

Supportive Leadership and Post-Adoption Use of MOOCs: The Mediating Role of Innovative Work Behavior

Fawad Ahmed, Xi'an Jiaotong-Liverpool University, China

 <https://orcid.org/0000-0002-3495-7404>

Naveed Ahmad Faraz, Hunan University, China*

Nisar Ahmad, University of Science and Technology of China, China

Muhammad Khalid Iqbal, University of Management and Technology, Sialkot, Pakistan

ABSTRACT

Educational institutions face significant challenges in extracting interest from their investments in massive open online courses (MOOCs). This study examined the impact of supportive leadership style on university employees' continued use of MOOCs and assessed the mediating role of their innovative work behavior. It uses a multi-theory perspective as opposed to the majority of past studies that use singular theoretical perspectives and extends the information system continuance (ISC) model with the leadership concept. Researchers collected multi-source dyadic data for this cross-sectional study from 632 employees and 316 supervisors from 19 Chinese universities. Data were analyzed using structural equation modeling with partial least squares through SmartPLS 3.2.9. Results indicate supportive leadership influences employees' innovative behavior, which mediates between supportive leadership and employees' satisfaction, perceived usefulness, and intention to continue using MOOCs.

KEYWORDS

Expectation Confirmation Theory, Information Systems Continuance, Innovative Work Behavior, Massive Open Online Courses, MOOCs, Organizational Support, Social Exchange Theory, Supportive Leadership

INTRODUCTION

Massive Open Online Courses (MOOCs) have taken a life of their own, proving the need for adoption and continued use of such information systems by academic employees. The spring semester for 2020 began with empty classrooms amidst the new Coronavirus outbreak in China. Universities used online course platforms for more than ten million students to attend school from home (CGTN, 2020). More recently, universities have started teaching live classes online throughout China on a mass scale (CGTN, 2020), including 200 million domestic and international students (Jin et al., 2021).

MOOCs surfaced as a phenomenal methodology for making education more accessible to a broader geographical range with global outreach prospects for educational institutions. It has gained

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*Corresponding Author

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momentum and popularity since 2012 in the USA, United Kingdom, and Europe. The year 2012 was termed the year of the MOOCs by the New York Times (Pappano, 2012), while Coursera, Udacity (for-profit), and edX (non-profit) emerged as three of the biggest names in MOOCs. Although information systems (IS) for educational institutions is a relatively new concept in the backdrop of online learning, it is being studied extensively (Al-Emran et al., 2016; Briz-Ponce et al., 2017; Kim & Rha, 2018). Its most significant advantage is learner mobility and quicker access to information; freedom from spatial and temporal dependence, leading to faster response time and problem-solving through communication between tutors and learners alike.

With a barrage of technological advancements, existing research is saturated with studies on initial adoption, while less attention is paid to post-adoption continuance intention (Bhattacharjee, 2001). Initial acceptance of technology and continued use are two distinct concepts. Bhattacharjee (2001) defines IS continuance as users' decision to continue using technology over the long run, against the initial acceptance based on the users' decision to start using technology. MOOCs have been here for several years now. The employees' decision to continue using this technology to innovate and create shall determine its real input into the educational infrastructure. Thus, determinants of initial acceptance are not the ultimate aim for researchers (Alraimi et al., 2015); instead, the continued use should be studied further for its enablers and inhibitors, especially from employees' perspectives.

Most of the recent research on MOOCs related information technology is based on the learner's adoption perspective. It includes evaluation of antecedents through social support theory (Hsu et al., 2018), social interactions of learners (Fang et al., 2019), barriers from a technology-user-environment perspective (Ma & Lee, 2019), and variables such as trust, optimism, discomfort, social influence, subjective norms, self-efficacy (Ahmad et al., 2017; Bach et al., 2016; Doğru, 2017; Erdoğan & Esen, 2011; Lai et al., 2012; Liljander et al., 2006). Huang et al. (2017) also studied students' post-adoption continued use of MOOCs. However, there is a dearth of research on teachers' role as active agents (Ross et al., 2014). As much as the learner's behavior is essential in MOOC usage, no one can discount the significance of academic employees' propensity to continue using information systems. The university teachers' active consultation is necessary for course completion rates (Gregori et al., 2018). This is why MOOCs' continued use by academic employees is crucial in avoiding student attrition from MOOCs and making it an effective means to education. As Granić and Marangunić (2019) report in their systemic literature review on technology adoption, participants in studies related to e-learning included merely 17% sample groups other than students. Although there are a few studies on academic employees in technology literature, those are restricted to exploring facilitating conditions, perceptions, and social factors as antecedents of technology and have not covered leadership roles or employees' extra-role behaviors such as innovative work behavior. A recent study by Tseng et al. (2019) examined MOOCs adoption by teachers through the unified theory of acceptance and use of technology (UTAUT2) model, exploring facilitating conditions for adoption. They found that hedonic motivation did not prove to be a significant driver in MOOCs adoption. So, it begs the question, what kind of roles drive such motivation among academic employees to be innovative and more open to continue using MOOCs in the long run.

Challenges and factors affecting university employees' involvement in developing a MOOC need to be further researched (Blackmon, 2018). The few studies on academic employees' behavior towards MOOCs use or similar online learning platforms are limited to the pedagogical perspective (Ross et al., 2014); initial adoption behavior within the context of technology acceptance (Tseng et al., 2019); or their personal beliefs of self-efficacy, barriers and technology-specific constructs (Oskay, 2017). Educational technology literature is wanting in extensive research on organizational and human resource management mechanisms that predict teachers' behavior towards technology usage (Yanmei, 2015). This calls for further research on factors that need to be examined for their impact as external variables to technology use (Al-Emran et al., 2018). Specifically, from work and career contexts such as a supportive leader and innovative work behavior as predictors towards continued use of MOOCs among university teachers.

