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Adoption and use of MOOCs by undergraduates in selected universities in Ibadan, Nigeria

Goodness Johanna Otitoju[1], *Williams Ezinwa* Nwagwu[1]

[1]*Department of Data and Information Science, University of Ibadan, 6 Benue Rd., Ibadan, 200132, Nigeria*

Abstract. This research examines the utilisation of Massive Open Online Courses (MOOCs) by university undergraduates in Ibadan, Nigeria, for digital skill development. A survey of 378 undergraduates from the University of Ibadan, Lead City University, and Dominican University is conducted. Principal Component Analysis (PCA) simplifies UTAUT variables, while regression analysis explores factors influencing MOOC usage. Results show a substantial 77.8% adoption rate of MOOCs, indicating a growing interest in online learning. Performance expectancy, effort expectancy, social influence, facilitating conditions, and internet accessibility significantly influence MOOC usage, though higher values for performance expectancy and facilitating conditions unexpectedly correspond to reduced utilisation. Demographic factors like age and gender do not significantly impact adoption. Limitations include the focus on Ibadan university students, potentially limiting generalizability, and the study's cross-sectional nature, which may not capture long-term trends. Nonetheless, the research sheds light on digital education in Nigeria, emphasising MOOC utilisation among students. Rigorous statistical analyses and incorporating the UTAUT framework provide a robust foundation for interpretation. The results highlight prevalent MOOC usage and offer insights into adoption factors. Implications extend to educational institutions, instructors, digital literacy initiatives, and policy-making, stressing the importance of enhancing MOOC adoption for digital skill development among Nigerian university students.

Keywords: MOOCs, digital skills development, universities in Ibadan, Nigeria, information technology

1. Introduction

1.1. Background to the study

The manner of life of individuals and organisations worldwide has undergone enormous and substantial changes in the 21st century. The diverse disruptions result from recent information technology inventions and advancements, each with unique advantages and problems. One of the major transformations caused by the technological advancements in this century is evident in the field of education [23]. Education drives all human innovations, and with the introduction of information technology, the field of teaching and training has rapidly grown in its content and delivery method. The transformative and progressive trends in information technology have resulted in significant developments in different aspects of education at all levels [41].

Digitalisation has revolutionised the general way of life of people and institutions worldwide. With the invention of new technologies, digital skills have also required change. Digital skills are essential, and students, in their quest to obtain and develop the required digital skills, turn to online learning platforms like MOOCs to access the necessary skills [16]. MOOCs have been

willieezi@yahoo.com (W. E. Nwagwu)
0009-0009-9047-005X (G. J. Otitoju); 0000-0002-5225-2934 (W. E. Nwagwu)

established as critical channels through which education, knowledge, and competencies have been accessed by subject area experts/professionals and students from third-world countries. The type of digital skills required and gathered by any individual is based on personal needs, peculiarities, and capabilities; for example, the digital skills required by computer scientists are quite different from those required by a linguist [13]. Each person's proficiency determines the type of digital skills they are comfortable using and the level of command they possess over simple and complex digital tools and technologies. This study will examine some mediums through which digital natives, mainly undergraduate students, acquire and develop the digital skills required to exist in the 21st century.

Recent studies have highlighted the importance of personalised learning experiences in MOOCs. Zhu et al. [54] propose a novel approach using graph convolution and matrix factorisation to recommend personalised course resources efficiently. By decomposing heterogeneous graphs into subgraphs and leveraging attention mechanisms, their method improves recommendation performance while addressing scalability and data sparsity issues. Group discussions and assignments contribute significantly to learning outcomes in traditional classrooms and online settings. Ma, Luo and Yang [33] introduce a principled method, Personas-based Student Grouping (PSG), which utilises clustering techniques and reinforcement learning to facilitate personalised and efficient group formations. PSG demonstrates superior performance in both effectiveness and efficiency compared to manual or random grouping mechanisms.

Understanding the impact of content release timing on learning behaviours is crucial for designing effective MOOC platforms. Lu, Bradlow and Hutchinson [31] investigate the effects of transitioning from scheduled to on-demand content release formats. While on-demand formats increase short-term firm revenue by attracting a broader user base, they also lead to decreased engagement and performance over time, necessitating new strategies to maintain user engagement.

Emerging technologies such as virtual and augmented reality offer opportunities to enhance learning experiences in MOOCs. Zhang et al. [53] introduce the concept of Massive Open Metaverse Courses (MOMCs), which integrate immersive 3D experiences into online learning environments. Their case study demonstrates the potential of MOMCs in providing engaging and interactive learning experiences, albeit with current limitations that require further exploration.

Technology-enhanced learning, exemplified by MOOCs, has shown promising results in various educational contexts. Yin [52] investigates the effectiveness of using MOOCs to teach guzheng, the Chinese national instrument, demonstrating improved learning outcomes and high participant satisfaction. The study underscores the potential of modern technology in enhancing traditional teaching methods. Personalised recommendation algorithms are crucial in improving user engagement and learning outcomes in MOOCs. Hui, Man and Sabri [22] propose a hybrid recommendation model that combines collaborative filtering with learning and learner models to address sparsity and cold start issues. Their model outperforms traditional collaborative filtering methods, offering more accurate and effective recommendations.

Effective courseware collection is essential for providing diverse learning resources in MOOCs. Guo, Li and Xu [19] present a mathematical model and algorithms for maximising type diversity within budget constraints. Their study demonstrates the efficacy of their approach in optimising resource allocation and enhancing the variety of course offerings. Enhancing user engagement and motivation is critical for the success of MOOCs. Mhd Salim et al. [37] propose a conceptual

framework, PEDAL, which integrates motivational factors, learning strategies, and persuasive design principles to create engaging e-learning experiences. Their framework provides a comprehensive approach to designing effective MOOC platforms that promote behaviour change and maximise learning outcomes.

The concept of MOOCs is based on the principles of the Self-Regulated Learning (SRL) theory combined with Collaborative Learning (CL), as it provides an environment that gives room for participant autonomy as well as communication and interaction between educators and participants [26]. MOOC courses do not fit into the university's traditional session and semester curriculum structure, so they can start at any time and be of any length. Scalability is the principal strength of MOOCs, and this characteristic is what makes MOOCs one of the best alternatives for short period courses that provide focus and greater emphasis on a subject area, which then propels the learner towards a deeper grasp of a subject/knowledge area [43]. The design of these courses considers a large number of participants, content access from anywhere by users with an internet connection, and openness. It offers a complete course module and experience without any cost [12]. It is, therefore, expedient for any potential participant in a MOOC to possess the necessary digital tools and technologies as well as skills required for complete and active participation.

An efficacious instrument utilised in MOOCs for passing instructions between the facilitator and students is online tutorials. Online tutorials embedded within Massive Open Online Courses are a form of online education that provides interactive and self-paced learning experiences for students [51]. These tutorials may cover programming, data analysis, or design and are usually integrated into the course material to provide a more interactive and engaging learning experience. They can also include various media, including videos, images, audio recordings, and interactive exercises. The tutorials are designed to give students a comprehensive understanding of a particular subject and can be accessed from anywhere with an internet connection. They are usually integrated into the MOOC platform. These tutorials aim to help students understand complex ideas by breaking them down into smaller, manageable pieces and providing immediate feedback and guidance as they work through the exercises. Students can use them to supplement their learning and reinforce their understanding of the course material [40]. Subject matter experts often create these tutorials, a key component of the MOOC learning experience.

Commonly, embedded online tutorials are asynchronous, according to Ko and Rossen [27], this implies that learning activities are not carried out directly between facilitators and learners; there is also no real-time interaction between the tutor and the learners, facilitators often communicate with students using discussion forums, instant messages, and email communications. Hadianti [20] opined that a critical element in online tutorials is technology; without technological infrastructures like the internet and personal digital devices, tutors and students will be unable to facilitate or access the tutorials. When learners gain familiarity with online tutorials, an expectation is that they will experience high-quality learning support and intermediate familiarity with the use of technology in their learning.

Alkathiri [2] reported that the content diversity of online tutorials results in creating a new sphere of educational environments that are more engaging and purpose-driven. The new educational environments appeal to the curiosity and task needs of students. They can be useful for teaching digital skills as they present lessons/tutorials in simulations or real-life situations and contexts. In addition, the content diversity of online tutorials makes them one of the most

convenient and effortless means of engendering necessary 21st-century digital skills. According to Zobrist and Brandes [55], digital technologies are present in all spheres of human endeavours, and handling these technologies requires that users obtain and develop their digital skills.

University students often have to develop digital skills for operating many digital technologies through trial-and-error methods without direct support from their educational institutions [44]. Calonge and Shah [7] reported that many countries, institutions, and organisations have utilised MOOCs to bridge the digital skills gap by developing vital digital skills. This narrative is supported by evident facilitation provided by the World Bank and MOOC platforms like Coursera, Udemy and Udacity, which perceive MOOCs as effective instruments for equipping students with relevant digital skills [14]. Gordillo, López-Pernas and Barra [18] postulated that MOOCs' content diversity and flexibility provide learners with a platform to gain digital skills with a focus on digital content creation.

