Impact of motivation and technology factors to predict satisfaction and continued intentions toward online courses

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A B S T R A C T

The rapid developments and diffusion of new technologies abruptly changed world dynamics. This study pursued the motivational factors (controlled and autonomous) and technology factors (perceived ease of use and perceived usefulness) to predict the students' perceived satisfaction and continued intention toward MOOCs. Using an online survey, this research collected data from 333 students, and analysis performed through PLS-SEM. The findings revealed that controlled motivation positively influenced the perceived satisfaction. However, autonomous motivation positively affected students perceived satisfaction and continued intention toward MOOCs. The technology factors such as PEU strongly impacted PU. Similarly, PU positively impacted students perceived satisfaction and continued intention toward MOOCs. This research guides essential theoretical insights and provides practical guidelines to educational institutions and technologists to develop and implement systems and strategies in online environments.

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Introduction

The rapid developments and diffusion of ICTs (information and communication technologies) meaningfully alter today's environment, as ICTs provide new and diverse approaches for effectively delivering education (Lee, 2010). Similarly, recent developments in the world wide web (WWW) and other digital technologies, including mobile or live stream technologies, have revolutionized the world (Atique et al., 2021; Chen & Chen, 2018), and the educational sector has also been reformed by following this digital revolution. Thus, access to new learning resources has increased dramatically in recent years, and new technologies supported educational opportunities in different ways. Consequently, the higher education sector (HES) introduced online learning platforms and offered many online courses to influence students while reducing costs (Daniel et al., 2015). In recent years, competition between private and public higher education institutions has increased at the worldwide level. Therefore, many universities are taking new measures to develop strategies to attract students worldwide with an innovative and quality education that creates value. Thus, the new innovative digital system reflects a favorable impact on society (Atique et al., 2021). Since online learning's rapid growth observed to develop theory and practice, in the same way, students' perceptions, behaviors, and motivations have been studied in different online environments (Gupta Kriti, 2019).

The modern development in distance learning by introducing Massive Open Online Courses (MOOCs) can be observed as a big transformation in the education sector (Wang et al., 2021; Zhou, 2016). According to I. Pozón et al. (2019), MOOCs help students through different online learning worldwide to achieve their objectives. Thus, it is important for researchers to extensively research this topic in the education sector and mainly in the higher education sector. MOOCs are the most innovative and advanced online learning approach considered a revolutionary change in open online educational resources (Al-Adwan, 2020). Gameel and Wilkins (2019) defined that "MOOCs are online learning courses that enable students to register and participate in an online education process that might consist of thousands of other students." As large numbers of students enrolled, MOOC learning platforms enhance...
education quality worldwide, and many online courses are available in different disciplines. Thus, MOOCs are increasingly famous for their easy adaptability, transparency, and self-organization during the past few years.

Prior research found that students high drop-out from using MOOCs gained researchers attention to investigate MOOCs as a disruptive technology that can be viewed from two perspectives: first to consider benefits of better access to society and education, and second, it is a new learning platform and marketing opportunity (Conole, 2016). Similarly, previous research mainly focused on developing a better understanding by following various goals and motivations underlying the experience of MOOC students (Alraimi et al., 2015; de Barba et al., 2016; Zhou, 2016). Thus, these research studies highlighted motivation being a psychological concept, indicating that motivation influences learners to complete or continue to use MOOCs. Other research studies found that while using MOOCs, learners’ internal motivation influence them such as personal interests, a curiosity of new learning, and many external factors that influence them to participate in MOOCs such as universities reputation and job competency development (Alraimi et al., 2015; Wu & Chen, 2017). Therefore, many students use MOOCs to gratify their interest with little or no intentions to complete the entire course (Anderson, 2013). Thus, it shows that students’ motivation complexity and their use of MOOCs patterns required further investigation (Joo et al., 2018).

The TAM (technology acceptance model) (Davis et al., 1989) is one of the most common frameworks used for technology adoption in various perspectives. Using the external variables, PEU and PU, the TAM predicts the learner’s behavioral intention and actual use of technology (Venkatesh & Davis, 2000). The TAM is also considered the best fit model for investigation, particularly in adopting different online learning technologies from various perspectives (Bazelaïs et al., 2018). Although TAM is widely applied in different industries and environments but considering the TAM role in the development of MOOCs, prior research investigated the TAM to predict behavioral intentions in Taiwan, China, and Jordan (Al-Adwan, 2020; Hu et al., 2018; Teo & Dai, 2019), and to predict emotions, satisfaction, and MOOC use intention in Spain (Irma et al., 2020). Besides, research is on the topic still in a limited scope (Joo et al., 2018). The TAM application is still lacking, particularly with controlled and autonomous motivation to predict the users’ perceived satisfaction and continued intentions toward using MOOCs.

The idea of an intention to continue with adopting new technology or system was proposed by Bhattacharjee (2001), who suggested that people are continuously using it when they experience and happy with the initial uses. The continuing intent helps to broaden understanding of the students' motivation and participation toward MOOCs. For example, Huang et al. (2017) argued that many MOOC studies focused on early involvements, and few studies are available about students' intentions to continue MOOC usage. Wu and Chen (2017) also suggested that MOOC is included in two phases, first, an initial stage of perception and adoption and an advantages stage, which implies the need to examine, over and above initial acceptability, factors influencing the continual use of MOOCs by learners. Thus, this study is worthwhile for further investigating MOOCs to check the students' perceived satisfaction and continuation intentions.