Despite the notable focus in the existing literature on the impact of leadership behaviors on innovative behavior during the past few decades, contrasting and fragmented results still leave room for definitive answers (Anderson et al., 2014), specifically for educational technology implementation and in ‘academics’ innovative work behavior in educational institutions. The same holds for how employees’ innovative work behavior interplays with supportive leadership to bring about desired results in technology-specific change-management processes. Supportive leaders influence employee attitudes (Lee et al., 2017). Supportive management policies play a moderating role in learning management systems adoption (Khan et al., 2017). A thorough review of the technology literature suggests that research lacks on the influence of such supportive leadership through the mediating mechanism of innovative behavior in general (Jo, 2018) and for MOOCs specifically. There is a need to examine how supportive leaders inculcate innovative behavior to create university employee’s continuance intention towards MOOCs post-adoption use. Although experts in educational fields can develop specialized courses for online students, they may need support to be more innovative and satisfied with MOOCs’ use. We aim to study if supportive leadership is a predictor of innovative work behavior amongst university employees. This mechanism needs exploring as an antecedent of continued post-adoption use of MOOCs.

This study draws on the organizational support theory, social exchange theory, and expectation confirmation theory (ECT) to study how supportive leaders influence university employee’s intention to continue using MOOCs. It shows that innovative behavior serves as a link explaining how supportive leaders build employee propensity to continue using MOOCs and related information systems. This study aims to ascertain if supportive leadership influences the innovative work behavior of employees in using information systems and establish if innovative work behavior mediates the relationship between supportive leadership and employees’ decision to continue using MOOCs related information systems.

These objectives shall help contribute to existing literature. First, it responds to multiples calls for research in the education sector on academic employees’ behavior as technology users from human resources perspective (Ahmed et al., 2019; Granić & Marangunić, 2019), and call for research in China on IS specific to MOOCs (Zhao et al., 2020). Secondly, since there is a scarcity of research on leadership behavior in the education sector for its leader-follower impact on ‘teachers’ behavior and less is known from a human resources perspective for teachers’ adoption behavior. A study by Al-Rahmi et al. (2019) showed the integrative impact between innovation diffusion theory and technology acceptance. In a similar vein, this study contributes by integrating the social exchange theory with ISC model from technology literature to address this gap in research on supportive leadership’s relationship with university teachers’ innovative work behavior and bridges an existing gap of how innovative behavior mediates the relationship between leadership support and post-adoption continued use of MOOCs. Thirdly, from a methodological perspective, it responds to a call for research by using supervisor-reported employees’ innovative work behavior by Zhao et al. (2020); multi-source and supervisor-reported data were used in this study, as against the majority of existing studies that have used single-source and self-reported data.

Subsequent sections discuss relevant literature from existing works on MOOCs technology use, supportive leadership, and innovative work behavior. Then conceptual model and hypotheses are presented, and research methods and data analysis follow later. Next, the results are discussed with implications. Finally, limitations and future research are proposed with concluding remarks.

LITERATURE REVIEW AND HYPOTHESES

MOOCs Use in Universities

The Chinese University of Hong Kong officially joined Coursera in January 2013 to offer 5 courses to the platform. Later in May the same year, Tsinghua University joined hands with edX and launched the first Chinese online course platform called “xuetangx.com”; in July Fudan University and Shanghai

Table 1. Recent studies related to online learning technologies adoption

Author(s)	Type	Sample Size/ Profile	Location	Theoretical Perspective	Purpose
Blackmon (2018)	Qualitative	8 / Teachers	USA	unspecified	Explore challenges faced by teachers in developing MOOCs
Zhao et al. (2020)	Quantitative	591/University teachers	Britain	TAM	Assessed the role of institutional support, self-efficacy, personal innovativeness on acceptance of education management information systems
Tseng et al. (2019)	Quantitative	161/Teachers	Taiwan	UTAUT2	Social factors affecting initial adoption of technology among teachers
Nikou and Economides (2019)	Quantitative	161 STEM teachers	Europe	TAM	Examined influence of institutional support, facilitating conditions and output quality on acceptance of mobile-based assessments
Hsu et al. (2018)	Quantitative	Students	Taiwan	social support theory	Learners adoption of MOOCs through the role of perceived convenience, computer self-efficacy, sense of community, and perceived gains as the constructs of social support perspective
Gil-Jaurena and Domínguez (2018)	Qualitative	24/Teachers	Spain	community of inquiry model used as a theoretical framework	analyse many of the changes that can occur in teaching when an open context applies, as in the case of MOOCs
Wu and Chen (2017)	Quantitative	252/Students	China	TAM and task Technology Fit	MOOCs features and social motivation to investigate continuance intention to use MOOCs
Ma and Lee (2019)	Qualitative	64/students	China	innovation resistance theory	Understanding the Barriers to the Use of MOOCs in a Developing Country

Jiao Tong University also signed agreements with Coursera; Guokr.com was launched that same year as the largest MOOC in China. So, 2013 was the year of MOOC in China.

In May 2014, the Chinese University MOOC project was formally launched online. As of January 2018, People's Daily reported that China had topped the world in most MOOCs offered by any country with over 3,200 courses (Li, 2018), while Xuetangx alone offers more than 1900 courses. The teacher's adoption, use, and adequacy in IS are vital to the success of MOOCs because they are actively engaged with students. They send welcoming messages; disseminate initial messages and

information in the forums; provide responses and feedback; address concerns and make suggestions about content; writing a summary at the end of a course. A study conducted by Blancato and Iwertz (2016) on the roles of students and teachers in a MOOC showed that the instructor played a significant role by interacting with students both formally through IS and informally through MOOC online platforms. Hew and Cheung (2014) report that instructors are involved in MOOC-related platforms through weekly or bi-weekly posts; some answered selective students' queries through online office hours while others engaged in a live exchange with students. Moreover, Liu (2019) opine that availability of MOOC courses "makes it much easier and cheaper to learn a specific skill/knowledge and obtain a proof for it" (p.2).

Supportive Leadership and Innovative Work Behavior

House (1981) defines a supportive leader as the leader that ensures his/her subordinates receive emotional support, appraisal support, informational support, and instrumental support. However, social support is inadvertently the same as emotional support, whereby leaders provide sympathy, care, listen to followers and show evidence of liking them. (Rafferty & Griffin, 2006) refined the individualized consideration dimension of transformational leadership and drew upon House's (1981) concept to define supportive leadership as "occurring when leaders express concern for and take account of, followers' needs and preferences when making decisions" (p. 39). Support from leaders, management support is defined as employee's "global beliefs concerning the extent to which the organization values their contributions and cares about their well-being" (Rhoades & Eisenberger, 2002).

Rhoades and Eisenberger (2002) state that support is "generally characterized by the power the organization's agents exert over individual employees." Researchers have suggested that support from leaders could predict perceived usefulness (Davis, 1985). Tarafdar and Vaidya (2006) found a strong positive relationship of support from management with information systems assimilation.