The most crucial digital skill that MOOCs offer is the ability to use modern digital technologies to create, connect, disparate, and disseminate knowledge, both human and artifactual [35]. Developing and expressing one's content/knowledge and expressing it through a coherent and cogent commentary or contribution using blog entries, videos, mind maps, or other techniques, otherwise known as digital content creation, is a necessary skill for 21st-century learners. According to Otitoju and Nwagwu [42], MOOCs' flexibility, content diversity and online tutorials ensure that they are gaining exponential recognition as a tool for keeping up to date with the latest 21st-century digital skills.

Lehdonvirta, Margaryan and Davies [28] surmised that learners are beginning to take responsibility for bridging digital skills gaps by employing skill-based MOOCs. This phenomenon is gaining momentum because educational institutions often find it challenging to predict the future demands of the labour market, and students turn towards virtual learning platforms like MOOCs to obtain and develop the required digital skills [6]. It is important to note that the use of MOOCs for the development of digital skills can be limited if learners lack knowledge about the digital skills required for manipulating the MOOC software/platform [14, 34]. Furthermore, lack of access to essential infrastructures and devices, including personal computers and internet availability/ accessibility, can also limit learners' participation in the virtual learning platforms.

1.2. Statement of the problem

MOOCs are open and online channels for digitalising learning at all levels and disciplines. Online learning platforms like MOOCs have been established as products of information technology and education; they have been deployed in several areas, including language development, digital archaeology, information literacy, and digital skills development. MOOCs are being utilised for the acquisition and development of 21st-century digital skills by university undergraduates; the noticed rise in the utilisation of MOOCs is influenced by the content diversity, flexibility, cost-effectiveness, and open participation they offer participants. Goglio [17] reported that the ability to utilise online learning platforms as a medium of academic development and establishing a global platform for the sharing, acquiring, and developing digital skills are some factors that contributed to using MOOCs.

Several studies have been conducted to investigate MOOCs' use to develop digital skills. Khalid et al. [25] investigated the factors influencing the behavioural intention to use MOOCs. The

study reported that social influence, absorptive capacity, facilitating conditions, and perceived autonomy significantly influenced students' intention to use MOOCs in Thailand and Pakistan. Calonge and Shah [7] examined the use of MOOCs in filling up graduates' skill gaps and how the gaps affect graduates' employability. Edelsbrunner et al. [14] investigated in detail how employees' digital skills can be developed using a MOOC and reported that MOOC is an efficacious mechanism to support the development of digital skills among employees.

Several other studies [1, 15, 45] discussed the utilisation of MOOCs in higher education to provide better and cheaper access to education. Despite the evident advantages of MOOCs in developing digital skills, no study has been conducted to comprehensively investigate the utilisation of MOOCs for digital skills development by university undergraduates in Ibadan, Nigeria. This study focuses only on undergraduate students and examines their use of MOOCs for digital skills development.

1.3. Hypotheses

H1: Performance expectancy has no significant effect on the use of MOOCs by university undergraduates in Ibadan, Nigeria, for digital skills development.

H2: Effort expectancy has no significant effect on the use of MOOCs for digital skills development by university undergraduates in Ibadan, Nigeria.

H3: Social influence has no significant effect on the use of MOOCs for digital skills development by university undergraduates in Ibadan, Nigeria.

H4: Facilitating conditions has no significant effect on the use of MOOCs for digital skills development by university undergraduates in Ibadan, Nigeria.

H5: Internet availability/accessibility has no significant effect on university undergraduates' use of MOOCs for digital skills development in Ibadan, Nigeria.

H6: The demographic characteristics of the students have no significant effect on their use of MOOCs for digital skills development.

1.4. Theoretical framework

The Unified Theory of Acceptance and Use of Technology [47] is the most widely used theory in technology acceptance and usage intention [4]. The UTAUT model was designed to explain the intention to use a technology or innovation and simultaneously measure users' usage behaviour of a technology, innovation or information system. The model argues that by measuring real-world user technology intention and use behaviour with the identified constructs, it will be possible to identify the key influencers of a technology or innovation's acceptance and use by assessing the users' intention to use. These core constructs are:

- *Performance expectancy* (PE) is the degree to which an individual believes that using the system will enable him or her to attain gains in job performance [46]. Performance expectancy is influenced by gender and age. Hence, it has a more substantial effect on men and younger users. Suppose the utilisation of a technology or innovation will improve job performance or academic performance. In that case, a high intention to use will be the typical response to that technology.

- *Effort expectancy* (EE) is the degree of ease associated with using the system [46]. It captures the notion of perceived ease of use, the degree to which the user expects a technology to be free of effort. Effort expectancy has a more substantial effect on women, older users, and those with little experience. EE is influenced by age, gender, and experience. The degree of ease of use directly impacts adopting a new technology or innovation [15].
- *Social influence* (SI) is the degree to which an individual perceives that important others believe he or she should use the new system [46]. Social influence is the extent to which an individual perceives that someone whose opinion he/she values believes she should use a particular technology [8]. It affects individual behaviour through compliance, internalisation, and identification. Social influence has a more substantial impact on women and older users; this impact comes into play under mandatory use and limited experience.
- *Facilitating conditions* (FC) is the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system [46]. Facilitating conditions refer to how users consider existing conditions to support new technologies [8]. The effect of technology usage increases with experience and the availability of Facilitating conditions. However, Facilitating conditions is entirely dependent on Effort expectancy.

1.5. Review of empirical literature

In the study titled "Promoting Digital Skills for Austrian Employees through a MOOC: Results and Lessons Learned from Design and Implementation", Edelsbrunner et al. [14] investigated in detail how employee's digital skills can be developed using a MOOC, the procedures involved and the effects it has on employees' digital skills. The study combined design-based research and approach-oriented action research to describe the basics of their evaluation of existing European competence frameworks for digital skills and European projects that used MOOCs, the development and design of the MOOC, the evaluation based on learning analytics insights and a questionnaire, as well as a reflection. The MOOC was offered as Open Educational Resources (OER) on the Austrian MOOC platform iMOOX.at from March 2021 to April 2021. A total of 2083 participants registered for the course, out of whom only 381 completed the course, and a total of 4765 accomplishment badges and 369 certificates were issued.

Ghobrini [16] conducted qualitative research titled "Voicing the Unvoiced: Potential of Offline MOOCs e-content to Cater for Nondigitally-fluent Students". The study was designed as a reflective qualitative research design, and it aimed at revealing how nondigitally fluent English foreign language university students in Algeria develop their digital skills using MOOCs. The study concluded by providing an e-solution based on re-using MOOCs and disseminating OERS to the noon-digitally fluent students to help them develop 21st-century digital skills. Calonge and Shah [7] in their study titled "MOOCs, Graduate Skills Gaps, and Employability: A Qualitative Systematic Review of the Literature", carried out a systematic literature review highlighting the use of MOOCs as a tool for bridging the mismatch in graduate digital skills. The study reviewed 16 reports and documents, and the potential of MOOCs in bridging the digital skills gap was investigated. The literature review covered the following concepts: higher education

and graduate skills gap, today's graduates and employability, and MOOCs and graduate skills. A global perspective on MOOCs and the digital skills gap was examined with nine articles from the United States, one from Australia, three from India, two from the United Kingdom, and one from France. The results of the review showed that the disruptive potentials of MOOCs in bridging the skill gap are being explored and used through collaborations by corporations, MOOC providers and tertiary institutions.

Alrajhi et al. [3] tackle the challenge of determining when instructor intervention is needed in MOOC environments by applying eXplainable Artificial Intelligence (XAI) techniques. By interpreting a model for urgent comment detection, they demonstrate how XAI can support annotators in creating high-quality datasets for intervention, thereby improving the effectiveness of MOOCs. López-Pernas et al. [32] introduce a bot designed to aid MOOC participants in completing programming assignments by providing timely formative feedback. The positive perception of students toward the bot indicates its utility in assisting learners with assignments, highlighting the potential of intelligent systems in enhancing learning experiences.

Coad et al. [11] evaluate the effectiveness of MOOCs in educating healthcare professionals (HCPs) involved in germline genomic testing. Their study significantly improves learners' confidence and knowledge, particularly among genomics specialists. However, challenges remain in adapting course materials for non-genomics clinicians to maximise learning outcomes. Cisel [10] explores learners' perspectives on using their data in MOOC platforms, revealing generational differences in attitudes toward data exploitation. The study highlights ethical concerns regarding data transmission to third parties and underscores the importance of transparency and user consent in data usage practices.

Liu and Huang [30] investigate the impact of teacher influence on learners' continuance learning intention in Chinese MOOCs. Their findings suggest that teacher influence indirectly affects learners' intention through perceived usefulness and satisfaction, emphasising the role of teachers in promoting continuous learning engagement. Liu [29] examines the impact of lecture characteristics on academic listening comprehension in MOOCs. The study finds that MOOC lectures, characterised by higher lexical density and speech rate, demand higher-level academic listening skills from learners, highlighting the need for tailored instructional strategies.

Wang et al. [50] explore students' experiences of MOOC-based flipped learning through the lens of the revised Community of Inquiry (CoI) framework. Their study demonstrates that MOOC-based flipped courses enhance all four types of presences outlined in the CoI framework, providing valuable insights for practitioners designing integrated learning experiences. Munigadiapa and Adilakshmi [38] propose a sentiment analysis system using Long Short-Term Memory (LSTM) architecture to evaluate MOOCs. Their system outperforms other machine learning models in sentiment classification, offering a promising approach for analysing student opinions and improving course quality.

