# Intention to Participate in MOOCs: Case of University Students in Northwestern Nigeria During COVID-19 Pandemic

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**Abstract—**Massive open online courses (MOOCs) have been introduced over the past few decades to account for the twenty-first-era education and recent COVID-19 pandemic trials driven by the spread of internet-based technology on the internet. This research seeks to give an extended model investigating the intention to use MOOCs based on students at public universities in northwestern Nigeria. The extended TAM model was tested via PLS structural equation modelling using data collected from 451 students at public universities in northwestern Nigeria. The research findings indicated that the proposed extended model delivers a 72.0% descriptive effect. The creative technology acceptance TAM model establishes a strong signal for the effects of PU, PR, PEOU, SN, and TA on intentions to practice MOOCs technology among students in Nigerian public universities during the COVID-19 pandemic. The outcomes present practical and theoretical implications that MOOC developers can use to justify why MOOCs are not high within public universities in Northern-western Nigeria. The findings also indicated that PU, PEOU, PR SN, and TA significantly impact students' intention to use MOOCs. The research has provided insight into extended TAM in Nigerian learning environments to discover the issues influencing students' intention to use MOOCs. Dissimilar to preceding empirical reviews, this research broadly investigated the intention to participate in MOOCs of public University students in northwestern Nigeria during the COVID-19 pandemic, delivering crucial discoveries and commendations for impending research openings. The findings could practically enlighten administrators, instructors, developers, and policymakers in making informed decisions.

**Keywords—**intention, MOOCs, public university, Nigeria, COVID-19, pandemic

### 1.1 Overview

Throughout the ages, the massive open online courses (MOOCs) sector has become among the fastest expanding worldwide due to individuals' continuous and comprehensive broadening. MOOCs aid by giving open access to learning and offering generous learning openings to the world, which helps reduce the accessibility rate to become higher throughout the globe. In turn, MOOCs are considered a stimulating global learning environment and thus among the modern electronic learning technology. MOOCs are also considered a disruptive technology in the Industrial Revolution era, developed to educate students on a large scale. MOOCs provide a means for anyone whose circumstances make traditional face-to-face learning difficult or impossible to access and study. In contrast, others utilize it to complement the conventional university learning system.

MOOCs have the potential to expand higher education in developing countries, where there is a greater demand for higher education and where the provider's capacity is restricted, especially public universities. Global MOOCs Marketplace is estimated at USD 67.18 by 2027, from USD 7.34 Bn in 2020, expanding at a CAGR rate of 37.2% from 2021 to 2027 [1]. Nigeria is known as the country with the highest population in Africa, which serves as its strength. Therefore, the education sector, mainly the public universities, performs a significant role in developing countries growth, especially in achieving sustainable development goals. MOOCs are rapidly influencing individual student behaviour, as evidenced by the expansion of ICT in recent years. Thus, MOOCs is a free electronic-based distance learning programs intended for vast groups of students worldwide. MOOC usage in the United States and other developed countries is comparatively mature, mainly focusing on improving users' continued use of the MOOC platform[2]. In the Malaysian context, online education has been widely utilized across institutes and campuses to transfer knowledge to more than 1.2 million students [2]. The usage of online devices on campuses during the COVID-19 pandemic is understood as an aid to online transformation among the university’s students. Therefore, factors influencing the intention to use massive open online courses will be examined in this study (MOOCs). Students at specified Nigerian universities in Nigeria's northwestern states will be questioned for the research. In the context of this research, the epidemic brought uncertainties among university individuals, with a lack of information on how long the consequence of the virus will take nor the significant effects, and how the recovery phase will be.

## 2 Literature review

This part offers a comprehensive review of existing research associated with MOOCs technology, which summarizes the relevant established individual information technologies theories related to the acceptance behaviour of MOOCs and related technologies. The literature review intends to comprehensively assess existing research associated with using MOOCs during the COVID-19 pandemic and further summarises the extended Technology Acceptance Model (TAM). The literature has documented that the effect level of COVID-19 has an impact on the students' intention to participate in MOOCs. Universities' use of online tools during the COVID-19 pandemic was perceived to increase [3]. Thus, the pandemic necessitated students to adopt MOOCs technology. The psychological hardship linked with COVID-19 increased the sense of intention to use MOOCs [4]. The additional adverse effect of COVID-19 is that numerous scholars have been forced to endure learning online from home due to the shutting of universities and to deny face-to-face lessons [5]. However, the pandemic denied individuals the ability to work face-to-face.

The transition from face-to-face to online education has fetched digital disparity to the fore for economically underprivileged students [5]. Many individuals need access to technological apparatuses and enabling conditions to influence the adoption of MOOCs technology. Based on the above view, 56 million children in sub-Saharan African countries experience digital inequality, as the mobile networks do not provide adequate service, which results in experiencing problems daily [6]. Thus, in several advanced countries, it is indicated that millions of students stay in their homes with no Internet service (Jung et al., 2021). The need for internet access tends to hinder the adoption of online learning. Additional space disparity in access to university education brought about by the COVID-19 pandemic has added to the number of out-of-school individuals globally, especially in developing countries like Nigeria.

