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Personalized Learning for Art Major Students Based on Learner Characteristics

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A Dissertation by

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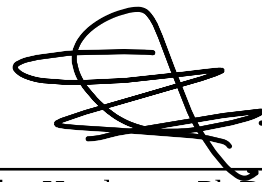

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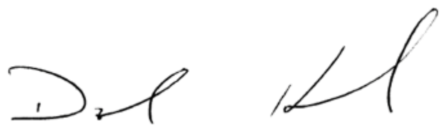

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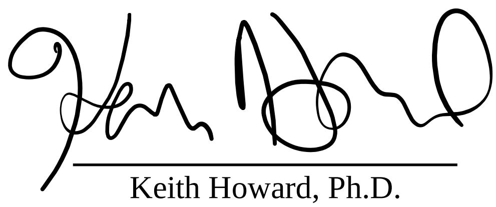

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April 2024

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by Jiayu Shao

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In the fleeting years of academic pursuit, akin to a dream, time slips away, and my 4-year doctoral journey concludes in haste. Throughout this perplexing yet radiant odyssey of learning, I have had the privilege to encounter numerous individuals who not only warmed my heart but also sparkled brightly. Here, I wish to convey my heartfelt gratitude to each one of them.

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ABSTRACT

Personalized Learning for Art Major Students Based on Learner Characteristics

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Recognizing the existing research gaps concerning learner characteristics in the realm of personalized learning in Chinese higher art education, this study initially analyzed prevailing patterns in personalized learning research and its current implementation in higher education through an extensive literature review. Subsequently, a quantitative investigation was carried out at S University in Shanghai, aiming to delve into their learner characteristics, investigate the interrelationships among these characteristics, and propose customizable personalized learning designs. The research included a comprehensive quantitative study using a learner characteristics questionnaire survey involving 455 art students at S University, employing various statistical methods, including ANOVA, factor analysis, cluster analysis, and multiple regression. The study extensively explored eight distinct learner characteristic factors and successfully identified three learner clusters with statistically significant differences, providing detailed descriptions of the characteristics within each cluster to support personalized learning. Furthermore, the paper, through multiple regression analysis, revealed the direct impacts of self-efficacy and spatial orientation ability on learning behavior, while also elucidating the moderating role of learning anxiety in this relationship. Ultimately, personalized learning recommendations for higher art education were formulated based on the identified learner characteristics in distinct groups of art students in higher education.

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CHAPTER 1: INTRODUCTION

Starting in 2019, the COVID-19 outbreak forced schools to transition to online teaching. During these times of social isolation and lockdown, schools underwent emergency digitalization or forced digitalization (Acebes et al., 2022; Cone et al., 2022). At the beginning of 2020, the Ministry of Education (MOE, 2020) of the People's Republic of China of China advocated for students to stop going to school without stopping learning. In response, enterprises and schools launched online learning on a large scale, and the expectation of using online-based technology as an educational learning model rapidly rose. The MOE (2020) reported the number of visits to the national cloud platform of the primary and secondary school network reached 2.073 billion, and the number of visitors had reached 1.711 billion.

The forced digitalization phenomenon caused by the COVID-19 global pandemic occurred not only in China but also in other countries all over the world. A global survey of more than 400 higher education institutions in 106 countries found 67% of these institutions were successful in substituting online distance learning for classroom instruction at the start of the pandemic (Marinoni & van't Land, 2020). Furthermore, Marinoni and Van't Land (2020) concluded educators' attitudes toward technology had changed because of being required to learn and test new digital tools and approaches, which gave rise to the possibility of investigating more flexible learning paths and making them an integral component of lesson plans.

Despite this promising possibility, the COVID-19 global pandemic severely affected education (Engzell et al., 2021; Tomasik et al., 2020), and schools seemed unprepared for emergency digitalization (Kuhfeld et al., 2020; Maldonado & De Witte, 2020). As Mospan

(2023) pointed out, the shift from analog-based to digitally-based education that took place throughout 2020–2021 in higher education worldwide was described as chaotic and haphazard.

But this chaos was also a chance to implement educational reforms that had been discussed before the COVID-19 global pandemic but had never been completely implemented (Zhao & Watterston, 2021). Personalized learning (PL) became integrated into federal and state policies and was funded by millions of dollars in private investments (Regan & Steeves, 2019). For example, in the United States, the Every Student Succeeds Act (2015) provided federal funding to states to implement personalized learning, and state laws either mandated certain personalized learning techniques or promoted personalized learning through statewide programs. Student-centered personalized learning was identified as a significant shift that should take place in education after the COVID-19 global pandemic (Zhao & Watterston, 2021).

Problem Statement

Bloom (1984) found using the conventional teaching method as the baseline, students' performance improved by one standard deviation under mastery learning conditions, and students receiving one-on-one tutoring showed an improvement of two standard deviations. Bloom contended the two-sigma difference was attributable to the efficacy of individualized, one-on-one training rather than individual variations in intelligence or ability. Nevertheless, in traditional educational environments, offering one-on-one instruction to every student is neither realistic nor feasible (Eyre, 2007). Hence, the two-sigma problem refers to the difficulty of identifying educational methods or approaches that can raise the typical student's performance to that of a student who receives one-on-one tutoring (Essa & Laster, 2017). This issue has significant ramifications for educators who want to enhance student outcomes and close achievement gaps.

The two-sigma problem has been particularly prominent in Chinese art education. The early workshop-style tradition in art education used the apprenticeship system. The greatest advantage of that system was the master taught by example, and the teaching process was flexible and diverse (Coy, 1989). The workshop system effectively integrates life, society, and learning because the students benefit not only from the mastery of skill but also from the understanding of truth to achieve the unity of knowledge and practice (Adewumi, 2019). Gu (2019) compared modern art education with traditional artistic skill inheritance passed on between generations and found that the most prominent change in current art education was the traditional apprenticeship system was replaced with classroom teaching. This replacement has led to a fundamental shift in teaching content and methods. To meet the needs of the classroom setting, textbooks have appeared, and the one-on-one teaching method has also been replaced by a one-to-many structure.

Because the experience of beauty is consistent with the creation of beauty (Diessner et al., 2008), art education is not only the development of knowledge and skills but also the cultivation of character and behavior. One-to-many signifies one teacher to many students, which is the standard way of modern school education and the product of scientific education. Although it has improved the efficiency of the transfer of knowledge and skills, the cultivation of aesthetic feelings and students' personalized expression in artistic creation is missing in this process (Gu, 2019). To solve the two-sigma problem in the arts, personalized learning supported by technology could lower the barriers (Grant et al., 2016). Computer-based programs that strive to adapt to students' learner characteristics and requirements have been the dominating form of personalized learning (Pane et al., 2015).

The primary advantage of personalized learning is its ability to accommodate the needs of diverse student populations, according to a study designed to understand students' different learning needs (Taylor & Gebre, 2016). Dearmond and Maas (2018) also found it is necessary to accommodate different learner characteristics. These characteristics influence how learners react to technology-based instruction. Such influences involve dynamic and complex issues, so researchers have put considerable effort into studying this topic (Hsieh & Chen, 2019; Ku et al., 2016; Vergara et al., 2023; Zhao & Tavangar, 2016; Zhao & Watterston, 2021). These studies demonstrate the importance of considering learner characteristics in the design and implementation of technology-based personalized learning tools. Furthermore, by considering learner characteristics such as cognitive style and personality, educators can create more effective and engaging learning experiences for their students.

However, the current research on personalized learning has primarily concentrated on math, computer science, biology, and other natural science fields (Bernacki et al., 2021; Shemshack & Spector, 2020). Research on personalized learning in art education was scarce, which may be because of the lack of previous research on the learner characteristics of art major students in higher education or because art students are difficult to access as a sample. Additionally, the unestablished definition of personalized learning makes it challenging to determine what kind of personalized method to adopt for teaching art students in higher education (Walkington & Bernacki, 2021). How to define personalized learning and apply it to art education remains for further discussion.

Purpose of the Study

Given gaps in the research on the learner characteristics of students in Chinese higher art education for personalized learning, the current study first identified trends in personalized learning research and how personalized learning has been currently applied in the context of higher education through a literature review. Then, a quantitative study at S University in Shanghai was conducted to explore learner characteristics of art major students, examine the learning differences from multiple dimensions, and investigate the features in detail by grouping students with different learner characteristics. Finally, personalized learning recommendations for art education in higher education were developed based on learner characteristics of groups of art students in higher education.

The purpose of this study was to (a) identify the general learner characteristics of art major students, (b) examine the interrelationships among learner characteristics, and (c) provide personalized learning design recommendations for art students that fit their learner characteristics. Based on the research purpose, I used a quantitative research design with an online survey method.

Research Questions

To identify the general learner characteristics of art major students, examining the interrelationships among these characteristics, and providing personalized learning design recommendations tailored to their learner traits, the current study used the following research questions (RQs):

- RQ1: What are the background and general learner characteristics of the art major students at S University
- RQ2: Is there any difference in learner characteristics for art students depending on their background information?
- RQ3: What are the underlying factors that influence learner characteristics among art major students at S University?

- RQ4: In what ways can students at S University be classified into different groups based on learner characteristics?
- RQ5: How spatial orientation ability (SOA), self-efficacy (SE), and learning anxiety (LA) might affect learning behavior (LB)?
- RQ6: How could the schools support students to enhance their personalized learning?

Theoretical Framework

A portion of the research on personalized learning and related theories focuses on the micro level, which includes learner characteristics such as behavior, cognition, and emotion (Bandura, 1986; Bloom, 1968; Cronbach, 1975; Elliot, 1999; Fry & Kolb, 1979; Kalyuga, 2007; Pekrun & Perry, 2014; Sweller, 2011). However, some theories also focus on the macro level—the whole learning system—such as constructivism (Bada & Olusegun, 2015). Considering the focus on the learner and technical support features of personalized learning, as well as the micro and macro levels of learning theories, I used constructivism theory and Bandura's (1986) self-efficacy theory to conduct research at the micro and macro level, analyzing the learner characteristics of art major students through the dimensions of behavior, and cognition.

Bandura's Self-Efficacy Theory

Bandura's (1986) self-efficacy theory emphasizes that individuals' evaluation and confidence in their ability will affect their behavior, thinking, and emotional response. Bandura believed self-efficacy is an individual's confidence and belief that they can complete a specific task or achieve a specific goal. A person's high level of self-efficacy means they believe they can succeed, and a low level of self-efficacy means they may doubt their ability. Bandura (1977, 1978) pointed out self-efficacy beliefs are formed in four ways:

- Experience: through the personal experience and success of individuals, they will enhance their confidence in their abilities. Successful experience will increase self-efficacy beliefs, and failure experience may reduce beliefs.
- Observation: by observing the experience of others, individuals can learn about the success or failure experience of others, thus affecting their self-efficacy beliefs.
- Social evaluation: the evaluation and feedback of others will affect individual self-efficacy beliefs. Positive social evaluation may enhance beliefs, and negative evaluation may reduce beliefs.
- Physical and emotional states***:*** individuals' physical states (such as health status) and emotional states (such as anxiety or relaxation) also affect their self-efficacy beliefs.

Constructivism

Constructivism is a learning theory that places a strong emphasis on learners' active engagement in the creation of information and meaning, which holds that learning happens when students actively participate in the process of creating their knowledge of the world around them (Huitt, 2009). According to the constructivist theory, students actively seek out information and try to make sense of it considering their prior experiences and knowledge (Fosnot & Perry, 1996). The main tenets of constructivism in learning include: (a) students build their knowledge through a process of assimilation and adaptation, and (b) learning is social and collaborative.

In the context of personalized learning, constructivism supports and guides personalized learning by stressing students' active engagement in building their knowledge and understanding of the world. The constructivist approach focuses on personal experiences and environment-based learning that allow students to develop their knowledge of the content in a relevant and engaging way by adapting the learning experience to their needs and interests. Furthermore, constructivist ideology also supports the use of technology and other instruments in personalized learning, which fits the current features of technology-supported personalized learning (Morrison & Collins, 1995; Solvie & Kloek, 2007).

Significance of the Study

Being able to accommodate diverse needs is the primary advantage of personalized learning. It is necessary to consider learner characteristics such as cognitive style and personality in the design and implementation of personalized learning. However, the current body of research on personalized learning is lacking in the study of art students. Thus, I conducted this study to fill in the research gap and provide an analysis of the learner characteristics of students in Chinese higher art education through a quantitative study. The results of my research could be applied to improve academic outcomes for art students by creating learning experiences tailored to meet each student's needs. Finally, based on my findings, I provided suggestions for educators in art pedagogy to adopt effective teaching techniques, content, and assessments to match the needs of art students by understanding their individual needs, strengths, and challenges.

Operational Definitions

For this study, I used the key terms of personalized learning and learner characteristics (including learning behavior, spatial orientation ability, self-efficacy, and learning anxiety). Certain terms are defined broadly, and others hold specific meanings within this study. The subsequent section elucidates the definitions and significance associated with these terms.

Personalized Learning

Personalized learning refers to a wide range of methodologies and programs for tailoring instruction to the characteristics of the learner to accomplish learning outcomes. The use of technology for individualized instruction, rotation models in which students move between different instructional formats, learner profiles that aid teachers' decision making, student-driven academic goal setting, project-based learning, social-emotional learning, and competency-based learning in which students master concepts at their own pace are all examples of possible personalized learning approaches (Walkington & Bernacki, 2021).

Learner Characteristics

The concept of learner characteristics is employed in the science of cognition and learning. It is used to assess a target student population and define features of their academic, social, or cognitive self that might affect how and what they learn (Drachsler & Kirschner, 2012). The following learner characteristics were used in my study:

- Learning behaviors are ingrained practices that help learners obtain knowledge and engage in fruitful social interactions. These habits are formed both within and outside the classroom (Mutiawati et al., 2023).
- Spatial orientation ability is the learner's perception of self-orientation in learning. It is the ability to determine the location of information as well as the strategies and activities necessary to obtain the required information (G. H. Wang & Fu, 2018).
- Self-efficacy refers to thoughts about one's ability to learn or accomplish certain activities at specific levels (Schunk & Pajares, 2002).
- Learning anxiety refers to the level of anxiety that learners experience in the learning process. In my study, learning anxiety specifically refers to the level of anxiety experienced in online learning (Heckel & Ringeisen, 2019).

CHAPTER 2: REVIEW OF THE LITERATURE

Throughout the 1960s, substantial changes occurred in several sectors of the United States, including in women’s and civil rights. The contemporary educational climate has reflected these social and political shifts, focusing more on student-centered teaching and raising awareness of the need to address the individual needs of each learner. In this setting, Bloom’s (1968) mastery learning theory evolved into a means of delivering more individualized instruction and support for student achievement, which includes dividing challenging learning objectives into small and more manageable units to offer individualized feedback and remedial measures to ensure every student master’s them.

In the 1990s, differentiated instruction became more relevant because of the increasing access and technical support in education (Edyburn, 2004; Putnam et al., 2002). As computers became more prevalent in classrooms, educators started considering the possibility of using technology for individualized instruction. As a result, computer-based systems were created that gave students personalized coaching and feedback depending on their performance (Kulik & Kulik, 1991).

Furthermore, early in the 21st century, the continued growth of technology contributed to the rise in popularity of differentiated instruction. With the ubiquitous use of computers and the Internet, instructors began using various online resources and technologies to facilitate individualized instruction, including digital textbooks, multimedia materials, and online assessments (Levy & Murnane, 2004). In addition, technology enabled the development of more engaging and interactive instructional resources, such as simulations and games, that could be used in several ways to promote student learning (Gee, 2003). In response to students’ diverse needs in higher education and the evolution of technology, the notion of differentiated instruction evolved. Differentiated instruction has been viewed as a reaction to the need for inclusive classrooms that embrace children from many backgrounds, including students with special needs, second language learners, and students from lower socioeconomic backgrounds (Coady et al., 2016). As technology has become more widely used in education, customized learning has evolved into a more tailored and learner-driven experience.

During the 2000s, the term “personalized learning” started to catch on in the United States as many funding sources outside of the traditional national funding stream started to focus on it (Regan & Jesse, 2019). In 2010, the Bill and Melinda Gates Foundation launched Next Generation Learning to support the development of personalized learning tools and strategies. Foundations such as the Bill and Melinda Gates Foundation and Chan Zuckerberg Initiative, which have a technology background, put great emphasis on how technology could help to meet the personalized learning needs of students and explore how humans learn through data-driven methods (Regan & Steeves, 2019). Barbour and Reeves (2009) considered personalized learning as combining the best of traditional education with 21st-century technology to give each student instruction and information that fit their strengths, weaknesses, and areas of interest. By giving students access to tools and resources that may be used to enhance their learning, technology can play a crucial part in providing personalized instruction (Fitzgerald et al., 2018).

Technology has enhanced personalized learning in various ways. For instance, with adaptive learning, the complexity of activities and assignments changes based on the student’s individual development (Aeiad & Meziane, 2019; T. C. Yang et al., 2013). Learning analysis can provide teachers with real-time feedback on their students’ performance so they can modify instruction to better match students’ needs (Ferguson, 2012; Guo et al., 2014; Siemens, 2013).

Adaptive learning technology and learning analysis can assist teachers in understanding students' learning processes and individual needs and adjusting instruction accordingly (Knox, 2020). In addition, e-portfolios and other types of online evaluations can give students a more individualized and meaningful method to demonstrate their talents and interests (Miller, 2009). These strategies optimize each student's educational experience, promote their academic performance, and expand the content and influence of personalized learning in the field of education.

Educators and researchers have continued to find that when students have ownership and control over their learning, they are more engaged and proactive (Lee & Hannafin, 2016; Schmitz & Wiese, 2006). Researchers have been paying more attention to the self-determination of learners, which may boost learning motivation, promote deeper learning, and eventually improve learning outcomes by allowing students to choose their learning objectives (Reeve, 2012; Ryan & Deci, 2000).