Borchard et al. [5] compare discussion board engagement between family carers and non-carers in a dementia care MOOC. Family carers demonstrate significantly higher engagement, particularly in discussions related to personal experiences and meaningful activities, highlighting the potential of MOOCs in facilitating peer support. Wang and Yang [49] propose an online evaluation method based on decision tree-based big data classification for MOOC teaching quality. Their method achieves high accuracy in evaluating teaching quality, providing a valuable tool for educators and administrators to improve MOOCs' educational effectiveness.

Abderrahmane and Mebitil [1] investigated students' and teachers' attitudes towards using MOOCs for language learning and teaching; the study aimed to examine the factors that impact students' inclination and teachers' attitudes to use MOOCs and to explore the symbiotic relationship between students' predilection and teachers' role in training them to use these online sources because teachers are the critical component of the learning process. The study was designed as a descriptive study using questionnaires and interviews as the primary research tools for collecting data. Data was collected from 47 2nd year EFL Didactics master students from Ibn Khaldoun University, Tiaret. The survey results indicated that EFL students and teachers have positive attitudes towards online learning courses; their readiness to use MOOCs is still moderately low. The results also revealed a correlation between MOOC adoption and Perceived Usefulness with Perceived Ease of Use. ICT competence, ICT preparedness, technological expertise, and ICT training directly impact users' attitudes.

Gordillo, López-Pernas and Barra [18] examined the effectiveness of MOOCs in teacher training in safe ICT use. The study aimed to investigate the instructional effectiveness of MOOCs for training teachers in safe and responsible ICT use. The study was based on the fact that despite the efforts placed into teacher ICT training, there is still a wide gap between the digital competence of teachers and the one they require in developing students' digital competence. The study examines MOOCs as a plausible solution to the abridging of the digital competence gap. The study was carried out as a mixed-method quantitative research, which involved the analysis of three different courses; the analysis was carried out using three different techniques: a questionnaire to measure the perception of course participants, pre-tests and post-tests to evaluate the measure of knowledge imparted and acquired by participants and lastly, Learning Object Review Instrument (LORI) to measure the quality of digital educational resources created by the participants. The research sample consisted of a total of 809 teachers in both private and public schools in Madrid and Castilla y Leon, Spain. The study's findings revealed that MOOCs prove to be an effective strategy to train teachers in the safe and responsible use of ICT; in addition, the study suggested that MOOCs are an effective tool for developing digital competence with a focus on content creation.

1.6. Conceptual framework

The conceptual framework proposed for this study is adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT). The conceptual framework for this research was developed with empirical insight from relevant theories, literature, and empirical studies. The study adopted the four constructs of the UTAUT, i.e., Performance expectancy, Effort expectancy, Social influence, and Facilitating conditions; the study also adopted the Internet availability/accessibility variable to evaluate its influence on the use of MOOCs.

In figure 1, the conceptual framework for this study is illustrated. The model is divided into the dependent variable, namely, the use of MOOCs for digital skills development, and the independent variables, namely, Performance expectancy, Effort expectancy, Social influence, Facilitating conditions of MOOCs, and Internet availability/accessibility (IA/A); and three moderating variables, namely, Gender, Age, and Experience. The conceptual model for this study shown above explains the potential relationship between the independent and dependent variables. The arrow-headed lines depict the relationships and the directions of influence

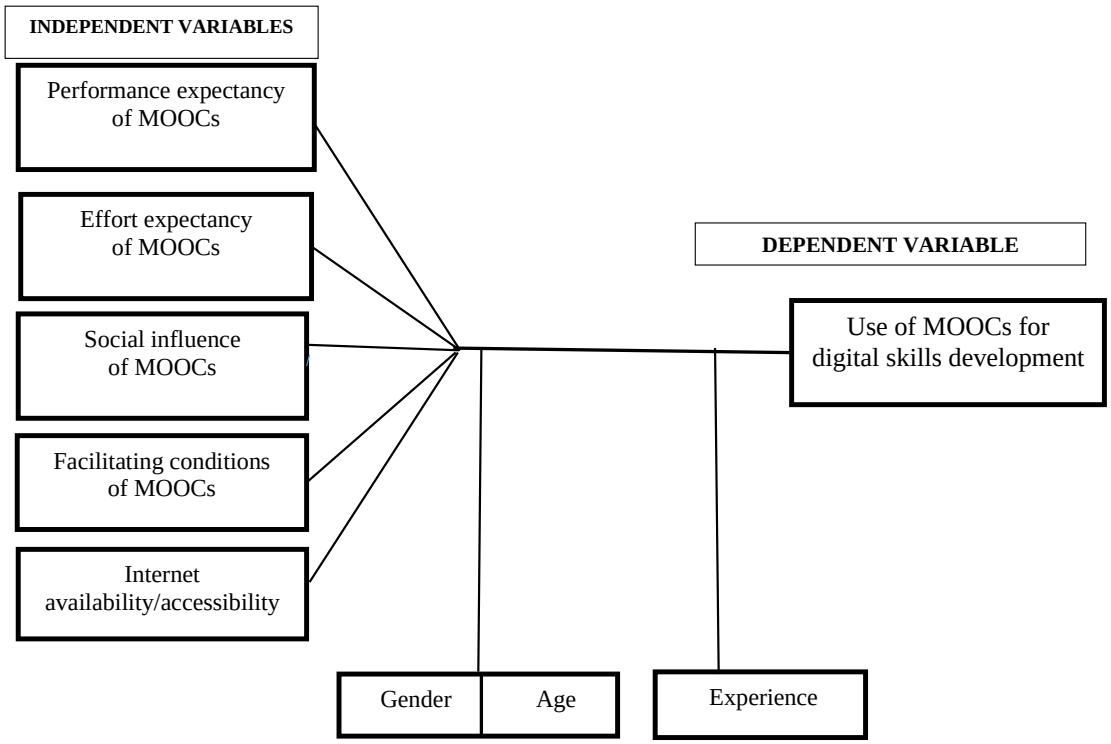

Figure 1: Conceptual framework.

between each variable of the study.

The assumptions in this framework suggest that 1) the use of MOOCs for digital skills development is dependent on Internet availability/accessibility, Performance expectancy, Social influence, Facilitating conditions, and Effort expectancy of MOOCs, and 2) Gender, Age, and Experience moderate the relationship between the independent variables and the dependent variable. It is implied that the Performance expectancy, Social influence, Facilitating conditions and Effort expectancy, and Internet availability/accessibility will influence the utilisation of MOOCs for digital skills development.

2. Methodology

This study adopted a descriptive survey research design and a quantitative survey method for data collection. The use of the descriptive survey method is appropriate for this research because it is a valuable research method that provides a cost-effective and efficient way to collect and analyse data on a large sample of people, allowing for the generalisation of results to a larger population. The descriptive research approach was appropriate for this study and can be used to gather information about the current status of a phenomenon, attitudes, opinions, or characteristics of a population. This research targets undergraduate students in private and public universities in Ibadan Metropolis, Oyo state.

This study deployed a multi-stage sampling technique to determine the sample size for this research. In the first stage, the researcher used the purposive sampling technique to select three universities from the six universities in the Ibadan Metropolis. The universities were selected based on metrics including location, accessibility, popularity, and availability of respondents. In the second stage, proportionate sampling was utilised to select each university's sample. In the final stage, accidental sampling was used for the face-to-face data collection. Using Kardaun's [24] sample proportion formula, the total sample size was divided according to the population of undergraduates in each university. Using Kardaun's [24] sampling scheme, a sample of 378 was determined. The proportional to size sampling (PPS) scheme: *(Number of undergraduates in an institution/Total number of undergraduates) X Determined sample size* was then used to determine the sample component from each of the institutions as shown in table 1.

Table 1
Proportionate-to-population sample sizes for the three universities.

S/N	Name of institution	Number of undergraduate students	Number of sample proportion
1.	University of Ibadan	15479	268
2.	Lead City University, Ibadan	5985	103
3.	Dominican University	300	6
	Total	21764	377

The researchers designed a questionnaire to collect data for the study. The questionnaire contains seven sections.

Section A: This section collected respondents' demographic characteristics, including institution name, age, gender, faculty, level, and digital skills category.

Section B: This section asked questions that examined respondents' level of use of MOOCs for digital skills development. Questions from this section were adapted from Tsabedze and Tella [45]. Responses were obtained using a "Yes" and "No" scale, except the frequency of use item that utilises a Likert measurement scale (5-point scale).

Section C: This section examined undergraduates' performance expectancy of MOOCs. Responses were obtained using a Likert scale of measurement (4-point scale). Questions from this section were adapted from Wan, Xie and Shu [48].

Section D: This section examined undergraduates' effort expectancy of MOOCs on digital skills development. Questionnaire items in this section were adapted from existing literature [36, 39], and responses will be obtained using a Likert measurement scale (4-point scale).

Section E: This section captured questions related to undergraduates' social influence of MOOCs. Questionnaire items in this section were adapted from Fianu et al. [15] and Meet, Kala and Al-Adwan [36]. Responses will be obtained using a Likert measurement scale (4-point scale).

Section F: This section covered questions related to undergraduates' facilitating conditions of MOOCs. Questionnaire items in this section were adapted from existing literature,

specifically from Chu and Dai [9], and respondents expressed their opinion using a Likert measurement scale (4-point scale).

