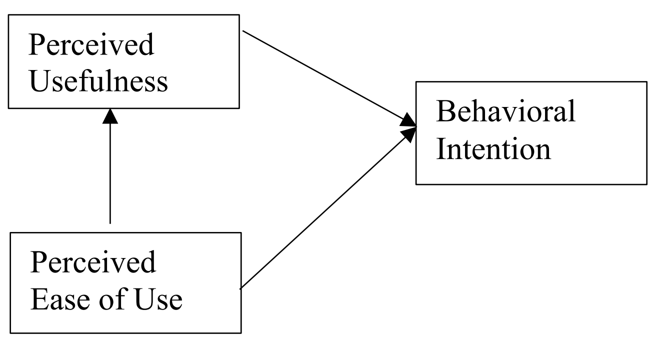
Furthermore, some of the studies reporting direct effects for perceived ease of use on behavioral intention show such effects to be significantly weaker than those found for perceived usefulness (Aharony & Bar-Ilan, 2016; Lee et al., 2009; Miller & Khera, 2010). Therefore, since previous research have established that there are situations where perceived ease of use cannot directly influence behavioral intention without the presence of perceived usefulness but has consistently been found to be a strong determinant of perceived usefulness, interpreting the effects of perceived ease of use on behavioral intention, without consideration for perceived usefulness may lead to an incomplete portrayal of its potential effects. Hence, this study investigates how people’s perceptions about how free of effort the use of MOOCs would be in the context of study is influencing their intention to adopt and use them. The expectation is that, the easier people believe MOOCs are to use, the more likely they are to adopt them. Also, the easier people believe MOOCs are to use, the more likely they are to find them useful or valuable, and the more likely they are to adopt them. The following hypotheses were therefore proposed for this study:

H2a: Perceived ease of use will positively influence perceived usefulness of MOOCs for people in Nigeria

H2b: Perceived ease of use will positively influence behavioral intention to use MOOCs among people in Nigeria.

H2c**:** Perceived ease of use will have an indirect positive effect on behavioral intention to use MOOCs in Nigeria through perceived usefulness.

Figure 1: Original TAM Framework



Note. Model of Technology Acceptance (adapted from Davis, 1989)

Extending the Technology Acceptance Model (TAM)

The core framework of TAM has been extended by numerous studies that essentially examine external factors likely affecting the key constructs of perceived usefulness and perceived ease of use (Abbas, 2016; Ozkan & Koseler, 2009; Park et al., 2009; Venkatesh, 2000; Venkatesh & Davis, 2000). For instance, Venkatesh and Davis (2000) suggested that factors such as result demonstrability, job relevance, output quality and perceived ease of use all predict perceived usefulness and factors such as computer anxiety and playfulness predict ease of use

(Venkatesh, 2000). Similarly, Park et al. (2009), found relevance and perceived ease of use to be significant predictors of perceived usefulness. These studies therefore suggest the need to consider the importance of such external variables influencing TAM constructs in the design and implementation of effective information systems, in efforts to further facilitate adoption of such systems, including in developing countries (Park et al., 2009).

Mathieson (1991) further emphasizes the importance of such variables by suggesting that examining TAM without consideration for external factors that are likely influencing the different constructs will only provide a broad view of user opinions about the system with no specific information that can inform the design of a better or enhanced system. Hence, specifying external factors for TAM constructs not only predicts use intention but further offers an explanation as to why a particular system is not being adopted, so that corrective measures can be put in place (Davis, 1989; Venkatesh & Davis, 2000).

This section discusses the factors that this study examined as extension to the TAM model, in efforts to improve the model's effectiveness in predicting behavioral intention to use MOOCs in the Nigerian context. These factors include: facilitating conditions, social influence, and the individual espoused cultural values (namely: power distance, uncertainty avoidance, masculinity and collectivism). The study investigated if these external factors are directly influencing people's behavioral intention to use MOOCs and if they are indirectly influencing intention through the core TAM constructs, perceived usefulness, perceived ease of use.

Facilitating Conditions

Facilitating conditions was first operationalized in the UTAUT model developed by Venkatesh *et al.* (2003) and refers to an individuals' perception about the available resources and support for the performance of a behavior (Venkatesh *et al.,* 2012). These typically involve the environmental factors that affect the use of a technology (Venkatesh *et. al., 2012*). This concept has been found to have a direct effect on people's intention to use a system, such that, with more perceived favorable facilitating conditions available to facilitate the use of a technology comes a higher intention to use (Venkatesh *et. al., 2012;* Venkatesh *et. al.,* 2003). In the context of a resource constrained environment like Nigeria, facilitating conditions have often been classified as barriers to adoption of technology by several authors and have been cited to include factors such as network coverage, lack of electricity, cost of internet services as well as other costs associated with the technology, availability and speed of internet in certain areas, among others (Dwivedi *et. al.,* 2016; Nanyombi and Ejiri, 2016; Déglise, Suggs, & Odermatt, 2012; Chib *et. al.*, 2015; Mtebe *et. al.,* 2016; Mechael *et. al.* 2010; Albabtain, AlMulhim, Yunus, & Househ, 2014). Furthermore, lack of knowledge and skills are among the main barriers that have been cited to be affecting the adoption of technology in developing countries like Nigeria (Friederici, Hullin & Yamamichi, 2012). Within the context of TAM, Nordin *et.al.* (2016) found a positive relationship between facilitating conditions and the behavioral intention to adopt MOOCs in Malaysia. Kang *et. al.* (2015) and Mtebe & Raisamo (2014) found facilitating conditions to be equally important in predicting intention to adopt m-learning in Korea and East Africa respectively. Nanyombi & Ejiri (2016) also found that facilitating conditions significantly predicted intention to adopt mobile health in Uganda. Hence, it is expected that for this context, the more people perceive that they have adequate facilitating conditions to use MOOCs, the more likely they are to want to use it.

In addition to directly influencing people's intention to adopt a technology, facilitating conditions have also been found to have a direct relationship on perceived usefulness and perceived of use of a system (Chen & Aklikokou 2019; Teo, 2011; Althunibat, 2015).

Particularly, in their study examining determinants of perceived usefulness of e-learning among pre-service teachers, Teo (2011) found facilitating conditions to be the strongest predictor of perceived usefulness. Also, Chen & Aklikokou (2019) found facilitating conditions to be a strong predictor of perceived ease of use in e-government adoption and Althunibat (2015) found facilitating conditions to be strongly predicting perceived usefulness and ease of use of m-learning in higher education in Jordan. This indicates that, in the presence of the necessary conditions required to use a system, participants are more likely to have positive usefulness and ease of use perceptions about the system. Furthermore, because of its relationship to both perceived usefulness and ease of use, facilitating conditions have also been found to be indirectly affecting intention to adopt a technology through those variables. For instance, in their study examining e-government services adoption by Togolese citizens, Chen & Aklikokou (2019) found that facilitating conditions had indirect effects on intention adopt e-government services, through perceived usefulness and perceived ease of use. And Teo (2010) in their study examining influence of facilitating conditions and social influence on behavioral intention to adopt e-learning found indirect effects of facilitating conditions on behavioral intention through both perceived usefulness and perceived ease of use.

The following hypotheses were therefore proposed for the study:

H3a: Facilitating conditions will positively influence perceived usefulness of MOOCs in Nigeria.

H3b: Facilitating conditions will positively influence perceived ease of use of MOOCs in Nigeria

H3c: Facilitating conditions will positively influence behavioral intention to use MOOCs in Nigeria.

H3d: Facilitating conditions will have an indirect positive effect on behavioral intention to use MOOCs in Nigeria through perceived usefulness.

H3e: Facilitating conditions will have an indirect positive effect on behavioral intention to use MOOCs in Nigeria through perceived ease of use.

Social Influence

Social influence refers to the extent to which an individual perceives that those important to them believe they should use a particular technology (Venkatesh *et. al.,* 2012). The concept has been found to have a positive influence on the behavioral intention to use a system (Venkatesh *et. al.,* 2012). People in developing countries tend to live a somewhat communal life, sometimes relying on family and close friends to help them in making decisions. In a study of MOOCs adoption in Malaysia, Nordin *et. al.* (2016) confirms that a positive relationship exists between social influence and intention to use, while Kang *et. al.* (2015) and Mtebe & Raisamo (2014) reported the similar results in the context of m-learning adoption. Furthermore, Bhatiasevi (2015) and Oliveira *et. al.* (2014) found social influence to be an important predictor of behavioral intention to use mobile banking in their different studies. And in the study of adoption of a mobile health technology in Uganda, social influence significantly impacted the intention to use (Nanyombi & Ejiro, 2016).

In addition to directly influencing people's intention to adopt a technology, social influence have also been found have a direct relationship on perceived usefulness and perceived ease of use of a system (Chen & Aklikokou 2019; Teo, 2011a, Teo, 2011b, Adbullah & Ward, 2016). For instance, social influence was found to be a significant predictor of perceived ease of use in e-government adoption (Chen & Aklikokou, 2019), and e-learning adoption (Adbullah & Ward, 2016, Teo, 2011a, Teo, 2011b), indicating that people are more likely to consider a system useful and easy to use if people close to them and those whose opinion they value encourage them to use the system. And since perceived ease of use is often a significant predictor of behavioral intention, social influence is likely to have an indirect relationship to behavioral intention through how easy a system is perceived to be. Although this indirect relationship to behavioral intention was found to be true in some studies (Teo, 2010, Teo, 2011b), others who found a direct relationship of social influence on perceived ease of use, failed to find an indirect effect on behavioral intention through the variable (Chen & Aklikokou, 2019).

This study argues that, in the case of MOOCs, the extent to which an individual believes that those important to them or those whose opinions they value wants them to use MOOCs will directly influence their perceived usefulness, perceived ease of use and intention to use MOOCs, and indirectly influence intention through perceived usefulness and perceived ease of use. The following hypotheses were therefore proposed for the study:

H4a: Social influence will positively influence perceived usefulness of MOOCs in Nigeria.

H4b: Social influence will positively influence perceived ease of use of MOOCs in Nigeria

H4c: Social influence will positively influence behavioral intention to use MOOCs in Nigeria.

H4d: Social influence will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived usefulness.

H4e: Social influence will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived ease of use.

Individual Espoused Cultural Values: Hofstede's Cultural Dimensions

Culture is a very prominent part of everyday life, and the way people tend to approach their daily activities are most times influenced by the values or beliefs they hold. Essentially, people's cultural beliefs tend to shape their perceptions of the world. Hence, it is a reasonable assumption that such cultural beliefs are likely to influence peoples' attitudes and intentions towards the use of a technology, especially when the use of the technology is not mandatory (Teo & Huang, 2019). It has therefore been often argued that there exists a tendency for cultural differences to influence peoples' perceptions of a technology and potentially their willingness to adopt and use them (Kizilcec et al., 2013; Nkuyubwatsi, 2014).

However, regardless of the widely acknowledged importance of culture in technology adoption, there remains limited understanding of how cultural values affect technology adoption and use, especially with regards to cultural values espoused on the individual level (Srite & Karahanna, 2006). And research involving technology acceptance theories such as TAM have often neglected the potential effect of such espoused cultural values on technology adoption (Aldhaban, Daim & Harmon, 2015; Srite & Karahanna, 2006).

Hofstede (2001) defines culture as "the collective programming of the mind that distinguishes the members of one group or category of people from another " (p.9). He originally identified four main dimensions in which a country's culture can be characterized by, namely: power distance, uncertainty avoidance, individualism/collectivism and masculinity/femininity (Hofstede, 1986, 2011). These dimensions are such that, depending on the cultural characteristics exhibited within a country, it would be placed on either a low (weak), neutral or high (strong) point on a continuum for each dimension. Hofstede's cultural dimensions have often been used in understanding effects of cultural values on technology adoption. However, given that the conceptualizing of culture within Hofstede's model is at the national level, the majority of the studies that have examined such cultural values have done so with consideration of country level differences (Lai et al., 2016; Srite & Karahanna, 2006).

Individuals are however different and as such tend to espouse national cultural values at different levels (Fang, 2012; Srite & Karahanna, 2006). For instance, although Nigeria is characterized as a collectivist country with high power distance levels, according to Hofstede's dimension scores (Hofstede Insights, 2020), we are aware that the strength of these characteristics will vary for individuals, as other factors may be causing them to identify with the national culture at different levels. Hence, using overall established national cultural value scores in understanding individual behaviors would be inappropriate and overgeneralizing (Hoehle, Zhang & Venkatesh, 2015; McCoy, Galletta & King, 2005; Srite & Karahanna, 2006; Straub, Loch, Evaristo, Karahanna & Srite, 2002). It essentially puts less emphasis on potential influence of other social group memberships, such as family, religion, organizational, among others, on values individuals choose to espouse (Straub et al., 2002).

Researchers have therefore argued that on the individual level, espoused natural cultural values should be used in understanding the influence of culture on individual level behaviors (Srite & Karahanna, 2006; Straub et al., 2002; Yoo, Donthu & Lenartowicz, 2011). Srite and Karahanna (2006) defined espoused national cultural values as the "degree to which an individual embraces the values of his or her national culture" (p.681) and adapted Hofstede's framework in providing definitions for these individual level espoused cultural dimensions, some of which were refined for this study. Few studies have utilized Hofstede's culture framework to examine the impact of individual espoused cultural values on technology adoption (Baptista & Oliveira, 2015; Faqih & Jaradat, 2015; Shiu, Walsh, Hassan & Parry, 2015; Srite & Karahanna,

2006) and a number of them argue that these cultural factors have some influence on people's intention and usefulness perceptions of a system (Hwang & Lee, 2012; Lee, Trimi & Kim, 2013; Lai et al., 2016). For instance, Lai et al. (2016) argues that the role of these cultural factors on technology adoption may be dependent on the context, such as the type of technology being studied, stage of adoption, among other factors. Hence, more studies in different contexts are needed to further improve our understanding of the nature of the effects of these espoused cultural values on technology adoption (Lai et al., 2016; Shiu et al., 2015).

Online learning is a relatively new approach to learning, and often include different teaching and learning styles, and relationships and communications among teachers and learners can get complicated due to the nature of the environment. Several studies therefore have suggested that, assessing cultural values and their effects on users are essential for the success of e-learning systems (Downey, Wentling, Wentling & Wadsworth; Srite & Karahanna, 2006; Srite, 2006; Lai et al., 2016; Teo & Huang, 2019). MOOCs as an online learning concept are even newer in the online learning environment, and their informal nature further exacerbates issues that are likely to be encountered in more formal online learning environments, thereby placing more importance on the need to examine how peoples' cultural values are influencing their attitudes towards accepting and using the technology. However, studies within the online learning context are particularly lacking in this aspect and as far as the researcher is aware, no study has examined the effect of these individual espoused cultural values within the context of MOOCs adoption and use, let alone, MOOCs adoption in the Nigerian context.

This study will therefore be examining if individual espoused values will be influencing people's attitudes and use intention towards MOOCs. Only the direct and indirect effects (through perceived usefulness and ease of use) of the cultural values on intention were explored in this study because, first, the few studies that have explored these individual cultural values tended to focus on the moderating roles they are likely to play in technology acceptance, with only a few of them exploring direct or indirect effects on intention in the e-learning context (Srite & Karahanna, 2006, Al-Ammari, & Hamad, 2008). Also, some studies that were found that explored acceptance of e-learning technologies failed to find moderating effects for some or all of these cultural values (Lai et al., 2009, Srite & Karahanna, 2006; Sanchez-Franco et al., 2009; Lai et al., 2016). The four individual cultural factors that were examined for this study, namely, power distance, uncertainty avoidance, collectivism and masculinity are described in the section below.

Power Distance

Power distance refers to the extent to which an individual accepts large power differentials and inequality as normal (Srite and Karahanna, 2006; Hofstede, 1980). For instance, in the case of learning, power distance will condition the extent to which the student accepts that his or her teachers have more power over them (Srite and Karahanna, 2006). In online learning, power distance can be determined by how accessible and available instructors are to students (Wilhelm, 2003), and how willing they are to involve them in the learning process. MOOCs by their nature tend to already promote a level of power distance given that as an online learning platform, a physical barrier already exists between the teachers and the students. This issue is further exacerbated in MOOCs because of the informal and asynchronous nature of the learning environment. Hence, in this situation, the teacher is practically king and the opinion of the student is rarely acknowledged, and there exists little to no interaction going on between the two parties. Hence this study argues that, those with high power distance values will appreciate the structure of the teacher-student relationship existent in MOOCs, indicating that they may be likely to have more positive attitudes towards their use and more likely to intend to use them. The following hypotheses were therefore proposed for the study:

H5a: Power distance will positively influence perceived usefulness of MOOCs in Nigeria.

H5b: Power distance will positively influence perceived ease of use of MOOCs in Nigeria

H5c: Power distance will positively influence behavioral intention to use MOOCs in Nigeria.

H5d: Power distance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived usefulness.

H5e: Power distance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived ease of use.

Uncertainty Avoidance

Uncertainty avoidance refers to the extent to which an individual feels threatened by ambiguous situations, i.e., the level of risk they are willing to accept (Srite and Karahanna, 2006; Hofstede, 1980). For instance, some authors argued that individuals with high uncertainty avoidance will have less intention to adopt a technology due to their tendency to avoid ambiguous or unstructured events which would potentially influence their usefulness perceptions of that technology (Hwang & Lee, 2012; Lee, Trimi & Kim, 2013). Another study found a direct negative effect of uncertainty avoidance on self-directed use of technology for language learning (Lai et al., 2016).

This dimension has often been argued as having a negative association with intention to adopt a technology because risk-averse people are generally less inclined to accept new ideas or behaviors and therefore may be unwilling to accept and use a new technology (Hofstede, 1980; Hofstede, 2008; Hofstede, 2011; Lai, Wang, Li & Hu, 2016). However, in online learning, this cultural orientation is more associated with how students perceive the structure of their learning (Wilhelm, 2003). Where those with high uncertainty avoidance levels tend to prefer a learning process that is more structured, and that have learning instructions and guidelines well outlined, and those with lower uncertainty avoidance levels would prefer a more flexible approach to the learning structure (Srite & Karahanna, 2006). MOOCs are typically structured, mirroring more traditional forms of learning. Although the time one can learn is flexible, the courses themselves are structured in such a way that students are made aware of what the goals and expectations of the class are, just like is obtainable in a traditional classroom. Hence, this study argues that those with high uncertainty avoidance are more likely to appreciate the structure of MOOCs, indicating that they may be likely to have more positive attitudes towards their use and more likely to intend to use them

The following hypotheses were therefore proposed for the study:

H6a: Uncertainty avoidance will positively influence perceived usefulness of MOOCs in Nigeria.

H6b: Uncertainty avoidance will positively influence perceived ease of use of MOOCs in Nigeria

H6c: Uncertainty avoidance will positively influence behavioral intention to use MOOCs in Nigeria.

H6d: Uncertainty avoidance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived usefulness.

H6e: Uncertainty avoidance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived ease of use.

Collectivism

Collectivism refers to the extent to which an individual emphasizes the needs of the group over his/her own needs and prefers to act a member of a group rather than an individual entity (Srite and Karahanna, 2006; Hofstede, 1980). Collectivism has been argued to have the potential to positively influence intention to use a system, based on the premise that higher collectivist people are more likely to stick to the norm and adopt a technology, as explained by Lai et al., (2019). However, MOOCs by their nature promote individualistic learning, as learning occurs in an online environment which is often isolated, and interaction between teachers and students and with other students are often limited. Hence, this study argues that those who perceive learning as a collective process, that involve working with a group and prioritizing group success over that of the individual, may be less likely to want to partake in MOOCs. The following hypotheses were therefore proposed for the study:

H7a: Collectivism will negatively influence perceived usefulness of MOOCs in Nigeria.

H7b: Collectivism will negatively influence perceived ease of use of MOOCs in Nigeria.

H7c: Collectivism will negatively influence behavioral intention to use MOOCs in Nigeria.

H7d: Collectivism will have an indirect negative effect on intention to use MOOCs in Nigeria through perceived usefulness.

H7e: Collectivism will have an indirect negative effect on intention to use MOOCs in Nigeria through perceived ease of use.

Masculinity

Masculinity refers to the extent to which the individual espouses certain gender connotated values, with individuals who emphasize work goals such as assertiveness, competitiveness, advancement, earnings and performance considered to be espousing masculine values and individuals who emphasize personal goals such as warm personal relationships, non-assertiveness and friendly atmosphere considered to be espousing feminine values (Srite and Karahanna, 2006; Hofstede, 1980). It is therefore argued that people who have more masculine values are expected to be more focused, driven and have more work-related goals and less people oriented (Hofstede, 1980; Srite & Karahan, 2006). This value orientation indicates that, those who have a higher masculine orientation are more likely to adopt a technology if they believe it will help in advancing their professional and career-related goals (Hofstede, 2008; Hofstede, 2011). Since MOOCs as a learning platform aims to encourage personal development in terms of acquiring skills for ones' career goals, and one needs a certain level of drive to be able to dedicate the time and effort required to participate in MOOCs, it is expected that those with high masculine values will generally find MOOCs more valuable. This indicates that those with more masculine values may be more likely to have positive attitudes towards MOOCs and hence may be more likely to intend to use them to achieve their goals.

The following hypotheses were therefore proposed for the study:

H8a: Masculinity will positively influence perceived usefulness of MOOCs in Nigeria.

H8b: Masculinity will positively influence perceived ease of use of MOOCs in Nigeria

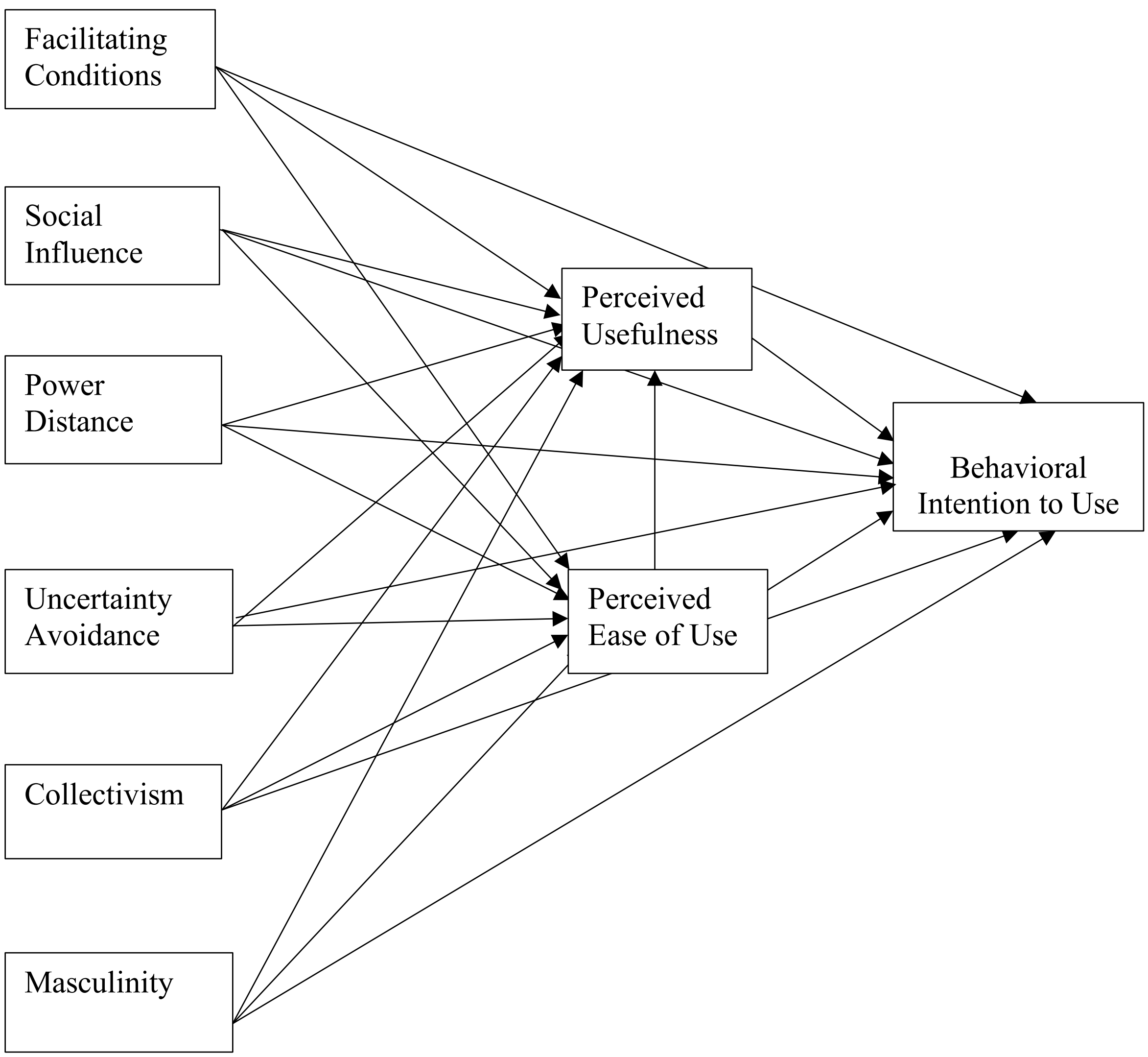
H8c: Masculinity will positively influence behavioral intention to use MOOCs in Nigeria.

