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# The Assessment of Students' Learning Motivation, Perceived Learning Effectiveness, and Satisfaction Toward Blended Learning in Zhanjiang, China

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## Abstract

**Purpose:** The study aims to uncover the elements of blended learning in China that significantly impact student satisfaction. Seven variables were examined, and six hypotheses were formulated among system quality, information quality, learning motivation, perceived usefulness, perceived learning effectiveness, computer self-efficacy, and satisfaction. **Research design, data, and methodology:** It utilized quantitative techniques and analyzed 500 questionnaires at a normal university in Zhanjiang in Guangdong Province, China. Confirmatory factor analysis (CFA) and a structural equation model (SEM) were employed for hypothesis testing. **Results:** Findings reveal that system quality significantly influences satisfaction in blended learning. Information quality enhances students' perception of blended learning. Learning motivation significantly impacts satisfaction. Perceived usefulness significantly drives students' motivation to participate in blended learning. Additionally, perceived learning effectiveness positively affects satisfaction. Furthermore, computer self-efficacy is closely associated with students' perceived learning effectiveness in blended learning. **Conclusions:** The findings of this research shed light on essential factors that significantly influence student satisfaction in blended learning. Prioritizing system and information quality, learning motivation, perceived usefulness, perceived learning effectiveness, and computer self-efficacy can improve students' satisfaction and overall success in blended learning environments. This study highlights the significance of students' learning motivation and satisfaction in the era of Internet + education.

**Keywords:** Learning Motivation, Perceived Learning Effectiveness, Computer Self-Efficacy, Satisfaction

**JEL Classification Code:** E44, F31, F37, G15

## 1. Introduction

The exponential growth of information and communication technologies (ICTs) has significantly impacted classroom dynamics since the 1980s. The digital revolution has brought the digital online education platform and changed the educational paradigm worldwide. This has led to the adoption of hybrid and fully online curricula in K-12 and higher education. The spread of the COVID-19 epidemic has intensified this tendency worldwide (Record Trend., 2022).

Blended learning is the process of combining conventional classroom instruction with online learning. It can be based on a predetermined curriculum or allow students to choose their own pace. It combines traditional face-to-face communication, online mediation, and tech-based strategies. Research on blended learning in other countries can be broken down into three time periods: the early in 2000, middle in 2003, and late in 2008 periods (Wang & Beydoun, 2007). In the first stages, blended

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learning is presented but has yet to be defined. At this point, in-person and online education are complementary but distinct processes. Blended education is at its most formative during its intermediate phase (Byrne, 2016). While there is no universally agreed-upon definition of blended learning, Sloan Alliance (now known as Online Learning Alliance) defined it as a course in which the proportion of online learning reaches 30%-79%. Graham (2006), on the other hand, does not use online learning time as a metric and counts blended learning so long as it includes both digital and in-person instruction. He classifies blended learning as either generative, facilitative, or transformational, depending on the underlying goal of the mix (Record Trend., 2022).

This study explores the causal relationship between system quality, information quality, learning motivation, perceived usefulness, perceived learning effectiveness, computer self-efficacy, and satisfaction in blended learning among students at a normal university in Zhanjiang. This research's significance rests in examining how students at China's Zhanjiang Early Childhood Normal College feel about their experiences with blended learning. The significance of blended learning makes it a perennial area of study in higher education. However, education is a complex system with many moving parts, and the existing reach and impact of blended learning suggest that it needs to provide the intended outcomes. System quality, information quality, learning motivation, perceived usefulness, perceived learning effectiveness, computer self-efficacy, and satisfaction are among the characteristics investigated here. This research aims to identify the factors that significantly influence satisfaction with blended learning (Barnard-Brak et al., 2009; Graham, 2006)

The study of blended learning among students provides the most direct basis for optimizing the education and teaching of blended learning in colleges and universities by analyzing the satisfaction of blended learning of college students from the actual situation, as well as analyzing the overall learning satisfaction of college students, the learning satisfaction of each measurement dimension, and the existing problems in the process of blended learning (López-Pérez et al., 2011).