Section G: This section covers questions related to undergraduate internet availability and accessibility. Respondents' opinions were obtained using the "Yes" and "No" response options.

2.1. Validity and reliability of instrument

Reliability in quantitative research refers to the exact repeatability of the processes and the results, and validity is the degree to which a research instrument measures what it is designed to measure. The researcher's supervisor reviewed the questionnaire for its face validity, and his suggestions, comments, and corrections were considered to improve the instrument as appropriate. The face validation issues process involved appropriateness of the title and explanation of the purpose of the instrument to respondents, grammatical expression of questions, answer options, item sequencing, and ensuring that the questions and answer options would be adequately able to collect the required data for analysis to answer the research questions of the study.

The questionnaire was pre-tested using a pilot test on a sample of 20 undergraduate students at the University of Ilorin, located in the Ilorin South LGA of Kwara State, Nigeria. For the reliability test, the Cronbach alpha reliability coefficient value was calculated from the pilot-administered questionnaire to determine the internal consistency of the related multiple questions used to measure the same variables.

The internal consistency reliability of the research instrument was measured using Cronbach's alpha. Cronbach's alpha assesses how well the items in a scale or measure correlate, indicating the degree to which the items measure the same underlying construct. The reliability coefficient, Cronbach's alpha, for each subscale was greater than the recommended value of 0.7. According to Hair et al. [21], the internal consistency of a questionnaire is regarded as an acceptable instrument when all values exceed 0.7. Hence, the reliability of the scales for this research is acceptable (table 2).

Table 2
Cronbach's alpha Result for the constructs in the instrument used.

	Constructs	Number of items	Cronbach's alpha
1	Performance expectancy	5	0.734
2	Effort expectancy	5	0.840
3	Social influence	5	0.780
4	Facilitating conditions	5	0.756

The researcher personally administered the questionnaire to the students, assisted by two research assistants. The questionnaire was administered to respondents using two techniques: the first through face-to-face administration and the second through a web-based questionnaire, which was developed using Google Forms and housed in a password-protected folder, the data from which was accessible only by the researcher. Two data collection techniques were used using the web-based questionnaire; the first involved collecting data from students who were

available and willing to participate, and the second involved asking respondents to share the questionnaire link with their colleagues and friends in the selected universities.

The data collected with the questionnaire were extracted, coded, and subjected to appropriate statistical analyses using the Statistical Package for Social Science (SPSS). Descriptive statistics were used to analyse the respondents' demographic characteristics, including frequency counts, percentages, and charts. Data collected regarding the research questions were analysed and presented using descriptive statistics, including percentages, mean and standard deviation. Hypothesis testing was carried out using a simple regression analysis approach, and a decision was made at a significance level of 0.05. The choice of simple regression was based on the need for straightforward relationships between the UTAUT/availability variables and adoption variables to ease interpretability and avoid complications. The results were summarised in single tables for the sake of parsimony.

3. Results

3.1. Demographic characteristics of the students

The demographic characteristics of the respondents are presented in this section. The respondents' demographic data include their name of institution, age, gender, level, and digital skill category, and is presented in table 3.

Table 3 shows that the majority of respondents were undergraduates from the University of Ibadan (70.9%), followed by Lead City (27.2%) and Dominican University (1.9%). The data analysed reported a higher percentage of 300-level respondents (37.8%), followed by undergraduates in the 200 level (26.5%), immediately followed by 400 level (23.0%), 100 level (8.5%), and lastly, 500 level (4.2 %). The results also indicated that most students fall between the ages of 21-25 (45.5%), 40.5% of respondents fall within the range of 16-20 years, and 14% of students fall within the range of 26+ years of age. There is a higher proportion of male respondents (51.1%) than female respondents (49.9%) in the selected universities. Further results showed a majority of respondents fall within the Intermediate digital skill category (61.9%), followed by the beginner digital skill category (25.4%), and lastly, the advanced digital skills category (12.7%), indicating that the majority of the respondents were average digital literates.

3.2. Use of MOOCs for digital skill development

Table 4 shows the frequency distribution of respondents' use of MOOCs for digital skills development. The frequency distribution of the use of respondents' use of MOOCs shows that a higher proportion of the respondents utilise MOOCs (77.8%), 72% of respondents indicated that they have enrolled for a MOOC on a MOOC platform, and 60.8% of respondents further revealed that they completed the class they enrolled for.

In addition, 69.6% of respondents have enrolled in a course on digital skills on any MOOC platform, and 72.2% of respondents revealed that they could perform a digital skill after learning digital skills using MOOCs.

Table 3
Frequency distribution of respondents' demographic characteristics.

Variable	Value	Frequency	%
Name of institution	University of Ibadan	268	70.9
	Lead City University	103	27.2
	Dominican University	7	1.9
	Total	378	100.0
Level	100	32	8.5
	200	100	26.5
	300	143	37.8
	400	87	23.0
	500	16	4.2
	600	0	0.0
	Total	378	100.0
Age	16-20	153	40.5
	21-25	172	45.5
	26–above	53	14.0
	Total	378	100.0
Gender	Male	193	51.1
	Female	185	49.9
	Total	378	100.0
Digital skills category	Beginner	96	25.4
	Intermediate	234	61.9
	Advanced	48	12.7
	Total	378	100.0

3.3. Familiarity with MOOC platforms

From figure 2, it can be deduced that most respondents (56.88%) are familiar with Coursera, while they had a low familiarity with other MOOC platforms.

FutureLearn showed the lowest level of familiarity (12.90%), while they were moderately familiar with Udemy (35.66%).

3.4. The UTAUT variables and use MOOCs for digital skills development

Table 5 presents the responses on UTAUT variables related to the usage of MOOCs for digital skills development.

Performance expectancy: Respondents generally have positive perceptions regarding the effectiveness of MOOCs for digital skills learning and development, with an average mean score of 3.20 to 3.35 out of 5. Most respondents agree that MOOCs are beneficial for improving digital skills and saving time, with agreement percentages ranging from 49.7% to 64.8%.

Effort expectancy: Participants express varying levels of comfort and ease in using MOOC platforms, with mean scores ranging from 2.91 to 3.10. While many respondents agree that MOOCs make it easy to achieve their digital skills development goals, there are mixed perceptions

Table 4
Use of MOOCs for digital skills development.

Variable	Yes		No	
	Frequency	%	Frequency	%
Do you use MOOCs?	294	77.8	84	22.2
Have you enrolled in any MOOC classes such as Coursera, Udacity, or Udemy before or now?	272	72.0	106	28.0
Did you complete the courses you enrolled in in the MOOCs class?	230	60.8	148	39.2
Have you ever enrolled in a course on digital skill development on any MOOC platform?	263	69.6	115	30.4
Were you able to perform a digital task after using a MOOC to learn a digital skill?	273	72.2	105	27.8

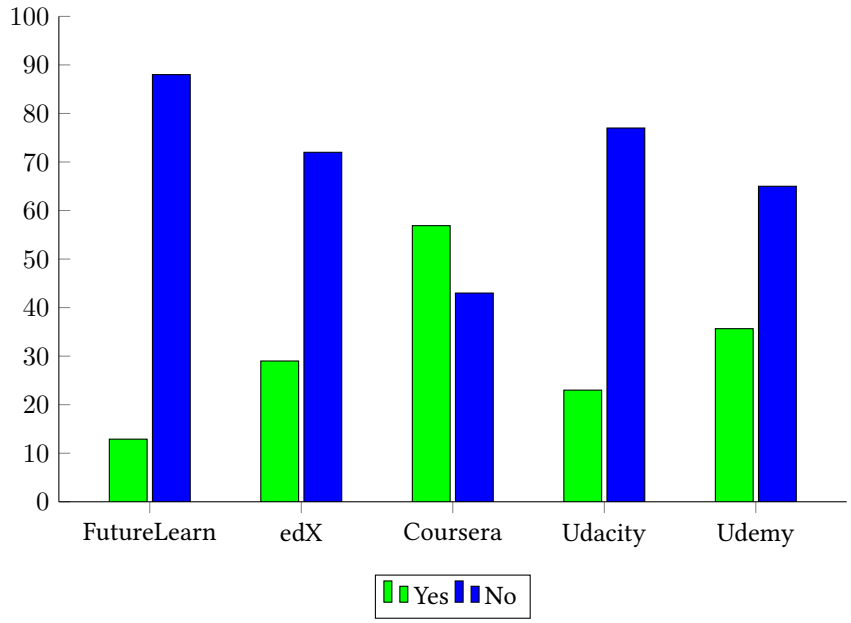

Figure 2: Undergraduates' level of familiarity with selected MOOC platforms.

regarding the clarity of interactions and the time required for learning.

Social influence: The influence of friends and educators on the decision to use MOOCs appears moderate, with mean scores ranging from 2.54 to 2.83. While some respondents report receiving recommendations from friends and educators to use MOOCs, there are lower levels of agreement regarding the actual usage of MOOCs by friends and partners.

Facilitating conditions: Respondents generally perceive adequate accessibility, connectivity, and resources for using MOOCs, with mean scores ranging from 2.48 to 3.13. However, there are concerns about the availability of financial support and institutional facilities for utilising MOOCs, as indicated by lower mean scores in these areas.

Table 5
The UTAUT Variables and use of MOOCs for digital skills development.

