Examining key factors of beginner’s continuance intention in blended learning in higher education

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Accepted: 20 April 2022 / Published online: 26 May 2022
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Abstract
With the outbreak of the COVID-19 pandemic, blended learning became exceptionally widespread, especially in higher education. As a result, many college students became beginners in this learning method. To identify key factors that impact beginners’ continuance intention in blended learning, this study surveyed 1845 first-year college students at a university in central China in the falls of 2020 and 2021 who used blended learning for the first time. Structural equation modeling was employed to verify a model that integrates intrinsic motivation and academic self-efficacy in the Expectation-Confirmation Model of Information System Continuance. The results show that performance expectancy, intrinsic motivation, and satisfaction significantly impact beginners’ continuance intention in blended learning. Moreover, performance expectancy, intrinsic motivation, and confirmation significantly impact beginners’ continuance intention through mediating variable satisfaction. Academic self-efficacy does not directly impact college students’ continuance intention but indirectly impacts their continuance intention through intrinsic motivation. Finally, this study provides suggestions for educators to improve beginners’ blended learning experience thus promoting their continuance intention in blended learning.

Keywords Blended learning · Continuance intention · Expectation-confirmation model · Intrinsic motivation · Academic self-efficacy

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Introduction

Blended learning refers to face-to-face (F2F) instructions combined with computer-mediated instructions (Bonk & Graham, 2012). It is in line with the values of higher education institutions and has been shown to improve both the efficacy and efficiency of meaningful learning experiences (Garrison & Kanuka, 2004). Numerous studies have shown that this method can improve pedagogy, increase access and flexibility, and improve cost-effectiveness (Baepler & Driessen, 2014; Bonk & Graham, 2012; Wei et al., 2017; Yang, Zhu, & MacLeod, 2016). Therefore, blended learning has attracted much attention from educators and has been predicted to become the mainstream learning method in the future and a short-term key trend for the promotion of the application of higher education technology (Johnson et al., 2015). This is particularly true in light of the current worldwide outbreak of the COVID-19 pandemic, in response to which the promotion of flexible learning methods such as blended learning has reached an unprecedented level. Studies reported that blended learning will become an everyday learning model rather than a crisis-response migration method (Johnson, Veletsianos, & Jeff, 2020; Pelletier et al., 2021). For example, in China, a nationwide survey of over 600 million instructors and students at universities, which was implemented from 7 to 14 April 2020, showed that more than 80% of instructors planned to implement online learning or blended learning after the pandemic (Yang, 2020). This outlook is widely supported not only in China but also in the rest of the world (Pelletier et al., 2021).

In such a large-scale transformation of the prevailing teaching and learning mode, many students with diverse backgrounds in higher education become new practitioners of blended learning. The question remains whether these beginners will continue to use blended learning as their mainstream course model even after the pandemic. Compared with their acceptance level, their continuance intention can reflect their direct attitude, rather than indirect willingness impacted by others. Identifying the key factors that impact beginners’ continuance intention is important for supporting their learning and helping them to succeed in continuing with blended learning courses. It is also important for administrators, course designers, and instructors to understand students’ perspectives and provided feedback on blended learning (Pelletier et al., 2021). Although considerable research has focused on the acceptance of blended learning (Padilla-Meléndez et al., 2013; Tselios et al., 2011), research on the willingness of beginners to continue with such a new learning model after initial attempts is rare. Therefore, this study tracked the continuation intention of new learners following their first blended learning course in college and identified key factors that impact beginners’ continuance intention in blended learning. The authors hope that the results of this study will help instructors, course designers, and administrators to design, refine, and maintain large-scale blended learning in higher education.
Theoretical framework

This study is mainly based on the Expectation-Confirmation Model of Information System Continuance (ECM-ISC). In addition, two key personal factors (i.e., intrinsic motivation and academic self-efficacy) are considered because of the complexity of blended learning.

