Examining Individuals' Utilization of SPOC: Extending the Task-Technology Fit Model with Online and Offline Perspective

Completed Research Paper

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Abstract

Small Private Online Course (SPOC) platform enables individuals to carry out their learning tasks both online and offline. In order to understand individuals' utilization of SPOC, this study develops a research model to examine the joint influences of three types of perceived fit manifested in perceived technology-task fit (TTF), perceived individual-technology fit (ITF) and perceived online-offline fit (OOF). A survey was conducted in a famous university of China and 371 data were collected from students who selected courses on the SPOC platform. Structural equation modelling method was used to examine the research model. The empirical results suggest that ITF is the most significant antecedent of individual performance expectancy, followed by OOF and TTF. Moreover, individual performance expectancy has a positive influence on user satisfaction and individuals' continuance intention in the SPOC platform. A post-hoc analysis further indicates that student's GPA positively moderates the relationship between online participation behavior and course performance. This study extends the traditional perceived fit framework by introducing perceived online-offline fit, and uncovers the antecedents and outcomes of individuals' utilization in the emerging research context of SPOC.

Keywords: SPOC, Perceived Fit, Task-technology Theory, Utilization, Performance.

Introduction

With the development and popularity of information and communication technologies, a combination of online learning with the traditional offline learning method has become a new way of modern education in the past decade. In particular, Small Private Online Courses (SPOC) is advocated by Harvard University and Berkeley University boldly for a more customized learning experience (Fox, 2013; Coughlan, 2013). SPOC is defined as a blended learning course with a combination of offline and online learning. Different from the "massive" and "open" of MOOCs, SPOC is a small private and sometimes costly mixed-mode course, and the registered number is usually restricted within ten to hundreds (Fox, 2013; Chen and Yang, 2015). Because of the high participation rates and interactive feedbacks compared with MOOCs (Yousef et al., 2014; Jong, 2016; Yang et al., 2017), SPOC has attracted a lot of interest as a new technology-related blended learning model in higher education (Uijl et al., 2017; Jong, 2016; Fox et al., 2014; Kong, 2014; Fox, 2013). Recently, various online platforms have emerged in support of this emerging learning pattern. For example, the famous platforms of edX, Coursera, NovoED, and CUS-Global have adopted different forms of SPOC learning. Compared with developed countries, China responds to this new education market demand quickly. In 2017, China's online education market reached 194.12 billion RMB, and various teaching platforms developed rapidly, especially the SPOC platforms like iCourse, CNMOOC, Xuetangx, Rain Classroom, Moso Teach, Ketangpai, Unipus and Chaoxing (IResearch, 2017).

In the past five years, researchers have begun to investigate the technology-enhanced participation behaviors of SPOC from three general categories. The first category of research focused on task characteristics. Using the SPOC platform, students and teachers complete a series of online and offline actions for the purpose of learning and teaching activities, such as teaching requirements of fixed lectures, Q&A, video learning, discussion, homework and earning grades and certificates. (Uijl et al., 2017; Jong, 2016; Baepler et al., 2014; Kong, 2014; Hecking et al., 2014). The second research category oriented on individual characteristics. Scholars pointed out that based on the online learning and offline face-to-face interaction environment unique to SPOC, individual characteristics such as self-efficacy, competition, personalization, and habits have played important roles in improving learning outcomes (Liu et al., 2018; Freitas and Paredes, 2018; Kaplan and Haenlein, 2016). While the third category of research focused on technology characteristics. Platform technical guarantees such as technical feedback, interaction and sharing, online assessment metrics, and pedagogical strategies were identified as significant antecedents (Filius et al., 2018; Muñoz-Merino et al., 2015; Basogain et al., 2017; Cheng et al., 2017; Fox et al., 2014； Piccioni et al., 2014).

Although previous studies have provided us a theoretical foundation to understand individuals' learning behaviors in SPOC, most of the extant literature focused on one aspect of characteristics, whereas few studies have integrated the three sources of influence in a single research model. There lacks a comprehensive theoretical framework to explicate the joint influences of task, technology and individual characteristics on individual' precursors of utilization (beliefs, affect, etc) and subsequent behavioral intention in the SPOC platform (Wu and Chen, 2017). Drawing upon task-technology fit (TTF) theory, perceived task-technology fit and perceived individual-technology fit are indeed pivotal facilitators of task performance (Goodhue and Thompson, 1995). In the context of online learning, Yu and Yu (2010) examined the fit between individual characteristic and technology characteristics on learners' behavioral intention and utilization. In a recent study, Ouyang et al. (2017) investigated the effect of fit between task and technology characteristics on the outcome of technology utilization in the context of MOOCs. However, to our knowledge, little research has been conducted in the context of SPOC (Cheng et al., 2017; Pearson et al., 2012). It remains largely unclear regarding the fit issue in the new type of mix-mode learning.