In this background, designing attractive and effective online learning environments requires various factors (i.e., motivation and technology) that influence students’ perceptions and learning. Therefore, this research examines the motivation and technology factors that affect the users’ perceived satisfaction and continuous intentions to use MOOCs. This research follows the self-determination theory and TAM that persuade the adoption of online information systems. These theories contributed to an empirical analysis of perceived satisfaction and continued intentions toward MOOCs. Thus, it is essential to answer the following questions in order to achieve the research objectives:

To what extent motivational factors (self-determination theory) influence users’ perceived satisfaction and continued intentions toward MOOCs?

How technology factors (TAM) influence the users’ perceived satisfaction and continued intentions toward MOOCs?

Does perceived satisfaction influence users’ continued intentions toward MOOCs?

This study is organized in the following structure. First, we introduce the topic with importance, research gaps, and research questions. Then, we explain the supportive literature, theoretical framework, and research methodology. Finally, we perform analysis, discussions of results, and research concluded with implications and provided future research guidelines.

**Literature Review**

This research investigates the motivational factors (self-determination theory) and technology factors (TAM) to predict the users’ perceived satisfaction and intentions to use MOOCs continuously. Thus, it is essential to understand the SDT and TAM in the MOOCs context.

**Theoretical and Conceptual Review**

This research followed self-determination theory (Ryan & Deci, 2000) and its underlying motivational factors considered essential to influence students' participation in MOOCs. The self-determination theory (SDT) involved two motivational factors controlled and autonomous motivation. Prior research demonstrated that the motivation of learners' for MOOCs applied both autonomous and controlled factors, indicating the need to measure students' level of self-determination. When external factors inspire the person's autonomous behavior, the self-determination level decreases. On the other hand, the self-determination level is high when a person's...
autonomous behavior is internally motivated. The SDT plays an essential role in technology acceptance research in online learning settings (Nikou & Economides, 2017).

Davis et al. (1989) presented a technology acceptance model comprised of perceived ease of use (PEU) (“the degree to which a person believes that using a particular system would be free of physical and mental effort”) and perceived usefulness (PU) (“the degree to which a person believes that using a particular system would enhance his/her job performance”). Similarly, PEU affects the PU, and simultaneously these variables effects acceptance intentions. Many researchers attempted to extend the TAM with the help of these two variables, which do not adequately reveal acceptance (Venkatesh et al., 2003; Venkatesh et al., 2012). However, TAM is still a simple and most accepted model commonly used when evaluating individuals' intentions toward technological perspectives (King & He, 2006).

Empirical Review and Hypotheses Development

Recent research has sought to uncover the diversity and complexity of students' motivation to participate in MOOCs. This phenomenon is discussed by Clow (2013), who explains that MOOC students went through a process of four steps as “awareness, registration, activity, and progress” toward the use of MOOC. Clow concluded that very few learners achieve the fourth stage. Several qualitative research studies have guided through valuable understandings into various motivation and student participation patterns (Littlejohn et al., 2016; Zheng et al., 2015). On the other hand, empirical studies revealed that how motivation works in MOOC perspectives is still in a limited scope and at the initial stage (de Barba et al., 2016). For example, Zhou (2016) used self-determination theory and concluded that students’ autonomous motivation positively affected their attitude toward MOOCs, stressing their less autonomous position in open learning settings such as MOOCs. Joo et al. (2018) used SDT and found that self-determination did not affect Korean students' satisfaction toward K-MOOC. Thus, prior research also revealed inconsistent findings that requires more research to generalize the results.

Previous research endeavored to incorporate the TAM and SDT to observe learners’ intention toward mobile assessment systems and found that PEU positively affected PU (Nikou & Economides, 2017). Wu and Chen (2017) found that PEU significantly impacted PU in the MOOC usage context. Similarly, the TAM factors significantly impacted user satisfaction that enhanced continuance intentions in Korea (Joo et al., 2018). Hsu et al. (2018) found that external factors such as perceived convenience, sense of community, computer self-efficacy, and perceived gains positively impacted PEU and PU significantly affected user attitude and behavioral intentions in Taiwan. Teo and Dai (2019) found that the TAM factors explained 45% variance toward MOOCs in China. However, the time factor was not associated with attitude and intention, but it was an important predictor of PU. Recently, Al-Adwan (2020) found that the TAM factors effectively impacted user attitude and behavioral intentions toward MOOCs in Jordan. Likewise, the TAM factor such as PU was significantly impacted satisfaction that enhanced the user intentions toward MOOCs in Spain. Besides all the above discussion, still, this topic discussed in a limited scope and required more research (Joo et al., 2018). This research employed the SDT and TAM factors (PEU and PU) to determine the students' perceived satisfaction and continued intentions toward MOOCs.

Theoretical Model Development

This study follows the self-determination theory and TAM to predict the users perceived satisfaction and continued intentions to use the MOOCs. Figure 1 depicts the theoretical model of the proposed research.

Autonomy is the central concept of self-determination theory, described as “the perceived origin or source of one’s own behavior. Autonomy concerns acting from interest and integrated values. When autonomous, individuals experience their behavior as an expression of the self…” (Ryan & Deci, 2000, p. 8). Control is opposed to autonomy. Individual behavior can be stimulated through internal induced incentives (called “autonomous motivations”), as well as through external evoked incentives (called “controlled motivations”) (Zhou, 2016).