Expectation-confirmation model of information system continuance

One of the most common models for measuring continuance intention is ECM-ISC (Bhattacherjee, 2001), which is based on Expectation Confirmation Theory (ECT) and Technology Acceptance Model (TAM). ECT is a cognitive theory that was widely used in consumer behavior literature to evaluate consumer satisfaction after purchase and intention of repurchase (Oliver, 1977, 1980). It originally appeared in psychology and marketing literature. TAM is a theory of information systems that describes how consumers accept and use an information system. TAM considers that perceived usefulness and ease of use are linked to information system acceptance behavior (Davis, 1989).

As shown in Fig. 1, the ECM-ISC model includes four core variables: perceived usefulness, confirmation, satisfaction, and information system continuance intention. Previous studies showed that this model could be used for effective measurements of continuance intention in e-learning (Roca & Gagné, 2008; Sørebo et al., 2009), massive open online courses (Daneji, Ayub, & Khambari, 2019; Zhou, 2017), mobile learning (Alshurideh et al., 2019), and blended learning (Cheng, 2014; Sabah, 2020).

Perceived usefulness originated from TAM and was defined as the degree to which a person believes that the use of a particular system would enhance his or her job performance. In blended learning, perceived usefulness refers to learning performance (Davis, 1989). In other related studies, perceived usefulness was sometimes referred to as performance expectancy (Venkatesh, Morris, Davis, & Davis, 2003).

Post-adoption satisfaction refers to the extent to which a person is pleased or content with a product, service, or technology artifact after having gained direct experience with it. ECT posits that satisfaction is directly influenced by disconfirmation of beliefs and perceived performance, and indirectly influenced by both expectations

![Fig. 1 The ECM-ISC Model](image)
and perceived performance via a mediational relationship that passes through the disconfirmation construct.

Confirmation refers to a person’s judgment or evaluation of products, services, or technical artifacts. These assessments or judgments are compared with people’s initial expectations. When a product, service, or technical artifact exceeds these initial expectations, confirmation is positive, which is assumed to increase satisfaction after purchase or adoption. When products, services, or technical artifacts are lower than people’s initial expectations, confirmation is negative, which is considered to reduce post-adoption satisfaction (Bhattacherjee, 2001).

Intrinsic motivation and academic self-efficacy

Intrinsic motivation refers to people’s spontaneous cognition of the activities they are engaged in (Teo et al., 1999). Previous research showed that intrinsic motivation is a direct factor with which e-learning continuance intention can be predicted (Roca & Gagné, 2008). Moreover, intrinsic motivation exerts a positive impact on satisfaction (Sorebø et al., 2009). Intrinsic goal orientation is a component of the Motivation Scales for Learning Questionnaire (MSLQ) questionnaire, and is concerned with the degree to which students perceive themselves to be participating in a task for reasons of intrinsic motivation (e.g., challenge, curiosity, and mastery) (Pintrich et al., 1993). This study employed intrinsic goal orientation to test intrinsic motivation.

Self-efficacy is an individual’s subjective evaluation of his or her ability to complete a certain aspect of work (Bandura, 1986). Academic self-efficacy refers to students’ beliefs and attitudes towards their capacities to attain academic achievements, as well as their belief in their capacity to complete academic activities and study materials successfully (Bandura, 1997; Schunk & Ertmer, 2000). Previous research indicated that self-efficacy could affect motivation both positively and negatively. In general, people with high self-efficacy are more likely to make efforts to complete a task, and persist longer in their efforts, than people with low self-efficacy (Schunk, 1990). In addition, previous research also identified self-efficacy as an effective measurement for continuance intention (Mathieson, 1991). For example, Bhattacherjee et al. (2008) found that continuance intention was significantly affected by information technology self-efficacy.

Research model and hypotheses

Literature review indicated that students’ performance expectancy, confirmation, satisfaction, intrinsic motivation, and academic self-efficacy can influence continuance intention. Therefore, as shown in Fig. 2, these factors are assumed to potentially influence students’ continuance intention on blended learning. The following hypotheses are tested:

Hypothesis 1 (H1) Performance expectancy is positively related to the degree of blended learning continuance intention.
Hypothesis 2 (H2) Students’ satisfaction with blended learning is positively related to the degree of continuance intention.

Hypothesis 3 (H3) Students’ intrinsic motivation is positively related to the degree of blended learning continuance intention.