MOOCs' intention adoption in China, their research model, tested the effect of Usefulness, Performance-to-cost, Interactivity, Accessibility, Self-Regulation, Experience, Gender, and Social Environment: Learning Tradition, Peers' Impact, Instruction, and Publicity on the intention to adopt MOOCs, data was collected from 870 students; they infer that MOOC use in developing countries is still low[7]. In this regard, the findings of linked studies published in the literature revealed that attitudes about MOOCs and perceived behavioural control (PBC) remained considerable elements of intention to utilize MOOCs [8]. Though the literature from Asia revealed that attitudes impact the intention to use MOOCs in countries like China, that is different in developing countries, where facilitating conditions and other factors drive the intention to use MOOCs. Therefore, the theoretical framework is developed based on the issues identified in the literature review, which has assisted in developing the research question. Therefore, two research questions were formulated to seek empirical evidence of the following research question:

1. What is the level of the student's intention to use MOOCs?
2. What factors may influence Nigerian students' intention to use MOOCs during the COVID-19 pandemic?

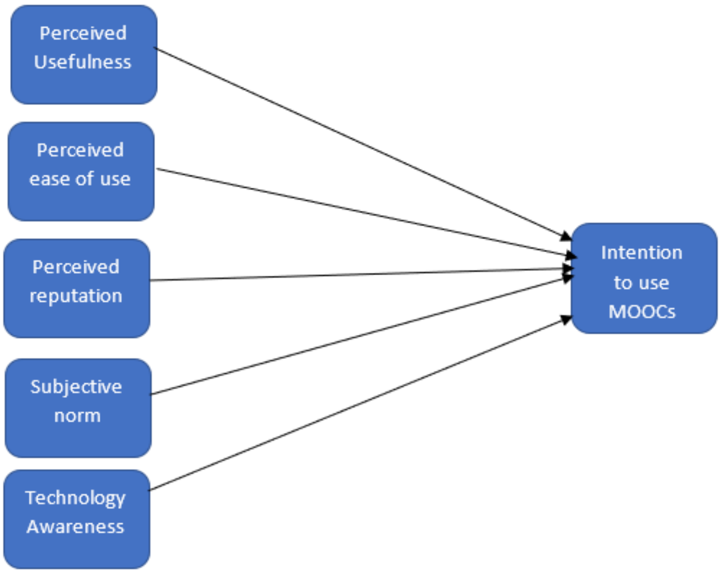


**Fig. 1.** Research framework

In Chinese university students' adoption of MOOCs, researchers found that individuals' attitudes regarding MOOCs and perceived behavioural control influence their desire to utilize MOOCs [8]. However, [9] extended UTAUT2 to see what factors influenced their acceptance of multimedia-enhanced content based on long-term usage. The findings indicated that facilitating conditions gave a meaningful positive result of 14.8 per cent on the acceptance of the technology. The above findings are contrary to the findings based on the literature from the context of China, where the facilitating condition does not negatively affect the intention to use MOOCs. Therefore, the inconsistency based on the findings has necessitated the need to investigate the intention to use MOOCs, which could fill the identified gap in the literature. From Taiwanese universities, the findings revealed that students' decision-making process and learning behaviour in MOOCs needed to be adequately investigated in the literature[10]. Despite the significance of investigating individuals' behavioural intention to use MOOCs, previous findings have indicated a wide gap in that aspect that needs to be addressed by previous scholars.

Findings based on previous literature have focused on the level of MOOC technology implementation between users and adopted several theoretical models to understand users' behaviour in adapting to MOOCs. Among these theories, TAM has frequently been utilized to study the plan to use MOOCs[11]. Besides, the TAM is efficient in conquering the limitations of TRA, and the TAM can forecast technology approval in mandatory and voluntary backgrounds[12]. Furthermore, several investigations also revealed that TAM could be employed in forecasting various technologies.

Subsequently, the epidemic brought uncertainties among university individuals, with a lack of information on how long the consequence of the virus will take and how the recovery phase would be, which necessitated the increase in intention to use MOOCs during the Pandemic [13]. Many prior findings were aimed at the organizational context (i.e., government agencies, civil service, instructors, and administrators). Consequently, other research looked into how MOOCs technologies were adopted to promote knowledge and influence performance at work [14]. Hence, the principal drive of the present research is to undertake an empirical investigation of research with an emphasis on massive open online courses or e-learning intention to use during COVID-19 and make recommendations to scholars and administrators concerning impending in the context of Nigerian public universities. Consequently, the current study attempts to employ TAM to understand better how users interact with MOOCs.

In an attempt to use the TAM from the Nigeria perspective, this research includes factors such as perceived reputation (PR), subjective norm (SN), and technology awareness (TA) in the model, perceived reputation (PR), subjective norm (SN), and technology awareness (TA). These factors are considered to have a substantial consequence on behavioural intention to practice MOOCs. Therefore, by adding perceived reputation (PR), subjective norm (SN), and technology awareness (TA) in the extended TAM, the current study examines users' behaviour intentions to use MOOCs in the context of Nigeria, filling in gaps in the literature.

