Online learning adoption by Chinese university students during the Covid-19 pandemic

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Abstract

The 2019 Novel Coronavirus Pandemic has severely challenged the continuity of post-secondary education around the world. Online learning platforms have been put to the test, in a context where student engagement will not occur as a simple matter of course. To identify the factors supporting online learning under pandemic conditions, a questionnaire based on the Unified Theory of Acceptance and Use of Technology was adapted and administered to a sample of 704 Chinese university students. Structural equation modelling was applied to the resulting data, to identify the most relevant theoretical components. Effort expectancy, social influence, and information quality all significantly predicted both students' performance expectancies and the overall adoption of their university's Moodle-based system. Performance expectancy mediated the effects of effort expectancy, social influence, and information quality on symbolic adoption. Internet speed and reliability had no clear impact on adoption, and neither did gender. The direct impact of information quality on symbolic adoption represents a particularly robust and relatively novel result; one that is not usually examined by comparable

research. As outlined, this is one of three key factors that have predicted online learning engagement, and the viability of educational continuity, during the Coronavirus pandemic. The same factors can be leveraged through user-focused development and implementation, to help ensure tertiary education continuity during a range of crises.

Keywords: *Online learning, technology adoption, business continuity, pandemic.*

Introduction

At the time of writing, the 2019 Novel Coronavirus (COVID-19) pandemic continues to present substantial challenges to the world's universities. Although the current pandemic's progression has caught many institutions by surprise, smaller-scale antecedents have included the severe acute respiratory syndrome (SARS-CoV) of 2003 and the H1N1 pandemic of 2009. The global scale of the COVID-19 pandemic came foreshadowed by the 1918-1919 Spanish Influenza, which killed between 24.7 and 50 million people around the globe (Johnson & Mueller, 2002; Oxford et al., 2002). This pandemic also left many millions of students studying by distance (Ammond, 2001; Lilley et al., 2020; Mamelund, 2017; Rosner, 2010), in a sudden departure from normal student life.

There have been important changes to the scale and nature of education since the latter antecedent to the current pandemic. University level studies have become much more commonplace since the beginning of the twentieth century. In 1900, there were approximately 500,000 university enrolments throughout the world, growing to over 100 million by the year 2000 (Schofer & Meyer, 2005). The same shift has been even more recent for Chinese universities, which experienced an increase of almost 40 million tertiary students from 1950 to 2019. By 2019, total university enrolments reached 34,205 times the number of students enrolled as at 1949 (China Ministry of Education, 2020).

Even more recent decades have seen many universities and other education providers develop online platforms to deliver tertiary level courses, and course-related content (OECD, 2005; Allen & Seaman, 2013). Among other capabilities, this has enabled universities to

deliver blended learning, combining both online and offline activities into the same set of courses. Rasheed et al. (2020) identified a wide range of relevant shifts towards a blend of place-based and online learning, with respective challenges for students, teachers, and institutions. Studies by Shea and Bidjerano (2014) and by Shi et al. (2020) have shown how students nonetheless tend to benefit from this blended mode of learning, in terms of improved learning outcomes and even increased college graduation rates. This has meant that millions of university students have been able to continue their studies online, using portable devices such as cell phones and laptops during the COVID-19 pandemic (Huang et al., 2020), rather than waiting for paper-based courses to be delivered by mail. This switch to online education during a pandemic also follows antecedents. Similar situations were experienced by institutions in many countries, who prepared online modes of education in response to the H1N1 pandemic. This included an estimated 67 % of universities in the USA, who made plans to switch to online education delivery in response to the pandemic (Allen & Seaman, 2010) .

In the decade separating the H1N1 pandemic from the COVID-19 pandemic, online education became part of business as usual in universities around the world. A range of graduate and postgraduate material was already taught online before COVID-19, and many courses included online learning alongside classroom-based teaching. This trend has extended to parts of the world that have traditionally been described as *developing* countries. For example, online education was already being developed by many Chinese educational institutions well before the COVID-19 pandemic (Zhu, 2010). By 2014, the Chinese Ministry had already run 24 different massive open online courses within the Chinese mainland (Qiu, 2014)**.** The current paper focuses on this developing educational context, which has advanced rapidly but which has also tended to be under-researched and under-reported in the English language.

