Journal of Information Systems Education

Volume 34
Issue 4
Fall 2023

MOOC Relevance: A Key Determinant of the Success for Massive Open Online Courses

Ying Wang, Hong "Wendy" Wang, and Leslie Jordan Albert

Recommended Citation: Wang, Y., Wang, H., & Albert, L. J. (2023). MOOC Relevance: A Key Determinant of the Success for Massive Open Online Courses. *Journal of Information Systems Education*, 34(4), 456-471.

Article Link: https://jise.org/Volume34/n4/JISE2023v34n4pp456-471.html

Received: May 21, 2022
First Decision Made: August 16, 2022
Accepted: October 30, 2022
Published: December 15, 2023

ISSN: 2574-3872 (Online) 1055-3096 (Print)

Journal of Information Systems Education, 34(4), 456-471, Fall 2023

MOOC Relevance: A Key Determinant of the Success for Massive Open Online Courses

Ying Wang
College of Business
Northern Illinois University
DeKalb, IL 60115, USA
ywang15@niu.edu

Hong "Wendy" Wang
Sanders College of Business and Technology
University of North Alabama
Florence, AL 35632, USA
hwang21@una.edu

Leslie Jordan Albert
School of Information Systems & Technology
San Jose State University
San Jose, CA 95192, USA
leslie.albert@sjsu.edu

ABSTRACT

The MOOC (Massive Open Online Course) providers promote their courses as education that builds marketable skills. However, little research examines the role of relevance in the success of MOOCs or how this relevance influences learner behaviors. This study highlights the importance of MOOC relevance by decomposing it into personal relevance and social relevance and then examining their effects on learner satisfaction. Based on Expectation-Confirmation Model and DeLone and McLean's information system success model, our proposed theoretical framework elaborates on the relationship among personal relevance, social relevance, perceived usefulness, subjective norms, confirmation, satisfaction, and continuance intention. We analyzed survey data collected from 343 MOOC learners, finding both personal and social relevance positively associated with confirmation and satisfaction. Confirmation positively influences perceived usefulness and satisfaction, while continuance intention is enhanced by learner satisfaction and subjective norms. However, the impact of perceived usefulness on satisfaction is not significant. This study contributes to Information Systems (IS) literature by demonstrating the role of relevance in the growth and success of MOOCs. Additionally, our findings contribute to the IS education literature by highlighting the need for more personally and socially relevant curricula if traditional IS programs are to remain competitive in an era of increasing educational opportunities.

Keywords: MOOC, Personal relevance, Social relevance, Online education, User satisfaction, IS education

1. INTRODUCTION

Enrollment in massive open online courses (MOOCs), online courses aimed at unlimited participation and open access via the Web (Kaplan & Haenlein, 2016), grew to 220 million learners in 2021 (Shah, 2021). MOOC popularity stems from their low cost, their wide availability, and their ability to create pathways that support lifelong learning (Pilli & Admiraal, 2017). Although learners differ in their desired learning outcomes, many are motivated to enroll in MOOCs for career development (Kizilcec & Schneider, 2015). Therefore, MOOC providers promote their courses as education that aims to build marketable skills (Rivas et al., 2020). The COVID-19 pandemic catapulted MOOC popularity to new heights during spring 2020 with Coursera enrollments increasing 607% between March 17 and April 16, 2020 over the same period in 2019, and with personal and career development courses seeing the largest enrollment increases (McCluskey, 2020). Similarly, the "quarantine special" courses that Udacity offered focused on developing job skills and saw a 44.8% increase in weekly active users over the same four-week period the previous year.

While MOOCs have attracted millions of users worldwide, most participants are well-educated and well-paid individuals from developed countries (van de Oudeweetering & Agirdag, 2018). Further, a global survey suggests that participants are more likely to enroll in MOOCs for career benefits, such as

improving performance in their current job or finding a new job than for educational benefits alone (Zhenghao et al., 2015). The survey also shows that roughly half of the respondents confirmed they took MOOC courses primarily to meet career goals while 87% reported that MOOCs benefit their careers (Zhenghao et al., 2015). Compared with students in traditional higher education institutions, whose primary objectives are often course completion and degree certification, MOOC learners enroll to achieve a selective set of pre-defined learning goals, taking what they need from these courses, often without completing them (Ahearn, 2018). MOOC learners may also value career-related practical knowledge more than theoretical knowledge as the former can be directly applied to their real-world working environment and help them improve job performance (Christensen et al., 2013; Milligan & Littlejohn, 2017). Therefore, examining course relevance, the extent to which course content is related to learners' job requirements and career goals, may provide important insights into the drivers behind learners' expectations and satisfaction with MOOCs. Existing literature has not considered course relevance as an antecedent of MOOC success.

As MOOCs provide an easy-access, cost-efficient, and scalable way to provide education, many have viewed them as disruptive innovations in higher education (Christensen et al., 2013). An extensive number of studies have investigated the success of MOOCs by examining critical drivers of MOOC satisfaction. The earliest of these papers focuses on learners' perceptions of MOOCs and found MOOC reputation, openness, usefulness, and enjoyment significantly influenced learner satisfaction (e.g., Alraimi et al., 2015), as did perceived ease of use, usefulness, and self-determination (e.g., Joo et al., 2018). The second line of research on MOOC satisfaction investigates the role of learner characteristics, including educational level, goal setting, and previous MOOC experience. (e.g., Li, 2019; Zalli et al., 2019). The third collection of studies explores the effects of platform characteristics on satisfaction, such as system quality, information quality, and service quality (e.g., Albelbisi et al., 2021; Aparicio et al., 2019; Freeze et al., 2010). However, MOOC relevance, one dimension of information quality, has not been well-studied, even though MOOC learners may value relevance more than learners enrolled in other forms of education.

In the Information Systems (IS) literature, DeLone and McLean's (2003) information system success model (D&M model) has been widely adopted to examine user satisfaction and continuance intention in IS adoption. The model theorizes that system characteristics, such as system quality, information quality, and service quality influence user satisfaction. Although information relevance has been counted as one aspect of information quality in the IS literature (DeLone & McLean, 1992; Wang & Strong, 1996), it has been understudied compared to other dimensions of MOOC information (content) quality. For instance, Albelbisi et al. (2021) discuss MOOC content quality via five dimensions of information quality: usability, understandability, importance, availability, and conciseness. Aparicio et al. (2019) measure MOOC information quality in terms of usefulness, understandability, interest, and reliability. However, information (content) relevance is rarely assessed despite the potential importance of relevance to MOOC learners.

This study highlights the importance of MOOC relevance in the success of these courses. It examines its interactions with other key drivers of satisfaction as identified in prior literature, including confirmation - the extent to which a MOOC learner's course expectation is confirmed (Bhattacherjee, 2001a; Oliver, 1980), perceived usefulness, and subjective norms - social pressures influencing an individual's intention to perform (Kulviwat et al., 2009). In this study, we build a theoretical framework and propose related hypotheses based on D&M IS success model and Expectation-Confirmation Model (ECM). Data was collected from 343 MOOC learners via an online Qualtrics survey conducted in October 2021. Our results suggest that personal and social relevance positively affect learners' confirmation and satisfaction. Additionally, we find that confirmation positively influences satisfaction directly rather than indirectly through perceived usefulness, and that continuance intention is enhanced by satisfaction and subjective norms. This research contributes to MOOC literature by illustrating the importance of educational relevance in MOOCs, given its close relationships to learners' motivation, goals, satisfaction, and adoption behaviors. Although relevance has been considered one dimension of information quality influencing satisfaction, few studies have evaluated the importance of relevance to career-oriented MOOC learners. This study's proposed theoretical framework and findings elaborate on the role of relevance in the success of MOOCs and demonstrate its relationship with other known key drivers of satisfaction, enriching our understanding of students' ongoing interest in MOOCs. Our findings also extend the IS education literature by suggesting how maximizing the personal and social relevance of IS courses may bolster flagging demand for IS programs even as students are tempted by less traditional and often less costly educational avenues (Bohler et al., 2020).

The paper is organized as follows. We first demonstrate the research gap related to relevance in MOOC literature, discuss the concept of relevance, and review the ECM and D&M IS success model to build a solid theoretical foundation. We then develop hypotheses elaborating the relationships between key drivers (social relevance, personal relevance, perceived usefulness, and subjective norms) and MOOC success constructs (confirmation, satisfaction, and continuance intention). We next describe the applied methodology, including data collection and data analysis. After presenting the results, we discuss contributions, limitations, and implications for MOOC research and IS education.

2. THEORETICAL FOUNDATIONS

2.1 Satisfaction in MOOCs

In the literature discussing MOOC success and its key drivers, definitions, and measurements of success vary across stakeholders. For example, institutions investing in MOOCs have adopted variables related to return on investment as measures of success, including recruitment, number of paid students, and branding (Liyanagunawardena et al., 2017). From the learners' perspective, satisfaction with learning outcomes, obtaining course credits, and developing learning networks have been used to measure the success of a MOOC (Cormier & Siemens, 2010). The proxy for these measures includes satisfaction, completion rate, dropout rate, final grade, and learning community engagement. Satisfaction could be a more appropriate measure of success than the completion rate or dropout rate, as completion is not always the goal of individual learners (Littlejohn et al., 2016). Many students come to

MOOCs with pre-defined, specific learning objectives and thus may not be motivated to earn a certificate after completion (Ahearn, 2018).