Compared with MOOCs, a significant characteristic of SPOC is the combination of online and offline learning. Thus in addition to the perceived task-technology and perceived individual-technology fit, a worthwhile research question is to discover how online-offline task fit influence individuals' utilization and subsequent learning performance, and how does the influence mechanism occur. The conceptualization of online to offline fit has been proposed in several research contexts. For example, Levin et al. (2005) argued that online product information should match the offline physical perception in e-commerce like multi-channel retail alliances. In the context of SPOC, online-offline fit demonstrates that online learning materials must be malleable and can perfectly correspond to the desired knowledge points of offline learning in the classroom. Thus, the online-offline fit is extremely important in the context of SPOC and should be conceptualized in the research framework to examine its influence on individuals' learning behaviors.

The remaining open research question drives the research motivation of this study. Overall, this study has three major research motivations. Firstly, this study aims to examine the influence of three types of perceived fit in the context of SPOC, regarding perceived task-technology fit, perceived individual-technology fit and perceived online-offline fit, on individuals' cognitive and affective reactions. Secondly, this study aims to investigate if individuals' cognitive and affective reactions are positively associated with their utilization (manifested in continuance intention and participation behaviors). Thirdly, this study aims to examine if there is a positive relationship between individuals' participation behaviors and course performance in the SPOC learning. The rest of the paper is organized into five sections. The next section thoroughly presents perceived fit theory as a theoretical foundation. Then we establish a research model and propose the potential relationships among constructs. Section four describes the research method, discusses statistical analysis outcomes of the main model, and conducts a post-hoc analysis. The last two sections summarize research findings and implications.

Perceived Fit Theory

Goodhue and Thompson (1995) proposed the theory of task-technology fit (TTF) based on cognitive psychology and behavior analysis, and explored the mechanism of task requirements and information technology characteristics on utilization and task performance. Drawing upon TTF, information technology must match the user's task requirements in order to predict the utilization and generate good performance (Cane and McCarthy, 2009; Aljukhadar et al., 2014; Oliveira et al., 2014; Wu and Chen, 2017). Later, researchers extended TTF model by introducing a new construct of individual-technology fit (ITF), which emphasizes the match between technology attributes and individual characteristics (Yu and Yu, 2010; Liu et al., 2011; Parkes, 2013). The TTF theory has been widely applied in research contexts of e-commerce, mobile commerce, social network and e-learning (Goodhue and Thompson, 1995; Aljukhadar et al., 2014; Oliveira et al. 2014; Lee et al., 2007; Lu and Yang, 2014; Wu and Chen, 2017). This study draws upon TTF theory as an overarching framework, and introduces both task-technology fit and individual-technology fit in the research model to examine their effects on individuals' utilization behaviors. Specifically, task-technology fit is defined as the degree to which a technology assists an individual in performing his or her portfolio of tasks (Goodhue and Thompson, 1995; Lee et al., 2007). Individual-technology fit refers to the ability of technical tools to match operational utilization and problem resolution based on individual requirements (Yu and Yu, 2010; Liu et al., 2011; Parkes 2013).

In the context of SPOC, the online-to-offline fit is recognized as another significant attribute that influences individuals' learning behaviors. In order to enhance learning performance, online and offline contents must be highly related and consistent. In particular, SPOC's online learning contents must match offline classroom education. Students first achieve online resources, share knowledge, techniques and methods, complete tasks initiatively in the online learning platform. Then teachers will lead students to project training and summarize key knowledge points in the offline classroom education. After class, students will achieve a series of contents, like online testing and homework training to strengthen consolidations of the knowledge. Although the contents in the online platforms are well packaged, the quality of compatibility and complementary between online and offline learning is barely satisfactory (Margaryan et al., 2015). Accordingly, this study introduces online-to-offline fit in the research model to examine its influence on students' performance expectancy and subsequent continuance intention in the SPOC platform, and defines it as the degree to which the online task content is relevant and consistent with the offline classroom learning.

Research Model and Hypotheses

Overall, this study adopts and extends Goodhue and Thompson (1995)'s TTF framework to test the effects of three significant fit antecedents, specifically TTF, ITF and OOF, on users' utilization in the SPOC platform. We argue that the three perceived fits are positively associated with individuals' cognitive and affective reaction, which in turn facilitate their continuance intention of SPOC. Besides, there will be a positive relationship between individuals' continuance intention and actual online participation behaviors. Drawing upon TTF framework, performance expectancy is introduced in our research model as a cognitive reaction to the three fit antecedents. Moreover, satisfaction is introduced in the research model as an affective reaction to performance expectancy, as suggested in the previous literature (Bhattacherjee, 2011).The proposed theoretical model is presented in Figure 1.