Innovative behavior, defined by Scott and Bruce (1994) as an employee's "ability to generate and implement new and useful ideas at work," has become a competitive advantage for highly skilled human capital in the current fast-paced technological age. With the advent of technology, globalization brought by the internet, fast-paced changes in the economic environment, and ever-growing competitive market needs, innovative work behavior by employees has gained undeniable significance (Stock & Gross, 2016; Woods et al., 2018) over the past two decades. Innovative work behavior has been narrated as a cognitive process of highly motivated employees visible in specific work settings.

The heterogeneous findings in existing literature for leadership's impact on innovative work behavior (Anderson et al., 2014) call for further empirical research. A wide range of studies uses the "forward" approach to examine the relationship of leadership with creative and innovative behavior (Mainemelis et al., 2015). This had started from established popular leadership styles such as transformational leadership and leader-member exchange in an attempt to examine how these explain innovative work behavior. However, despite its usefulness in understanding the overall impact of leadership on innovation, this approach does not identify which specific behaviors of the leader facilitate innovative work behavior. (Vincent-Höper & Stein, 2019). This makes perfect sense because these have not been developed specifically with the purpose of predicting innovative work behavior among employees.

Supportive leadership does not have this limitation. It is closely knit with the social exchange theory and increases the expectation of aid when needed, and strengthens self-efficacy (Kurtessis et al., 2017). The theory states that each of the involved parties has a specific set of perceptions concerning the behavior of the other. Moreover, supportive leadership can potentially be used as an enabler of innovative behavior to provide an enhanced understanding of the continued use of IS. Contrary to employees' expectations, if there is a lack of management support, there may be a decline in performance and job outcomes (Stinglhamber & Vandenberghe, 2003). If such a mechanism exists in an organization that allocates enough resources to facilitate technology adoption, fewer constraints are encountered during adoption (Stan et al., 2012). Thus it is hypothesized that:

H1: Supportive leadership has a positive effect on the innovative work behavior of employees.

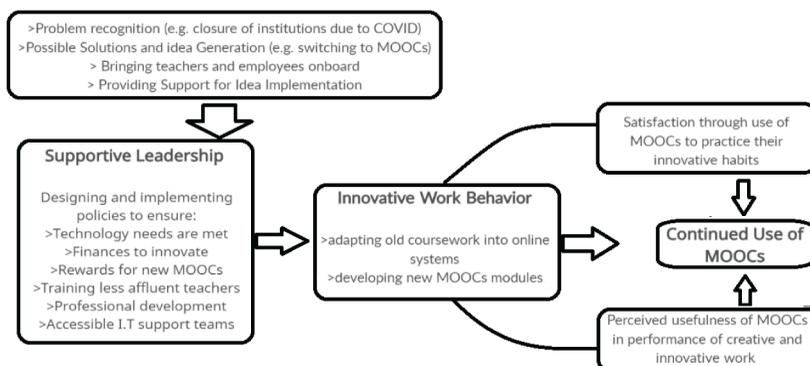
Information Systems Continuance Model

Bhattacharjee (2001) developed an information systems continuance model modified from the Expectation-Confirmation theory (ECT) by Oliver (1980). This theory has been applied in technology research for acceptance of e-portfolios (Ahmed & Ward, 2016), e-health adoption (Leung & Chen, 2019), consumers’ intention to continue the use of smart wearable devices (Park, 2020). Information systems’ continuance behavior depends on the post-adoption variables, i.e., satisfaction and perceived usefulness. Bhattacharjee (2001) made certain theoretical changes and adapted ECT to the information systems continuance model by excluding two confirmation pre-consumption predictors of perceived success and expectation because their effect is captured within confirmation and satisfaction. This study also follows the same approach. Similar to other IS products and services, the expectation is vital for MOOCs as well because changes occur in the initial expectations over time. Therefore, an ex-post-expectation variable of perceived usefulness (PU) is added as recommended by Bhattacharjee (2001).

The subjective probability that a particular user will consider a given technology or application system to be useful in increasing job performance in a workplace setting is called perceived usefulness (Davis et al., 1989). Perceived usefulness refers to the personal opinion of any given technology user that using technology facilitates task performance and goal achievement at the place of work. It is appropriate to state that current research on technology use in educational settings is not new. Past studies measured technology readiness and adoption, such as Caisson (2008) and Walczuch et al. (2007). However, the field is still lacking in studies that address employees as a type of user, existing applications for learning domains, and learning technologies in an educational context (Granić & Marangunić, 2019). Technology usage behavior has been assessed in a few studies for teachers’ adoption of digital technologies as a whole (Scherer et al., 2019), but no study exists about post-adoption use of MOOCs at the time this study was being conducted. Figure 1 presents a flowchart of how institutional support and continued use of MOOCs are interlinked in this regard.

Lee et al. (2013) found that continued intention to use was directly affected by perceived usefulness. In line with the past studies on technology adoption by Davis (1985); Davis et al. (1989); Venkatesh and Davis (2000), Bhattacharjee (2001) strongly argued that perceived usefulness could have a continuous effect on the decision to continue using information systems, and thus, theorized that perceived usefulness is a determinant of satisfaction. The continuance model also posits a usefulness to intention relationship, which was formed under Technology Acceptance Model (TAM) by Davis et al. (1989). This effect between usefulness and intention is likely to recur in the continuity of the

Figure 1. Flowchart of MOOCs needs and implementation



initial adoption. This continuity intention among humans is interpreted as a sequence of decisions that are free of temporal restrictions or the behavioral stages (Roca et al., 2006). As observed in a recent study (Wang et al., 2021) perceived satisfaction of users is a critical factor in continued use of MOOCs in the pandemic era. Thus, there is a direct effect of perceived usefulness on MOOCs' continued intention to use and an indirect effect through satisfaction.

Therefore, this study hypothesized as under:

H2a: Perceived usefulness (PU) of MOOCs related Information Systems is related to intention to use (IU) such systems.

H2b: Satisfaction (SAT) from the use of MOOCs related Information Systems is related to intention to use (IU) such systems.