Hypothesis 4 (H4) Students’ academic self-efficacy is positively related to the degree of blended learning continuance intention.

Hypothesis 5 (H5) Performance expectancy is positively related to the degree of blended learning satisfaction.

Hypothesis 6 (H6) Students’ confirmation of blended learning is positively related to satisfaction.

Hypothesis 7 (H7) Students’ intrinsic motivation is positively related to satisfaction with blended learning.

Hypothesis 8 (H8) Students’ confirmation of blended learning is positively related to performance expectancy.

Hypothesis 9 (H9) Students’ academic self-efficacy is positively related to intrinsic motivation.
Method

Participants and settings

To investigate the key factors impacting college students’ continuance intention in blended learning, a questionnaire was developed based on the proposed research model. This questionnaire was used to conduct two surveys at a university in central China in the fall semesters of 2020 and 2021. In both surveys, participants were first-year students who took a blended learning course named “Fundamentals of the Computer” in their first semester. This course covers computer operating systems, productivity tools (such as word processing, spreadsheet, and presentation software), computer networking, and multimedia applications (among other topics). Through participation in this course, students should be able to master basic computer knowledge and skills. The course lasts for one semester and is required for all first-year college students who are not majoring in computer science. These first-year college students were arguably beginners in blended learning, given that K-12 schools in China are still dominated by traditional F2F classrooms, with little or no implementation of blended learning.

This course employs a flipped classroom-like instruction in blended learning. Because of the nature of the course and the fact that not all students possess their own computers and applications, certain learning activities in this course are conducted and completed within computer labs rather than via typical flipped classroom instruction, which primarily combines class and home learning activities. Overall, one-third of the course time is dedicated to F2F classroom instruction, one-third of the course time is dedicated to lab practice, and one-third of the course time is dedicated to online learning. For each of these learning units, F2F classroom instruction and lab practice are arranged matching the schedule for typical classrooms and computer labs. Students must be physically present for the learning activities. In addition, students are required to read and review two set online learning materials before and after F2F classroom instructions. The first set of online learning materials such as micro-videos, courseware, leading questions, examples, and cases are provided in the learning management system and students are expected to finish learning tasks at their own pace and in their own space before the F2F classroom instruction. In the F2F classroom instruction, instructors deliver key concepts and skills to students, facilitate discussions with students, and answer students’ questions. After F2F classroom instruction, the second set of online learning materials such as assignments, quizzes, notes, and other resources are provided in the learning management system; thus, students can practice and review what they have learned during the F2F classroom instruction and can complete the learning tasks in the labs. All instructors of this course have been working together on the curriculum design and development to ensure consistent content, progress, and similar pedagogy.

Instrument

The questionnaire for both surveys adopted elements from the ECM-ISC scale, Unified Theory of Acceptance and Use of Technology (UTAUT) questionnaire, and MSLQ.
Specifically, satisfaction (four items), confirmation (three items), and IS continuance intention (three items) in the questionnaire were adopted from the ECM-ISC scale. The ECM-ISC scale was developed by Bhattacherjee et al. (2001) and the dimensional reliabilities reported in his paper were as follows: satisfaction (alpha = 0.87), confirmation (alpha = 0.82), and IS continuance intention (alpha = 0.83). Each item was measured on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). One representative item for satisfaction is: “I am very pleased to participate in the current way of learning.” A representative item for confirmation is: “My experience with the current learning method is better than I expected.” An example item for continuance intention is: “My intentions are to continue using the current learning method rather than any other methods (such as traditional learning methods).”

Performance expectancy (four items) in the questionnaire was adopted from the UTAUT questionnaire. The UTAUT questionnaire was developed by Venkatesh et al. (2003). The original reliability of performance expectancy exceeded 0.90, and a representative item of this scale is: “The current learning method is more useful for my study.” UTAUT also used a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Intrinsic motivation and academic self-efficacy items in the questionnaire were adopted from MSLQ. The MSLQ was developed by Pintrich et al. (1993). Intrinsic Goal Orientation (four items, alpha = 0.74) was employed to express intrinsic motivation. Self-efficacy (eight items, alpha = 0.93) of MSLQ was also employed in this study. One representative item of intrinsic motivation is: “In the current study of this course, I prefer course material that arouses my curiosity, even if it is difficult to learn.” An example of academic self-efficacy is: “I’m certain I can understand the most difficult material presented in this course.”