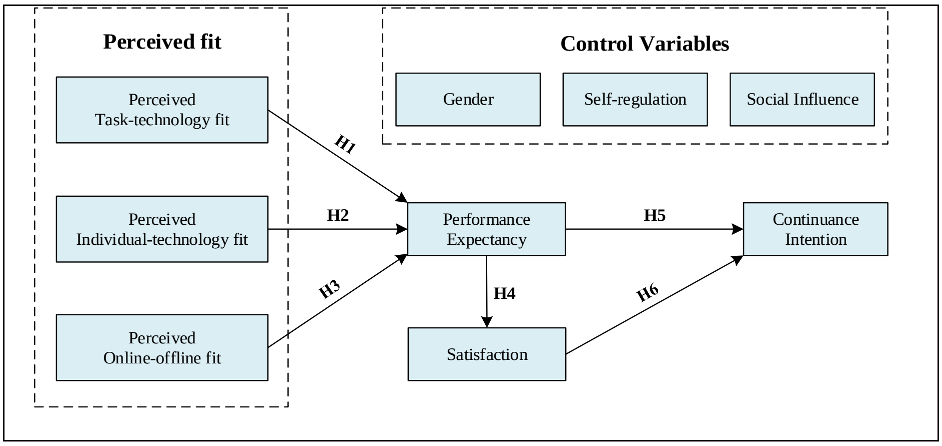

Figure 1. Research Model

Perceived Fit and Performance expectancy

Drawing upon task-technology fit theory, a match between technology features and task requirements can lead to a positive attitude (Liu et al., 2011; Parkes, 2013; Cane and McCarthy, 2009). In the context of SPOC, perceived task and technology fit (TTF) is defined as the degree to which the features provided in the online platform "fit" the requirements of students' tasks (Wu and Chen, 2017). Ouyang et al., (2017) reported that the explicit connection between the technology and task offered in the MOOCs platform could determine the individual's perception of utilization. Lin (2012) revealed that task and technology fit was positively related to individuals' perceived value when using Virtual Learning System. In a classroom environment, Raven et al., (2010) found that there was a significant fit between digital video technologies and usefulness (precursors of utilization). In the context of SPOC, individuals' evaluation regarding whether the platform technology meets the needs of users' tasks will positively affect expected consequences of utilization in the platform (Goodhue and Thompson, 1995).

In addition to the fit between the technology and task, the match between individuals' needs with technology features (ITF) also plays a significant role in facilitating individuals' attitude and utilization (Goodhue and Thompson, 1995; Parkes, 2013; Liu et al., 2011; Yu and Yu, 2010; McGill andKlobas, 2009; Zigurs and Khazanchi, 2008). A higher consequence of utilization is guaranteed when an appropriate and useful technology is provided in accordance with individuals' learning habits and abilities (Goodhue and Thompson, 1995). In this study, ITF is defined as whether the online technology functionalities and features in the SPOC platform match with individuals' learning styles (Yu and Yu, 2010; Wu and Chen, 2017). When there exists a higher fit between technology and individuals' learning styles, a higher expectation of utilization will be generated (Cane and McCarthy, 2009)

Moreover, this study introduces the perceived fit between online and offline contents (courses and tasks) as a significant antecedent of users' precursor of utilization. In the context of SPOC, online-offline fit (OOF) refers to the degree to which online course and task characteristics match with the offline learning contents. OOF demonstrates that online learning materials must be malleable and can perfectly correspond to the desired knowledge points of offline learning in the classroom. Specifically, the designed contents of online unit tests, assignments and exams (Uijl et al., 2017; Jong, 2016; Baepler et al., 2014; Kong, 2014; Hecking et al., 2014) must be consistent with the offline learning contents. In the SPOC environment, students are more likely to generate a positive attitude towards the SPOC learning style when they perceive a greater fit between online and offline contents.

Performance expectancy is defined as the extent to which students believe that using the SPOC platform will help them to attain benefits in course performance (Wang et al., 2009). Goodhue and Thompson (1995) indicated that there was a positive relationship between perceived fit and precursors of utilization. Accordingly, this study introduces performance expectancy as a significant precursor of utilization in the context of SPOC, and considers the three perceived fit as significant antecedents of performance expectancy in terms of using SPOC. The following hypotheses are proposed:

H1. TTF is positively related to performance expectancy of SPOC;

H2. ITF is positively related to performance expectancy of SPOC;

H3. OOF is positively related to performance expectancy of SPOC.