Technological advances in China and around the world have created many opportunities for delivering education by distance in the contemporary world. Internet capable devices have become much cheaper, and more accessible to a wider range of students (Cronje, 2016). Online courses are also becoming more accessible, with most designed to be compatible with a wide of range of hardware including desktop, laptop and mobile devices (Lambert, 2020). Internet speeds have also substantially improved over the last decade. Internet speed from a regular internet service provider is now

ten times faster, delivering hundreds of megabits per second compared, to the tens of megabits per second delivered only ten years ago (Feamster & Livingood, 2019). These advances are particularly relevant for the relatively wealthy context studied in the current paper, characterized by a high level of student hardware and communications infrastructure. Over the same period, server capacities have become a key component of universities' IT infrastructure. These capacities have dramatically increased to host learning management systems (LMSs) and in turn, to ensure successful e-learning delivery (Alsabawy, 2013; Asalla, 2017). To enhance the clarity of the current paper, the resulting LMSs are referred to as online learning platforms.

Despite the potentials outlined above, universities that heavily invested in online learning platforms can run the risk of widening a pre-existing digital divide: between those that can and cannot make good use of online technologies (Warschauer, 2003). This concept of a divide helps to highlight how online learning does not occur as a matter of course. Even a very basic online course has several costly requirements, including: a rapid and stable internet connection; a sizeable internet data allowance, to accommodate video content; a screen that is big enough for extended viewing; and a functioning keyboard, for even minimal interactions. As highlighted by Warschauer (2003), technology users also need certain technological skills, to take full advantage of these kinds of technological tools and associated software.

Even when students have reliable access to online learning platforms, the COVID-19 pandemic has put those platforms under largely unprecedented demands. Rather than being an optional or complementary mode of delivery, they have become the only way for many institutions to continue functioning (Huang et al., 2020). Students' adoption of online learning platforms has therefore become even more important than blended and online learning options provided during business as usual. The importance of online learning platforms has been particularly tangible in populous countries such as China, where a governmental, open education platform received 8 million clicks within the first day of operation in February 2020 (Huang et al., 2020). Towards improving university student engagement during the current pandemic and future crises, the current research aimed to identify technology and user characteristics predicting Chinese university students' adoption of a specific online learning platform. As outlined below, decades of prior research into predicting LMS adoption

has been adapted to help meet challenges presented by the COVID-19 pandemic.

Prior Research

The current research focuses on student engagement with an LMS called iSpace. This LMS had been developed and implemented at a liberal arts university in the South of China over a period of more than five years. However, the platform had not yet been used to teach exclusively online. To reflect challenges posed by exclusively online teaching during the COVID-19 pandemic, the iSpace system is the online learning platform of interest for the remainder of the current paper. It is based on the generic Modular Object-Oriented Dynamic Learning Environment (Moodle) platform, which was "designed to provide educators, administrators and learners with a single robust, secure and integrated system to create personalized learning environments" (Moodle HQ, 2020, para 1). As at June 2020, there were over 213 million Moodle users throughout the world, making it the world's most widely used online learning platform (Moodle HQ, 2020). Generic Moodle capabilities are maintained by an expansive community of programmers and contributors throughout the world, coordinated by a group of 80 Moodle Partner service companies (Moodle HQ, 2020). The basic Moodle platform has also been customized by universities around the world, for delivering online educational content and activities as part of tertiary level courses. The basic Moodle platform is nonetheless non-proprietary and open source. This means that universities who have not yet fully leveraged its potential can do at minimal cost and inconvenience.

Like many other technologies, students' adoption of Moodle-based online learning platforms can be explained and studied using the unified theory of acceptance and use of technology (UTAUT) (McKeown & Anderson, 2016; Raman et al., 2014). Before outlining several examples of relevant research in the following Section 1.2, a brief introduction to the UTAUT theoretical model helps to explain why it suits research into online education engagement. The UTAUT framework emanated from the need to unify competing theoretical models, including the theories of reasoned action (TRA) (Ajzen & Fishbein, 1980) and of planned behavior (TPB) (Ajzen & Madden, 1986), and the technology acceptance model (TAM) (Davis, 1986, 1989). These theoretical antecedents had previously provided robust explanations of users' engagement with a range of technologies, by defining a very wide range of aspects and relevant concepts. The UTAUT model (Venkatesh et al., 2003) synthesized a more concise set of key concepts by combining these pre-existing models, to define the main factors leading to active technology adoption. The first of these key concepts is effort expectancy, which is "the degree of ease associated with the use of the system" (Venkatesh, 2003, p. 450). This concept is sometimes referred to as perceived ease of use and may be particularly important for students studying under relatively improvised and distressful conditions. This is because those students may not be able to concentrate on novel, and unnecessarily complicated, technological demands.