Data collection and analysis

Both surveys were administered at the end of the semester. At the beginning of the survey, all students were informed about the purpose of this study. All responses were both anonymous and voluntary. Participants took the survey in paper format. In the survey of the fall of 2020, a total of 403 (from 471) beginners responded to the survey, with a recovery rate of 85.6%. 342 valid questionnaires were collected, with an applicable rate of 84.9%. In the survey of the fall of 2021, a total of 1078 (from 1374) beginners responded to the survey, with a recovery rate of 78.5%. 987 valid questionnaires were collected, with an applicable rate of 91.6%. SPSS19.0 was employed to process the data in this study. Smart PLS v.3.3.2 was used to build a research model and validate the mutual relationship between key impact factors of students’ continuance intention of blended learning.
Results

Overview of the survey

As shown in Table 1, the results of both surveys were very similar. The response range of the survey in the fall of 2020 ranged between 3.91 and 3.94. Continuance intention (M = 3.91, SD = 0.73) turned out to have the lowest average response value examined, while intrinsic motivation (M = 3.97, SD = 0.64) turned out to have the highest average response values of the survey. The response range of the survey in the fall of 2021 ranged from 3.64 to 3.83. Academic self-efficacy had the lowest means (M = 3.64, SD = 0.67) and continuance intention (M = 3.83, SD = 0.71) had the highest means.

Reliability and validity analysis

Standardized Root Mean Residual (SRMR) is a fitting measure of Partial Least Squares Structural Equation Modeling (PLS-SEM), which is commonly used to avoid model misspecification (Hair, Henseler, et al., 2014; Hair, Sarstedt, et al., 2014). A value less than 0.08 is considered to indicate a good fit (Hu & Bentler, 1998). The values of SRMR of this model calculated from the surveys of both 2020 and 2021 were 0.04 and 0.035, respectively, thus, the proposed model was acceptable.

Cronbach’s Alpha and Composite Reliability (CR) were used to measure the degrees of internal consistency of the results. Average Variance Extracted (AVE) was used to assess validity (Wong, 2013). As shown in Table 2, the parameters of Cronbach’s alpha and CR exceeded 0.7 and all parameters of AVE exceeded 0.5. The correlations among the square root of AVE and the latent variables were compared to gauge discriminant validity (Fornell & Larcker, 1981). The result showed that all latent correlations were below the corresponding AVE square roots. Therefore, the constructs of the survey used in this study had good reliability and validity.

| Table 1 | Descriptive statistics of the survey results |
|---------|---------------------------------------------|
| Variable | Fall 2020 Survey | Fall 2021 Survey |
|         | Mean  SD        | Mean  SD        |
| AS      | 3.94  0.60      | 3.64  0.67      |
| CO      | 3.93  0.73      | 3.80  0.70      |
| CI      | 3.91  0.73      | 3.83  0.71      |
| IM      | 3.97  0.64      | 3.81  0.63      |
| PE      | 3.94  0.73      | 3.81  0.71      |
| SA      | 3.95  0.70      | 3.82  0.71      |

AS Academic self-efficacy, CO Confirmation, CI Continuance intention, IM Intrinsic motivation, PE Performance expectancy, SA = satisfaction
Hypotheses testing

The PLS algorithm was used to assess the fitness of the structural model with available data. Within the PLS method, the coefficient of determination ($R^2$) is a commonly used parameter (Tompson et al., 1995). An $R^2$ of 0.75 is considered substantial and a value of 0.50 is considered moderate (Hair, Henseler, et al., 2014; Hair, Sarstedt, et al., 2014). In both surveys, $R^2$ for continuance intention endogenous latent variable and satisfaction endogenous latent variable exceeded 0.75. $R^2$ for performance expectancy endogenous latent variable and intrinsic motivation exceeded 0.50 in both surveys. Therefore, all endogenous latent variables were well explained.