Performance expectancy and satisfaction

In the context of SPOC, satisfaction represents a pleasurable or positive emotional state resulting from the feelings and appraisals of the learning experience on the SPOCs platform (Liaw, 2008). Satisfaction pertains to the precursors of utilization as the construct of affect toward using (Goodhue and Thompson, 1995, p.218). Researchers have empirically tested the positive link between perceived fit, expected consequences and affect (satisfaction) respectively (Venkatesh et al 2003; Lin, 2012; Ouyang et al., 2017; Goodhue and Thompson, 1995). Bhattacherjee (2001) highlighted that the "belief-affect-intention" was the causality characteristic of most IS use theories. In particular, a good performance expectancy (belief) has a positive effect on users' affective reaction (Szajna and Scamell, 1993). Therefore, we propose the following hypothesis:

H4. Performance expectancy is positively related to satisfaction of SPOC.

Performance expectancy and continuance intention

In the context of SPOC, continuance intention refers to the continued learning in the SPOC platform by adopters, where a continuance decision follows an initial acceptance decision (Wu and Zhang, 2014; Wu and Chen, 2017). Researchers have empirically tested the positive relationship between performance expectancy and utilization (Goodhue and Thompson, 1995; Cane and McCarthy, 2009). Utilization can be regarded as the behavioral intention to adopt and use a technology (Lin, 2012; Yen et al., 2010; Zhou et al., 2010). Venkatesh et al. (2003) pointed out that performance expectancy had a significant influence on behavioral intention. Wang et al. (2009) also empirically proved that performance expectancy could significantly affect continuance intention. There, we propose the following hypothesis:

H5. Performance expectancy is positively related to continuance intention of SPOC.

Satisfaction and continuance intention

Satisfaction is a significant affective reaction based on expectation-confirmation theory (ECT) (Oliver, 1980). The positive relationship between satisfaction and continuance intention is reported in various research contexts (Bhattacherjee, 2001; Susanto et al., 2016; Oghuma et al., 2016). Specifically, Ouyang et al. (2017) revealed that higher satisfaction was beneficial to promote the continuance intention of online learning. Lin (2012) proposed that satisfaction had a positive effect on continuance intention of virtual learning system in blended-learning instruction. Accordingly, this study proposes that when users are satisfied with SPOCs, their continuance intention will be significantly enhanced. The following hypothesis is proposed:

H6. Satisfaction is positively related to continuance intention of SPOC.

Research Methodology

Data collection

A survey was conducted to empirically examine the research model. Previous literature argued that university students were a major group of SPOC learning since they have to complete a series of online and offline actions based on required pedagogic material prepared by universities (Kaplan and Haenlein, 2016). Thus, this study collected data from university students via a SPOC platform at a well-known university in China. Questionnaires were distributed to two groups of students from Sept.17th to Nov.8th in the year of 2017 and 2018 respectively. Subjects of investigations were students at Sophomore level who have taken the specific course (Management Information Systems) by one SPOC platform called iCourse to integrate with offline learning. Two learning groups were treated with identical learning content and teaching staff. After two-week study (e.g. watching relevant videos, interaction, sharing and online assessment metrics), a survey link was administered to students on the SPOC platform. The students were encouraged to participate in the investigation to get extra credit. The sample collected during two semesters consisted of 384 students. After filtration of invalid samples with missing or inaccurate data, 10 respondents of 23 invalid samples was contacted to refill the questionnaire carefully. Finally, we got 371 valid datasets for analysis left with only 13 invalid. Moreover, objective data (completion ratio, learning duration) collected from the backstage database on the SPOC platform purvey as the complement to single data sources and corroboration for actual participation. Participants' first-year GPA were obtained from their university records (with permission). Table 1 describes the demographics of the overall sample.

Table 1. Sample Characteristics

Items	Types	N	%	Items	Types	N	%
Gender	Male	182	49.1	Completion ratio	100	170	45.8
	Female	189	50.9		80-100	95	25.6
					60-80	42	11.3
					Below 60	64	17.3
Learning Duration	Above 5 hours	63	17.0	GPA Percentile	Above 90	46	12.4
	4-5 hours	55	14.8		80-90	166	44.7
	3-4 hours	58	15.6		70-80	104	28.0
	2-3 hours	71	19.2		60-70	41	11.1
	1-2 hours	56	15.1		Below 60	14	3.8
	Below 1 hour	68	18.3				