Facilitating conditions are another key aspect of the UTAUT model. This concept refers to "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh, 2003, p. 453). As outlined in Section 1.0, it cannot be assumed that all students have equal access to online learning. A persistent digital divide between students may have seen many of them attempting to study online without rudimentary requirements such as a reliable internet connection.

Social influence is another key aspect of the UTAUT model. This concept addresses "how strongly an end user perceives that others believe that he or she should use the new system" (Prasanna & Huggins, 2016, p. 171). This aspect of online learning has been particularly important during the COVID-19 pandemic, for Chinese students forced to study back in their family apartments or other family home environments. Although the students may have become relatively independent, the current crisis may have returned them to considerable pressure from their parents and other family members. This temporary context for social influence is distinct from, and perhaps more salient than, more rudimentary contexts studied by prior LMS adoption research.

Relatively recent adaptations to the UTAUT model highlight how information technologies can be effectively redundant unless they provide useful information. Information quality generally addresses "whether a system is free of errors, whether it provides the information needed for the user to complete their work at the time they need it, and whether information is provided in a format which is easy to read" (Prasanna & Huggins, 2016, p. 171). Although this factor has not traditionally been addressed by LMS adoption research, it was particularly relevant for the current study. The concept of information quality creates unique challenges for a broad range of organizations (Jayawardene, 2016, Jayawardene et al., 2021). It is particularly relevant and challenging for educational institutions tasked with delivering robust and engaging learning materials

through online platforms (Hansen & Gissel, 2017). These learning materials can include: videos, additional readings, forum prompts, and glossaries. This is why information quality makes an intuitive addition to more standard applications of the UTAUT model, because the quality of LMS content is just as important as the quality of learning content delivered through any given mode of instruction. Ideally, any learning content will be delivered in a way that leverages student attention spans (Bradbury, 2016; Hartley & Davies, 1978) to good effect, and promotes learning that extends well beyond the most basic level of simply remembering the course material (Anderson, 2001).

The UTAUT model treats each of the preceding concepts as a technology characteristic that will either lead to, or undermine, performance expectancy: "the degree to which an individual believes that using the system will help him or her to attain gains in… . performance" (Venkatesh, 2003, p. 447). Within the UTAUT model, performance expectancy mediates how each of the preceding technology characteristics affect technology adoption (Venkatesh, 2003; Prasanna & Huggins, 2016). The resulting level of adoption is typically gauged in terms of symbolic adoption: "an end-user's mental acceptance of a new system" Prasanna & Huggins, 2016, p. 171). As discussed in further detail below, symbolic adoption is often used as a proxy for adoptive behaviors, due to a consistently close correlation with the latter (Prasanna & Huggins, 2016).

Many studies have used and/or adapted the UTAUT model for researching online education engagement. For example, a recent study by Mehta et al. (2019) found that an adapted version of the UTAUT model predicted online learning adoption, among adults studying in Gambia and the United Kingdom. This followed research by Amornkitpinya and Wannapiroon (2015), Arteaga Sanchez and Duarte Hueros (2010), Raman et al. (2014), Lahkal et al. (2013), and by Lee and Mendlinger (2011), which demonstrated how the UTAUT, or the antecedent technology adoption model (TAM), reliably predict online learning engagement in a wide range of settings.