The bootstrapping method (5000 resamples) was used to calculate path coefficients ($\beta$ value) for each survey. Table 3 shows T-values, $p$-values of the path coefficients, and $R^2$. As shown in Table 3 and Fig. 3, both surveys had similar results. All other path coefficients were statistically significant except for AS $\rightarrow$ CI. This means that only H4 was rejected, while others were supported.

For the fall 2020 survey, PE ($\beta=0.199$, $p<0.01$), SA ($\beta=0.598$, $p<0.001$), and IM ($\beta=0.136$, $p<0.05$) were positively related to CI, accounting for 78.8% of $R^2$. Similarly, for the fall 2021 survey, PE ($\beta=0.164$, $p<0.001$), SA ($\beta=0.677$, $p<0.001$), and IM ($\beta=0.057$, $p<0.05$) were positively related to CI, accounting for 76.4% of $R^2$. In addition, for the fall 2020 survey, PE ($\beta=0.233$, $p<0.01$), CO ($\beta=0.485$, $p<0.001$), and IM ($\beta=0.231$, $p<0.001$) positively impacted SA, accounting for 79.0%. Similarly, for the fall 2021 survey, PE ($\beta=0.363$, $p<0.001$), CO ($\beta=0.483$, $p<0.001$), and IM ($\beta=0.119$, $p<0.001$) positively impacted SA, accounting for 80.1% of $R^2$. CO ($\beta=0.863$, $p<0.001$) of the fall 2020 survey and CO ($\beta=0.826$, $p<0.001$) of the fall 2021 survey both had significant positive
Table 3 Verification of research hypotheses

| Hypothesis Path | Fall 2020 Survey | Fall 2021 Survey |
|-----------------|------------------|------------------|
|                 | Path coefficient | T value | p value | Result | R²   | Path coefficient | T value | p value | Result | R²   |
| 1 PE—> CI       | 0.199            | 2.64**   | 0.008   | Supported | 0.788 | 0.164            | 4.29*** | 0.000 | Supported | 0.764 |
| 2 SA—> CI       | 0.598            | 7.49***  | 0.000   | Supported | 0.677 | 16.34***         | 0.000   | Supported |
| 3 IM—> CI       | 0.136            | 1.98*    | 0.048   | Supported | 0.057 | 2.07*            | 0.038   | Supported |
| 4 AS—> CI       | 0.006            | 0.12     | 0.902   | Rejected  | 0.022 | 0.90             | 0.369   | Rejected |
| 5 PE—> SA       | 0.233            | 3.12**   | 0.002   | Supported | 0.790 | 0.363            | 9.41*** | 0.000 | Supported | 0.801 |
| 6 CO—> SA       | 0.485            | 6.57***  | 0.000   | Supported | 0.483 | 11.49***         | 0.000   | Supported |
| 7 IM—> SA       | 0.231            | 4.48***  | 0.000   | Supported | 0.119 | 4.29***          | 0.000   | Supported |
| 8 CO—> PE       | 0.863            | 43.24*** | 0.000   | Supported | 0.826 | 59.76***         | 0.000   | Supported |
| 9 AS—> IM       | 0.771            | 21.89*** | 0.000   | Supported | 0.593 | 0.727            | 32.83***| 0.000 | Supported | 0.529 |

*p < 0.05; **p < 0.01; ***p < 0.001
effects on PE, accounting for 74.3% and 68.4% of $R^2$, respectively. Furthermore, AS ($\beta = 0.771, p < 0.001$) of the fall 2020 survey and AS ($\beta = 0.727, p < 0.001$) of the fall 2021 survey had significant positive effects on IM, accounting for 59.3% and 52.9 of $R^2$, respectively.

**Analysis of indirect and total effects among key factors**

Fig. 3 and Table 4 show the direct and indirect effects of each factor. PE and IM had both direct and indirect impacts on CI, and S acted as the mediating variable. Although the direct path from AS to CI was rejected, two indirect paths were found to lead from AS to CI, where IM and the combination of IM and S acted as partial mediators.