Controlled Motivation

The word motivation comes from the concept of movement that refers to an individual's instincts and impulses that influence to act accordingly. Researchers established a distinction between extrinsic and intrinsic motivation as essential factors (Magen-Nagar & Cohen, 2017). Controlled motivation is contrary to autonomous motivation. Thus, controlled motivation acts as an obstacle to develop positive perceptions, though the effects can differ between self-perceptions and technology (Zhou, 2016). Prior research found that controlled motivation negatively affects behavioral intentions. For example, Ryan and Deci (2000) discussed that controlled motivation might cause negative outcomes for individuals due to internal and external pressures. Similarly, recent research revealed that controlled motivation had non-significant impacts on user intentions toward MOOCs (I. Pozón et al., 2019; Irma et al., 2020) and continues intentions toward MOOCs (Abdollatif & Velázquez-Iturbide, 2020). Self-determination theory explains that higher motivation does not mean to yield positive outcomes, mainly if the motivation is controlled than autonomous (Ryan & Deci, 2000). Similarly, prior research revealed that controlled motivation negatively impacts satisfaction, such as in the context of employee satisfaction and turnover (Gillet et al., 2013) and child and parent association context (Jungert et al., 2015). Thus, we assume the following hypothesis:

H₁: Controlled motivation negatively impacts users continued intentions toward MOOCs.
\( H_2: \) Controlled motivation negatively impacts users perceived satisfaction toward MOOCs.

**Autonomous Motivation**

Autonomous motivation is more important than controlled motivation—autonomous motivation is considered an inner reward that motivates individual behavior (Zhou, 2016). Prior research found that autonomous motivation positively related to students' use intentions toward MOOCs (I. Pozón et al., 2019; Irma et al., 2020) and continuous intentions toward MOOCs (Abdullatif & Velázquez-Iturbide, 2020). Similarly, previous research found the positive relationships of autonomous motivation and satisfaction, such as in the context of employee satisfaction and turnover (Gillet et al., 2013), child and parent association context (Jungert et al., 2015). Thus, we develop the following hypotheses:

\( H_3: \) Autonomous motivation positively impacts users continued intentions toward MOOCs.

\( H_4: \) Autonomous motivation positively impacts users perceived satisfaction toward MOOCs.

**Perceived Ease of Use**

Perceived ease of use (PEU) is commonly used in literature by considering different empirical research studies from various perspectives. Empirical evidence revealed that PEU had significant relationships on user intentions (directly/indirectly) and its positive effect on PU (Venkatesh & Davis, 2000). When students believe the e-learning system is likely to be easy to use, they will accept and use the system more positively and continuously (Lee et al., 2009). Cigdem and Ozturk (2016) discussed that the direct effects of PEU on perceived usefulness could inspire to reflect that system is functioning well and beneficial for the users. Huanhuan and Xu (2015) revealed that PEU positively affected and interacted with user intentions toward MOOCs. Thus, in view of these two factors, the authors assessed the ease of the platform, i.e., whether the user was prepared to participate and finish the online course as well as whether interactive learning was important to them. Similarly, past research demonstrated that PEU positively impacted perceived usefulness and users’ continuance intentions toward online learning technologies (del Barrio-García et al., 2015; Lee, 2010; Xu, 2015). Therefore, we assume the following hypotheses:

\( H_5: \) Perceived ease of use positively impacts users continued intentions toward MOOCs.

\( H_6: \) Perceived ease of use positively impacts users perceived usefulness toward MOOCs.

**Perceived Usefulness**

According to Sun et al. (2008), the perceived usefulness and easy use of online courses offer and file transfer system positively impacted students' attitude toward online learning. Further, they found that perceived usefulness was positively enhanced learning and adoption of e-learning systems. Some other empirical research studies found that perceived usefulness positively impacted students’ behavioral intentions toward online learning through MOOCs (Al-Adwan, 2020; Tawafak et al., 2020; Teo & Dai, 2019) and continuance intentions toward e-learning use (Saeed Al-Maroof et al., 2021). Similarly, several past research studies provided empirical backup for the significance of perceived usefulness on satisfaction in e-learning contexts (Cigdem & Ozturk, 2016; Lee, 2010; Thong et al., 2006) and toward MOOCs (I. Pozón et al., 2019; Irma et al., 2020). del Barrio-García et al. (2015) found that the system’s perceived usefulness positively influenced the students' satisfaction, especially among students who had a high need of cognition. Thus, we define the following hypotheses:

\( H_7: \) Perceived usefulness positively impacts users continued intentions toward MOOCs.

\( H_8: \) Perceived usefulness positively impacts users perceived satisfaction toward MOOCs.

**Perceived Satisfaction**

Perceived satisfaction is used to evaluate a system's success or failure (Cigdem & Ozturk, 2016), especially user satisfaction positively affected to use the e-learning system continuously (Mohammadi, 2015). Therefore, many research studies confirm empirical support to the direct effect of satisfaction on the users' use intention of technology in MOOCs contexts (I. Pozón et al., 2019; Irma et al., 2020). Some other research studies also found that perceived satisfaction significantly impacted the user continuance intentions toward MOOCs use (Alraimi et al., 2015; Joo et al., 2018; Shahijan et al., 2016). So, we propose following hypothesis:

\( H_9: \) Perceived satisfaction positively impacts users continued intentions toward MOOCs.
Research and Methodology