H8d: Masculinity will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived usefulness.

H8e: Masculinity will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived ease of use.

Below in *Figure 2* is a depiction of the theoretical framework developed for the study based on the proposed relationships:

Figure 2: Theoretical Framework for the Study



Note. Study model with full hypothesized relationships

Study Contribution to the Literature

The study hopes to contribute to the existing literature in the following way:

- The effects due to the factors being examined have been inconsistent across the literature, particularly those related to cultural values, so the study adds to this body of research to provide a better understanding about how the proposed factors are affecting people's intention to adopt MOOCs within a developing country context.
- There is limited research examining these factors in MOOCs within the Sub-Saharan African developing context and little to no research examining these factors in the Nigerian context (many of the studies are specific to developed countries or to more high performing developing countries such as China).
- The factors related to individual level cultural values remains unexplored within the context of MOOCs, as well as in online learning and the Nigerian context in general.
- There is limited research integrating the examined factors (particularly, the individual espoused cultural values) within the Technology Acceptance Model (TAM) framework in understanding adoption of MOOCs or online learning in general.

Conclusion

This chapter reviewed the literature and developed the theoretical framework guiding the study. The relationships expected for the study were presented based on findings from the literature. It was hypothesized that the primary TAM antecedents, perceived ease of use and perceived usefulness and the additional determinants, facilitating conditions, social influence, power distance, uncertainty avoidance, collectivism and masculinity will have direct effects on peoples' intention to use MOOCs within the context of study. It was also hypothesized that perceived ease of use, facilitating conditions, social influence, power distance, uncertainty avoidance, collectivism and masculinity will all influence perceived usefulness of MOOCs within the context. And that facilitating conditions, social influence, power distance, uncertainty avoidance, collectivism and masculinity will all directly influence perceived ease of use of MOOCs. Furthermore, it is expected that perceived ease of use will indirectly influence behavioral intention through perceived usefulness, and that all the proposed external variables will indirectly influence behavioral intention to use MOOCs through perceived usefulness and perceived ease of use. The next chapter discusses how the study was designed and how data was collected to answer the research questions posed for the study

CHAPTER 4: METHODS

Overview

This chapter discusses the research design, sampling, data collection and analysis techniques that were utilized in the study in addressing its objectives and research questions. A quantitative research method approach, employing survey questionnaires as a data collection tool, was chosen for the study. A convenience sampling technique was used to recruit participants for the study and participants were screened to determine their eligibility before participating. Data was analyzed using multiple regression analysis and path analysis in R statistical software.

Study Design

The study adopted the TAM framework to examine factors influencing individual's usefulness and ease of use attitudes and use intentions of MOOCs in Nigeria. The study extended the TAM framework by examining external factors that are likely contributing to attitudes and adoption or non-adoption behaviors among individuals within the context of study. Hence, in addition to the main TAM constructs, perceived usefulness (PU) and perceived ease of use (PEOU), other factors, namely, facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA), collectivism (COL), and masculinity (MASC) were included in the original TAM model to determine their role in predicting both usefulness and ease of use perceptions and behavioral intention to use MOOCs (BI) in Nigeria. Demographic and other individual characteristics data were also examined to shed light on what a typical target MOOC user in the context of study might look like.

The specific research questions addressed in the study were:

1. What are the individual characteristics of a target MOOC user in Nigeria?

2. What factors influence perceived usefulness, perceived ease of use and behavioral intention to use MOOCs in Nigeria

The study was initially designed as a convergent mixed method study, given the strengths of that method of allowing for data to be gathered both quantitatively and qualitatively in answering the proposed research questions, thereby bringing together the weakness of both approaches (Creswell & Plano Clark, 2017). However, due to travel restrictions posed by the COVID-19 pandemic and the lack of resources that was associated with it for the researcher, it was not possible to conduct user interviews for this study as initially planned. Hence, a solely quantitative method, involving surveys was adopted for the research and as such, only the quantitative component of the study was retained and reported in this dissertation.

Although the initially planned mixed methods research was not utilized for this study, the researcher considers the chosen research method an appropriate one, because quantitative research methods, specifically surveys, are commonly utilized in studies involving technology adoption (Mingers, 2003; Tarhini, Hone & Liu, 2014), and it has been utilized by a wide range of studies examining technology adoption using the TAM framework to study online learning adoption (e.g., Aharony & Bar-Ilan, 2016; Chu, Ma, Feng & Lai, 2015; Al-Adwan, Al-Adwan, & Smedley 2013; Lee et al., 2009; Mohammadi, 2015; Miller & Khera, 2010; Tarhini, Hone & Liu, 2014; Shen, Laffey, Lin, & Huang, 2006). Also, the structure of this study, with its aim to test hypothesized relationships among specified variables that were based on already established scales, makes it ideal for survey research (Creswell, 2014). Furthermore, surveys allow for data to be collected from a large number of participants, which makes it easier for more generalizable conclusions to be made.

Sampling Procedure

A purposive, convenience sampling technique was used to identify people who were suited for this study. This method was considered appropriate because it allows the researcher make the decision about who can be included a study, particularly if they have a specific group in mind (Creswell & Plano Clark, 2017). This study was specific to people who have some knowledge of and/or experience with MOOCs as a learning technology, hence only those meeting these criteria were considered equipped to answer the questions in the survey. Therefore, a screening questionnaire was utilized to screen people in and out of the study based on specified inclusion criteria.

Inclusion Criteria

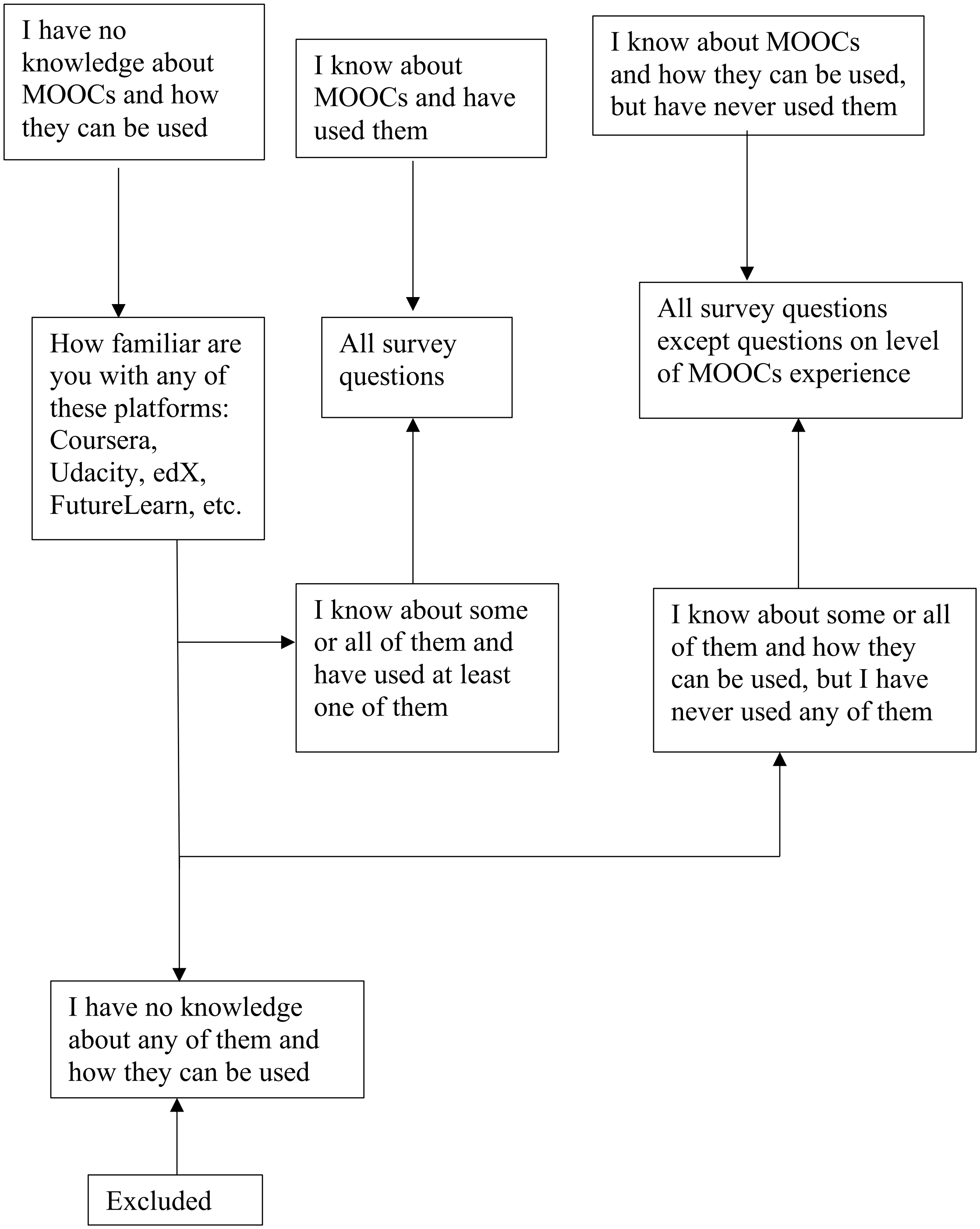
First, the main criterion for participation was having some knowledge and/or experience about MOOCs. Those with prior experience were termed "users" and those with knowledge about MOOCs and how they can be used, but have no use experience, were termed "non-users" for the study. The study was conducted to better understand their perceptions and intention behavior towards learning online using MOOCs. Represented in *Figure 3* below is a flowchart on how people were directed to the appropriate survey based on this criterion. Feedback from the pilot study conducted for the study indicated that it was necessary to direct those who indicated they had no knowledge about MOOCs to a question asking them about their familiarity with some popular MOOC platforms (e.g., Coursera, Udacity, edX, FutureLearn). This was because, some people may not be aware of the term MOOCs but are familiar with those popular platforms, hence eliminating them without going through this second stage would be premature.

The decision to include non-users is because it will help the researcher gain insights as why these people who are aware of MOOCs and perhaps their potential benefits have decided not to partake in them. The number of users and non-users to be recruited for the study were expected to be approximately the same, so that adequate information would be gathered from each group on their characteristics and attitudes. Furthermore, only participants over the age of 18 were included in the study. The participants were also required to be internet users (mainly because MOOCs are only available online), however, having access to the internet is a criterion for completing the online survey, hence no further action was taken to exclude people based on this category.

Recruitment and Incentive

Participants for the study were mainly recruited through key contacts in institutions and organizations in Nigeria. Additional participants were recruited through word of mouth. Participants were not rewarded for taking the survey because the researcher was made aware that compensation would cause more harm than good for the study within this context, as participants may complete and replicate surveys solely for the purposes of the compensation. Hence, a decision was made to offer monetary compensation only to the people who served as research assistants in helping recruit participants from their different institutions. A total of ten (10) facilitators were recruited for the study and each of them was paid N100,000 (approximately $200) to help with the recruitment process.

Figure 3: Flow Chart of Survey Inclusion Criteria



Note. Flow chart representing how participants were screened in or out of the study

Measures

Survey instrument measuring characteristics variables and the main study constructs was created for the study (*Appendix A*). The survey started by asking general demographic questions about age and gender (questions 1-2). Then the next question was used to determine participant's knowledge or experience with MOOCs in order to direct them to the right survey questions to complete (question 3). After these, 9 multi-item questions measuring the TAM constructs and the proposed external determinants (questions 4-13) followed. The remaining questions gathered information about specific participant characteristics related to their technological device ownership, use and confidence, e.g., the type of devices they own, how often they access the internet, devices they use to access the internet, internet reliability and efficiency, reasons for accessing the internet, confidence in internet and online learning use, etc. (questions 14-27). More demographic information was gathered from participants at the end of the survey, namely, information on education level, employment status and income (questions 28-30). Those with prior MOOCs experience were asked 9 additional questions about their experience, namely, their motivation for using MOOCs, number of years of MOOCs usage, frequency of MOOCs learning, etc.

Demographics and Characteristics Variables

The demographic and characteristics variables were mainly collected to be used to answer the first research question of the study about what the characteristics of the target users within the context were. The descriptive data gathered from them were presented as descriptive statistics. These questions allowed for characteristics of users and non-users to be compared within the context of study. Data from this section also allowed for the creation of user personas, outlining the characteristics of the target MOOCs learners within the context of study. Age and gender were also used as control variables in the main study analysis to control for their potential effects on the proposed relationships. The questions asked in this section were informed by previous research investigating characteristics of MOOCs learners in different contexts, especially in developing countries (e.g., Brasher et al., 2016; Christensen et al., 2014; Greene et al., 2015; Huang & Hew, 2017; Khalil & Ebner, 2014; Kizilcec et al., 2013; Nesterko et al., 2013; Stich & Reeves, 2017; Adebo & Ailobhio, 2017; Garrido et al., 2016; Muhammad et al., 2016; Deboer et al., 2013; Morris et al., 2015; Kaveri et al., 2016; Muhammad et al., 2016)

TAM Constructs and the External Determinants

The scales used to measure the TAM constructs and the external determinants were from already established scales with high internal reliability and validity and that have been found to explain a high percentage in variance in behavioral intention to use a technology (Davis, 1989; Venkatesh, 2000; Venkatesh *et. al.,* 2012; Yoo et al., 2011). The items for the original TAM constructs, perceived usefulness, perceived ease of use of and behavioral intention to use MOOCs were adapted from the original TAM model proposed by (Davis, 1989; Venkatesh, 2000), but were however modified to fit the context and phenomenon of study. Facilitating conditions were measured using the scale developed by Venkatesh *et. al.* (2012) in their study validating the UTAUT2 model of consumer acceptance and use of technology. The scale used for the espoused cultural values were adapted from studies that developed and validated a cultural value scale (CVSCALE) measuring Hofstede's dimensions at the individual level (Yoo et al., 2011) and those that examined the influence of individual level cultural values on technology adoption in different contexts (Lai et al., 2016; Srite & Karahanna, 2006; Tarhini et al., 2017). These questions were asked on a 5-point Likert scale, where participants were asked to indicate to what extent they agreed or disagreed with a statement, with (1) representing strongly disagree and (5) representing “strongly agree”.

The specific items used to measure these constructs are described in *Tables 1, 2* and *3* below:

Table 1: Perceived Usefulness, Perceived Ease of Use and Behavioral Intention

Perceived Usefulness (PU) PU1: I (would) find MOOCs useful in achieving my learning or job-related goals PU2: Using MOOCs enables (will enable) me to achieve my learning or job-related goals faster PU3: Using MOOCs increases (will increase) my learning or job productivity PU4: Using MOOCs will be beneficial for me in finding a job or in preparing for further education PU5: Using MOOCs would make it easier for me to gain desirable learning or job-related skills
Perceived Ease of Use (PEOU) PEOU1: I (would) find MOOCs easy to use PEOU2: Learning to use MOOCs is (will be) easy for me PEOU3: My interaction with MOOCs (would be) is clear and understandable PEOU4: It is (or would be) easy for me to become skillful at using MOOCS
Behavioral Intention (BI) BI1: I intend to use (continue using) MOOCs for learning BI2: I would want to use (continue using) MOOCs for learning BI3: I predict that I would use (continue using) MOOCs for learning

Note. Measure items for perceived usefulness, perceived ease of use and behavioral Intention to use MOOCs (Adapted from (Davis, 1989; Venkatesh, 2000)

Table 2: Facilitating Conditions and Social Influence

Facilitating Conditions (FC) FC1: I have the resources necessary to use MOOCs FC2: I have the knowledge necessary to use MOOCs FC3: MOOCs is compatible with other technologies I use FC4: I can get help from others when I have difficulties using MOOCs
Social Influence (SI) SI1: People who are important to me think I should use MOOCs SI2: People who influence my behavior think I should use MOOCs SI3: People whose opinions that I value think that I use MOOCs SI4: People who have authority over me think I should use MOOCs

Note. Measure items for facilitating conditions and social influence (Adapted from Davis (1989) and Venkatesh *et al.,* 2012)

Table 3: Individual Espoused Cultural Values

Power Distance (PD) PD1: Teachers should make most decisions without consulting students PD2: Teachers should not ask the students for advice or opinions PD3: Teachers should not engage in social interaction with students PD4: Teachers should not delegate important decisions to students PD5: Students should not question or disagree with decisions made by their teachers PD6: Teachers should always show authority and power when dealing with students
Uncertainty Avoidance (UA) UA1: It is important to have course requirements and instructions spelled out in detail so that I always know what I am expected to do UA2: Rules and regulations are important to me in a course because they inform me of what the teacher expects of me UA3: Order and structure are very important to me in a course UA4: It is important to me to closely follow instructions and procedures in a course UA5: Having Instructions for the course is important for my learning UA6: Standardized less flexible teaching and learning procedures are important for my learning

Table 3 (cont'd)

Collectivism (COL) COL1: Working as part of a group in a course is more important than working as an individual COL2: Group success is more important than individual success COL3: Being loyal to my group is more important individual gain COL4: It is unlike me to abandon a group I belong to in in the face of difficulty COL5: I am willing to sacrifice my self-interest for the good of my group COL6: The welfare of my group is more important that any individual rewards I can get COL7: It is more important for a teacher to encourage loyalty and sense of duty in students that is to encourage individual initiative
Masculinity (MASC) MASC1: It is important to me to have a professional career MASC2: It is preferable to me that my teacher is male rather than a female MASC3: I am capable of excelling in any course MASC4: Outstanding academic achievements are important to me in my studies MASC5: I prefer to solve problems more logically than intuitively MASC6: Achievements and material success matter to me more than relationships and quality of life

Note. Measure Items for individual espoused cultural values (Adapted from: Yoo et al., 2011; Lai et al., 2016; Srite & Karahanna, 2006; Tarhini et al., 2017).

Data Collection and Analysis Procedure

Number of participants and data collection procedure

Approximately 200 participants, were expected to be recruited for the study. This number was considered appropriate for obtaining statistical relevant results within a high confidence interval using the chosen statistical method (multiple regressions and path analysis). The target was to have about 100 participants each from the group with some experience, and the group with knowledge about MOOCs, but no experience, to reduce the tendency of bias as a result of level of the experience variable. There were thirty (30) questions in total for the main survey, although 9 of those were multi-item questions measuring the main study constructs, with the number of sub-questions for each construct ranging from 3-7. There were nine (9) additional single item questions measuring the level of experience with MOOCs for those with prior experience. The survey took an average of 15-20 minutes to complete for most participants. Questions on the TAM constructs and the additional determinants were represented on a 5-point multi-item Likert scale type questions. Participants were reminded that the survey was voluntary and were allowed to withdraw at any point and were only required to answer questions to the best of their ability. A pilot test with individuals that were representative of the sample participants helped validate the appropriateness of the survey questions in addressing the research questions and helped to better approximate the completion time for the survey. See *Appendix A* for the full survey questions used for the study.

Informed Consent and Confidentiality

At the beginning of the survey, participants were briefed about their rights and the confidentiality of the data gathered through the study. They were informed that participation is voluntary and that they had to right to withdraw at any time during the course of the survey.

They were also informed that there will be no personal identifiable information attached to their data, and that any information they provide as part of the study will be protected and only accessible by members of the research team and will not be used for any other purpose outside of the study without their permission.

Data Analysis

Data from the study was analyzed to test for the proposed hypotheses and research questions. Multiple regression analysis was used to test for the direct effects of the predictor variables on the outcome variables and path analysis was used to model the indirect effects of the predictors on the main outcome variable, behavioral intention to use MOOCs, through perceived usefulness and perceived ease of use.

CHAPTER 5: DATA ANALYSIS & RESULTS

Overview

This chapter presents the results of the data analysis conducted for the data obtained in this study. Data screening and cleaning were done using IBM SPSS statistic software, version 27.0. All data analysis was done using R statistical software. These include preliminary data analysis, specifically, descriptive statistics, confirmatory factor analysis, reliability analysis and independent samples t-test, as well as inferential data analysis involving multiple regressions and mediational path analysis. Missing data were excluded using listwise deletion for the analysis.

Data Screening and Cleaning

The data from respondents were imported into SPSS to be examined for irregularities, particularly missing data due to incomplete surveys. This examination also involved excluding data from those who were screened out from participating in the main survey based on the specified criteria, i.e., those who were not aware of what MOOCs were and had never used them for learning. The data screening revealed that, out of the 324 respondents who attempted the survey, 31 of them indicated not being aware of what MOOCs were and were not familiar with any of the major MOOC platforms mentioned in the survey. These 31 respondents were therefore excluded from further data analysis for the study because they were screened out from completing the main study survey. Furthermore, data from an additional 66 respondents were eliminated from further analysis because they included people who either started the survey but responded only to the demographic questions, leaving the main study variables empty or almost empty. These 66 respondents essentially dropped out of the survey without providing enough responses to meaningfully contribute to data analysis. This resulted to the final responses used for analysis being 227. This number was acceptable to achieve a medium effect size based on the a priori power analysis conducted for the study which suggested a minimum sample size of 112, based on 9 predictors and a power of .80

Descriptive Statistics of Individual Characteristics Variables

Participant Profile

Total Sample

This study targeted Nigerians who were either users of MOOCs or have knowledge about MOOCs but have no experience using them. Out of 227 data responses retained, 98 (43.2%) of them were in the user category and 129 were in the category of non-users with MOOCs awareness.