Therefore, it is important to further the academic research results in this field by clarifying the influence of learning motivation, self-efficacy, and other factors on the satisfaction of blended learning and the influence of blended learning on students' achievement goals. This will provide a research basis for the continued promotion of blended learning in higher education and will aid college teachers, administrators, course builders, and students in better implementing the blended learning model.

## 2. Literature Review

### 2.1 Satisfaction

According to Martin (1988), satisfaction is the degree to which an individual's expectations and experiences are the same. You are happy when your expectations are met or exceeded and dissatisfied when they are not met with the experience you had. Satisfaction describes a person's general reaction to the effects of several external variables on their immediate surroundings under a certain set of conditions (Petter et al., 2013). According to Shankar et al. (2003), satisfaction comes from meeting one's needs and fulfilling one's aspirations. Customer expectations are what it means when it talks about their satisfaction. Customers are happy with a product or service if it meets or exceeds their expectations (Kotler, 1999). According to research by Siritongthaworn et al. (2006), the most extensive research has been done on customer satisfaction. In this context, satisfaction is how well a product, service, or experience meets an individual's needs.

### 2.2 System Quality

Researchers have long used satisfaction with the system itself as a proxy for success (Farid et al., 2018). The quality of an e-learning system may be measured by how user-friendly, engaging, inventive, and dependable it is (Wang et al., 2007). Satisfaction in e-learning refers to how happy students are with their experience and the results they have achieved (Wang et al., 2007). Learners' perceptions and use of e-learning platforms are impacted by many elements, including the quality and pleasure of the platform itself (Liaw & Huang, 2013; Wang et al., 2007). System quality remains an essential criterion for gauging the performance of online electronic systems, and this is no different for e-learning systems (Al-Fraihat et al., 2020). Liaw and Huang (2013) investigated what factors led to successful self-regulation in online courses and found that system quality positively correlated with student satisfaction. An increase in system quality may boost e-learning's popularity and success among students. Effectiveness in an e-learning system can only be attained if a high degree of system quality is reached (Farid et al., 2018). Based on this literature review, hypothesize:

**H1:** System quality has a significant influence on satisfaction.

### 2.3 Information Quality

According to Farid et al. (2018), academics have long used a person's level of system satisfaction as a surrogate for traditional success measures. Learners' perceptions of the

quality of the information they get from an online learning system may be broken down into four categories: accuracy, completeness, relevance, and timeliness (Wang et al., 2007). Language learners may feel more fulfilled if the information they encounter is high quality. However, the information quality depends on the instructor's material's precision, the content's quality, and the LMS service. Therefore, information quality is based on course-related content information, such as information about course materials, lectures, and information about information services that students can access (Ohliati & Abbas, 2019). Adopting LMS and student satisfaction is negatively impacted when educators lack access to timely data (Sharma et al., 2017). Liaw and Huang (2013) and Wang et al. (2007) note that information's perceived quality and pleasure are significant in shaping students' attitudes and behavior toward e-learning systems. Accordingly, it concludes from the studies mentioned above that:
**H2:** Information quality has a significant influence on satisfaction.

## 2.4 Learning Motivation

The ability to motivate oneself is a mental phenomenon. According to Hulleman et al., (2008), intrinsic motivation describes a self-driving force that causes beneficial actions and steady advancement toward a goal. Satisfaction with learning encompasses a wide range of responses to the educational experience. Satisfaction and contentment are felt by students throughout instructional activities (Kuo & Chang, 2014). Existing research shows that high levels of interaction between students, instructors, and learning resources improve student satisfaction with the learning process. Gains in learning motivation and effectiveness have been linked to higher levels of learner satisfaction (Kuo et al., 2013; Lovecchio et al., 2015). The learner's drive to learn is the most important aspect influencing learning satisfaction. Some empirical research (Whillier & Lystad, 2015) has indicated that students' attitudes toward instructors and learning motivation and experience may affect students' performance and satisfaction. The more invested the student is in their success, the more they will enjoy the process of learning. This research concludes that learning motivation and learning satisfaction in blended learning have a significant influence based on the literature mentioned above (Huang, 2021). Based on this literature review, it is hypothesized as follows.
**H3:** Learning motivation has a significant influence on satisfaction.