Instrument Design and Measurement Scale

The structured questionnaire was designed in the English language. The questionnaire was designed in two sections and prepared in MOOCs context. Before designing the questionnaire, we explained the research motives and research ethics about user information privacy. The first section consisted of research 26 questions asked from intended users to accomplish the research objectives. The second section was based on users’ demographic information. We used the established scales of prior research, such as controlled motivation (CM) with 4 items and autonomous motivation (AM) with 5 items were adapted from Zhou (2016) and Irma et al. (2020). Similarly, perceived ease of use (PEU) with 4 items and perceived satisfaction with 7 items were adapted from Sun et al. (2008). Perceived usefulness (PU) with 3 items taken from Alraimi et al. (2015). The continued intention with 3 items was adapted from Chiu and Wang (2008). All items were measured based on a seven-point (“1=strongly disagree and 7=strongly agree”) Likert scale. After preparation, this questionnaire was discussed with five Ph.D. students and two associate professors. After incorporating their feedback, we finalized the questionnaire for data collection.

Data Collection and Sampling

We posted the final questionnaire on a leading online survey website in China (https://www.wjx.cn). The online survey was launched in three public universities in Wuhan, China, and asked the intended students to fill the questionnaire. We used convenience sampling, commonly used in massive open online courses research (Al-Adwan, 2020; Wang et al., 2021). Further, convenience sampling is a useful technique commonly used for data collection from intended respondents in a timely and efficient manner (Safeer et al., 2020; Sekaran & Bougie, 2016). Finally, we collected data from 333 students who were currently participating in different online courses in the MOOCs context. After thoroughly data screening, removing biased responses and outliers, we considered 305 responses for final analysis. The demographics information of respondents is revealed in the following table 1.

Table 1: Participants Demographics Information

| Description   | Number | %    |
|---------------|--------|------|
| Sample Size   | 305    |      |
| Gender        |        |      |
| Male          | 237    | 77.70%|
| Female        | 68     | 22.30%|
| Age           |        |      |
| 18 – 23       | 51     | 16.72%|
| 24 – 29       | 127    | 41.64%|
| 30 – 34       | 93     | 30.49%|
Results and Discussions

This research applied the partial least square (PLS) via structural equation modeling (SEM) through Smart PLS 3.2.8 version software (Ringle et al., 2015). PLS-SEM technique supports researchers in managing complex models and multiple relationships without data normality assumptions (Safeer et al., 2020). When the research objectives are predictions and contribute to theory, PLS-SEM is the best fit to apply according to the recommendation of Sarstedt et al. (2017) and Hair Joseph et al. (2019). PLS-SEM involves assessing the model in two parts. The first part was related to model measurement evaluation, and the second part consisted of structural model evaluation.

Measurement Model Evaluation

The measurement model is comprised of two parts. The first part is related to measures the constructs ICR (internal consistency reliabilities) by including item loadings, Cronbach’s Alpha, and Composite reliability. The second part comprised the constructs’ validity by including AVE (average variance extracted), discriminant validity.

Hair Joseph et al. (2019) recommended that item loading values should be higher than 0.708. However, values between 0.60 to 0.70 are also acceptable for data analysis appropriately in PLS-SEM. Similarly, several other authors recommended that Cronbach’s alpha and composite reliability values must be more than 0.70 and AVE values must be greater than 0.50 for suitable analysis in PLS-SEM (Chin, 1998; Hair Jr et al., 2017; Sarstedt et al., 2017). Our all values of item loadings, Cronbach’s alpha, and composite reliability fulfilled the recommended criteria (see table 2 for detailed results). However, the item loading value of PS7 was 0.694, which was less than the recommended criterion (0.708), but it was acceptable for analysis (see figure 2). Similarly, all values of AVE were also greater than 0.50, which had satisfied the criterion. Therefore, constructs ICR was established.

Table 2: Internal Consistency Reliability and Validity

| Constructs                     | Items | Loadings | Cronbach’s Alpha | CR   | AVE   |
|--------------------------------|-------|----------|------------------|------|-------|
| Controlled Motivation (CM)     | CM1   | 0.830    | 0.783            | 0.858| 0.602 |
|                                | CM2   | 0.712    |                  |      |       |
|                                | CM3   | 0.835    |                  |      |       |
|                                | CM4   | 0.719    |                  |      |       |
| Autonomous Motivation (AM)     | AM1   | 0.881    | 0.922            | 0.941| 0.762 |
|                                | AM2   | 0.884    |                  |      |       |
|                                | AM3   | 0.834    |                  |      |       |
|                                | AM4   | 0.884    |                  |      |       |
|                                | AM5   | 0.879    |                  |      |       |
| Perceived Ease of Use (PEU)    | PEU1  | 0.852    | 0.889            | 0.923| 0.750 |
|                                | PEU2  | 0.853    |                  |      |       |
|                                | PEU3  | 0.865    |                  |      |       |
Table 3 revealed that the discriminant validity also fulfilled the criterion recommended by Fornell and Larcker (1981), explaining that the constructs’ AVE values must be greater than the other constructs’ correlation values. Thus, our results have also established discriminant validity.