### 2.1 Perceived usefulness (PU)

Perceived usefulness (PU) is described as emotional settlement and belief that technology is beneficial to achieve the belief. Perceived usefulness (PU) is among the variables that affect technology acceptance[15]. The perception of PU affects the end-users impression of innovative innovation, and it is the most potent factor that defines if acceptance or adoption of a new technology product[16]. PU has reflected an encouragement to use information systems. From the background of online learning (MOOCs) research, PU has been the subject of various studies to increase users' willingness to use technology. For example, [17] focused on PU predicting scholars' intention to adopt MOOCs. Likewise, PU is chosen as it serves as a construct in MOOC adoption investigations and encourages people to follow through on their intentions [18]. Comparable to most technological tools, MOOCs provide access to students anywhere, anytime, as far as the internet is available [19]. Notably, previous findings clarified the association between perceived usefulness and intention to use technologies in the discipline of information systems [20]. Therefore, PU will be used to investigate the intention of public university students in northwestern Nigeria during the COVID-19 pandemic to participate in MOOCs.

H1: PU of MOOCs positively correlates with the behavioural intention to use MOOCs during COVID-19 Pandemic.

### 2.2 Perceived Ease of Use (PEOU)

The user-friendliness and simplicity of interaction when utilizing MOOCs are the emphasis of this study.MOOCs should be simple to use, fulfilling the individuals' beliefs and hopes, especially in learning with MOOCs [11]. PEOU in MOOCs can reveal the individuals' impression of MOOCs, which can assist in accomplishing their goals smoothly [21]. Thus, PEOU positively impacts the mindset of using the learning management system. PEOU has been considered a critical gauge of intention to use MOOCs[22].

H2: PEOU of utilizing MOOCs has a positive connection with the behavioural intention to use MOOCs during COVID-19 Pandemic.

### 2.3 Perceived Reputation (PR)

The universities/institutes establish their suitable representation across the value of activities. Perceived reputation plays a significant role in users' behavioural intentions to use MOOCs since they profoundly rely on any program's reputational position[23].

Perceived reputation is a theme studied in different disciplines [24]. Perceived reputation is a significant and indefinable variable that influences an individual's choice of a university[25]. Thus, a university's reputation is a subjective expression of the institution's excellence, impact, and dependability. MOOCs platforms associated with reputable institutions are expected to obtain direct credibility. Thus, this research hypothesis that:

H3: Perceived Reputation will positively influence the user's intention to utilize MOOCs technology during the COVID-19 pandemic.

### 2.4 Subjective Norm (SN).

Prior literature shows that subjective norms (SN) influenced the intention to use e-learning. The student's behavioural intention toward online learning could be motivated by people near the individual, such as family members, friends, and others [26]. Subjective Norm was conceptualized as the extent to which a student perceives pressure from associates in his or her environment to use e-learning systems[27]. The effects of subjective norms on will play any responsibility in forming judgments regarding behavioural intention[28]. Subjective Norms' impact on learners' e-learning approval has been examined intensively in the literature [29].

Likewise, the subjective norm is generated based on others' significance of their intentions to participate in MOOCs. In the context of M-learning, Subjective Norms (SN) are strongly associated with the acceptance intention for an M-learning policy[30]. Subsequently, the subjective norm is also expected to affect the intention to use new technology[31]. Hence, people might employ specific technology if suggested or encouraged by contemporaries, relatives, lecturers, parents, etc. [32]. Thus, the impact of others (social and peer) is essential in how valuable the online system is perceived [33]. Therefore, the study suggested that social peers could influence Nigerian university students to use MOOCs technology. Therefore, the following hypothesis is proposed.

H4: Subjective norms will influence the intention to use MOOCs during COVID-19 Pandemic.

### 2.5 Technology Awareness (TA)

Technology Awareness (TA) could be well-defined as the extent of knowledge[34]. Technology awareness is crucial in innovation adoption. Likewise, preceding empirical findings have shown that technology awareness was an important influence in the intention to adopt m-government and e-government[35]. It is established that one of the most significant aims for users' hesitancy to adopt innovative technology is their unawareness of its services and benefits. Based on the above, technology awareness has been tested in a different context. It could be replicated in Nigerian university students to determine its influence on the student's intention to use MOOCs. Technology awareness denotes stakeholders and their understanding regarding services' availability, benefits, and use [36]. Thus, technology awareness is a crucial factor in the innovation adoption procedure. It is concluded that technology awareness has a significant positive effect on adopting new technology [37].

Technology awareness is the knowledge of the significance and value of technology[38]. Several types of research maintained that technology awareness is vital and positively influences the intention to use MOOCs. Thus, technology awareness drives behavioural intention to adopt/use new technology [35]. Thus, technology awareness has proven to be significant and capable of determining the use intention of MOOCs established on the experimental findings of previous authors. This paper's hypothesis is that:

H5: Technology Awareness will positively impact user intention to use MOOCs during COVID-19 Pandemic.

## 3 Methodology

The participant of the current study is the individuals in Nigeria. The participants were Nigerians students at public universities (Ahmadu Bello University, Kaduna State University, Bayero University Kano, Kano State University of Technology, Federal University Dutsima, Umaru Musa Yaradua University Yola, Usman Danfodio University Sokoto, Sokoto state university, Federal University Kebbi, Kebbi State University, Federal University Gusau, Zamfara state university, etc.). The purposive sampling method was utilized in the current research to choose the respondents. In deciding individuals that satisfied the conditions placed by the investigators, a question is placed to screen the participants in the survey. The sum of 451 people responded to the questionnaire online.