Table 1 lists a sample of empirical studies investigating MOOC satisfaction, demonstrating that three categories of factors significantly influence satisfaction:

- learners' perceptions, such as confirmation, perceived usefulness, perceived enjoyment, perceived reputation, perceived openness (Alraimi et al., 2015), and perceived task-technology fit (Wang et al., 2021).
- learners' characteristics, including degree level, goals, and previous MOOC experience (Li, 2019; Zalli et al., 2019).
- MOOC characteristics, such as information quality, system quality, and service quality (Albelbisi et al., 2021; Aparicio et al., 2019; Freeze et al., 2010).

Study	Antecedents of Satisfaction	Applied Theory
Lu et al. (2019)	Confirmation, perceived usefulness, perceived interest, flow experience	ECM
Li (2019)	Highest degree, previous MOOC experience, goal setting, environment structuring strategy usage, and perceived effective learning	Self-regulated learning literature
Joo et al. (2018)	Perceived ease of use, usefulness, self-determination	Technology Acceptance Model
Zalli et al. (2019)	Goal setting, environment structuring, task strategies, time management, help-seeking, self-evaluation	Self-regulated learning literature
Daneji et al. (2019)	Confirmation, perceived usefulness	ECM
Alraimi et al. (2015)	Perceived reputation, perceived openness, perceived usefulness, perceived enjoyment	ECM
Albelbisi et al. (2021)	Information quality, system quality, service quality	D&M IS success model; self-regulated learning theory
Aparicio et al. (2019)	Information quality, system quality, service quality	D&M IS success model
Freeze et al. (2010)	System quality, information quality	D&M IS success model
Wang et al. (2021)	Confirmation, perceived usefulness, task-technology fit	ECM; task-technology fit
Lu et al. (2019)	Confirmation, perceived usefulness, perceived interest, flow experience	ECM
Li (2019)	Highest degree, previous MOOC experience, goal setting, environment structuring strategy usage, and perceived effective learning	Self-regulated learning literature
Joo et al. (2018)	Perceived ease of use, usefulness, self-determination	Technology Acceptance Model
Zalli et al. (2019)	Goal setting, environment structuring, task strategies, time management, help-seeking, self-evaluation	Self-regulated learning literature

Table 1. Empirical Studies on MOOC Satisfaction

Among studies investigating information quality as an antecedent of satisfaction, the vast majority consider information quality as a single construct and measure it via multiple dimensions, including usefulness, understandability, interestingness, reliability, and consistency (e.g., Aparicio et al., 2019; Freeze et al., 2010), but rarely in terms of relevance.

2.2 Relevance in MOOCs

Educational relevance focusing on the function or purpose of education for individuals and societies (Albrecht & Karabenick, 2018) has been discussed by motivation researchers in both education and psychology for over a century (e.g., Dewey, 1900). Rooted in educational psychology, philosophers have long argued that in addition to serving individual goals, education should also serve collective purposes, such as producing human capital for industry and promoting social development (Ozmon & Craver, 1995). Keller (1987) identified three methods to increase students' sense of relevance – familiarity, motive matching, and goal orientation. Balaban-Sali (2008) implemented Keller's model to describe a software program's instructional design in the education context. It was found that students will be more satisfied with an instructional product (e.g., education) if it relates to their experience, responsibilities, and values. Paralleling this position, Bruner (1973) viewed educational relevance as possessing two facets – personal relevance and social relevance.

Personal relevance means that what is taught should be self-rewarding by some existential criterion of being real or meaningful to the individual, while social relevance suggests what is taught should help create solutions to problems facing society (Bruner, 1973; Shemuda, 2018). Motivational psychologists posit that one way to develop personally and socially relevant courses is to consider focal issues. Focal issues are those personally meaningful to students, such as students' interests, intrinsic and extrinsic goals, short- and long-term goals, and identity targets (Albrecht & Karabenick, 2018; Gijsbers et al., 2020). A recent survey found that US educators, parents, and students believe career preparation is one of the most common and essential focal issues (Albrecht & Karabenick, 2018). As such, courses that provide career preparation may be viewed as more personally relevant than courses that do not.

Addressing societal needs and ills may also be an engaging focal issue for today's college students, most of whom are Gen Z, a generation of individuals touted as socially-minded activists (Tyson et al., 2021). In addition to designing their courses around focal issues, educators may be able to further strengthen the relevance of their courses by including practical project-based exercises. Research suggests students may prefer to enroll in courses that employ project-based learning (PBL) that directly illustrates the applicability of course content to the real world (Devgun, 2013; Setor & Joseph, 2021). Indeed, education specialists endorse PBL as a prominent instructional approach for connecting courses to students' daily lives in many disciplines, including STEM disciplines, for its ability to promote literacy and knowledge and to provide solutions to social issues (Given, 2008; Morales et al., 2013; Thomas, 2000). Using PBL can help courses offer personal and social relevance, helping learners develop necessary competencies to improve their careers and ultimately improve their satisfaction.

2.3 Relevance in IS Programs

Extant studies exploring MOOCs from educational and information system (IS) perspectives have posited that motivational factors significantly impact adult learners' willingness to engage in MOOCs (Saadatdoost et al., 2015). Online learners' primary motivations for engaging in MOOCs are career-related, such as learning new skills to further their career goals (Kizilcec & Schneider, 2015). Information system education has been considered a dynamic discipline driven by dramatic developments in information technologies and the explosion in the use of IT by organizations for both operational and strategic functions. The IS curricula are expected to keep up with the realities of corporate information systems, enabling students to obtain competitive edges in job markets (Gill & Hu, 1999). Therefore, course relevance is crucial in IS education when competing with MOOCs.

While many traditional undergraduate programs face growing competition from for-profit options (e.g., MOOCs and certifications), the IS discipline may face a more acute enrollment crisis than others. According to Bohler et al. (2020, p. 234), "The reported percentage of CIS/MIS (Computer Information Systems/Management Information Systems) programs that offered undergraduate degrees from AACSB (Association to Advance Collegiate Schools of Business) accredited schools declined from 48% in 2011-12 to 36.8% in 2017-18 (AACSB, 2012-2019)." This reduction occurred before the COVID-19 pandemic pushed many away from traditional programs, making educational relevance in IS programs all the more important to maintain enrollments. Further, many traditional college IS programs are expanding into certifications and online education - spaces in direct competition with MOOCs (Instructional Connections, 2021). Thus, understanding how educational relevance in MOOC impacts student satisfaction and continuance intentions can extend the IS education literature that already notes the need for relevant programs and courses (Bohler et al., 2020; Cummings & Janicki, 2020; Saulnier et al., 2019).

The importance of relevance in college IS programs has been emphasized by recent literature. For example, Saulnier et al. (2019) suggest the need for continual innovation in IS programs to provide personal relevance to students seeking jobs. According to Bohler et al. (2020), to be relevant, IS curricula must prepare students to deliver organizational value; however, Cummings and Janicki (2020) demonstrate the changes of organizations' emphasis on different skills and technologies over time. As personal relevance to student interest and engagement becomes increasingly essential, instructors are encouraged to "define and concisely describe marketable skills that students could add to their resumes after taking the course" (Babik & Lending, 2020, p. 266). Setor and Joseph (2021) found that hands-on experiences raise graduating students' employability, providing both career readiness-based personal relevance and PBL social relevance. Some IS education researchers also note that universities are placing "...an increased emphasis on relevance and service to society…" (Saulnier et al., 2019, p. 230), signaling a potential focus on social relevance and a shift in how universities serve their students and support their communities (Bohler et al., 2020).

Like traditional courses, MOOCs can be educationally relevant to students in two main ways: by helping them excel in their current careers or prepare for future careers and by teaching them content and knowledge applicable to real-world problems. For example, actively engaging students in solving real-life problems in an authentic context may facilitate students' interest and performance, thus producing better learning outcomes (Barak & Watted, 2017) and positively influencing learners' perceptions of MOOCs. Since both personal and social relevance relate to learners' motivations and expectations, it is critical to investigate how they influence the degree to which learners believe MOOCs meet their needs to create a complete picture of MOOC success.

2.4 Expectation-Confirmation Model and D&M IS Success Model

User satisfaction measures the successful interaction between an information system and its users and is defined as the extent to which users believe the information system meets their needs (Ives et al., 1983). In the MOOC literature, the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001b) and D&M IS success model (DeLone & McLean, 2003) are the most widely used to build theoretical foundations to predict users' satisfaction. The ECM is based on the expectation confirmation theory developed by Oliver (1980), commonly used in marketing studies to examine consumer satisfaction and post-purchase behaviors. IS scholars later revised the model and applied it to analyze users' behavior in IS adoption (e.g., Bhattacherjee, 2001b; Gelderman, 1998; Melone, 1990), positing that confirmation and usefulness are antecedents of satisfaction and that satisfaction influences users' continuance intention. As MOOCs are technology-enabled learning information systems, ECM is commonly adopted to examine the key drivers of MOOC users' satisfaction (e.g., Daneji et al., 2019; Lu et al., 2019). Thus, our research model includes confirmation, perceived usefulness, and continuance intention based on ECM.