Table 3: Fornell-Larcker Criterion

| Construct         | AM  | CI   | CM   | PEU  | PS   | PU   |
|-------------------|-----|------|------|------|------|------|
| AM                | 0.873 |      |      |      |      |      |
| CI                | 0.817 | 0.883 |      |      |      |      |
| CM                | 0.738 | 0.720 | 0.796 |      |      |      |
| PEU               | 0.782 | 0.730 | 0.670 | 0.866 |      |      |
| PS                | 0.838 | 0.805 | 0.776 | 0.747 | 0.852 |      |
| PU                | 0.830 | 0.798 | 0.715 | 0.782 | 0.786 | 0.908 |

Structural Model Evaluation

Generally, structural model evaluated through applying various tests in PLS-SEM such as testing multicollinearity, testing of $R^2$ (coefficient of determination) for checking explained variance, model predictive power ($Q^2$ value), model fit, and hypotheses testing for evaluation of results (Hair Jr et al., 2017). First, we tested the data multicollinearity and found that all collinearity values were less than 5, matching the recommended criterion by Hair Joseph et al. (2019). Thus, there was no multicollinearity problem in the data. Next, we tested the $R^2$ to evaluate the explained variance in endogenous constructs and found that the $R^2$ value of perceived usefulness was 0.611 (61.1%), considered medium to strong, and the $R^2$ value of perceived satisfaction was 0.767 (76.7%) considered strong. The $R^2$ value of continued intention was 0.746 (74.6%), also considered strong (Chin, 1998). Thus, our proposed model revealed a strong explained variance in endogenous constructs. Figure 2 displayed the $R^2$ values of all endogenous constructs.
Next, we tested the $Q^2$ values to check the model's predictive power or accuracy. Therefore, we applied the blindfolding procedure of Geisser (1974) to test the $Q^2$ values of all endogenous constructs and found that the $Q^2$ value of perceived usefulness was 0.475 and perceived satisfaction was 0.437, both values were considered medium to strong, and continued intention $Q^2$ value was 0.543 considered strong as recommended by Hair Joseph et al. (2019). Thus, our proposed model had medium to strong predictive power or accuracy.

According to Chin (1998) and Hair Jr et al. (2017), the model fit can be evaluated by checking the RMSEA value in PLS-SEM. This study found the RMSEA value of 0.061, which was good. However, a value less than 0.08 is considered acceptable (Chin, 1998).

**Hypotheses Testing and Results Discussion**

Next, we tested the proposed hypotheses. The total scores and constructs’ measurement errors may affect the path coefficients. Therefore, we used the bias-corrected and accelerated (Streukens et al., 2010) bootstrapping with 5000 subsamples, two tails at 0.05 significance level to check the path coefficient, p-values, and t-values for testing hypotheses (Hair Jr et al., 2017). All results are displayed in table 4.

**Table 4: Hypotheses Testing Results**

| Hypothesis | Constructs | Path Coefficient | t value | p-value | Support |
|------------|------------|------------------|---------|---------|---------|
| H1         | CM -> CI  | 0.099            | 1.780   | 0.075   | No      |
| H2         | CM -> PS  | 0.304            | 6.021   | 0.000   | Yes     |
| H3         | AM -> CI  | 0.272            | 3.313   | 0.001   | Yes     |
| H4         | AM -> PS  | 0.456            | 8.210   | 0.000   | Yes     |
| H5         | PEU -> CI | 0.066            | 0.978   | 0.328   | No      |
| H6         | PEU -> PU | 0.782            | 26.869  | 0.000   | Yes     |
| H7         | PU -> CI  | 0.251            | 3.486   | 0.000   | Yes     |
| H8         | PU -> PS  | 0.190            | 3.157   | 0.002   | Yes     |
| H9         | PS -> CI  | 0.254            | 3.729   | 0.000   | Yes     |

This research found that controlled motivation (CM) did not affect user continued intentions (CI) as $CM -> CI$ ($β=0.099$; $p=0.075$). Thus, null hypothesis $H_1$ was accepted. The current literature lacks the relationship between CM and CI. However, similar research supported this finding that Irma et al. (2020) and I. Pozón et al. (2019) that controlled motivation did not affect user MOOC use...
intention in Spain. Although these relationships were not significant, differing from other reviewed studies, they found similar results compared to the previous studies. For instance, reviewing Mikalef et al. (2016), the current research could not find significant relationships between controlled motivation and user continued intention. The finding was also consistent with the self-determination theory. Thus, it explained that controlled motivation did not influence the students to use massive open online courses continuously.

H2 found that CM significantly impacted perceived satisfaction (PS) as CM -> PS ($\beta=0.304; p=0.000$). So, null hypothesis H2 was rejected. Although literature lacks in the current research context and no similar research found on the topic. However, these relationships found contrary results compared to previous research of Gillet et al. (2013), who found that work-controlled motivation negatively impacts work satisfaction. Similarly, Koestner et al. (2008) found that controlled motivation was not related to personal goal progress. Self-determination explains that controlled motivation consists of external factors or regulations, which has shown a kind of motivation that influences individuals to act for external rewards (Ryan & Deci, 2000). Thus, we can expect that university and MOOC regulations influence the students’ satisfaction to act and follow regulations for a certificate (a kind of achievement).

H3 – H4 revealed that autonomous motivation (AM) positively impacted CI and PS. Therefore, H3 – H4 was supported. Figure 3 revealed the path coefficients and significance level of all constructs. Our findings followed the prior similar research of I. Pozón et al. (2019), who found that autonomous motivation enhances MOOC users’ intention in Spain. Similarly, Zhou (2016) found that autonomous motivation positively enhances students’ intention to use MOOC in China. However, there is scarce research in the context of continuous intention. Similarly, our findings also supported earlier research in perceived satisfaction perspectives. For example, Gillet et al. (2013) revealed that autonomous work motivation positively enhanced employee work satisfaction. Thus, our findings also discovered that autonomous motivation positively enhanced the students perceived satisfaction toward MOOC. Similarly, this study’s findings are also in line with the self-determination theory (Ryan & Deci, 2000).