Furthermore, CO had no direct impact on CI but had three indirect paths to CI through PE, SA, and their combination. IM, PE, and CO had a direct impact on SA. The results showed that IM played a mediating role between AS and SA, while PE played a mediating role in the relationship between CO and SA.

**Discussion**

The effectiveness of blended learning has been demonstrated by numerous studies. In the case of a compulsive course like a course on the fundamentals of the computer, previous studies have shown that the use of a flipped classroom-based blended learning approach can improve students’ higher-order thinking and computational thinking skills (Cai et al., 2018; Gong, Yang, & Cai, 2020). Therefore, it is essential to encourage students to participate in blended learning courses on an ongoing basis. A better understanding of the factors that affect beginners’ continuance intention in blended learning can help instructors to design, develop, implement, and evaluate blended learning courses that improve students’ learning experience and learning.
Table 4  Analysis of indirect and total effects between key factors

| Path          | Fall 2020 Survey | Path          | Account (indirect/total) | Fall 2021 Survey | Path          | Account (indirect/total) |
|---------------|------------------|---------------|--------------------------|------------------|---------------|--------------------------|
|               | Effect value     | coefficient   |                          |                  |               |                          |
| PE- > CI      | 41.3%            | 0.199         | 0.164                     | 40.0%            | 0.164         |                          |
| Direct effect |                  |               |                          |                  |               |                          |
| Indirect effect | PE- > SA- > CI   | 0.233*0.598 = 0.140 | 0.140                     | 0.363*0.677 = 0.246 | 0.246         |                          |
| Total effect  |                  | 0.339         | 0.410                     |                  |               |                          |
| CO- > CI      | 100%             | 0.863*0.199 = 0.172 | 0.172                     | 0.826*0.164 = 0.135 | 0.135         |                          |
| Direct effect |                  |               |                          |                  |               |                          |
| Indirect effect | CO- > SA- > CI   | 0.485*0.598 = 0.290 | 0.290                     | 0.483*0.677 = 0.327 | 0.327         |                          |
| Total effect  |                  | 0.582         | 0.665                     |                  |               |                          |
| IM- > CI      | 50.4%            | 0.136         | 0.136                     | 0.057            | 0.138         |                          |
| Direct effect |                  |               |                          |                  |               |                          |
| Indirect effect | AS- > IM- > CI   | 0.771*0.136 = 0.178 | 0.178                     | 0.727*0.057 = 0.041 | 0.041         |                          |
| Total effect  |                  | 0.285         | 0.100                     |                  |               |                          |
| CO- > SA      | 29.3%            | 0.105         | 0.087                     | 0.087            | 0.087         |                          |
| Path       | Effect value | Path coefficient | Account (indirect/total) | Effect value | Path coefficient | Account (indirect/total) |
|------------|--------------|------------------|--------------------------|--------------|------------------|--------------------------|
| Direct effect | 0.485        |                  |                          | 0.483        |                  |                          |
| Indirect effect | CO- > PE- > SA | 0.863*0.233 = 0.201 | 0.201                   | 0.826*0.363 = 0.300 | 0.300            |                          |
| Total effect   | 0.686        |                  |                          | 0.783        |                  |                          |
outcomes. The findings of this study therefore have strong practical implications for instructors.

To identify the relationship between key impact factors and beginners’ continuance intention in blended learning, two surveys were implemented in the fall semesters of 2020 and 2021 on first-year students who had just taken their first blended course in college. In both surveys, participants completed the same questionnaire and the same blended course, and the only difference was that they had different majors. Smart PLS was used to calculate the results of both surveys separately. Both surveys had a similar result, and the three key factors of performance expectancy, satisfaction, and intrinsic motivation directly impacted continuance intention. In addition, confirmation and academic self-efficacy indirectly impacted continuance intention.

Students’ satisfaction with blended learning had the strongest effect on their continuance intention which was consistent with a previous study (Alshurideh et al., 2019). The subjective, comprehensive feeling of students and the common judgment element of teaching quality received research attention. Learning satisfaction and its impact factors, such as computer self-efficacy, system functionality, content feature, performance expectancy, interaction, and learning climate have been addressed (Wu et al., 2010).