From the literature, it is evident that the genesis and development of personalized learning have been impacted by various factors, including social culture, technology development, the boom in student-centered learning in the context of technology support, and a continuous conversation on the role of education in promoting fairness and social justice (Guthrie & McCracken, 2010). Personalized learning as a concept and its use in the classroom has developed dramatically, reflecting broader transformations in the educational system and the use of technology (Nandigam et al., 2014).

The Definition of Personalized Learning

Personalized learning has been defined in a variety of ways. For example, the British Educational Communications and Technology Agency (2009) defined personalized learning as a student-centered, inclusive learning method to meet the needs of all students, especially those with learning difficulties. British Educational Communications and Technology Agency (2009) suggested a student's learning difficulty also may contribute to a learning difference, which indicates the broader usage of personalized learning. Similarly, in their National Education Technology Plan, the U.S. Department of Education (2017) defined personalized learning as a kind of training tailored to each student's individual needs in terms of learning pace and instructional strategy. It was noted that the learning objectives, instructional methodologies, and content may differ depending on the learner's needs and that learning activities are driven by students' interests and frequently self-initiated (U.S. Department of Education, 2017). Furthermore, Dörnyei (2009) emphasized the idea of using learner characteristics—including learning differences among students as well as different learning methods, needs, and paces—is crucial for students to gain success in learning.

A common theme of personalized learning notes starting from the students' personality characteristics, considering the actual needs of students, and formulating corresponding personalized programs to meet those needs (Keller, 1968). According to Xie et al. (2019), it has been widely recognized in various learning and psychological theories that learning experiences and acquired information are unique. Chen and Wang (2021), on the other hand, were concerned about the differences in learning methods, support systems, learning environments, resource support, and feedback adopted through personalized learning for the assessment of students' learning. Despite slight differences between the conceptualizations of personalized learning, these definitions have the following characteristics in common: (a) the rate of learning might be modified; (b) the learning objective, technique, material, and tools were tailored to each student;

(c) students could select when, where, and how to learn; and (d) the learning was driven by student interests (Kong et al., 2016; Li, 2016).

Personalized Versus Standardized Learning

The analysis of the definition of personalized learning revealed many differences between personalized and standardized learning. Researchers compared multiple aspects of personalized learning and standardized learning, which are summarized in Table 1 (Gao, 2014; Kong, 2017; Sharma et al., 2017). Overall, compared with standardized learning, personalized learning has the advantage of flexibility. It is more targeted at individual needs, providing learning materials and resources according to students' learning needs and levels. By adjusting the learning progress and difficulty, students can learn more independently and enhance their learning interests and enthusiasm; personalized learning can also provide more diversified learning methods, such as game-based learning, online learning, and group cooperation.

Personalized Learning in Higher Education

Though many aspects of personalized learning have been discussed and reviewed, how and to what extent it can play a role in higher education has remained a topic of further exploration. Thus, I reviewed the empirical research of personalized learning in higher education following the guidelines outlined by Petticrew and Roberts (2006) and Page et al. (2021).

Table 1

Comparison of Essential Factors of Personalized and Standardized Learning

Essential factor	Personalized learning	Standardized learning
System output	Mass customization	Mass production
Teaching and learning method	Autonomous learning and asynchronous teaching in the knowledge era	Unified learning and standard pace teaching in the Industrial era
Course length and evaluation	Continued tracking of courses and dynamic evaluations of students' knowledge, skills, learning styles, and interests	Completion of courses according to the term schedule and summative evaluation
Teacher Role positioning	Student-centered; Teacher Guide students to form a collaborative learning community	Teacher centered; The teacher teaches content according to the course plan
Location	Flexible; a combination of online, in-person, and hybrid learning in an informal or formal setting	Fixed; in-person learning only in a formal setting
Learning time	Flexible	Fixed
Teaching location	Different teaching locations	Fixed location
Teaching resources	Unlimited and diversified virtual resources	Resources restricted by teaching location
Student work archives	Movable and accessible at any time	Limited access
Primary learning media	Digital and interactive resources	Print and static texts

Literature Search Strategy

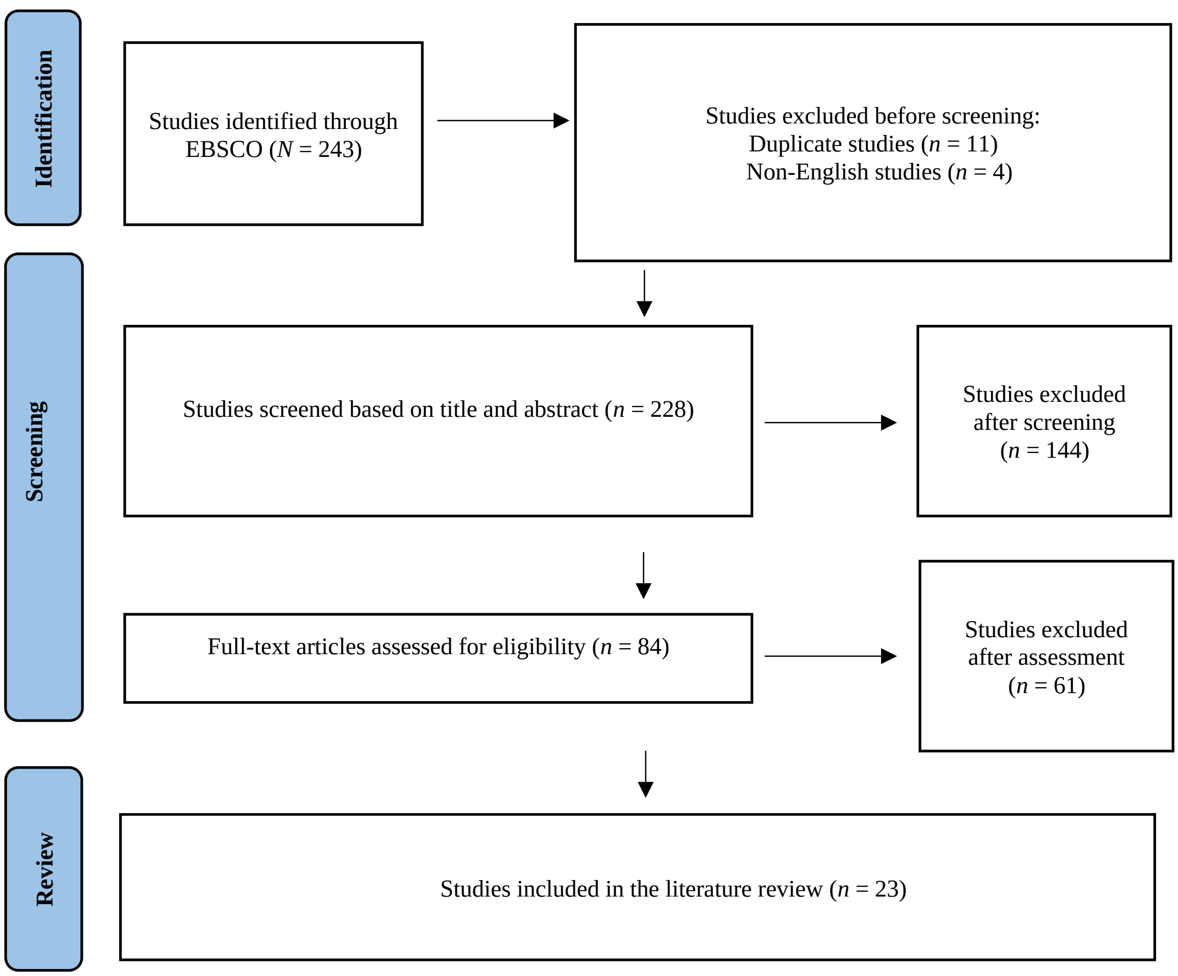
As a search approach, a Boolean search string was used for EBSCO databases on February 25, 2023. The search terms included the following categories: (a) the personalized component, (b) the school context, and (c) the study design. The resulting search string was: "AB ((personalized AND learning) AND (higher AND education) AND (effect OR empirical OR intervention OR experiment))." Furthermore, the following additional filters were applied: (a) online full text, (b) peer-reviewed, (c) past 5 years (2018–2023), (d) academic journals, and (e) published in English.

Screening Procedure

The screening technique comprised four steps (see Figure 1). The Boolean search phrase was used during the identification step, yielding 243 studies. Eleven duplicates were eliminated, and four studies were excluded because the publishing language was not English, resulting in 228 papers from the following databases: Complementary Index, ERIC, Education Full Text, Academic Search Premier, and MEDLINE.

Figure 1

Screening Procedure for Eligible Studies



During the screening process, I evaluated the titles and abstracts of the articles according to explicit inclusion and exclusion criteria. Studies were excluded if they failed to disclose pertinent empirical findings, including both quantitative and qualitative information. The following criteria were used to determine if empirical findings were relevant: (a) they revealed connections between personalization and learning outcomes, (b) they reported precise results based on experimental design, (c) they could be used to assist the delivery of personalized learning, (d) they were not meta-analyses or literature reviews, and (e) the research subjects were students in higher education. Based on these six criteria, 144 articles were excluded, including six studies that were observational or only described the adaptive tool instead of the impact on learner outcomes.

If it could not be determined from the title, abstract, and keywords if a study met the standards, it was included in the next stage to go through a thorough quality evaluation. In this next phase, the remaining 84 full-text papers were assessed for eligibility based on the same criteria, resulting in another exclusion of 61 papers. In the last phase, the remaining 23 papers were included in the review, of which 20 studies (87% of the total) used quantitative methods, two used mixed methods, and one used qualitative methods. The sample size ranged from 8 (qualitative study) to 1,040. Most of the applied subjects were science (computer or math; *n* = 10) and language (*n* = 3).

Findings

Through an in-depth analysis of existing literature, it became evident that personalized learning has significantly contributed to enhancing learning outcomes, academic skills, and academic engagement, and promoting equality in educational settings. Research findings consistently highlighted the positive impact of personalized learning methodologies on students' educational experiences The specific analysis was as follows:

Enhanced Learning

As shown in Table 2, by providing a more tailored and flexible learning experience that meets the unique needs and preferences of each student, personalized learning can enhance learning outcomes (15 out of 23), learning engagement (6 out of 23), learning skills (6 out of 23), and equity (2 out of 23).

Table 2

Learning Components, Interventions, and Research Methods of Included Studies

Study	Learning component				Intervention	Learner characteristics factor(s) applied	Method
	OT	**LS**	**EG**	**EQ**			
Abedi et al. (2021)	x	x			Personalized online learning	Cognitive style	Quant
Arsovic & Stefanovic (2020)	x		x		Learning management system	Learning style, prior knowledge	Quant
Cano & Leonard (2019)				x	Alarm system, data mining	Background information	Quant
Cavaleri et al. (2019)			x		Feedback (in the form of written/video)	Learning behavior	Qual
Chikasha et al. (2022)	x				Multimedia	Cognition style, prior knowledge	Quant
Cornelisz & van Klaveren (2018)			x		Computerized, personalized practicing	Background information, cognition (task perception), learning behavior	Quant
Dawson et al. (2021)	x			x	Multimedia	Cognition (mental effort, Dyslexia or not)	Quant
Fung et al. (2019)		x			Personalized weekly assessment and evaluation	Cognition (motivation)	Quant
Alamri et al. (2020)		x			Personalized learning activities	Psychological needs satisfaction, motivation	Qual

Study	OT	LS	EG	EQ	Intervention	Learner characteristics factor(s) applied	Method
H**orváth** (2021)	x				Extended reality	Cognition style	Quant
Karaoglan Yilmaz (2022)	x				Adaptive learning, learning feedback	Metacognition	Mixed
Lim et al. (2021)	x				Feedback in the learning process	Learning behavior	Quant
Lim et al. (2023)	x				Adaptive learning system	Not Appliable	Quant
Lluch Molins & Cano García (2023)		x			Self-regulation of the learning sequence, peer feedback, and Learning Management system	Learning behavior	Quant
Loeffler et al. (2019)		x			Assessment, interaction	Learning behavior, Metacognition	Quant
Nikimaleki & Rahimi (2022)	x		x		Extended reality	Not Applicable	Quant
O'Connell & Lang (2018)	x		x		Personalized email reminders	Not Applicable	Quant
Sáiz-Manzanares et al. (2019)	x				Adaptive learning management system	Learning behavior	Quant
Tang et al. (2022)	x				Adaptive learning game	Learning behavior, self-efficacy	Quant
Xiang & Liu (2019)	x				Web-based mapping tools	Learning style	Quant
Yang & Liu (2022)		x	x		Extended reality	Not Applicable	Quant
Zhang et al. (2022)	x				Recommendation algorithm	Not Applicable	Quant
C. Zhou (2022)	x				AI–supported personalized learning platform	Not Applicable	Quant

Note. OT = learning outcome; LS = learning skills; EG = engagement; EQ = equity; AI = artificial intelligence; Quan = Quantitate method , Qual=Qualitative Method, Mix=Mixed method

Learning Outcomes. Arsovic and Stefanovic (2020) found that the adaptive learning environment positively impacted learning performance and results. The students who participated in the adaptation course achieved the best results; they had the longest log-on session and higher efficiency of activity implementation. Likewise, Sáiz-Manzanares et al. (2019) found implementing a personalized system predicted learning outcomes accurately by 42.3%, particularly quiz scores, and it predicted 74.2% of beneficial behavioral patterns. Moreover, another study reported the efficacy of an adaptive learning system used within an institution, particularly its impact on course scores (L. Lim et al., 2023).

Learning Skills. Loeffler et al. (2019) studied self-regulated learning in higher education, finding that metacognitive strategies and internal resource-management strategies progressed with intervention. Similarly, Abedi et al. (2021) and Fung et al. (2019) found the same improvement in self-regulated learning in the experimental group when personalized learning was applied. Furthermore, Lluch Molins and Cano García (2023) found by incorporating personalized feedback and interaction into the learning process to help students identify areas for improvement and work toward mastery, students could improve their self-regulated learning skills. Finally, technology can be used in personalized learning to provide students with access to a wide range of resources and tools to support their learning. For example, P. Yang and Liu (2022) reported students could use interactive simulations and games to develop problem-solving and critical-thinking skills or access online resources to deepen their knowledge in a particular subject area.

Academic Engagement. Engagement in personalized learning refers to the level of involvement, motivation, and interest that students experience (Alamri et al., 2020). Personalized learning can enhance engagement by providing a more relevant, flexible, and interesting learning experience that meets the unique needs and interests of each student. This can include real-world relevance (Nikimaleki & Rahimi, 2022), immediate feedback, collaboration, and autonomy (Karaoglan Yilmaz, 2022), all of which can help keep students motivated and engaged in the learning process. According to Fung et al. (2019), by promoting engagement in personalized learning, students were more likely to take an active role in their learning, develop a deeper understanding of the material, and be better prepared for success in their future endeavors. Furthermore, Cornelisz and van Klaveren (2018) pointed out that when adaptive practice is low-stakes, perceived usefulness is key for student effort. Considering student differences and preferences, likeability, and test preparation boosts engagement. Effective computerized personalized practice demands a comprehensive approach for all students' engagement.

Equity. Personalized learning can assist in identifying and addressing each student's particular needs to support students with learning difficulties, language learners, and students from lower socioeconomic backgrounds. This support can help narrow achievement disparities and promote educational fairness. Dawson et al. (2021) explored different modalities and learning materials for use with college students with and without dyslexia, the personalized design of learning materials provided students with multiple options to gain learning success. Additionally, Cano and Leonard (2019) designed an interpretable multiview early warning system adapted to underrepresented student populations to increase retention and improve the academics of those students.

Technology-Enhanced Personalized Learning Interventions

Technology, along with intervention tools, is pivotal in shaping personalized learning. These tools enable tailored learning experiences by analyzing student progress and learning styles. Technology facilitates real-time assessment, customizes instructional materials, and promotes interactive learning through virtual classrooms and collaborative platforms. These intervention tools are summarized in the following section.

Learning Resource Recommendation Systems. One of the intervention methods used in studies relevant to my research was the learning resource recommendation system. It provides personalized recommendations of learning resources, including, but not limited to, the learning content and learning material modality (in the format of video, audio, or multimedia). For instance, L. Lim et al. (2023) designed a human-centered artificial intelligence course recommendation system to assist students with course selection from different departments. Results showed the system had a greater influence on satisfaction with course recommendation results, and 83.6% of students were more interested in courses at the top of the recommendation list (L. Lim et al., 2023). Additionally, researchers found the recommendation system could be adapted based on feedback in combination with learning analysis technology, which made the recommendation more flexible and suitable to individual learning needs (Karaoglan Yilmaz, 2022; Zhang et al., 2022).

Learning Management Systems. Learning management systems give students access to online learning tools, such as videos, interactive quizzes, and multimedia content. Teachers can also use a learning management system to keep track of student performance, give students feedback, and change their lessons to meet the needs of each student. Arsovic and Stefanovic (2020) developed an adaptive learning model and tested it on a student sample (n = 160), which proved successful. Cavaleri et al. (2019) examined the impact of audiovisual feedback compared to written-only feedback on undergraduate students’ engagement with the feedback. It was contended that the use of audiovisual feedback, characterized by its multimodal format, conversational style, verbal explanations, and personalized touch, facilitated more effective interaction with feedback, especially benefiting students who had a limited grasp of the English language. O’Connell and Lang (2018) found that customized email reminders have the potential to enhance study consistency and academic performance in a foundational undergraduate course by increasing exam performance by 0.2 standard deviations.

Extended Reality and Game-Based Learning. In recent years, extended reality and game-based learning technology have also been applied to personalized learning. Extended reality merges physical and virtual worlds for immersive experiences, aiding individualized learning (Horváth, 2021). Virtual and augmented reality enhance skill transfer and abstract concept comprehension, depending on learner engagement (Nikimaleki & Rahimi, 2022; P. Yang & Liu, 2022). Game-based learning incorporating game elements boosts student motivation (Qian & Clark, 2016). Adaptive learning games adjust difficulty based on student performance, fostering skill development (Vergara et al., 2023). Role-playing games enhance communication and problem-solving skills (Tang et al., 2022).