Note: N represents numbers, % represents percentage

Instrument design

This study referred to the previous literature to operationalize the items for each construct, using 7-point Likert scale ranging from "strongly disagree"(1) to "strongly agree"(7). All psychometrical properties of scales were measured as first-order reflective constructs by three items. Perceived task-technology fit and perceived individual-technology fit were adopted from SPOC literatures (Wu and Chen, 2017; Yu and Yu, 2010). Performance expectancy, satisfaction and continuance intention were adopted from e-learning literature (Wang et al., 2009; Liaw, 2008; Wu and Zhang, 2014). Items for perceived online-offline fit were developed following a procedure of literature review, expert panel and content validity test, and three items were developed for this construct. Sample items are illustrated as follows: *"Contents on the SPOC platform fit for the requirements of my learning in offline courses"*, *"Contents on the SPOC platform fit with my knowledge expansion from offline courses"*, *"Contents on the SPOC platform are suitable for helping me absorb knowledge in offline courses"*.

Specifically, participation behavior is modeled as a first-order latent variable using the first-hand objective data (learning duration and completion ratio). Learning duration and completion ratio for learning tasks are identified as evaluation index for utilization rate in e-learning context (Farinella, 2007; Cane and McCarthy, 2009). Performance impacts are measured by the examination scores of the course using the first-hand objective data (Baepler et al., 2014). GPA percentile is gleaned to reflect the student ability/aptitude spectrum (Baepler et al., 2014). The objective measurements are employed in post-hoc analysis. The items were translated into Chinese and a double check was conducted by Ph.D. students to guarantee the translation accuracy of the instrument. A pilot study was conducted before the final data collection, and a total of 57 SPOC participants were invited to complete the questionnaires. We adjusted a few items with factor loadings lower than 0.7 to improve the validity of the constructs (Chin et al., 2003). Table 2 describes the items for each construct and the corresponding references.

Structural equation modeling analysis

Structural Equation Modelling (SEM) approach was used to examine the research model (Gefen et al., 2000). In particular, SmartPLS v3.2.1 was selected as a primary tool for statistical analysis since its suitability for handling large and complex model (Chin, 2010; Addas, 2018), and is more appropriate for theory exploration and prediction compared with covariance-based SEM methods (Gefen et al., 2000). The sample size of 371 can satisfy the requirements of PLS—either 10 times the larger measurement number within the same construct or 10 times the larger construct number affecting the same construct (Chin et al., 2003). Moreover, research on how perceived fit impacts SPOC continuance intention is at an early stage of theoretical development, thus it is more appropriate to apply PLS for data analysis since it does not impose stringent restriction (e.g. uncorrelated measurement error) for nascent research (Chin, 2010; Addas, 2018).

Measurement model analysis

Following a two-step analysis procedure, the measurement model was examined to assess the reliability, convergent validity, and discriminant validity of the constructs. As illustrated in Table 2, the item loadings of each construct have exceeded 0.7, and the Cronbach's alpha for each construct is highly above 0.7, indicating a good internal consistency and reliability of the items. In addition, the average variance extracted (AVE) from each construct is higher than 0.5, demonstrating an adequate convergent validity of the measurement model (Chin et al., 2003).

Discriminant validity of the constructs is evaluated by examining if the square root of the AVE for each construct exceeds that construct's correlation with other constructs (Chin et al., 2003). This study conducted a correlation analysis according to the above criterion. As noted in Table 3, the square root of the AVE for each construct (the values on the diagonal) is higher than that construct's correlation with other constructs, suggesting an adequate discriminant validity of the measurement model (Chin et al., 2003).

Table 2. Descriptive Statistics and Reliability Coefficients for Constructs

Construct	Items	Loading	Alpha	CR	AVE	Scales Sources
Perceived Task-technology Fit (TTF)	TTF1 TTF2 TTF3	0.915^{***} 0.952^{***} 0.938^{***}	0.93	0.96	0.88	Adapted from Wu & Chen (2017)
Perceived Individual-technology Fit (ITF)	ITF1 ITF2 ITF3	0.933^{***} 0.933^{***} 0.830^{***}	0.88	0.93	0.81	Adapted from Yu & Yu (2010); Wu & Chen (2017)
Perceived Online-offline Fit (OOF)	OOF1 OOF2 OOF3	0.907^{***} 0.908^{***} 0.895^{***}	0.89	0.93	0.81	Adapted from Lu & Yang (2014)； Wu & Chen (2017)
Performance Expectancy (PE)	PE1 PE2 PE3	0.917^{***} 0.924^{***} 0.913^{***}	0.91	0.94	0.85	Adapted from Wang et al. (2009)
Satisfaction(SAT)	SAT1 SAT2 SAT3	0.936^{***} 0.925^{***} 0.945^{***}	0.93	0.95	0.85	Adapted from Liaw (2008)
Continuance Intention(CI)	CI1 CI2 CI3	0.968^{***} 0.969^{***} 0.946^{***}	0.96	0.97	0.92	Adapted from Wu & Zhang (2014)； Wu & Chen (2017)