Mediating Role of Innovative Work Behavior

Owing to the increased competitive job market, employees must learn to do tasks that are not just related to their in-role behaviors but also the tasks that are beyond routine activities. They must lookout for the latest technologies, provide suggestions on how to improve existing methods of task accomplishment, bring to work new methods, and keep vigilant to obtain resources that facilitate implementation of such new methods (de Jong & den Hartog, 2010). All these concepts are collectively referred to as innovative work behavior; it can be defined as an employee's "intentional introduction, promotion and realization of new ideas, products, processes, and procedures within a work role, workgroup or organization, in order to benefit role performance, the group, or the organization" (Afsar et al., 2019). It can be argued that not every employee is equally innovative, nor do all the employees have the innovativeness trait.

Research on supportive leadership further shows that employees' perceptions to use technology are positively affected by an organization's HR practices, infrastructure support, and technical support (Bhattacharjee & Hikmet, 2008). The social exchange theory posits that it is an employee's felt obligation to repay an organization if they are receiving a high level of support from management (Rhoades & Eisenberger, 2002). Employees tend to develop a level of belief with respect to how much their contribution is valued, as postulated by the organizational support theory (Eisenberger et al., 1986). This opportunity to exercise innovative behavior in exchange for supportive leadership brings employee satisfaction during information systems use for their tasks. It is, therefore, hypothesized that:

H3a: Innovative work behavior (IWB) of employees mediates the relationship between SL and satisfaction (SAT).

Innovative work behavior and similar proactive behaviors are essential because they are linked to performance; employees who are proactive to change and redesign aspects of their job are more likely to enhance organizational effectiveness (Tims et al., 2012). MOOCs extend an opportunity to instructors to innovate within the pedagogical realm for online courses (Hew & Cheung, 2014). A longitudinal study found that among the reasons for conducting a MOOC, "pedagogical experimentation and innovation" was rated as the most important by the teachers experienced in MOOCs (Gil-Jaurena & Domínguez, 2018). This includes such elements as gamification (game-designed elements to motivate and engage students), teaching with short videos peer assessment and support, and online social interaction.

Innovative behavior is among such personality traits that help mold an individual's perception of his/her ability to cope with change (Thatcher and Perrewé, 2002). Mahat et al. (2012) observed that innovativeness significantly affects a user's intentions towards m-learning adoption. Previous research has called to incorporate additional variables into the technology usage studies (Marangunić & Granić, 2015). Hwang (2014) found a positive impact of innovative behavior on perceived ease

of use. Hew and Cheung (2014) identified that one of the reasons for teaching staff's adoption of IS for MOOCs related IS was "a sense of intrigue about MOOCs and wanting to experience teaching/connecting to a large and diverse audience." This is synonymous with the trait of innovative behavior, which is defined as "an individual's willingness to try out a relatively new information technology" (Agarwal & Karahanna, 2000). Thus, we hypothesize that:

H3b: Innovative work behavior (IWB) of employees mediates the relationship between SL and perceived usefulness (PU) of MOOCs.

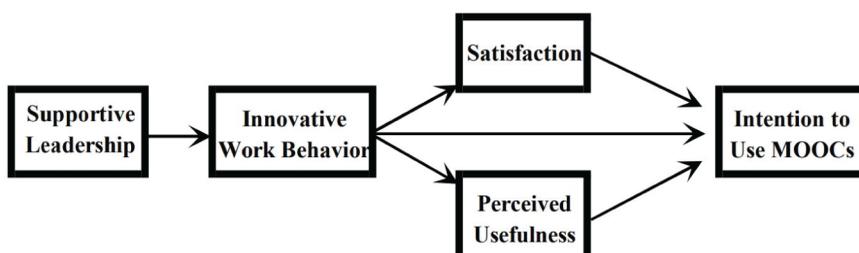
Innovativeness develops a more positive intention to use technology (Kabra et al., 2017). Parveen and Sulaiman (2008) identified that m-learning adoption is influenced by the innovativeness of respondents and had a direct positive effect on perceived usefulness. Another study on cloud classrooms by Cao et al. (2019) indicated the positive influence of innovative behavior of individuals was positively related to the intention to use technology. Similar findings were reported for ERP systems user acceptance (Hwang, 2014). The intrinsic motivation of teaching employees to innovate new courses can be fulfilled by being creative in developing MOOCs' course content. This study posits that employees see the opportunity to develop new courses for the MOOCs platform as an opportunity that fulfills their need for innovative behavior. The teachers would, therefore, be willing to use the MOOCs related information systems. Thus, it is hypothesized that:

H3c: Innovative work behavior (IWB) of employees mediates the relationship between SL and intention to use (IU) MOOCs.

METHODOLOGY

The sample was drawn from high-ranking public sector comprehensive universities in China. Authors shortlisted numerous Chinese universities listed on the official website of Quacquarelli Symmonds World Rankings, listing 1,397 top universities. There were 71 universities from China, including 43 comprehensive universities (offering almost all major disciplines) in the top 1000 world rankings. The sample included respondents from only the large comprehensive universities because their in-house innovative activities and abilities are more intense; as reported in earlier studies, larger organizations have this advantage over smaller ones (Afsar et al., 2019; Zhao et al., 2020). Researchers reached out to the managerial staff of these 43 universities for liaison and shortlisted 25 universities after confirming they were actively engaged in using MOOCs technology with credit hour courses. Researchers met the management of these universities in person to explain the purpose of this study, and 19 agreed to participate after approval from authorized persons to proceed with data collection.

Figure 2. Research model



This study uses a deductive research approach to build the underlying theoretical model. Under this approach, the data is collected on the basis of rational reasoning and analyzed to explain the relationship of the variables with each other, subsequently concluding that either proves or disproves the hypotheses developed earlier. A survey questionnaire was used for data collection from employees and respective managers (Dean, head of the department, program managers) of various departments of the different universities across the Chinese Mainland. Simple random sampling was used. First, the employee-related questionnaires were circulated and returned during the third and fourth week of September 2020. The supervisor-reported innovative work behavior questionnaire was subsequently distributed after two weeks during the second week of October 2020. Questionnaires were placed online on a third-party service provider website. The link to the questionnaire was sent to the authorized liaison persons at the universities who then distributed these to participants.

The questionnaires were distributed to 902 employees of 19 universities in 10 major cities of 9 provincial/autonomous regions i.e., Harbin, Beijing, Shanghai, Nanjing, Wuhan, Chengdu, Xiamen, Guangzhou, Shenzhen, and Guilin. A total of 712 responses were returned. However, 698 (77.38%) responses were finally deemed usable after removing unusable responses with straight-lining issues and missing values. Respondents comprised of 408 (58.45%) males, 471 (67.47%) respondents were over 40 years of age, 396 (56.73%) had a Ph.D., and the rest had a Master degree. Descriptive statistics are given in table 2.