Table 4: Study Sample by User Category

	N	%
Users	98	43.2
Non-Users	129	56.8
Total	227	100.0

Note. Table showing number of respondents with MOOCs experience (users) and no experience (non-users)

Demographics

Age

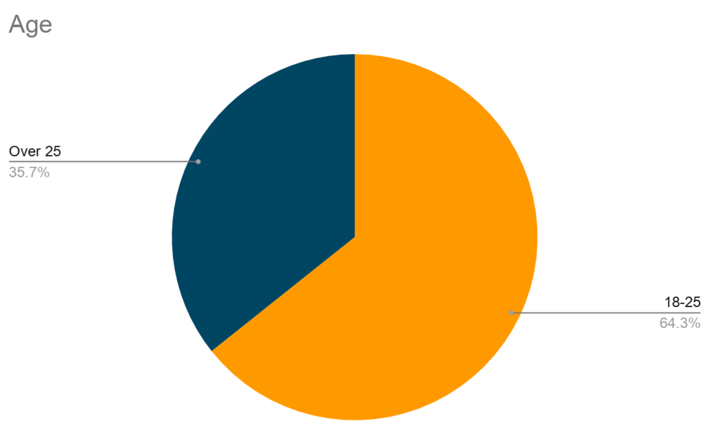
With regards to age, 64.3% (136) of the total respondents were between 18 – 25 years old, while those over 25 made up 34.7% (91) of the total sample. While examining the age of respondents based on if they were users or not, it was found that the age ranges were similarly split among the different categories. With the younger group making up over 50% of the respondents for both users and non-users.

Table 5: Age

	Total		Users		Non-User	
	N	%	N	%	N	%
18 – 25	146	64.3%	63	64.3%	83	64.3%
Over 25	81	35.7%	35	35.7%	46	35.7%

Note. Table representing age profile of respondents

Figure 4: Total Participants by Age



Gender

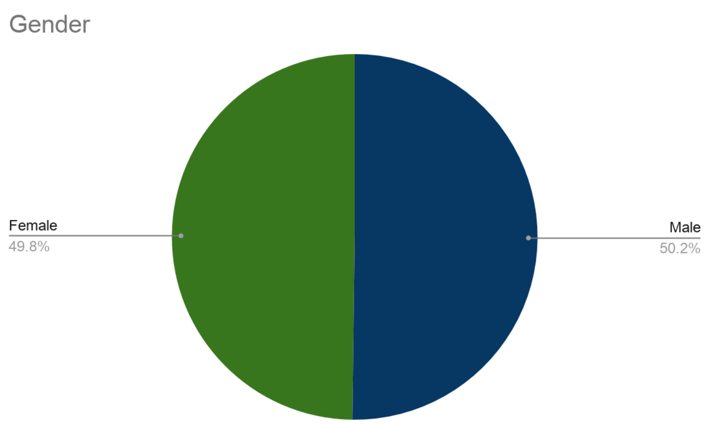
In examining the gender component of the of respondents, it was found that the gender was split almost equally among the participants, with 114 (50.22%) of the respondents being men and 113 (49.78%), female. However, there were more men than women among those in the user group (58.2% male vs 41.8% female), while the non-user group had more women than men in general (55.8% male vs 44.2% female).

Table 6: Gender

	Total		Users		Non-User	
	N	%	N	%	N	%
Male	114	50.2%	57	58.2%	57	44.2%
Female	113	49.8%	41	41.8%	72	55.8%

Note. Table representing gender profile of respondents

Figure 5: Total Participants by Gender



Educational Level

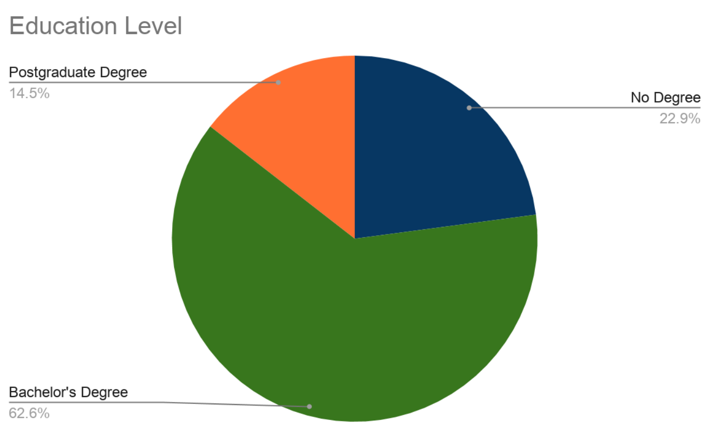
Table 7 shows that majority of the respondents were bachelor degree holders, with 62.6% of the total sample indicating having already obtained their bachelor's degree. The rest of the sample either had no formal degree yet (22.9%) or have obtained a postgraduate degree (14.5%). On the other hand, non-users had a slightly higher percentage of people with a bachelor's degree than users (66.7% vs 57.1%). Interestingly, users had both a higher percentage of people with a postgraduate degree (17.3% for users vs. 12.4% for non-users), and no degree at all (25.5% for users' vs 20.9% for non-users).

Table 7: Educational Level

	Total		Users		Non-Users	
	N	%	N	%	N	%
No Degree	52	22.9%	25	25.5%	27	20.9%
Bachelor's Degree	142	62.6%	56	57.1%	86	66.7%
Postgraduate Degree	33	14.5%	17	17.3%	16	12.4%

Note. Table representing educational level profile of respondents

Figure 6: Total Participants by Education Level



Employment Status

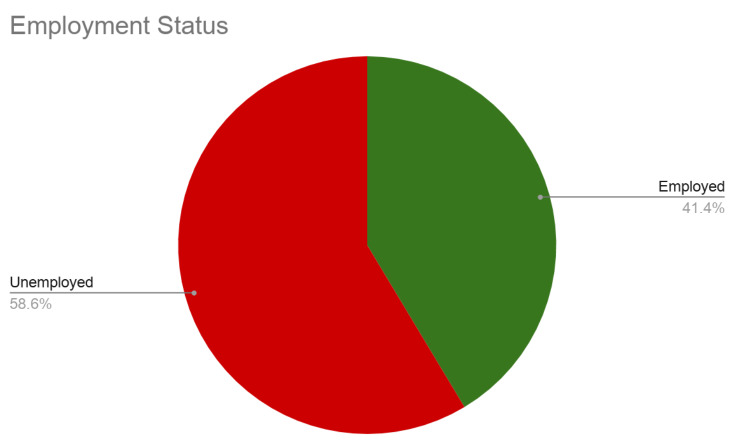
A higher percentage of the participants (58.6%) were unemployed, while the remaining indicated having some form of employment. The user category had slightly more participants that were employed (51%), while the non-users were more likely to be unemployed (54.3%). Furthermore, users had a higher percentage of people who were employed than non-users

Table 8: Employment Status

	Total		Users		Non-Users	
	N	%	N	%	N	%
Employed	94	41.4%	50	51%	59	45.7%
Unemployed	133	58.6%	48	49%	70	54.3%

Note. Table representing employment status profile of respondents

Figure 7: Total Participants by Employment Status



Individual Characteristics

Type of Devices Owned

While examining the types of devices owned by participants, it was found that Smartphones made up the highest percentage of device ownership, with almost 87% of respondents indicating owing one. Laptops were a close second, with 64% of the total sample having access to one. Other devices participants owned included, tablets (14.5%) and desktop computers (5.7%). These results were consistent across the samples of users and non-users.

Table 9: Devices Owned

	Total		Users		Non-Users	
	N	%	N	%	N	%
Smartphone	197	86.8%	85	86.7%	112	86.8%
Laptop	145	63.9%	66	67.3%	79	61.2%
Desktop	13	5.7%	4	4.08%	9	7.0%
Tablet	33	14.5%	20	20.4%	13	10.1%
Others	1	.4%	0	.0%	1	.7%

Note. Table showing devices owned by respondents

Internet Access Device

Similar to the type of devices owned, it was found that participants utilized their Smartphones more frequently in accessing the internet than any other device (See *Table 10* below). Laptops, desktops and tablets were used by some, although Smartphones appear to be the preferred choice, both for users and non-users.

Table 10: Internet Access Device

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Smartphone	198 (87.2%)	84 (85.7%)	114 (88.3%)
Laptop	18 (7.9%)	8 (8.2%)	10 (7.8%)
Desktop	4 (1.8%)	0 (0.0%)	4 (3.1%)
Tablet	7 (3.1%)	6 (6.1%)	1 (0.8%)

Note. Table showing devices respondents use to access the Internet the most

Type of Internet Access

To get an idea of how the participants generally access the internet, they were asked to indicate the type of internet access they had (see Table 11). Consistent with previous results, mobile broadband was found to be the most common type of internet access within the study sample, making up about 79% of all internet access among the participants. Mobile broadband and home Wi-Fi made up about 92% of all internet access among participants, showing that public Wi-Fi use were less common.

Table 11: Internet Access Type

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Mobile broadband	180 (79.3%)	79 (80.6%)	101 (78.3%)
Home Wi-Fi	30 (13.2%)	10 (10.2%)	20 (15.5%)
School Wi-Fi	5 (2.2%)	2 (2.0%)	3 (2.3%)
Work Wi-Fi	6 (2.6%)	2 (2.0%)	4 (3.1%)
Other Public Wi-Fi	2 (0.8%)	2 (2.0%)	0 (0.0%)
Public Internet Cafe	4 (1.8%)	3 (3.1%)	1 (0.8%)

Note. Table showing means through which participants access the internet

Internet Access Reason

As seen in Table 12, majority of the participants indicated learning purposes as their main reason for accessing the internet, with the second most popular reason being social media. Interestingly, it was found that a higher percentage of MOOC users accessed the internet for learning than non-users (66.% users vs. 47.3% non-users), while a greater percentage of non-users went online mainly for social media than users (36.4% non-users vs. 24.5% of users).

Table 12: Internet Access Reason

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Social media	71 (31.3%)	24 (24.5%)	47 (36.4%)
Learning (reading scholarly materials, watching educational videos, taking online classes etc.)	126 (55.5%)	65 (66.3%)	61 (47.3%)
News	17 (7.5%)	4 (4.1%)	13 (10.1%)
Others	13 (5.7%)	5 (5.1%)	8 (6.2%)

Note. Table showing means through which participants reasons for accessing the Internet

Internet Access Frequency

Table 13 shows that the respondents had adequate access to the internet. 83.3% of them indicated having access multiple times a day and another 11.5% for at least 5 to 7 times a week. In comparing users and non-users, it was found that a higher percentage of users access the internet more often than non-users, with 88.8% of users accessing the internet multiple times a day in comparison to 79.1% of non-users.

Table 13: Internet Access Frequency

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Not very often (About once a week)	3 (1.3%)	2 (2.0%)	1 (0.8%)
Somewhat often (About 2-3 times a week)	9 (4.0%)	4 (4.1%)	5 (3.9%)
Fairly often (About 5-7 times a week)	26 (11.5%)	5 (5.1%)	21 (16.3%)
Very often (Multiple times a day)	189 (83.3%)	87 (88.8%)	102 (79.1%)

Note. Table showing respondents frequency of internet access

Internet Efficiency

To get an idea of the quality of internet access respondents had, they were asked about the efficiency of their internet. Table 14 shows that around 70% of the respondents had internet access that was moderate or very efficient, indicating that the respondents typically found their internet access efficient enough for the purposes they were using them for. While examining the differences in internet efficiency for users and non-users it was found that about 20% of non-users considered their internet as not efficient or slightly efficient in comparison to 17% of users. Also, about 73% of users found their internet access to be moderate or very efficient in comparison to 69% of non-users. Finally, slightly more non-users found their internet access extremely efficient than users (10.9% vs. 9.2%).

Table 14: Internet Access Efficiency

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Not efficient at all	8 (3.5%)	4 (4.1%)	4 (3.1%)
Slightly efficient	35 (15.4%)	13 (13.3%)	22 (17.1%)
Moderately efficient	102 (44.9%)	48 (49.0%)	54 (41.9%)
Very efficient	59 (26.0%)	24 (24.5%)	35 (27.1%)
Extremely efficient	23 (10.1%)	9 (9.2%)	14 (10.9%)

Note. Table showing respondents answer to how efficient their internet access is

Internet Cost Efficiency

As seen in Table 15, the respondents were divided on how cost efficient their internet access was, with each category (ranging from not cost efficient to extremely cost efficient) having almost an equal percentage of participants, except for extremely cost efficient, which was the least selected category. Overall, we had about 40% of respondents indicate that their internet access was not cost efficient at all or only slightly cost efficient, another 50% indicated that their internet cost was moderate or very cost efficient, with only about 9% of the respondents considering their internet cost as extremely efficient. Comparing the responses of users and non-users on this category indicated that a slightly larger percentage of users considered their internet access as not cost efficient or only slightly cost efficient (52% of users vs. 40% of non-users). On the other hand, a slightly higher percentage of non-users considered their internet access to be moderately or very cost efficient (50% of non-users vs. 41% of users) and finally about 11% of non-users considered their internet access to be extremely cost efficient in comparison to 7% of users.

Table 15: Internet Cost Efficiency

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Not cost efficient at all	47 (20.7%)	23 (23.5%)	29 (22.5%)
Slightly cost efficient	45 (19.8%)	28 (28.6%)	22 (17.1%)
Moderately cost efficient	74 (32.6%)	20 (20.4%)	42 (32.6%)
Very cost efficient	40 (17.6%)	20 (20.4%)	22 (17.1%)
Extremely cost efficient	21 (9.3%)	7 (7.1%)	14 (10.9%)

Note. Table showing respondents answer to how cost efficient their internet access is

Internet for Learning

Interest and ability to engage in online learning online is essential for MOOCs, hence respondents were asked to indicate how often they use the internet for learning purposes. It was found that majority of them use the internet to learn with about 61% indicating they use it very often and 26% use it fairly often for learning purposes. Furthermore, while comparing MOOCs users and non-users, it was found that the percentage of users that used the internet often for learning was higher than non-users (please see Table 16 below).

Table 16: Frequency of using the Internet for Learning

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Rarely	7 (3.1%)	3 (3.1%)	4 (3.1%)
Not very often	24 (10.6%)	6 (6.1%)	18 (14.0%)
Fairly often	58 (25.6%)	20 (20.4%)	38 (29.5%)
Very often	138 (60.8%)	69 (70.4%)	69 (53.5%)

Note. Table showing respondents frequency of using Internet for learning

Internet Skill Confidence

As the ability to use the internet is a requirement to engage with MOOCs, respondents were asked to indicate their level of confidence with regards to using the internet. Table 17 indicates that the study participants were fairly confident in their internet use skills, with about 70% indicating they are very or extremely confident in their internet skills and about 21% indicating their skills as moderate. Only about 5% of respondents indicated not being confident or only slightly confident in their internet use skills. In comparing user and non-users, we can see from the table below that the results for each sample was similar to what we have for the overall sample, however, users appeared to have slightly more confidence in their internet use abilities than non-users as they were more likely to be very or extremely confident in their skills.

Table 17: Internet Use Confidence

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Not confident at all	3 (1.3%)	2 (2.0%)	1 (0.8%)
Slightly confident	9 (4.0%)	3 (3.1%)	6 (4.7%)
Moderately confident	43 (18.9%)	13 (13.3%)	32 (24.8%)
Very confident	106 (41.3%)	44 (44.9%)	55 (42.6%)
Extremely confident	66 (29.1%)	36 (36.7%)	35 (27.1%)

Note. Table showing respondents level of confidence in their Internet use skills

Online Learning Confidence

Respondents were further asked about their level of confidence in using the internet to learn online. Table 18 indicates that the study participants were fairly confident in their online learning skills, with about 76% indicating they are very or extremely confident in their internet skills and about 18% indicating their skills as moderate. Only about 6% of respondents indicated not being confident or only slightly confident in their internet use skills. In comparing user and non-users, we can see from the table below that the results for each sample was consistent with that for the overall sample, however, users appeared to have slightly more confidence in their online learning abilities than non-users as they were somewhat more likely to be very or extremely confident in their skills (76% of users vs. 71% of non-users).

Table 18: Online Learning Confidence

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Not confident at all	2 (0.8%)	0 (0.0%)	2 (1.6%)
Slightly confident	12 (5.3%)	4 (4.1%)	8 (4.7%)
Moderately confident	41 (18.1%)	14 (14.3%)	28 (21.7%)
Very confident	102 (44.9%)	41 (41.8%)	60 (46.5%)
Extremely confident	70 (30.8%)	33 (33.7%)	31 (24.0%)

Note. Table showing respondents level of confidence in their online learning abilities

Power Supply Reliability

Given that access to electricity is essential for powering the devices used to access MOOCs, participants were asked about how reliable they considered their power supply to be. About 48% of the respondents indicated that the current power supply they had access to was either not reliable or only slightly reliable. Only about 18% of the respondents had power supply they considered very or extremely reliable, while about 34% indicated their power supply reliability as moderate. In comparing users and non-users on their power supply reliability, it was found that the percentage of people from both groups that indicated having no or slightly reliable power supply were comparable, however, slightly more non-users had moderate reliable power supply (36.4% of non-users vs. 31.6% of user) and slightly more users had very reliable or extremely reliable power supply (20% of users vs. 16% of non-users).

Table 19: Power Supply Reliability

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Not reliable at all	55 (24.2%)	22 (22.4%)	32 (24.8%)
Slightly reliable	55 (24.2%)	25 (25.5%)	29 (22.5%)
Moderately reliable	76 (33.5%)	31 (31.6%)	47 (36.4%)
Very reliable	31 (13.7%)	13 (13.3%)	18 (14.0%)
Extremely reliable	10 (4.4%)	7 (7.1%)	3 (2.3%)

Note. Table showing level of reliability of power supply available to the respondents

Alternative Power Supply

As it was suspected that a good number of the respondents will have access to power supply that lacked in reliability, they were further asked to indicate if they had access to an alternative power supply to augment their primary power supply. Majority (80.2%) of the respondents indicated having access to an alternative power supply, and the results were similar for users and non-users, with users having only a slightly higher percentage of people with alternative power supply than non-users (81.6% of users vs. 77.5% of non-users).

Table 20: Availability of Alternative Power Supply

	Total	Users	Non-Users
	N (%)	N (%)	N (%)
Yes	182 (80.2%)	80 (81.6%)	102 (77.5%)
No	45 (19.8%)	18 (18.4%)	27 (20.9%)

Note. Table showing whether respondents have access to alternative power supply

Descriptive Statistics Specific to Users

MOOCs Usage Experience

Length of MOOC Use

From *Table 21*, we see that majority (45.9%) of those who have used MOOCs within the sample indicated having only used them for less than a year. Only about 35% of them have used MOOCs for over a year. This shows that even the users within this sample are still fairly new to MOOCs, with majority of them having only used it for a year or less.

Table 21: Length of MOOC Use

	N	%
Less than a year	45	45.9%
About a year	19	19.4%
Over a year	34	34.7%

Note. Table showing how long participants have used MOOCs for

Frequency of Learning with MOOCs

Among the participants who have experience with MOOCs, a little over half of them (about 56%) indicated learning on MOOCs fairly or very often, while the rest indicated not learning quite often or rarely with MOOCs. With about 15% rarely learning on the platform at all.

Table 22: MOOC learning Frequency

	N	%
Rarely	14	14.3%
Not Often	29	29.6%
Fairly Often	38	38.8%
Very Often	17	17.3%

Note. Table showing participants frequency of learning with MOOCs

Number of MOOCs Enrolled

Majority (79%) of the user participants indicated having enrolled in a total of less than 5 MOOCs till the time of the survey, with about 47% only having enrolled in 1 or 2 MOOC classes. Only about 21% of them indicating having taken over 5 MOOC classes in total.

Table 23: MOOCs Enrollment

	N	%
1-2	46	46.9%
3-5	31	31.6%
Over 5	21	21.4%

Note. Table showing participants MOOCs enrollment levels

Number of MOOCs Completed

It was found that about 27% of users within this sample have actually never completed a MOOC class, while almost 40% of them have only completed 1 or 2 classes. The remaining indicated having complete over 3 classes.

Table 24: MOOCs Completion

	N	%
None	26	26.5%
1-2	39	39.8%
3-5	21	21.4%
Over 5	12	12.2%

Note. Table showing participants level of MOOCs completion

Number of MOOCs Certificate Earned

An even higher number of the user participants (about 39%) indicated not having completed and earned a MOOC certificate with 38% indicating having earned 1 or 2 certificates. Only very few of them (9%) have earned 3 or more certificates from the participation in MOOCs.

Table 25: MOOCs Certificate Earned

	N	%
None	38	38.8%
1-2	37	37.8%
3-5	14	14.3%
Over 5	9	9.2%

Note. Table showing participants level of MOOCs certification

MOOCs Usage Preferences

Devices Used to Access MOOCs

The users utilized their Smartphones more in accessing MOOCs than any other device, with 63% of them indicating using their phones to access MOOCs, compared to 27% that prefer to use their laptop.

Table 26: MOOCs Access Device

	N	%
Smartphone	62	63.3%
Laptop	26	26.5%
Desktop	3	3.1%
Tablet	7	7.1%
Other	0	0%

Note. Table showing the devices participants use to access MOOCs

Most Commonly Used Platform

Users were asked about the platforms they used the most in accessing MOOCs and it was found that Coursera was very common among users in this sample, representing 47% of usage. edX and Udacity were also used, but at a lesser percentage. Other less popular platforms that participants use include, Udemy, Plural Sight, YALI and Lynda.

Table 27: Most Used MOOCs Platforms

	N	%
Coursera	46	46.9%
edX	18	18.4%
Udacity	12	12.2%
Others	22	22.4%

Note. Table showing the most commonly used MOOCs platforms among participants

Location of MOOCs Access

Participants indicate home as their preferred location to access MOOCs from, with almost 80% preferring to use MOOCs at home than any other location.

Table 28: MOOCs Access Location

	N	%
Home	77	78.6%
Work	12	12.2%
School	8	8.2%
Others	1	1.0%

Note. Table showing participants preferred location for accessing MOOCs

Main Motivation for Using MOOCs

To get an idea about what motivates participants to decide to enroll in MOOCs, they were asked to select from a list of options about what their main motivation for taking MOOCs was. It was found that many (39%) of the participants use MOOCs because of their personal gain or interest. While a good percentage of them took MOOCs to help them prepare for a new or future career or for academic achievement reasons.

Table 29: Main Motivation for Using MOOCs

	N	%
Personal gain/interests	38	38.8%
Support in current job	6	6.1%
New/future career	24	24.5%
Support current education	11	11.2%
Prepare for further education	15	15.3%
Others	4	4.1%

Note. Table showing participants main reason for MOOCs use

Model Assessments and Hypotheses Testing

Construct Reliability and Validity

Inter-item correlations indicate the extent to which items in a scale are related to each other and is used to examine internal consistency reliability of a scale (Piedmont, 2014), with correlations greater than .30 generally considered acceptable (Hair et al., 2010). A decent correlation among the items indicates that they are measuring the same trait as intended. Described below are the inter-item correlations for the items making up each construct included in the study. A fully detailed inter-item correlations tables for all the constructs are detailed in *Appendix B.*

Table 30: Inter-Item Correlations for the Construct Items

Construct	No of Items	Inter-Item Correlation
Perceived Usefulness	5	.31 - .57
Perceived Ease of Use	4	.32 - .58
Behavioral Intention	3	.74 - .79
Facilitating Conditions	4	.35 - .51
Social Influence	4	.47 - .75
Power Distance	6	.40 - .70
Uncertainty Avoidance	6	.09 - .71
Masculinity (Scale Dropped)	6	-.11 - .42
Collectivism	7	.18 - .69

Note. Table displaying inter-item correlations of the items within each construct

The results indicate that although most of the variables had correlations that were at acceptable levels, some of them, particularly, uncertainty avoidance, collectivism and masculinity, had correlation levels that were questionable for some of their items. Factor analysis was conducted to further examine scales to determine which items makes sense within each construct, especially given the items with low reliabilities. The decision was to drop items with a factor loading of less than .50 within a scale, as recommended by Byrne (2006), and to retain only constructs with Cronbach Alpha level of .70 and above, which is a generally acceptable level of construct reliability (Hair et al., 2006).