Accommodation Learner Characteristics

In the intricate landscape of personalized learning, recent studies have meticulously dissected a multitude of personal variables. Seventeen studies used in this literature review took learner characteristics, into account, which indicates its importance for personalized learning (see Table 2). These variables go beyond the surface and delve into the very core of the learner's being. More specifically, the research focused on an array of personal attributes, including learning behavior, cognition, prior knowledge, background information, and various other learner characteristics. These aspects, akin to the pieces of a complex puzzle, were meticulously examined in the studies aimed at tailoring educational experiences to individual needs.

Learning Behavior. As a fundamental aspect of this exploration, learning behavior refers to the diverse ways individuals engage with educational content. Understanding these behavioral patterns provides essential insights into how individuals approach learning (Lim et al., 2021). For example, Cavaleri et al. (2019) collected the homework correction behavior after receiving feedback from the teacher. They specifically investigated the impact of technology-enhanced feedback, including methods such as audio and video feedback, on students' engagement and interaction with the feedback provided by teachers. Moreover, by capturing the online learning behavior, Loeffler et al. (2019) adapted the usage of interactive ambulatory assessment for self-regulated learning in daily routines. Thus, adapting learning behavior in personalized learning enables educators to create environments that resonate with each student's unique preferences.

Cognition Factors. Cognition factors include learning style and metacognition, which were also pivotal variables delving into the intricate processes of thought, perception, and understanding. In terms of learning style, the Felder–Silverman learning style model, Honey and Mumford's learning style model, and VARK (Visual, Audio, Reading/Writing, and Kinesthetic) models were used in the paper reviewed. Alternatively, researchers explored the cognitive mechanisms underlying learning, unraveling how individuals process information, make connections, and form knowledge structures (Arsovic & Stefanovic, 2020). Furthermore, this deep understanding of cognition has paved the way for the development of instructional strategies that align with the natural cognitive processes of learners, optimizing comprehension and retention.

Other Learner Characteristics. Furthermore, the research studies examined for this study meticulously considered a range of other learner characteristics. These encompassed various traits, including learning styles, motivation levels, prior knowledge, and background information. Acknowledging and integrating these diverse learner characteristics became instrumental in shaping personalized learning approaches that were not only effective but also culturally sensitive and inclusive.

Conclusion

Through analysis of the literature on personalized learning, I found the term has been defined in various ways. Although personalized learning has expanded with the development of science and technology, its core features of being student-centered and designed around learner characteristics have stayed the same. The strong connection between personalized learning and technology, especially online learning, was an inevitable trend. Examples of technology-based personal learning interventions include extended reality, adaptive learning management systems, resource recommendation systems, and game-based learning. Despite the progress made in personalized learning, it was noted that certain technology-based systems still relied heavily on test-based performance (Lim et al., 2023; P. Yang & Liu, 2022; C. Zhou, 2022; Zhang et al., 2022). Instead of tailoring educational experiences based on the rich tapestry of learner characteristics, these systems predominantly assessed learner progress through standardized assessments. This disconnect between the comprehensive understanding of learner characteristics and the assessment methodologies used in some technological platforms highlighted a crucial gap in the evolution of personalized learning technologies.

Another point worth mentioning is the importance given to cognition factors in personalized learning research, including learning styles, learning motivation, and learning emotions (Alamri et al., 2020; L. Lim et al., 2023). This may be related to the development of technology-based learning analysis, shifting the focus from behavior analysis to emotion analysis. The trend may also have emerged because of the COVID-19 global pandemic as many students experienced loneliness and anxiety due to their prolonged isolation and lack of face-to-face social interaction, which in turn could affect their studies. Emotions play an essential role in learning; the literature mainly reflects this influence on learning behavior, learning achievement, and learning experience. Unfortunately, there are very few studies on emotions and personalized learning, which leaves a research gap that needs to be studied further.

Finally, personalized learning differs from traditional learning in many ways; it places higher demands on learners' abilities, and for college students, personalized learning varies in different learning situations. Several researchers (Pituch & Lee, 2006; Rydzewski et al., 2010; Vandewaetere et al., 2011) have raised the question of whether learners who are successful in personalized learning share specific personal characteristics, and whether these common characteristics can predict learners' persistence in digital learning and explain the high dropout rate of digital learning. These characteristics, including learning behaviors, spatial orientation ability, and learning anxiety, are considered learner characteristics that should be researched and discussed further. Learners' responses to information technology are influenced by their learner characteristics. Researchers have invested a lot of time and effort into this subject because these influences are dynamic and complicated (Birrell et al., 1985; Conklin, 1987; Weinstein et al., 2002; Tsai & Tang, 2017; Bandura, 2002). These studies show how crucial it is to consider learner characteristics holistically while creating and using tailored technology-based learning tools. However, none of the research studies in this literature review focused on personalized learning in the context of art pedagogy, leaving room for further exploration.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter presents the research methodology for this study. The purpose of this study was to (a) identify the learner characteristics of the art major students at S University, (b) examine the relationships between the learner characteristics variables, and (c) describe the difference in learner characteristics among groups to meet the personalized learning needs of art students in S school. Based on the research purpose, a quantitative research design with a web-based survey method was used.

Research Questions

This study included the following research questions (RQ):

- RQ1: What are the background and general learner characteristics of the art major students at S University
- RQ2: Is there any difference in learner characteristics for art students depending on their background information?
- RQ3: What are the underlying factors that influence learner characteristics among art major students at S University?
- RQ4: In what ways can students at S University be classified into different groups based on learner characteristics?
- RQ5: How spatial orientation ability (SOA), self-efficacy (SE), and learning anxiety (LA) might affect learning behavior (LB)?
- RQ6: How could the schools support students to enhance their personalized learning?

These questions were answered through quantitative methods using the data collected through the Learner Characteristics Survey (LCS), designed by G. H. Wang (2020). This survey included a mix of close-ended and one open-ended questions, used to describe the general learner characteristics of art major students at S University. Throughout the data collection process, background variables were controlled to determine if there was any difference in learning behaviors to answer RQ1 and RQ2. After collecting participant data, a factor analysis was used to check the structure of the correlations among the learner characteristic variables followed by a cluster analysis to determine how to classify students based on their learner characteristics differences that aimed to answer RQ3 and RQ4. Furthermore, to reply to RQ5, a multiple regression was conducted to understand the relationship among learner characteristics variables and to predict learning behavior. Finally, RQ6 was answered by findings from an open-ended question that was induced and discussed.

Research Methods and Design

In this section, the research background, participants, samples, data collection procedures, and analysis techniques are discussed in detail. The environmental context of the research is described, presenting the location and relevant background information where the study took place. Additionally, the process of selecting participants and samples is elaborately explained, ensuring the chosen samples accurately represent a broader research population, thereby enhancing the study’s credibility. Furthermore, various methods for data collection and the rationale behind their selection are thoroughly described, ensuring the capture of necessary information effectively. In terms of data analysis, relevant analytical approaches and specific methods are outlined, guaranteeing in-depth exploration of the data and meaningful interpretation. Through this comprehensive exposition, the research methodology is presented, providing a solid foundation for subsequent research endeavors.

Method

Survey research is the most used quantitative method for social science data collection (Leavy, 2017). Surveys are methodical ways to collect data from a sample of things to build quantitative descriptors of the characteristics of the wider population to which the entities belong (Simon, 2022). Fowler (2013) noted standardized questions can be used to collect data and stressed two fundamental principles of the survey process: (a) the sample group must have characteristics like the larger target population so results can be generalized, and (b) respondents' answers must accurately measure the characteristics to be described. Measurement and sampling errors occur if researchers ignore survey principles (Fowler, 2013; Leavy, 2017).

Survey research is judged by its reliability and validity. Hosford (1960) defined reliability as measuring the same way across occasions or things; he further noted that validity refers to survey measurement accuracy. Survey research relies on validity, which requires reliability. Guion (2004) pointed out, "Reliability assesses random error" (p. 51) and "validity evaluates systematic error" (p. 53) induced by variables extraneous to the measurement.

By applying a survey methodology, data were collected from undergraduate students who volunteered to participate as indicated by their signed consent at the end of the survey. According to Creswell (2009), quantitative research is a way to discover and comprehend the meaning that certain people or groups assign to social or human issues. In the current study, use of quantitative methods allows for a better understanding of the learner characteristics of art major students at S University. Furthermore, the final open-ended question was also helpful to the participants to understand and benefit from their education by using their voices.

The findings of this research could inform art educators and curriculum designers on how to develop effective teaching strategies to address the diverse learning needs of students in higher art education. Furthermore, the participants' feedback could contribute to improving the quality of personalized art education programs and enhancing students' overall learning experiences at S University.

Setting

This study was conducted at S University, a prestigious art institution in Shanghai, China. At the time of this study, the university had seven secondary colleges: School of Design, School of New Media Arts, School of Fashion, School of Fine Arts, School of Performance Art, School of Cultural and Creative Industry Management, and School of Pop Music and Dance. In April 2015, the school leaped to 71st place of the QS World University Rankings in the art and design discipline, and again made it on the list in 2020, 2021, and 2022, maintaining a stable position in the art and design discipline rankings (Office of Admission at S University, 2022).

Population and Sample

According to data from the Office of Student Affairs at S University, the total number of students at S University in 2022 was 4,434 (Office of Admission at S University, 2022). The distribution of students in each secondary college and major is shown in Table 3. Thus, the total target population of this research was 4,434. The study employed a convenience sampling approach to choose the sample. Random sampling is the selection of a population's conveniently available members (Terrell, 2015). Finally, the survey received 455 valid responses, which accounted for more than 10% of the total student population (N = 4,434) and could be used to represent the characteristics of art major students at S University to ensure the generalizability of the survey results.

Table 3

Distribution of Students by School and Major at S University, 2015

School	Major	*n*	%
Design	Product design	232	5
	Environmental design	465	10
	Visual communication design	277	6
New Media Arts	Animation	327	7
	Radio and television director	182	4
	Photography	191	4
	Art and technology	467	11
Fashion Design	Fashion performance	84	2
	Fashion design	487	11
	Craft art	201	5
Fine Arts	Painting	89	2
	Sculpture	77	2
	Public art	79	2
	Digital media art	91	2
	Cultural relics restoration and protection	167	4
Performing Art	Performing art	214	5
	Broadcasting and hosting art	112	3
Cultural and Creative Industries Management	Cultural industry management	462	10
Pop Music and Dance	Pop music	110	2
	Pop dance	120	3

Note. (*N* = 3972). Adapted from *Student Admission Report*, by Office of Admission at S University, 2022, https://info.siva.edu.cn. Copyright 2022 by S University.

Data Collection

With the use of an online platform called *Wen Juan Xing*, which is popular in China, the current study employed an individual-based strategy to gather data from art students on their earner characteristics. The survey included background variables, such as age, gender, college year, major, and years of art study, which were gathered from survey participants. The survey was created on the *Wen Juan Xing* platform, and the survey QR code was generated to collect information. The survey QR code was sent to the student affairs office at S University and then distributed to all the student WeChat groups. Students could use their smartphone, desktop, laptop, or tablet to participate. The survey was available to all students who volunteered to take it from July 15, 2023, to August 31, 2023. Data collection began after the research proposal received approval from the institutional review board.

Students received an informed consent form at the start of the survey. Students could choose to start the survey by clicking "Yes" if they consented to the study. If not, they could click "No" to exit the survey. The informed consent form contained the following information: (a) the goal of the study, (b) participation requirements, (c) possible risks and benefits, (d) details on the protection of their information, (e) their rights as research subjects, (f) presentation of the results, (g) estimated time to finish the survey, and (f) the option to discontinue at any time.

Instrument

Based on the theoretical framework and literature review, personalized learning is learner-centered and involves an adaptive strategy with technical support that is often applied in a blended way (Alamri et al., 2021; Gynther, 2016; Headden, 2013; X. Wang et al., 2009; C. C.-Y. Yang & Ogata, 2022). Thus, the design of personalized learning lies in having a clear understanding of the learner online and offline. As shown in the literature review in Chapter 2, learner characteristics in personalized learning have been studied using a single individual difference and multiple individual differences. By employing a series of scales related to learner characteristics, the research used a quantitative research design. To address my quantitative research questions, I used a survey research design via the survey developed by G. H. Wang (2020). The LCS was designed and tested to assess the learner characteristics of university students in China (G. H. Wang et al., 2021).

It took 6 years for G. H. Wang et al. (2021) to design and refine the LCS, and among similar sample scales, the factors investigated are relatively comprehensive. The survey underwent six rounds of revisions, with a total of 9,900 participants (including students from social science and natural science) and 20 expert discussions to ensure good reliability and validity (G. H. Wang, 2020). The survey is mainly applicable to college students and adult learners who participate in online and offline hybrid learning (G. H. Wang et al., 2021). On April 8, 2023, I received permission from the author to use the survey.

The LCS consists of 10 learner characteristic scales, including the learning strategy scale, the learning style scale, the metacognitive scale, the web spatial orientation ability scale, the learner attitude scale, the learning anxiety scale, the learning motivation scale, the learning self-efficacy scale, and the learning behavior scale (G. H. Wang, 2020). The scales were developed based on three main sources: (a) further revision of the test scale used in China and abroad, (b) revision of testing tools that were more authoritative abroad but less commonly used in China, and (c) compilation of a scale based on relevant research theories (G. H. Wang, 2020).

The LCS scales are composed of single-choice questions using a Likert 5-point scale, ranging from 1 (*completely disagree*) to 5 (*completely agree*). The learning behavior (LB) persistence dimension of the learning behavior scale and the spatial orientation ability (SAO) scale are scored in reverse. The average score is noted for each dimension included in each learner characteristic scale. The total average score of the scale is obtained by adding the average scores of the dimensions and dividing the sum by the number of dimensions. The higher the total average score, the higher the level of the learner characteristic.

Reliability and Validity

The use of test-retest, equivalency, split-half, and internal consistency reliability tests has been widespread (Leavy, 2017). Measurement results are more consistent, steady, and dependable with higher coefficients (Kimberlin & Winterstein, 2008). Cronbach's alpha (α) is the most frequently used internal consistency reliability estimate (DeVellis, 2016), and it is determined by the scale's number of items and average intercorrelations (Kimberlin & Winterstein, 2008). DeVellis (2016) offered the following Cronbach's alpha ranges: less than 0.60 (unsuitable), 0.60–0.65 (unpleasant), .65–.70 (minimally acceptable), 0.70–0.80 (good), and 0.80–0.90 (excellent). In a study with a sample size of 1,889, G. H. Wang (2020) checked Cronbach's alpha of the nine scales and found that, except for the learning style scale (test-retest $\alpha = 0.54–0.69$), all the scales fell above 0.70, which was an acceptable reliability according to DeVellis. Furthermore, Lu (2022) found that Cronbach's alpha of the entire survey was 0.926 ($N = 252$), which shows very good reliability.

According to DeVellis (2016), validity is inferred from how a scale was built, its capacity to predict certain events, or its relationship to measures of other constructs. This relates to three different validity types: construct, content, and criterion validity (DeVellis, 2016). G. H. Wang (2020) used expert validity and construct validity to ensure the adequacy of the LCS. In terms of structural validity, Lu (2022) used confirmatory factor analysis and found that the model fit index was relatively ideal, and every scale (except for the learning style and spatial orientation ability scale) met the adaptation criteria.

The LCS was chosen for the current study because the survey was designed to assess the learner characteristics of university students in China (G. H. Wang et al., 2021) and covered different types of learner characteristics, which fit my research goals. Furthermore, the survey was tested and revised through six rounds with a large test sample size and showed good reliability and validity. Finally, the survey was written in Chinese, which was suitable for my target population, whose primary language was Mandarin. The reliability and validity results of this study were further discussed in the Data Processing section.

Scales and Variables

This study applied four of the nine scales of the LCS from G. H. Wang et al. (2021) as learner characteristics. The study also includes background information composed of four questions (gender, major, grade, and years of formal art training before entering S University), which were designed to collect background information for research purposes. Furthermore, one open-ended question was designed to collect the personalized learning needs of the students. Overall, there were 52 items in this study (see Table 4).

Five LCS scales (learning style, metacognition, learning motivation, learning attitude, and learning strategy) were not used for the study for several reasons. First, previous research (Kirschner & van Merriënboer, 2013; Knoll et al., 2017; Stahl, 1999) showed that the reliability of learning styles was insufficient. For example, Clark's (1982) meta-analysis of learner preferences for selecting a specific form of instruction indicated that the reported choice was frequently not associated with what and how much was learned, at best, or was adversely correlated. In other words, learners who stated they liked a certain method of learning did not often learn better or fared worse when the method was applied. Kirschner (2017) also urged people to "stop propagating the learning styles myth" (p. 166). Thus, the learning style scale was excluded from the study. Second, the items of the metacognition scale from the LCS have some coverage with other scales (e.g., the dimensions of metaknowledge and meta supervisory control overlap with the learning strategy scale, and the dimension of meta emotion coverage with the learner attitude scale). The coverage was also found in the learning strategy scale (with the learning behavior scale). Therefore, the metacognition scale and learning strategy scale were not used in my study. Third, because it is difficult to adapt or affect motivation and learning attitude as well as learning flexibility (in learning behavior scale) through personalized learning design, these scales and items were not included in this study.

Table 4

Scales Included in This Study

Component	Name	Dimensions	Scale reference	Coding type	No. of items
Learner characteristic	Learning behavior scale	4	NSSE (Kuh et al., 2007); NSSE-China (Luo et al., 2009)	Scale	19
	Spatial orientation ability scale	1	G. H. Wang & Fu (2018)	Scale	5
	Learning anxiety scale	4	Heckel & Ringeisen (2019); Wang & Fu (2018)	Scale	12
	Self-efficacy scale	2	Scholz et al. (2002)	Scale	11
Background information	Gender	1		Nominal	1
	Years of art learning	1		Ordinal	1
	Grade	1		Ordinal	1
	School	1		Nominal	1
Open-end question	In which areas do you think the school should provide personalized support for students majoring in arts?			String	1

Note. NSSE = National Survey for Student Engagement; LASSI = Learning and Study Strategies Inventory.