The D&M IS success model (DeLone & McLean, 2003) offers another valuable assessment of IS success in various research contexts, such as the success of e-commerce systems (Wang, 2008), knowledge management systems (Wu & Wang, 2006), e-government systems (Wang & Liao, 2008), and MOOCs (Freeze et al., 2010; Lu et al., 2019). The D&M model provides six interrelated dimensions of IS success: system quality, information quality, service quality, use, user satisfaction, and net benefits. Of these, system quality, information quality, and service quality are widely acknowledged as antecedents of MOOC success as they influence students' satisfaction and their continued use intention (Albelbisi et al., 2021; Aparicio et al., 2019). This study follows suit, proposing that relevance, one dimension of information quality, significantly influences MOOC learners' satisfaction.

3. HYPOTHESES DEVELOPMENT

We propose a research framework based on the D&M model and the ECM to explore the impact of relevance on MOOC success. The research model is composed of seven dimensions: personal relevance (PR), social relevance (SR), perceived usefulness (PU), subjective norm (SN), confirmation (CNF), satisfaction (SF), and continuance intention (CI). Figure 1 represents the proposed model.

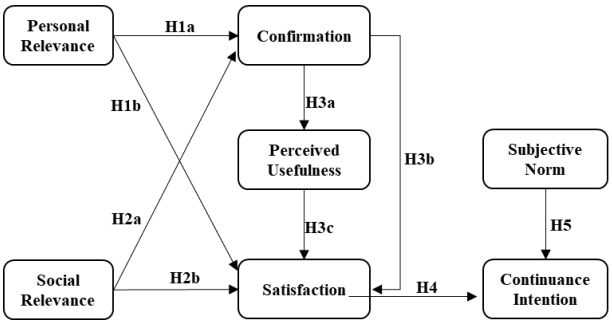


Figure 1. Research Model

Personal relevance refers to a personally meaningful connection between education and the individual's life (Albrecht & Karabenick, 2018; Priniski et al., 2018). As MOOC learners are often job-oriented and seek marketable skills (Zweifler, 2013), personal relevance in MOOC courses could be further interpreted as the connection between MOOCs and learners' careers. MOOC learners register for courses with initial expectations of building in-demand skills, obtaining competitive advantages in the job market, and advancing their careers (Christensen et al., 2013; Milligan & Littlejohn, 2017). Confirmation refers to the perceived difference between the actual performance of an IS and the user's initial expectations (Bhattacherjee, 2001b; Oliver, 1980), indicating the extent to which the information system's expectation is achieved (Lu et al., 2019). Thus, we suggest that the more personally relevant a MOOC is to a learner's job, the more likely that MOOC will meet the learner's initial expectations and the higher the learner's confirmation.

Personal relevance may also influence learners' satisfaction with MOOCs. According to DeLone and McLean (2003), information quality significantly affects students' e-learning satisfaction (Al-Samarraie et al., 2018). From a learner's view, information quality is measured by multiple dimensions, such as completeness, timeliness, understandability, consistency, and relevance (Lee et al., 2002; Wang & Strong, 1996). As such, the relevance of the information provided by MOOCs may influence learners' satisfaction. Therefore, we propose that,

H1a. Personal relevance is positively associated with confirmation.

H1b. Personal relevance is positively associated with learners' satisfaction.

Social relevance in education means that what is taught should help create solutions to problems facing the world (Bruner, 1973; Shemuda, 2018). Higher education is expected to deliver not only excellent education and research but also to provide those outputs in ways that are relevant to the productive process and to the shaping of societal knowledge (Jongbloed et al., 2008). The curriculum is argued to be an avenue for solving society's problems (Eyisi, 2016). Nurmohamed et al. (2013) proposed that MOOCs can be used as platforms for real-world problem-solving by connecting firms with courses to empower learners to solve real-world problems. In this manner, MOOCs enable a wide range of businesses to take advantage of the global student body's insights and creativity, which benefits society. MOOC learners enroll in these courses seeking solutions for real problems (Barak et al., 2016) and thus are likely to expect that MOOCs have social relevance. Further, prior online education studies have found that the use of exercises based on real-world situations and scenarios, such as role-playing exercises, case studies, and problem-based activities, are highly effective methods for encouraging online students' engagement and improve academic growth and development (Britt et al., 2015). Therefore, the more practical knowledge MOOCs introduce, the more likely they are to help learners address real-world issues, and the more likely learners' expectations of MOOCs will be confirmed. In other words, MOOCs with higher social relevance may lead to higher learner confirmation.

Similarly, MOOC social relevance may influence learners' satisfaction. In traditional education, the more students are encouraged to "do" and "apply" their knowledge to real-life problems, the more satisfying their learning experience (Hmelo-Silver, 2004). MOOC learners also take courses to gain practical skills that can be applied to real-world issues (Devgun, 2013). The more practical skills and capabilities they obtain from these courses, the more likely it is that their expectations are confirmed, and thus, the more likely learners will be satisfied with MOOCs. Therefore, we propose:

H2a. Social relevance is positively associated with confirmation.

H2b. Social relevance is positively associated with learners' satisfaction.

Bhattacherjee's (2001b) ECM proposes that users' satisfaction with an information system is an emotional evaluation of that system based on users' confirmation of experience. In MOOCs, confirmation plays a significant role in students' satisfaction with learning (Dai et al., 2020). If students find MOOCs' actual performance exceeds their original expectations, their confirmation of MOOCs will be positive. However, if students believe that MOOCs' performance falls short of their expectations, their confirmation will be negative. Thus, the higher the perceived congruence between actual system performance and learners' initial expectations, the higher their satisfaction (Yang & Lee, 2021).

Confirmation of learning experience is also a driver behind students' perceptions of IS usefulness, which is defined as "the degree to which a person believes that using a particular system would enhance [their] job performance" (Davis, 1989, p. 320). This relationship has been empirically validated in various contexts, such as online banking systems (Bhattacherjee, 2001b), business-to-consumer e-commerce systems (Bhattacherjee, 2001a), and e-learning systems (Hayashi et al., 2004).

By extension, MOOC learners will perceive the course useful if their initial expectations of learning practical career-related skills are confirmed. As revealed in prior literature, perceived usefulness positively enhances users' satisfaction (Alraimi et al., 2015; Joo et al., 2018). Therefore, we propose that learners will feel satisfied with MOOCs if they perceive the courses as useful to their job performance and their careers. Therefore, we propose:

H3a. Confirmation is positively associated with learners' satisfaction.

H3b. Confirmation is positively associated with perceived usefulness.

H3c. Perceived usefulness is positively associated with learners' satisfaction.

The ECM proposes that users' satisfaction with an information system influences their continuance intention. User satisfaction usually leads to positive outcomes, significantly enhancing customer reuse and loyalty (Zhao et al., 2012). Similarly, consumer behavior research has found evidence supporting the positive impact of customer satisfaction on repurchase intention (Cronin et al., 2000). Similar results are observed in information system adoption behavior literature. For instance, Nascimento et al. (2018) found that users intend to continue using a smartwatch if they derive satisfaction from the product. Zheng et al. (2013) reveal that people will continue to contribute to a virtual community if they are satisfied with that community. We extend this literature to propose that happy, satisfied MOOC learners intend to continue taking courses that teach them skills needed by today's employers.

H4. Satisfaction is positively associated with learners' continuance intention.

In addition to being affected by satisfaction, MOOC learners' continuance intention may also be influenced by subjective norms - the social pressures influencing an individual's intention to perform (Kulviwat et al., 2009). According to the Theory of Planned Behavior (Ajzen, 1991), subjective norms significantly impact an individual's intention to use computer technology. For example, Jaruwachirathanakul and Fink (2005) found that Thai cultural collectivism is a potential barrier to the adoption of Internet banking as face-to-face conversation is a valued and expected social norm in both personal and business settings. Hu et al. (2003) posit that teachers may partially adopt PowerPoint in their teaching because their school administrators encourage its use. Teo et al. (2019) argue that students' intention to use Moodle is influenced by the opinions of individuals significant to them. Therefore, individuals' behavior intentions may be affected by the belief that important entities (e.g., friends, peer groups, authority figures, and organizations) will approve and support a particular behavior. As potential employers are significant individuals in MOOC learners' lives, their perceptions of MOOCs may influence learners' MOOC adoption intentions. In this study, the subjective norm of interest is the value that potential employers place on MOOCs, as perceived by the learner. If learners believe that potential employers view MOOCs as credible and value MOOC education in hiring processes, learners will have strong continuance intentions. Therefore, we propose that

H5. Subjective norm (employer value of MOOC) is positively associated with continuance intention.

4. METHODOLOGY

4.1 Instrument Development

We developed the survey instruments based on associated measures in the existing literature, adapting and rewording them to fit the context of MOOCs. Table 2 demonstrates the operational definitions and instrument measures for each construct. All items were measured using a 5-point Likert-type scale (1 = strongly disagree/much less than, 5 = strongly agree/much more than). The statistical summaries of all items are shown in the appendix.

4.2 Data Collection

In fall 2021, we surveyed a total of 343 MOOC learners via an online survey conducted by Qualtrics Consumer Panels (QCP). Using QCP provides several benefits. First, researchers may specify criteria for subject selection. This enabled us to collect data from our targeted population – MOOC participants. Second, we were also able to restrict participation to those geographically located in the United States to limit potential inter-country computer and digital literacy differences that could introduce underlying factors and influence learner satisfaction (Daniel et al., 2015). Third, QCP recruits subjects from a wide range of industries, professions, age groups, work histories, and MOOC experiences, improving the generalizability of the study's findings. Fourth, subject responses are anonymous, thus removing concerns regarding the disclosure of personally identifiable information. Subjects are compensated by Qualtrics for their participation in QPC surveys based on survey length and specificity of the subject selection criteria.