These criteria led to the masculinity scale being dropped completely because, only one item in the scale had a factor loading of >.50. This confirms the low item reliability as we observed from the correlation results above, hence, the researcher considered this construct unreliable for examining the study data and hence excluded it from further analysis. The inconsistency with the masculinity variable may be due to the fact that it has been found to be more beneficial in examining IT-enabled process change (Luo & Amberg, 2014), rather than in the consumer acceptance stage (Lai et al., 2016). As a result, its effect on technology adoption, especially e-learning adoption, have often been found to be non-significant (Lin, 2014; Baptista & Oliveria, 2015; Al-Ammari, & Hamad, 2008). Some studies therefore decide to exclude the dimension completely as a cultural value influencing e-learning adoption, due to these reasons (Lai, Wang Li & Hu, 2016). Hence, its exclusion from the overall analysis was not considered a disadvantage for this study.

Furthermore, the last item on the uncertainty avoidance scale (UA6) was also dropped because it was loading substantially low with the other items on the scale at .20. Additionally, the fourth item on the collectivism scale (COL4) was also dropped as its factor loading was less than .50. Full results of factor loadings from each construct are depicted in *Appendix C*.

The inter-item correlations for all the retained items ranged from .26 - .79 and the Cronbach's Alpha (α) for all retained constructs ranged from .74 - .90, indicating good internal consistency and reliabilities. Below is the table of inter-item correlations and Cronbach alpha reliabilities for the modified scales.

Table 31: Inter-Item Correlations and Cronbach Alpha Reliabilities for Modified Scale

Construct	No of Retained Items	Inter-Item Correlation	Cronbach's Alpha (α)
Perceived Usefulness	5	.32 - .61	.81
Perceived Ease of Use	4	.36 - .56	.78
Behavioral Intention	3	.70 - .79	.90
Facilitating Conditions	4	.35 - .51	.74
Social Influence	4	.47 - .75	.85
Power Distance	6	.40 - .70	.87
Uncertainty Avoidance	5	.49 - .71	.88
Collectivism	6	.26- .69	.83

Note. Table displaying inter-item correlations and reliability values for the study constructs

Descriptive Statistics of Main Study Constructs

The means and standard deviations of the construct items displayed in *Table 32* shows that the responses of the participants were not uniform across the constructs, with the means ranging from 2.12 for power distance and 4.52 for uncertainty avoidance. The participants scored below average for power distance (*M*=2.12, *SD*=1.035), moderately high for social influence (*M*=3.46, *SD*=1.15), facilitating conditions (*M*=3.86, *SD*=0.826) and collectivism (*M*=3.75, *SD*=0.860), and very high on uncertainty avoidance (*M*=4.52, *SD*=0.685), perceived usefulness (*M*=4.18, *SD*=0.754), and perceived ease of use (*M*=4.08, *SD*=0.751). The standard deviations for the items were narrowly spread around the mean indicating that participants were similar in their responses for each construct. The overall results and results of the user and non-user samples indicated that, the participants,

- agreed that MOOCs will be useful to them
- believed that MOOCs will be easy to use.
- are moderately influenced by their peers and those close to them
- indicated having moderate to high facilitating conditions (i.e., resources required) to use MOOCs
- had a low power distance in terms of their relationship with their teacher, showing that they do not agree that teachers should always exert power over students
- had a high uncertainty avoidance in terms of their approach to learning and learning content, showing that they prefer a more structured and guided type of learning
- showed a moderate to high preference towards collectivism than individualism, indicating that they may be more likely to prefer working together with others than alone.

Table 32: Means and Standard Deviations of Constructs

	Total		Users		Non-Users	
	M	*SD*	*M*	*SD*	*M*	*SD*
Perceived Usefulness	4.18	0.754	4.24	.723	4.14	.776
Perceived Ease of Use	4.08	0.751	4.14	.760	4.02	.742
Social Influence	3.46	1.15	3.05	1.311	3.75	.912
Facilitating Conditions	3.86	0.826	4.08	.769	3.72	.836
Power Distance	2.12	1.035	2.06	1.122	2.14	.966
Uncertainty Avoidance	4.52	0.685	4.44	.776	4.58	.603
Collectivism	3.75	0.860	3.71	.987	3.78	.767

Note. Table displaying means and standard deviations of participant responses to the questions representing the study constructs

Independent Samples T-test Comparing Users and Non-users

An independent samples t-test was conducted to examine if the differences observed in the means of the user and non-user samples were statistically significant for the main study constructs. *Table 33* details the results of the t-test showing the group differences in those MOOC acceptance perceptions and espoused cultural values.

Table 33: T-test for Equality of Means for the Constructs

	t	Mean Difference	*SE*
Perceived Usefulness	.887	.09	.106
Perceived Ease of Use	1.171	.12	.105
Social Influence	-4.315***	-.70	.162
Facilitating Conditions	3.527**	.37	.113
Power Distance	-.572	-.08	.145
Uncertainty Avoidance	-1.496	-.14	.096
Collectivism	-.258	-.03	.126

Note: *=p<.05, **=p<.01, ***p<.001

The results from the t-test revealed that non-users had a significantly higher social influence score than users (t=-4.315, p<.001) and users typically had a significantly higher facilitating conditions score than non-users with regards to MOOCs (t=3.527, p<.01). This indicates that non-users may typically be more likely to take MOOCs as a result of social influence and users generally may have more supporting conditions to use MOOCs. No statistically significant differences were found for levels of perceived usefulness, perceived ease of use and the individual espoused cultural values between the samples.

Testing the Original Technology Acceptance Model

The original TAM model was first tested to determine how much it predicted intention to use MOOCs within this sample prior to including the additional determinants proposed in the study. The model proposes that perceived usefulness and perceived ease of use will predict behavioral intention to use a technology and that perceived ease of use will also have a direct influence on perceived usefulness (Davis, 1980). These relationships were tested using multiple regression analysis. Age and gender were included as covariates in the regression model predicting use intention to control for their potential effects, as those are often examined in studies on technology adoption and use (Breslow et al., 2013; Guo & Reinecke, 2014; Konstan et al., 2015; Morris et al., 2015; Zhang et al., 2019) User category (i.e., user vs. non-user grouping) was also included as a covariate to control for the effect of experience.

Table 34: Regression results using Behavioral Intention as the Criterion

Predictor	*b*	Fit
(Intercept)	1.87**	
PU	0.44**	
PEOU	0.21**	
		R^2 = .325**

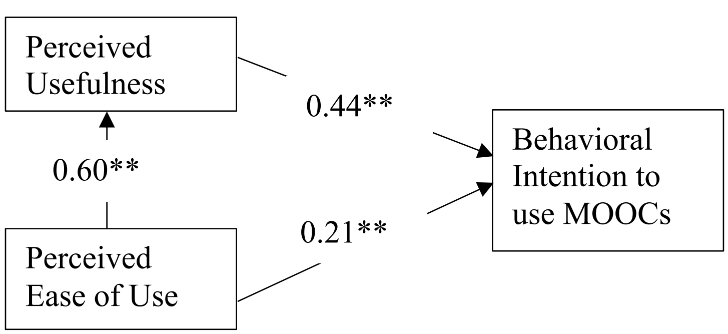
Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 35: Regression results using Perceived Usefulness as the Criterion

Predictor	*b*	Fit
(Intercept)	1.76**	
PU	0.59**	
		R^2 =. 345**

Note. * indicates $p < .05$. ** indicates $p < .01$.

Figure 8: Predicting Model using the Original TAM Constructs



Note. Model showing effects observed for the predictors in the original TAM model (R^2 = .325)

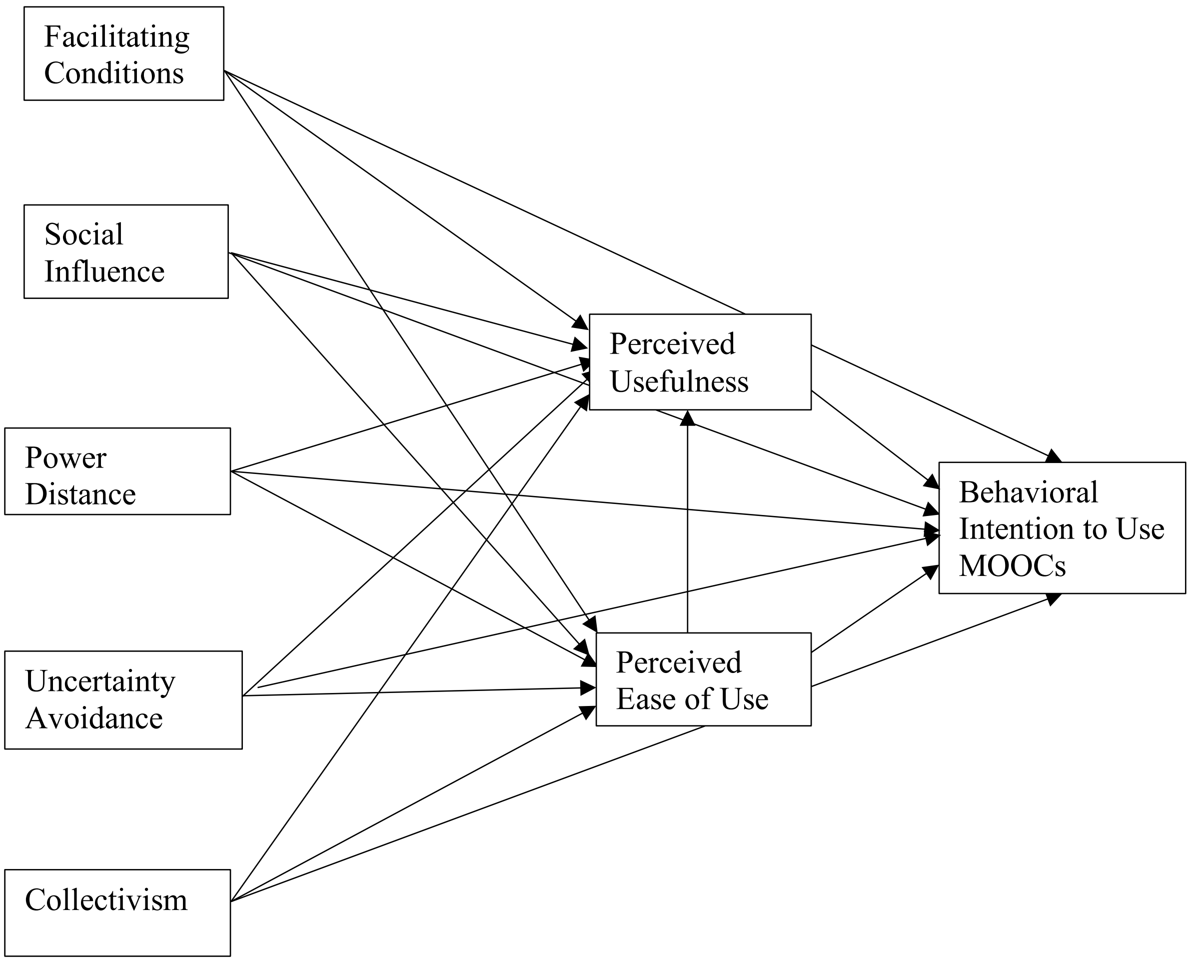
The results from the regressions indicated that the original TAM framework does have a reasonable predictive power of intention to use MOOCs for people within this context, with a stronger effect found for perceived usefulness (*b*=0.44, $p<.01$) than perceived ease of use (b=0.44, $p<.01$). Both constructs accounted for 33% ($R^2 = 0.33$) of the variance observed for intention to use MOOCs among the study participants. Also, perceived ease of use was found to be significantly predicting perceived usefulness in a positive direction (*b*=0.59, $p<.01$) and accounts for about 36% of the variance observed in the variable, while controlling for age, gender and user category. These results indicate that, without the additional constructs, the TAM model can predict use intention and perceived usefulness of MOOCs within the study sample.

Testing the Extended Technology Acceptance Model

Multiple linear regressions were used to test the hypothesized direct relationships for the study. Assumptions of multiple linear regression, namely, linearity, normality, homoscedasticity and multicollinearity were assessed for each multiple regression model prior to conducting the analyses. A normal Q-Q plot of standardized residuals was used to assess the normality. A Q-Q plot with most of the points lying along the regression distribution for a multiple regression indicates that the normality assumption is reasonably met. Linearity and homoscedasticity were assessed using residuals scatter plot. A residuals plot with points roughly distributed symmetrically along the horizontal line and that show roughly equal variance, with no obvious pattern in the distribution indicates that linearity and homoscedasticity are both met for a multiple regression model. Finally, multicollinearity was assessed using VIF. A VIF of over 10 indicates multicollinearity, suggesting that the predictors are highly related and may not be meaningful for all to be included in the model (Pallant, 2010).

The modified hypothesized model for how the independent variables (PU, PEOU, FC, SI, PD, UA and COL) will influence BI (excluding the masculinity construct) is displayed in *figure 9* below:

Figure 9: Modified hypothesized model without the Masculinity Construct

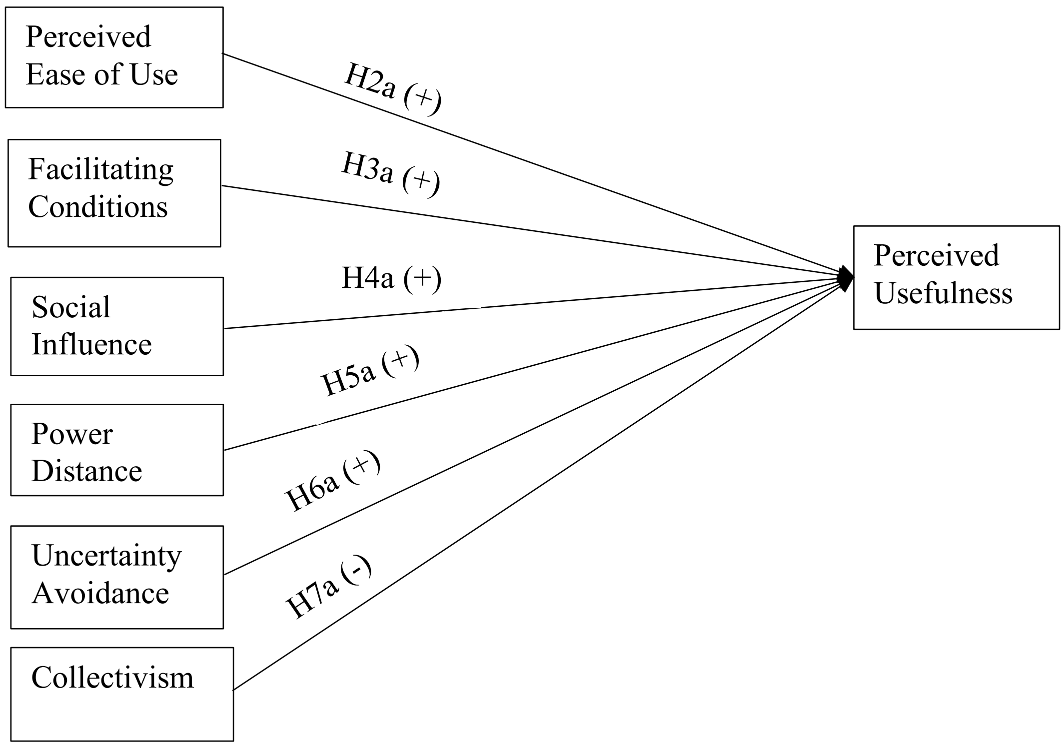


Note. Original study model was modified to exclude the masculinity construct due to lack of internal reliability and validity

Multiple Linear Regression: Direct effects on Perceived Usefulness

A multiple linear regression analysis was conducted to examine whether the independent variables, perceived ease of use, facilitating conditions, social influence, power distance, uncertainty avoidance and collectivism were influencing perceived usefulness of MOOCs for the sample.

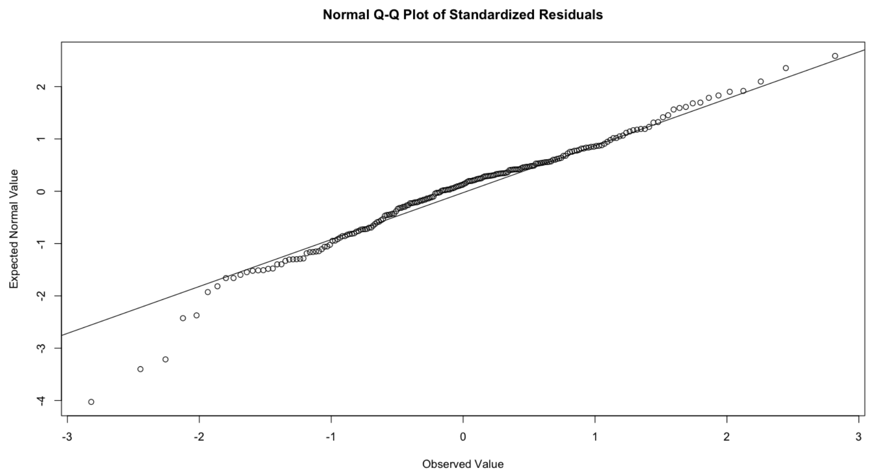
Figure 10: Hypothesized Direct Effects on Perceived Usefulness

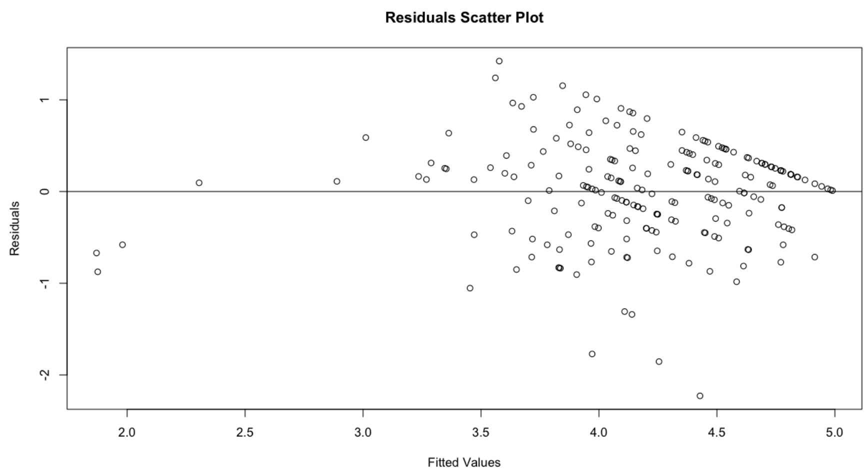


Note. Model of hypothesized direct effects on perceived usefulness of MOOCs

The standardized residuals plot and residuals scatter plot (*Figure 11*) show that the assumptions of normality, linearity and homoscedasticity were met for the multiple regression predicting perceived usefulness. Also, absence of multicollinearity was confirmed using VIF, with all the predictors having a VIF value of less than 2 (see *Table 3*6), which is well below the recommended value of 10, the assumption of multicollinearity was considered to be met for this regression model.

Figure 11: Normal Q-Q Plot and Scatter plot of Residuals for all Hypothesized Direct Effects on PU





To test the hypotheses of direct effects on the dependent variable, PU, all the hypothesized independent variables (perceived usefulness (PU), perceived ease of use (PEOU), facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL)) were included in the regression model. The result of the multiple linear regression (*Table 36*) shows that the independent variables were significantly predicting perceived usefulness, F (6, 201) = 29.58, p<.001, accounting for about 47% of the variance in the variable (R^2 = .47). The result indicates that the significant predictors of perceived usefulness in the model were, perceived ease of use (*b*=0.42, p<.001), UA (*b*=0.31, p<.001) and social influence (*b*=.008, p<.05), with perceived ease of use and uncertainty avoidance contributing the most to variance observed in perceived usefulness. This result shows that perceived ease of use, social influence and uncertainty avoidance are indeed related to the potential mediator variable, perceived usefulness, indicating that they will most likely influence the main outcome variable behavioral intention through it. This result also signifies a reasonable improvement from the result obtained from the base model that only accounted for 35% of the variance in perceived usefulness. The addition of the constructs to the model therefore significantly improved its predictive power of perceived usefulness, with most of the added effect attributed to uncertainty avoidance.

Table 36: Multiple Linear Regression with PEOU, FC, SI, UA, PD and COL predicting PU

Predictor	*b*	*SE*	*t*	*p*	VIF	Fit
(Intercept)	0.50	0.313	1.589	0.114		
Perceived Ease of Use	0.42	0.064	6.560	0.000***	1.515	
Facilitating Conditions	0.05	0.057	0.941	0.348	1.483	
Social Influence	0.08	0.038	2.096	0.037*	1.268	
Power Distance	-0.04	0.042	-0.984	0.326	1.234	
Uncertainty Avoidance	0.31	0.069	4.496	0.000***	1.486	
Collectivism	0.05	0.052	0.956	0.340	1.217	
						R^2 = .47**

(*F* (6, 201) = 29.58, p<.001**)** *Note.* *=p<.05, **=p<.01, ***=p<.001

Table 37: Results of Hypotheses of Direct Effects on PU

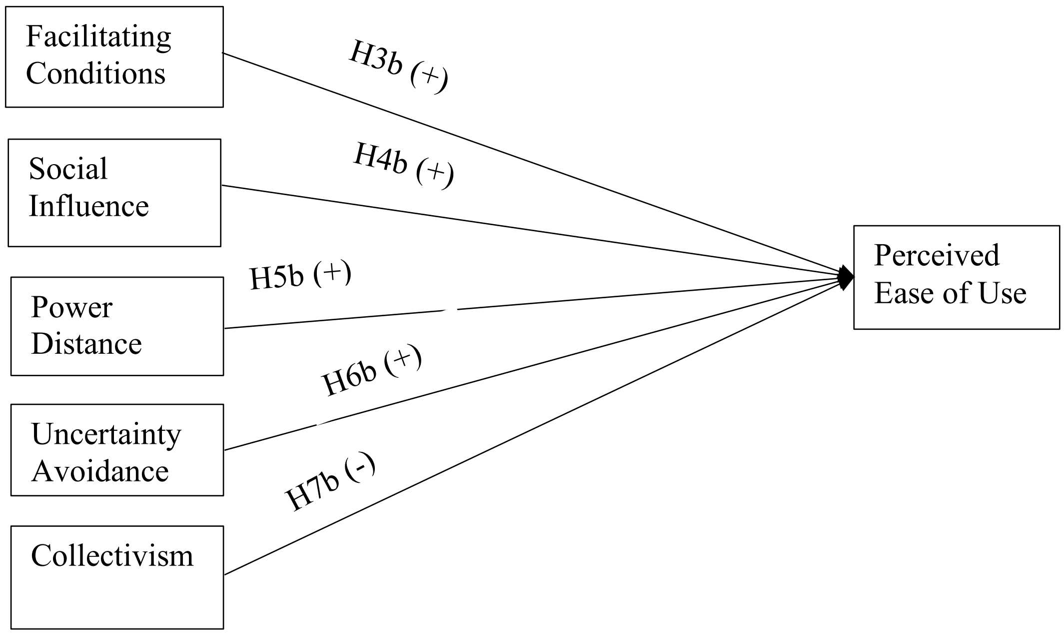
Hypothesis	Direct Effect Hypothesis	Result
H2a	PEOU → PU (+)	Supported***
H3a	FC → PU (+)	Not supported
H4a	SI → PU (+)	Supported*
H5a	PD → PU (+)	Not supported
H6a	UA → PU (+)	Supported***
H7a	COL → PU (-)	Not supported

Note. *=p<.05, **=p<.01, ***=p<.001

Multiple Linear Regression: Direct Effects on Perceived Ease of Use

A multiple regression analysis was conducted to examine how the independent variables, facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL) are influencing perceived ease of use. *Figure 12* shows the proposed direct effect model for perceived ease of use.