LB. Swift and Spivack (1969) discovered that students with greater challenges with classroom behavior performed worse academically. Similarly, other behavioral factors (e.g., attentiveness, independence, and task orientation) were discovered to be significantly associated with academic success (McKinney et al., 1975). Birrell et al. (1985), Harper et al. (1978), and McDermott (1984) found strong connections between LB and student accomplishment. Schaefer and McDermott (1999) investigated the connections between intelligence, learning behaviors, teacher-assigned grades, and standardized achievement test scores. They discovered learning behavior was a better predictor of teacher-assigned grades than IQ scores after controlling for several background variables.

G. H. Wang et al. (2021) noted two main types of measurement of LB: (a) analyzing learners' explicit learning behavior on online learning platforms (e.g., learning duration, number of posts, browsing content) through learning analysis technology or data mining technology, and (b) analyzing the learning behavior through questionnaires. In this study, self-reported learning behaviors were captured for analysis.

The learning behavior scale (LB) of the LCS includes five dimensions: participation (LB_participation), persistence (LB_persistence), focus (LB_focus), interaction (LB_interaction), and flexibility (LB_flexibility). Respectively, the subscales are designed to measure learners' behavioral performance in participating in various activities and tasks organized as part of the curriculum, persisting in completing course learning when encountering learning difficulties or pressures, learning without external interference, and focusing on completing learning, actively communicating, and discussing with teachers or classmates, and applying new tools and technologies to complete learning tasks.

Self-Efficacy. Bandura (1997, 2002) explained self-efficacy (SE) through the lens of social cognitive theory, arguing that SE influences objectives and outcome expectations, both of which are determinants of action. Chu and Tsai (2009) found that online SE played an essential role in determining students' intellectual gains and communication in Internet activities in web-based learning. Moreover, Yukselturk and Bulut (2007) argued SE signified individual confidence and belief in one's ability to master and operate Internet functionalities and that this influenced online course achievement. Furthermore, SE also been found to play a predictive role in the learning performance in math, reading, and writing (Carmichael & Taylor, 2005; Pajares & Miller, 1994; Schunk, 2003). The social cognitive features of SE were taken into consideration in the exploration of cognition features in personalized learning to check if it still could have impact on learning behavior.

The learning SE scale in the LCS measures learners' confidence in using computers, the Internet, and other existing resources or tools effectively to complete hybrid learning and improve and develop themselves. The general self-efficacy (SE_general) dimension measures learners' general ability to complete learning tasks in hybrid learning. The special self-efficacy (SE_special) dimension refers to the judgment of one's abilities in the process of completing a specific or specific learning task.

Learning Anxiety. Butz et al. (2016) demonstrated learning anxiety (LA) functions as a moderator in elucidating how control impacts the attainment of technological success. Similarly, a study involving over 2,400 Chinese college students engaged in online learning (J. Zhou & Yu, 2021) identified a moderating impact on learning anxiety. Among students with minimal anxiety related to online learning, the positive correlation between online learning self-efficacy and well-being was more evident compared to their counterparts experiencing anxiety. Additional research found that high levels of anxiety could be detrimental; however, low to moderate levels could be functionally activating because they helped with sufficient preparation and deeper information processing (Fonseca et al., 2014). Furthermore, the research of Adeyemo (2007) noted emotion plays a moderating role in the connection between academic self-efficacy and achievement.

Thus, LA was analyzed as a learner characteristic in this study to check if it had a direct impact or had a moderate effect on the learning behavior of art students at S University.

The LA scale in the LCS measures the level of anxiety that learners experience in learning. Dimensions include (a) network delay anxiety (LA_delay), such as anxiety caused by slow downloading of resources and slow loading or jumping of web pages; (b) network search anxiety (LA_search), caused by learners' inability to accurately determine search keywords or effectively extract information from a large amount of information; (c) network terminology anxiety (LA_terminlology), caused by learners encountering words or abbreviations during learning that are difficult to understand, which hinders the smooth progress of learning; and (d) general network anxiety(LA_general), caused by weak self-regulation and self-management abilities and poor outcomes.

SOA. The SOA scale is designed to measure learners' perception of self-orientation in learning. The lack of SOA is called disorientation, which is the state of not knowing where one is in the surrounding environment (Conklin, 1987; Elm & Woods, 1985). According to Hammond (1993), disorientation can occur for a variety of reasons, including difficulty comprehending the structure of the environment and a failure to connect the learning components. Disorientation issues harm student learning in a variety of ways. One of the disadvantages is that learners may feel uneasy about determining the best path for themselves (Saadé & Otrakji, 2007). Furthermore, disorientation may prevent learners from achieving their targeted learning outcomes (Webster & Ahuja, 2006). As a result, good performance cannot be attained, which may lead to learners losing motivation and confidence while using web-based learning tools. Because of these losses, learners may eventually reject the usage of web-based learning systems in the future (Demirbilek, 2009). The spatial positioning perception scale of the LCS has five questions and is a single-dimensional scale, in which items are scored using a reverse scoring method; furthermore, the higher the total score, the higher the level of spatial positioning of learners (G. H. Wang, 2020).

Data Analysis

IBM SPSS 25.0 was used to evaluate the data. First, I transformed the data to SPSS format and developed a codebook (see Table 5) with all the variables defined, labeled, and numerically coded (Pallant, 2016). Each response to the questionnaire was given a distinct variable name and numerical code. Each variable's frequencies were examined to look for values that were outside the range of possible values for that variable. After the data preprocessing phase (i.e., coding, screening, cleaning, reliability check, and validity check) concluded, the analysis process was started. Preliminary descriptive analyses of the data was followed by factor analyses, cluster analyses, and finally, an examination of the relationships between the variables by using multiple regression (shown in Table 5).

Table 5

Research Questions and Analysis Methods for the Study

Research question	Variable	Method of analysis
1	Learner characteristics (Learning behaviors, spatial orientation ability, self-efficacy, learning anxiety) Background information (Gender, years of art learning, grade, schools)	Descriptive statistics
2	Learner characteristics [a] Background information [b]	Analysis of variance
3	Learning behaviors, spatial orientation ability, and learning anxiety are considered learner characteristics	Factor analysis (EFA)
4	Learner characteristics (Learning behaviors, spatial orientation ability, self-efficacy, learning anxiety) Background information	Cluster analysis
5	Learning behaviors [a] Spatial orientation ability [b] Self-efficacy [b] Learning anxiety [b]	Multiple regression
6	Open-end question	Summary

Note. [a] Dependent variable [b] Independent variable.

Data Preprocessing

The following steps were taken in the preprocessing component:

- Screening. The final survey results included 552 responses. The following criteria were used to determine if the response was valid: (a) they shall click “yes” in the informed consent paper, (b) answering time shall be between 120 seconds~1800 seconds, and (c) there are no missing values. Finally, 455 valid responses were received.
- Coding. The scale, variables, and coding are shown in Appendix A. For the convenience of reference, the coding names were used to refer to the corresponding variables in the following paragraph.

- Reliability Check. The coefficient values (shown in Appendix B) of the research data were higher than 0.9, and the CITC values were both greater than 0.6, indicating that the data have a high-reliability quality and can be used for further analysis.
- Validity Check. EFA was used to analyze the validity of LB, SE, LA, and SOA separately. From Appendix C, the commonality values corresponding to all research items were higher than 0.4, indicating that research item information can be effectively extracted. From the validity check on the LB scale, it was noted the subvariable of LB_ flexibility was tangled with LB _ interaction. In consideration of the unclear definition of flexibility and its hard application in personalized learning, I deleted the LB_ flexibility variable.

Finally, the Kaiser-Meyer-Olkin (KMO) values of LB, SOA, SE, and LA were 0.913, 0.898, 0.943, and 0.936, respectively. The KMO value was greater than 0.8, which showed the research data were very suitable for extracting information and showed good validity. In addition, the cumulative variance interpretation rate after the rotation of factors within each scale was over 50%, meaning the amount of information in the research item can be effectively extracted. Finally, combined with the factor loading coefficient, it can be confirmed that there was a good correspondence between the factors and the dimensions of the research item scale, which had good structural validity.

Descriptive Statistics

Descriptive statistics is a branch of statistics that deals with summarizing and describing the main features or characteristics of a dataset (Kaur et al., 2018). It provides a way to organize, simplify, and present data in a meaningful and comprehensible manner, enabling researchers, analysts, and decision makers to gain insights into the data’s central tendencies, variability, and distribution (Cambardella et al., 1994). Descriptive statistics are essential for understanding data before more advanced statistical analyses are performed (Lang & Altman, 2014). The study used descriptive statistics to gain background information and a general view of participants' learner characteristics from students from S University by using the means, standard deviation and percentage statistics.

Analysis of Variance

To determine whether the variability in mean scores within each level was significantly different from one another, mean scores of the learner characteristics (DV) on the background information (IV) were compared by applying the one-way between-groups analysis of variance (ANOVA). As Pallant (2016) noted ANOVA was used to determine whether there is a statistically significant difference between the means of two or more groups of one independent variable (IV) taking the same dependent variable (DV). The F ratio, which the ANOVA generates, was calculated as the variance between groups divided by the variance within groups. A high F ratio suggests that the IV generated more variation between the groups than it did within each group (Pallant, 2016). Should an overall ANOVA analysis reveal statistical significance, specifically when the Sig. value is equal to or less than .05, the subsequent posthoc tests provided in this table will elucidate the precise locations of disparity among the various groups (Pallant, 2016). The partial Eta square was used to analyze the variance, and the critical points for distinguishing small, medium, and large effects, which were 0.01, 0.06, and 0.14, respectively (Cohen, 1973). Cohen's f was also used to represent the magnitude of the effect. Cohen's f represents when the magnitude of the effect is small, and the critical points for distinguishing small, medium, and large effects are 0.10, 0.25, and 0.40, respectively (Bewick et al., 2004)

Factor Analysis

Factor analysis is a reduced dimensional multivariate statistical method that selects a small number of comprehensive indicators from multiple variable indicators. Factor analysis can be broadly divided into two categories: exploratory and confirmatory (Kline, 2014). The goal of EFA is to identify the types of constructs that influence a set of responses. Confirmatory factor analysis (CFA) examines whether a particular set of components is having the predicted impact on responses (DeCoster, 1998).

To conduct an EFA analysis, there are two steps. Firstly, the KMO test was done to measure the suitability of data for factor analysis. According to Tabachnick et al. (2013), KMO values between 0.8 and 1.0 show that the sampling is sufficient; KMO levels between 0.6 and 0.69 are mediocre, whereas those between 0.7 and 0.79 are merely average. KMO values below 0.6 indicate insufficient sampling and corrective action should be taken. Secondly, Bartlett's Test of Sphericity was also done to test if the variables were orthogonal. If the corresponding *p*-value of Bartlett's test is less than 0.05, it also indicates that factor analysis is suitable (Shrestha, 2021).

In this study, EFA was applied for factor analysis to explore the dimensions from the learner characteristics scales and gain the main features of the learning of art students. Furthermore, because not all variables of LCS were used for the study, an EFA could ensure that the scale fit the goal of the research. Finally, the results of EFA also served as data preparation for the cluster analysis in the study.

Cluster Analysis

Clustering is used to classify groups of data according to their similar characteristics so that people can have a general understanding of the data. The general principle of clustering is that the distance between the data in the class (the square root of the new data and the initial point data) should be within a set range; the centers between classes should be as far apart as possible (Romesburg, 2004). The purpose of clustering is to gather similar objects into a class, which is done by accurately describing and measuring the relevant attributes, comparing the similarity between objects, and merging the closest objects into the same class (Hennig et al., 2015).

According to X. Wu et al. (2020), there are five types of clustering analysis methods including partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model-based methods. Among the various algorithms, hierarchical clustering and *k*-means clustering are the most commonly used methods (J. Wang et al., 2012). If the number of observations is large (more than 200) or the data file is very large, the fast cluster analysis method is more suitable (M. L. Wu, 2000). Because the intended sample size of this study is larger than 200, it is appropriate to use a fast-clustering method for analysis.

This research used cluster analysis to dive into the learner characteristics of students at S University to determine their specific learning behavior features that could be applied for adaptive design in personalized learning.

Multiple Regression

Multiple regression analysis is a powerful statistical technique that has become a cornerstone of modern data analysis (Joseph et al., 2010). It allows researchers and analysts to unravel complex relationships between a DV and multiple IVs, providing insights, predictions, and a deeper understanding of the world around us (Tabachnick et al., 2013). Multiple regression makes a few assumptions about the data for reliable results. It stresses the need for careful consideration of sample size. Tabachnick et al. (2013) provided a formula to determine the necessary sample size, considering the desired number of independent variables: $N > 50 + 8\text{m}$

(where *m* = number of independent variables). In this research, there were three IVs; thus, the minimal sample size requirement was 84. With the total sample size of 455 bigger than 84, the research satisfied the requirement for sample size. The standard multiple regression equation could be expressed as follows:

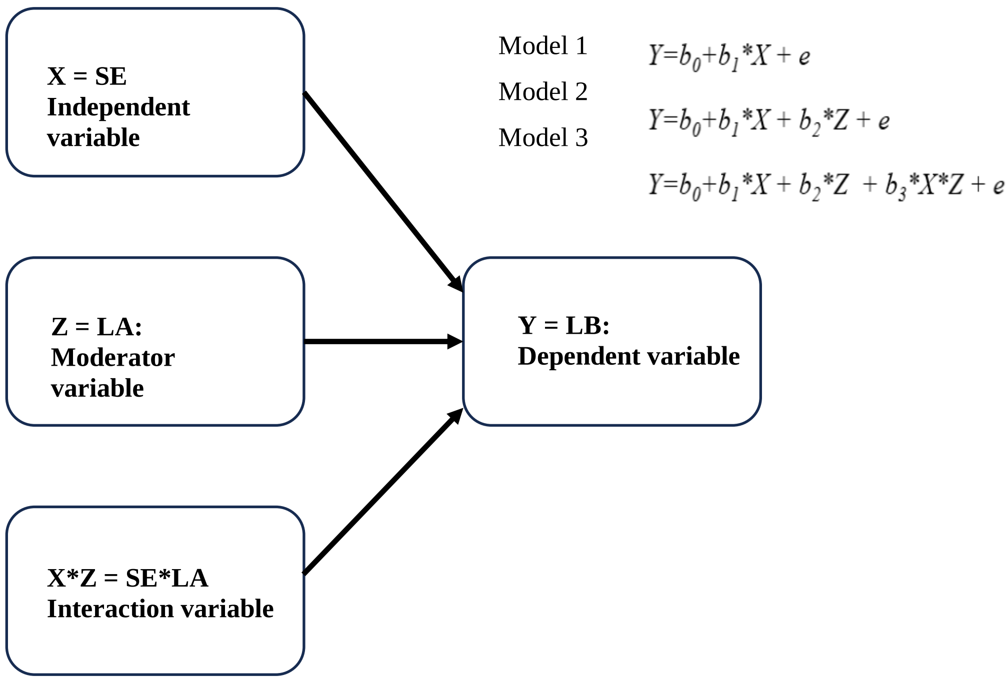
$$Y' = A + B_1X_1 + B_2X_2 + ... + B_kX_k$$

Tabachnick et al. (2013) noted that Y is the predicted value on the DV (continuous variable), A is the Y-intercept (the value of Y when all the X values are zero), the X's represent the various IVs (continuous or categorical variable). The current study used multiple regression to explore the relationships among learner characteristics variables. In this research, standard multiple regression was employed to examine the distinct impact of SOA, SE, and LA on LB. The analysis involved one DV (LB) and three IVs (SOA, SE, and LA), all of which were continuous variables.

As shown in Figure 2, the moderating effect is also a linear regression method. It is divided into three models, with Model 1 including the IV and one control variable. The purpose of Model 1 was to investigate the impact of the IV on the DV without considering the interference of the moderating variable. Then, Model 2 adds a moderating variable to Model 1, and Model 3 adds an interaction term (the product of the IV and the moderating variable) to Model 2 (SÜRÜCÜ et al., 2023). The moderating effect can be examined by examining the significance of the interaction term in Model 3. In the moderate analysis, LB was considered as DV, LA was considered as the moderating variable, treating SOA as the control variable. Hence, a moderating effect analysis was performed to assess whether the influence of SE on LB significantly differs under various conditions (shown in Figure 2).

Figure 2

Three Models for Moderating Effect Analysis



Ethics

The three guiding principles for using human subjects in research are beneficence, respect for individuals, and fairness (Terrell, 2015). As a result, I treated participants with respect when gathering data to make sure that every research step was planned and carried out to maximize benefits and minimize dangers to participants (Fowler, 2013). Furthermore, I explained the survey's aim to participants during the process, assuring them that their participation was voluntary. Also, to prevent negative consequences for participants, their responses were anonymous. After potential participants had signed the informed consent form, I gathered all the data on a secure network. Also, I saved the data and information on a password-protected computer, and I will delete it after 1 year.

Finally, there were ethical issues to consider, given that I conducted my research study at my place of employment. To prevent participants from feeling compelled to participate in the research, I chose students not enrolled in my classes. I also took care to properly distribute poll results with the permission of respondents and the institution.

Limitations and Delimitations

Art students in Shanghai were the population examined for this research project. These students may have shared comparable educational experiences and backgrounds in Shanghai. As a result, the experiences of other students in different regions or academic majors may not be comparable to those of the target group. In addition, all the quantitative data in this study were provided by the participants themselves. In other words, students had the choice of whether to submit their responses and whether to respond to survey questions. Therefore, the findings are limited because some students may have chosen not to submit their responses or reply to all the survey questions. In addition, the quantitative data were restricted to the art students' memories and experiences.