Self-regulation(SR)	SR1 SR2 SR3	0.904*** 0.909*** 0.923***	0.90	0.94	0.83	Adapted from Wang et al. (2009)
Social Influence(SI)	SI1 SI2 SI3	0.942*** 0.953*** 0.896***	0.92	0.95	0.87	Adapted from Giannakos &Vlamos (2013); Wu & Chen (2017)
Participation(PA)	Duration Completion	0.935*** 0.898***	0.81	0.91	0.84	

Note: T test are significant at: *P<0.05, **P < 0.01, ***P < 0.001

Table 3. Correlations of Latent Variables

	Mean	S.D.	TTF	ITF	OOF	PE	SAT	CI	SR	SI	PA
TTF	5.907	0.917	**0.94**								
ITF	5.618	1.091	0.72	**0.90**							
OOF	5.886	0.936	0.76	0.72	**0.90**						
PE	5.836	0.977	0.75	0.80	0.72	**0.92**					
SAT	5.832	0.891	0.71	0.72	0.67	0.78	**0.92**				
CI	5.844	1.025	0.70	0.77	0.63	0.80	0.79	**0.96**			
SR	5.355	1.088	0.43	0.51	0.36	0.45	0.46	0.42	**0.91**		
SI	5.580	1.128	0.64	0.56	0.60	0.57	0.52	0.57	0.31	**0.93**	
PA	4.518	1.859	0.08	0.05	0.04	0.08	0.09	0.05	0.06	0.06	**0.83**

Structural model analysis for the full sample

The structural modelling analysis was conducted to examine the path relationship and explanatory power of the research model. Bootstrapping procedure method was used to calculate the statistical significance of the parameter estimates, which is beneficial to derive valid standard errors or t-values (Temme et al., 2006). In particular, this study included gender, self-regulation and social influence as control variables in the research model, as suggested in the previous literature. The analysis result is described in Figure 2.

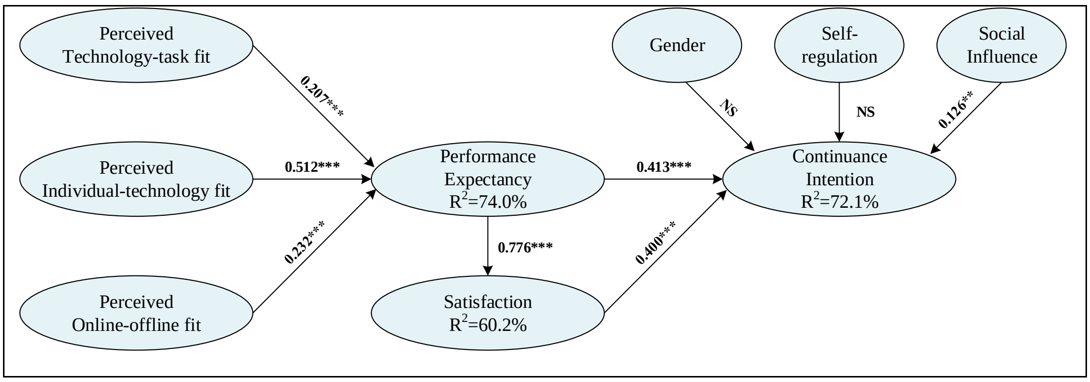

Figure 2. Structural model analysis

As illustrated in Figure 2, perceived task-technology fit, perceived individual-technology fit and perceived online-offline fit have strong influences on performance expectancy (β1=0.207, p<0.001; β2=0.512, p<0.001; β3=0.232, p<0.001). Performance expectancy is positively associated with satisfaction and continuance intention (β1=0.776, p<0.001; β2=0.413, p<0.001). Satisfaction is positively related to continuance intention (β1=0.400, $p<0.001$). The empirical results can support the hypotheses of H1-H6, which suggest that positive perceptions based on three dimensions of perceived fit, boost performance expectancy directly, and satisfaction indirectly, which promote the continuance intention on the platform eventually. In terms of the influences of control variables, Figure 2 suggests that social influence is positively associated with continuance intention (β1=0.126, $p<0.01$), while gender, self-regulation have no significant influences on continuance intention. The results indicate that individuals are more likely influenced by peers' suggestions and recommendations when participating in the SPOC platform.