Figure 12: Hypotheses of Direct Effects on Perceived Ease of Use



Note. Model of hypothesized direct effects on perceived ease of use of MOOCs

The assumptions of normality, linearity, and absence of multi-collinearity assumptions were all met for the multiple regression model predicting perceived ease of use as shown in *Figure 13* and *Table 38* below.

Figure 13: Normal Q-Q Plot and Scatter plot of Residuals for all Hypothesized Direct Effects on PEOU

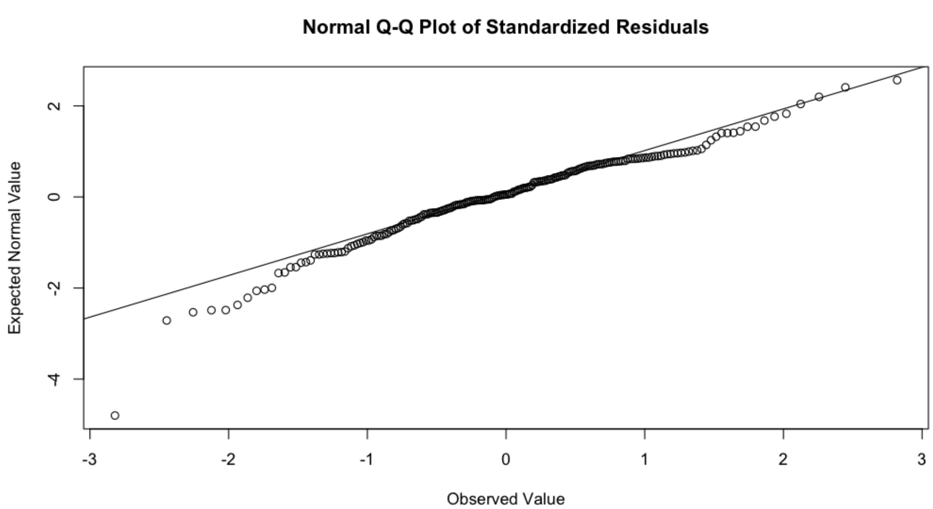
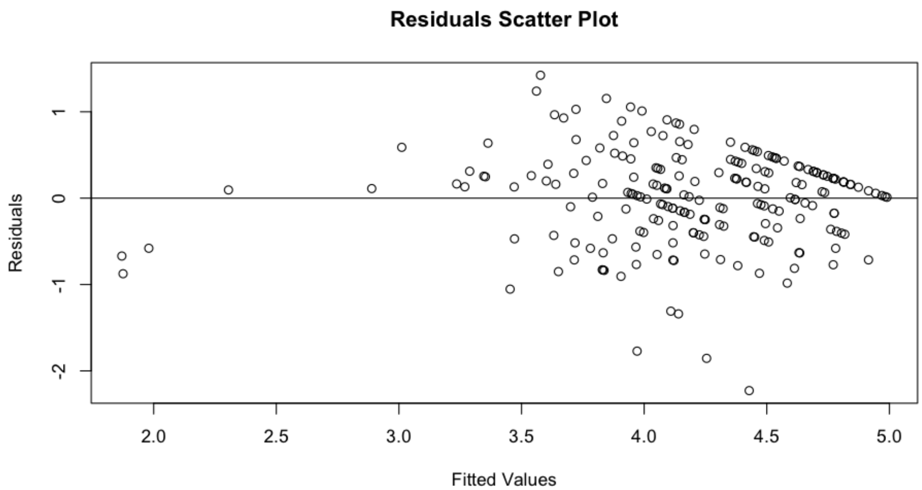


Figure 13 (cont'd)



To test the hypotheses of direct effects on the dependent variable, perceived ease of use, all the hypothesized independent variables (facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL)) were included in the regression model. The result of the multiple linear regression (*Table 38*) shows that the independent variables were significantly predicting perceived ease of use, F (5, 202) = 20.82, p<.001, accounting for about 34% of the variance in the variable (R^2 = .34). The result indicates that the significant predictors of perceived ease of use in the model were, facilitating conditions (b=0.40, p<.001) and uncertainty avoidance (b=0.26, p<.001).

Table 38: Multiple Linear Regression with FC, SI, UA, PD and COL predicting PEOU

Predictor	*b*	*SE*	*t*	*p*	VIF	Fit
(Intercept)	1.16	0.337	3.460	0.001**		
Facilitating Conditions	0.40	0.056	7.093	0.000***	1.187	
Social Influence	-0.01	0.041	-0.288	0.774	1.268	
Power Distance	0.03	0.046	0.649	0.517	1.231	
Uncertainty Avoidance	0.26	0.074	3.563	0.000***	1.399	
Collectivism	0.04	0.057	0.644	0.520	1.215	
						R^2 = .34**

(*F* (5, 202) = 20.82, p<.001**)** *Note.* *=p<.05, **=p<.01, ***=p<.001

Table 39: Results of Hypotheses of Direct Effects on PEOU

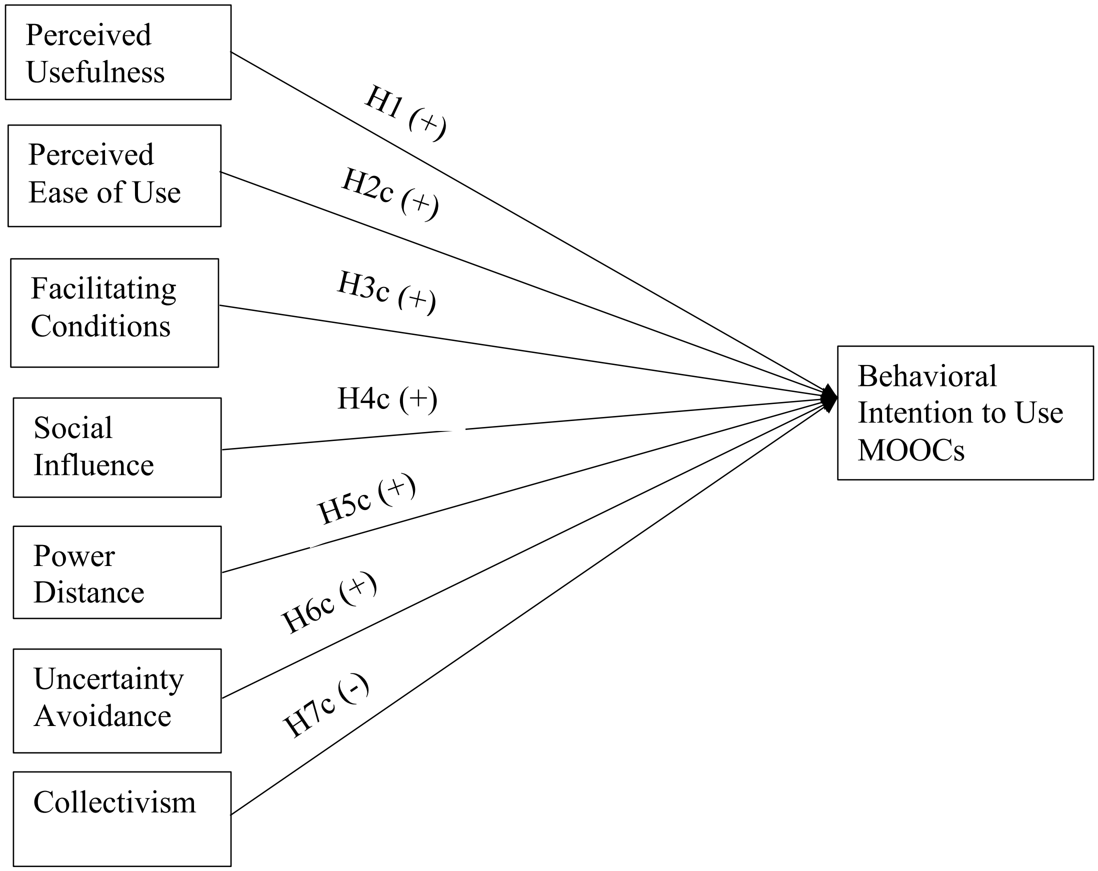
Hypothesis	Direct Effect Hypothesis	Result
H3b	FC → PEOU (+)	Supported***
H4b	SI → PEOU (+)	Not supported
H5b	PD → PEOU (+)	Not supported
H6b	UA → PEOU (+)	Supported***
H7b	COL → PEOU (-)	Not supported

Note. *=p<.05, **=p<.01, ***=p<.001

Multiple Linear Regression: Direct Effects on Behavioral Intention to Use MOOCs

A multiple regression analysis was conducted to examine how the independent variables, perceived usefulness (PU), perceived ease of use (PEOU), facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL) are influencing the main outcome variable, behavioral intention (BI). Below is a figure of the proposed direct effect model for behavioral intention to use MOOCs.

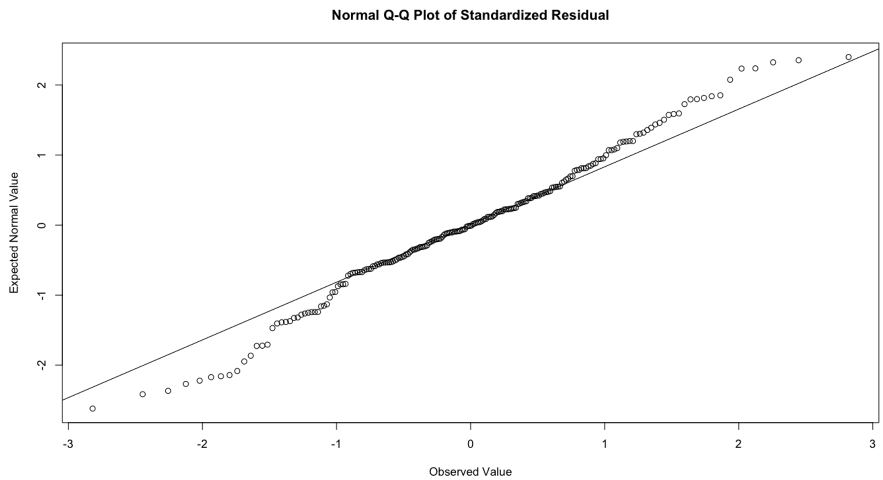
Figure 14: Hypotheses of Direct Effects on Behavioral Intention to Use MOOCs

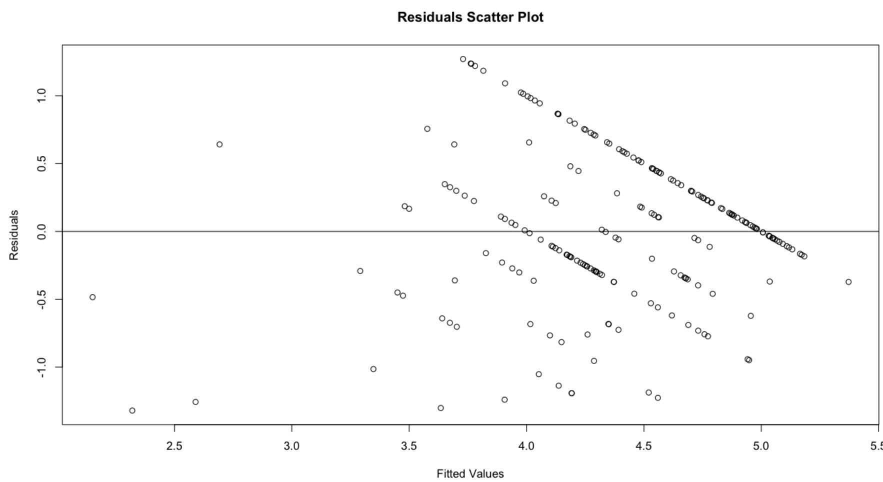


Note. Model of hypothesized direct effects on behavioral intention to use MOOCs

The residual plots in figure 15 below show that multiple linear regression assumptions have been met for predicting behavioral intention to use MOOCs within this sample. And VIF values in *Table 40* shows no signs of multicollinearity.

Figure 15: Normal Q-Q Plot and Scatter plot of Residuals for all Hypothesized Direct Effects on BI





To test the hypotheses of direct effects on the dependent variable, behavioral intention (BI), all the hypothesized independent variables (perceived usefulness (PU), perceived ease of use (PEOU), facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL)) were included in the regression model. Age, gender and user category were included as control variables. The result of the multiple linear regression (*Table 40*) shows that the independent variables were significantly predicting behavioral intention, F (10, 197) = 17.39, p<.001, accounting for about 47% of the variance in the variable

(R^2 = .47). The result indicates that the significant predictors of behavioral intention were, perceived usefulness (*b*=0.31, p<.001), facilitating conditions (*b*=0.30, p<.001), and collectivism (*b*=0.11, p<.05), with perceived usefulness and facilitating conditions contributing the most and almost equally to the variance observed in behavioral intention to use MOOCs in the data. The results show a significant improvement from the predicting power of the base model, which was found to be 33% for this study sample, indicating that including the additional determinants in TAM (especially facilitating conditions and collectivism), were beneficial in predicting behavioral intention to use MOOCs for people in this context. Unlike the base model, no direct effects were found for perceived ease of use with the added constructs. Meaning that including those constructed completely suppressed its effects. Because no direct on behavioral intention was found for perceived ease of use, it will be unable to play the role of a mediator for other variables as hypothesized.

Table 40: Multiple Linear Regression with PU, PEOU, FC, SI, UA, PD and COL predicting BI

Predictor	*b*	*SE*	*t*	*p*	VIF	Fit
(Intercept)	1.28	0.465	2.745	0.007 **		
Perceived Usefulness	0.31	0.072	4.314	0.000***	1.935	
Perceived Ease of Use	0.08	0.071	1.111	0.268	1.880	
Facilitating Conditions	0.30	0.062	4.897	0.000***	1.739	
Social Influence	0.01	0.042	0.271	0.787	1.551	
Power Distance	-0.06	0.043	-1.310	0.192	1.279	
Uncertainty Avoidance	0.03	0.074	0.447	0.656	1.692	
Collectivism	0.11	0.053	2.009	0.046*	1.265	
						R^2 = .47**

(F (10, 197) = 17.39, p<.001**)** *Note.* *=p<.05, **=p<.01, ***=p<.001

Table 41: Results of Multiple Regression Test for Direct Effects on BI

Hypotheses	Direct Effect Hypothesis	Result
H1	PU → BI (+)	Supported***
H2c	PEOU → BI (+)	Not supported
H3c	FC → BI (+)	Supported***
H4c	SI → BI (+)	Not supported
H5c	PD → BI (+)	Not supported
H6c	UA → BI (+)	Not supported
H7c	COL→ BI (-)	Not Supported (Significant*, but in the opposite direction expected)

Note. *=p<.05, **=p<.01, ***=p<.001

Path Analysis: Testing the Mediation Models (Indirect Effects)

Composite-based path modeling method was used to test the mediation models of indirect effects of the external variables on behavioral intention to use MOOCs. This approach utilizes a composite-based approach, using composite weights of variables in the structural model. This method was considered more appropriate for this study because, covariance-based structural equation modeling using latent variables are more suitable for confirming theories (Hair, Sarstedt, Hopkins & Kuppelwieser, 2014). However, this study was more explanatory, as it aimed to construct a model, by adding additional components to an existing model, rather than confirming the model. Hence, composite-based path modelling was considered more appropriate for the purpose of the study. Although the multiple regression results indicated that perceived ease of use not directly influencing behavioral intention in this study, the full model path proposed for the study was retained for the path analysis because there is enough evidence in the literature to support the relationship between perceived ease of use and behavioral intention (Abbas, 2016; Al-Adwan et al., 2013; Lee et al., 2011; Park et al., 2009; Teo, 2009; Venkatesh, 2000), hence the model may be misleading for future studies if that path is omitted. Also, there are suppression and enhancements effects that may not be detected by ordinary least squares regression but would be detected in a mediation path analysis.

The path analysis included three multiple regression models. (i) The first regression model represented the direct effects of the predictors (perceived ease of use (PEOU), facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL)) on the potential mediator, perceived usefulness (PU)). (ii) The second regression model represented the direct effects of the predictors (facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL) on the potential mediator, perceived ease of use (PEOU). (iii) The third regression model represented the direct effects of all the potential explanatory variables (perceived usefulness (PU), perceived ease of use (PEOU), facilitating conditions (FC), social influence (SI), power distance (PD), uncertainty avoidance (UA) and collectivism (COL) on the main outcome, behavioral intention (BI). Age, gender and user category (i.e., user vs. non-user grouping) were controlled for. The direct and indirect effects on the outcome variable were then specified for the path analysis based on these regression models using structural equation modeling path analysis technique.

Running the hypothesized path analysis model revealed the following fit results for the study data:

Table 42: Goodness of Fit Statistics and Indices for the Mediation Model

Fit Index	Recommended Values (Hair, 2006; Hair et al., 2010)	Result	Decision
X^2	p-value > 0.05	X^2=7.983, df=6, p=0.239 (p>.05)	Good fit
CFI	$\geq$0.90	0.994	Good fit
TLI (NNFI)	$\geq$0.95	0.973	Good fit
RMSEA	<.0.08	0.040	Good fit
SRMR	<0.008	0.016	Good fit

Note. Confirmatory Factor Index (CFI), the Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), X^2 (Chi-Square), Non-Normed Fit Index (NNFI)

The fit indices indicated that the proposed model showed a reasonably good fit: X^2 (df=6) =7.983, p=0.239; CFI= 0.994; TLI = 0.973; RMSEA=0.040; SRMR=0.016.

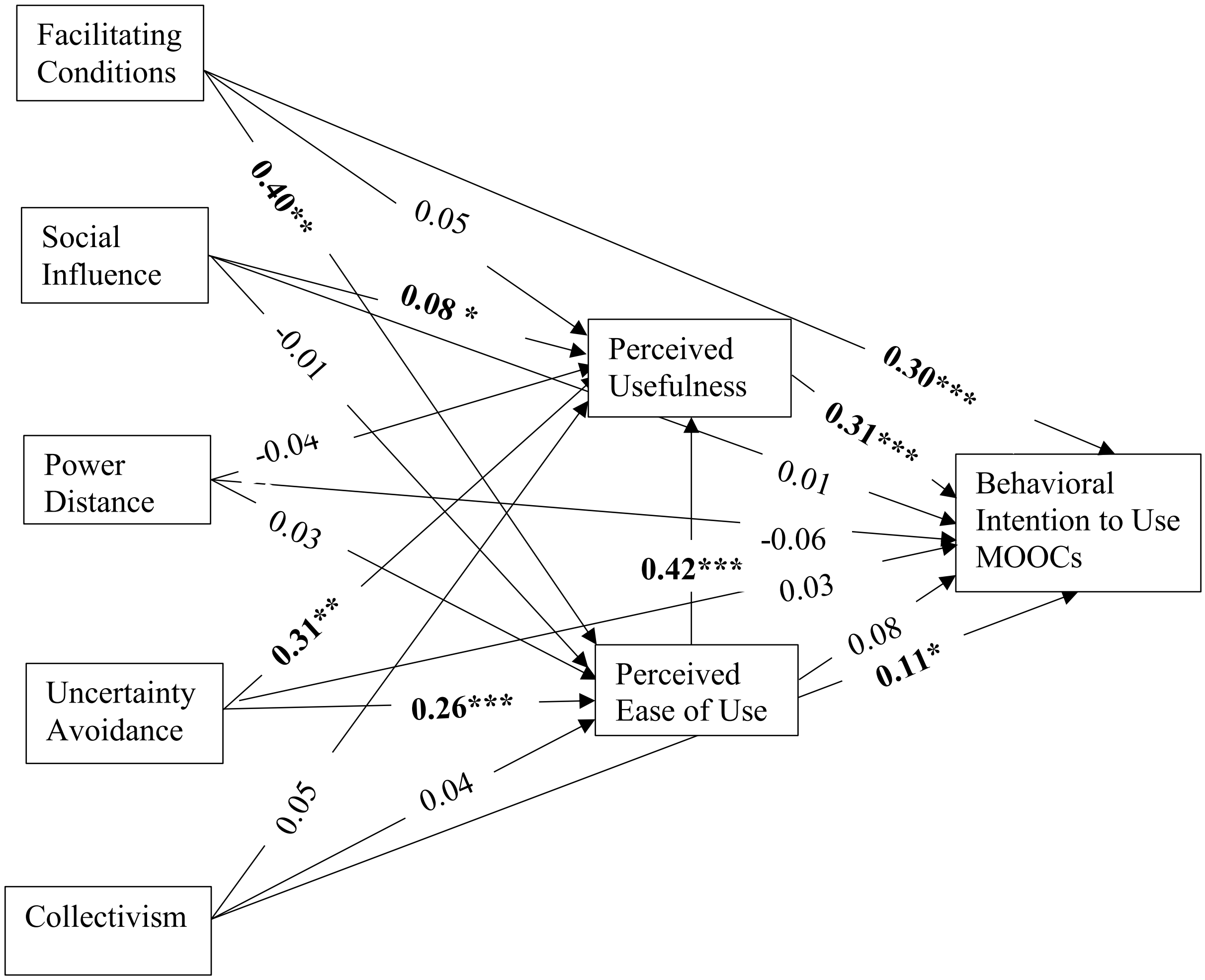
Table 43: Indirect Effects of Predictors on BI through proposed Mediators (PU and PEOU)

Hypothesis	Proposed Relationships	Mediated Effect Estimates	Result
H2d	PEOU → PU → BI (+)	*b*=0.129**; *SE*= 0.047; 95%CI: [0.056, 0.241]	Supported**
H3d	FC → PU → BI (+)	*b*=0.017; *SE*= 0.020; 95%CI: [-0.015, 0.063]	Not supported
H4d	SI → PU → BI (+)	*b*=0.025; *SE*= 0.014; 95%CI: [0.003, 0.059]	Not supported
H5d	PD → PU → BI (+)	*b*=-0.013; *SE*=0.014; 95%CI: [-0.042, 0.017]	Not supported
H6d	UA → PU → BI (+)	*b*=0.096**; *SE*= 0.032; 95%CI: [0.046, 0.178]	Supported**
H7d	COL → PU → BI (-)	*b*=0.015; *SE*=0.018; 95%CI: [-0.012, 0.063]	Not supported
H3e	FC → PEOU → BI (+)	*b*=0.032; *SE*=0.035; 95%CI: [-0.028, 0.116]	Not supported
H4e	SI → PEOU → BI (+)	*b*=-0.001; *SE*= 0.006; 95%CI: [-0.018, 0.007]	Not supported
H5e	PD → PEOU → BI (+)	*b*=0.002; *SE*= 0.006; 95%CI [-0.003, 0.028]	Not supported
H6e	UA → PEOU → BI (+)	*b*=0.021; *SE*= 0.026; 95%CI [-0.013, 0.100]	Not supported
H7e	COL → PEOU → BI (-)	*b*=0.003; *SE*= 0.008; 95%CI [-0.005, 0.0034]	Not supported

Note. *=p<.05, **=p<.01, ***=p<.001

The mediation analysis showed that perceived usefulness significantly mediated the effects of both perceived ease of use and uncertainty avoidance on behavioral intention to use MOOCs (perceived ease of use: *b*=0.129; *SE*=,0.047; 95% CI: [0.056, 0.241]; p<.001; uncertainty avoidance: *b*=0.096, *SE* = 0.032, 95% CI: [0.046, 0.178]; *p*<.01). This was a complete mediation because, no direct effects on behavioral intention were found for perceived ease of use and uncertainty avoidance in the regression models. Hence, the results of this mediation indicates that about 13% of the variance in behavioral intention to use MOOCs was accounted for by the indirect relationship it has with perceived ease of use through perceived usefulness. Specifically, there was a 0.13 increase in behavioral intention to use MOOCs, for every 0.42 unit increase in the association between perceived ease of use and perceived usefulness. Similarly, about 10% of the variance in behavioral intention to use MOOCs was accounted for by the indirect relationship it has with uncertainty avoidance through perceived usefulness. Specifically, there was a 0.10 increase in behavioral intention, for every 0.31 unit increase in the association between uncertainty avoidance and perceived usefulness. The significance of the indirect effects was tested using bootstrapping method, with 1000 bootstrapped samples, this is to ensure that we are more confident that the results obtained can be replicated.