The participants in this study were restricted to those attending S University in Shanghai. In addition, this study's results were restricted to art students. As a direct consequence, the learner characteristics of students attending different schools or concentrating on different subjects may vary.

Conclusion

This chapter presented the quantitative-based methodology used to design and conduct this study. The outlined research methodology establishes a solid foundation for the study on learner characteristics among art major students at S University in Shanghai, China. By employing the LCS and integrating statistical techniques such as ANOVA, factor analysis, cluster analysis, and multiple regression, the study aimed to unravel the intricacies of personalized learning among undergraduate art students.

CHAPTER 4: FINDINGS

The study sought to identify common learner traits, examine their connections, and provide personalized learning suggestions based on these traits. Thus, an overview of the study's survey findings is provided throughout this chapter and organized into sections corresponding to the six research questions. Compared with the previous research, Research Question (RQ) 1 explored the participants' backgrounds and general learner characteristics through descriptive analysis. By further comparing the results of these learner characteristics with previous research, the results of RQ2 determined whether they were any differences among learning behavior and gender, years of art learning, grade, and school. Furthermore, a factors analysis was used in RQ3 to explore the correlations among the learner characteristics to gain a comprehensive examination of how different the learner characteristics variables were interrelated for art students.

Subsequently, in RQ4, findings from RQ3 were taken a step further by clustering art students into distinct groups based on their learner characteristics. These groups were meticulously described, shedding light on each cluster's unique attributes, which was instrumental in better understanding the diverse landscape of art students' learning behaviors. Continuing this analysis process, RQ5 delved deeper into the impact of specific factors such as spatial orientation ability, self-efficacy, and learning anxiety on learning behavior. This inquiry provided a deeper understanding of the aspects that shape how students approach and engage in their learning experiences. Finally, RQ6 was a q component for the quotative study that summarized the student's personalized learning needs with one open-ended question. These needs were derived from the rich information obtained through open-ended questions, bringing together all the knowledge acquired to inform the development of tailored strategies for personalized learning in art education.

RQ1: What Are the Background and General Learner Characteristics of the Art Major Students at S University?

To address RQ1 comprehensively, the study employed descriptive statistics. This involved the meticulous calculation of various parameters, including frequencies and percentages, to provide a clear understanding of the background information. Additionally, the study delved into the numerical aspects of the learner characteristics by determining the means and standard deviations. These detailed statistical analyses were instrumental in providing a thorough and detailed overview of the data, allowing for a comprehensive exploration of the learner characteristics under scrutiny. By presenting these descriptive statistics, the research aimed to offer a robust foundation for interpreting the findings and drawing meaningful conclusions related to the learner characteristics studied in RQ2.

Background

Table 6 illustrates the background information of the participants who took the survey; participants were art major students at S University. The sample included the frequencies and percentages of the background variables. A total of 455 students participated in this study. All the students had art training experience before they entered S University. Furthermore, 75% of the students had 1–5 years of art learning experience, followed by 25% of students who had more than 5 years of art learning. Nearly 60% of the participants were Grade 1 students. Eighty percent of the participants were women. The highest percentage of students in the sample were from the School of New Media (38.46%).

Table 6

Background Information

Variable	Categories	*n*	%
Years of art learning	None	0	0.00
	1–5years	340	74.73
	More than 5 years	115	25.27
Grade	Grade 1	272	59.78
	Grade 2	92	20.22
	Grade 3 and 4	91	20.00
Gender	Male	92	20.22
	Female	363	79.78
School	School of design	105	23.08
	School of New Media	175	38.46
	School of Fashion	105	23.08
	School of Fine Art	13	2.86
	School of Performing Arts	15	3.30
	School of Cultural and Creative Industries Management	32	7.03
	School of Pop Music	10	2.20
Total		**455**	**100.00**

General Learner Characteristics

Four scales were selected as learner characteristics for this survey: learning behavior (LB), self-efficacy (SE), learning anxiety (LA), and spatial orientation ability (SOA). The mean score of each scale of this survey was calculated and compared with G. H. Wang's (2020) research shown in Table 7. The learner characteristics of students at S University were consistent with G. H. Wang's results in general. However, there were specific differences in LB and SE (see Table 7). For example, in terms of learning persistence, art students from S University were 1.2 points higher than students from other comprehensive majors in G. H. Wang's (2020) study, which demonstrated a stronger persistence ability. Furthermore, compared with students in G. H. Wang's study, art students' SE score was 0.2 points higher. On the other hand, in terms of LA, the art students were 0.13 lower than students in G. H. Wang's (2020) research, but the standard deviation was 0.97, which was higher compared with Wang (2020), thereby showing a higher degree of variability in LA for art students in S University.

Table 7

Comparison of Means With the Former Study From G. H. Wang (2020)

	Mean		Std. deviation	
Items	S[a]	W[b]	S	W
LB	3.85	3.45	0.59	0.48
LB_ engagement	4.08	3.81	0.77	0.57
LB_ persistence	3.59	2.33	1.02	1.01
LB_ focus	3.72	3.64	0.75	0.57
LB_ interaction	3.84	3.66	0.76	0.61
SE	3.94	3.76	0.66	0.54
SE_ general	3.88	3.69	0.75	0.60
SE_ special	3.99	3.81	0.64	0.55
LA	3.46	3.59	0.97	0.72
LA_ delay	3.55	3.78	1.11	0.82
LA_ search	3.46	3.65	1.11	0.85
LA_ terminology	3.33	3.43	1.06	0.79
LA_ general	3.49	3.50	1.08	0.82
SOA	2.99	2.94	1.01	0.85

Note. [a]S represents the art students from the S university; [b]W represents the former research data of G. H. Wang (2020).

LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA= Spatial Orientation Ability.

RQ2: Is There Any Difference in Learner Characteristics for Art Students Depending on Their Background Information?

In this research investigation, a comprehensive exploration was conducted by considering certain background information, namely gender, years of art learning, grade, and school, as independent variables. These variables were chosen due to their potential impact on the learning process and were representative of the participants' diverse demographic and educational backgrounds. Simultaneously, this study identified four key learner characteristics: LB, SE, LA, and SOA, which were designated as the dependent variables. These characteristics provided valuable insights into the participants' behavioral patterns, confidence in their abilities, academic accomplishments, and emotional states during the learning process.

To examine the relationship between these background variables and learner characteristics, a one-way analysis of variance (ANOVA) was employed for RQ2. By treating the background variables as independent factors and the learner characteristics as dependent factors, the study sought to determine whether differences in background variables significantly influenced learner characteristics.

Gender

A set of ANOVAs was conducted in this study to assess the impact of gender on LB, SE, LA, and SOA, respectively. The objective was to determine whether there were significant differences in these traits between male and female participants. The participants were divided into two groups according to their gender (Group 1: Male, Group 2: Female). It was found that there was no statistically significant difference between the male and female groups at a $< .05$ level in LB: $F(1, 453) = 0.13$, $p = 0.72$; SE: $F(1, 453) = 0.28$, $p = 0.60$; LA: $F(1,453) = 2.16$, $p =$

0.14; SOA: $F(1, 453) = 1.12$, $p = 0.29$. The outcomes showed that in the context of this study, gender did not exert a statistically significant influence on specific learner characteristics.

Years of Art Learning

In this study, an ANOVA was employed to investigate the impact of the years of art learning on LB, SE, LA, and SOA. The primary aim was to determine whether noteworthy distinctions existed in these attributes based on varied art learning experiences. Participants were categorized into two groups based on their years of studying art: Group 1, comprising individuals with 1–5 years of art learning, and Group 2, consisting of those with more than 5 years of art learning. The results revealed there was no statistically significant difference between the compared group at the $p < .05$ level in LB: $F(1, 453) = 2.84$, $p = 0.09$; SE: $F(1, 453) = 3.37$, $p = 0.07$; LA: $F(1, 453) = 0.00$, $p = 0.99$; SOA: $F(1, 453) = 0.58$, $p = 0.45$. Therefore, the years of art learning did not exert a statistically significant impact on the specific learner characteristics under scrutiny.

Grade

From Table 8, it can be observed that an ANOVA was employed to explore the differences in LB, SE, LA, and SOA across different grade levels. Participants were categorized into three groups based on grade level: Group 1 was the first years, Group 2 was the sophomore, and Group 3 was the junior and senior.

The results indicated that among the various grade levels, there was no significant difference in SE ($p > 0.05$), implying a consistent pattern across these levels. Despite reaching statistical significance, the actual difference in mean scores between the groups was quite small. The effect size of gender on SOA, LB, and LA, calculated using eta squared, was all 0.02 (see Table 8).

Table 8

One-Way ANOVA: Grade

	Group1: First Year (*n* = 272)		Group2: Sophomore (*n* = 92)		Group3: Junior & Senior (*n* = 91)				Effect Size
	Mean	*SD*	Mean	*SD*	Mean	*SD*	*F*	*p*	Partial η^2
SOA	3.07	0.99	2.73	0.99	2.79	1.04	5.24	0.01**	0.02
LB	3.90	0.57	3.85	0.59	3.69	0.62	4.25	0.02*	0.02
SE	3.93	0.65	3.95	0.68	3.92	0.68	0.03	0.97	--
LA	3.34	0.96	3.66	0.93	3.62	1.00	5.44	0.01**	0.02

Note. * $p < 0.05$ ** $p < 0.01$.

LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA= Spatial Orientation Ability.

However, concerning LB, LA, and SOA there were statistically significant differences observed among different academic levels ($p < 0.05$), specifically:

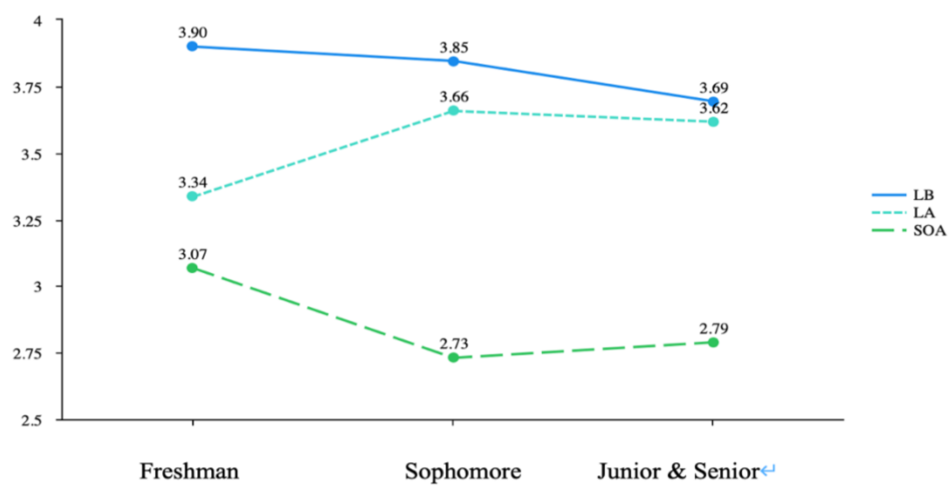
- LB exhibited a significant difference at the 0.05 level: $F(3, 451) = 4.25$, $p = 0.02$. Posthoc comparisons using the Tukey HSD test revealed a noticeable disparity between the average scores of different groups, indicating that the freshmen group ($M = 3.90$, $SD = 0.57$) had significantly higher scores compared to the junior & senior group ($M = 3.69$, $SD = 0.62$). From Figure 3, it could be concluded that with grade growth, the LB score decreased.
- LA showed a significant difference at the 0.01 level: $F(3, 451) = 5.44$, $p = 0.001$. Detailed comparisons by Posthoc comparisons using the Tukey HSD test unveiled distinct group average score differences: sophomores ($M = 3.66$, $SD = 0.93$)

outperformed freshmen (*M* = 3.34, *SD* = 0.96), and juniors and seniors (*M* = 3.62, *SD* = 1.00) outperformed freshmen. In summary, freshman has the lowest learning anxiety.

- SOA demonstrated a significant difference at the 0.01 level: $F(3,451) = 5.24$, $p = 0.001$. Further analysis revealed significant disparities in group average scores that freshmen (*M* = 3.07, *SD* = 0.99) had higher scores than sophomores (*M* = 2.73, *SD* = 0.99), and freshmen also outperformed juniors and seniors (*M* = 2.79, *SD* = 1.04). Thus, freshmen show a good SOA than any other grades (shown in Figure 3).

Figure 3

ANOVA: Grade difference on LB, LA, and SOA



School

Table 9 showed significant differences in school for SOA: $F(7,447) = 2.41$, $p = 0.02$ and LB: $F(7,447) = 3.47$, $p = 0.00$; there was no statistical significance in SE ($p = 0.23$) and LA ($p = 0.15$). The partial Eta square and Cohen's f of school on SOA were 0.04 and 0.02, and the partial Eta square and Cohen's f of school on LB were 0.05 and 0.23, which indicated a small effect size of school on learning behavior and spatial orientation ability. Because the SE and OLA show no significant difference in school, only the means of LB and SOA were further compared among different schools.

Table 9

One-Way ANOVA: School

School	SOA		LB		SE		OLA	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
School of Design (*n* = 105)	2.95	1.01	3.98	0.55	3.97	0.69	3.35	0.93
School of New Media Art (*n* = 175)	2.96	0.94	3.71	0.58	3.85	0.63	3.42	0.92
School of Fashion Design (*n* = 105)	2.92	1.04	3.9	0.57	3.96	0.65	3.57	1.02
School of Fine Arts (*n* = 13)	2.46	1.08	3.83	0.52	3.95	0.76	3.78	1.32
School of Performing Art (*n* = 15)	3.85	1.19	4.25	0.70	4.31	0.74	3.06	1.08
School of Cultural and Creative Industries (*n* = 32)	2.79	0.99	3.84	0.62	3.97	0.69	3.51	0.91
School of Management (*n* = 6)	2.63	1.04	3.80	0.31	4.03	0.56	4.03	1.06
School of Pop Music and Dance (*n* = 4)	2.85	1.45	3.54	0.90	4.07	0.68	4.08	0.78
F	2.41		3.47		1.21		1.54	
p	**0.02***		**0.00****		0.23		0.15	

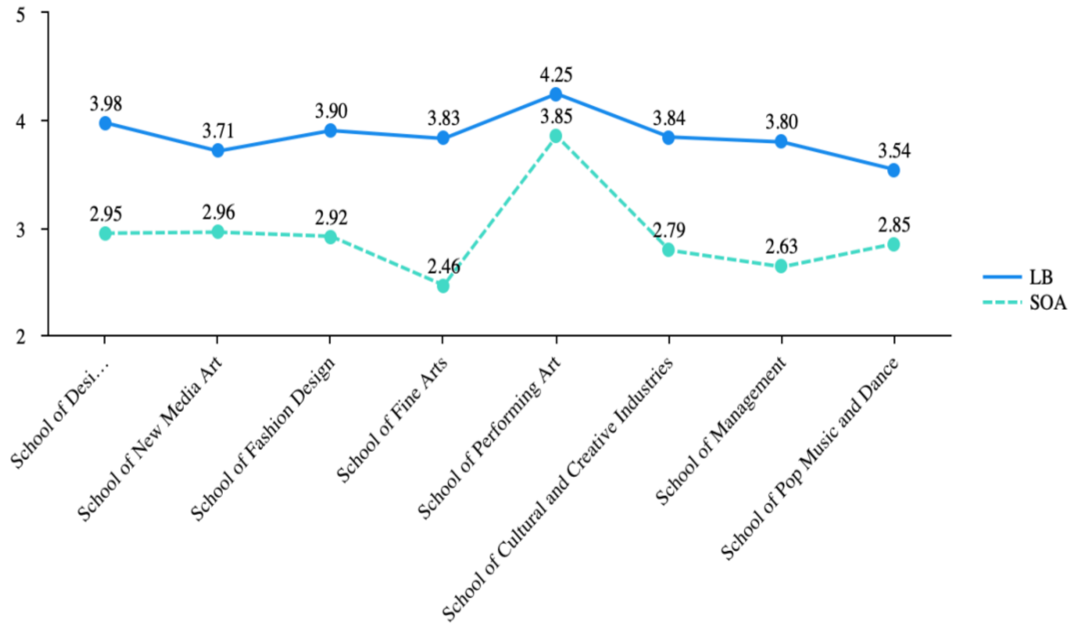
Note. * $p < 0.05$ ** $p < 0.01$.

LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA= Spatial Orientation Ability.

Figure 4 shows that the School of Performing Arts had the highest score in both LB (*M* = 3.85) and SOA (*M* = 4.25). On the other hand, students from the School of Fine Arts seemed to have the least ability to orient themselves during online learning with the lowest SOA average score of 2.46). Furthermore, the School Pop Music and Dance ranked last in LB with an average score of 3.54.

Figure 4

School Difference in the Mean Score of SOA and LB



Note. LB = Learning Behavior, SOA = Spatial Orientation Ability.

RQ3: What Are the Underlying Factors That Influence Learner Characteristics Among Art Major Students at S University?

Exploratory factor analysis was used to address RQ3. Firstly, the KMO (Kaiser-Meyer-Olkin) test was made to measure the suitability of data for factor analysis. Table 10 illustrated that the KMO was 0.93, greater than 0.60, which met the prerequisite requirements of factor analysis; thus, the data can be used for factor analysis research. Furthermore, the data passed the

Bartlett sphericity test ($p < 0.05$), indicating that the research data were suitable for factor analysis.

Table 10

KMO and Bartlett Test

KMO		0.93
	Approx. Chi-Square	20458.87
Bartlett test	*df*	1081
	p-value	0.00

The 47 items of the Learner Characteristics Survey (LCS) were subjected to explanatory factor analysis (EFA) using SPSS version 25. Before performing EFA, the suitability of data for factor analysis was assessed. Inspection of the correlation matrix revealed the presence of many coefficients of 0.30 and above. Table 10 shows that the KMO value was 0.93, exceeding the recommended value of 0.80 (Tabachnick et al., 2013) and Bartlett's Test of Sphericity (Shrestha, 2021) reached statistical significance, supporting the factorability of the correlation matrix.