## 2.5 Perceived Usefulness

According to the research of Glynn et al. (2005), kids' levels of intrinsic drive to study are a significant predictor of their persistence and success in school. The mental process of being motivated to learn is a kind of action that may direct other forms of learning toward their intended outcomes (MacIntyre & Blackie, 2012). The two main categories of learner motivation are intrinsic and extrinsic. Most people are internally driven because they want to learn (Ryan & Deci, 2000). Intrinsic motivation to learn is a drive not required of students. It has the potential to inspire kids to work hard toward their academic objectives. Intrinsically motivated students are more resilient to setbacks in their studies and have a greater capacity to sustain their interest in learning over time (Huang et al., 2011). For online courses to be effective, students must feel that utilizing the system will improve their performance (Wang et al., 2007). Learning motivation refers to a student's enthusiasm for and commitment to coursework. According to research by Lei et al. (2014), practicality boosts learning efficiency. Incentive elements have been shown in relevant TAM model research (Chen et al., 2016; Rupp et al., 2018) to increase the model's predictability. We might extrapolate from this to infer that students' intention to study is influenced by their belief in their usefulness to society. Therefore, it hypothesizes, based on the studies mentioned above:
**H4:** Perceived usefulness has a significant influence on learning motivation.

## 2.6 Perceived Learning Effectiveness

Satisfaction with the learning process shapes the learner's experience and may be linked to the result (Hu et al., 2007). Students' confidence in learning and growing due to e-learning is perceived as learning effectiveness (Wang et al., 2007). Satisfaction in e-learning refers to how happy students are with their experience and the results they have achieved (Wang et al., 2007). Learning satisfaction was established as an element of online learning by Tratnik et al. (2019). The level of student satisfaction with both synchronous and asynchronous components of online courses was analyzed by Zeng and Wang (2021). The importance of communication on students' enjoyment of online courses was also investigated by She et al. (2021). As a result, this may affect your satisfaction with your learning experience (Keller, 1983). Perceived efficacy in learning influences students' motivation and engagement (Sharm et al., 2022). Therefore, it hypothesizes, based on the studies mentioned above:
**H5:** Perceived learning Effectiveness has a significant influence on satisfaction.

## 2.7 Computer Self-efficacy

As computer science and technology develop, online education becomes more accessible and engaging for students (McBrien et al., 2009). Students in a networked classroom have access to course materials and instructors around the clock (Thurman, 2019). One's confidence in one's competence to utilize computers is known as computer self-efficacy (Karsten et al., 2012). Individuals' perceptions of and interactions with e-learning systems, as well as their ability to use and profit from such systems, may be impacted by this factor (Poon et al., 2022). Learners' openness to use tech-facilitated communication throughout the instructional process has been investigated in prior research. Therefore, the study looked at students' confidence in their computer skills and the role played by various information technologies in facilitating learning in higher education (Sharm et al., 2022). Therefore, it hypothesizes, based on the studies mentioned above:

**H6:** Computer self-efficacy has a significant influence on perceived learning effectiveness.

# 3. Research Methods and Materials

## 3.1 Research Framework

This work aims to investigate the elements that influence blended learning motivation, perceived Learning efficacy, and satisfaction among Zhanjiang normal students. IS, TAM, and the Self-Efficacy Model are used to aid in developing the conceptual framework by the researchers.

A proposal or conceptual framework may be used to describe a piece of research (Clark & Ivankova, 2016). A conceptual framework is a model that symbolizes all study variables and their interrelationships (Hair et al., 2013).