With respect to non-response bias, the early and late responders were categorized by dividing the data into two halves of the first 50 percent and last 50 percent (treating late responders as a proxy for non-responders). No significant differences were found. In the second round, the authors approached 349 supervisors of the participants of the first round of surveys to rate the innovative work behavior of their subordinates. In order to reduce the burden of rating, the maximum number of subordinates per supervisor was limited to 2 per supervisor, thus forming supervisor-subordinate paired data. After screening for missing values, 316 complete and usable paired responses were available for data analysis with 632 paired employee-supervisor responses. It is fairly more than an adequate sample size as per expert recommendations from the viewpoint of statistical power analysis for multiple regression and Structural Equation Modeling (SEM) analysis purposes (Hair et al., 2017). At an 80% level of power, for a minimum 25% R-square at 5% significance level, a minimum of 59 observations are required for a maximum of three predictors pointing at any one dependent variable (Wong, 2013).

Measures

This study adapted questionnaires used in past research to ensure that the tools and instruments being used do not have any content validity or reliability issues. The questionnaire was translated into Chinese language and was double-checked by reverse translation into the English Language. Questions were re-worded for the purposes of this study. Moreover, 01 Professor from School of Management, 01 Assistant Professor of English Literature, and 02 Chinese Ph.D. students at lead authors' university, who were all bilingual and fluent in English, checked the Chinese language statements and English language statements for all items to ensure face and content validity.

Perceived usefulness, satisfaction, and intention to use were measured with four items each, adapted from Bhattacharjee (2001). Supportive leadership (three statements) was measured with items adapted from (Rafferty & Griffin, 2006). Innovative work behavior was measured with supervisor-reported ten items adopted from (de Jong & den Hartog, 2010), also used by Afsar et al. (2019).

All measures used a 7-point Likert scale with "strongly disagree (1)" to "strongly agree (7)". A disclosure statement in each questionnaire explained the objectives of the survey, assured respondents of confidentiality as well as anonymity, and indicated that participation was voluntary and respondents could discontinue any time.

Meanwhile, some have urged to consider individual factors as boundary conditions for understanding IT use (Venkatesh et al., 2003). Therefore the study controlled for age, gender,

Table 2. Item loadings, construct's reliability and validity

Constructs	Items	Loadings	Reliability and Validity			
			α	rho_A	CR	AVE
Intention to Use (IU)	IU1	0.841	0.896	0.898	0.928	0.764
	IU2	0.904				
	IU3	0.926				
	IU4	0.822				
Innovative Work Behavior (IWB)	IWB1	0.484	0.787	0.824	0.927	0.566
	IWB2	0.836				
	IWB3	0.766				
	IWB4	0.823				
	IWB5	0.752				
	IWB6	0.823				
	IWB7	0.753				
	IWB8	0.802				
	IWB9	0.739				
	IWB10	0.681				
Perceived Usefulness (PU)	PU1	0.873	0.729	0.763	0.830	0.555
	PU2	0.685				
	PU3	0.605				
	PU4	0.788				
Satisfaction (SAT)	SAT1	0.711	0.807	0.861	0.869	0.626
	SAT2	0.842				
	SAT3	0.762				
	SAT4	0.842				
Supportive Leadership (SL)	SL1	0.856	0.761	0.822	0.873	0.697
	SL2	0.82				
	SL3	0.828				

Note: α = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted

education, and years of experience. However, none of these factors proved significant and thus were dropped from the structural model.

Data Analysis

The data were analyzed using SmartPLS 3.2.9 (Ringle et al., 2015). Preference was given to PLS because it is not affected by skewness and multi-collinearity comparatively. The software SmartPLS was preferred over other software applications such as SPSS and AMOS, considering that prediction was the main purpose in this study as recommended by experts in the field (Hair et al., 2019). In addition, for complex models, it is considered comparatively more appropriate as well because of its ability to simultaneously estimate multiple relationships between predictor and dependant variables in any structural model along with the measurements model's multiple observed or unobserved constructs (Ahmed et al., 2020) and in complex models including mediation (Faraz et al., 2021; Ma

et al., 2021). Smart-PLS has advantage of variance-based SEM as against covariance-based (CB-SEM) used in other applications (e.g. SPSS, AMOS) wherein separate treatment is required for data with respect to skewness and multi-collinearity before running the model. Moreover, it is not possible to simultaneously estimate multiple constructs in prediction-oriented models efficiently in other applications to handle multiple independent constructs despite the existence of multicollinearity.

Data analysis was performed in two stages. First, the measurement model was assessed through reliability, validity, internal consistency, and discriminant validity checks. For this purpose, composite reliability (CR), average variance extracted (AVE) were calculated. Subsequently, Discriminant validity was assessed through heterotrait-monotrait method (HTMT), which is now preferred by scholars in prediction-oriented studies and PLS-SEM. Stage two involved assessment of structural model through path coefficient, p-values, t-values, and confidence intervals. Model quality was assessed through PLS-PREDICT function as recommended by experts (Hair et al., 2020; Ringle et al., 2020).

RESULTS

A two-stage approach was used to assess results (Sarstedt et al., 2017). In first step measurement model is evaluated, and in the second step, the structural model is measured.

Assessing the Measurement Model

To evaluate the measurement model, items reliability constructs reliability, and validity were assessed through reflective indicators. Items' reliability of the latent constructs were measured through the minimum cut-off value of 0.5 for indicators. The majority of indicators Item loading exceeded the 0.70 value (see Table 3) and are between 0.484 and 0.926.

The internal consistency reliability of the variables was demonstrated through composite reliability (C.R.), considered a better measure of reliability as against Cronbach's alpha because it uses weighted items. All the variables have high CR ranging between 0.830 and 0.928, hence proposing sufficient reliability.

Convergent validity was measured through average variance extracted (AVE) suggested by Fornell and Larcker (1981). The AVE values of all the variables were higher than 0.5 and ranging between 0.553 and 0.764, therefore confirming that more than 50 percent of the variance in the construct is explained by its indicators, thus proves the convergent validity.