The prior research by Amornkitpinya and Wannapiroon (2015) and by Lee and Mendlinger (2011) also gauged self-efficacy, a student's belief in their own likelihood of success, as an additional factor predicting online education adoption. Their approach was consistent with Bandura's definition of self-efficacy: "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainment" (Bandura, 1997, p.3). In practical terms, this approach to predicting

adoption places a distinct onus on improving the self-confidence of students needing to study online. However, crisis situations such as the COVID-19 pandemic may not afford this luxury, before the crisis triggers a rapid switch to online learning. Students with a lack of relevant mastery experiences may not have established self-efficacy (Bandura, 1977). This is likely to limit their e-learning performance, and meaning there are benefits from supporting students who lack experience in technology-enabled, active learning environments (Shi et al., 2020). For the current study, this support is addressed through the concept of facilitating conditions, which normally include technical support for less confident users. The current research therefore takes a more technology-centric approach to online education adoption, where certain aspects of technology design and provision will improve effort expectancy, or perceived ease of use, for users with a wide range of personal characteristics and different degrees of technological familiarity.

Current Theoretical Model

To expand on research conducted in non-pandemic contexts, the current research used a specific UTAUT-based theoretical model developed and validated by Prasanna and Huggins (2016), for mandatory technologies used within a crisis context. This model was originally designed to address the adoption of emergency management software, among trained professionals. It nonetheless also aligns very closely with UTAUT iterations outlined above, which have successfully predicted online learning engagement.

Results reported by Prasanna and Huggins (2016) showed that even mandatory technologies, such as obligatory online education, are adopted to widely varying degrees. According to their results and analysis, the adoption of software mandated by users' employers

Figure 1.
Theoretical model of hypothetical relationships between factors
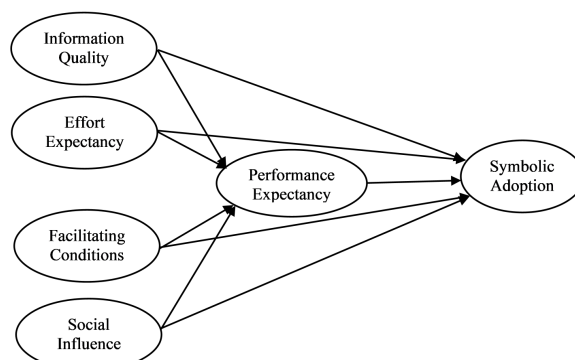
varied as systematically as did the adoption of non-mandated technology. These results led to the validation of the UTAUT iteration shown in Fig. 1, above. As outlined by Prasanna and Huggins (2016), the level of commitment involved in the symbolic adoption of mandated technologies entailed more system usage. It also led to more effective system usage, through familiarity and well-rehearsed human-computer interactions. Considering this high degree of relevance to the current research context, the theoretical model shown in Fig. 1 was used to structure the current research. For this purpose, it included the following constituent hypotheses:

1) That performance expectancy would be predicted by effort expectancy, facilitating conditions, social influence, and information quality.
2) That symbolic adoption would be directly predicted by effort expectancy, facilitating conditions, social influence, and information quality.
3) That symbolic adoption would also be indirectly predicted by effort expectancy, facilitating conditions, social influence, and information quality – mediated by performance expectancy.

Methods

Scale items were adapted from prior technology adoption research by Arteaga Sanchez & Duerte Hueros (2010), Lahkal et al. (2013), Lee & Mendlinger (2011), and by Prasanna and Huggins (2016). Adaptations were minimal and primarily aimed to address the current online learning platform, instead of prior wording that addressed other platforms and technologies. Participants were asked to answer the resulting question items using a Likert scale, running from: 1 – "Strongly Disagree"; 3 – "Neutral"; to 5 – "Strongly Agree".

Adapted scale items were complemented by demographic questions, concerning gender and major enrolment. The complete questionnaire was administered using the Typeform (Version 2, 2020) online survey platform, following piloting and adjustment with the same group of five students who had previously used the same Moodle-based online learning platform, but had not used it during the COVID-19 pandemic.

All students who had used the Moodle-based online learning platform between February and July 2020 were then invited to participate. At this time, no student or teacher were allowed on the university campus, meaning that all students and teachers were restricted to on-line classes. They were emailed an invitation complete with the Typeform URL, via university administrators. Their invitation included the offer to enter a 20 RMB prize draw in compensation for their time, with one prize for every ten entries. Before granting informed consent on the first page of the survey, participants were assured that their participation and any personally identifiable data would remain confidential, and that it would be anonymized during data collation and analysis.