In this paper, performance expectancy, intrinsic motivation, and confirmation were the main factors impacting satisfaction. Performance expectancy and intrinsic motivation in particular impacted continuance intention both indirectly and directly, which agreed with the results of a previous study (Daneji et al., 2019). In this paper, performance expectancy denotes students’ beliefs regarding whether the use of blended learning can enhance their learning performance. Previous research on “online learning” and “mobile learning” both showed that performance expectancy was a significant determinant of users’ intention for using technology-based learning systems (Chen & Hwang, 2019; Joo, Ham, & Jung, 2014; Wang, Wu, & Wang, 2009). Research also indicated that students who assumed blended learning to be useful for their education would be more likely to adopt it (Tselios et al., 2011). Such a result indicates that it is important for instructors to understand students’ attitudes toward technologies in online or blended learning, especially when dealing with different situations, such as under the influence of COVID-19 (Jiang et al., 2021) and help students to build a positive belief in blended learning at the early stage of learning. Effective strategies include the use of lectures or social influences to help students understand the potential advantages of blended learning and the presentation of successful blended learning courses to students. Intrinsic motivation enables students to engage more deeply in learning, gain better conceptual learning, and persist longer (Vansteenkiste et al., 2006). A previous study showed that intrinsic motivation impacted satisfaction (Brown & Huning, 2010). A previous experiment also showed that students in a blended learning environment had significantly higher levels of intrinsic motivation and better satisfaction than students in a F2F learning environment (Sucaromana, 2013). To improve intrinsic motivation and increase both learning satisfaction and continuance intention, instructors are required to design and implement effective strategies to improve students’ intrinsic motivation. Examples are asking students thought-provoking questions to maintain
their attention, showing how to use course information to solve real problems, making classroom expectations clear, and giving students ample time to practice new skills (Carman, 2005).

In the research model tested in the present paper, although confirmation and academic self-efficacy did not directly affect continuance intention, they still exerted indirect effects. Confirmation refers to the benefits of blended learning students experienced personally after a period of blended learning. Confirmation positively impacts continuance intention through performance expectancy, satisfaction, and their combination, which is consistent with other research results (Bhattacherjee, 2001). This indicates that the accomplishment of students’ expectations on the performance of blended learning is positively connected to their satisfaction and indirectly impacts their continuance intention (Alshurideh et al., 2019). Interestingly, academic self-efficacy was shown to not directly impact continuance intention. This finding contradicts the original hypothesis. However, academic self-efficacy has an indirect relationship with continuance intention. Intrinsic motivation as well as the combination of intrinsic motivation and satisfaction are partial mediators between academic self-efficacy and continuance intention. This means that improving students’ academic self-efficacy helps to enhance their intrinsic motivation and improve their intention to adopt blended learning. Research demonstrated that teaching methods and the type of learning environment affected self-efficacy in the classroom. The designing of suitably challenging tasks, use of specific teaching and learning strategies, implementation of peer learning, concentration on student interests and choices, strengthening efforts and using the right strategies, emphasizing recent successes, as well as providing focused, frequent, and task-specific feedback and stress functional attribution statements are proven ways for improving academic self-efficacy (Margolis & McCabe, 2006).

Limitations and future studies

While the findings of this study have certain important implications for the design, development, implementation, and evaluation of blended learning for beginners, two limitations must be noted. First, both instructors and students can be beginners of blended learning but this study only focused on the student’s perspective while ignoring the instructor’s perspective. Existing research has indicated that observing and addressing instructors’ concerns regarding blended learning are important for their continuous intention in blended learning (Jong, 2019). Second, this study only examined the key factors influencing beginners’ continuance intention in blended learning from one course, namely Fundamentals of the Computer. The survey results are likely influenced by the nature of the course and the knowledge required. Further studies should include instructors who are new to blended learning and should include various types of courses to obtain more comprehensive and accurate results.

Acknowledgements This study is supported by the key project Scientific Research Project of the Education Department of Hubei Province (D20193002) and Hubei Province Teaching research project (2020674). It is also supported by China Postdoctoral Science Foundation-funded project (2018M640738).
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**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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