Data were collected in two waves, a soft launch (pilot) of 33 responses which we used to evaluate question wording and survey flow, and a final launch that included 310 responses. No edits following the soft launch were required allowing us to combine the two datasets for analysis. We collected respondents' demographic characteristics (e.g., gender, age, employment status, and income) and information regarding constructs in the proposed theoretical framework. Table 3 gives the respondents' demographics, MOOC experiences, and MOOC motivation. The respondents in our study have typical MOOC learners' characteristics: working adults with job-oriented learning goals.

4.3 Data Analysis

We analyzed the data using SmartPLS 3.0 to conduct partial least squares (PLS) analysis as PLS does not require a normal data distribution (Hair et al., 2014). Our data contains 343 observations, meeting the minimum sample size requirement addressed by Chin et al. (2003). We first evaluated the measurement model by checking convergent validity, construct reliability, indicator reliability, and discriminant validity. Results are shown in Tables 3 and 4. We then applied the PLS bootstrap resampling procedure using 5,000 subsamples to test the research hypotheses.

Self-selection bias may exist when using self-reported data (Podsakoff et al., 2003). Therefore, we conducted a common method bias test to check if this bias posed a concern for this study. We performed a Harman's one-factor test in which all items were entered into an un-rotated exploratory factor analysis to determine whether a single factor emerges or accounts for most of the variance. The results showed that 29 factors emerged. The largest factor accounted for 29% of the variance, which is lower than the recommended threshold of 50%. Therefore, we concluded that self-selection bias (common method bias) was unlikely to be a serious concern.

5. RESULTS

5.1 Measurement Model Assessment

Convergent validity is checked to ensure that the indicators for a single construct are more correlated with each other than with those of other constructs. We evaluated the average variance extracted (AVE), as shown in Table 4. Values ranged from

0.647 to 0.723, all greater than the recommended threshold of 0.5, indicating AVE values explained more than half of the variance of the indicators (Hair et al., 2013). Confirmatory factor analysis (CFA) was performed to test reliability and construct validity for all items. The composite reliabilities for all constructs in Table 4 range from 0.880 to 0.915, all higher than a commonly accepted cut-off value of 0.7 for reliability (Nunnally, 1978). Factor loadings of items listed in Table 5 demonstrate good construct reliability, with construct item loadings higher than the respective cross-loadings. Cronbach's alpha values in Table 4 for all constructs are greater than 0.80, evidence of high loadings on their corresponding constructs. Thus, all constructs in the model demonstrate good internal consistency. Finally, discriminant validity was tested by checking inter-construct correlation, as shown in Table 4. As the square roots of the AVE of each construct are greater than the correlation between the corresponding construct and other constructs, our model demonstrates discriminant validity (Fornell, 1987). Factor loadings of items shown in Table 5 provide additional support as all items load higher on their respective constructs than on others (Chin, 1998).

Construct	Operational Definition	Instrument Items		Source
Personal Relevance (PR)	The degree to which learners believe MOOCs are related to their career	PR1	It is clear to me how the course content was related to my work.	(Bruner, 1973; Huang et al., 2006; Lee et al., 2002)
		PR2	Course materials were relevant to my career goals.	
		PR3	There were sufficient diagrams and examples to illustrate how the course content applied to my career.	
		PR4	The topics taught were related to issues I face at work or were of interest to me.	
Social Relevance (SR)	Learners' perception of the practicality of MOOCs	SR1	Course projects and/or examples addressed real-world problems.	(Bruner, 1973; Huang et al., 2006; Lee et al., 2002)
		SR2	Course content was applicable to real-world scenarios.	
		SR3	The courses offered project-based learning opportunities.	
Confirmation (CNF)	Learners' perception of the congruence between the expectation of MOOCs and their actual performance	CNF1	My experiences with MOOCs have been better than I expected.	(Alraimi et al., 2015; Bhattacherjee, 2001b)
		CNF2	The course services (e.g., feedback, tests, quizzes, exam, and some limited tutoring) was better than I expected.	
		CNF3	Course content was better than I expected.	
		CNF4	Overall, most of my expectations about participating in MOOCs were met.	
Perceived Usefulness (PU)	The degree to which learners believe MOOCs benefit them in their jobs	PU1	MOOCs helped me improve my job performance.	(Aparicio et al., 2019; Bhattacherje, 2001b; Zhang, 2016)
		PU2	MOOCs helped me learn new skills that are beneficial in my area of work.	
		PU3	MOOCs enhanced my awareness and recall of job-related information.	
		PU4	MOOCs helped me work more efficiently and productively.	
		PU5	MOOCs helped me improve my job situation (getting a wage increase or obtaining a better job)	
Subjective Norm (SN)	The degree to which learners believe that employers would value MOOCs	SN1	I believe employers value MOOCs (much more than/somewhat more than/the same as/somewhat less than/much less than) college courses.	(Yang & Su, 2017)
		SN2	I believe employers value MOOCs (much more than/somewhat more than/the same as/somewhat less than/much less than) professional certificates.	
		SN3	I believe employers view MOOCs as credible.	
		SN4	I believe employers recognize MOOCs as legitimate alternatives to formal education.	
Satisfaction (SF)	Learners' perception of enjoyment and accomplishment in MOOCs	SF1	The content of the MOOCs I participated in was satisfactory.	(Freeze et al., 2010); Yu et al., 2010)
		SF2	The courses offered excellent learning opportunities.	
		SF3	I learned what I wanted from these courses.	
		SF4	I am satisfied with my experiences in these courses.	
		SF5	I was pleased with the content offered in these courses.	
Continuance Intention (CT)	Learners' intention to continue using MOOCs	CT1	I intend to continue participating in MOOCs.	(Alraimi et al., 2015)
		CT2	I plan to enroll in more MOOCs in the future.	
		CT3	I recommend MOOCs to others.	
		CT4	I will participate in additional MOOCs.	

Table 2. Operational Definitions and Instrument Items of Model Construct

Measure	Frequency	Percentage
Gender		
Female	197	57.43%
Male	144	41.98%
Non-binary	2	0.58%
Age		
18-25	78	22.74%
25-29	52	15.16%
30-39	114	33.24%
40-49	50	14.58%
50-59	29	8.45%
60 and over	20	5.83%
Employment Status		
full-time	206	60.06%
not currently employed	57	16.62%
Other	3	0.87%
part-time	60	17.49%
Retired	17	4.96%
Income		
$0 to $14,999	43	12.54%
$15,000 to $29,999	58	16.91%
$30,000 to $49,999	81	23.62%
$50,000 to $74,999	70	20.41%
$75,000 to $99,999	26	7.58%
$100,000 to $149,999	49	14.29%
$150,000 or greater	16	4.66%
MOOC Experience		
Less than one year ago	68	19.83%
1-2 years	114	33.24%
2-3 years	93	27.11%
3-5 years	46	13.41%
5-7 years	10	2.92%
More than 7 years	12	3.50%
MOOC Motivation		
increase in professional knowledge and skills	101	29.45%
personal challenge	60	17.49%
interest in the topic	46	13.41%
social community engagement	32	9.33%
certificate given for successful completion	28	8.16%
recommended or required by my advisor/professor	18	5.25%
review of concepts	16	4.66%
preparation for an advanced exam	15	4.37%
to earn continuing education units (CEU)	11	3.21%
to earn credits towards a degree	10	2.92%
Other	6	1.75%

Table 3. Respondents' Demographics, MOOC Experiences, and MOOC Motivation (N=343)

5.2 Structural Model Assessment

The PLS results of the proposed model are shown in Figure 2. All proposed hypotheses are supported except for H3c. Both personal relevance ($\beta = 0.430$, $p < 0.001$) and social relevance positively ($\beta = 0.362$, $p < 0.001$) influence confirmation. Both personal relevance ($\beta = 0.291$, $p < 0.001$) and social relevance ($\beta = 0.186$, $p < 0.001$) positively influence satisfaction as well. Confirmation positively influences satisfaction directly ($\beta = 0.457$, $p < 0.001$) but not indirectly through perceived usefulness ($\beta = 0.684$, $p < 0.001$; $\beta = 0.055$, $p > 0.05$). Continuance intention is positively affected by satisfaction ($\beta = 0.626$, $p < 0.001$) and subjective norm ($\beta = 0.567$, $p < 0.001$). Regarding the R-squared value, all are greater than 0.10 and thus meet the criteria proposed by Falk and Miller (1992), indicating an adequate explanation of endogenous construct variance. Personal relevance and social relevance explain 53.4% of the variance in confirmation. Confirmation explains 46.6% of the perceived usefulness variance. 77.5% variation in satisfaction is explained by personal relevance, social relevance, and confirmation. Satisfaction and subjective norm explain 56.7% variation in continuance intention.