The discriminant validity (Table 4) was measured through the Fornell-Larcker as well as heterotrait-monotrait (HTMT) criteria formulated by Henseler et al. (2014), applying ratios of the correlations to measure the discriminant validity. HTMT for all the variables was under the threshold of 0.85, hence, confirming the discriminant validity (Sarstedt et al., 2017). The square root of AVE values is greater than other values in the relevant columns below the diagonal, thus confirming discriminant validity (Fornell & Larcker, 1981). Table 5 displays variance inflation factor (VIF) values that were below the recommended threshold of 3.

Table 3. Descriptive statistics

	Mean	SD	IU	IWB	PU	SAT	TMS
IU	5.27	0.106	1				
IWB	5.61	0.092	0.66	1			
PU	4.98	0.103	0.64	0.625	1		
SAT	4.83	0.205	0.501	0.481	0.449	1	
TMS	5.49	0.056	0.538	0.62	0.603	0.444	1

Table 4. Discriminant validity (HTMT)

	IU	IWB	PU	SAT	SL
IU					
IWB	0.565				
PU	0.594	0.585			
SAT	0.713	0.607	0.609		
SL	0.706	0.481	0.596	0.756	

Table 5. Collinearity statistics - Variance Inflation Factor (VIF)

	IU	IWB	PU	SAT	SL
IU					
IWB	1.51		1.02	1.14	
PU	1.33				
SAT	1.51				
SL		1.03			

Structural Model Assessment

For analyzing the structural model, the authors adopted the approach suggested by Hair et al. (2019). Firstly, the R^2 value of each latent construct was found to assure the in-sample predictive power; secondly, the out-of-sample predictive power was measured by PLS-Predict in SmartPLS. At last, bootstrap was run to assure the path coefficient significance in the structural model. Bootstrap 5000 samples were applied for this research, which comprised on identical numbers of observations as original sample to make the t values and standard errors.

R-square is the explanatory power and in-sample predictive power of a model. R^2 value explained the variance percentage in the dependent variable. The assessment of the structural model was carried out through a t-value test at a significance level of 0.05 while applying two-tailed estimation (Hair et al., 2013). According to the rule of thumb i.e., 1.96, all the hypotheses study were supported. Table 6 depicts the results of the structural model with R-square in the endogenous variable, while table 7 shows mediation path results. Researchers such as Chin (1998) suggested R-square values of 0.67 for substantial, 0.33 for moderately strong, and 0.19 for weak. The analysis indicates SL ($\beta=0.612$) explained 48.6% variance in IWB; while IWB explained 28.6% variance in SAT ($\beta=0.535$), 39.1% variance in PU ($\beta=0.437$). For IU, SAT ($\beta=0.479$), PU ($\beta=0.239$) and IWB ($\beta=0.320$) together explained 48.7% variance.

Model Quality, Predictive Strength, and Robustness

There is a possibility of overstating the predictive ability of any model if it only relies on the in-sample prediction, also known as an over-fitting problem, which indicates the limitation of any given model's ability to predict out-of-sample observations. For this purpose, additional checks are run using the PLS-predict function, which generates holdout-samples to predict outcome variable's indicators (Hair et al., 2019). As per expert advice, the authors performed PLSpredict with 10 folds ($k=10$) setting (Shmueli et al., 2019).

Results are interpreted by comparing values of RMSE between PLS and linear model (L.M.) because the errors had symmetric distribution. To ascertain the strength and robustness, the outcome

Table 6. Structural model results

	B	SD	t-Value	p-Value	Confidence Interval	
					2.50%	97.50%
SL -> IWB	0.612	0.008	76.50	<0.001	0.396	0.827
IWB -> IU	0.320	0.037	8.65	0.001	0.051	0.193
IWB -> PU	0.437	0.038	11.47	<0.001	0.361	0.507
IWB -> SAT	0.535	0.03	17.63	<0.001	0.465	0.589
PU -> IU	0.238	0.052	4.57	<0.001	0.132	0.334
SAT -> IU	0.479	0.043	11.06	<0.001	0.392	0.567

β = path coefficients, SD = standard deviation

Table 7. Specific indirect effects (Mediation)

	β	SD	T values	P Values	Confidence Interval	
					2.50%	97.50%
SL -> IWB -> IU	0.309	0.033	9.363	0.001	0.06	0.175
SL -> IWB -> PU	0.399	0.034	11.834	<0.001	0.33	0.461
SL -> IWB -> SAT	0.488	0.03	16.403	<0.001	0.42	0.541

must show all (for high predictive power) or the majority (for medium predictive power) of the items of predicted constructs to have lower RMSE values for PLS. If an equal number or a minority of indicators shows lower RMSE under PLS as compared with LM, then the model indicates low predictive power. Table 8 shows that all items had a lower RMSE for PLS, which indicates the strong predictive power of the model in this study.

Discussion

This study integrates organizational support and social exchange theories with ECT and technology literature. It serves as a response to earlier calls for research on teachers' technology acceptance (Nistor et al., 2014; Zhao et al., 2020) and academics' use of educational information systems (Al-Emran et al., 2016; Al-Emran et al., 2018). Moreover, it adds to the literature by studying the employees of higher education institutions from human resource management and change management perspective, analyzing the importance of the employee as a unit of change and user of technology. It adds to the knowledge-base on the subject of MOOCs and ISC model through the roles of supportive leadership and innovative work behavior in affecting behavioral change amongst employees.

Examining the continued use of IS, the current study empirically indicates that the use of group-based technologies in work settings is subject to supportive leadership and is also determined by individual employee's innovative work behavior. Furthermore, it contributes to the knowledge regarding the information systems and technology acceptance model from the employees' perspective in addition to the role of supportive leadership from the change management perspective.

It can be argued that any technology's ultimate success depends on continued post-adoption use rather than the initial acceptance. The underlying reason is its increasingly critical engagement of the student population in educational use; irregular or ineffective use by university employees contributes to the corporate failure of the educational system in the long run. This study helps understand supportive leadership's role and mechanism of its influence on continued use (distinct from initial acceptance) of technology.