This work aims to investigate the elements that influence blended learning motivation, perceived Learning efficacy, and satisfaction among Zhanjiang normal students. The researchers plan to examine six interrelated concepts within the conceptual framework:

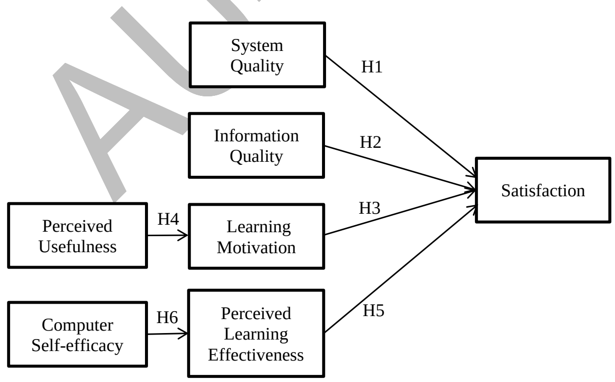


**Figure 1:** Conceptual Framework

**H1:** System quality has a significant influence on satisfaction.
**H2:** Information quality has a significant influence on satisfaction.
**H3:** Learning motivation has a significant influence on satisfaction.
**H4:** Perceived usefulness has a significant influence on learning motivation.
**H5:** Perceived learning Effectiveness has a significant influence on satisfaction.
**H6:** Computer self-efficacy has a significant influence on perceived learning effectiveness.

## 3.2 Research Methodology

Screening questions, questions about symmetry on a 5-point Likert scale (strongly disagree = 1 to strongly agree = 5), and questions on demographics (gender, grade, topic of study, blended learning experience) were included. For system quality, the measurement of this construct contained three items. All items were organized by Mirabolghasemi et al. (2021). For information quality, this structure had 4 measures. All these items were organized by Mirabolghasemi et al. (2021). For learning motivation, this structure had 4 measures. All these items were organized by Huang (2021). For Perceived Usefulness, this structure had 5 measures. All these items were organized by Huang (2021). For perceived learning effectiveness, this structure had 4 measures. All these items were organized by Sharma et al. (2022). For computer self-efficacy, this structure had 4 measures. All these items were organized by Sharma et al. (2022). For satisfaction, this structure had 3 measures. All these items were organized by Mirabolghasemi et al. (2021).

To assess the validity and reliability of the questionnaire, we employed the Cronbach's Alpha method. This involved an initial evaluation, encompassing both an examination of Item-Objective Congruence (IOC) and the execution of a pilot test. For IOC analysis, three experts were engaged to evaluate each scale item, resulting in all items receiving a rating of 0.6 or higher. Additionally, a pilot test involving a sample of 50 participants was conducted, and the reliability was computed using the Cronbach alpha coefficient. The findings revealed that every item in the questionnaire demonstrated strong internal consistency, with a reliability score exceeding 0.7 (Dikko, 2016).

## 3.3 Population and Sample Size

The structural equation modeling (SEM) requires a higher sample size than regular regression-based statistical approaches, this factored into the determination of the sample size (Westland, 2010). Using a calculator for a priori sample size for SEM research (Soper, 2020), the sample size was determined based on the conceptual model and questionnaire (described below) and a modest effect size (0.2). Soper (2019) suggest using a sample size of at least 425 for such an investigation. The researcher chose a sample size of 500 from the population, which is enough for the study as it is larger than the minimum need.

### 3.4 Sampling Technique

The study's multi-stage sample design, which included non-probabilistic (judgment and convenience sampling) and probabilistic (stratified random sampling), is provided here. First, the students in this research all had at least one semester of blended learning experience at Zhanjiang Early Childhood Normal College and were selected using a judgmental sampling technique. As a second step, it used a probabilistic sampling strategy known as stratified random sampling. The fraction of the total number of pupils was determined using a sample size of 500, which included 195 first graders, 174 second graders, and 131 third graders. Third, school personnel delivered in-person and online surveys to students in three targeted grades and majors using a mix of judgment and convenience sampling (non-probability sampling).