This result has no problem with common method bias, given that the total variance extracted by one factor is 46.486%, which is lower than the mentioned limit of 50%. Furthermore, the unrotated solution does not merge into a single factor. The research's target population comprises students from fourteen public universities in the Northwest states of Nigeria; the purposive sampling technique will be embraced for this study. The justification behind using (non-probability) sampling; judgmental (purposive) sampling is the following reason. Due to confidentiality rights for purposive (non-probability) sampling, obtaining a name list for all the 106,561 students from the fourteen public universities in northern Nigeria is challenging. The study variables exhibited satisfactory reliability, with Cronbach's alpha ranging from 0.880 to 0.904, showing that the appropriate variables were selected for the research.

The experiment size must meet the power of 0.80 in the G*Power 3 software with an effect size of 0.15, a margin error of 5%, power of $(1-\beta) = 80\%$, and four predictors were utilized [39]. The questionnaire contains four segments, in which respondents are to assess their answers on a 5-point Likert Scale (1 = "strongly disagree" and five = "strongly agree"). The dimensions for the current analysis are modified from dependable resources, such as five items on PU [40], four items on PEOU[40], four items on PR[41], three items on the subjective norm[8], four items on technology awareness[42], four items on Behavioral Intention to use [40]. In addition, demographic elements of the respondents and MOOCs' knowledge (level of technology awareness) were included in this study. The IBM SPSS Statistics and the Smart PLS software packages were used to generate the analysis of the records. The reason for utilizing Smart PLS software is to simultaneously discover the direct and indirect connection between the latent variables and endogenous variables. The findings will extend the scope of intention to use MOOCs during the Pandemic of COVID-19. The contributions are helpful for future research.

Furthermore, the study also added novelty to TAM by proposing perceived reputation, subjective norm, and technology awareness as additional variables in studies on MOOCs adoption. Finally, it further provided a better understanding of the critical innovation characteristics as determinants of Nigerian public university students' intention in the context of studies on MOOCs adoption during the Pandemic of COVID-19.

# 4 Findings

According to the data, the standard construct validity through a substantial loading value fluctuated from 0.732 to 0.945, more significant than the suggested loading value of 0.5 [43]. Items with a loading value of less than 0.5 were eliminated. The concurrent validity result of the measurement model (e.g., loadings, average variance extracted, and composite reliability) indicators are shown in Table 1. The loadings are more significant than 0.70, which according to the literature, is regarded as acceptable [44]. The AVE values varied from 0.843 to 0.968, implying satisfactory convergent validity. As a result, the CR varied from 0.587 to 0.883.

PEOU, PR, PU, SN, and TA can support users' intentions. PEOU ($ß = 0.131$ $p < 0.05$) was discovered to be positively related, and so was PR ($ß = 0.328$, $p < 0.01$), PU ($ß = 0.291$, $p < 0.01$), SN ($ß = 0.279$, $p < 0.01$), SN ($ß = 0.279$, $p < 0.01$) and TA ($ß = 0.235$, $p < 0.01$) also remained to be positively associated to intention to use. This implies that higher perceived usefulness will increase users' intention to use MOOCs. The result is consistent with the TAM theory and existing literature [45], even though contrasted with some studies on MOOCs/e-learning adoption.

These findings suggest enhancing and improving individuals' intention to use MOOCs technology. This implies that perceived ease of use is essential to users' intention to use MOOCs. Thus, in exploring Students' acceptance of E-Learning, PEOU was found to influence students' intention to use it [11].

Perceived reputation significantly influenced the intention to use MOOCs. The study is consistent with previous studies on MOOCs; for example, [24] found that intention is significantly influenced by perceived reputation. In the same vein, [36]. This outcome implied that subjective norms encourage users to use MOOCs technology. The findings in this study are supported by previous research that revealed subjective norm influences entrepreneurial intention among public higher educational institutions (PHEI) in Malaysia [46]. Correspondingly, from the Saudi Arabian context, technology awareness is among the key factors significant to students' intention to use the E-Learning system at King Faisal University, Saudi Arabia [47]. The above findings align with the outcome of this research that found that technology awareness influences the intention to use MOOCs technology.

### 4.1 Convergent validity

In establishing convergent validity, consideration was given to the outer loadings of a construct. AVE as a criterion is defined as the grand mean value of the squared loading of the indicators associated with the construct or the sum of squared loading divided by the number of indicators. In the same rule of thumb, [48] recommend that an AVE of a particular construct be higher than 0.50 to establish convergent validity.