Regarding the explanatory power of the research model. As presented in Figure 2, the three dimensions of perceived fit can explain 74.0% of variance for performance expectancy, which in turn explains 60.2% of variance for satisfaction and 72.1% of variance for continuance intention. Basically, the analysis results suggest a good explanatory power of the theoretical model.

Mediation Test

In order to examine if performance expectancy mediates the relationship between perceived fit and satisfaction, this study followed Sobel (1986)'s procedure to test if the relationship between independent variables (IV) and dependent variables (DV) are reduced (partial mediation) or completely diminished (full mediation) after adding mediation variables (MV) into the structural model. As noted in Table 4, all mediation path relationships have passed the significance examination. We then used the bootstrapping method with bias-corrected confidence estimates to test the mediating effects. The analysis showed that the indirect effects of TTF, ITF and OOF on intention were significantly mediated by performance expectancy, and the indirect effects of performance expectancy on intention was significantly mediated by satisfaction, with a 95% confidence interval excluding zero (Preacher and Hayes, 2008). Overall, results from the Sobel test and bootstrapping method are consistent.

Table 4. Mediation Test Results

Path	Sobel test	Boot β	Boot SE	Confidence interval (95%)		Mediation effect
				Lower	Upper	
TTF→PE→SAT	3.44***	0.41	0.0459	0.32	0.50	Partial
ITF→PE→SAT	9.90***	0.37	0.0455	0.28	0.46	Partial
OOF→PE→SAT	4.61***	0.42	0.0425	0.34	0.51	Partial
PE→SAT→CI	4.26***	0.34	0.0553	0.24	0.46	Partial

Note: *P < 0.05, **P < 0.01, ***P<0.001

Post-hoc Analysis

Drawing upon Goodhue and Thompson (1995)'s framework, utilization is positively associated with individual performance. In the context of SPOC, utilization is manifested in students' continuance intention and participation behaviors in the platform, and performance refers to their examination scores of the course. With regard to the potential influence of participation on performance, this study further conducts a post-hoc analysis to examine the relationship between utilization and individual performance in the SPOC platform. Statistical analysis results suggest that continuance intention has no significant effect on participation (β=0.050, NS), whereas participation is significantly associated with individual performance (β=0.388, p＜0.001). The results indicate that individuals' actual participation behaviors play a more significant role in enhancing their performance in the SPOC. However, continuance intention is not significantly associated with participation. The result is understandable in SPOC context, since studying on SPOC may not get much enjoyment and autonomy (Ouyang et al., 2017). In the beginning, students are likely to have initiative and intention to the SPOC platform to equip themselves, but long-term participation is consuming and inevitably arouse the feelings of tedious even reluctant (Ouyang et al., 2017), leading to the incoherence between continuance intention and participation.

Furthermore, previous literature demonstrates that the effects of participation on individual performance may be contingent upon their GPA (Grade-Point Average) (Farinella, 2007; Baepler et al., 2014). Thus this study also conducts a post-hoc analysis to explore whether the impact of participation on performance differs according to the GPA level in the context of SPOC. The overall sample is divided into two groups based on the average score of the participants (80.04), with one group of participants' GPA level more than 80.04 (High-GPA, N1=212), and the other group of participants' GPA level less than 80.04 (Low-GPA, N2=159). Following the calculation approach suggested by Zhou et al. (2014), this study statistically tests the significance of path coefficient differences across the two sub-groups.

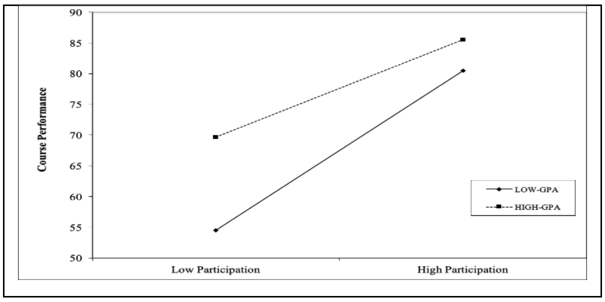

Figure 3. Interaction Effect Plot

The multi-group PLS test results reveal that participation behavior has a significant effect on performance for both the High-GPA group and Low-GPA group (β_High-GPA=0.168, SE=0.067, $p<0.05$; β_Low-GPA=0.301, SE=0.074, $p<0.001$; tspooled=18.09, $p<0.001$). To further interpret the significance of interaction effect, we employed a two-way interaction plot (Serrano and Karahanna, 2016) (see Figure 3). Notably, when participants' learning skills are low (low GPA grade), their participation behaviors in SPOC platform becomes an important determinant of course performance. It explicates that participation behaviors can compensate for personal learning skills (manifested in GPA).