**Table 1:** Sample Units and Sample Size

| Programs | Population Size | Proportional Sample Size |
|---|---|---|
| **Grade One** | 1131 | 195 |
| **Grade Two** | 1006 | 174 |
| **Grade Three** | 758 | 131 |
| **Total** | **2895** | **500** |

**Source:** Constructed by author

## 4. Results and Discussion

### 4.1 Demographic Information

Demographic information is concluded in Table 2 and collected from respondents based on gender, year of study, and age. Questionnaires were distributed to 500 students at the Zhanjiang Early Childhood Normal College. The respondents are 263 females and 237 males, representing 52.6 percent and 47.4 percent, respectively. For the year of study, 195 first-year students account for 39.0 percent, and 131 junior students account for 26.2 percent. For the age, the sample consists of individuals from three age groups: 18-20 years old, comprising 189 individuals (37.8%); 21-22 years old, comprising 238 individuals (47.6%); and those over 23 years old, comprising 73 individuals (14.6%).

**Table 2:** Demographic Profile

| Demographic and General Data (N=500) | | Frequency | Percentage |
|---|---|---|---|
| **Gender** | Male | 237 | 47.4% |
| | Female | 263 | 52.6% |
| **Year of study** | Freshman | 195 | 39.0% |
| | Sophomore | 174 | 34.8% |
| | Junior | 131 | 26.2% |
| **Age** | 18-20 years old | 189 | 37.8% |
| | 21-22 years old | 238 | 47.6% |
| | Over 23 years old | 73 | 14.6% |

**Source:** Constructed by author

### 4.2 Confirmatory Factor Analysis (CFA)

The Measurement Model is shown in Table 3 Confirmatory factor analysis (CFA) was applied to assess the correlations of items within the latent variables and the fitness of the measurement model. The result revealed that the constructs have a coefficient of internal consistency under the rules of thumb that the value must be 0.70 or above to represent as acceptable (Dikko, 2016). As shown in Table 3, the internal consistency of all questionnaire measurements is at least 0.760, which indicates that the questionnaire has good reliability. Composite reliability (CR) and Average variance extracted (AVE) are other scale reliability and consistency measurements. System quality is the construct with the highest internal consistency according to composite reliability. The value of CR and AVE is acceptable at 0.7 or higher and at 0.4 or higher, respectively, as per Fornell and Larcker (1981) suggestion. CR are ranged from 0.774 to 0.870. AVE was also greater than 0.5, ranging from 0.507 to 0.625.

**Table 3:** Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

| Variables | Source of Questionnaire (Measurement Indicator) | No. of Item | Cronbach's Alpha | Factors Loading | CR | AVE |
|---|---|---|---|---|---|---|
| System Quality (SQ) | Mirabolghasemi et al. (2021) | 3 | 0.806 | 0.723-0.788 | 0.808 | 0.584 |
| Information Quality (IQ) | Mirabolghasemi et al. (2021) | 4 | 0.795 | 0.522-0.729 | 0.800 | 0.507 |
| Learning Motivation (LM) | Huang (2021) | 4 | 0.858 | 0.762-0.798 | 0.858 | 0.601 |
| Perceived Usefulness (PU) | Huang (2021) | 5 | 0.843 | 0.517-0.792 | 0.847 | 0.531 |
| Perceived Learning Effectiveness (PL) | Sharma et al. (2022) | 4 | 0.870 | 0.767-0.800 | 0.626 | 0.518 |
| Computer Self-efficacy (CF) | Sharma et al. (2022) | 4 | 0.849 | 0.737-0.803 | 0.870 | 0.870 |
| Satisfaction (SAT) | Mirabolghasemi et al. (2021) | 3 | 0.760 | 0.690-0.729 | 0.774 | 0.533 |

The acceptable values of goodness-of-fit indices presented the model fit for the Measurement Model in Table 4. The statistical values of indices were compared to the acceptable criteria. In which, the values were CMIN/DF = 1.685, GFI = 0.932, AGFI = 0.915, NFI= 0.917, CFI = 0.964, TLI = 0.959, and RMSEA = 0.037.