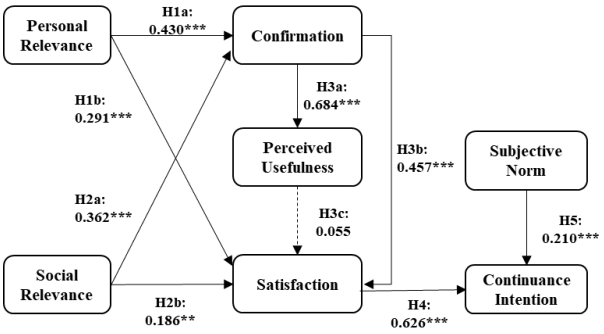


Figure 2. PLS Results of the Proposed Model

To further assess the structural model, we checked the research model's multicollinearity issues, in-sample explanatory power, and out-of-sample predictive power. First, we followed a procedure suggested by Hair et al. (2019) to check the multicollinearity issue via the variance inflation factor (VIF) for each construct. The results show that all VIF scores range from 1.664 to 2.828, which is less than the threshold of three. Therefore, there are no multicollinearity concerns. Second, we examined the R-square value of all endogenous constructs in the research model, which is considered in-sample predictive power and ranges from 0 to 1. The minimum acceptable R-square is 0.10, and the value of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak. In our study, all R-square and adjusted R-square values range from 0.540 to 0.779, showing that the in-sample predictive power is moderate or substantial. Third, we ran a PLSpredict analysis and applied the Q-square value to measure the predictive capability of the proposed research model, combining in-sample explanatory and out-of-sample prediction power. As shown in Table 6, all Q-square scores are above 0.25, indicating that the model has medium predictive relevance (Ghozali & Latan, 2015). Therefore, the proposed model can predict the relationship between research variables.

Constructs	Cronbach's α	AVE	Composite Reliability	Inter-Construct Correlation						
				1	2	3	4	5	6	7
1. Personal Relevance (PR)	0.840	0.675	0.893	**0.822**						
2. Social Relevance (SR)	0.831	0.664	0.887	0.441	**0.815**					
3. Confirmation (CNF)	0.836	0.671	0.891	0.322	0.393	**0.819**				
4. Perceived Usefulness (PU)	0.869	0.657	0.905	0.471	0.432	0.384	**0.811**			
5. Subjective Norm (SN)	0.819	0.647	0.880	0.533	0.559	0.502	0.303	**0.804**		
6. Satisfaction (SF)	0.884	0.684	0.915	0.480	0.464	0.212	0.424	0.502	**0.827**	
7. Continuance Intention (CI)	0.872	0.723	0.913	0.383	0.332	0.331	0.404	0.524	0.433	**0.851**

Table 4. Construct Reliability and Validity

Constructs	Items	PR	SR	CNF	PU	SN	SF	CI
Personal Relevance (PR)	PR1	**0.852**	0.333	0.187	0.360	0.443	0.376	0.167
	PR2	**0.820**	0.315	0.161	0.338	0.410	0.345	0.174
	PR3	**0.797**	0.168	0.142	0.172	0.464	0.197	0.490
	PR4	**0.817**	0.320	0.170	0.361	0.446	0.343	0.312
Social Relevance (SR)	CR1	0.300	**0.807**	0.134	0.141	0.487	0.195	0.490
	CR2	0.319	**0.841**	0.163	0.300	0.410	0.314	0.170
	CR3	0.178	**0.800**	0.185	0.331	0.492	0.348	0.141
Confirmation (CNF)	CNF1	0.189	0.197	**0.804**	0.195	0.408	0.355	0.164
	CNF2	0.173	0.164	**0.818**	0.152	0.110	0.361	0.107
	CNF3	0.166	0.148	**0.844**	0.169	0.423	0.382	0.160
	CNF4	0.122	0.171	**0.809**	0.121	0.311	0.381	0.133
Perceived Usefulness (PU)	PU1	0.347	0.323	0.167	**0.821**	0.481	0.300	0.172
	PU2	0.182	0.168	0.166	**0.822**	0.374	0.188	0.189
	PU3	0.340	0.186	0.118	**0.802**	0.186	0.170	0.159
	PU4	0.319	0.194	0.180	**0.819**	0.492	0.310	0.191
	PU5	0.338	0.196	0.139	**0.788**	0.119	0.163	0.155
Subjective Norm (SN)	SN1	0.409	0.380	0.378	0.408	**0.776**	0.371	0.333
	SN2	0.357	0.365	0.354	0.457	**0.766**	0.332	0.347
	SN3	0.452	0.101	0.438	0.105	**0.837**	0.434	0.475
	SN4	0.490	0.127	0.451	0.156	**0.835**	0.477	0.102
Satisfaction (SF)	SF1	0.336	0.320	0.226	0.157	0.382	**0.842**	0.197
	SF2	0.347	0.329	0.360	0.176	0.402	**0.830**	0.335
	SF3	0.366	0.327	0.326	0.198	0.451	**0.809**	0.165
	SF4	0.191	0.326	0.203	0.300	0.440	**0.822**	0.308
	SF5	0.383	0.357	0.365	0.355	0.423	**0.830**	0.323
Continuance Intention (CI)	CI1	0.314	0.307	0.305	0.349	0.459	0.352	**0.892**
	CI2	0.171	0.104	0.103	0.117	0.430	0.173	**0.806**
	CI3	0.162	0.177	0.176	0.314	0.454	0.353	**0.823**
	CI4	0.176	0.158	0.157	0.317	0.438	0.310	**0.879**

Table 5. Factor Loadings of Items

5.3 Mediation Analysis

We conducted mediation analyses following the steps proposed by Baron and Kenny (1986), which consisted of three sets of regression using an independent variable, a dependent variable, and a mediator. We tested four possible mediating effects in our proposed model by applying a bootstrapping algorithm. First, the direct effect of personal relevance on continuance intention disappeared after adding the mediator satisfaction, indicating that satisfaction completely mediates the relationship between personal relevance and continuance intention. Second, the direct effect of social relevance on continuance intention disappeared after adding the mediator satisfaction, indicating that satisfaction completely mediates the relationship between social relevance and continuance intention. Third, confirmation partially mediates the relationship between personal relevance and satisfaction. Fourth, confirmation also partially mediates the relationship between social relevance and satisfaction. The results of the mediation analysis are consistent with our proposed research model.

6. DISCUSSION

The proposed MOOC success research model built on the ECM (Bhattacherjee, 2001b) and the D&M IS success model (DeLone & McLean, 2003). Analysis of the results provides some insights into factors that drive MOOC success.

First, personal relevance positively influences confirmation and satisfaction, indicating that MOOCs closely related to career development are likely to meet learners' expectations and create high satisfaction. Unlike other online learners with a wide range of motivations for enrolling in a course, MOOC learners are primarily motivated by potential career benefits. Thus, the more closely MOOCs related to learners' career goals, the higher the congruence between MOOC performance and learners' expectations, and the higher the learners' satisfaction.

Constructs		VIF	R^2 (Adjusted R^2)	Q^2
Personal Relevance (PR)	PR1	2.077		
	PR2	1.855		
	PR3	1.766		
	PR4	1.820		
Social Relevance (SR)	CR1	1.835		
	CR2	2.027		
	CR3	1.709		
Subjective Norm (SN)	SN1	1.760		
	SN2	1.745		
	SN3	1.973		
	SN4	1.919		
Confirmation (CNF)	CNF1	1.697	0.549 (0.540)	0.393
	CNF2	1.814		0.361
	CNF3	2.030		0.344
	CNF4	1.821		0.334
Perceived Usefulness (PU)	PU1	2.073	0.567 (0.562)	0.391
	PU2	2.139		0.338
	PU3	1.997		0.367
	PU4	2.063		0.365
	PU5	1.810		0.367
Satisfaction (SF)	SF1	2.309	0.779 (0.773)	0.441
	SF2	2.176		0.459
	SF3	1.999		0.473
	SF4	2.039		0.412
	SF5	2.087		0.506
Continuance Intention (CI)	CI1	2.828	0.570 (0.561)	0.419
	CI2	1.874		0.335
	CI3	1.855		0.373
	CI4	2.663		0.370

Table 6. Results of Structural Model Assessment

Second, social relevance positively influences both confirmation and satisfaction. We conclude that MOOCs providing project-based, practical knowledge applicable to learners' careers will confirm learners' course expectations and earn high learner satisfaction. This result confirms that MOOC learners prefer to learn valuable job skills to solve real-world problems. Social relevance has relatively minor effects on confirmation and satisfaction compared to personal relevance, indicating that learners value the connection between courses and their individual career goals more than the courses' applicability to societal issues.

Third, confirmation positively influences satisfaction directly rather than indirectly via perceived usefulness, a result inconsistent with prior MOOC studies (e.g., Lu et al., 2019). One plausible explanation is that MOOC participants may be unable to leverage what they have learned for work immediately after finishing a course and thus fail to see the usefulness of these courses to their careers in the short run. Among our respondents, more than 80% have fewer than three years of MOOC experience and 19.83% were new MOOC learners with less than 1-year experience. As such, these participants may not have yet been able to apply newly learned skills for productivity or career benefits.

Fourth, continuance intention is positively influenced by satisfaction and subjective norms. The positive effect of satisfaction is consistent with the findings in prior literature (e.g., Alraimi et al., 2015; Yang & Lee, 2021), which suggests that learners' satisfaction drives MOOC success. The positive impact of subjective norms on satisfaction shows that potential employers' perceptions of MOOCs are essential to learners and influence learners' intention to use MOOCs. The positive effect of employers' perceptions on continuance intention supports the argument that MOOC learners are job-oriented and expect to develop market-valued competencies by participating in these courses and highlights the importance of relevance in MOOC success. Thus, MOOC providers should make courses valuable for learners and employers to enhance enrollment growth.