Theoretical and Practical Implications

This study makes three major contributions to the existing literature. Firstly, this study uncovers the three aspects of perceived fit that promote individuals' performance expectancy. Previous literature primarily examined one aspect of task-technology fit (TTF) or individual-technology fit (ITF) on individual' affective reaction and subsequent behavioral intention (Wu and Chen, 2017; Ouyang et al., 2017; Lin, 2012; Raven et al., 2010; Parkes, 2013; Liu et al., 2011; Yu and Yu, 2010), while ignoring the combination of online and offline learning in the emerging context of SPOC. In particular, this study extends Goodhue and Thompson (1995)'s framework by introducing the online and offline fit (OOF) in the context of SPOC. It is found that students' performance expectancy will be significantly enhanced if they perceive a higher fit between online and offline learning. The research findings can enrich our understanding of SPOC learning from a perceived fit theoretical perspective. Secondly, our research model warrants a likelihood of a connection among perceived fit with performance expectancy, satisfaction and continuance intention. The results reveal the mediating effect of performance expectancy between perceived fit and satisfaction, compensating for direct effects tested by previous literature (Ouyang et al., 2017; Oliveira et al., 2014; Lin, 2012). The proposed model is supported by high explanatory power, whichexplains 74.0% of variance of performance expectancy compared to 48.5% by Oliveira et al. (2014), and explains 60.2% variance of satisfaction compared to 35% by Lin (2012). Thirdly, our research offsets the deficiency of the existing literature that uses subjective data to measure individuals' participation (Lin, 2012; Yu and Yu, 2010). In particular, we use the first-hand objective data to measure students' online participation behaviors from two aspects of learning duration and completion ratio. We confirm the positive relationship between online participation behaviors and course performance, and identify the interaction effect of participation behaviors and GPA on students' performance in the context of SPOC learning.

The empirical findings also provide several important practical implications for the business operators and practitioners of SPOC platform. The platform operators need to provide more automation usability of tools to make a better match between task and individual characteristics, in order to promote students' learning efficiency and customization (e.g. AI, Big Data). Specifically, the operators should develop a design framework that can standardize high-quality SPOC contents, and pay attention to the combination of online and offline learning experience. Meanwhile, the business operators should recognize that course campaigns have focused on prominent advantages (like good online & offline contents quality, customization) to enhance students' positive affective reactions and subsequent utilization. Last but not least, the practitioners must deepen the blended learning scenarios to increase the importance of online learning and stimulate students' initiative and fun instead of just earning grades. For the issue of GPA differences, it is necessary to remind and encourage Low-GPA achievers to participate in platform learning in order to achieve better results, especially when they do not have good knowledge offline. However, for High-GPA achievers, participation in SPOC is not as significant as Low-GPA achievers. These students can be motivated to follow their own offline learning and flexibly combined with SPOC platform to reinforce their knowledge.

Conclusions and Future Research Directions

Drawing upon Goodhue and Thompson (1995)'s TTF framework, this study develops a theoretical model to examine the perceived fit antecedents that promote individuals' performance expectancy, satisfaction and continuance intention in the SPOC platform. A survey was conducted in a famous university of China, and 371 valid Data was collected. Structural equation model-ling (SEM) method was used to examine the research model and corresponding hypotheses. The empirical results show that perceived task-technology fit, perceived individual-technology fit and perceived online-offline fit are significant antecedents of individuals' performance expectancy. Furthermore, performance expectancy is beneficial to increase participants' satisfaction, which in turn promotes their continuance intention in the SPOC platform. Meanwhile, a post-hoc analysis further indicates a positive relationship between participation behaviors and online course performance, and reveals a significant moderating effect of GPA regarding the influence of participation on performance. Although this study provides several theoretical and practical contributions, there are still some limitations that leave open future research directions. Firstly, the survey data of this study is based on one university of China, future research can be conducted in other universities or countries, to generalize the research findings of this study. Secondly, given the fact that the participants are from one specific teaching program, the generalization of the results should be cautiously taken when implementing a different teaching program. Thus we suggest future works to employ a more rigorous experimental design to verify the results. Thirdly, it will be an intriguing study to investigate the online and offline fit in various business contexts, like physical and online retailing, games with augmented reality or sharing economy. Fourthly, the relationship between SPOC continuance intention and participation should be further tested, and the participation construct should be developed and integrated with more items, like use frequency and online comment quantity. Last but not least, future study can incorporate other demographic variables (e.g., use experience, educational level and nationality) as moderators, to examine if there exist behavioral differences in different user groups.

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