**Table 4:** Goodness of Fit for Measurement Model

| Fit Index | Acceptable Criteria | Statistical Values |
|---|---|---|
| **CMIN/DF** | < 5.00 Al-Mamary & Shamsuddin, 2015；Awang, 2012) | 1.685 |
| **GFI** | ≥ 0.85 (Sica & Ghisi, 2007) | 0.932 |
| **AGFI** | ≥ 0.80 (Sica & Ghisi, 2007) | 0.915 |
| **NFI** | ≥ 0.80 (Wu & Wang, 2006) | 0.917 |
| **CFI** | ≥ 0.80 (Bentler, 1990) | 0.964 |
| **TLI** | ≥ 0.80 (Sharma et al., 2005) | 0.959 |
| **RMSEA** | < 0.08 (Pedroso et al., 2016) | 0.037 |
| **Model Summary** | | **In harmony with empirical data** |

**Remark:** CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index and RMSEA = Root mean square error of approximation.

As illustrated in Table 5, the square root of AVE for all constructs at the diagonal line was greater than the inter-scale correlations. Hence, the discriminant validity was guaranteed.

**Table 5:** Discriminant Validity

| | SQ | IQ | LM | PU | PLE | CS | S |
|---|---|---|---|---|---|---|---|
| **SQ** | **0.764** | | | | | | |
| **IQ** | 0.116 | **0.712** | | | | | |
| **LM** | 0.257 | 0.327 | **0.712** | | | | |
| **PU** | 0.253 | 0.133 | 0.203 | **0.716** | | | |
| **PLE** | 0.377 | 0.234 | 0.362 | 0.299 | **0.719** | | |
| **CS** | 0.227 | 0.076 | 0.220 | 0.163 | 0.389 | **0.933** | |
| **S** | 0.383 | 0.429 | 0.663 | 0.267 | 0.494 | 0.500 | **0.730** |

**Note:** The diagonally listed value is the AVE square roots of the variables
**Source:** Created by the author.

## 4.3 Structural Equation Model (SEM)

The structural equation model incorporates the multivariate principle to help determine relationships between variables. To determine whether one variable cause another, SEM may be used (Wanichbancha, 2014). The AMOS program analyzed an in-depth model (Sumsiripong, 2016) and established causal links or impact chains. According to Klem (2000), the structural equation model is a multivariate statistical method that uses factor analysis to assess the significance of associations between variables. Statistical evidence is analyzed by SEM (Ringle et al., 2005). (Buabeng-Andoh, 2018) SEM was used to examine the information. The results of statistical values were CMIN/DF = 2.382, GFI = 0.899, AGFI = 0.880, NFI = 0.877, IFI = 0.924, TLI = 0.917, CFI = 0.924, and RMSEA = 0.053. The fitness of the structural model is confirmed.

**Table 6:** Goodness of Fit for Structural Model

| Index | Acceptable | Statistical Values |
|---|---|---|
| **CMIN/DF** | < 5.00 Al-Mamary & Shamsuddin, 2015; Awang, 2012) | 2.382 |
| **GFI** | ≥ 0.85 (Sica & Ghisi, 2007) | 0.899 |
| **AGFI** | ≥ 0.80 (Sica & Ghisi, 2007) | 0.880 |
| **NFI** | ≥ 0.80 (Wu & Wang, 2006) | 0.877 |
| **CFI** | ≥ 0.80 (Bentler, 1990) | 0.924 |
| **TLI** | ≥ 0.80 (Sharma et al., 2005) | 0.917 |
| **RMSEA** | < 0.08 (Pedroso et al., 2016) | 0.053 |
| **Model Summary** | | **In harmony with Empirical data** |

**Remark:** CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index and RMSEA = Root mean square error of approximation.

## 4.4 Research Hypothesis Testing Result

The correlation magnitude among the independent and dependent variables proposed in the hypothesis is measured by regression coefficients or standardized path coefficients. As presented in Table 7, six proposed hypotheses were supported.