7. CONTRIBUTION

This study contributes to the IS and education literature by exploring the role of relevance in the success of MOOCs and highlighting the importance of MOOC information quality. According to prior studies that apply the IS success model, all three qualities – system quality, information quality, and service quality – are critical drivers of user satisfaction. Recent MOOC literature has demonstrated that compared with system quality and service quality, information quality is a more robust and reliable driver of MOOC satisfaction. Aparicio et al. (2019) reveal that unlike system quality and service quality, which may lose importance in explaining satisfaction, when other characteristics of MOOCs (e.g., gamification) are included in the model, information quality retains its explanatory power. Based on these studies, we have investigated how information quality influences MOOC learners' satisfaction.

This study further contributes to both sets of literature by emphasizing the importance of relevance when measuring MOOC information quality. Relevance, one of 23 dimensions of information quality proposed by DeLone and McLean (1992), is understudied, with most practitioners measuring information quality via usefulness, timeliness, and completeness (e.g., Aparicio et al., 2019; Freeze et al., 2010; Lee et al., 2002). We propose that academics and practitioners should actively promote relevance in examining the success of MOOCs as experts consider it an indispensable element in education. As a technology-enabled learning system, successful MOOCs should be valuable for users as educational platforms, not just as information systems. They should offer content relevant to learners' lives. This study also reveals that information quality is a critical driver of IS success and that its dimensions need to be carefully selected based on the research context.

Moreover, this study contributes to the literature by integrating educational and IS success research further to deconstruct relevance into personal relevance and social relevance, deepening the understanding of MOOC relevance and information quality. Although it has been acknowledged that MOOC learners are job-oriented, few studies have addressed this distinctive characteristic when investigating the MOOC phenomenon. By drawing on the education literature to explore both personal and social relevance, we advance the understanding of the role information quality plays in MOOC success.

Our paper also has practical implications. First, it implies that MOOC providers, like traditional educational institutions, must provide courses with content relevant to success. If learners believe MOOCs are aligned with their individual career goals and provide knowledge applicable to real-world problems, they will feel more satisfied with MOOCs they have taken and intend to continue to take more such courses.

Therefore, it is crucial for MOOC providers to align with in-demand skills. Instructors should build links between course content and skills highly sought after by employers to demonstrate career benefits to learners. Moreover, due to the impact of subjective norms on continuance intention, MOOC providers should consider how employers view and value their course offerings.

Second, this study deepens IS educators' understanding of how they may improve their online programs' attractiveness and competitiveness. With the increasing demand for IS professionals, such as data scientists, software developers, and information security analysts, higher education institutions are offering a variety of online education programs and classes to feed job market needs. Facing intense competition, IS educators can leverage the findings of this study to help inform curriculum decisions and improve course content design. For example, to enhance students' satisfaction and continuance intentions in online programs, universities can effectively prepare students for the real world by providing job-oriented knowledge, applied PBL, and strengthening problem-solving skills rather than focusing on standardized tests and rote memorization (Babik & Lending, 2020; Bohler et al., 2020; Cummings & Janicki, 2020; Setor & Joseph, 2021). To keep up with rapid changes in the IS-related job market, IS educators should monitor technology innovations to predict incoming in-demand skills and adjust course design accordingly (Saulnier et al., 2019). Furthermore, IS educators must understand how employers view online programs differently from in-person ones. Employers' opinions are crucial for the success of online education targeting working professionals.

8. LIMITATIONS AND FUTURE WORK

As with any research, this study is not without its limitations. The data is cross-sectional and was collected via a single survey. As learning is an ongoing process, learners' perceptions of critical elements (course relevance, perceived usefulness, confirmation, and satisfaction) may evolve over time. A longitudinal study may provide a more comprehensive picture of MOOC learners' behavior and elaborate model of the critical drivers of MOOC success. Prior literature has demonstrated that learner demographics, such as education level, may influence their perceptions and behaviors in MOOCs. Just as risk perceptions vary across education levels, perceived relevance may not be the same among learners with different educational backgrounds. Future studies could further examine the interaction between education level and perceived relevance in the success of MOOCs. Considering the interdependency between course content and MOOC platforms, some constructs were measured by a mix of items focusing on both aspects. Future studies could improve the robustness of the proposed model by measuring course content and platforms separately. Additionally, our survey did not collect data on the types of courses our subjects had participated in, nor did it collect data about when they participated. Our understanding of MOOC success factors could be further extended by research considering how these factors may influence MOOC participants' satisfaction and continuance intentions.

9. CONCLUSIONS

In recent years, education has changed dramatically. With the rise of e-learning and the maturity of online platforms, MOOCs have played, and will continue to play, an essential and disruptive role in the education industry. The increasing popularity of MOOCs enables large populations to acquire new skills more conveniently and effectively than traditional educational platforms. Therefore, it is critical to understand how learners perceive the success of MOOCs and what can be done to improve learner satisfaction and continuance intention. Our study contributes to both IS education and MOOC literature by formally assessing online course relevance via personal and social relevance, demonstrating the importance of job-related factors in MOOC success, and providing IS educators with practical implications for developing online programs.

10. REFERENCES

Ahearn, A. (2018). Stop Asking About Completion Rates: Better Questions to Ask About Moocs in 2019. https://www.edsurge.com/news/2018-11-28-stop-asking-about-completion-rates-better-questions-to-ask-about-moocs-in-2019

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211.

Al-Samarraie, H., Teng, B. K., Alzahrani, A. I., & Alalwan, N. (2018). E-Learning Continuance Satisfaction in Higher Education: A Unified Perspective From Instructors and Students. *Studies in Higher Education*, 43(11), 2003-2019.

Albelbisi, N. A., Al-Adwan, A. S., & Habibi, A. (2021). Impact of Quality Antecedents on Satisfaction Toward MOOC. *Turkish Online Journal of Distance Education,* 22(2), 164-175.

Albrecht, J. R., & Karabenick, S. A. (2018). Relevance for Learning and Motivation in Education. *The Journal of Experimental Education*, 86(1), 1-10.

Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs Continuance: The Role of Openness and Reputation. *Computers & Education*, 80, 28-38.

Aparicio, M., Oliveira, T., Bacao, F., & Painho, M. (2019). Gamification: A Key Determinant of Massive Open Online Course (MOOC) Success. *Information & Management*, 56(1), 39-54.

Babik, D., & Lending, D. (2020). Visualizing IS Course Objectives and Marketable Skills. *Journal of Information Systems Education*, 31(4), 260-268.

Balaban-Sali, J. (2008). Designing Motivational Learning Systems in Distance Education. *Turkish Online Journal of Distance Education*, 9(3), 149-161.

Barak, M., & Watted, A. (2017). Project-Based MOOC: Enhancing Knowledge Construction and Motivation to Learn. In *DigitalTools and Solutions for Inquiry-based STEM Learning* (pp. 282-307). IGI Global.

Barak, M., Watted, A., & Haick, H. (2016). Motivation to Learn in Massive Open Online Courses: Examining Aspects of Language and Social Engagement. *Computers & Education*, 94, 49-60.

Baron, R. M., & Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research:

Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology*, 5, 1173-1182.

Bhattacherjee, A. (2001a). An Empirical Analysis of the Antecedents of Electronic Commerce Service Continuance. *Decision Support Systems*, 32(2), 201-214.

Bhattacherjee, A. (2001b). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, 25(3), 351-370.

Bohler, J. A., Larson, B., Peachey, T. A., & Shehane, R. F. (2020). Evaluation of Information Systems Curricula. *Journal of Information Systems Education*, 31(3), 232-243.

Britt, M., Goon, D., & Timmerman, M. (2015). How to Better Engage Online Students with Online Strategies. *College Student Journal*, 49(3), 399-404.

Bruner, J. (1973). *The Relevance of Education*. WW Norton & Company.

Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. *Modern Methods for Business Research*, 295(2), 295-336.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and an Electronic-mail Emotion/Adoption Study. *Information Systems Research*, 14(2), 189-217.

Christensen, G., Steinmetz, A., Alcorn, B., Bennett, A., Woods, D., & Emanuel, E. (2013). The MOOC Phenomenon: Who Takes Massive Open Online Courses and Why? Available at SSRN 2350964.

Cormier, D., & Siemens, G. (2010). The Open Course: Through the Open Door: Open Courses as Research, Learning, and Engagement. *EDUCAUSE Review*, 45(4), 30-39.

Cronin, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the Effects of Quality, Value, and Customer Satisfaction on Consumer Behavioral Intentions in Service Environments. *Journal of Retailing*, 76(2), 193-218.

Cummings, J., & Janicki, T. N. (2020). What Skills Do Students Need? A Multi-Year Study of IT/IS Knowledge and Skills in Demand by Employers. *Journal of Information Systems Education*, 31(3), 208-217.

Dai, H. M., Teo, T., Rappa, N. A., & Huang, F. (2020). Explaining Chinese University Students' Continuance Learning Intention in the MOOC Setting: A Modified Expectation Confirmation Model Perspective. *Computers & Education*, 150, 103850.

Daneji, A. A., Ayub, A. F. M., & Khambari, M. N. M. (2019). The Effects of Perceived Usefulness, Confirmation and Satisfaction on Continuance Intention in Using Massive Open Online Course (MOOC). *Knowledge Management & E-Learning*, 11(2), 201-214.

Daniel, J., Vázquez Cano, E., & Gisbert Cervera, M. (2015). The Future of MOOCs: Adaptive Learning or Business Model? *International Journal of Educational Technology in Higher Education*, 12(1), 64-73.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319-340.