Figure 16: Study Model with Significance Results



Note: *=p<.05, **=p<.01, ***=p<.001

Conclusion

Overall, the results indicate that the proposed model on direct relationships on behavioral intention to use MOOCs accounted for 47% (R^2=0.47) of the variance in the variable, with significant effects found for perceived usefulness, facilitating conditions and collectivism. The results therefore indicate that, the higher the perceived usefulness, facilitating conditions and collectivism-related values an individual within this sample has, the higher their behavioral intention to use MOOCs. This provides support for H1, H3a, while the result was in the opposite direction than expected for H7a. Furthermore, perceived ease of use and uncertainty avoidance had indirect effects on behavioral intention through perceived usefulness such that, part of the variance observed in behavioral intention was as a result of the positive relationships that perceived ease of use and uncertainty avoidance have with perceived usefulness. This provides support for the mediation hypotheses, H2b and H6d.

The model of direct effects on perceived usefulness was also found to be significant, with the proposed model predicting 47% of the variance in perceived usefulness in this study. Both perceived ease of use and uncertainty avoidance were found to be significantly predicting perceived usefulness, with a higher effect found for perceived ease of use. These results provided support for hypotheses H2a and H6a. Furthermore, the model of direct effects on perceived ease of use was also found to be significant, with the proposed model predicting 34% of the variance in perceived ease of use in this study. Both facilitating conditions and uncertainty avoidance were found to be significantly predicting perceived ease of use, with a higher effect found for facilitating conditions. These results provided support for hypotheses H3c and H6c.

Hence, only 9 of the hypothesized relationships were supported in this study, namely: (i) positive direct effect of perceived usefulness on behavioral intention (ii) positive indirect effect of perceived ease of use on perceived usefulness (iii) positive indirect effect of perceived ease on behavioral intention through perceived usefulness (iv) positive direct effect of facilitating conditions on behavioral intention. (v) positive indirect effect of facilitating conditions on perceived ease of use. (vi) positive direct effect of social influence on perceived usefulness. (vii) positive direct effect of uncertainty avoidance on perceived usefulness. (viii) positive direct effect of uncertainty avoidance on perceived ease of use. (ix) positive indirect effect of uncertainty on behavioral intention through perceived usefulness. Although collectivism had a direct effect on behavioral intention to use MOOCs, it was in the opposite direction expected, hence the hypothesis was not considered to be supported.

Table 44: Summary of Hypotheses and Results

Hypothesis	Result	Implication
H1: Perceived usefulness will positively influence peoples' intention to use MOOCs in Nigeria.	**Supported*** **	The more useful people consider MOOCs to be in helping them achieve their goals, the more likely they are to intend to use them.
H2a: Perceived ease of use will positively influence perceived usefulness of MOOCs in Nigeria	**Supported*** **	The easier to use people perceive MOOCs to be, the more likely they are to consider them useful in achieving their goals.
H2b: Perceived ease of use will positively influence behavioral intention to use MOOCs among people in Nigeria.	Not supported	
H2c: Perceived ease of use will have an indirect positive influence on peoples' behavioral intention to use MOOCs in Nigeria through perceived usefulness.	**Supported*** **	The easier to use people consider MOOCs to be, the more likely they are to find them useful and the more likely they to intend to use them as a result.
H3a: Facilitating conditions will positively influence perceived usefulness of MOOCs in Nigeria.	Not Supported	
H3b: Facilitating conditions will positively influence perceived ease of use of MOOCs in Nigeria	**Supported*** **	The more resources and skills to engage in MOOCs people perceive themselves have, the more likely they are to consider them easy to use.

Note. * =p<.05, **=p<.01 ***=p<.001

Table 44 (cont'd)

Hypothesis	Result	Implication
H3c: Facilitating conditions will positively influence behavioral intention to use MOOCs in Nigeria.	**Supported*** **	The more resources and skills to engage in MOOCs people perceive themselves to have, the more likely they are to intend to use them.
H3d: Facilitating conditions will have an indirect positive effect on behavioral intention to use MOOCs in Nigeria through perceived usefulness.	Not supported	
H3e: Facilitating conditions will have an indirect positive effect on behavioral intention to use MOOCs in Nigeria through perceived ease of use.	Not supported	
H4a: Social influence will positively influence perceived usefulness of MOOCs in Nigeria.	**Supported***	People who believe those close to them want them to use MOOCs are more likely to perceive MOOCs as being useful in helping them achieve their goals.
H4b: Social influence will positively influence perceived ease of use of MOOCs in Nigeria	Not supported	
H4c: Social influence will positively influence behavioral intention to use MOOCs in Nigeria.	Not supported	
H4d: Social influence will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived usefulness.	Not supported	

Note. * =p<.05, **=p<.01 ***=p<.001

Table 44 (cont'd)

Hypothesis	Result	Implication
H4e: Social influence will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived ease of use.	Not supported	
H5a: Power distance will positively influence perceived usefulness of MOOCs in Nigeria.	Not supported	
H5b: Power distance will positively influence perceived ease of use of MOOCs in Nigeria	Not supported	
H5c: Power distance will positively influence behavioral intention to use MOOCs in Nigeria.	Not supported	
H5d: Power distance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived usefulness.	Not supported	
H5e: Power distance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived ease of use.	Not supported	
H6a: Uncertainty avoidance will positively influence perceived usefulness of MOOCs in Nigeria.	**Supported*** **	Those that prefer a well-structured type of learning are more likely to consider MOOCs useful.
H6b: Uncertainty avoidance will positively influence perceived ease of use of MOOCs in Nigeria	**Supported*** **	Those that prefer a well-structured type of learning are more likely to consider MOOCs easy to use.
H6c: Uncertainty avoidance will positively influence behavioral intention to use MOOCs in Nigeria.	Not supported	

Note. * =p<.05, **=p<.01 ***=p<.001

Table 44 (cont'd)

Hypothesis	Result	Implication
H6d: Uncertainty avoidance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived usefulness.	**Supported****	Those that prefer a well-structured type of learning are more likely to consider MOOCs useful and are more likely to intend to use them as a result.
H6e: Uncertainty avoidance will have an indirect positive effect on intention to use MOOCs in Nigeria through perceived ease of use.	Not supported	
H7a: Collectivism will negatively influence perceived usefulness of MOOCs in Nigeria.	Not supported	
H7b: Collectivism will negatively influence perceived ease of use of MOOCs in Nigeria.	Not supported	
H7c: Collectivism will negatively influence behavioral intention to use MOOCs in Nigeria.	Not supported (**Significant***, but in the opposite direction expected)	Those that prefer working as part of a group rather than individually are more likely to intend to use MOOCs.
H7d: Collectivism will have an indirect negative effect on intention to use MOOCs in Nigeria through perceived usefulness.	Not supported	
H7e: Collectivism will have an indirect negative effect on intention to use MOOCs in Nigeria through perceived ease of use.	Not supported	

Note. * =p<.05, **=p<.01 ***=p<.001

CHAPTER 6: DISCUSSION

Overview

This chapter discusses in more depth, the findings from this study, comparing them to already existing findings in the literature. This section consists of two parts, the first part was used to discuss the findings from the descriptive part of the study, allowing for user personas to be developed for the sample. The second part analyzes the findings based on the hypotheses and research questions proposed for the study.

Participant Personas

Personas are fictional characters meant to represent typical characteristics of a potential user group (LeRouge, Ma, Sneha, & Tolle, 2013). They represent conceptual models of the targeted user group, which are essential in determining if products or designs will be capable of meeting the needs of the intended users (LeRouge, Ma, Sneha, & Tolle, 2013). It has also been argued that personas can amplify the effectiveness of the other methods used in understanding a particular population (Pruitt & Grudin, 2003). Hence, they were included in this study to determine how they can help in providing a better understanding or overview of the sample population, what challenges they face and what they need to ensure efficient participation in MOOCs if they choose to.

From the descriptive statistics, it was observed that participants in this sample were more likely to be between the ages of 18 – 25, with almost an equal split between males and females. A high percentage of the participants already have a bachelor's degree, but are unemployed. Furthermore, in terms of devices, participants were more likely to own Smartphones than any other technological device. Laptops were the second highest owned devices, although at a much lower percentage than smartphones. Also, the primary means of internet access for the participants were their Smartphones, connected through mobile broadband internet. These agree with previous findings that mobile broadband represents the primary means of internet access for most people in developing countries (Ericsson, 2015).

It was also found that the two most common reasons for accessing the internet among participants were for learning (e.g., reading scholarly materials, watching educational videos etc.) and social media. They also are frequent online visitors, typically going online multiple times a day. However, they mostly described the efficiency of their internet access as moderate, although some people also indicated having very efficient internet access. This supports previous finding that identified poor internet connectivity as a major challenge facing technology adoption in Nigeria (Adebo and Ailobhio, 2017). Participants were split on the issue of cost efficiency of their internet use, with almost half of them indicating that the cost associated with their internet use was not efficient, while others considerate it moderate to very efficient. This indicates that, while cost may be an issue for some, it may not be for others. However, previous studies have cited high cost of internet as a barrier to technology adoption in Nigeria (Muhammad, Mustapha and Haruna, 2016)

Also, participants in this sample were more likely to indicate that they have experience using the internet to learn. This is important as being able to engage in online learning is the basis for MOOCs. Also, in addition to being comfortable learning online, participants were more likely to have a high confidence in their ability to use the internet and on their overall ability to learn online. This shows that learning in MOOCs may not be such a difficult task for participants within this sample. Furthermore, there was a consensus about the available power supply being unreliable or only moderately reliable. This represents a barrier for MOOC adoption in this context because, reliable power supply is essential for technological devices to function. This result was consistent with previous studies that report unreliable power supply as a major barrier to technology adoption in Nigeria (Ekundayo & Ekundayo, 2009; Adebo and Ailobhio, 2017; Muhammad, Mustapha and Haruna, 2016). Many of the participants however have access to alternative power supply, which is beneficial and encouraging for MOOCs use within this context, although access to such alternative power supply can be straining in terms of additional costs associated with their use, e.g., petrol for generators, etc.

Participant profiles for both users and non-users were very similar to that observed for the overall sample, although some subtle differences were found. For instance, it was found that a higher percentage of users were men who had employment, while non-users consisted more of women without employment. These findings coincide with previous findings in developed country populations that found that MOOC users are typically educated, male and employed individuals (Christensen et al., 2013).

Also, users had a slightly higher chance of owning a laptop device than non-users, while non-users had a higher percentage of accessing the internet for social media reasons than users. Owning a laptop may be more beneficial for MOOCs use because it may be essentially harder to perform an intensive task such as online learning using a phone than with a laptop. This in support of previous studies that found lack of resources as a major issue impeding MOOC use in developing countries. For instance, in their study exploring MOOC awareness and adoption by Nigerian students, Adebo and Ailobhio (2017) found that, the most selected reason among students for not participating in e-learning in Nigeria was lack of access to a personal computer, a device they often associate with learning. Additionally, an interesting finding by Garrido et al. (2016) indicated that the device used in accessing MOOCs can influence participation and completion for developing country participants. Specifically, they found that the use of mobile phones as the main device for accessing the internet was prohibitive for user's MOOC progress in South Africa and the Philippines. Specifically, their findings indicated that among the users surveyed, the higher the use of a laptop or desktop as the main device for accessing the internet, rather than a mobile phone, the higher the rate of completion and certification Garrido et al., 2016, p.28). This is a very important finding that may likely translate to the Nigerian context, given that majority of internet access occurring in Nigeria is through mobile phones (ITU, 2018; Muhammad et al., 2016). And since fixed broadband is a far-fetched goal in this context, innovative ways of exploiting mobile broadband for MOOC purposes needs to be explored for benefits due to them to be achieved. This can mean utilizing Smartphones as hotspots for laptops, or MOOC providers making it possible for their content to be downloaded on mobile phones for easy transfer onto laptops or desktops for offline use.

Overall, the results of the descriptive statistics show that, participants have reasonable skills and resources to learn online through MOOCs, although issues related to cost of accessing the internet, internet efficiency, power supply reliability and less access to a laptop and not accessing the internet through them were reported. Furthermore, the result from the t-test confirmed that facilitating conditions and social influence may be very important factors for people in this context to use MOOCs, as users had a statistically significantly higher facilitating conditions level than non-users, and non-users had a statistically significantly higher social influence level than non-users. This indicates that there is a likelihood that providing people with the necessary facilitating conditions may be associated with usage and that there is a need to explore how social influence can be exploited to increase chances of use.

Further descriptive statistics involving only users, that sought to understand their level of experience and motivation for using MOOCs indicated that, many of them access MOOCs mostly for personal gain or interests, while a majority of them use MOOCs to either prepare or venture into a new or future career or support their educational goals. This is in support of previous studies that found that those in developing countries are more invested in job-related benefits when it comes to MOOCs, with this representing a major motivation for them to participate. For instance, Aboshady, Radwan, Eltaweel, Azzam, Aboelnaga et al. (2015) found that medical students in Egypt who saw MOOCs as providing opportunity for future job purposes were more likely to complete the courses. Garrido et al. (2016) also found that for MOOC users in South Africa, Philippines and Colombia, gaining specific job skills was their major motivation, with other important motivations including finding a new job, preparing for additional education and obtaining professional certification. Furthermore, Alcorn, Christensen and Kapur (2015) suggests that, in India, the primary objective of MOOC students is to develop current or future job skills, as a result, students are less willing to participate in MOOCs that are unable to establish a link from gaining knowledge to employment. This has caused MOOC providers targeting the Indian market to work more to validate their course certificates with leading firms in the country, in efforts to appeal more to the population (Anders, 2015).

Specific to Nigeria, a study investigating the interest, awareness and enrolment in MOOCs among postgraduate students in a Nigerian University found that majority of the respondents indicated employment or job-related advancement opportunities as their main rationale for enrolling in MOOCs (Stepehen & Molara, 2017). Similarly, Muhammad et al.(2016) also reported employment related motivations for MOOC participation for another set of Nigerian University students and specifically found that non-recognition of MOOC certificate by employers was considered a main barrier to using MOOCs among participants. These developing country outcomes is in contrast with results from developing countries like the US where taking courses for educational achievement or job related gains are not the primary purposes of learning with MOOCs among that population (Christensen, Steinmetz, Alcorn, Bennet, Wood et al., 2013). For instance, in a survey of 32 MOOCs offered by the University of Pennsylvania, it was found that more than half of the US respondents took MOOCs out of curiosity or fun (Li, 2017), while Stich and Reeves (2017) found that educational achievement in MOOCs does not represent a motivation for MOOC participants in the US, as fun purposes seem to be the primary motivation. This trend has been considered to be because students in developed countries have “the least opportunity cost in taking MOOCs” given that a huge amount of the population are already well educated and in employment when compared to those in developing countries (Li, 2017 p.133).

Additionally, majority of participants in the user group for this study have only been using MOOCs for about a year or less, but however tend to use them often for learning. Furthermore, many of them have only taken 1 or 2 MOOC classes in total, although a good number of them have taken 3 or more classes in total. This indicates that MOOC usage level is still at the rudimentary stage for even for learners indicate to be users. Also, many of users have not completed a MOOC before or earned a MOOC certificate, indicating that they are likely not motivated enough to participate at that level, especially since previous studies have found that when adequately motivated, developing country students are more likely to complete MOOC courses and earn certificates in comparison to their developed country counterparts (Nesterko et al., 2013; Garrido et al., 2016). For instance, a study found that despite making up 42.3% of the MOOC population for a course, only 3.7% of US students earned a completion certificate, while Nigerians making up 2.1% of the course participants had a 5% completion rate. Similar rates of certificate achievement relative to the number of registrants were recorded for other developing countries in the study, suggesting they tend to persist in MOOCs more than their developed country counterparts when motivated (Nesterko et al., 2013).

The low completion rates in developed countries such as the US has been widely reported, and many have associated it with the motivation these users have in partaking in MOOCs, which has mostly been identified as just for curiosity or fun, while the higher completion rates among developing country participants have been associated with their motivation of potential tangible educational or job-related achievements (Christensen et al., 2013; Garrido et al., 2016; Li, 2017; Khalil & Ebner, 2013). These studies clearly show that students in a developing country such as Nigeria will be more motivated to participate and complete MOOCs if they offer tangible employment related benefits. Hence there is a need for more focus to be placed on making MOOCs in this context more specific to labor market related skills to engender such participation. Perhaps if MOOCs become more tailored to the Nigerian job market, we can have more population motivated to participate in MOOCs. For instance, it has been found that MOOC providers targeting the Indian market engage in efforts to validate their course certificates with leading firms in the country, in order to appeal more to the population (Anders, 2015). Consequently, a few studies have shown MOOC participation to be higher in India than many other countries, as it continues to rank among the top 3 MOOC using country in the world (Li, 2017; Nesterko et al., 2013; Bayeck, 2016).

Finally, with regards to preferred MOOCs platforms, participants in this study were more likely to use Coursera than any other platform. Other platforms used include, edX, Udacity and Plural Sight. Users also preferred to access MOOCs from home and often used their Smartphones for accessing MOOCs than any other device.

Based on these findings, personas were created for typical target MOOC users within this context.

Figure 17: Primary Persona for Target MOOC Users

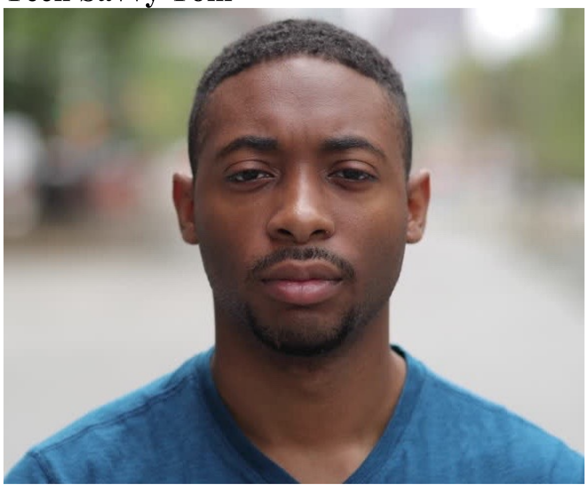
Tech Savvy Tom	**Behaviors**
 **Age**: 23 **Gender:** Male **Location**: Lagos, Nigeria **Life Stage**: Single, just finished college with a BSc. in Computer Science. **Occupation**: Currently employed in an entry level role	• Owns both a Smartphone and a laptop, but prefers to access the internet using his phone • Likes to go online to read scholarly materials, watch educational videos and take online classes when possible • Uses social media occasionally • Is frequently online, typically accessing the internet multiple times a day for different purposes • Very tech savvy, not requiring any help with using the internet or learning online. • Is currently taking online classes to enhance his personal knowledge in his field of interest
Pain Points • Wants an easier way of accessing useful online learning resources to help him develop his personal knowledge in his area of interest • Would prefer to learn online using his laptop, but accessing the internet through his phone is easier • Available internet access is not always reliable, making it difficult to use it efficiently for the purposes he needs it for. • Cost associated with internet access poses a burden on him financially • Available power supply is typically unreliable, making it essential to rely on alternative means, which can get expensive.	**Needs** • A platform with well-structured learning materials, goals and instructions and that has tangible learning-related benefits • Online learning content that is optimized for Smartphones • Freely available internet access in public spaces or more affordable mobile internet access • Learning resources that can be assessed offline or on a low bandwidth network • Cheaper access to alternative power supply

Figure 18: Secondary Persona for Target MOOC Users

<table>
<tr>
<td>
Social Stacy

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Age: 22
Gender: Female
Location: Enugu, Nigeria
Life Stage: Recently graduated from college with a degree in Economics
Occupation: Unemployed
</td>
<td>
Behaviors

Only owns a Smartphone, which is her primary means of accessing the internet.
Enjoys being online and requires no assistance using the internet for her needs.
Splits her time between being on social media and reading or watching educational materials online.
Is more likely to learn online with her friends

</td>
</tr>
<tr>
<td>
Pain Points

Is currently try to go into a new career different from her degree
Would like the opportunity to learn with others as group
Considers the cost associated with her internet access a huge burden, especially since she is unemployed
Her mobile internet is not very efficient for the tasks she like to perform.
She has to rely on alternative power supply most times to power her devices, which is not economical

</td>
<td>
Needs

Needs useful learning resources to help her prepare towards a new career
A learning platform with tangible career-related value
A learning platform that encourages learning with others or more interactivity
Online resources that can be accessed over a low bandwidth network
More affordable internet access means
More reliable power supply

</td>
</tr>
</table>

Levels and Differences in Participant Perceptions and Cultural Beliefs

Findings from this study reveal that in general, participants within the sample believe that MOOCs would be a very useful tool in helping them accomplish their educational and/or job-related goals and also perceive them as being easy to use. They also tended to have sufficient resources and skills required to participate in MOOCs and are somewhat more likely to be influenced by their peers and those close to them. Furthermore, participants showed low levels of power distance, indicating that they believe teachers should relate closely with students, seeking and respecting their opinions and delegating important decisions to them. This contradicts the suggestion that people in developing countries such as Nigeria typically have high levels of power distance values (Hofstede, 2011). Participants however displayed high uncertainty avoidance levels, indicating that they prefer standardized methods of teaching and learning, where instructions are clearly set about student expectations (Srite & Karahanna, 2006). This supports the suggestion that people in developing countries tend to show higher uncertainty avoidance levels (Hofstede, 2011). Furthermore, the participants generally also had higher collectivism levels, indicating that they may typically have higher preference for working with others as part of a group than perform tasks individually (Srite & Karahanna, 2006). This supports the suggestion that those in developing countries are more likely to hold more collectivist than individualistic values (Hofstede, 2011).