**Table 1.** Convergent Validity

| Variable | Items | Loadings | CA | rho_A | CR | AVE |
|---|---|---|---|---|---|---|
| Intention to Use | ITU1 | 0.842 | 0.724 | 0.744 | 0.843 | 0.642 |
| | ITU2 | 0.793 | | | | |
| | ITU3 | 0.767 | | | | |
| Perceived Ease of Use | PEOU1 | 0.808 | 0.814 | 0.815 | 0.878 | 0.642 |
| | PEOU1 | 0.810 | | | | |
| | PEOU1 | 0.831 | | | | |
| | PEOU1 | 0.732 | | | | |
| Perceived Reputation | PR1 | 0.933 | 0.956 | 0.956 | 0.968 | 0.883 |
| | PR2 | 0.937 | | | | |
| | PR3 | 0.945 | | | | |
| | PR4 | 0.945 | | | | |
| Perceived Usefulness | PU1 | 0.749 | 0.787 | 0.831 | 0.849 | 0.502 |
| | PU2 | 0.796 | | | | |
| | PU3 | 0.777 | | | | |
| | PU4 | 0.746 | | | | |
| | PU6 | 0.754 | | | | |
| Subjective Norm | SN1 | 0.878 | 0.873 | 0.873 | 0.922 | 0.797 |
| | SN2 | 0.891 | | | | |
| | SN3 | 0.909 | | | | |
| Technology Awareness | TA1 | 0.843 | 0.835 | 0.838 | 0.890 | 0.670 |
| | TA2 | 0.806 | | | | |
| | TA3 | 0.832 | | | | |
| | TA4 | 0.792 | | | | |

Note: PU5 is deleted due to low loading

### 4.2 Discriminant validity

The fornell-Larcker criterion [49] and cross-loadings [50]were the dominant approaches used in testing discriminant validity in the past. [51] argued that the Fornell-Larcker criterion and cross-loadings are inadequately sensitive to detect discriminant validity in the variance-based PLS-SEM, particularly with multiple constructs. Instead, they recommend a heterotrait-monotrait ratio of correlations (HTMT) to assess discriminant validity in variance-based PLS-SEM better. A two-way assessment was applied using the HTMT [51] in discriminant validity assessment.

First, the HTMT is used as a criterion to compare with a predefined threshold value. When the HTMT value of a construct is higher than the predefined threshold values, the construct is concluded as lacking discriminant validity. The threshold values suggested in the literature are 0.85 [52], whereas others suggested 0.90 [53]. Table 2 illustrate the Heterotrait-Monotrait ratio (HTMT) based on this study.

**Table 2.** Discriminant Validity

| | INT | PEOU | PO | PR | PU | SN | TA |
|---|---|---|---|---|---|---|---|
| INT | | | | | | | |
| PEOU | 0.516 | | | | | | |
| PO | 0.738 | 0.696 | | | | | |
| PR | 0.474 | 0.595 | 0.664 | | | | |
| PU | 0.532 | 0.767 | 0.646 | 0.506 | | | |
| SN | 0.447 | 0.547 | 0.746 | 0.787 | 0.488 | | |
| TA | 0.581 | 0.775 | 0.721 | 0.510 | 0.726 | 0.536 | |

Note that the diagonal represents the AVE, while the others represent the correlation. As shown in Table 2, the HTMT ratio of all the constructs was below the conservative threshold value of 0.85. Therefore, the constructs of the study are distinct, and hence discriminant validity is not a challenge within the research. Overall, all measurements, as shown in Table 2, all computations yielded values below the threshold value of 0.85. The criteria were met and supported the measure's reliability and validity.

### 4.3 Structural model evaluation

Before assessing the links among latent variables, collinearity issues in the structural model must be addressed to test the bias of the path coefficient in cases where the predictor constructs are significantly collinear. The hypotheses testing of the latent variables is shown in Table 3 from the structural model evaluation of this study.

**Table 3.** Structural Model Evaluation

| Hypothesis | Relationship | β | t-values | P-values | Decision | $R^2$ | $Q^2$ | $f^2$ | VIF |
|---|---|---|---|---|---|---|---|---|---|
| H1 | PEOU -> INT | 0.100 | 2.554 | 0.005 | Endorsed | 0.720 | 0.464 | 0.021 | 2.408 |
| H2 | PR -> INT | 0.215 | 4.537 | 0.000 | Endorsed | | | 0.088 | 2.629 |
| H3 | PU -> INT | 0.061 | 1.715 | 0.043 | Endorsed | | | 0.008 | 2.210 |
| H4 | SN -> INT | 0.164 | 3.464 | 0.000 | Endorsed | | | 0.051 | 2.610 |
| H5 | TA -> INT | 0.213 | 5.280 | 0.000 | Endorsed | | | 0.079 | 2.823 |

It is noteworthy that the results attained from the [54]method suggested that PEOU, PR, PU, SN, and TA in this study have direct impacts on the users' intention to use MOOCs, as shown.

### 4.4 Assessment of the structural model

As for the VIF, corresponding to Table 1, the VIF is lower than 5 for all constructs. Thus, this shows the absence of collinearity troubles amongst the constructs of this study.