DeLone, W. H., & McLean, E. R. (1992). Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research*, 3(1), 60-95.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, 19(4), 9-30.

Devgun, P. (2013). Prospects for Success of MOOC in Higher Education in India. *International Journal of Information and Computation Technology*, 3(7), 641-646.

Dewey, J. (1900). Psychology and Social Practice. *Science*, 11(270), 321-333.

Eyisi, D. (2016). The Usefulness of Qualitative and Quantitative Approaches and Methods in Researching Problem-Solving Ability in Science Education Curriculum. *Journal of Education and Practice*, 7(15), 91-100.

Falk, R. F., & Miller, N. B. (1992). *A Primer for Soft Modeling*. University of Akron Press.

Fornell, C. (1987). A Second Generation of Multivariate Analysis: Classification of Methods and Implications for Marketing Research. In Houston, M. J. (Ed.), *Review of Marketing* (pp. 407-450). American Marketing Assoication.

Freeze, R. D., Alshare, K. A., Lane, P. L., & Wen, H. J. (2010). IS Success Model in E-learning Context Based on Students' Perceptions. *Journal of Information Systems Education*, 21(2), 173-184.

Gelderman, M. (1998). The Relation Between User Satisfaction, Usage of Information Systems and Performance. *Information & Management*, 34(1), 11-18.

Ghozali, I., & Latan, H. (2015). *Partial Least Squares Concepts, Techniques and Applications Using the SmartPLS 3.0 Program*. Semarang: Diponegoro University Publishing Agency.

Gijsbers, D., de Putter-Smits, L., & Pepin, B. (2020). Changing Students' Beliefs About the Relevance of Mathematics in an Advanced Secondary Mathematics Class. *International Journal of Mathematical Education in Science and Technology*, 51(1), 87-102.

Given, L. M. (Ed.). (2008). *The Sage Encyclopedia of Qualitative Research Methods*. Sage publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning*, 46(1-2), 1-12.

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool in Business Research. *European Business Review*, 26(2), 106-121.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to Use and How to Report the Results of PLS-SEM. *European Business Review*, 31(1), 2-24.

Hayashi, A., Chen, C., Ryan, T., & Wu, J. (2004). The Role of Social Presence and Moderating Role of Computer Self Efficacy in Predicting the Continuance Usage of E-learning Systems. *Journal of Information Systems Education*, 15(2), 139-154.

Hmelo-Silver, C. E. (2004). Problem-Based Learning: What and How Do Students Learn? *Educational Psychology Review*, 16(3), 235-266.

Hu, P. J. H., Clark, T. H., & Ma, W. W. (2003). Examining Technology Acceptance by School Teachers: A Longitudinal Study. *Information & Management*, 41(2), 227-241.

Huang, W., Huang, W., Diefes-Dux, H., & Imbrie, P. K. (2006). A Preliminary Validation of Attention, Relevance, Confidence and Satisfaction Model-Based Instructional Material Motivational Survey in a Computer-Based Tutorial Setting. *British Journal of Educational Technology*, 37(2), 243-259.

Instructional Connections, (2021). What Are the Fastest Growing Online Education Programs in 2021? https://instructionalconnections.com/fastest-growing-online-education-programs-2021/

Ives, B., Olson, M. H., & Baroudi, J. J. (1983). The Measurement of User Information Satisfaction. *Communications of the ACM*, 26(10), 785-793.

Jaruwachirathanakul, B., & Fink, D. (2005). Internet Banking Adoption Strategies for a Developing Country: The Case of Thailand. *Internet Research*, 15(3), 295-311.

Gill, T. G., & Hu, Q. (1999). The Evolving Undergraduate Information Systems Education: A Survey of US Institutions. *Journal of Education for Business*, 74(5), 289-295.

Jongbloed, B., Enders, J., & Salerno, C. (2008). Higher Education and Its Communities: Interconnections, Interdependencies and a Research Agenda. *Higher Education*, 56(3), 303-324.

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.

Kaplan, A. M., & Haenlein, M. (2016). Higher Education and the Digital Revolution: About MOOCs, SPOCs, Social Media, and the Cookie Monster. *Business Horizons*, 59(4), 441-450.

Keller, J. M. (1987). Development and Use of the ARCS Model of Instructional Design. *Journal of Instructional Development,* 10, 2-10.

Kizilcec, R. F., & Schneider, E. (2015). Motivation as a Lens to Understand Online Learners: Toward Data-Driven Design With the OLEI Scale. *ACM Transactions on Computer-Human Interaction*, 22(2), 1-24.

Kulviwat, S., Bruner, G. C., & Al-Shuridah, O. (2009). The Role of Social Influence on Adoption of High Tech Innovations: The Moderating Effect of Public/Private Consumption. *Journal of Business Research*, 62(7), 706-712.

Lee, Y. W., Strong, D. M., Kahn, B. K., & Wang, R. Y. (2002). AIMQ: A Methodology for Information Quality Assessment. *Information & Management*, 40(2), 133-146.

Li, K. (2019). MOOC Learners' Demographics, Self-Regulated Learning Strategy, Perceived Learning and Satisfaction: A Structural Equation Modeling Approach. *Computers & Education*, 132, 16-30.

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.

Liyanagunawardena, T. R., Parslow, P., & Williams, S. A. (2017). Exploring 'Success' in MOOCs: Participants' Perspective. In Bennett, R., & Kent, M. (Eds.), *Massive Open Online Courses and Higher Education: What Went Right, What Went Wrong and Where to Next?* (pp. 92-108). Routledge.

Lu, 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.

McCluskey, M. (2020, April 17). Taking a MOOC During COVID-19: What to Know. *USNews.* https://www.usnews.com/higher-education/online-education/articles/taking-a-mooc-during-coronavirus-pandemic-what-to-know

Melone, N. P. (1990). A Theoretical Assessment of the User-satisfaction Construct in Information Systems Research. *Management Science*, 36(1), 76-91.

Milligan, C., & Littlejohn, A. (2017). Why Study on a MOOC? The Motives of Students and Professionals. *International Review of Research in Open and Distributed Learning*, 18(2), 92-102.

Morales, T. M., Bang, E., & Andre, T. (2013). A One-Year Case Study: Understanding the Rich Potential of Project-Based Learning in a Virtual Reality Class for High School Students. *Journal of Science Education and Technology*, 22(5), 791-806.

Nascimento, B., Oliveira, T., & Tam, C. (2018). Wearable Technology: What Explains Continuance Intention in Smartwatches? *Journal of Retailing and Consumer Services*, 43, 157-169.

Nunnally, J. C. (1978). *Psychometric Theory*, 2nd ed. McGraw-Hill.

Nurmohamed, Z., Gillani, N., & Lenox, M. (2013). A New Use for MOOCs: Real-World Problem Solving. *Harvard Business Review*. https://hbr.org/2013/07/a-new-use-for-moocs-real-world

Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, 17(4), 460-469.

Ozmon, H., & Craver, S. (1995). Philosophy, Education, and the Challenge of Postmodernism. In *Philosophical Foundations of Education* (pp. 361-392). Merrill.

Pilli, O., & Admiraal, W. F. (2017). Students' Learning Outcomes in Massive Open Online Courses (MOOCs): Some Suggestions for Course Design. *Journal of Higher Education*, 7(1), 46-71.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, 88(5), 879-903.

Priniski, S. J., Hecht, C. A., & Harackiewicz, J. M. (2018). Making Learning Personally Meaningful: A New Framework for Relevance Research. *The Journal of Experimental Education*, 86(1), 11-29.

Rivas, M. J., Baker, R. B., & Evans, B. J. (2020). Do MOOCs Make You More Marketable? An Experimental Analysis of the Value of MOOCs Relative to Traditional Credentials and Experience. *AERA Ope*n, 6(4), 2332858420973577.

Saadatdoost, R., Sim, A. T. H., Jafarkarimi, H., & Mei Hee, J. (2015). Exploring MOOC From Education and Information Systems Perspectives: A Short Literature Review. *Educational Review,* 67(4), 505-518.

Saulnier, B., Ceccucci, W., Sendall, P., & Peslak, A. (2019). Four Important Strategic Issues for Computer Information Systems Education. *Journal of Information Systems Education*, 30(4), 327-335.

Setor, T. K., & Joseph, D. (2021). College-Based Career Interventions: Raising IT Employability and Persistence in Early Careers of IT Professionals. *Journal of Information Systems Education*, 32(4), 262-273.

Shah, D. (2021, December 28). A Decade of MOOCs: A Review of Stats and Trends for Large-Scale Online Courses in 2021. *EdSurge*. https://www.edsurge.com/news/2021-12-28-a-decade-of-moocs-a-review-of-stats-and-trends-for-large-scale-online-courses-in-2021

Shemuda, M. (2018). Strategies for Teaching Gifted Students English Grammar. *Advanced Education*, 2018(9), 107-113.

Teo, T., Zhou, M., Fan, A. C. W., & Huang, F. (2019). Factors That Influence University Students' Intention to Use Moodle: A Study in Macau. *Educational Technology Research and Development*, 67(3), 749-766.

Thomas, J. W. (2000). A Review of Research on Project-Based Learning. *Procedia-Social and Behavioral Sciences*, 18, 1019-1024.