The questionnaire was attempted by 742 out of approximately 5,400 online learning platform users, studying at the university in question. 711 survey responses were completed without obvious response sets or associated problems with response variability. Some of these responses were not accompanied by voluntary, demographic information. The final sample of participants nonetheless numbered 503 females, 201 males, 4 students who declined to name their gender, and 3 students who identified as an "Other" gender. Students who named their program of studies were studying business management (39%), science and technology (34%) humanities and social sciences (11%), or arts (9%). A sub-total of 361 (49%) respondents were first year students, meaning that the overall sample was evenly split between participants who had previously used iSpace and those that had not.

Analysis

The initial set of questionnaire items was refined and validated through parallel factor analysis, to ensure the validity and reliability of each model factor. The remainder of analysis used structural equation modelling to validate factors and test whether the relationships between them matched the theoretical model shown in Fig. 1 of Section 1.2. This analysis used the IBM Statistical Package for the Social Science (SPSS) version 25 and Analysis of Moment Structures (AMOS) version 25 software to perform a two-stage structural equation modelling process. The first stage of this process involved measurement model assessment through combined parallel and exploratory factor analysis (EFA), before conducting confirmatory factor analysis (CFA). The second stage involved structural model assessment, which was used to evaluate the causal relationships between factors.

Combined parallel and exploratory factor analysis followed the iterative process conducted by Wood et al. (2015). The current parallel analysis used the O'Connor (2000) rawpar.sps script, which produces eigenvalues from the raw data and compares them with eigenvalues resulting from Monte Carlo simulations, using randomly

generated data. Parallel analysis for the current study used 5,000 simulations to produce the randomly generated eigenvalues, with a 95th percentile cutoff.

Multiple iterations of this process were used to identify the optimal number of factors for the overall model. Each iteration was followed by an assessment of identified factors using EFA using maximum likelihood extraction with oblique rotation. The EFA involved generating pattern matrices based on the number of factors determined in the parallel analysis; pursuing solutions with factor loadings above the thresholds set by Hair et al. (2014) and reliability thresholds from Fornell and Larcker (1981). This resulted in distinct groupings of variables with strong correlations, confirming that the previously theorized number of factors could be adequately determined.

After determining the number of factors through the combination of parallel analysis and EFA, CFA was conducted using AMOS software. This involved reviewing modification indices to find a model fitting Hu and Bentler's (1999) criteria for fit. Reliability and both convergent and divergent validity of the measurement model were also assessed. Reliability was assessed against Hair et al.'s (2014) suggested threshold. Convergent validity was confirmed by an average variance extracted (AVE) for all factors higher than thresholds defined by Hair et al. (2014). Following Hair et al. (2014), discriminant validity was assessed by a square root of AVE for factors that was higher than the absolute value of between-factor correlations. This CFA process was used to confirm whether analysis had arrived at a stable measurement model, with retained items that could adequately measure the theorized constructs. The resulting measurement model was then subjected to structural analysis. As outlined below, this involved using the same AMOS software to evaluate causal relationships between the validated factors.

Results

The parallel factor analysis of all survey responses led to the retention of 17 of 25 items, excluding: effort expectancy (EE) item 3; facilitating condition (FC) items 1, 4 and 5; information quality (IQ) item 1; social influence (SI) items 3 and 4; and symbolic adoption (SA) item 4. All performance expectancy (PE) items were retained, along with all other retained items shown in Table 1. Each resulting factor met standards for composite reliability

Table 1.
Analytical summary for refined factors

| Factor	CR	AVE	SA	PE	IQ	EE	FC	SI
Symbolic Adoption	0.84	0.63	**0.79**					
Performance Expectancy	0.90	0.70	0.72	**0.84**				
Information Quality	0.83	0.62	0.77	0.68	**0.79**			
Effort Expectancy	0.82	0.61	0.61	0.66	0.62	**0.78**		
Facilitating Conditions	0.85	0.75	0.31	0.33	0.33	0.44	**0.86**	
Social Influence	0.71	0.55	0.61	0.59	0.54	0.40	0.30	**0.74**

Note: CR = Composite Reliability, AVE = Average Variance Extracted, SA = Symbolic Adoption,

PE = Performance Expectancy, IQ = Information Quality, EE = Effort Expectancy, FC = Facilitating Conditions, SI = Social Influence. The square root of AVE for each factor is presented in bold, on the diagonal.