**Table 7:** Hypothesis Results of the Structural Equation Modeling

| Hypothesis | (β) | t-Value | Result |
|---|---|---|---|
| H1: SQ→S | 0.184 | 3.397* | Supported |
| H2: IQ→S | 0.248 | 4.417* | Supported |
| H3: LM→S | 0.296 | 8.912* | Supported |
| H4: PU→LM | 0.207 | 3.979* | Supported |
| H5: PLE→S | 0.296 | 5.191* | Supported |
| H6: CS→PLE | 0.402 | 7.698* | Supported |

**Note:** * $p<0.05$
**Source:** Created by the author

System quality is a significant factor impacting satisfaction, with a standardized path coefficient of 0.184 and a t-value of 3.397 in **H1.** Information quality significantly impacts satisfaction with a standardized path coefficient of 0.248 and a t-value of 4.417 in **H2.** Learning motivation significantly impacts intention to use with a standardized path coefficient of 0.296 and t-value at 8.912 in **H3.** The path relationship of perceived usefulness and learning motivation has a standardized path coefficient of 0.207 and a t-value of 3.979 in **H4.** The path relationship of computer self-efficacy and perceived learning effectiveness has a standardized path coefficient of 0.296 and a t-value of 5.191 in **H5.** Student interactions are the last significant factor impacting satisfaction, with a standardized path coefficient of 0.402 and a t-value of 7.698 in **H6.**

## 5. Conclusion and Recommendation

### 5.1 Conclusion and Discussion

This research aims to determine what variables in China's higher education system drive people toward blended learning. This research aims to identify the elements of blended learning at a normal university in Zhanjiang in Guangdong Province, China, that influence student satisfaction. This study reviews the relevant literature to examine existing research models and provide a theoretical architecture that accounts for the stated hypotheses. This investigation has seven variables and six hypotheses among system quality, information quality, learning motivation, perceived usefulness, perceived learning effectiveness, computer self-efficacy, and blended learning satisfaction. Data was gathered and analyzed using quantitative techniques. Quantitative analysis and 500 questionnaires are used to survey a representative cross-section of the population for this study. The sample size is proportionally dispersed across the first, second, and third years at a normal university in Zhanjiang. To ensure the model was well-fitting and to identify the direction of the causality between the variables used in testing the hypotheses, the data were subjected to a confirmatory factor analysis (CFA) and a structural equation model (SEM). The research described the findings as follows. First and foremost, the research findings prove that system quality significantly influences satisfaction in blended learning. The quality of the learning management system, online resources, and technological support all play pivotal roles in shaping students' overall satisfaction with the blended learning experience (Song et al., 2017).

Additionally, information quality emerges as a critical determinant of satisfaction in blended learning. Accurate, up-to-date, and relevant information enhances students' understanding and fosters a positive perception of the blended learning approach (Jing & Yoo, 2013). Moreover, the study uncovers a substantial impact of learning motivation on satisfaction in blended learning. When students are intrinsically motivated to learn and actively engage in the blended learning environment, their satisfaction levels increase significantly. Furthermore, perceived usefulness is a significant factor driving students' motivation to participate in blended learning at a normal university in Zhanjiang. When students perceive that the blended learning approach offers tangible benefits and helps them achieve their academic goals, they are more likely to be motivated to participate and excel in their studies.

Additionally, perceived learning effectiveness is pivotal in shaping students' satisfaction with blended learning. When students feel that the blended learning methods and resources effectively contribute to their learning outcomes, their overall satisfaction with the approach is positively impacted (Francis & Shannon, 2013). Lastly, the study establishes a clear association between computer self-efficacy and students' perceived learning effectiveness in blended learning at a normal university in Zhanjiang. Higher levels of computer self-efficacy empower students to navigate and utilize the technological aspects of blended learning more efficiently, resulting in a greater perception of the approach's effectiveness (Prifti, 2022).

In conclusion, this research provides valuable insights into the factors influencing satisfaction in blended learning. System quality, information quality, learning motivation, perceived usefulness, perceived learning effectiveness, and computer self-efficacy are all critical elements that deserve attention to enhance students' overall satisfaction and success in blended learning environments. This research indicates that in the age of Internet + education, it is important to focus on the blended learning mode and the variables impacting blended learning to enhance the quality of blended learning in higher education. As a result, it may increase students' learning motivation and satisfaction.