To aid in the interpretation of these eight components, maximum variance rotation method (varimax) rotation was performed. The rotated solution revealed the presence of a simple structure (Thurstone, 1947), with components showing strong loadings and all variables loading substantially on one component (see Appendix D), which shows a good correspondence between measurement items and factors created. It also indicated that the new factors after rotation mostly followed the intended dimensions of learning Learner characteristics.

The eight factors were LA, SE, interaction, SOA, engagement, persistence, focus, and delay anxiety (see Appendix D). As shown in Table 11, exploratory factor analysis revealed the presence of 8 components with eigenvalues exceeding 1, the 8 factors explaining 18.30%, 18.10%, 9.29%, 8.39%, 8.14%, 5.23%, 4.90%, 2.77% of the variance respectively after the rotation.

Table 11

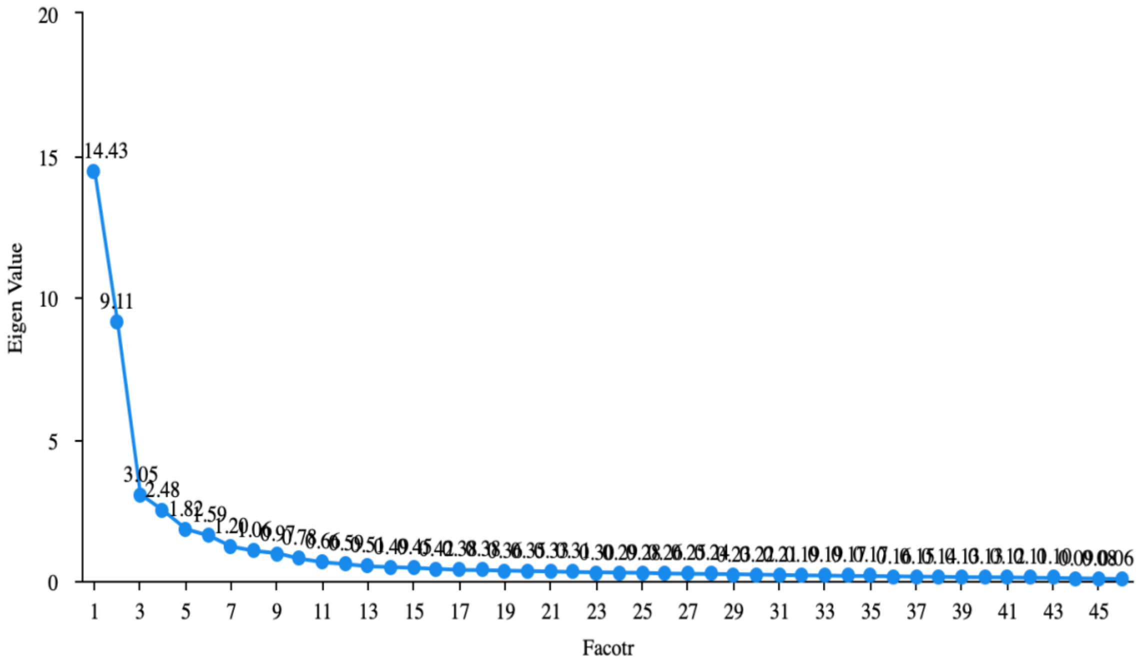
Variance Explained by the 8 Factors

Factor	Eigen values			% of variance (Rotated)		
	Eigen	% of Variance	Cum. % of Variance	Eigen	% of Variance	Cum. % of Variance
Factor1 Learning anxiety	14.805	31.501	31.501	8.598	18.294	18.294
Factor2 Self-efficacy	9.222	19.622	51.123	8.509	18.103	36.397
Factor3 Interaction	3.055	6.501	57.624	4.369	9.295	45.692
Factor4 Spatial orientation ability	2.522	5.367	62.991	3.945	8.394	54.086
Factor5 Participation	1.825	3.884	66.875	3.826	8.141	62.227
Factor6 Persistence	1.613	3.431	70.306	2.470	5.256	67.483
Factor7 Focus	1.216	2.587	72.892	2.301	4.895	72.377
Factor8 Delay	1.060	2.256	75.148	1.302	2.770	75.147

An inspection of the scree plot revealed a clear break after the 8th component (shown in Figure 5). The eight-component solution explained a total of 75.15% of the variance. Finally, the factor scores were saved for the cluster analysis in RQ4.

Figure 5

Plot for Factor Analysis



Scree

RQ4: In What Ways Can Students at S University Be Classified Into Different Groups Based on Learner Characteristics?

The K-means clustering analysis method was applied to address RQ4. The factor component scores (see Appendix D) of the eight factors created in factor analysis were saved and used for cluster analysis. Factor scores represent the relative strength or contribution of each factor in a factor analysis to the observed variables (Berghaus et al., 2005). Table 12 shows the final clustering results in three types of groups. Overall, the distribution of the three groups of people was 23.74% (*n* = 108), 44.18% (*n* = 201), and 32.08% (*n* = 146) respectively. Furthermore, the *p*-value in Table 12 shows that there is a statistically significant difference in the variance of the clustering groups which indicates the clustering effect is good overall. By comparing with the means of the factors scores and checking the description of items under each factor in the survey, the three clusters are named separately: self-motivated learners, focused learners, and persistent interactive learners.

Table 12

Results of Differences in Clustering Category Analysis of Variance Based on Factor Score

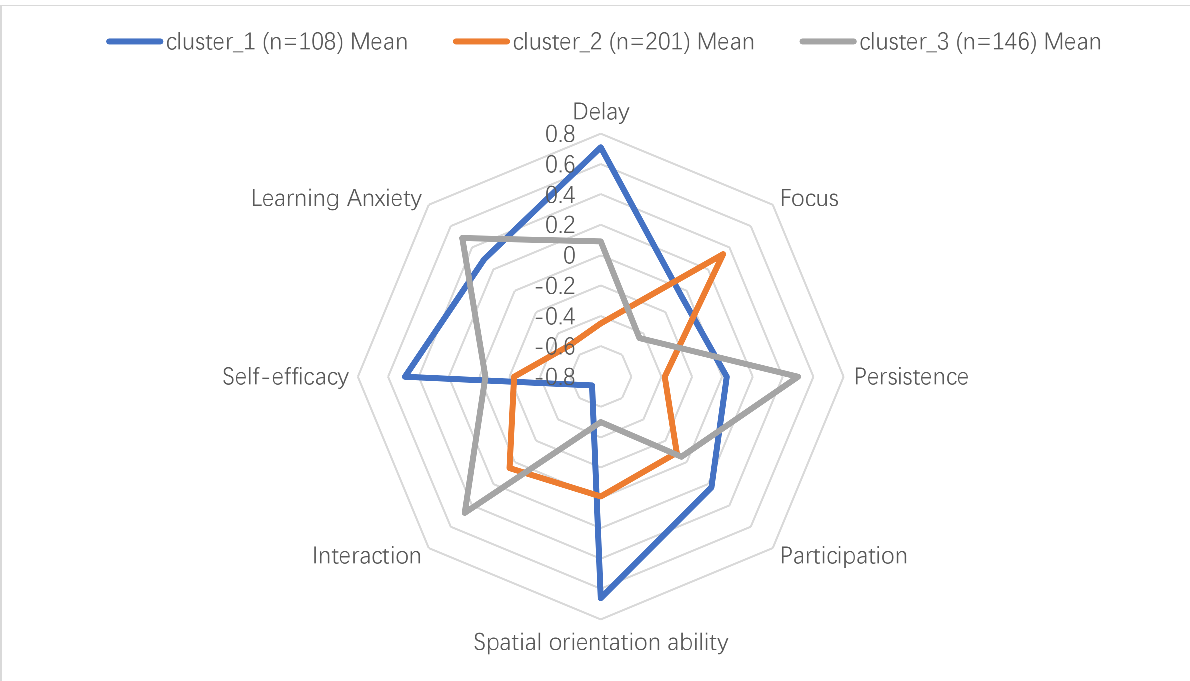
	Cluster_1 Self-motivated learners (*n* = 108)		Cluster_2 Focused learners (*n* = 201)		Cluster_3 Persistent interactive learners (*n* = 146)		
Factor	Mean	Std. deviation	Mean	Std. deviation	Mean	Std. deviation	*p*
Delay	0.71	1.08	-0.45	0.76	0.09	0.90	0.00**
Focus	-0.05	0.98	0.34	0.77	-0.44	1.11	0.00**
Persistence	0.03	0.90	-0.38	1.02	0.50	0.81	0.00**
Participation	0.23	0.87	-0.09	0.79	-0.05	1.29	0.03*
Spatial orientation ability	0.66	0.86	-0.01	0.92	-0.50	0.92	0.00**
Interaction	-0.72	1.15	0.05	0.74	0.47	0.88	0.00**
Self-efficacy	0.49	0.87	-0.23	0.99	-0.04	0.99	0.00**
Learning anxiety	0.29	0.90	-0.51	0.96	0.49	0.76	0.00**

Note. * $p < 0.05$ ** $p < 0.01$.

A radar chart (see Figure 6) was made for displaying and comparing the means of the factor scores in multivariate variables among each cluster. The radar chart consists of multiple axes radiating from a central point. Each axis represents a different variable being measured. The data points are plotted along each axis, indicating the value of the corresponding variable, in this chart the range is from -1.0 to 1.0. These points are connected to create a polygon, giving a visual representation of the data's pattern, for example, in the axis of delay, it could be found that Cluster 1 (M = 0.7) has the highest mean score in delay, followed by Cluster 3 and Cluster 2, which means Cluster 1 is very sensitive to the online delay than other two groups.

Figure 6

Comparison of Learner Characteristics in the Three Clusters



Through a careful analysis of the average values of factor scores (see Figure 4) and a detailed examination of the survey, with a particular focus on the descriptions of specific items corresponding to each factor, this paper has constructed and outlined the unique learning characteristics within each group. The subsequent descriptions provide a comprehensive overview of learner profiles for each group. This in-depth analysis reveals the distinctive features of learners within their respective groups. These detailed and comprehensive analyses contribute to a better understanding of the diverse needs of different learning groups, providing robust support for personalized and effective teaching methods. The specific portraits of learner characteristics for each group are as follows:

Cluster 1 Portrait: Self-Motivated Learners

This group of learners got the highest score in the factors of SE (M = 0.49, SD = 0.87), delay (M = 0.71, SD = 1.08), and spatial orientation ability (M = 0.66, SD = -0.86). Still, the lowest score on interaction (M = -0.72, SD = 1.15) is shown in Table 12 and Figure 4, which indicates that the group of learners exhibited a good command of self-directed command of online learning skills with great confidence but liked to work alone.

This type of learner generally took the initiative to participate in tasks and learning activities. They also liked to complete assignments even if not required and actively participated in self-learning activities conducive to course learning, such as looking for self-test questions to check their knowledge and mastery of skills. Such learners also had a good sense of self-efficacy. They can deal with problems encountered in the process of learning with full confidence.

In addition, such learners were full of confidence in their online learning skills. They firmly believed they could accurately find the learning resources they needed from numerous network information and navigated through all information without getting lost. However, such learners were very sensitive to any delay due to connection issues like slow network speed. Such technical interruption could easily cause their anxiety which affected their learning performance.

Furthermore, this group of learners seemed to be more exclusive of interpersonal interaction as they gained the lowest score in the interaction factor (see Figure 4). They were more willing to solve problems in learning by consulting the internet rather than by teachers and classmates.

Cluster 2 Portrait: Focused Learners

As shown in Table 12 and Figure 6, this group of learners had the highest score in learning focus (M = 0.34, SD = 0.77) and lowest LA (M = -0.51, SD = 0.96), which indicates that during their learning process, they could concentrate for a long time and were not easily interrupted by external factors unrelated to learning. If they found themselves distracted, they could immediately become aware and make adjustments.

Based on the items of the survey about LA, it could be inferred that this group of learners can maintain a calm and peaceful attitude whenever online connectivity is interrupted or delayed, whenever the search for learning resources is difficult, whenever they encounter confusing network terms, or whenever they are faced with a poor learning effect. However, such learners' self-efficacy was the lowest (M = -0.23, SD = 0.99) among the three groups. They seemed not so confident about their learning success.

Cluster 3 Portrait: Persistent Interactive Learners

As shown in Figure 6 and Table 12, this group of learners had strong interactivity and learning persistence. They usually liked to discuss with teachers or classmates about learning content. They were willing to share their views and speak actively in the classroom or online forums. They felt relaxed during discussions and interactions and especially benefited from it.

Table 12 also shows that persistence in learning for this group was the highest of the three groups (M = 0.50, SD = 0.81), which means they could study unremittingly until they completed their original plans and met their goals. Meanwhile, such learners had the highest score of LA and the lowest concentration among the three groups (M = 0.49, SD = 0.76).

RQ5: How SOA, SE, and LA Might Affect LB

Standard multiple regression was used to check the specific effect of SOA, SE, and LA on LB. There was one dependent variable (LB) and three independent variables (SOA, SE, and LA), which were all continuous variables. Preliminary analyses were conducted to ensure no violation of the assumptions of normality, linearity, multicollinearity, and homoscedasticity.

Assumptions Check

Normalization and correlation analysis were made to ensure the data satisfied the primary condition for multiple regression. Figure 7 shows that the variables were in normalized distribution and the slope of the correlation fitting curve was not zero. Therefore, the Pearson coefficient was used to analyze the correlation between variables.

As shown in Table 13, the correlation coefficient between LB and SE was 0.75, showing a significant level of 0.01, followed by SOA (coefficient = 0.30, $p < 0.01$), indicating a significant positive correlation between LB and SE. In other words, the higher the correlation, the better performance on the learning behavior. The correlation coefficient between LB and LA was -0.21, $p < 0.01$, indicating a significant negative correlation between LB and LA. Furthermore, Table 13 also shows a significant positive correlation between SOA and SE (coefficient = 0.15, $p < 0.01$), which implies a mutually reinforcing relationship between the two. Finally, LA was found to have a negative correlation with other learner characteristics, especially with a coefficient score of -0.47, $p < 0.01$ (shown in Table 13).

Figure 7

Normalization and Correlation Check Among the Variables

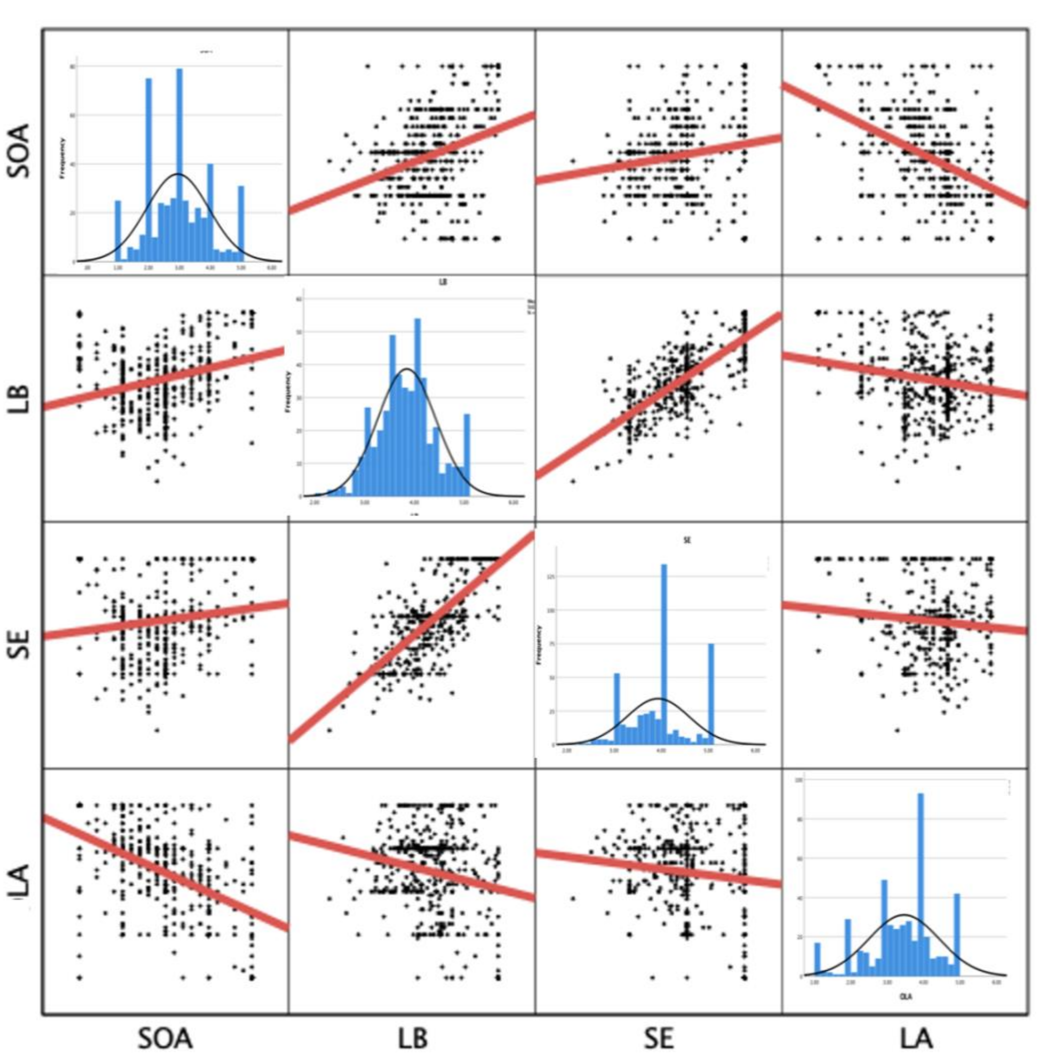


Table 13

Pearson Correlation of the Scales

	LB	SOA	SE	LA
LB	1			
SOA	0.303**	1		
SE	0.748**	0.154**	1	
LA	-0.206**	**-0.472****	-0.118*	1

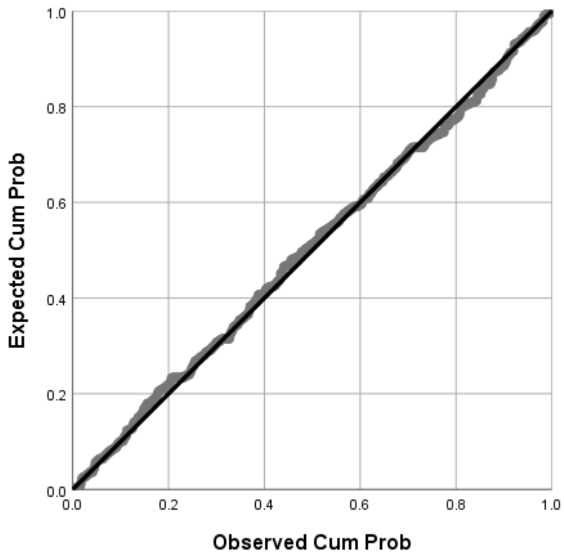
Note. * $p < 0.05$ ** $p < 0.01$.

LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA= Spatial Orientation Ability.

As instructed by Pallant (2016), the outliers, normality, linearity, homoscedasticity, and independence of residuals were checked by the normal probability plot (P-P) of the regression standardized residual (see Figure 8) and the scatterplot (see Figure 9). In Figure 8, the points lie in a reasonably straight diagonal line from the bottom left to the top right which suggests no major deviations from normality.

Figure 8

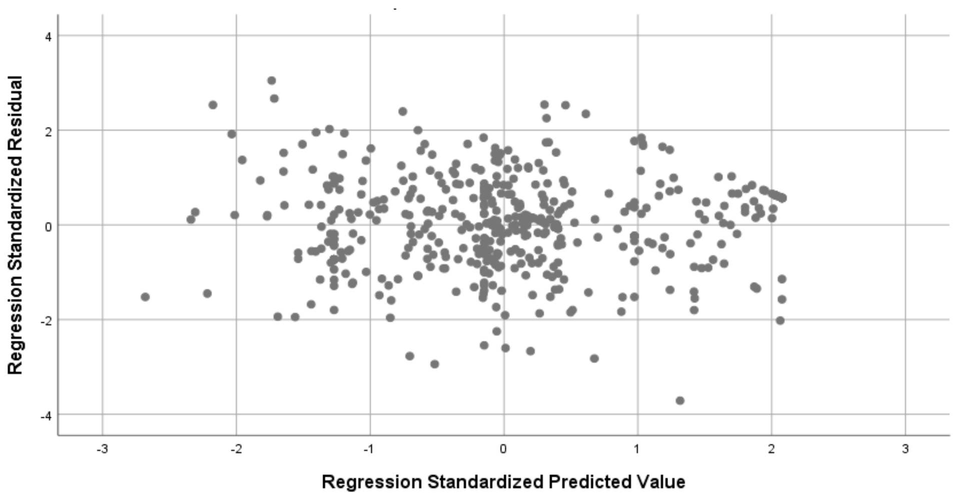
Normal P-P Plot of Regression Standardized Residual



In the scatterplot of the standardized residuals (see Figure 9), the residuals are roughly rectangularly distributed, with most of the scores concentrated in the center (along the 0 points), which suggests no violation of the assumptions (Tabachnick et al., 2013, p. 125). Finally, all these initial analyses were performed to verify that there were no violations of the assumptions related to normality, linearity, multicollinearity, and homoscedasticity.

Figure 9

Scatterplot of Regression Standardized Residual and Predicted Value



Model Evaluation

Table 14 shows the results of the regression. The *R*-squared value of the model was 0.596, indicating that the total variance explained by the model as a whole was 59.6%, $F(3,451) = 222.172$, $p < 0.01$. Only the two control measures were statistically significant, with the SE recording a higher standardized coefficients value ($\beta = 0.716$, $p < .001$) than the SOA ($\beta = 0.175$, $p < .001$). However, LA does not have any impact on LB. In addition, when testing the multicollinearity of the model, the variance inflation factor values in the model were less than 5, indicating that there was no collinearity problem; furthermore, the D-W value was near the number 2, indicating that the model had no autocorrelation.

Table 14

Multiple Regression Report of the Scale

Parameter estimates (n = 455)						
	Unstandardized coefficients		Standardized coefficients	t	p	Collinearity diagnosis
	B	Std. error	*Beta*			VIF
Constant	1.140	0.152	-	7.509	**0.000****	-
SE	0.633	0.027	**0.716**	23.621	**0.000****	1.027
LA	-0.024	0.021	-0.039	-1.157	0.248	1.290
SOA	0.101	0.020	**0.175**	5.114	**0.000****	1.303
R^2	**0.596**					
Adj R^2	0.594					
F	**F (3,451) = 222.172, p = 0.000****					
D-W	1.770					
Dependent variable: LB						

Note. * p < 0.05 ** p < 0.01.

LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA = Spatial Orientation Ability.

The Moderating Effect Analysis

Standard multiple regression showed that there was no direct impact of LA on LB, which may be because LA overlapped with other independent variables in the model. Thus, the moderating effect analysis was conducted to examine whether the magnitude of SE's impact on LB varied significantly under different conditions with the moderating variable LA when SOA was treated as the controlling variable.

Table 15

Data Handling Method on the Variables

Type	Items	Data type	Data handling
Dependent	LB	Quantitative	-
Independent	SE	Quantitative	Centralization
Moderator	LA	Quantitative	Centralization
Control	SOA	-	-

Note. LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA = Spatial Orientation Ability

Followed by the guidance of SÜRÜCÜ et al. (2023) on moderation, the independent and moderating variables shall be centralized to reduce the problem of multicollinearity. The data handling of the variables for the moderate analysis are summarized in Table 15. Finally, the parameter estimates of the three models are summarized in Table 16.

Table 16 showed that the SE was significant (t = 23.704, p < 0.01), meaning SE had a significant impact on LB. The moderating effect was viewed by examining the significance of the interaction terms in Model 3. The interaction term between SE and LA was significant (t = -2.640, p < 0.05), which implied that when SE affects LB, there was a significant difference in the magnitude of the moderating variable (LA) at different levels, which could be seen through the following simple slope plot (see Figure 10).

Table 16

Parameter Estimates (Summary) on the Moderating Variable (LA)

	Model 1					**Model 2**					**Model 3**				
	B	Standard Error	*t*	*p*	*β*	*B*	Standard Error	*t*	*p*	*β*	*B*	Standard Error.	*t*	*p*	*β*
Constant	3.518	0.055	64.524	0.000**	-	3.550	0.061	58.387	0.000**	-	3.555	0.060	58.826	0.000**	-
SOA	0.112	0.018	6.368	0.000**	0.193	0.101	0.020	5.114	0.000**	0.175	**0.098**	0.020	4.953	0.000**	0.168
SE	0.635	0.027	23.704	0.000**	0.718	0.633	0.027	23.621	0.000**	0.716	**0.627**	0.027	23.475	0.000**	0.709
OLA						-0.024	0.021	-1.157	0.248	-0.039	0.002	0.023	0.081	0.935	0.003
SE*OLA											**-0.071**	0.027	-2.640	0.009**	-0.091
R^2	0.595					0.596					**0.603**				
Adj. R^2	0.593					0.594					0.599				
F	F (2,452) = 332.340, p = 0.000					F (3,451) = 222.172, p = 0.000					**F (4,450) = 170.577, p = 0.000**				
$\triangle R^2$	0.595					0.001					0.006				
$\triangle F$	F (2,452) = 332.340, p = 0.000					F (1,451) = 1.338, p = 0.248					F (1,450) = 6.969, p = 0.009				

Note. Dependent Variable: LB.

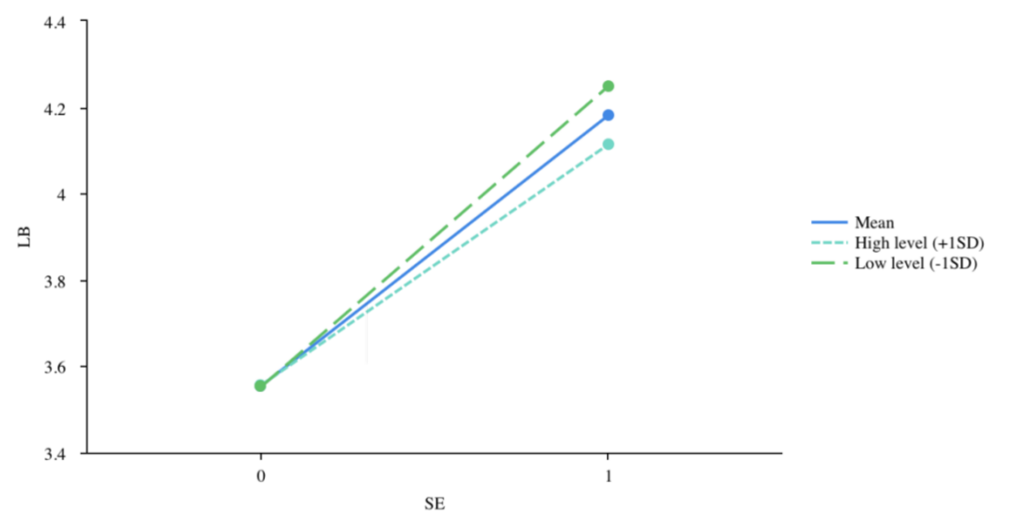
* $p < 0.05$ ** $p < 0.01$.

LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA = Spatial Orientation Ability.

Simple slope analysis was also made to evaluate the influence of the independent variable on the dependent variable (e.g., the significance of the regression coefficient) when adjusting for variables at three different levels. The three levels of moderating variables were average level, high level (average plus 1 standard deviation), and low level (average minus 1 standard deviation), as shown in Figure 10. The simple slope plot analysis shown in Figure 10 indicates that when LA was at low levels, SE (Regression Coef. = 0.697) had a greater impact on LB than in high levels (Regression Coef. = 0.588); that is, when students were at low learning anxiety, self-efficacy could better produce good learning performance.

Figure 10

Simple Slope of SE on LB With Different Level of LA



Note. LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety.

Finally, the final model and impact power of each variable are shown in Figure 11 and Table 17. The total variance explained by the model as a whole was model was 59.9%. with $F(4,450) = 170.577$, $p < .01$. In the final model, SE recorded a higher B value ($B = 0.627$, $p <$

0.01) than the SOA ($B = 0.098$, $p < 0.01$). On the other hand, LA had a moderating effect on SE's impact on LB ($B = -0.071$, $p < 0.01$).

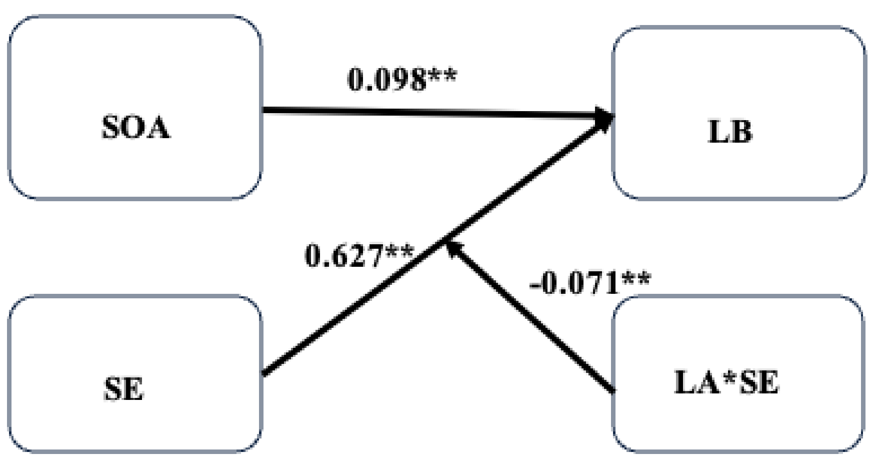
Table 17

Simple Slope Plot Analysis

Level	Regression Coef.	*t*	*p*	95% CI	
Mean	0.627	23.475	0.000	0.575	0.680
High Level（+1SD）	**0.558**	14.310	0.000	0.481	0.634
Low Level（-1SD）	**0.697**	19.418	0.000	0.626	0.767

Figure 11

The Final Model



RQ6: How Could the Schools Support Students to Enhance Their Personalized Learning?

To collect further information regarding the student's expectations of personalized learning, the survey asked students one open-ended question about what kind of support they hope the school could provide to support their personalized learning. In general, students clearly expressed the importance of learning space and equipment for their personalized learning. They also emphasized that the course setting could be more personalized in learning resources, assessments, and extended courses. Furthermore, they hoped to have more chances to practice. Finally, they hoped the school could reduce their academic burden and provide them with sufficient free time. The following sections provide a summary of the student's responses and quotes to the open-ended questions at the end of the survey.

Learning Space and Equipment

Concerning the personalization of the learning environment, students' main demands focused on the following aspect: personalized learning spaces. They believed that self-study rooms and professional studios could be more effective and enable them to engage in their learning. Also, they requested updating and intercommunication of machinery and equipment. Students hoped to share professional equipment across colleges and simplify the application process; finally, they suggested improving the network speed and making learning more efficient. The following are the quotes from students.

- "To establish a better self-study environment, the inter-professional machine loan system still needs to be improved. Each major can go deep into the direction of establishing a studio to learn in the school."
- "The approval process for the equipment booking in each studio should be simplified."
- "I need a good display environment for my design work."
- "Add a self-study room; So that students can spend the night in the professional classroom without going through too complicated procedures."
- "I hope the tools and machines in the school's various studios can keep up with the pace of the times."
- "Increase the available area for student creation and work display."

Course Resources and Flexible Class Schedule

Many students put forward suggestions on curriculum resources. They were mainly faced with three main problems. One was the conflict of course time, which made them unable to choose their favorite courses; the other was the professional restrictions, resulting in their lack of ability to choose courses; and finally, the curriculum resources, especially the software learning were insufficient. The following are the quotes from students regarding this topic:

- "I hope I can study at a relatively flexible time. Everyone's work and rest time is different. "
- "I want to take more comprehensive literacy elective courses, but the schedule makes me unable to attend due to time conflicts."
- "I hope the school will provide more flexible and personalized support for students' independent choice of courses."
- "Create more extended courses or activities, which can be put in elective courses to learn useful knowledge that is not available in the professional courses."
- "For me now, I hope to learn computer technology, such as AI."
- "I hope the school can support me with a multi-procurement knowledge base to provide online teaching of cutting-edge scientific and technological software."
- "I hope our school could open more online courses for me to learn knowledge across majors and broaden the application of professional knowledge; Provide me with a more open and inclusive environment for artistic creation and encourage students from different majors to cooperate and create together, and make up for the limitations of the creation of a single major."
- "High-quality design resources, such as collections of works of art."

- "I hope the school can provide some learning resources for designing software and some information for designing competitions."

Improve the Assignment Design

Students emphasized the diverse needs of course evaluation, and they hoped to have more personalized choices for the completion form and specific content of course assignments. It was worth noting that some students were evasive of group work, and they hoped that the teacher could provide the choice of completing individual or group assignments. Finally, students also hoped that teachers could improve their flexibility in course evaluation. The following are the quotes from students regarding this topic:

- "The choice of assignment format for the courses can be varied. Everyone is good at different things."
- "Grouped by student's learning type have strong creativity but weak self-control. I am arranged in groups with weak freedom and different interests. I am extremely tortured, which makes it difficult to advance my homework."
- "Teachers should not be too rigid in scoring assignments. Teachers should be flexible in judging students' progress in learning, rather than using a unique scoring standard. Everyone's starting position is different."

Extracurricular Activities

Students expressed that the school could provide personalized extracurricular activities, such as exhibitions or workshops master lectures. The following are the quotes from students regarding this topic:

- "We can arrange buses to the downtown once or twice a week. Only downtown can we have new things and various art exhibitions, to broaden our horizons."

- “Schools could arrange more activities such as music festivals for me to have a better learning experience.”
- “More extracurricular practical activities shall be arranged in the school, which can help me find inspiration.”
- “Arrange Off-campus exhibitions, sketching.”
- “Courses can be simplified, and more art workshops or master lectures shall be provided to expand aesthetic taste and vision.”

Networking and Professional Development Opportunities

Due to the practical characteristics of the art major, students’ practical demands for the course were urgent. They hoped the school could help them connect with social resources, create more channels for cooperation with companies and society, and improve their design ability through art practice. The following are the quotes from students regarding this topic:

- “Teachers should not always stick to the school’s curriculum content but combine it more with social practice.”
- “Schools can provide more practice and job opportunities that align with society’s needs.”
- “I hope the school can provide relevant resources and recommendation channels to the company based on the characteristics of students.”
- “More venues and opportunities can be provided in the practice of professional courses.”
- “I hope that the learning content can be combined with the actual needs of the enterprise, with more practical projects, so that I feel that my knowledge can be applied in real life and my design work is meaningful.”

Demands Extra Time for Study Exploration

Students did not want the school to arrange too many courses and assignments. On the contrary, they preferred extra time for thinking and precipitation, exploration of their study interests, and learning diversified knowledge. There was an urgent need for autonomous learning from the students. The following are the quotes from students regarding this topic:

- "I hope to reduce course hours and homework. The amount of homework is too large, and I have no extra time to reflect and explore new things."
- "The course schedule is too intensive, and the academic burden is so heavy that I don't have the time for myself."
- "Don't fill up the time with the course. My class usually ends at 9 p.m. and there's no time to do the assignments."
- "Leave enough spare time for me to study independently."

Conclusion

In Chapter 4, a thorough examination was conducted of the results of the quantitative data analysis. The chapter provided a detailed report on a comprehensive study of the learner characteristics of art students, including background information, LB, SOA, SE, and LA. Previous research findings were compared in terms of general learner characteristics. This discussion not only offered a comprehensive overview but also allowed for a nuanced understanding of the consistency or differences between the current research results and existing knowledge in the field.