(CR), from Kline (2000) and Kline et al. (2012), and for AVE, from Hair et al. (2014). The latter standards were also applied to the square root of AVE for each factor, marked in bold in Table 1. The remainder of Table 1 shows correlations between each factor, which were consistently less than unitary values of CR and AVE for each individual factor. The full set of retained questionnaire items are marked with an "*" in Appendix A.

All constituent factors could be retained, meaning that the original theoretical model from Fig. 1 was then retained for structural equation modelling. The statistical significance of predicted correlations is displayed in Fig. 2, providing strong if partial support for the current theoretical model. The current results indicate that both performance expectancy and symbolic adoption were directly predicted by information quality, effort expectancy, and by social influence, but not by facilitating conditions.

Figure 2.
Empirical relationships between components of the current theoretical model
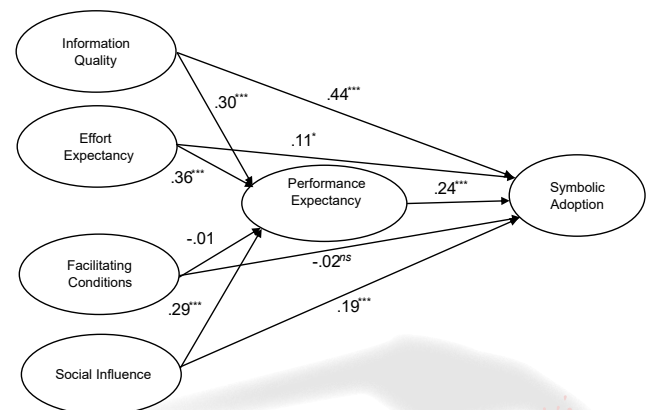
n = 711
* $p < .05$; ** $p < .01$; *** $p < .001$

Table 2 shows mediated effects for information quality, effort expectancy, and social influence, on symbolic adoption. This indicates that the effects of information quality, effort expectancy, and social influence on symbolic adoption, were all mediated by performance expectancy. These results supported the majority of hypothesis 3: That symbolic adoption would also be predicted by effort expectancy, facilitating conditions, social influence, and information quality – as mediated by performance expectancy. Although responses to five-point Likert scales for facilitating conditions had the highest level of variance (SD = 1.13) of any items, this data had no clear relationship with performance expectancy or symbolic adoption.

Table 2.
Summary of indirect effects on symbolic adoption

Pathway	Estimate	95% Confidence Interval	
		Lower Limit	Upper Limit
IQ → PE → SA	.08**	.03	.14
EE → PE → SA	.10**	.05	.16
SI → PE → SA	.05**	.02	.10

n = 711
** p < .01
IQ = Information Quality, PE = Performance Expectancy, SA = Symbolic Adoption, EE = Effort Expectancy, SI = Social Influence

Discussion

Each of the following hypotheses were partially supported by the current results, to a large extent: 1. That performance expectancy would be predicted by effort expectancy, facilitating conditions, social influence, and information quality; 2. That symbolic adoption would be directly predicted by effort expectancy, facilitating conditions, social influence, and information quality, and; 3. That symbolic adoption would also be indirectly predicted by effort expectancy, facilitating conditions, social influence, and information quality – mediated by performance expectancy. All but one of the predictive factors included in the UTAUT model from Prasanna and Huggins (2016) were found to be a valid part of these hypotheses. This also reflected the majority of results from prior research by Mehta et al. 2019), Amornkitpinya and Wannapiroon (2015), Arteaga Sanchez and Duarte Hueros (2010), Raman et al. (2014), Lahkal et al. (2013), and by Lee and Mendlinger (2011).

Effort expectancy was the predominant predictor of performance expectancy. The extent of this relationship replicates results from Arteaga Sanchez and Duarte Hueros (2010), who researched e-learning adoption under non-crisis conditions. It is also intuitively relevant for the current research, where students facing the demands and emotional strains posed by the COVID-19 pandemic were less likely to adopt learning that required even more effort.