H5 found that PEU had no effect on CI as PEU -> CI ($\beta=0.066; p=0.328$). The results are in line with earlier similar research of I. Pozón et al. (2019), who found the perceived ease of use had no effect on MOOC users’ intention in Spain. However, other research of Yang et al. (2017) deviated from our results, who found that perceived ease of use positively affected continued intention toward participating in MOOCs. Thus, these inconsistent findings may require further research to generalize the findings.

Figure 3: Path Coefficients and Significance Level

H6 found that perceived ease of use strongly affected perceived usefulness. Thus, hypothesis H6 was supported. Our finding is consistent with earlier similar research of Irma et al. (2020) and Yang et al. (2017), who found that perceived ease of use positively facilitated users to enhance their usefulness toward MOOCs. Thus, the TAM factors supported enhancing the students’ continued intention toward MOOCs.

H7 – H8 revealed that perceived usefulness significantly affected continued intention and perceived satisfaction. So, H7 – H8 were supported. Our findings supported Yang et al. (2017) earlier work, who found that perceived usefulness enhanced the students’ continued intention in massive open online courses. Similarly, Ouyang et al. (2017) found that perceived usefulness not only enhances
the students' satisfaction but also positively increases the students' continued intentions to use MOOC. Thus, our study contributed and generalized the findings by following prior research.

He found that perceived satisfaction positively impacted users’ continued intention. Therefore, H0 was supported. The findings explained that perceived satisfaction was a very important determinant that increased students' continued intention toward MOOCs. Our findings are consistent with previous research of Lu et al. (2019), who found that satisfaction was an essential factor of user continued intention, particularly in the MOOC perspective. Similarly, Ouyang et al. (2017) verified that satisfaction was important for users to increase their intentions continuously. Therefore, technology factors are important for students to enhance their perceived satisfaction and continue using MOOCs.

Conclusions

The investigation of behavior continuity is valuable in the information system and more essential than behavior acceptance (Ouyang et al., 2017). This research aimed to investigate the motivation and technology acceptance factors to predict the users’ perceived satisfaction and continued intention toward MOOCs. The findings revealed controlled motivation is an essential factor that enhanced the users' perceived satisfaction. However, autonomous motivation significantly affected users' perceived satisfaction and continued intentions toward massive open online courses. Likewise, technology factors such as perceived ease of use enhanced the usefulness. While perceived usefulness positively enhanced the users’ perceived satisfaction and continued intentions simultaneously. Therefore, technology acceptance factors perfectly influenced users toward MOOCs. Thus, educational institutions and technology experts may focus on these important motivational factors and technological factors for developing ease use and effective MOOCs online platforms to influence multiple users for enhancing their perceived satisfaction and continuance use of MOOCs.

This research develops a better understanding of students' perceived satisfaction and continued intention about MOOCs and provides important practical guidelines to educational institutions and MOOCs designers who offer multiple online courses to influence students. Considering controlled and autonomous motivation factors, they can influence the students' perceived satisfaction, mainly through following their achievements such as certificates, personal growth, and developments for their better future career. The findings revealed that perceived ease of use was strongly affected perceived usefulness. This study can help technologists to develop user-friendly and useful online platforms. Thus, useful online platforms enhance the users' perceived satisfaction and their continuous intentions to use online platforms, especially in MOOCs. Similarly, successful MOOCs platforms may help the users for their career growth, personal development, and willingness to learn new skills by using new technologies. Thus, technology ease of use and usefulness may enhance their loyalty toward MOOCs.

This research provides important insights and contributions to the SDT and TAM toward MOOCs. However, some limitations have been found in this research. It also suggests future research avenues to researchers to investigate in future research. First, we used convenience sampling for this research. While results generalization needs to use random sampling with a larger sample size in future research. Second, our study was limited to direct relationships of constructs. Future researchers may investigate the same model by checking the simple and serial mediation effects to contribute to theory and literature. Third, we collected data from three public universities in Wuhan, China. Future researchers may collect data from other cultures with a larger sample size to generalize the findings. Finally, the proposed model used the motivation and technology factors to predict the students perceived satisfaction and continuance use of MOOCs. Further research may consider more variables to check the effects of other theoretical variables and increase the intended users with various backgrounds (such as working professionals in government and private organizations) for more contributions and valuable insights.

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References

Abdullatif, H., & Velázquez-Iturbide, J. Á. (2020). Relationship between motivations, personality traits and intention to continue using MOOCs. *Education and Information Technologies, 25*(5), 4417-4435. https://doi.org/10.1007/s10639-020-10161-z

Al-Adwan, A. S. (2020). Investigating the drivers and barriers to MOOCs adoption: The perspective of TAM. *Education and Information Technologies, 25*(6), 5771-5795. https://doi.org/10.1007/s10639-020-10250-z

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

Anderson, T. (2013). Promise and/or peril: MOOCs and open and distance education. *Commonwealth of learning, 3*, 1-9.