	D (%)	SD (%)	A (%)	SA (%)	Mean	Std.
Performance expectancy						
Using MOOCs is the best approach to digital skills learning and development	2.1	4.2	49.7	43.9	3.35	.665
MOOCs are better for digital skills learning than using physical classrooms and lab interactions with lecturers	4.2	4.5	54.0	37.3	3.24	.728
MOOCs can improve my current digital skills	5.3	5.0	53.7	36.0	3.20	.763
MOOCs help me save time when developing my digital skills	5.0	5.0	64.8	25.1	3.10	.703
Using MOOCs helps in measuring the amount of knowledge or skills obtained	4.2	5.6	64.3	25.9	3.12	.686
Effort expectancy						
I have adequate knowledge of how to use MOOCs	17.7	3.4	47.6	31.2	2.92	1.026
My interactions with MOOC platforms are clear and understandable	14.0	6.1	54.5	25.4	2.91	.933
MOOCs make it easy to achieve my goal of digital skills development	9.0	4.8	59.3	27.0	3.04	.823
I find it easy to use any Online Educational Resources (MOOCs etc.)	6.6	4.8	61.1	27.5	3.10	.761
It does not take me much time to learn digital skills when I use MOOCs	8.2	5.8	64.0	22.0	3.00	.779
Social influence						
I get adequate support from friends/ other students when I face difficulties in using MOOCs	17.7	5.6	53.2	23.5	2.83	.986
My friends often recommend that I use MOOCs for digital skills development	18.0	5.8	56.9	19.3	2.78	.961
My teachers/lecturers often recommend that I use MOOCs for digital skills development	18.3	7.7	49.7	24.3	2.80	1.007
My friends/partners use MOOCs for digital skills development	24.6	14.3	42.1	19.0	2.56	1.060
The attitudes and opinions of important people in my life influence my decision to use MOOCs for digital skills development	27.2	12.7	39.2	20.9	2.54	1.102
Facilitating conditions						
I have sufficient online accessibility and connectivity to use MOOCs	7.9	4.5	54.2	33.3	3.13	.825
I have enough money to fund my use of MOOCs for digital skills development	10.1	14.0	56.6	19.3	2.85	.846
Your university provides adequate facilities and support for me to use MOOCs for my digital skills development	14.3	40.5	28.3	16.9	2.48	.936
I can find helpers in time if I encounter problems when using MOOCs for digital skills development	14.0	11.1	58.7	16.1	2.77	.885
I have the necessary resources for MOOCs (such as computers, smartphones, internet, and usage funds)	8.7	5.0	62.4	23.8	3.01	.799

3.5. Digital skills of students

Table 6 comprehensively summarises respondents' proficiency levels in various digital skills. Across the board, proficiency levels show noticeable diversity, reflecting the varying degrees of familiarity and competence with different digital tasks. Regarding social media networking, a considerable majority (45.2%) of respondents exhibit good skills, followed by 24.9% with very good skills and 18.0% with excellent skills. This indicates a robust proficiency in navigating social media platforms and engaging with online networks. Similarly, smartphone and mobile phone usage skills are prevalent among respondents, with 39.7% reporting good skills, 27.0% with very good skills, and 26.7% with excellent skills. This suggests a widespread ability to effectively utilise mobile devices for communication and other tasks.

Table 6
Digital skills of the students.

Digital skills	Poor (%)	Fair (%)	Good (%)	Very good (%)	Excellent (%)	Mean	Std.
Social media networking	3.4	8.5	45.2	24.9	18.0	3.46	.993
Smartphone/mobile phone use	1.6	5.0	39.7	27.0	26.7	3.72	.966
Internet surfing	3.7	7.1	32.8	29.6	26.7	3.69	1.057
E-mail	2.9	14.0	41.5	20.9	20.6	3.42	1.056
Mobile and video games	7.4	36.2	28.3	13.0	15.1	2.92	1.179
Word processing and presentation software	6.1	26.7	35.2	19.6	12.4	3.06	1.097
Spreadsheet	9.0	36.8	31.7	14.6	7.9	2.76	1.065
Video conferencing	9.0	18.5	29.6	26.7	16.1	3.22	1.188
Blogging/Vlogging	14.3	30.4	37.3	10.8	7.1	2.66	1.076
Online discussions and forums	7.4	16.7	33.9	28.8	13.2	3.24	1.108
File sharing services	6.9	28.3	34.1	19.0	11.6	3.00	1.103
Cloud computing	15.9	31.7	34.4	10.1	7.9	2.62	1.110
Website design	19.3	37.8	22.0	13.5	7.4	2.52	1.164
Data entry and analysis	15.9	37.0	27.2	12.7	7.1	2.58	1.116
Database management	20.1	37.3	23.8	11.4	7.4	2.49	1.152

Internet surfing skills also show a solid grasp among respondents, with 32.8% reporting good skills and 29.6% with very good skills. This indicates a comfortable familiarity with browsing the internet and accessing online content. Email proficiency is widespread, with 41.5% of respondents demonstrating good skills and 20.9% exhibiting very good skills. This suggests that respondents are adept at managing and communicating through email platforms. However, proficiency levels vary across different areas. For instance, while word processing and presentation software skills show a balanced distribution, with 35.2% reporting good skills, other areas, such as spreadsheet usage, indicate room for improvement, with 36.8% exhibiting fair skills and 9.0% with poor skills.

Similarly, while video conferencing skills are fairly distributed, with 29.6% reporting good skills and 26.7% very good skills, proficiency in blogging/vlogging and file-sharing services exhibits more varied distributions. Cloud computing and website design skills show potential areas for enhancement, with a considerable percentage of respondents reporting poor to fair

skills in these domains. Data entry and analysis skills are evenly distributed, while database management skills are varied, with fair skills being the most prevalent. The table highlights strengths and areas for improvement in respondents' digital skills. It underscores the importance of ongoing education and training initiatives to ensure that individuals are equipped with the necessary competencies to effectively navigate and leverage digital technologies in today's digital landscape.

3.6. Level of internet availability/accessibility to the students

Table 7 offers insights into respondents' internet accessibility and availability, providing a glimpse into their ownership of devices and access to internet services. A large proportion of respondents report owning devices capable of internet access, with 90.7% owning a laptop, desktop, or tablet computer and 97.4% owning a smartphone for this purpose. These figures indicate widespread ownership of internet-capable devices among the surveyed population. However, when considering access to these devices, specifically at home or school, the percentage drops to 54.2%. This suggests that while many respondents own devices, not all have convenient access to them for internet browsing when needed. Regarding financial capacity for data subscription, 63.5% of respondents state that they have sufficient personal funds for this purpose. However, a significant minority (36.5%) indicate a lack of financial capacity, potentially limiting their ability to access the internet regularly.

Table 7
Level of internet availability/accessibility.

Internet availability/accessibility	Yes (%)	No (%)
Do you own a laptop, desktop, or tablet computer that you can use to access the Internet any time you need to?	90.7	9.3
Do you own a smartphone that you can use to access the Internet any time you need to?	97.4	2.6
Do you have easy access to a laptop, desktop, or tablet computer at home or school that you can use to access the Internet when you need to?	54.2	45.8
Do you have sufficient personal funds to subscribe for adequate data for browsing the Internet for your academic/educational purposes as you need to?	63.5	36.5
Do you often connect to the internet for e-mail or internet surfing?	94.2	5.8

Despite potential financial constraints, most respondents (94.2%) report frequent internet connection for email or general surfing purposes. This high percentage underscores internet connectivity's importance for communication and online information in respondents' daily lives. The table paints a nuanced picture of internet accessibility and availability among respondents. While ownership of internet-enabled devices is widespread, factors such as access to these devices and financial constraints play a role in determining individuals' ability to connect to the internet regularly. Nonetheless, most demonstrate a frequent connection to the internet for various purposes, highlighting its significance in their lives.

3.7. Testing the hypotheses

The dimensions of the UTAUT variables were reduced for the sake of parsimony. The main objective is to reduce the dimensions of the variables while as much of the original variability of the dimensions of each variable as possible. This way, noise in the data would be reduced, and the complexity of the datasets would be removed. Bartlet's Test of Sphericity (BTS) was used to test the probability that the correlation matrix has significant correlations among some of the variables in a dataset as a prerequisite for principal component analysis (PCA).

Table 8
Test of sampling adequacy and sphericity.

	BTS	P	KMO
Performance expectancy	χ^2=802.587, DF=10	0.000	0.793
Effort expectancy	χ^2=973.137, DF=10	0.000	0.787
Social influence	χ^2=959.382, DF=10	0.000	0.820
Facilitating conditions	χ^2=364.589, DF=10	0.000	0.746
Internet availability/accessibility	χ^2=137.060, DF=10	0.000	0.688

Usually, the Kaiser-Meyer-Olkin (KMO) test is conducted when it is necessary to examine the strength of the partial correlations to know how the factors might explain each other. KMO values closer to 1.0 are ideal, while those less than 0.5 are unacceptable. Table 8 shows that all the variables have significant correlations with the other variables (p<0.05) and that the KMO values are higher than 0.5. Thus, the reduction of the variables for higher analysis is accepted. Varimax rotation was adopted to simplify and enhance the interpretability of the principal components. By aligning the axes with the most significant features, it was easier to understand the underlying structure of the data.

3.8. Principal components of the UTAUT variables

Table 9 relates to reducing the dimensions of the constructs.