It is most important to note that the direct relationship between information quality and symbolic adoption (r = .44, p < .001) was twice as strong as the relationship identified by Prasanna and Huggins (2016). There was also a statistically robust pathway running from information quality to performance expectancy and then symbolic adoption. This mediated pathway had an estimated upper limit exceeding .1 and was statistically significant at the level of p < .01. As outlined in the introduction, information quality had been included in the current theoretical model to reflect the importance of user confidence in the information being provided under crisis conditions. As identified by Prasanna and Huggins (2016), users' perceptions of information quality are a key driver of whether the same users will actively engage with that information during a crisis scenario. The importance of information quality during crises is also reflected in a growing body of research, concerning a wide range of decision-making scenarios (Jayawardene, 2016; Jayawardene, 2021). For the current research, it can be assumed that students would simply select other information available on the internet, when quality information was not being provided through the online learning platform. Vice versa, high quality information appears to have led students to return to the online learning platform in pursuit of further high quality information.

The importance of results concerning information quality is illustrated by the example of an online glossary of terms. Any Moodle-based course can include a simple glossary of terms, relating to a particular course or to an overall topic. Teachers and university administration can take certain steps to optimize the quality of glossary information, in terms of: "whether a system is free of errors, whether it provides the information needed for the user to complete their work at the time they need it, and whether information is provided in a format which is easy to read" (Prasanna & Huggins, 2016, p. 171).

Student-generated glossaries can be particularly useful, because student entries directly identify and address the technical terms and associated concepts which they find most interesting. Students are also free to select the terms they find most difficult to understand and apply. In sum, their contributions help ensure that the glossary contains only the most necessary information, i.e. "the information needed". Teachers can help ensure that

Figure 3.
Clicking a highlighted glossary term opens up the approved glossary entry
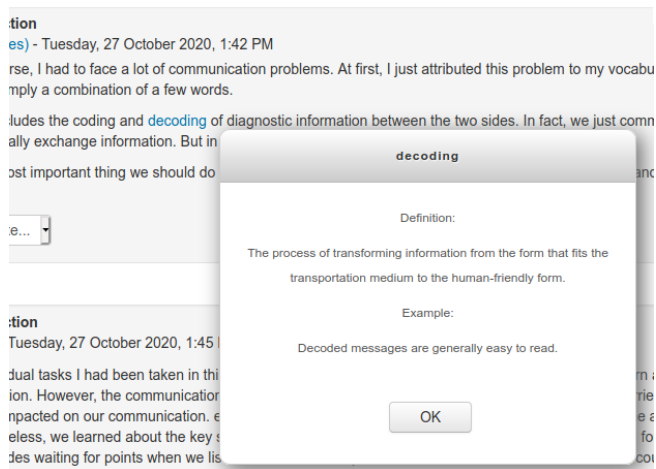
a student-generated glossary is "free from errors" by making sure that individual student entries are checked and approved before being added.

Accessible and timely access to the glossary, i.e. "at the time they need it" can be provided in many ways. As shown in Fig. 3, direct lookup access to the glossary will give students a chance to correct any misunderstandings while making their own forum contributions. Automatically detecting and linking of all glossary terms, used in student forum entries, allows their fellow students to use highlighted and linked glossary terms to check their own knowledge, when reading and responding to the same forum post. Pop-up information and other interface characteristics help ensure that the glossary information is provided "in a format that is easy to read". These approaches to Moodle-based glossaries illustrate how online education can use dynamic and integrated information, to support the application of course content, in addition to basic remembering and subsequent levels of revised Bloom's taxonomy (Krathwohl, 2002). Once these levels of learning are attained, students will be much more prepared to advance towards analysis, evaluation and creativity (Krathwohl, 2002). At the tertiary level of education, they will be supported to become a more engaged and capable learner.

On the other hand, facilitating conditions did not predict either performance expectancy or symbolic adoption. A broader range of facilitating conditions items had been eliminated during factor analysis, meaning that this factor was effectively limited to internet speed and reliability. The lack of a statistical relationship between these items and adoptive factors could have been due to the temporary nature of iSpace usage during COVID-19. At the time of data collection, the pandemic appeared

to be under control throughout most of China and most students would have been confident about returning to studying on campus in the following semester. Any temporary issues with internet connectivity were likely to be resolved in the relatively near future, while symbolic adoption tends to gauge technology adoption over a longer timeframe. Furthermore, many interruptions to connectivity were likely to be minor, due to the advanced state of internet infrastructure across the majority of the Chinese Mainland. While expectations for connectivity may have been high, it is unlikely that the participants faced the kind of critical and ongoing issues with connectivity faced by students in many other parts of the world.