While comparing level of beliefs for users and non-users, the findings show that although individuals in both samples tend to perceive MOOCs as useful and easy to use at similar levels, MOOC users had higher facilitating conditions to participate in MOOCs than non-users. That is, they are more likely to have more resources and knowledge required to participate in MOOCs than non-users. Having lesser adequate resources and skills required to participate in MOOCs may be a discouraging factor for non-users. Such factors can include, not having access to the right devices, not having reliable internet access, among others. Promoting access to such resources can increase how prepared they believe they are to participate in MOOCs. Non-users on the other hand are more likely to be influenced by their peers or those close to them with regards to their decision to use MOOCs. This indicates that, non-users tend to value the opinion of others more in terms of their decision making and would most likely value being encouraged by their family or friends to participate in MOOCs. Furthermore, finding no statistically significant differences for the cultural values espoused by the individuals within each sample indicate that, both users and non-users have similar cultural beliefs in terms of power distance uncertainty avoidance and collectivism, which in this case were, low power distance, high uncertainty avoidance and high collectivism.

The Extended TAM Model of Behavioral Intention to Use MOOCs

The following section will discuss the results from the hypotheses proposed for the study. The effects of the predictors on the outcome variables were discussed in more depth. Specifically, this section discusses, (i) the directs effects observed for the predictors, perceived ease of use, facilitating conditions, social influence, power distance, uncertainty avoidance and collectivism on perceived usefulness of MOOCs, (ii) the directs effects observed for the predictors, facilitating conditions, social influence, power distance, uncertainty avoidance and collectivism on perceived ease of use of MOOCs, (iii) the direct effects observed for the predictors, perceived usefulness, perceived ease of use, facilitating conditions, social influence, power distance, uncertainty avoidance and collectivism on behavioral intention to use MOOCs, (iv) the indirect effect of perceived ease of use on behavioral intention to use MOOCs through perceived usefulness, and (v) the indirect effects of facilitating conditions, social influence, power distance, uncertainty avoidance and collectivism on behavioral intention to use MOOCs through perceived usefulness and perceived ease of use.

Determinants of Perceived Usefulness of MOOCs

It was hypothesized that perceived ease of use, facilitating conditions, power distance, uncertainty avoidance and collectivism will all have direct effects on peoples' usefulness perceptions of MOOCs within the context of study. However, this relationship was only found to be true for perceived ease of use, uncertainty avoidance and social influence, although the effect found for social influence on perceived usefulness was significantly weaker than for the other two variables. The results therefore indicate that the more people in this context perceive that MOOCs will be free of effort to use, the more likely they are to consider them useful. And the more they indicate being risk-averse to learning situations that are not very detailed and well-structured, the more likely they are to consider MOOCs useful. Also, they are more likely to consider MOOCs useful as a result of influence from their peers or people important to them.

The relationship found between perceived usefulness and perceived ease of use is consistent with previous studies in online learning that show perceived usefulness to be a very strong predictor of how useful people consider an e-learning system to be (Tarhini et al., 2014; Al-Adwan et al., 2013; Lee et al., 2011; Park et al., 2009; Teo, 2009). On the other hand, the relationship between uncertainty avoidance and perceived usefulness is inconsistent with previous findings that argue for a negative relationship with the premise that people with high uncertainty avoidance are more likely to avoid ambiguous and unstructured situations, characteristics which are often associated with the use of technology (Hwang & Lee, 2012; Lee, Trimi & Kim, 2013). For instance, a direct negative effect of uncertainty avoidance on self-directed use of technology for language learning was found by Lai et al. (2016). This outcome was understandable because it is difficult for one to design their own learning goals and to venture into all the intricacies involved in finding useful resources to achieve those goals. However, due to the more structured nature of MOOCs, this study argued for the opposite outcome, because although the learning is informal, it is less self-directed, as students enroll in MOOCs like they do in actual formal classes, and instructions and expectations of the class are well spelt out for them. Furthermore, although social influence positively influenced perceived usefulness, the effect was relatively weak compared to perceived ease of use and uncertainty avoidance. However, this positive relationship provides support for previous studies that found a direct positive effect of social influence on perceived usefulness (Chen & Aklikokou 2019; Teo, 2011a, Teo, 2011b, Adbullah & Ward, 2016). The result indicates that, people within this context are more likely to consider MOOCs useful as a result of influence or encouragement from their peers, close contacts or those who have authority over them.

From these results, it can be concluded that, if value is to be seen in MOOCs among people within the context of study, it is important for them to be as easy to use as possible, because if they perceive that participating in MOOCs will require so much effort than they are willing to offer, then they may consider them as not being a very useful tool to aid them accomplish their goals. Also, unlike previous studies that expect a negative relationship between uncertainty avoidance and intention to use a technology, the characteristic of learning in MOOCs being similarly structured to traditional learning environments is beneficial for those with low-risk tolerance. Hence, maintaining this structure, and perhaps improving on MOOCs to be even more detailed and straightforward with their learning content and expectations can make those with a higher uncertainty avoidance consider them more useful. Furthermore, since there is evidence from this study to suggest that with higher social influence comes higher usefulness perceptions, it may be beneficial to determine how to involve those who already have experience with MOOCs or employers to educate target users about MOOCs and their potential benefits, as such interaction will likely increase usefulness perceptions of MOOCs among them.

Determinants of Perceived Ease of Use of MOOCs

It was hypothesized that facilitating conditions, power distance, uncertainty avoidance and collectivism will all have direct effects on peoples' perceived ease of use of MOOCs within the context of study. However, this relationship was only found to be true for facilitating conditions and uncertainty avoidance. The results therefore indicate that the more people in this context have adequate resources and skills to be able to participate in MOOCs, the more likely they are to consider them easy to use. And the more they indicate being risk-averse to learning situations that are not very detailed and structured, the more likely they are to consider MOOCs easy to use.

The relationship found between perceived ease of use and facilitating conditions is consistent with previous studies in online learning that found facilitating conditions to be a very strong predictor of perceived ease of use (Chen & Aklikokou 2019; Teo, 2011; Althunibat, 2015). Although studies examining the relationship between uncertainty avoidance and perceived ease of use are lacking, an overall negative relationship is typically expected between uncertainty avoidance and people's intention to use a system (Hwang & Lee, 2012; Lee, Trimi & Kim, 2013), so it may be expected to negatively perceived ease of use as well such that those who are more risk averse will be more likely to attach high effort to the use of a system. However, this study argues that this may not be the case for MOOCs given their more structured approach that reduces the risk associated with the level of effort required in more self-directed online learning situations. Uncertainty avoidance significantly predicted perceived ease of use of MOOCs, thereby confirming the positive relationship expected for this study.

From these results, it can be concluded that, if MOOCs are to be considered to be free of effort among people within the context of study, it is important that the facilitating conditions required for such use be made available to them. Knowing that they have the appropriate resources and skills required can potentially enhance their ease of use perceptions which can in turn influence their perceived usefulness and intention to use the platform. Also, unlike would be expected in general technology use, it was found that those who are more risk averse are more likely to find MOOCs easy to use, perhaps because of the well-structured nature of the learning on the platform that eliminates ambiguities associated with more informal self-direct online learning. Hence, continuing to ensure that classes are well structured and easy to follow, and perhaps improving on MOOCs to be even more detailed and straightforward with its learning content and expectations, will make those with a higher uncertainty avoidance to consider them easier to use in achieving their goals.

Determinants of Behavioral Intention to Use MOOCs

Direct Determinants of Behavioral Intention to Use MOOCs

It was hypothesized that perceived usefulness, perceived ease of use, facilitating conditions, power distance, uncertainty avoidance and collectivism will have direct effects on behavioral intention to use MOOCs for people in this study. However, direct effects on behavioral intention were only found for perceived usefulness, facilitating conditions and collectivism for the proposed model. No significant effects on behavioral intention were found for perceived ease of use, social influence, power distance, uncertainty avoidance and collectivism.

The relationship found between perceived usefulness and behavioral intention to use MOOCs is very consistent with previous studies in online learning adoption that have found perceived usefulness to be the strongest predictor of behavioral intention (Teo, 2010; Park et al., 2009; Aharony & Bar-Ilan, 2016; Chu, Ma, Feng & Lai, 2015; Al-Adwan, Al-Adwan, & Smedley 2013; Lee et al., 2009; Mohammadi, 2015; Miller & Khera, 2010). The hypothesis was strongly supported as perceived usefulness was found to be the highest contributor to people's intention to use MOOCs in the study. This indicates that people are more likely to intend to use MOOCs within this context if they find that it will be useful for them in achieving their goals. It specifically provides support for previous studies that argue that people will be motivated to use MOOCs if they find that it will be useful for them in achieving their academic related (Brasher et al., 2016; Christensen et al., 2014; Greene et al., 2015; Huang & Hew, 2017; Khalil & Ebner, 2014; Kizilcec et al., 2013; Nesterko et al., 2013; Stich & Reeves, 2017) and job-related goals (Aboshady et al., 2015; Alcorn et al., 2015; Christensen et al., 2014; Garrido et al., 2016; Khalil & Ebner, 2014; Orolade & Oyewusi, 2017).

Furthermore, the relationship found between facilitating conditions and behavioral intention to use MOOCs is consistent with previous studies in online learning adoption that have found that facilitating conditions positively influenced people's intention to use such systems, especially in developing country contexts (Nordin *et.al,* 2016; Kang *et. al.* (2015; Mtebe & Raisamo, 2014). The hypothesis was strongly supported as facilitating conditions was found to have almost as strong of an effect as perceived usefulness on peoples' intention to use MOOCs in this study. This indicates that people are more likely to be motivated to use MOOCs within this context if they have the resources and skills required to do so. This finding is particularly important especially in a low resource country like Nigeria, as it means that, when people are provided with adequate technological resources required, like reliable internet, devices, and power supply, they will be more motivated to use a learning technology like MOOCs.

Additionally, a negative relationship was expected between collectivism and behavioral intention to use MOOCs in the study because, MOOCs are inherently individualistic, as learning occurring on MOOC platforms tend to be isolated and lacking in the level of interaction available in more traditional learning environments. Hence, it was expected that those who tend to prefer acting as members of a group may be less likely to adopt MOOCs. This hypothesis was not supported, however, a significant effect in the opposite direction was found. That is, individuals who showed higher collectivist values in the sample were more likely to have a higher intention to use MOOCs. This result may be due to the fact that higher collectivist people are more likely to stick to the norm and adopt a technology, as suggested by Lai et al., (2019) in their study that found that collectivism positively predicted technology use. Or it may be that people in this context generally take or want to take MOOCs as a group, or believe they would be active participants in the interactive components of MOOCs (e.g., discussion forums), or are more willing to go the extra length to associate with their classmates while on the platform. For instance, Thompson & Ku (2006) found in their qualitative study about student's experiences and attitudes towards online learning that, students identified easy resource sharing, convenience of discussion boards and record keeping as features they valued the most about online learning. Although the specific reason behind this finding may not be explained by this study, it is important to understand how to make MOOCs attractive to such a group by appealing to their need of wanting to associate and work with others . Either way, the results indicate that, if MOOCs are to be appreciated, valued and potentially used by those that hold collectivist values within this context, it may be beneficial to appeal to those values by creating avenues for the courses to be more interactive and to support more socially receptive or group-based learning.

Also, although previous research supports the hypothesis that the easier to use people perceive a system to be, the more likely they are to use it (Davis, 1989; Lee et al., 2009; Miller & Khera, 2010; Venkatesh, 2000, Teo, 2010), this relationship was not found to be existent in the presence of other additional constructs included in the study. This supports other studies that found no direct relationship between perceived ease of use and behavioral intention to use online learning (Park *et al.,* 2009, Abbas, 2016; Chu et al., 2015; Mohammadi, 2015). This indicates that, within this context, the other predicting factors are more important than perceived ease of use with regards to directly predicting peoples' intention to use MOOCs. Also, social influence failed to directly predict intention in this study, which is inconsistent with previous findings that found a direct positive relationship between social influence and intention to use e-learning (Nordin *et. al.,* 2016; Mtebe & Raisamo, 2014; Teo, 2011a, Teo, 2011b, Adbullah & Ward, 2016). This indicates that influence of peers, close contacts or those in authority may be not a strong motivator for people to want to use MOOCs within this context, regardless of the fact that it may have some influence on their usefulness perceptions of MOOCs as mentioned earlier.

Furthermore, although a direct positive effect of power distance on behavioral intention was proposed for this study as it was expected that, the teacher-led approach adopted by MOOCs (where most of the decisions regarding the class and the learning content practically lie on the teacher, and enrolled students typically go along with how the class is structured, with little to no interaction or communication occurring between them and the teacher), may be more appealing to those with high power distance levels. This is because they may be more likely to believe that their only job as a student is to learn from the teacher and not offer any contribution to the class.

This hypothesis was however not supported, indicating that power distance did not influence peoples' intention to adopt MOOCs. Although the fact that many of the participants generally had low levels of power distance may have led to the results obtained. More research needs to be done to understand the extent of this relationship. Finally, a direct positive relationship between uncertainty avoidance and behavioral intention to use MOOCs was proposed for this study because it was expected that those who prefer less ambiguous, more structured learning environments may prefer to use MOOCs for their informal learning needs, due to their more structured approach that closely mirror more traditional forms of learning, where students know what is expected of them and instructions and guidelines for partaking in the class is provided. This hypothesis was however not supported, as no direct effect on behavioral intention to use MOOCs was found for uncertainty avoidance.

Overall, the results of the direct effects indicate that, the most important factors directly contributing to people's intention to use MOOCs within this context were perceived usefulness, facilitating conditions and collectivism. Hence, with regards to this context, more focus may need to be placed on these factors and how they can be explored and used as a means to increase intention to use MOOCs among people. First, there may be need to clearly establish the value that using MOOCs is likely to provide for them, both academically and career-wise. Perhaps, intentionally and strategically creating a path from MOOC learning and certification to higher learning institutions and hiring companies can improve MOOC use intention among this population. Also, given that this is a developing country, with different environmental-related barriers to technology use, providing adequate resources and skills required to participate in MOOCs is essential for its adoption within this context. Finally, given that people within this context tend to lean more toward collectivist values, it may be necessary to emphasize interactive and group/community-based components in MOOCs to encourage those who place importance on those values to appreciate and want to use them more.

Indirect Determinants of Behavioral Intention to Use MOOCs

It was hypothesized that perceived usefulness and perceived ease of use will play mediating roles in the relationships between the other study constructs (facilitating conditions, social influence, power distance, uncertainty avoidance) and behavioral intention to use MOOCs, given their already established strong predictive power of behavioral intention to use a technology (Davis, 1989; Lee et al., 2009; Miller & Khera, 2010; Venkatesh, 2000, Teo, 2010). Furthermore, consistent with previous studies, perceived ease of use was also hypothesized as influencing intention indirectly through perceived usefulness (Abbas, 2016; Bhatiasevi, 2011; Chu et al., 2015; Mohammadi, 2015).

Significant indirect effects of perceived ease of use and uncertainty avoidance on behavioral intention to use MOOCs, through perceived usefulness were found. Specifically, it was found that perceived usefulness mediated the relationship between perceived ease of use and behavioral intention such that, as perceived usefulness increases as a result of increases in perceived ease of use, people's intention to use MOOCs also increases. This simply means that, the relationship that perceived usefulness has with perceived ease of use explains some of the variance observed in peoples' behavioral intention to use MOOCs in the study. Similarly, uncertainty avoidance also indirectly predicted behavioral intention through perceived usefulness, indicating that, the relationship that perceived usefulness has with uncertainty avoidance also explains some of the variance observed in peoples' behavioral intention to use MOOCs. These significant indirect effects through perceived usefulness emphasize the importance of not only perceived usefulness, but also, that of perceived ease of use and uncertainty avoidance in predicting behavioral intention to use MOOCs in the context of study. Indicating that, these factors also have to be put into consideration when designing MOOCs that will appeal to people within this context. Interestingly, although direct effects on perceived usefulness were found for social influence which is consistent with previous studies (Chen & Aklikokou 2019; Teo, 2011a, Teo, 2011b, Adbullah & Ward, 2016), however, this effect did not translate into people's intention to use MOOCs in the sample, as no indirect effect of social influence through perceived usefulness was found in the path analysis. This indicates that social influence was only playing a role of a covariate in the direct relationship between perceived usefulness and behavioral intention to use MOOCs. No significant indirect effects on behavioral intention to use MOOCs through perceived usefulness were found for facilitating conditions, power distance and collectivism.

Furthermore, although direct effects on perceived ease of use were found for facilitating conditions and uncertainty avoidance, indirect effects on behavioral intention through the variable was not found for this study. This was specifically because perceived ease of use was not significantly predicting behavioral intention in the study, and thereby lacked the capacity to play the role of a mediator for other variables in predicting behavioral intention. This indirect relationship can however be examined in future studies given that there is enough evidence from the literature to show that perceived ease of use can be a significant predictor of behavioral intention (Davis, 1989; Lee et al., 2009; Miller & Khera, 2010; Venkatesh, 2000, Teo, 2010), indicating that for such situations, positive indirect effects for uncertainty avoidance and facilitating conditions through perceived ease of use are likely to be existent.

Overall, the results of the mediation analysis indicated that, the relationship between perceived usefulness of MOOCs and behavioral intention to use MOOCs is partially explained by the relationship it has with both perceived ease of use and uncertainty avoidance, such that, the stronger those relationships are, the more perceived usefulness is likely to predict behavioral intention to use MOOCs.

CHAPTER 7: CONCLUSIONS AND FUTURE RESEARCH

Conclusion

This study utilized the Technology Acceptance Model (TAM) to examine factors that are likely contributing to peoples' acceptance of MOOCs in Nigeria. It expanded on the predicting power of the model by including external factors to help predict intention to use MOOCs among participants, as well as to understand the specific factors influencing usefulness and ease of use perceptions of MOOCs among them. The additional determinants included in the model were facilitating conditions, social influence and individual espoused cultural values of power distance, uncertainty avoidance and collectivism. It was found that the proposed model with the additional determinants improved the predicting power of the original TAM model in predicting perceived usefulness and intention to use MOOCs among the Nigerian participants. This indicates that the extended model represents a good model to use to measure peoples' attitudes and intention towards MOOCs use within the context of study.

Findings from the study indicated that perceived usefulness and facilitating conditions played the most significant roles in predicting people's intention to adopt MOOCs. Collectivism also significantly predicted behavioral intention to use MOOCs among participants, although its effect was not as strong as those observed for perceived usefulness and facilitating conditions. Furthermore, perceived ease of use and uncertainty avoidance played a major role in peoples' perceived usefulness of MOOCs, an effect that translated into their intention behavior. And facilitating conditions and uncertainty avoidance played significant roles in peoples' perceived ease of use of MOOCs in this study.

These results therefore indicate that with regards to MOOCs acceptance and use within this context, more focus needs to be placed on how useful people perceive MOOCs to be. For instance, this can involve developing strategies that ensure that the value associated with MOOCs are made more apparent. Also, as the study shows, positive usefulness perceptions can be achieved by ensuring that the platforms are free of effort to use (i.e., easy to use) and that the structure of the learning process is unambiguous, with clearly defined goals (to help address peoples' tendency to avoid a situation due to level of ambiguity that may be associated with it). Also, word of mouth encouragement through close connections, mentors or employers can increase how useful people within this context will consider MOOCs to be and their intention to use them for learning purposes. Another way to increase value perceptions would be to establish a strategic connection between MOOCs learning, higher learning institutions and employers of labor, as a way of showcasing that the time and effort invested in MOOCs for one's self-development is being valued.

Furthermore, another aspect that needs to be focused on when discussing MOOCs acceptance and use within a context such as Nigeria is the availability of facilitating conditions to enable such use. Given that sparseness of resources and other environment-related barriers may impede efficient use of MOOCs. For instance, having efficient internet is required to watch the lecture videos in MOOCs, and if a person continues to experience internet reliability issues while trying to learn, they may be likely to abandon it. Also, Smartphones appear to be the most common technology used to access the internet among the participants in this study, however, MOOCs are optimally made for access via larger screens, such as laptops. Designing MOOCs in such a way that it is easier to participate using a Smartphone is essential for acceptance for people in this context. Although, ideally, having access to a laptop would be more efficient, as trying to learn via a mobile phone has other numerous challenges that are beyond the scope of this study. Generally, more reliable and affordable access to the internet and other technological devices and resources that make it easier to learn on MOOCs is necessary to increase acceptance among people within this context.

The findings also suggested that how collectivist values influence intention has to be taken into consideration to improve acceptance and use of MOOCs within the context of study. Although it was proposed by the study that having such values will lead to people favoring MOOCs less, due to their more individualistic nature, however, it was found that the opposite was the case, as those higher on collectivist values intended to use MOOCs more. Although the exact nature of this relationship was not examined any further in this study, it may be that people who take MOOCs within this context plan with others to take it together, and/or are active or plan to be active participants on the interactive components of MOOCs such as the discussion forums. Also, it should be noted that MOOCs does encourage peer-assessment. Hence, these may all be factors that make it attractive for high collectivist individuals. Regardless, it would clearly serve people in this context if MOOCs are positioned to promote more interactive and group-based components to further appeal to those who hold high collectivist values. This will especially be beneficial because participants were found to espouse higher collectivist than individualistic values towards learning.

Finally, findings from this study, particularly that related to the power distance variable, also throws light on the potential disadvantage of classifying people within a particular country as espousing cultural values at the same level. Specifically, Nigeria is a classified as a high power distance country on the Hofstede continuum for that dimension (Hofstede, 2011), however, while measuring individual power distance levels in this study, it was found that almost all the participants had low power distance levels, with the mean of the power distance variable being 2 on a 5 point scale. This supports the notion that care must be taken in using national levels of cultural values to interpret people behaviors, especially in situations as peculiar and personal as technology adoption.

Practical Implications

The results of this study indicate that, in an effort to increase people's intention to use MOOCs in Nigeria, certain provisions have to be made, especially to improve how useful people consider learning in MOOCs to be, what resources and skills are available to support their use, and what cultural values people hold towards learning in such a space in general. Specifically, MOOC platforms can partner with institutions of higher learning in the country to create a pathway for course credits to be associated with MOOC classes, or allow for some pre-requisite courses for degree requirements to be completed as MOOCs courses. Also, to allow for people to see more value with MOOCs, partnerships with employers where a clear pathway from MOOC learning and certifications to employment is established would be very beneficial. Establishing these partnerships are important because findings from this study and previous studies indicate that the more useful people in this context find MOOCs to be, the more they are likely to adopt them for learning and also because it appears that the main reasons for taking MOOCs among them are for academic and job related purposes.

Furthermore, as the results of the study indicated, lack of resources (such as reliable and cost effective internet access and computing devices) and skills available to participate in MOOCs is a major factor impeding their use within this context. Hence, it would be essential to partner with both governmental and non-governmental institutions to make available resources such as a free to access study centers equipped with computers and the internet available to encourage people to participate in MOOCs. Furthermore, skill building courses, such as how to use the internet and/or participate in MOOCs can be made available to those that are interested in learning with MOOCs, but lack the adequate skills to do so.

Also, it would be beneficial to establish MOOC learning that emphasizes collective/group-based type of learning among people in this context, especially since the result from this study indicates that those who preferred learning to work as part of a group, rather than individually are more likely to use MOOCs in this context. This intervention can include establishment of MOOC clubs supported by individuals, groups or institutions with the aim of encouraging people to take MOOCs together in order to support and hold each other accountable through the learning process. Also, ensuring that the interactive components within MOOCs platforms are robust enough to encourage working in groups and associating with other members of the class.