A bootstrapping technique with 5000 resamples was applied to obtain the critical t-value for the one-tail test with a significance level of 5% To establish the significance of path coefficients and evaluate the hypothesized relationships of this study [55]. Table 1 summarises the results of the structural model evaluation for this study. Table 1 reveals the result of the bootstrapping for the direct relationships. Specifically, perceived ease of use (H1: $\beta = 0.100$, $t = 2.554$, $p = 0.005$), perceived reputation (H2: $\beta = 0.215$, $t = 4.537$, $p = 0.000$), perceived usefulness (H3: $\beta = 0.061$, $t = 1.715$, $p = 0.043$), subjective norm (H4: $\beta = 0.164$, $t = 3.464$, $p = 0.000$), technology awareness (H5: $\beta = 0.213$, $t = 5.280$, $p = 0.000$). The results indicate that relationships among perceived ease of use, perceived reputation, perceived usefulness, subjective norm, technology awareness, and intention to use MOOCs were all significant and in the proposed direction. Hence, H1, H2, H3, H4, H5 were all supported.

### 4.5 Coefficient of determination

The coefficient of determination measures the structural model's predictive accuracy. R2 values usually fluctuate from zero to one. A considerable R2 value represents the greater predictive power of the structural model. As revealed in Table 1 and Figure 2, the PLS path model of the analysis has an R2 value of 0.720. This demonstrated that the combined effects of the proposed determinants account for 72.0% of the variance in the intention to utilize MOOCs by the students. [56] have classified R2 values of 0.720 as moderate—accordingly, the PLS path model of this study exhibit moderate explanatory power. The following table indicates the Hypotheses testing.

To determine the indirect effect, a bootstrapping study was suggested to be performed on the sampling distribution [48]. Likewise, the [54] method improves PLS structural equation model-ling (PLS-SEM) analysis since it does not assume the division of variables. Furthermore, it can be used with modest sample sizes [48]. It is noteworthy that the results indicated that PEOU, PR, PU, SN, and TA directly affect the users' intention to use, as demonstrated in Table 4.

**Table 4.** Hypotheses Testing

| Hypothesis | Relationship | B | SD | t-value | p-value | Decision |
|---|---|---|---|---|---|---|
| H1 | PEOU -> INT | 0.131 | 0.047 | 2.809 | 0.003 | Supported |
| H2 | PR -> INT | 0.328 | 0.052 | 6.291 | 0.000 | Supported |
| H3 | PU -> INT | 0.072 | 0.038 | 1.923 | 0.028 | Supported |
| H4 | SN -> INT | 0.279 | 0.047 | 5.889 | 0.000 | Supported |
| H5 | TA -> INT | 0.235 | 0.045 | 5.240 | 0.000 | Supported |