Table 8. PLS-Predict results for model quality

	LM		PLS		Better predictive power (lower RMSE value)
	RMSE	Q ² _predict	RMSE	Q ² _predict	
IU1	0.727	0.184	0.650	0.348	PLS
IU2	0.710	0.172	0.634	0.339	PLS
IU3	0.688	0.243	0.640	0.345	PLS
IU4	0.662	0.230	0.620	0.324	PLS
SAT1	0.827	0.070	0.792	0.147	PLS
SAT2	0.957	0.085	0.913	0.167	PLS
SAT3	0.548	0.003	0.499	0.157	PLS
SAT4	0.566	0.151	0.503	0.330	PLS
PU1	0.717	0.106	0.681	0.194	PLS
PU2	0.540	0.154	0.476	0.341	PLS
PU3	0.775	0.386	0.620	0.606	PLS
PU4	0.450	0.110	0.411	0.257	PLS
IWB1	0.645	0.665	0.000	1.000	PLS
IWB2	0.881	0.392	0.820	0.473	PLS
IWB3	0.639	0.412	0.623	0.441	PLS
IWB4	0.617	0.723	0.581	0.630	PLS
IWB5	1.355	0.072	1.291	0.084	PLS
IWB6	0.714	0.736	0.619	0.643	PLS
IWB7	0.975	0.434	0.820	0.341	PLS
IWB8	0.707	0.456	0.623	0.441	PLS
IWB9	0.683	0.800	0.556	0.883	PLS
IWB10	1.500	0.080	1.291	0.157	PLS

The results on the ISC model variables are similar to a previous study by Bhattacharjee (2001), wherein satisfaction was a stronger predictor compared to perceived usefulness. The satisfaction of the user and perceived usefulness of the user are important or indirect predictors of continuance behavior of the user which is suggested by the strong intention-behavior association (Davis et al. 1989; Taylor and Todd 1995). The results show that innovative work behavior predicts perceived usefulness, satisfaction from use, and intention to continue using MOOCs. The influence of innovative behavior on perceived usefulness contrasts with the results of a study by Agarwal and Karahanna (2000), wherein an individual’s innovativeness, specific to technology, was not significantly related to perceived usefulness. Innovativeness has been indicated in the past research as negatively related to perceived usefulness (ham, 2009). However, the results are consistent with some studies indicating innovativeness predicts perceived usefulness (Cao et al., 2019; Dai et al., 2015; Lu et al., 2005). Joo et al. (2014) studied mobile learning technology adoption behavior among 350 students and found personal innovativeness to have a significant effect on perceived usefulness and perceptions of ease of use. Lewis et al. (2003), who concluded in a study of 161 faculty and instructors of universities to check the influence of individual and institutional factors on technology adoption, found

personal innovativeness was a significant predictor of PU and PEU. The results are also similar to a recent study that showed that institutional support in British higher education institutions helps better implementation of education management systems (Zhao et al., 2020). Similarly, in a study on the adoption of mobile technologies, innovativeness was a significant predictor of user perceptions (Lu et al., 2005). Dai et al. (2015) found that personal innovativeness is a predictor of technology innovativeness and adoption behavior.

Theoretical Implications

This study shows how the underlying principles of organizational support theory and social exchange theory translate from supportive leadership into innovative work behavior. It also integrates these human resource management concepts with the information system continuance model from the technology literature to explain employee perceptions in academic settings. Some interesting patterns emerge if we compare the result of the study and the prior TAM-based studies of acceptance of information systems. Satisfaction with IS use is the strongest predictor of users' continuance intention for MOOCs, followed by innovative work behavior and perceived usefulness, comparatively weaker yet significant predictors.

The impact of apparent value on employee expectations in both adoption and continuation settings verifies the vigor and remarkable quality of this relationship across transient phases of MOOCs use. The expectation confirmation theory (ECT) offers some intuitions to help understand this phenomenon. The pre-adoption attitude of the users is solely dependent on cognitive belief systems such as the perceived usefulness and ease of use. These beliefs possibly form through secondary information obtained from popular media, referent persons, or similar sources, which could possibly be biased. Therefore, user attitudes could become uncertain, inappropriate, and unrealistic.

On the contrary, post-adoption satisfaction depends on users' own primary experience of IS use. Therefore, bias is less likely to occur and is comparatively more realistic. Users could handle such uncertainties in effect because their more certain satisfaction overweighs uncertainties in continuance of technology use and underweighting more uncertain attitude in technology acceptance. This observation brings about significant practical implications for IS use. If the pre-acceptance behavior of the users is ignored, it may not have a severe effect on IS products or services acceptance between the new users. However, if the post-adoption user's satisfaction is ignored, it may sabotage the user's retention and continued use. As perceived usefulness is essential for the initial acceptance, satisfaction is crucial for the continuance intention. Organizations and others supply-side government bodies predisposed with increasing MOOCs usage can maximize their return on investment in employee training by following a two-fold strategy: inform new users about the possible benefits of MOOCs usage and educate the old user (continued) regarding the use of IS related to MOOCs effectively for maximizing their satisfaction and confirmation with the IS functions. Furthermore, satisfaction can also be crucial for illustrating the acceptance-discontinuance anomaly, a little-understood phenomenon in the IS usage studies. TAM, which anticipates the users' intention on the basis of attitude and perceived usefulness, may not explicate this anomaly satisfactorily unless either or both determinants change from positive to negative from the pre-acceptance stage onto the post-acceptance period.

Past research argued that technology acceptance behavior is not affected if users presumed the use of technology as an easy task or felt that a given technology would be advantageous (Brown, 2002 and Yu, 2012). Academic employees must receive continued supportive leadership. Such support improves their innovative work behavior, which induces continued use of MOOCs because it provides them with a platform to harness their innovative thoughts and abilities. Thus, there is a significant role of supportive leadership in predicting innovative work behavior of employees, which in turn positively affects their perceived usefulness and satisfaction for IS; this is also consistent with the results of a past study by Kim et al. (2010).

Practical Implications

Innovative ideas must translate into such applications that are beneficial in practice. The implementation of such ideas depends on activities that aim to introduce a new product/service, a new way to perform a task at the workplace, and the adoption of such stable practices to fit the context of organizational goals. Leaders have to be supportive of such innovative ideas through the provision of necessary resources needed to ensure implementation (Vincent-Höper & Stein, 2019) and encourage future efforts and ideas.