Tyson, A., Kennedy, B., & Funk, C. (2021). *Gen Z, Millennials Stand out for Climate Change Activism, Social Media Engagement with Issue*. Pew Research Center. https://www.pewresearch.org/science/wp-content/uploads/sites/16/2021/05/PS_2021.05.26_climate-and-generations_REPORT.pdf

van de Oudeweetering, K., & Agirdag, O. (2018). Demographic Data of MOOC Learners: Can Alternative Survey Deliveries Improve Current Understandings? *Computers & Education*, 122, 169-178.

Wang, R. Y., & Strong, D. M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. *Journal of Management Information Systems*, 12(4), 5-33.

Wang, T., Lin, C. L., & Su, Y. S. (2021). Continuance Intention of University Students and Online Learning During the COVID-19 Pandemic: A Modified Expectation Confirmation Model Perspective. *Sustainability*, 13(8), 4586.

Wang, Y., & Liao, Y. (2008). Assessing eGovernment Systems Success: A Validation of the DeLone and McLean Model of Information Systems Success. *Government Information Quarterly,* 25(4), 717-733.

Wang, Y. S. (2008). Assessing E-Commerce Systems Success: A Respecification and Validation of the DeLone and McLean Model of IS Success. *Information Systems Journal*, 18(5), 529-557.

Wu, J., & Wang, Y. (2006). Measuring KMS Success: A Respecification of the DeLone and McLean's model. *Information & Management*, 43(6), 728-739.

Yang, H., & Su, C. (2017). Learner Behaviour in a MOOC Practice-Oriented Course: An Empirical Study Integrating TAM and TPB. *International Review of Research in Open and Distributed Learning*, 18(5), 35-63.

Yang, Q., & Lee, Y. (2021). The Critical Factors of Student Performance in MOOCs for Sustainable Education: A Case of Chinese Universities. *Sustainability*, 13(14), 8089.

Yu, A. Y., Tian, S. W., Vogel, D., & Kwok, R. C. W. (2010). Can Learning Be Virtually Boosted? An Investigation of Online Social Networking Impacts. *Computers & Education*, 55(4), 1494-1503.

Zalli, M. M. M., Nordin, H., & Hashim, R. A. (2019). The Role of Self-Regulated Learning Strategies on Learners' Satisfaction in Massive Open Online Course (MOOC): Evidence from Malaysia MOOC. *International Journal of Innovative Technology and Exploring Engineering*, 8(10), 2286-2290.

Zhang, J. (2016). Can MOOCs Be Interesting to Students? An Experimental Investigation from Regulatory Focus Perspective. *Computers & Education*, 95, 340-351.

Zhao, L., Lu, Y., Zhang, L., & Chau, P. Y. (2012). Assessing the Effects of Service Quality and Justice on Customer Satisfaction and the Continuance Intention of Mobile Value-added Services: An Empirical Test of a Multidimensional Model. *Decision Support Systems*, 52(3), 645-656.

Zhenghao, C., Alcorn, B., Christensen, G., Eriksson, N., Koller, D., & Emanuel, E. (2015). Who's Benefiting From MOOCs, and Why. *Harvard Business Review*, 25(Sept.), 2-8.

Zheng, Y., Zhao, K., & Stylianou, A. (2013). The Impacts of Information Quality and System Quality on Users' Continuance Intention in Information-Exchange Virtual Communities: An Empirical Investigation. *Decision Support Systems*, 56, 513-524.

Zweifler, S. (2013). *Study: MOOC Students Are Highly Educated, Job-Oriented: The Coursera Student Population Also Tends to Be Young and Male*. The Daily Pennsylvanian. https://www.thedp.com/article/2013/11/new-penn-study-moocs-far-from-revolutionizing-higher-education

AUTHOR BIOGRAPHIES

Ying Wang is an associate professor at Northern Illinois University. She received her Ph.D. in Management Information Systems and MBA in general business from Texas Tech University. Her research interests primarily focus on the digital economy, business analytics, deep learning, and text analytics techniques. Her work has appeared in journals, such as *Decision Support Systems*, *Communications of the Association for Information Systems*, and the *Asia Pacific Journal of Information Systems*, and has presented at top conferences, such as the *Americas Conference on Information Systems* and *International Conference on Information Systems*.

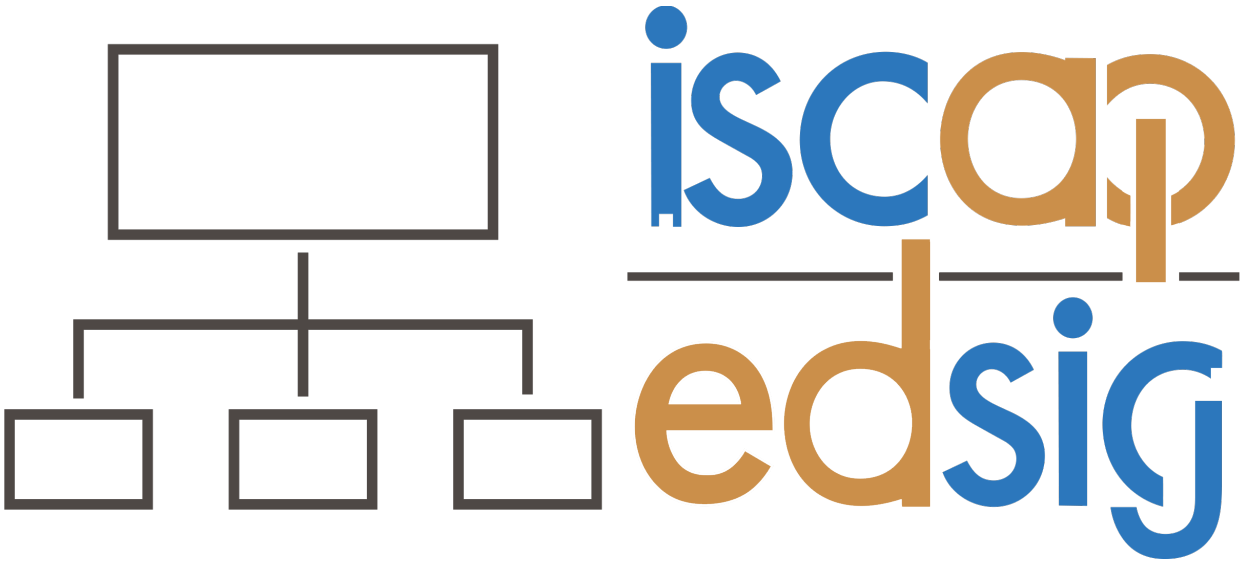
Hong "Wendy" Wang is an associate professor of computer information systems in the Sanders College of Business and Technology at the University of North Alabama in Florence, AL. She received her Ph.D. in Management Information Systems from the University of Mississippi. She has extensive research interests in behavioral, managerial, and technical aspects of information systems. She has published book chapters on how IT has changed the way we work and journal articles in the *Journal of the American Society for Information Science and Technology*, *Employee Relations, International Journal of Enterprise Information Systems*, *Journal of Decision Systems*, and *IEEE ACCESS*.

Leslie Jordan Albert is a professor of MIS and Director of the School of Information Systems & Technology at San Jose State University. She earned her Ph.D. in Management Information Systems from the University of Oklahoma. Her research interests include consumer perceptions of cyber risk, online learning, online identity, telecommuting, and Information Systems pedagogy. Her work has appeared in *Information Systems Frontiers*, *Decision Sciences Journal of Innovative Education*, *Technology in Society*, *Employee Relations*, and *Electronic Markets*.

APPENDIX

Statistical Summaries of All Items

Item	Maximum	Minimum	Mean	Standard Deviation	Skewness
PR1	5	1	3.977	0.973	-0.987
PR2	5	1	3.769	1.119	-0.755
PR3	5	1	3.845	1.029	-0.849
PR4	5	1	3.775	1.099	-0.805
SR1	5	1	3.924	1.020	-0.877
SR2	5	1	3.725	1.131	-0.808
SR3	5	1	3.763	1.092	-0.712
CNF1	5	1	3.711	1.040	-0.636
CNF2	5	1	3.825	0.960	-0.639
CNF3	5	1	3.822	1.014	-0.701
CNF4	5	1	3.790	1.021	-0.695
PU1	5	1	3.813	1.129	-0.853
PU2	5	1	3.819	1.127	-0.845
PU3	5	1	4.017	1.037	-1.094
PU4	5	1	3.897	1.053	-0.987
PU5	5	1	3.644	1.142	-0.689
SN1	5	1	3.518	1.067	-0.339
SN2	5	1	3.291	1.082	-0.141
SN3	5	1	3.892	1.010	-0.860
SN4	5	1	3.661	1.101	-0.739
SF1	5	1	4.026	0.899	-0.803
SF2	5	1	3.900	1.021	-0.786
SF3	5	1	4.026	0.953	-1.010
SF4	5	1	3.900	1.060	-0.836
SF5	5	1	3.906	1.041	-0.827
CI1	5	1	3.912	1.064	-0.878
CI2	5	1	4.122	0.959	-1.066
CI3	5	1	3.932	1.078	-0.922
CI4	5	1	3.822	1.147	-0.932



Information Systems & Computing Academic Professionals

Education Special Interest Group

STATEMENT OF PEER REVIEW INTEGRITY

All papers published in the ***Journal of Information Systems Education*** have undergone rigorous peer review. This includes an initial editor screening and double-blind refereeing by three or more expert referees.

ISSN: 2574-3872 (Online) 1055-3096 (Print)