Practical Implications

The practical implications of robust results concerning both effort expectancy and social influence are relatively straight-forward. For example, it appears that online learning platforms need to be user-friendly to optimize effort expectancy. This implication extends to ensuring that Moodle-based platforms are developed towards student user needs, rather than primarily focusing on teachers´ preferences and wider institutional objectives. In terms of Sowa and Zachman (1992), this would leverage the impact of user-focused development, on end-user engagement and resulting performance (Prasanna & Huggins, 2016). According to Huggins and Prasanna (2020) and Yang et al. (2014), this approach to development is exemplified when technology development focuses on end-user tasks and associated information needs (Huggins & Prasanna, 2020; Yang et al., 2014).

Social influence is a little different, but no less straight-forward. The positive impact of this factor can be leveraged by ensuring that LMS activities involve a students' wider network of peers and other influences. The current results concerning social influence suggest that performance expectancy and overall engagement will improve when members of these peers and other networks are both aware, and supportive, of online learning platform capabilities. This may result in other benefits for the host institutions, who are more likely to gain further enrolments due to positive perceptions of their online learning delivery.

The relationship between information quality and both performance expectancy and symbolic adoption may be even more important than other results from the current research. This is a more recent addition to the UTAUT model which appears to be particularly valuable in crisis

situations (Prasanna & Huggins, 2016). The example of Moodle-based glossaries outlined in Section 4.0 helps to illustrate how information quality is not accomplished as a matter of course. Many teachers making a rapid switch to e-learning will not have the skills required to implement this more technical, approach to Moodle-based glossaries or other learning content. Efficient professional development will be required, rather than waiting for teaching staff to develop a specific set of technology-related skills. As recommended by Prasanna and Huggins (2016), personnel will ideally be familiar with an Moodle-based LMS, long before the onset of a crisis requiring off-campus study. To achieve this level of familiarity, relevant professional development needs to be provided under non-crisis conditions, as a kind of business as usual. This approach to longer-term professional development can also promote the blend of online and offline learning that, according to Shea and Bidjerano (2014) and Shi et al. (2020), has improved student learning outcomes and even graduation rates in a range of contexts.

Further Research

The current results also have implications for further research, including opportunities to expand on methodological constraints that are relatively characteristic of technology adoption research. There is an ongoing opportunity to analyze a wider range of text and image-based qualitative data, in additional to Likert scale responses. Ongoing research can also be carried to consider actual use data, concerning how many clicks were made by respective participants, during the weeks following questionnaire completion. Most of the current participants explicitly consented to the use of this type data during the actual research protocol, permitting a re-assessment of the common assumption that symbolic adoption equates to adoptive behaviors.

Conclusion

The current research examined students' engagement with online learning during the COVID-19 pandemic; at a time when there was no alternative to continuing their university level studies by distance. This global health emergency had meant that online learning platforms were becoming an essential component of business continuity for universities around the world. Data was gathered from over 700 university students studying at a Chinese university during the COVID-19 pandemic, querying their perceptions and usage of a specific online learning platform. The students were asked to complete a questionnaire that included a number of adapted scales, reflecting the UTAUT model of technology adoption. The resulting data was subjected to factor analysis, which enabled the robust selection of questionnaire scales, for the purposes of SEM analysis.

This SEM analysis produced results in support of all but one aspect of the current theoretical model. In brief, students' symbolic adoption of the online learning platform was predicted by their associated levels of effort expectancy, social influence and perceived information quality. The same factors also predicted students' performance expectations, which in turn predicted symbolic adoption. In theoretical terms, these results have highlighted the validity of an adapted UTAUT model, for a Chinese population which may have therefore been neglected by prior technology adoption research.

Results of conducting the current research with participants with a Chinese ethnic background nonetheless reflect factors observed in many other parts of the world, including the results of research conducted in many developed western cultural contexts. Facilitating conditions were the only exception. Despite a high degree of variability, this factor did not predict student engagement with the LMS. This result may mark a unique characteristic of Chinese populations when engaging in online learning during a crisis. Further research with comparable samples may help strengthen this conclusion, in addition to research using a broader range of participant responses and actual usage statistics.

Acknowledgements

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