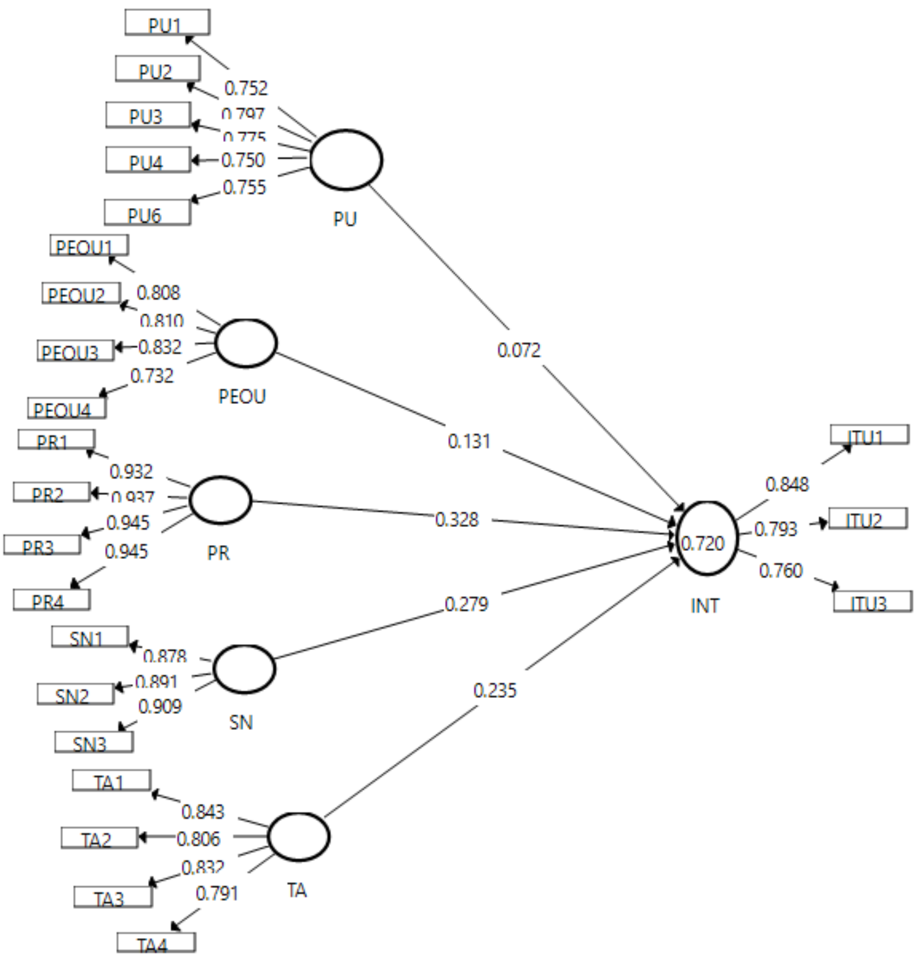


**Fig. 2.** PLS Algorithm Structural Model Result

### 4.6 The main effect model's effect size (f2)

The R2 value determines if the construct has a significant impression on the endogenous constructs. This measure is the effect size of (f2) [48]. The effect size is assessed as little if f2 equals 0.02, average once f2 equals 0.15, and large when f2 equals 0.35 [57]. In further categorization, [57] argued that 2% of effect sizes are small although satisfactory, 5-10% moderate, while 11% and beyond as significant. Perceived reputation has the greatest effect, with a value of 0. 088. As expected, four exogenous variables (PU, PEOU, SN, and TA) affect endogenous variables. The rule of thumb to evaluate effect size: f2 values of 0.02, 0.15, and 0.35 represent an exogenous construct's small, medium, or significant effect on an endogenous construct. Accordingly, it revealed that all the independent variables (PEOU, PR, PU, SN, and TA) have small effect sizes on the dependent variable of this study (INT).

### 4.7 Predictive relevance (Q2)

The same as shown in Table 1, the Q2 value of intention to use is 0.464, indicating that the endogenous construct of the analysis has predictive relevance since the value is greater than zero. The Q2 value of 0.464 portrayed that the PLS path model of the research gives a medium predictive relevance in line with [44].

## 5 Discussion

This is one of the first studies examining MOOCs' acceptance in public universities within the northwestern states of Nigeria during the COVID-19 pandemic. The research findings showed that expanded TAM account for 61.4% of intention to use MOOCs. Contrasted to the empirical findings of the TAM model, which account for about 36% of the variations, the extended TAM model in this survey demonstrates substantial enhancement in the model's explanatory and predictive (analytical) power. The research findings indicated that the proposed extended model delivers around 72.0% descriptive effect. The creative technology acceptance TAM model establishes a strong signal for the effects of PU, PR, PEOU, SN, and TA on intentions to practice MOOCs technology among students at Nigerian public universities in the Northwest context.

This research empirically extended the TAM by including perceived reputation, subjective norm, and technology awareness which are inherent variables in MOOCs whose importance has been overlooked or neglected by the previous study on MOOCs. In the extended TAM, all constructs remain predictors of behavioural intention. The impact of perceived usefulness on behavioural intention is significant. These findings confirm that individuals tend to develop an interest in using the technology in the future when they believe the MOOCs technology will be helpful to them and assist them in improving their academic performance. The result is consistent with [20], which indicated perceived usefulness of E-Learning influences Behavioral Intention. Particularly, students tend to use a technology they believe is convenient to accomplish the target outcome. Moreover, prior findings indicated that the connection between perceived usefulness and intention in computer technologies and information systems[58] indicated that PU directly affected and influenced mobile learning acceptance in higher education.

At a distance, PEOU directly influences behavioural intention. The findings concurred with previous findings that concluded that ease of use ultimately affected the use of MOOCs/ E-Learning [20]. PEOU has a positive impact with a significant impact on learners using internet-based technology[59]. The findings remained endorsed by numerous preceding literature [60]. These findings confirm that students consider the easiness of using MOOCs. They develop intentions to use the MOOCs technology since the individuals have used similar technology. Thus perceiving using MOOCs will be easy.

Moreover, the impact of perceived reputation on behavioural intention is significant. The researchers found that perceived reputation is positively connected with behavioural intention, which was in harmony with earlier findings' results [24]. Perceived reputation is among the significant predictors with a positive connection toward utilizing MOOCs and directly influencing behavioural intention. Students who perceive MOOCs offered by highly reputable universities/institutions tend to use MOOCs as a tool for learning. These findings confirm that students consider the reputation of the institutions that offer MOOCs and the renowned professors driving the courses. Moreover, the present study found that SN positively correlates with behavioural intention. This finding was consistent with the previous studies, which revealed that SN Subjective Norm has a significant positive relationship with Behavioural Intention and is the most critical factor that affects university students' behavioural intention on E-Learning[61].

Technology awareness has positively influenced behavioural intention in utilizing MOOCs. The technology awareness of massive open online courses among academic librarians in Ogun state, Nigeria, influences the behavioural intention to use the technology[62]. Thus, technology awareness is a significant determinant of student's intention to use MOOCs, and technology awareness of the individual determines students' perception.

Overall, the proposed extended TAM model of the current study sheds particular light on improving the Education sector in developing countries and Nigeria during the COVID-19 pandemic and beyond. Based on this perspective, the current study results are supported by TAM. The revision and extension of TAM are based on different contexts, which incorporate other variables. Notably, the theoretical connections were empirically established and supported. The present study successfully confirmed the factors influencing users' intention to use MOOCs. Most significantly, the results particularly emphasized the position of PR, SN, and TA and behavioural intention. The current research findings are promising efforts to analytically examine the intention to use MOOCs among students at public universities.