Finally, as found in the study, many of those who had no prior experience with MOOCs were female and unemployed, suggesting a gender and potentially an income-based component to peoples' adoption of MOOCs within this context. Hence, it is important to work with institutions to provide resources to support MOOCs use in order to relieve the burden for those without employment and to also work with women's groups to promote MOOCs learning and provide resources for participation for women and girls through those groups.

Limitations

This study is however not without limitations. First, the researcher intended to physically visit the country of study to actively participate in the recruitment of participants. However, those plans were impeded by the COVID-19 pandemic, which resulted in several restrictions and lack of approval of funds for international research for the researcher. This limited the number and variety of participants that were able to be reached for the survey, and perhaps more importantly, limited the ability of a qualitative study to be conducted in support of the quantitative survey, as initially planned. Combining the results of this study with results from a qualitative study would have significantly increased the overall understanding provided on the phenomenon being studied, about how the different factors are influencing perceived usefulness, perceived ease of use and intention to adopt MOOCs within the context of study

Also, survey responses tend to lend themselves to bias, and although the study tried to ensure that responses gathered were of high quality by carefully designing the survey, including attention check questions, pilot testing and following an adequate survey administration process. However, it is difficult to ensure that responses received are not biased, rushed or does not represent the participants actual opinions. For instance, it is suggested that questions can often be misunderstand in self-reporting surveys and they are also often associated with social desirability bias, where participants answer questions in a way that make them look good, or the way they think you expect them to answer (Fowler, 2014; Grimm, 2010). Hence, it may be necessary to conduct future studies, both quantitative and qualitative, to further validate the findings observed in this study**.**

Furthermore, in recruiting participants, it was assumed that they were all internet users because they had to complete the survey online. However, the level of internet usage is different for participants as indicated in the study. Future study can ensure that participants recruited have the same level of experience using the internet to reduce bias that may be related to internet use experience. Also, not having compensated participants directly may have limited the number of those that were willing to complete the study and those that may have taken their time to complete it. Although, several precautions were taken to ensure that only responses considered as valid were retained for analysis as described in the methods section. However, having a more efficient means of compensating the participants directly, while maintaining the quality of the responses may be more beneficial and rewarding, especially with regards to achieving a lager sample size for a future study.

Additionally, to further understand the role that the lack of adequate facilitating conditions such as reliable and affordable internet and availability of devices have to play in MOOCs adoption and use within the context of study, it would be beneficial to examine how such lack of resources are associated with income level of target users. For instance, it was found in this study that a higher percentage of those who identified as non MOOCs users were unemployed, suggesting that people in that group may be facing a greater challenge of not being able to afford the resources necessary to participate in MOOCs. Interestingly, majority of the participants are bachelor's degree holders, indicating that there may be a problem of employment within this context. Given that this is a developing country, with more people with limited resources, examining the role that income has to play as a factor that could potentially influence MOOCs acceptance and use would help in determining suitable interventions to increase adoption among them. Although this study attempted to gather information on income, many of the participants were unwilling to provide this information and majority of them were unemployed, and hence reported no income, so the variable was excluded from further analysis. This indicates the need to obtain income related information via other established means such as income, occupation and educational level of parents of the participants. This will help in determining how the socio-economic status of participants are likely contributing to their non-adoption of MOOCs within this context.

Also, the scope of this study only involved a specific set of variables that the researcher identified and wanted to explore further. There are serval other variables that may be contributing to the phenomenon being explored and future studies exploring how those other factors may be playing a role in MOOCs acceptance and use in the Nigerian context is necessary, especially since research in this area is still at a novel stage in the context of study. And as mentioned earlier, a qualitative study that seeks to explore why people hold the perceptions they do about MOOCs within this context can uncover more items and concepts that can further explain the results of this study.

Future Research

Although the models proposed for the study showed a reasonable predicting power of the outcome variables of behavioral intention to use MOOCs, perceived usefulness of MOOCs and perceived ease of use of MOOCs in the context of study, it still has a lot of room for improvement. The models can be modified by removing constructs that were barely contributing to their predicting power and more important variables that may have been found in the literature to be significantly influencing the outcome variables can be included in their respective models and tested for their predictive capabilities of attitudes and intention to use an online learning technology such as MOOCs. Also, future research can include a larger sample size to ensure that results will be more reliable and replicable with a higher confidence interval.

It would be particularly important for future research to examine whether some of the variables play moderating roles in predicting intention to use MOOCs in the context of study. For instance, gender may be a factor that will possibly moderate the relationship between the predictive variables and the outcome, especially since it was found that there were more women MOOCs non-users than men. Also, since facilitating conditions is playing a role of a barrier, it may potentially be a moderating factor in the relationship between the other independent variables and behavioral intention to use MOOCs. This is because, in the absence of conditions to facilitate use, the presence of the other factors may not have a huge impact. Also, it may be beneficial to include experience as a moderator, to tease out specific differences between those who have had some experience using MOOCs and those who do not. Exploring these potentially moderating relationships can further illuminate the role that the variables examined for this study play in predicting intention to use MOOCs within the context of study.

Also, it may be beneficial for future research that finds direct effect of perceived ease of use on behavioral intention to use MOOCs to test for mediating effects of the variable on facilitating conditions and uncertainty avoidance in predicting behavioral intention to use MOOCs or other online learning technologies. This is because, it was found that, although perceived ease of use was not directly influencing behavioral intention to use MOOCs in this study, facilitating conditions and uncertainty avoidance significantly predicted perceived ease of use. Indicating that the higher the facilitating conditions and uncertainty avoidance people have, the more likely they are to perceive a system as being easy to use. This suggests that a mediation effect may be significant for studies that find direct effects for perceived ease of use on behavioral intention.

Furthermore, collectivism was found to be positively predicting intention to adopt MOOCs for this study, however social influence was not. However, it is logical to think that those who prefer to be part of a group, or that emphasize group goals (i.e., those that have high collectivist values) may be more likely to be influenced by those around them. Hence, it may be worthwhile to test for the indirect effects of social influence on behavioral intention through collectivism in a future study.

Also, when conducting studies that involve impacts of culture, it may be more appropriate to include people from different cultural backgrounds to determine if the differences in their background influence their level of individual espoused cultural values and will also allow for a good comparison of how the different factors may be influencing perceived usefulness, ease of use and intention to adopt a technology like MOOCs based on where people come from. Also, the models presented in this study can be validated across different technological uses in the context of study to determine if findings were specific to MOOCs or if they can be extended to acceptance and use of other systems within that context.

Finally, as mentioned earlier, having a qualitative component to support the findings from this study would be very useful in providing a better understanding about what the situation of MOOCs acceptance and use is within the context of study. Such qualitative study would specifically involve conducting in-depth semi-structured interviews to answer questions like, why exactly people in this context find MOOCs useful, how exactly the lack of resources and skills are discouraging them from participating in MOOCs and other specific challenges they face with regards to adopting a technology like MOOCs, their overall perceptions and expectations of MOOCs, and what roles different cultural values play in their intention to adopt MOOCs. I would also qualitatively explore the role of gender, income and employment status (especially as it is associated with income) in peoples' intention to adopt MOOCs. Obtaining more in-depth information about these perceptions, experiences and characteristics would help in ensuring that more concrete recommendations are made as to how adoption and use can be improved among people within the context of study. For instance, learning more about peoples' experiences working collectively with others and their preferences in that regard would throw more light on how to design MOOCs that are more interactive and that promote group-based learning. Such qualitative study would help us identify new concepts that are perhaps specific to this context that may the lacking in the literature and that can be useful when discussing technology acceptance for people in this area in the future.

APPENDICES

APPENDIX A

MOOC Attitudes and Behavioral Intention Survey

Informed Consent
This ~20-minute study examines attitudes about online education. **You must be a resident Nigerian to participate (some other restrictions apply).**

This study involves low risks/discomforts and no financial compensation. Your participation will be greatly appreciated and will help this research improve education in Nigeria.

Participation is voluntary, you may choose not to participate or withdraw at any time. All data collected is confidential and password-protected. Anonymized results and/or data will be shared only for scholarly purposes.

This study has been reviewed according to the Michigan State University's Institutional Review Board. For questions, contact Chimobi Ucha, uchachim@msu.edu.
Do you voluntarily consent to participate?

○ I agree

○ I disagree

Q1. What is your age?

____

Q2. What is your gender?

○ Male (1)

○ Female (2)

Q3. How familiar are you with Massive Open Online Courses (MOOCs)?

○ Not at All. I have no awareness of MOOCs (1)

○ Somewhat. I am aware of MOOCs and how they can be used, but I have NEVER used them. (2)

○ I am aware of MOOCs AND have used them (3)

Q4. How familiar are you with any of the following MOOC Platforms?

	Not at all (1)	I am aware of it, but have NOT used it (2)	I have used it (3)
Coursera (1)	○	○	○
Udacity (2)	○	○	○
edX (3)	○	○	○
Khan Academy (4)	○	○	○
FutureLearn (5)	○	○	○
Udemy (6)	○	○	○

With the knowledge that Massive Open Online Courses (MOOCs) are online-based courses that are mostly free to access and are hosted on platforms such as edX, Coursera, and Udacity, please answer the questions that follow as carefully and truthfully as possible

Q5. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I (would) find MOOCs useful in accomplishing my education or job-related goals (1)	○	○	○	○	○
Using MOOCs enables/will enable me to accomplish my education or job-related tasks more quickly (2)	○	○	○	○	○
Using MOOCs increases/will increase my learning or job productivity (3)	○	○	○	○	○
Using MOOCs is/will be beneficial for me in preparing for further education or a new role (4)	○	○	○	○	○
Using MOOCs makes it/would make it easier for me to gain desirable skills I need for my studies or my job (5)	○	○	○	○	○

Q6. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I (would) find MOOCs easy to use (1)	○	○	○	○	○
Learning to use MOOCs is (or would be) easy for me (2)	○	○	○	○	○
My interaction with MOOCs is (or would be) clear and understandable (3)	○	○	○	○	○
It is (or would be) easy for me to become skillful at using MOOCS (4)	○	○	○	○	○

Q7. Please indicate the extent to which you agree or disagree with the following statements

I (will) enroll or participate in MOOCs if ...

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
my friends/family think I should (1)	○	○	○	○	○
people whose I opinion I value think I should (2)	○	○	○	○	○
people who are important to me think I should (3)	○	○	○	○	○
people who have authority over me (teacher, employer) think I should (4)	○	○	○	○	○

Q8. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I have the resources necessary to use MOOCs (1)	○	○	○	○	○
I have the knowledge necessary to use MOOCs (2)	○	○	○	○	○
MOOCs is compatible with other technologies I use (3)	○	○	○	○	○
I can get help from others when I have difficulties using MOOCs (4)	○	○	○	○	○

Q9. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I intend to use MOOCs in the future (1)	○	○	○	○	○
I will use MOOCs in the future (2)	○	○	○	○	○
I predict that I would use MOOCs in the future (3)	○	○	○	○	○

In the next couple of questions, we would like to learn more about your general beliefs/perceptions about learning and academic achievement/success

Q10. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Teachers should make most decisions without consulting students (1)	○	○	○	○	○
Teachers should not ask the students for advice or opinions (2)	○	○	○	○	○
Teachers should not engage in social interaction with students (3)	○	○	○	○	○
Teachers should not delegate important decisions to students (4)	○	○	○	○	○
Students should not question or disagree with decisions made by their teachers (5)	○	○	○	○	○
Teachers should always show authority and power when dealing with students (6)	○	○	○	○	○

Q11. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
It is important to have course requirements and instructions spelled out in detail so that I always know what I am expected to do (1)	○	○	○	○	○
Rules and regulations are important to me in a course because they inform me of what the teacher expects of me (2)	○	○	○	○	○
Order and structure are very important to me in a course (3)	○	○	○	○	○
It is important to me to closely follow instructions and procedures in a course (4)	○	○	○	○	○
Having Instructions for the course is important for my learning (5)	○	○	○	○	○
Standardized less flexible teaching and learning procedures are important for my learning (6)	○	○	○	○	○

Q12. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Working as part of a group in a course is more important than working as an individual (1)	○	○	○	○	○
Group success is more important than individual success (2)	○	○	○	○	○
Being loyal to my group is more important than individual gain (3)	○	○	○	○	○
It is unlike me to abandon a group I belong to in the face of difficulty (4)	○	○	○	○	○
I am willing to sacrifice my self-interest for the good of my group (5)	○	○	○	○	○
The welfare of my group is more important that any individual rewards I can get (6)	○	○	○	○	○
It is more important for a teacher to encourage loyalty and sense of duty in students than to encourage individual initiative (7)	○	○	○	○	○

Q13. Please indicate the extent to which you agree or disagree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
It is important to me to have a professional career (1)	○	○	○	○	○
It is preferable to me that my teacher is male rather than a female (2)	○	○	○	○	○
I am capable of excelling in any course (3)	○	○	○	○	○
Outstanding academic achievements are important to me in my studies (4)	○	○	○	○	○
I prefer to solve problems more logically than intuitively (5)	○	○	○	○	○
Achievements and material success matter to me more than relationships and quality of life (6)	○	○	○	○	○

Q14. Please indicate the types of devices you own (Select all that apply)

- ☐ Smartphone (1)
- ☐ Laptop (2)
- ☐ Desktop (3)
- ☐ Tablet (4)
- ☐ Others - Please Specify (5) ____

Q15. How often do you access the internet?

- ○ Not Very often (About Once a Week) (1)
- ○ Somewhat often (About 2-3 times a week) (2)
- ○ Fairly often (About 5-7 times a week) (3)
- ○ Very often (Multiple times a day) (4)

Q16. Please indicate the device you use in accessing the internet the most

- ○ Smartphone (1)
- ○ Laptop (2)
- ○ Desktop (3)
- ○ Tablet (4)

Q17. Please indicate your main means of accessing the internet

- ○ Mobile broadband (1)
- ○ Home Wi-Fi (2)
- ○ School Wi-Fi (3)
- ○ Work Wi-Fi (4)
- ○ Other Public Wi-Fi (5)
- ○ Public Internet Cafe (6)

Q18. Please indicate how performance efficient (speed, availability, reliability) you consider your means of accessing the internet

◯ Not efficient at all (1)

◯ Slightly efficient (2)

◯ Moderately efficient (3)

◯ Very efficient (4)

◯ Extremely efficient (5)

Q19. Please indicate how cost efficient you consider your means of accessing the internet

◯ Not cost efficient at all (1)

◯ Slightly cost efficient (2)

◯ Moderately cost efficient (3)

◯ Very cost efficient (4)

◯ Extremely cost efficient (5)

Q20. What is usually your main reason for accessing the Internet?

◯ Social media (1)

◯ Learning (reading scholarly materials, watching educational videos, taking online classes etc.) (2)

◯ News (3)

◯ Others - Please specify (4) ____

Q21. How often do you use the Internet for learning purposes?

- ◯ Rarely (1)
- ◯ Not very often (2)
- ◯ Fairly often (3)
- ◯ Very often (4)

Q23. How confident are you in your ability to use computing devices and the Internet?

- ◯ Not confident at all (1)
- ◯ Slightly confident (2)
- ◯ Moderately confident (3)
- ◯ Very confident (4)
- ◯ Extremely confident (5)

Q25. How confident are you in your ability to use the Internet for learning purposes?

- ◯ Not confident at all (1)
- ◯ Slightly confident (2)
- ◯ Moderately confident (3)
- ◯ Very confident (4)
- ◯ Extremely confident (5)

Q26. How reliable is the power supply at your home?

- ◯ Not reliable at all (1)
- ◯ Slightly reliable (2)
- ◯ Moderately reliable (3)
- ◯ Very reliable (4)
- ◯ Extremely reliable (5)

Q27. Do you have access to alternative power supply at home?

- ◯ Yes (1)
- ◯ No (2)

Q28. Please indicate the highest level of education you have completed

- ◯ No formal education (1)
- ◯ Primary education (2)
- ◯ Secondary education (3)
- ◯ Some college or technical education (4)
- ◯ Bachelor's degree (5)
- ◯ Postgraduate degree (Masters or PhD) (6)

Q29. What is your current occupation/employment status? (Select all that apply)

- ▢ Employed - full time (1)
- ▢ Employed - part time (2)
- ▢ Self-employed (3)
- ▢ Unemployed (4)

Q30. What is your monthly income in Naira?

- ○ Under 30,000 (1)
- ○ 30,000 - 50,000 (2)
- ○ 50,000 - 70,000 (3)
- ○ 70,000 - 100,000 (4)
- ○ Over 100,000 (5)
- ○ N/A (6)

Additional questions only asked to those with prior MOOCs experience are represented below.

The following questions will ask you about your level of experience with MOOCs

Q31. Which of the following indicates your main reason for taking MOOCs?

To learn more about a topic...

- ○ for my own personal gain or interests
- ○ to help me perform better in my current job
- ○ to help me prepare towards a different or future career
- ○ to help me perform better in my current studies
- ○ to help me prepare for further education in my field of interest
- ○ Others (Please specify) ____

Q32 Approximately how many years have you been a MOOCs user?

- ○ Less than a year (1)
- ○ About a year (2)
- ○ Over a year (3)

Q33. How often do you learn using MOOCs?

- ○ Rarely (1)
- ○ Not very often (2)
- ○ Fairly often (3)
- ○ Very often (4)

Q34. Approximately how many MOOCs classes have you enrolled in till date?

- ◯ 1 - 2 (1)
- ◯ 3 - 5 (2)
- ◯ Over 5 (3)

Q35. Approximately how many MOOCs classes have you completed till date?

- ◯ None (1)
- ◯ 1 - 2 (2)
- ◯ 3 - 5 (3)
- ◯ Over 5 (4)

Q36. Approximately how many MOOCs certificates have you earned till date?

- ◯ None (1)
- ◯ 1 - 2 (2)
- ◯ 3 - 5 (3)
- ◯ Over 5 (4)

Q37. What device do you use to access MOOCs the most?

- ◯ Smartphone (1)
- ◯ Laptop (2)
- ◯ Desktop (3)
- ◯ Tablet (4)
- ◯ Others - Please specify (5) ____________________

Q38. What MOOCs platform do you utilize the most?

◯ Coursera (1)

◯ edX (2)

◯ Udacity (3)

◯ Others - Please specify (4) ____

Q39. What location do you access MOOCs the most?

◯ Home (1)

◯ Work (2)

◯ School (3)

◯ Others - Please specify (4) ____

End of Survey

APPENDIX B

Means, Standard Deviations and Inter-Item Correlations of Construct Items

Table 45: Means, Standard Deviations, and Correlations for Perceived Usefulness

Item	*M*	*SD*	PU1	PU2	PU3	PU4
PU1	4.13	0.99				
PU2	3.98	1.07	.48**			
PU3	4.22	1.01	.44**	.52**		
PU4	4.33	0.89	.44**	.53**	.61**	
PU5	4.21	1.02	.33**	.32**	.48**	.46**

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 46: Means, Standard Deviations, and Correlations for Perceived Ease of Use

Item	*M*	*SD*	PEOU1	PEOU2	PEOU3
PEOU1	3.97	1.01			
PEOU2	4.08	0.97	.49**		
PEOU3	4.13	0.90	.43**	.45**	
PEOU4	4.12	0.92	.36**	.55**	.56**

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 47: Means, Standard Deviations, and Correlations for Facilitating Conditions

Item	*M*	*SD*	FC1	FC2	FC3
FC1	3.51	1.31			
FC2	3.93	1.06	.47**		
FC3	3.97	0.96	.45**	.51**	
FC4	4.05	1.02	.35**	.43**	.36**

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 48: Means, Standard Deviations, and Correlations for Social Influence

Item	*M*	*SD*	SI1	S12	SI3
SI1	3.21	1.44			
SI2	3.61	1.33	.65**		
SI3	3.55	1.27	.58**	.75**	
SI4	3.54	1.36	.47**	.54**	.56**

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 49: Means, Standard Deviations, and Correlations for Power Distance

Item	*M*	*SD*	PD1	PD2	PD3	PD4	PD5
PD1	2.13	1.26					
PD2	1.94	1.29	.51**				
PD3	1.67	1.13	.51**	.70**			
PD4	2.29	1.40	.41**	.54**	.59**		
PD5	2.05	1.26	.55**	.63**	.69**	.57**	
PD6	2.46	1.37	.43**	.46**	.48**	.40**	.59**

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 50: Means, Standard Deviations, and Correlations for Uncertainty Avoidance

Item	*M*	*SD*	UA1	UA2	UA3	UA4	UA5
UA1	4.46	0.97					
UA2	4.51	0.85	.68**				
UA3	4.56	0.75	.63**	.60**			
UA4	4.54	0.80	.58**	.54**	.67**		

UA5	4.57	0.74	.49**	.56**	.53**	.71**	
UA6	**4.01**	**1.10**	**.09**	**.18****	**.12**	**.19****	**.17***

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 51: Means, Standard Deviations, and Correlations for Collectivism

Item	*M*	*SD*	COL1	COL2	COL3	COL**4**	COL5	COL6
COL1	3.69	1.15						
COL2	3.50	1.27	.59**					
COL3	3.69	1.24	.52**	.49**				
COL4	**4.17**	**1.09**	**.25****	**.18****	**.37****			
COL5	4.06	1.00	.26**	.26**	.46**	**.29****		
COL6	3.77	1.16	.32**	.37**	.58**	**.31****	.69**	
COL7	3.79	1.16	.39**	.39**	.51**	**.34****	.45**	.53**

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table 52: Means, Standard Deviations, and Correlations for Masculinity

Variable	*M*	*SD*	MASC1	MASC2	MASC3	MASC4	MASC5
MASC1	4.56	0.86					
MASC2	2.58	1.29	.09				
MASC3	4.41	0.88	.20**	-.05			
MASC4	4.53	0.82	.31**	-.11	.32**		
MASC5	4.05	0.95	.25**	.03	.20**	.30**	
MASC6	2.80	1.39	.02	.42**	.03	-.04	.15*

Note. * indicates $p < .05$. ** indicates $p < .01$.

APPENDIX C

Factor Loadings of the Study Scale Items

Table 53: Factor Loadings of the Study Constructs

Construct	Factor Loadings
Perceived Usefulness (PU)	
PU1	0.59
PU2	0.72
PU3	0.79
PU4	0.69
PU5	0.58
Perceived Ease of Use (PEOU)	
PEOU1	0.59
PEOU2	0.70
PEOU3	0.63
PEOU4	0.69
Behavioral Intention (BI)	
BI1	0.78
BI2	0.75
BI3	0.70
Facilitating Conditions (FC)	
FC1	0.83
FC2	0.80
FC3	0.65
FC4	0.56
Social Influence (SI)	
SI1	0.96
SI2	1.00
SI3	1.00
SI4	0.81

Table 53 (cont'd)

Construct	Factor Loadings
Power Distance (PD)	
PD1	0.80
PD2	1.00
PD3	0.95
PD4	1.05
PD5	0.85
PD6	0.81
Uncertainty Avoidance (UA)	
UA1	0.74
UA2	0.64
UA3	0.59
UA4	0.65
UA5	0.55
UA6 (Dropped)	**0.21**
Collectivism (COL)	
COL1	0.65
COL2	0.72
COL3	0.95
COL4 (Dropped)	**0.48**
COL5	0.67
COL6	0.89
COL7	0.78
Masculinity (MASC) - Dropped	
MASC1	0.41
MASC2	-0.05
MASC3	0.40
MASC4	0.54
MASC5	0.45
MASC6	0.05

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