### 5.2 Recommendation

Institutions should focus on several key aspects to optimize satisfaction in blended learning. Firstly, enhancing system quality is essential for a smooth and efficient learning experience. This involves regular evaluations and upgrades to the learning management system, online resources, and technological infrastructure. Investing in advanced learning platforms and ensuring seamless integration of various tools will create a learner-centric environment. Additionally, offering comprehensive technical support and training to educators and learners will foster a positive attitude toward technology and enhance overall satisfaction.

Secondly, information quality is pivotal in students' satisfaction with blended learning. Educational institutions should prioritize curating accurate, up-to-date, and relevant content for online resources and course materials. Collaborating with subject matter experts and using reliable sources will ensure the authenticity and credibility of the information provided. Diverse and interactive learning materials, such as videos, infographics, and simulations, should cater to different learning styles and enhance student engagement. Regularly updating information and seeking student feedback will contribute to continuous improvement and ultimately lead to higher satisfaction.

Thirdly, cultivating learning motivation is vital for achieving higher satisfaction levels in blended learning. Institutions should focus on creating a supportive and inspiring learning environment that nurtures students' intrinsic motivation to learn. Incorporating real-life applications, problem-solving scenarios, and group activities can stimulate curiosity and drive students to participate in their learning journey actively. Recognizing and celebrating students' achievements and progress will reinforce their self-efficacy and motivation. Offering personalized learning pathways and providing regular feedback will further promote a sense of ownership and autonomy, enhancing students' satisfaction and commitment to their studies in a blended learning setting.

Fourthly, to increase students' motivation to participate in blended learning, it is crucial to emphasize the perceived usefulness of the approach. Educational institutions should explicitly communicate the benefits and advantages of blended learning in terms of flexibility, convenience, and improved learning outcomes. Demonstrating the practicality of the blended learning model in preparing students for real-world challenges can significantly influence their perception of its usefulness. Offering career-oriented courses, opportunities for skill development, and professional networking in the blended learning context can further enhance students' motivation and eagerness to engage actively in the learning process.

Fifthly, perceived learning effectiveness is a key determinant of student satisfaction in blended learning. To maximize students' satisfaction, institutions should focus on designing courses that align with clear learning objectives and outcomes. Providing well-structured and organized content and formative assessments will enable students to track their progress and understanding throughout the course. Incorporating peer learning and collaboration opportunities will also enhance students' perception of the approach's efficacy. Regularly seeking students' input on the course design and pedagogy will further reinforce the commitment to continuous improvement and cater to individual learning preferences, ultimately leading to higher satisfaction levels.

Lastly, empowering students' computer self-efficacy is crucial for improving their perceived learning effectiveness in blended learning. Educational institutions should provide comprehensive technology training and support to boost students' confidence using digital tools and platforms. Offering orientation sessions, workshops, and tutorials on various aspects of blended learning technology will alleviate students' apprehensions and enhance their digital literacy. Access to user-friendly and intuitive interfaces will foster a positive attitude towards technology, leading to a greater sense of competence and overall satisfaction with the blended learning experience. Continuous encouragement and recognition of students' technological achievements will reinforce their self-efficacy, motivating them to explore and utilize digital resources more effectively in their learning journey.

### 5.3 Limitation and Further Study

Despite the valuable insights gained from this study, several limitations should be acknowledged. Firstly, the relatively small sample size of 500 participants from a single normal university in Zhanjiang, Guangdong Province, China, may restrict the generalizability of the findings to a broader population. While the sample was representative of the specific context studied, caution should be exercised when applying the results to other regions or different types of universities. To address this limitation, future research could include a larger and more diverse sample from multiple universities to enhance the study's external validity and ensure a more comprehensive understanding of blended learning satisfaction across various settings.

Secondly, the cross-sectional design used in this research limits our ability to establish causal relationships between the variables. As a snapshot of data collected at a single point in time, the study can only provide associations and correlations rather than causation. Longitudinal studies that follow participants over an extended period provide a more robust understanding of the dynamics between the elements of blended learning and student satisfaction. By tracking changes and developments in students' perceptions and satisfaction levels over time, researchers can better ascertain the directionality of the relationships and uncover potential causal links between the variables.

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