The five dimensions of PE, EE, SI, and FC were reduced to one PC each. These PCs are a set of uncorrelated variables that are linear combinations of the original variables, and they have been sorted in the order in which they explain the maximum variance in the system.

3.9. Regression analysis of the use of MOOCs, UTAUT, and IA/A variables

Table 10 relates to the model summary of the regression analysis between adoption and UTAUT/accessibility variables, with R signifying the relationship between the dependent and the independent variables. Rs that are higher than 0.6 show a high relationship and higher predictability, R^2 is the proportion of the dependent variable explained by the independent variables.

Table 11 presents the ANOVA statistics for the regression model. The significant value (p) shows the significance level, indicating whether the regression is statistically significant or just chance. The generally accepted standard for significance is p<0.05, so the results of the regression in table 11 are significant (p=0.000). A value for the F-ratio (F) to provide an efficient

Table 9
Principal components of the UTAUT variables.

	Loadings	**Initial eigen value**	**Mean**	**SD**
Performance expectancy				
MOOCs can improve my current digital skills	0.750	61.678	3.20	0.763
Effort expectancy				
My interactions with MOOC platforms are clear and understandable	0.844	65.155	2.91	0.933
Social influence				
The attitudes and opinions of important people in my life influence my decision to use MOOCs for digital skills development	0.857	66.046	2.54	1.102
Facilitating conditions				
I have enough money to fund my use of MOOCs for digital skills development	0.745	48.427	2.85	0.846

Table 10
Regression analysis model summary.

Variable	R	R^2	Adjusted R^2	Std. error estimate
Performance expectancy	0.376	0.141	0.132	0.388
Effort expectancy	0.540	0.292	0.284	0.352
Social influence	0.359	0.129	0.120	0.391
Facilitating conditions	0.387	0.150	0.140	0.386
Internet availability/accessibility	0.362	0.131	0.120	0.391

model should be greater than 1. The values in the table are greater than 1, which is adequate for further analysis.

Table 12 presents the statistical coefficients that can be used to explain the linear regression between the dependent variable and the independent variables. The results of the linear regression indicate that there is a significant influence of the independent variables (Performance expectancy, Effort expectancy, Social influence, and Facilitating conditions) on the dependent variable (Use of MOOCs) (p<0.05), however, there is no significant influence of Internet availability/accessibility on the use of MOOCs for digital skills development (p>0.05).

Table 13 presents the statistical coefficients that can be used to explain the linear regression between the use of MOOCs and the demographic characteristics of respondents.

The table indicates that digital skills significantly explain the use of MOOCs (p<0.05), but there is no significant relationship between age and gender on the use of MOOCs by the respondents (p>0.05).

Table 11
ANOVA of the model.

Model		Sum of squares	Df	Mean square	F	Sig.
Performance expectancy	Regression	9.241	4	2.310	15.363	0.000
	Residual	56.092	373	.150		
Effort expectancy	Regression	19.070	4	4.767	38.437	0.000
	Residual	46.264	373	0.124		
Social influence	Regression	8.436	4	2.109	13.825	0.000
	Residual	56.898	373	.153		
Facilitating conditions	Regression	9.774	4	2.443	16.404	0.000
	Residual	55.559	373	.149		
Internet availability/accessibility	Regression	8.584	5	1.717	11.254	0.000
	Residual	56.749	372	.153		

Table 12
Regression between use of MOOCs, UTAUT, and IA/A.

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
PE	MOOCs can improve my current digital skills	-0.124	0.027	-0.226	-4.509	.000
EE	My interactions with MOOC platforms are clear and understandable	-0.221	0.020	-0.496	-11.085	.000
SI	The attitudes and opinions of important people in my life influence my decision to use MOOCs for digital skills development	-0.042	0.019	-0.110	-2.156	.032
FC	I have enough money to fund my use of MOOCs for digital skills development	-0.124	0.025	-0.253	-5.066	.000
IA/A	Do you own a smartphone that you can use to access the Internet any time you need to?	0.198	0.133	0.077	1.486	.138
	Do you have easy access to a computer laptop, desktop or table at home or school that you can use to access the Internet when you need to?	-0.063	0.043	-0.076	-1.469	.143

3.10. Evaluating the hypotheses

Table 14 shows the summary of the test of the hypotheses. The findings suggest that all the factors examined – performance expectancy, effort expectancy, social influence, facilitating conditions, internet availability/accessibility, and demographic characteristics – have a significant

Table 13
Regression between demographic characteristics and use of MOOCs.

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
Age	0.035	0.029	0.058	1.193	.233
Gender	0.015	0.041	0.018	0.364	.716
Digital skill category	-0.234	0.034	-0.340	-6.915	.000

Table 14
Evaluating the hypotheses.

	The hypotheses	Decision
H1:	Performance expectancy has no significant effect on the use of MOOCs by university undergraduates in Ibadan, Nigeria, for digital skills development.	Rejected
H2:	Effort expectancy has no significant effect on the use of MOOCs for digital skills development by university undergraduates in Ibadan, Nigeria.	Rejected
H3:	Social influence has no significant effect on the use of MOOCs for digital skills development by university undergraduates in Ibadan, Nigeria.	Rejected
H4:	Facilitating conditions has no significant effect on the use of MOOCs for digital skills development by university undergraduates in Ibadan, Nigeria.	Rejected
H5:	Internet availability/accessibility has no significant effect on university undergraduates' use of MOOCs for digital skills development in Ibadan, Nigeria.	Rejected
H6:	The demographic characteristics of the students have no significant effect on their use of MOOCs for digital skills development.	Rejected

effect on the use of MOOCs for digital skills development among university undergraduates in Ibadan, Nigeria.

4. Discussion of findings

The study begins by providing a comprehensive overview of the demographic characteristics of the university undergraduates surveyed. The sample size of 378 respondents represents a substantial number of students from the institutions in Ibadan, Nigeria. The distribution of respondents across the three universities – University of Ibadan, Lead City University, and Dominican University – offers an insight into the representation of these institutions within the study. The study's focus on using MOOCs for digital skill development is noteworthy, especially in the context of the rapidly evolving digital landscape in education. The fact that a substantial 77.8% of respondents reported using MOOCs indicates a growing awareness and interest in these online learning platforms. Moreover, the information on enrollment and course completion rates offers insights into how students actively engage with MOOC content, suggesting that these platforms are being explored and utilised effectively.

The study's foundation on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework underscores the rigorous theoretical framework underpinning the research. UTAUT

is a widely respected model for understanding technology adoption, making the study's findings more robust. Including factors like performance expectancy, effort expectancy, social influence, facilitating conditions, and internet availability/accessibility underscores the multidimensional nature of technology adoption, making the analysis comprehensive. Principal Component Analysis (PCA) is a sophisticated statistical technique that enhances the research's analytical rigour. By reducing the dimensions of the UTAUT variables while retaining maximum explanatory power, the researchers have ensured that the noise in the data is minimised and the complexity of the datasets is appropriately managed. This approach enhances the clarity of the findings and simplifies the interpretation of results.

The regression analysis is a cornerstone of this study, revealing significant insights into the relationships between various factors and the use of MOOCs. The model summary in table 10 gives a snapshot of how much variation in MOOCs is explained by the independent variables – Performance expectancy, Effort expectancy, Social influence, Facilitating conditions, and Internet availability/accessibility. The R^2 values offer insights into the strength of these relationships. ANOVA statistics in table 11 provide information about the overall fit of the regression model. The significant p-values ($p<0.05$) confirm that the model is not merely due to chance, emphasising the reliability of the findings. The F-ratio values higher than 1 reinforce that the model is efficient and suitable for further analysis.

The coefficients in table 12 are critical in understanding the strength and direction of the relationships. Each coefficient indicates how much the dependent variable changes for a one-unit change in the independent variable, holding other variables constant. For instance, negative coefficients for factors like Performance expectancy and Facilitating conditions suggest that as these factors increase, the use of MOOCs decreases. This counterintuitive result could lead to intriguing discussions about the nuanced nature of technology adoption.

The exploration of the relationship between demographic characteristics and the use of MOOCs highlights a nuanced picture. The significant influence of the digital skill category on MOOC usage is consistent with expectations, as students with higher digital skills might be more inclined and equipped to utilise online platforms effectively. The lack of significant influence from age and gender is an interesting finding, potentially indicating that MOOC adoption transcends traditional demographic boundaries.

The study reveals a substantial adoption of MOOCs for digital skill development among university undergraduates in Ibadan, Nigeria, with factors such as Performance expectancy, Effort expectancy, Social influence, and Facilitating conditions significantly influencing usage, while demographic factors like age and gender did not significantly impact. This study offers valuable insights into the dynamic landscape of digital education in Nigeria, focusing on MOOC usage among university undergraduates. The rigorous statistical analyses, comprehensive UTAUT framework, and multifaceted approach to understanding technology adoption provide a solid foundation for interpreting the findings. The results not only highlight the prevalence of MOOC usage but also offer a nuanced understanding of the factors shaping its adoption among university students.

5. Conclusion

5.1. Limitations

The study primarily focuses on university undergraduates in Ibadan, Nigeria, potentially limiting the generalizability of findings to other demographics or regions. While age and gender did not significantly influence MOOC adoption, other demographic variables, such as socio-economic status or educational background, might have been overlooked. The study's cross-sectional design restricts the examination of trends or changes in MOOC usage over time, suggesting the need for longitudinal studies. Also, the cross-examinations did not include all the possible relationships; only those specified in the study were undertaken.