Atique, M., Safeer, A. A., Ullah, A., & Iftikhar, H. (2021). A Study of Impacting Factors on Technology Adoption in the Public Sector of Pakistan. *Journal of Contemporary Issues in Business and Government*, 27(2), 1281-1302.
Bazelaiz, P., Doleck, T., & Lemay, D. J. (2018). Investigating the predictive power of TAM: A case study of CEGEP students’ intentions to use online learning technologies. *Education and Information Technologies*, 23(1), 93-111. https://doi.org/10.1007/s10639-017-9587-0

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 25(3), 351-370. https://doi.org/10.2307/3250921

Chen, C.-C., & Chen, C.-Y. (2018). Exploring the effect of learning styles on learning achievement in a u-Museum. *Interactive Learning Environments*, 26(5), 664-681. https://doi.org/10.1080/10494820.2017.1385488

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research*, 295(2), 295-336.

Chiu, C.-M., & Wang, E. T. G. (2008). Understanding Web-based learning continuance intention: The role of subjective task value. *Information & Management*, 45(3), 194-201. https://doi.org/10.1016/j.im.2008.02.003

Cigdem, H., & Ozturk, M. (2016). Factors affecting students’ behavioral intention to use LMS at a Turkish post-secondary vocational school. *International Review of Research in Open and Distributed Learning*, 17(3), 276-295. https://doi.org/10.19173/IROD.1v173.2253

Clow, D. (2013, 2013). MOOCs and the funnel of participation. Proceedings of the third international conference on learning analytics and knowledge, Conole, G. (2016). MOOCs as disruptive technologies: strategies for enhancing the learner experience and quality of MOOCs. *Revista de Educación a Distancia (RED)* (50).

Daniel, J., Cano, E. V., & Cervera, M. G. (2015). El futuro de los MOOC: aprendizaje adaptativo o modelo de negocio? *RUSC Universities and Knowledge Society Journal*, 12(1), 64-73.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, 35(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

de Barba, P. G., Kennedy, G. E., & Ainley, M. D. (2016). The role of students’ motivation and participation in predicting performance in a MOOC. *Journal of Computer Assisted Learning*, 32(3), 218-231. https://doi.org/10.1111/jcal.12130

del Barrio-García, S., Arquero, J. L., & Romero-Frias, E. (2015). Personal learning environments acceptance model: The role of need for cognition, e-learning satisfaction and students’ perceptions. *Journal of Educational Technology & Society*, 18(3), 129-141.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing research*, 18(1), 39-50. https://doi.org/10.1177/002224378101800104

Gameel, B. G., & Wilkins, K. G. (2019). When it comes to MOOCs, where you are from makes a difference. *Computers & Education*, 136, 49-60. https://doi.org/10.1016/j.compedu.2019.02.014

Gillet, N., Gagné, M., Sauvagère, S., & Fouquereau, E. (2013). The role of supervisor autonomy support, organizational support, and autonomous and controlled motivation in predicting employees' satisfaction and turnover intentions. *European Journal of Work and Organizational Psychology*, 22(4), 450-460. https://doi.org/10.1080/1359432X.2012.665228

Gupta Kriti, P. (2019). Investigating the adoption of MOOCs in a developing country: Application of technology-user-environment framework and self-determination theory. *Interactive Technology and Smart Education*, 17(4), 355-375. https://doi.org/10.1108/ITSE-06-2019-0033

Hair Joseph, F., Risher Jeffrey, J., Sarstedt, M., & Ringle Christian, M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications.

Hsu, J.-Y., Chen, C.-C., & Ting, P.-F. (2018). Understanding MOOC continuance: An empirical examination of social support theory. *Interactive Learning Environments*, 26(8), 1100-1118. https://doi.org/10.1080/10494820.2018.1446990

Huang, L., Zhang, J., & Liu, Y. (2017). Antecedents of student MOOC revisit intention: Moderation effect of course difficulty. *International Journal of Information Management*, 37(2), 84-91. https://doi.org/10.1016/j.ijinfomgt.2016.12.002

Huanhuan, W., & Xu, L. (2015). Research on technology adoption and promotion strategy of MOOC. 6th IEEE International Conference on Software Engineering and Service Science (ICSESS).

I. Pozón, L., Kalinic, Z., Higuera-Castillo, E., & Liébana-Cabanillas, F. (2019). A multi-analytical approach to modeling of customer satisfaction and intention to use in Massive Open Online Courses (MOOC). *Interactive Learning Environments*, 28(8), 1003-1021. https://doi.org/10.1080/10494820.2019.1636074

Irmak, P.-L., Higuera-Castillo, E., Muñoz-Leiva, F., & Liébana-Cabanillas, F. J. (2020). Perceived user satisfaction and intention to use massive open online courses (MOOCs). *Journal of Computing in Higher Education*, 1-36. https://doi.org/10.1007/s12528-020-09257-9

Joo, Y. J., So, H.-J., & Kim, N. H. (2018). Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. *Computers & Education*, 122, 260-272. https://doi.org/10.1016/j.compedu.2018.01.003
Jungert, T., Landry, R., Joussemeti, M., Mageau, G., Gingras, I., & Koestner, R. (2015). Autonomous and controlled motivation for parenting: Associations with parent and child outcomes. *Journal of Child and Family Studies*, 24(7), 1932-1942. https://doi.org/10.1007/s10826-014-9993-5

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, 43(6), 740-755. https://doi.org/10.1016/j.infman.2006.05.003

Koestner, R., Ouis, N., Powers, T. A., Pelletier, L., & Gagnon, H. (2008). Autonomous motivation, controlled motivation, and goal progress. *Journal of personality*, 76(5), 1201-1230. https://doi.org/10.1111/j.1467-6494.2008.00519.x

Lee, B.-C., Yoon, J.-O., & Lee, I. (2009). Learners’ acceptance of e-learning in South Korea: Theories and results. *Computers & Education*, 53(4), 1320-1329. https://doi.org/10.1016/j.compedu.2009.06.014

Lee, J.-W. (2010). Online support service quality, online learning acceptance, and student satisfaction. *The internet and higher education*, 13(4), 277-283. https://doi.org/10.1016/j.ijhered.2010.08.002

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2016). Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *The internet and higher education*, 29, 40-48. https://doi.org/10.1016/j.ijhered.2015.12.003

Luo, Y., Wang, B., & Lu, Y. (2019). Understanding key drivers of MOOC satisfaction and continuance intention to use. *Journal of Electronic Commerce Research*, 20(2), 105-117.