In the context of MOOCs' continued use, it is argued that supportive leaders can influence the employees through the internalization process. Leaders instill the employees with a value for MOOCs usage towards their job tasks and help them discover advantages of MOOCs for their work. This instigates a will to experience how the MOOCs can satisfy their needs as users. Supportive leadership, like a fiddle of pieces of training and feedback, additionally instills a propensity for learning and evaluating novel thoughts and software. This practice, when developed through a more extended timeframe, emerges as innovative behavior where the individuals are prepared to take on innovative ideas and are eager to participate in changing the system. Supportive leaders develop activities and ensure support by the technical teams for continuous specialized issues will encourage innovative behavior in the work environment; consequently driving on to better discernment towards the utilization of technology and satisfaction from its utilization, the ultimate result would be positive intentions to utilize MOOCs.

Support from leaders brings benefits for the management where feedback is returned by employees and also has an outgoing effect on employees' behavior. The feedback can let in suggested improvements for the plans for the post-implementation fixes required for ameliorating continued use among employees. For technologies to be more successful, for instance, IS for MOOCs, management needs to follow the fundamentals of the task-technology fit concept; which ensure that technology is well in line with the tasks required in the daily routines of the business and also in line with the employees' capability (Zhu et al., 2015). Employees that show high level of personal innovativeness (Kim et al., 2010), inclined to be critical for the task-technology fit viewpoint as well. The existence of supportive leadership assists in assuring timely judgment of change requires efficient systems that need timely and regular support from the employees.

The COVID-19 outbreak has triggered a surge in demand for distance-learning through online teaching in most parts of the world needing teachers to employ online learning platforms and techniques instead of the face-to-face mode. Closures of institutions has obliged teachers move swiftly onto online medium of instruction such as MOOCs. Universities need to provide moral, physical and financial support to employees to enhance their innovative behavior, and a fast pace due to the extreme conditions of COVID-19. Although modern times have seen reasonable focus on integrating technology at universities, more attention is needed to prepare and support the faculty in designing and using MOOCs to improve teacher capacity (Boltz et al., 2021). The Ministry of Education in China pushed institutions at all education levels to provide "Undisrupted Learning with Disrupted Classes" and have urged professional development of teachers to carry out online education (Huang et al., 2020). A wide-scale research (Dong et al., 2021) carried out in Beijing and Anhui provinces indicated positive attitude of the teachers in using MOOCs for "evaluation method, evaluation quantity, task exploration, and resource display, but learning resources, interactive platform, activity arrangement, classroom task, and communication quality."(p.24). The same has been indicated in clinical settings for providing continued education to students in the field of medicine (Olivares Olivares et al., 2021).

Supportive leadership lends a culture of inclusiveness for the employees. It would be helpful for the management in identifying the employees' innovativeness. In the post-implementation level, the communication and interaction made by the supportive leadership assist management in finding employees who have higher innovative tendencies. These innovative employees, who are possibly early adopters, are preferably the first group for rollout of MOOCs to confirm effective implementations and portraying positive insights onto co-workers for proposed technological change. Therefore,

supportive leadership may help establish the required steps to bring about the desired behavior among employees through suitable measures (Zainab et al., 2017). For instance, offering incentives to early adopters, assessing training needs, and holding awareness sessions.

LIMITATIONS

This research has been carried out to evaluate the university employees. Thus it is typically limited for the educational sector organizations. Moreover, from the technology usage point of view, the current study is carried out in an environment where the use of technology is mandatory and part of the routine task performance for employees during their job tasks. Therefore the results' generalizability is limited to only mandatory use work settings where the user does not have a choice to forego the technology use. Another important limiting aspect is that, although the results can be generalized within China and may need further confirmatory research in countries from the Asia Pacific region.

Similar to the study by Bhattacharjee (2001), this study also emphasized on current and continuing users of MOOCs. It is possible that current users may have biased perceptions as compared to discontinuers of MOOCs. However, it was beyond the scope of this study because it was not possible to contact the discontinued users to test for this bias. The individual responses show a range from 1 to 7 for the continuance intention model variables. This leads to conclude that some respondents may have intended to discontinue using MOOCs. Given that MOOCs are still in an early stage of evolution, it may be reasonably expected that some of these intended discontinuers would eventually discontinue MOOCs' use, which would alleviate the above bias. As in most cross-sectional studies, this study cannot establish causality between variables; therefore, future studies may be carried out with a longitudinal research design to establish causal relationships between leadership, innovative behavior, and MOOCs continued use. Furthermore, this study evaluated the role of supportive leadership as an enabler of innovative behavior; it did not include the employee creativity or creative self-efficacy towards MOOCs course design. Future works may include these variables, and study formal inclusive human resource practices and leadership styles such as inclusive leadership, servant leadership, and transformational leadership to establish which style is more influential in implementation and post-adoption continued use of MOOCs.

CONCLUSION

To successfully accept or adapt to the use of technology in an organization while considering the investment on systems and technology requires time and money; user acceptance is a critical aspect for this kind of change. This study supports the past research and also adds some in the literature with the effect of an organization's top-level management support to employees' attribute of innovative behavior, which helps in determining the long-term continued use of MOOCs and related information technology systems.

For future research, to make results more generalizable, more studies may be carried out outside of China in other developing countries where online education is on the rise and MOOCs are a relatively new concept. Furthermore, organizations other than the educational sector may be studied from the employee perspective of adoption and use of technology from a training and skill development perspective.

There is potential for replication of this study in the European region, particularly in Germany and UK. Technovia reported an anticipated growth rate of 15 percent in e-learning markets between 2019 and 2023. The UK was leading the e-learning market in 2018 with a 28% share, and Germany followed with France in third place (Businesswire, 2019). Germany had registered over 158,000 participants in distant learning programs in 2016, while approximately 17,000 e-learners enrolled for professional certification courses (Dieckmann & Zinn, 2017). MOOCs and related information systems can be of specific interest for future studies.

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Fawad Ahmed is an Assistant Professor with multidisciplinary research interests including leadership, innovation, technology management, organizational behavior and employee well-being. He recently completed his post-doctoral fellowship from Wuhan University of Technology and possesses over 15 years cumulative experience in operations management, business development, HR functions and technological change management with 07 years managerial experience in technology-intensive E-business environments.

Naveed Ahmad Faraz is a Postdoctoral Fellow in Hunan University. He obtained his PhD from Wuhan University of Technology. His research interests include servant leadership, green and pro-environmental behaviors and organizational behavior.

Nisar Ahmad is a PhD candidate in USTC. He is a graduate from school of information and management, Wuhan University.

Muhammad Khalid Iqbal works as an Assistant Professor. His research interests include marketing, e-commerce, technology management and internet of things.