5.2. Recommendations on future studies

- Consider broader demographic factors beyond age and gender to comprehensively understand MOOC adoption.
- Conduct longitudinal research to track MOOC usage trends and changes among university students.
- For a more comprehensive analysis, explore the impact of socio-economic status, prior educational background, and access to resources on MOOC adoption.
- Conduct comparative studies across diverse regions or educational levels to understand variations in MOOC adoption and its influencing factors.
- Investigate the long-term impact of MOOC usage on academic performance, career prospects, and skill enhancement among students.
- Explore the effectiveness of different instructional designs or pedagogical strategies employed within MOOCs for student cohorts.

5.3. Implications

Educational institutions can leverage the study's findings to tailor support services, enhance digital literacy initiatives, and promote online learning among students. Policymakers could utilise insights from the study to shape policies promoting digital education, fostering a conducive environment for MOOC usage and technological integration in education. Instructors can adapt pedagogical approaches within MOOCs based on factors influencing adoption, thereby enhancing student engagement and learning outcomes.

The findings suggest a generally positive attitude towards MOOCs for digital skills development, with perceived benefits in terms of effectiveness and convenience. Efforts may be needed to address concerns related to the clarity of interactions, financial support, and institutional infrastructure to enhance further the adoption and effectiveness of MOOCs for digital skills learning.

References

[1] Abderrahmane, D. and Mebitil, N., 2022. Examining EFL Students and Teachers Attitudes towards E-learning: A Focus on MOOCs. *AABHATH Review*, 7(1), pp.775–788. Available from: https://www.asjp.cerist.dz/en/downArticle/435/7/1/190035.

[2] Alkathiri, L.A., 2019. Students' Perspectives towards Using Youtube in Improving EFL Learners' Motivation to Speak. *Journal of Education and Culture Studies*, 3(1), pp.12–30. Available from: https://doi.org/10.22158/jecs.v3n1p12.

[3] Alrajhi, L., Pereira, F.D., Cristea, A.I. and Aljohani, T., 2022. A Good Classifier is Not Enough: A XAI Approach for Urgent Instructor-Intervention Models in MOOCs. In: M.M. Rodrigo, N. Matsuda, A.I. Cristea and V. Dimitrova, eds. *Artificial Intelligence in Education. Posters and Late Breaking Results, Workshops and Tutorials, Industry and Innovation Tracks, Practitioners' and Doctoral Consortium*. Cham: Springer International Publishing, *Lecture Notes in Computer Science*, vol. 13356, pp.424–427. Available from: https://doi.org/10.1007/978-3-031-11647-6_84.

[4] Barrane, F.Z., Karuranga, G.E. and Poulin, D., 2018. Technology Adoption and Diffusion: A New Application of the UTAUT Model. *International Journal of Innovation and Technology Management (IJITM)*, 15(06), pp.1–19. Available from: https://doi.org/10.1142/S0219877019500044.

[5] Borchard, J., Bindoff, A., Farrow, M., Kim, S., McInerney, F. and Doherty, K., 2023. Family carers of people living with dementia and discussion board engagement in the Understanding Dementia Massive Open Online Course. *Aging & Mental Health*, 27(5), pp.887–895. Available from: https://doi.org/10.1080/13607863.2022.2042188.

[6] Brunello, G. and Rocco, L., 2017. The Labor Market Effects of Academic and Vocational Education over the Life Cycle: Evidence Based on a British Cohort. *Journal of Human Capital*, 11(1), pp.106–166. Available from: https://doi.org/10.1086/690234.

[7] Calonge, D.S. and Shah, M.A., 2016. MOOCs, Graduate Skills Gaps, and Employability: A Qualitative Systematic Review of the Literature. *The International Review of Research in Open and Distributed Learning*, 17(5). Available from: https://doi.org/10.19173/irrodl.v17i5.2675.

[8] Chu, J., 2013. *Study on the influencing factors of B-to-B e-commerce sustainable adoption in small and medium-sized enterprises*. Ph.D. thesis. Liaoning University, Shenyang, China.

[9] Chu, J. and Dai, Y.Y., 2021. Extending the UTAUT Model to Study the Acceptance Behavior of MOOCs by University Students and the Moderating Roles of Free Time Management and Leisure-Study Conflict. *International Journal of Technology and Human Interaction*, 17(4), p.35–57. Available from: https://doi.org/10.4018/ijthi.2021100103.

[10] Cisel, M.T., 2023. On the Ethical Issues Posed by the Exploitation of Users' Data in MOOC Platforms: Capturing Learners' Perspectives. *The International Review of Research in Open and Distributed Learning*, 24(4), p.20–43. Available from: https://doi.org/10.19173/irrodl.v24i4.7265.

[11] Coad, B., Joekes, K., Rudnicka, A., Frost, A., Openshaw, M.R., Tatton-Brown, K. and Snape, K., 2023. Evaluation of two Massive Open Online Courses (MOOCs) in genomic variant interpretation for the NHS workforce. *BMC Medical Education*, 23(1), p.540. Available from: https://doi.org/10.1186/s12909-023-04406-x.

[12] Definition Massive Open Online Courses (MOOCs), 2015. Available from: https://www.openuped.eu/images/docs/Definition_Massive_Open_Online_Courses.pdf.

[13] Di Gregorio, A., Maggioni, I., Mauri, C. and Mazzucchelli, A., 2019. Employability skills for future marketing professionals. *European Management Journal*, 37(3), pp.251–258. Available from: https://doi.org/10.1016/j.emj.2019.03.004.

[14] Edelsbrunner, S., Steiner, K., Schön, S., Ebner, M. and Leitner, P., 2022. Promoting Digital Skills for Austrian Employees through a MOOC: Results and Lessons Learned from Design and Implementation. *Education Sciences*, 12(2), p.89. Available from: https://doi.org/10.3390/educsci12020089.

[15] Fianu, E., Blewett, C., Ampong, G.O.A. and Ofori, K.S., 2018. Factors Affecting MOOC Usage by Students in Selected Ghanaian Universities. *Education Sciences*, 8(2), p.70. Available from: https://doi.org/10.3390/educsci8020070.

[16] Ghobrini, R.E.A., 2021. Voicing the unvoiced: potential of offline MOOCs e-content to cater for non-digitally-fluent students. In: P. Limone and R.D. Fuccio, eds. *Proceedings of the First Workshop on Technology Enhanced Learning Environments for Blended Education - The Italian e-Learning Conference, teleXbe 2021, Foggia, Italy, January 21-22, 2021*. CEUR-WS.org, *CEUR Workshop Proceedings*, vol. 2817. Available from: https://ceur-ws.org/Vol-2817/paper31.pdf.

[17] Goglio, V., 2022. *The Diffusion and Social Implications of MOOCs: A Comparative Study of the USA and Europe*. London: Routledge. Available from: https://doi.org/10.4324/9781003009757.

[18] Gordillo, A., López-Pernas, S. and Barra, E., 2019. Effectiveness of MOOCs for teachers in safe ICT use training. *Comunicar*, 27(61), p.103–112. Available from: https://doi.org/10.3916/C61-2019-09.

[19] Guo, L., Li, M. and Xu, D., 2017. Approximation Algorithms for Maximum Coverage with Group Budget Constraints. In: X. Gao, H. Du and M. Han, eds. *Combinatorial Optimization and Applications*. Cham: Springer International Publishing, *Lecture Notes in Computer Science*, vol. 10628, pp.362–376. Available from: https://doi.org/10.1007/978-3-319-71147-8_25.

[20] Hadianti, S., 2022. Asynchronous Online Tutorial and What Lies Within: A Study in the Listening Course of Universitas Terbuka. *JELLT (Journal of English Language and Language Teaching)*, 6(2), p.23–31. Available from: https://jurnal.ustjogja.ac.id/index.php/JELLT/article/view/13285.

[21] Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E., 2010. *Multivariate Data Analysis*. 7th ed. New York: Pearson. Available from: https://www.drnishikantjha.com/papersCollection/Multivariate%20Data%20Analysis.pdf.

[22] Hui, X.J., Man, M. and Sabri, I.A.A., 2023. Hybrid Personalized Recommendation Model Focus on Improved Collaborative Filtering. *Journal of Theoretical and Applied Information Technology*, 101(19), pp.6145–6162. Available from: http://www.jatit.org/volumes/Vol101No19/29Vol101No19.pdf.

[23] Jung, Y. and Lee, J., 2018. Learning Engagement and Persistence in Massive Open Online Courses (MOOCS). *Computers & Education*, 122, pp.9–22. Available from: https://doi.org/10.1016/j.compedu.2018.02.013.

[24] Kardaun, O.J.W.F., 2005. *Classical Methods of Statistics: With Applications in Fusion-Oriented Plasma Physics*. Berlin, Heidelberg: Springer. Available from: https://doi.org/10.1007/

3-540-29288-8.

[25] Khalid, B., Lis, M., Chaiyasoonthorn, W. and Chaveesuk, S., 2021. Factors influencing behavioural intention to use MOOCs. *Engineering Management in Production and Services*, 13(2), pp.83–95. Available from: https://doi.org/10.2478/emj-2021-0014.