Magen-Nagar, N., & Cohen, L. (2017). Learning strategies as a mediator for motivation and a sense of achievement among students who study in MOOCs. *Education and Information Technologies*, 22(3), 1271-1290. https://doi.org/10.1007/s10639-016-9492-y

Mikalef, P., Pappas Ilias, O., & Giannakos, M. (2016). An integrative adoption model of video-based learning. *The International Journal of Information and Learning Technology*, 33(4), 219-235. https://doi.org/10.1108/IJILT-01-2016-0007

Mohammadi, H. (2015). Investigating users’ perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, 45, 359-374. https://doi.org/10.1016/j.chb.2014.07.044

Nikou, S. A., & Economides, A. A. (2017). Mobile-Based Assessment: Integrating acceptance and motivational factors into a combined model of Self-Determination Theory and Technology Acceptance. *Computers in Human Behavior*, 68, 83-95. https://doi.org/10.1016/j.chb.2016.11.020

Ouyang, Y., Tang, C., Rong, W., Zhang, L., Yin, C., & Xiong, Z. (2017). Task-technology fit aware expectation-confirmation model towards understanding of MOOCs continued usage intention. Proceedings of the 50th Hawaii International Conference on System Sciences, Hawaii.

Ringle, C., Da Silva, D., & Bido, D. (2015). Structural equation modeling with the SmartPLS. *Bido, D., da Silva, D., & Ringle, C.(2014). Structural Equation Modeling with the Smartpls. Brazilian Journal Of Marketing, 13(2).* https://doi.org/10.5585/remark.v13i2.2717

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

Saeed Al-Marool, R., Alhumaid, K., & Salloum, S. (2021). The Continuous Intention to Use E-Learning, from Two Different Perspectives. *Education Sciences*, 11(1), 2-20. https://doi.org/10.3390/eduscii11010006

Safeer, A. A., He, Y., & Abrar, M. (2020). The influence of brand experience on brand authenticity and brand love: an empirical study from Asian consumers’ perspective. *Asia Pacific Journal of Marketing and Logistics*. https://doi.org/10.1108/APJML-02-2020-0123

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. *Handbook of market research*, 26(1), 1-40.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.

Shahjahan, M. K., Rezaei, S., & Amin, M. (2016). International students’ course satisfaction and continuance behavioral intention in higher education setting: an empirical assessment in Malaysia. *Asia Pacific Education Review*, 17(1), 41-62. https://doi.org/10.1007/s12564-015-9410-9

Streukens, S., Wetzels, M., Daryanto, A., & De Ruyter, K. (2010). Analyzing factorial data using PLS: Application in an online complaining context. In *Handbook of partial least squares* (pp. 567-587). Springer.

Sun, P.-C., Tsai, R. J., Finger, G., Chen, Y.-Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education*, 50(4), 1183-1202. https://doi.org/10.1016/j.compedu.2006.11.007.

Tawafak, R. M., Malik, S. I., & Alfarsi, G. (2020). Development of framework from adapted TAM with MOOC platform for continuity intention. *Development*, 29(1), 1681-1691.

Teo, T., & Dai, H. M. (2019). The role of time in the acceptance of MOOCs among Chinese university students. *Interactive Learning Environments*, 1-14. https://doi.org/10.1080/10494820.2019.1674889

Thong, J. Y. L., Hong, S.-J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of human-computer studies*, 64(9), 799-810. https://doi.org/10.1016/j.ijhcs.2006.05.001

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, 46(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 27(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

Wang, Q., Khan, M. S., & Khan, M. K. (2021). Predicting user perceived satisfaction and reuse intentions toward Massive Open Online Courses (MOOCs) in the Covid-19 pandemic: An application of the UTAUTmodel and quality factors. *International Journal of Research in Business and Social Science*, 10(2), 1-11. https://doi.org/10.20525/jirbs.v10i2.1045

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221-232. https://doi.org/10.1016/j.chb.2016.10.028

Xu, F. (2015). Research of the MOOC study behavior influencing factors. Proceedings of international conference on advanced information and communication technology for education, Netherlands.

Yang, M., Shao, Z., Liu, Q., & Liu, C. (2017). Understanding the quality factors that influence the continuance intention of students toward participation in MOOCs. *Educational Technology Research and Development*, 65(5), 1195-1214. https://doi.org/10.1007/s11423-017-9513-6

Zheng, S., Rosson, M. B., Shih, P. C., & Carroll, J. M. (2015, 2015). Understanding student motivation, behaviors and perceptions in MOOCs. Proceedings of the 18th ACM conference on computer supported cooperative work & social computing.

Zhou, M. (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. *Computers & Education*, 92, 194-203. https://doi.org/10.1016/j.compedu.2015.10.012

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