Concerning the practical contribution, the present research results provide insights into students' behaviour toward using MOOCs technology. The actors (developers and policymakers) must know the importance of MOOCs in the education sector. MOOCs are indispensable for individuals who favour electronic learning to complement the conventional learning system. Understanding the considerations that affect student behaviour or the actors (developers, policymakers) might bring the programs to create a viable MOOCs learning approach, which can attract students globally to use the technology. Furthermore, the encouraging response to the user's ease of use helps a student learn using MOOCs. Individuals could use MOOCs technology that is useful and easy to use (learn), with the MOOCs. MOOCs' key players / public institutions must also be conscious of the influence of perceived reputation. A high perceived reputation regarding the MOOCs will increase behavioural intention to use the MOOCs technology during the pandemic, and vice versa, for a negative/low perceived reputation could decrease oral behavioural intention to use MOOCs.

Therefore, perceived reputation is of paramount value as the perceived reputation may be constructive (when the MOOCs are linked to reputable institutions or unrepeatable institutions) to the MOOCs' companies/ public institutions. The current research also suggests that it is essential to increase the perceived reputation of MOOCs by collaborating with reputable institutions and professors with a high pedigree. The present study found that subjective norm is a strong predictor of oral behavioural intention to use MOOCs and the crucial role of technology awareness of MOOCs as a powerful tool for oral behavioural intention to use MOOCs technology. The subsequent section will discuss the conclusion and implications of the research.

### 5.1 Conclusion and implications

The findings of this research offer numerous implications for scientists, software developers, and administrators in the era of the COVID-19 pandemic and beyond. The goal of this study was to enhance the explanatory, and predictive power of the TAM model in MOOCs' intention in the era of the COVID-19 pandemic has been achieved. A significant contribution of the current research is that it highlights the perceived usefulness's vital role in adopting MOOCs. Perceived ease of use has strong direct effects on the intention to use MOOCs of the model. Additionally, the current study contributes to the literature on TAM research by showing the impact of perceived reputation on the intention to use MOOCs. This noteworthy discovery indicates that if users perceive the reputations of institutions offering MOOCs before, they will not start using them. Our findings show that subjective norm influences the intention to use MOOCs among public university students in northwestern Nigeria. Likewise, the more influence from family and friends the students, the more they develop more interest in using MOOCs. For, technology awareness significantly impacts their perception regarding the intention to use the technology. Similar results emerged for the subjective norms.

Another contribution of this research is developing and validating perceived reputation, subjective norm, and technology awareness behavioural oral intention model. Perceived reputation, subjective norms, and technology awareness are essential in developing a positive intention to use MOOCs. MOOCs' perceived usefulness makes people use the technology, and the perceived ease of using the technology, the pleasure and easiness of using the technology that, makes students develop a positive intention towards MOOCs. There is a high individual perceived reputation of MOOCs due to highly reputable Professors as resource persons, and the reputation of the institutions over time is essential in determining the intention of individuals to use MOOCs technology. However, subjective norm attributes are sufficient to drive positive intention to use MOOCs; indeed, individuals seek the opinion of people close to them before making decisions.

Technology awareness is related to the intention to use MOOCs. It indicates users' knowledge of the MOOCs technology, increasing the perceived intention to use it. If individuals perceive MOOCs as practical, accessible, offered by reputable institutions, and understandable, they are more likely to use the system. Theoretically, this adds to TAM research by highlighting that as the new technology's usefulness, ease, and subjective norm increases, the intention toward MOOCs technology will become more positive during the pandemic. Therefore, MOOCs developers should ensure that the system is easy to use. They should also emphasize technology awareness when marketing MOOCs systems to individuals.

This theory is valid in the context of MOOCs. Subjective norm is a significant predictor of behavioural intentions. In the context of MOOCs, Subjective norm influences and triggers behavioural intentions as people are more likely to use MOOCs if their family and friends develop an interest in using MOOCs. Conclusively, the research questions were answered with empirical evidence that indicated the level of the student's intention to use MOOCs during the COVID-19 pandemic and subsequently indicated the factors that influence the intention to use MOOCs among Nigerian students during the COVID-19 pandemic. The finding of this study provides a guideline for MOOCs developers in making informed decisions.

### 5.2 Limitations and future studies

The current paper has some limits. This study was performed in the Nigerian context, so the research results may not correspond to respondents from other topographical regions/countries. Thus, it is necessary to imitate this kind of study in other geographic locations to augment the narrative. Future research may be extended to a broader geographic space. In addition, a cross-sectional approach was utilized in the current research, in which the data was gathered at a specific time (i.e., within one month). Therefore, it is also proposed to utilize longitudinal research in future studies. On one side, this research did not consider the role of a moderator in behavioural intention connection.

A future study looking into other potential moderators is crucial to find thorough insight into the drivers of behavioural intention to use MOOCs during the Pandemic. Moreover, the study did not consider moderating variables such as the facilitating condition and perceived openness to intention to use MOOCs, which are overlooked by previous studies. Also, further research may consider facilitating conditions and perceived openness as potential moderators. The results of this study should promote future research. The applicability of this model to other contexts would be a possible area of research. Future research might consider adding other antecedents of behavioural intention. Future studies are also advised to sample more users and compare the differences in various cultures. Thus, this sample may only represent part of the populace of Nigerian public university students and may not be sufficient to generalize the whole population of Nigeria. Therefore, future researchers can cover a large sample size, including all segments of the Nigerian populace and consider introducing moderators to the research model.

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