[26] Kizilcec, R.F., Pérez-Sanagustín, M. and Maldonado, J.J., 2017. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education*, 104, pp.18–33. Available from: https://doi.org/10.1016/j.compedu.2016.10.001.

[27] Ko, S. and Rossen, S., 2017. *Teaching Online: A Practical Guide*. 4th ed. New York, NY: Routledge.

[28] Lehdonvirta, V., Margaryan, A. and Davies, H., 2019. *Skills Formation and Skills Matching in Online Platform Work: Policies and Practices for Promoting Crowdworkers' Continuous Learning (CrowdLearn)*. University of Oxford. Available from: https://www.research.ed.ac.uk/en/publications/skills-formation-and-skills-matching-in-online-platform-work-poli.

[29] Liu, C.Y., 2023. A corpus-based study of vocabulary in massive open online courses (MOOCs). *English for Specific Purposes*, 72, pp.40–50. Available from: https://doi.org/10.1016/j.esp.2023.08.002.

[30] Liu, S. and Huang, F., 2023. Examining teachers influence on MOOCs learners continuance learning intention: The mediating effects of perceived usefulness and satisfaction. *Journal of Pedagogical Research*, 7(4), pp.237–250. Available from: https://doi.org/10.33902/jpr.202322513.

[31] Lu, J., Bradlow, E.T. and Hutchinson, J.W., 2024. More Likely to Pay but Less Engaged: The Effects of Switching Online Courses from Scheduled to On-Demand Release on User Behavior. *Journal of Marketing*, p.00222429241227145. Available from: https://doi.org/10.1177/00222429241227145.

[32] López-Pernas, S., Barra, E., Gordillo, A., Alonso, Á. and Quemada, J., 2023. Scaling Student Feedback in Software Engineering Massive Open Online Courses. *IEEE Software*, 40(5), pp.50–57. Available from: https://doi.org/10.1109/MS.2023.3275035.

[33] Ma, S., Luo, Y. and Yang, Y., 2023. Personas-based Student Grouping using reinforcement learning and linear programming. *Knowledge-Based Systems*, 281, p.111071. Available from: https://doi.org/10.1016/j.knosys.2023.111071.

[34] Martínez-Pérez, S., Cabero-Almenara, J., Barroso-Osuna, J. and Palacios-Rodríguez, A., 2022. T-MOOC for Initial Teacher Training in Digital Competences: Technology and Educational Innovation. *Frontiers in Education*, 7. Available from: https://doi.org/10.3389/feduc.2022.846998.

[35] McAuley, A., Stewart, B., Siemens, G. and Cormier, D., 2010. *The MOOC model for digital practice*. University of Prince Edward Island. Available from: https://www.oerknowledgecloud.org/record500.

[36] Meet, R.K., Kala, D. and Al-Adwan, A.S., 2022. Exploring factors affecting the adoption of MOOC in Generation Z using extended UTAUT2 model. *Education and Information Technologies*, 27(7), pp.10261–10283. Available from: https://doi.org/10.1007/s10639-022-11052-1.

[37] Mhd Salim, M.H., Mohamad Ali, N., Jalaludin, N.A., Mohd Johari, N.F. and Abd Rahman, M.A., 2023. A Conceptual Persuasive Development Framework to Change Students'

Behaviour in Massive Open Online Courses: A Review. *International Journal of Learning, Teaching and Educational Research*, 22(9), p.1–19. Available from: https://doi.org/10.26803/ijlter.22.9.1.

[38] Munigadiapa, P. and Adilakshmi, T., 2023. MOOC-LSTM: The LSTM Architecture for Sentiment Analysis on MOOCs Forum Posts. In: R. Buyya, S.M. Hernandez, R.M.R. Kovvur and T.H. Sarma, eds. *Computational Intelligence and Data Analytics*. Singapore: Springer Nature Singapore, *Lecture Notes on Data Engineering and Communications Technologies*, vol. 142, pp.283–293. Available from: https://doi.org/10.1007/978-981-19-3391-2_21.

[39] Nordin, N., Norman, H., Embi, M.A., Mansor, A.Z. and Idris, F., 2016. Factors for Development of Learning Content and Task for MOOCs in an Asian Context. *International Education Studies*, 9(5), pp.48–61. Available from: https://doi.org/10.5539/ies.v9n5p48.

[40] Ochieng', V., Mutisya, M. and Thiong'o, C., 2022. The Adoption of Massive Open Online Courses in Selected Sub-Saharan African Countries: The Experiences of Urban Learners. In: D. Cvetković, ed. *MOOC (Massive Open Online Courses)*. Rijeka: IntechOpen, chap. 11. Available from: https://doi.org/10.5772/intechopen.99321.

[41] Onyema, E.M., Eucheria, N.C., Uchenna, E.C., Nkiruka, E.P. and Eucheria, A.U., 2020. Impact of E-learning Platforms on Students' Interest and Academic Achievement in Data Structure Course. *CCU Journal of Science*, 1(1), pp.1–16. Available from: https://www.researchgate.net/publication/343933988.

[42] Otitoju, G.J. and Nwagwu, W.E., 2023. Use of Massive Open Online Course for digital skills development by undergraduates in selected universities in Ibadan, Nigeria. *Regional Journal of Information and Knowledge Management*, 8(2), pp.204–222. Available from: https://www.ajol.info/index.php/rjikm/article/view/263074.

[43] Raju, D.T., Murthy, G.R.K., Vinayagam, S.S., Krishnan, M. and Rao, C.S., 2020. *Impact of Massive Open Online Courses (MOOCs) on Capacity Building*. Hyderabad: ICAR-National Academy of Agricultural Research Management. Available from: https://www.researchgate.net/publication/355393479.

[44] Staboulis, M. and Lazaridou, I., 2020. MOOCs and Soft Skills in demand for today's labor markets. *EBES31 Conference, Eurasia Business and economics Society, Warsaw, Poland, April 15-17, 2020*. Available from: https://www.researchgate.net/publication/340830832.

[45] Tsabedze, V. and Tella, A., 2020. Awareness and use of massive open online courses among library and information science professionals in Eswatini. *Journal of Electronic Resources Librarianship*, 32(4), pp.253–266. Available from: https://doi.org/10.1080/1941126X.2020.1821990.

[46] Venkatesh, V., 2015. Technology Acceptance Model And The Unified Theory Of Acceptance And Use Of Technology. *Wiley Encyclopedia of Management*. John Wiley & Sons, Ltd, vol. 7. Management Information Systems, pp.1–9. Available from: https://doi.org/10.1002/9781118785317.weom070047.

[47] Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D., 2003. User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3), pp.425–478. Available from: http://www.jstor.org/stable/30036540.

[48] Wan, L., Xie, S. and Shu, A., 2020. Toward an Understanding of University Students' Continued Intention to Use MOOCs: When UTAUT Model Meets TTF Model. *Sage Open*, 10(3), p.2158244020941858. Available from: https://doi.org/10.1177/2158244020941858.

[49] Wang, J. and Yang, H., 2023. Research on online evaluation method of MOOC teaching quality based on decision tree-based big data classification. *International Journal of Continuing Engineering Education and Life-Long Learning*, 33(1), pp.10–22. Available from: https://doi.org/10.1504/ijceell.2023.127848.

[50] Wang, K., Zhu, C., Li, S. and Sang, G., 2023. Using revised community of inquiry framework to scaffold MOOC-based flipped learning. *Interactive Learning Environments*, 31(10), pp.7420–7432. Available from: https://doi.org/10.1080/10494820.2022.2071948.

[51] Westhuizen, C. van der, 2017. Using self-paced online tutorials to bridge the digital divide among first-year students. *Proceedings: Towards Effective Teaching and Meaningful Learning in Mathematics, Science and Technology Education. 23 – 26 October 2017 UNISA/ISTE Conference on Mathematics, Science and Technology Education. Held at the Mopani Camp in Kruger National Park, Limpopo, South Africa.* Available from: https://uir.unisa.ac.za/handle/10500/23428.

[52] Yin, M., 2023. Music teachers' professionalism: Realizing intercultural competence in guzheng education when using a MOOC. *Education and Information Technologies*, 28(10), pp.13823–13839. Available from: https://doi.org/10.1007/s10639-023-11710-y.

[53] Zhang, K., Shao, Z., Lu, Y., Yu, Y., Sun, W. and Wang, Z., 2023. Introducing Massive Open Metaverse Course and Its Enabling Technology. *IEEE Transactions on Learning Technologies*, 16(6), pp.1154–1164. Available from: https://doi.org/10.1109/TLT.2023.3289880.

[54] Zhu, J., Wang, L., Liu, Y., Chen, P.K. and Zhang, G., 2022. A Collaborative Graph Convolutional Networks and Learning Styles Model for Courses Recommendation. In: H. Gao, X. Wang, W. Wei and T. Dagiuklas, eds. *Collaborative Computing: Networking, Applications and Worksharing*. Cham: Springer Nature Switzerland, *Social Informatics and Telecommunications Engineering*, vol. 460, pp.360–377. Available from: https://doi.org/10.1007/978-3-031-24383-7_20.

[55] Zobrist, L. and Brandes, D., 2017. *What key competencies are needed in the digital age? The impact of automation on employees, companies and education.* Deloitte AG. Available from: https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/innovation/ch-en-innovation-automation-competencies.pdf.