Furthermore, this chapter used factor analysis on the variables of learner characteristics. This analytical approach helped to understand the inherent patterns within the data. The resulting eight factors were then employed for cluster analysis, ultimately identifying three clusters (self-motivated learners, focused learners, and persistent interactive learners) with significant differences in learner characteristics. Furthermore, the study provided in-depth descriptions of each cluster based on the eight-factor dimensions, offering a detailed understanding of the differences among these three clusters, and thereby enriching the exploration of the diversity of learner characteristics within the sample.

Additionally, the chapter delved into the complex relationships among learner characteristic variables. Through the application of multiple regression analysis, it revealed the direct impacts with statistical significance of SE and SOA on LB. Interaction detection through moderation analysis found that emotions played a moderating role in the relationship between self-efficacy and learning behavior. These findings aided researchers in better understanding the intricate interactions among various learner characteristics.

Finally, in the concluding section of the chapter, there was a discussion on the open-ended question responses from art students at S University. This qualitative component added a qualitative dimension to the quantitative findings, providing a more comprehensive perspective on the experiences and viewpoints of the participants. The integration of quantitative and qualitative data enriched the overall analysis, offering a comprehensive and in-depth view of the learner characteristics of art students at S University.

CHAPTER 5: DISCUSSION AND CONCLUSION

The main conclusions of this study are outlined in this chapter, along with a discussion of the quantitative results. This concluding chapter also discusses the implications of higher education policy and teaching practice. There is also a discussion about suggestions for future research. The goal of this study was to gain a deeper understanding of the learner characteristics of art students in the context of personalized learning. In other words, the study investigated the key elements that have a positive impact on art students at S University in their personalized learning.

Main Findings of the Study

The main findings are organized in Table 18. As shown in Table 18, the findings obtained from Research Question (RQ) 1 are used to ascertain general learner characteristics in contrast to previous research. Next, findings of RQ2 are used to discuss the impact of the background information impact on learner characteristics. Then, the outcomes of RQ3 and RQ4 are employed to formulate recommendations for the implementation of personalized learning for teachers. Additionally, the findings from RQ5 are deliberated in the discussion section, drawing connections with earlier studies. This analysis was grounded in the examination of three learner characteristics—self-efficacy, spatial orientation ability, and learning anxiety—and their influence on learning behavior. Lastly, the insights from RQ6 were incorporated into school-level recommendations for the effective integration of personalized learning.

Table 18

Main Findings of the Study

Theme	Research question	Key findings
The learner characteristics of art student	RQ1: What are the background and general learner characteristics of the art major students at S University?	• A total of 455 students participated in this study. • Nearly 60% of the participants were fresh students. 80% of the participants are females. The highest percentage of students in the sample were from the School of New Media (38.46%, *n* = 175). • The score of learning behavior and self-efficiency was higher for students in S University compared with the former study.
	RQ2: Is there any difference in learner characteristics for art students depending on their background information?	• Gender: no significant difference in learner characteristics. • Years of art learning: no significant difference in learner characteristics. • Grade: a small but significant effect of grades on SOA, LB, and LA (with grade growth, the LB score decreased; freshman had the lowest learning anxiety). • School: significant differences between SOA and LB
	RQ3: What are the underlying factors that influence learner characteristics among art major students at S University?	• 8 factors of learner characteristics were extracted • The 8 factors were: Learning anxiety, Self-efficacy, Interaction, Spatial orientation ability, Participation, Persistence, Focus, and Delay anxiety. • The cumulative variance interpretation rate after rotation was 75.15%.
	RQ4: In what ways can students at S University be classified into different groups based on learner characteristics?	• The art students at S University could be classified into 3 different groups based on the different learner characteristics factors: Cluster 1: Self-motivated learner Cluster 2: Focused leaner Cluster 3: Persistent interactive learners.

	Research question	Key findings
	RQ5: How spatial orientation ability (SOA), self-efficacy (SE), and learning anxiety (LA) might affect learning behavior (LB)?	• SOA and SE had a significant impact on LB. • The impact of SE is strong (B = 0.627, p < 0.01) • LA had no direct impact on LB, but it had a moderating effect on SE's impact on LB (SE had a more prominent effect on LB when LA was at a low level).
The design of personalized learning for art students	RQ6: How could the schools support students to enhance their personalized learning?	• Learning Space and Equipment • Course Resources and Flexible Class Schedule • Improve the Assignment Design • Extracurricular Activities Networking and Professional Development Opportunities • Demands more Time for Study Exploration

Note. LB = Learning Behavior, SE = Self efficacy, LA = Learning Anxiety, SOA = Spatial Orientation Ability.

Discussion

Learner Characteristics in General

Four learner characteristic scales—learning behavior (LB), self-efficacy (SE), learning anxiety (LA), and spatial orientation ability (SOA)—were assessed and compared with G. H. Wang's (2020) research. Overall, S University students exhibited similar learning characteristics to G. H. Wang's results. Notably, differences in self-efficacy were observed. Similar findings were also reported in Furnham et al.'s (2011) research that reported art students consistently exhibit higher creativity and confidence than their science counterparts. These findings might indicate art students have deep confidence in their creative ability, which internally affects their artistic expression and educational experience.

To gain a detailed description of learner characteristics of art major students for personalized learning, a deeper discussion on learning characteristics of SE, LA, and SOA are made in the following paragraphs. This detailed discussion connects the findings of this research with theory and former research and serves as a foundation for the specific needs and preferences of the art student population in personalized design. Understanding the nuances of these characteristics enables educators to craft learning experiences that resonate with the art student community's diverse learning styles and preferences for their learning engagement and learning success.

The Impact of Background Information on Learner Characteristics

Though some researchers have found gender differences in learner characteristics (Hindal et al., 2013; Park et al., 2019), the findings of this research showed gender had no significant difference on the four scales of learner characteristics. These results were consistent with the meta-analysis from Astleitner and Steinberg (2005), in which the findings indicated gender effects are insignificant on web-based learning. The inconsistency may be caused by cultural differences; for example, the sample taken from Hindal et al.'s (2013) research was from Kuwait where boys and girls were educated in separate schools. Furthermore, the years of art learning that were considered prior knowledge also did not exhibit significant differences in the identified learner characteristics. This finding supports the meta-analysis research from Simonsmeier et al. (2022) who noted the correlation between initial knowledge, as measured by pretest scores, and normalized knowledge gains was minimal, indicating limited predictive capability. In summary, the impact of grade and school variables demonstrated a significant but small effect on SOA, LB, and LA.

The Impact of SE on LB

The results of multiple regression analysis in this study revealed significant insights into the relationship between cognitive factors and learning behavior. Specifically, SE emerged as a potent and positively impactful determinant of LB, as evidenced by a substantial B value of 0.627 (t = 23.475, p < 0.01). This finding aligned seamlessly with Bandura's (1986) self-efficacy theory, emphasizing the crucial influence of individuals' assessments and confidence in their capabilities on their behavior.

Support for the result also comes from empirical research in G. H. Wang's (2020), Chu and Tsai's (2009), and Yukselturk and Bulut's (2007) studies, which also identified a significant influence of SE on LB. Extending beyond traditional academic domains, the current study underscored the universal applicability of SE in the realm of art pedagogy. This finding emphasized the broad relevance of SE not only in conventional academic fields but also in the acquisition of artistic skills.

The multiple regression results of this study found that cognitive factors modeled LB by revealing that SE had a significantly positive and powerful impact on LB with the B value of SE of 0.627 (t = 23.475, p < 0.01). This finding fit Bandura's (1986) theory of SE that underscores the influence of individuals' assessments and confidence in their capabilities on their behavior. This result also supported the empirical research of G. H. Wang (2020), in which the SE factor had a significant effect on LB.

Alternatively, the crucial role of SE in learning performance, as observed in various fields including math, reading, and writing (Carmichael & Taylor, 2005; Pajares & Miller, 1994; Schunk, 2003), was found equally applicable in the realm of art pedagogy. This finding emphasized the overarching importance of SE, demonstrating its relevance not only within conventional academic fields but also in the context of acquiring artistic skills.

Finally, when connecting SE with the open-ended question in RQ6, one may infer a close correlation between high SE and active LB. This finding was evidenced by students seeking extra time for self-exploration and expressing a desire to take initiative in course selection shown in the open-ended question (e.g., participants shared, “I hope the school will provide more flexible and personalized support for students’ independent choice of courses,” and “Leave enough spare time for me to study independently”). Such findings aligned with constructivism theory (Huitt, 2009), highlighting the importance of learners actively participating in knowledge construction. Bandura’s (1978) SE theory also supports these observations, suggesting that heightened SE enhances responsiveness and promotes active learning. Furthermore, this result also matches the overall view within the literature review that student engagement thrives with learning ownership (Lee & Hannafin, 2016; Schmitz & Wiese, 2006). In addition, the demand of students to take the initiative in learning found in open-ended questions also indicates that schools have the prerequisite for promoting personalized learning that emphasizes self-directed and self-managed learning.

This finding highlights the central role of SE in shaping LB for art major students, emphasizing the importance of students’ confidence in their abilities. These insights not only contribute to the understanding of cognitive factors in art education but also offer practical implications for personalized learning, emphasizing the need for student autonomy, active participation, and self-directed learning in educational settings.

The Impact of LA on LB

The result of the standard regression shows that LA appears to have no direct effect on learning behavior (p = 0.248, > 0.05), a moderate effect of LA on LB was checked. The analysis of the simple slope plot indicated that at lower levels of LA, the influence of SE on LB was more pronounced, with a regression coefficient of 0.697, compared to higher levels of LA where the impact was slightly lower at 0.588. These finding indicated that when students experience low levels of LA, their SE beliefs become a powerful driving factor of academic achievement. In essence, reducing anxiety clears the way for SE to have a greater positive impact on LB. This dynamic interaction not only emphasizes the importance of solving LA symptoms but also emphasizes the importance of enhancing students' self-confidence and confidence in their abilities.

These findings were consistent with Bandura's (1994) theory that acknowledges SE beliefs can be influenced by various factors, including stress and external influences may moderate the relationship between SE and LB. Bandura (1994) noted, "Those who believe they cannot manage threats experience high anxiety arousal. . . . Perceived coping self-efficacy regulates avoidance behavior as well as anxiety arousal" (p 75). The moderating effect of LA was also fit the finds in empirical research from Butz et al. (2016), J. Zhou and Yu (2021), and Fonseca et al. (2014).

Thus, these findings emphasize the intricate and interconnected nature of LA, SE, and LB. By comprehensively understanding these dynamics, educators and institutions can implement targeted interventions, creating supportive environments that empower students to overcome anxiety, enhance their self-belief, and actively participate in their learning journeys.

Such strategies are essential not only for academic success but also for fostering resilient, confident, and self-assured learners prepared for the challenges of the digital age.

The Impact SOA on LB

This study focused on SOA, a common digital literacy in online personalized learning design, to check its impact on learning behavior. In comparison with the mean score of SOA from G. H. Wang (2020), the study found little difference in SOA between art students and students (M = 2.99) from other majors (M = 2.94) that implies SOA as a key skill in the digital age for all disciplines.

Multiple regression results of this study revealed that SOA had a statistically significant impact on LB ($\beta = 0.098$, $p < 0.01$). The finding is consistent with the former research results that pointed out that better online searching and navigation ability could promote good LB and performance (Bronstein & Tzivian, 2013; Demirbilek, 2009; Moriyama et al., 2009; Webster & Ahuja, 2006). This finding indicates that the ability to locate and process digital in enhances students' dedication to do learning tasks and contributes significantly to their overall learning outcomes.

In essence, these findings accentuate the pivotal role of SOA in the realm of personalized learning, emphasizing its impact on LB and its interconnectedness with SE. Acknowledging the significance of these digital skills is paramount for educators and institutions aiming to enhance personalized learning experiences. By recognizing the importance of SOA and fostering its development among students, educational stakeholders can confidently empower learners to navigate the digital landscape, promoting effective personalized learning and improving overall academic achievements.

Cautious Consideration of Technological Integration in Personalized Learning Design

Research literature has indicated technological integration is an undeniable trend in personalized education. Technology brings numerous advantages to personalized learning, enabling the creation of customized learning paths based on student's needs and progress, allowing for adjustments in learning resources and tasks. Technology also facilitates automated and personalized learning.

However, especially in the context of art education, the use of technology requires careful consideration. Prior research has suggested highly creative individuals, particularly art students, might possess higher anxiety traits (Carlsson et al., 2000; Cross et al., 1967). With the consideration of the moderate effect of anxiety on LB, the technology integration in personalized learning for art students was suggested to be introduced with caution. Therefore, before introducing technology, a deep understanding of students' needs and learning styles is imperative. Different students vary in their acceptance and usage of technology. Hence, the chosen technological tools must align with learning objectives and content. Not all technologies are universally applicable. Options could include learning management systems, online courses, educational applications, virtual reality, or online collaboration tools, tailored according to specific needs, and students should receive appropriate training. This consideration also extends to educators, who shall adapt to new technological tools. To enhance teaching effectiveness, teachers must be provided with training and support, ensuring they have a comprehensive understanding of how to use these tools.

After technology implementation, evaluating its impact becomes crucial. Data collection and feedback are essential to understand whether technology genuinely enhances students' academic performance and participation (Drugova et al., 2021; Wijaya et al., 2021). Based on the evaluation results, adjustments and improvements to the use of technology should be made. These adjustments and improvements place higher demands on teachers, school technology departments, and government financial support.

Finally, although technology serves as a potent tool for advancing personalized learning, it must be balanced with face-to-face teaching, maintaining the human aspect of education. Technology should not replace the role of teachers but act as their strong ally, enhancing the learning experience and preserving the personalized and friendly nature of teaching.

The Social and Collaborative Aspects in Art Pedagogy

The theories discussed in Chapter 1 guide the design and implementation of personalized learning among art students. At the macro level, this paper adopted the theory of constructivism that emphasizes student learning is an active knowledge-building process, which is an individual's cognitive situation based on learning in the learning environment, and emphasizes the social and collaborative nature of learning.

However, when it comes to the social and collaborative aspects of learning among art students, notable differences have emerged. In this study's categorization, self-motivated learners tended to prefer solitary learning and exploration, whereas persistent interactive learners were inclined to acquire knowledge through communication and interaction. These findings are consistent with Gloor et al.'s (2011) speculation that there might be two different types of creativity—the "lonely genius" and the "swarm creative." This discrepancy has sparked discussions about social communication and creativity. Some scholars have argued enhancing social connections can better stimulate creativity (Perry-Smith, 2006; Singh & Fleming, 2010). But simultaneously, researchers also discovered individuals tend to develop perceptions of others’ creative abilities by viewing socially isolated individuals as possessing greater creativity, which contributes to the myth of the “signal creative genius” (Proudfoot & Fath, 2021).

However, directly linking social isolation with creativity might be oversimplified. Learning is a process of absorbing and transforming knowledge, whereas creativity focuses more on output and creation. Due to this mismatch, students might mistakenly assume that distancing themselves from social interactions could enhance creativity, although the actual effects require further in-depth research. Additionally, the accuracy of how teachers assess individual contributions in group assignments might influence students’ willingness to participate in collaborations. Even students who study alone or engage in online learning might collaborate socially through nonverbal and non-face-to-face means, such as online forums and social media comments. However, these forms of social interaction are often overlooked and sometimes even considered as social isolation.

Therefore, in the personalized learning design for art students, it is crucial to consider the diverse needs of students regarding collaborative communication. Schools should offer a variety of assignment formats for students, rather than simply emphasizing in-class group cooperation. Some students might prefer forming interdisciplinary teams, and others might enjoy the pleasure of solitary exploration. Teachers should respect students’ right to choose, viewing these choices as differences in learning methods, rather than deducing students’ social inclinations based on them, and avoid forcefully encouraging or guiding cooperation. Only by taking individual differences into account can educators truly achieve the goal of personalized education.

Recommendations

Recommendations for teachers to implement personalized learning were generated from the findings in factor analysis and cluster analysis in RQ3 and RQ4. Simultaneously, the findings from the open-ended question (i.e., RQ6) have been integrated into school-level recommendations to facilitate the effective integration of personalized learning in art universities. This comprehensive guidance framework not only focuses on providing teachers with tools for personalized learning but also emphasizes driving this concept throughout the entire school system. By implementing these recommendations, this study sought to offer art university students a transformative and enriching educational experience, enabling them to achieve comprehensive development in both academic achievements and creative artistic talents. The specific recommendations are outlined as follows.

For Teachers

Personalized learning, naturally, begins with the characteristics of individuals and ultimately serves them. Therefore, in personalized teaching, it is crucial to understand students' interests and talents comprehensively. This entails delving into each student's hobbies and strengths, aiding teachers in grasping the personalized learning needs. Apart from the questionnaires used in this study, teachers can employ methods like classroom observations, teacher–student interviews, or group discussions to gain an in-depth understanding of students' requirements. The cluster analysis provided in this study also serves as a reference for teachers to provide personalized teaching and guidance in teaching and specific suggestions:

- Cluster 1: Self-Motivated Learner: This group excels in self-directed online learning and exhibits high confidence. They are tech-savvy but sensitive to network issues that can impact their performance. They often prefer studying individually. For these learners, it is recommended to provide diverse learning resources, such as online courses or self-study software tools, and ensure high-quality learning devices. Tracking their progress through online learning evaluations can help them understand their learning situations better.

Given their preference for solitary learning, it is advisable to offer them various assignment formats while minimizing excessive group discussions and collaborative projects.

- Cluster 2: Focused Learner: This group demonstrates strong focus and calmness during learning. However, they possess lower self-efficacy and limited persistence, often giving up easily. To engage these students, efforts can be made to stimulate their interests, incorporating project-based learning or practical visits to enhance their learning experience. Encouragement and positive feedback from teachers are crucial to boost their self-efficacy and persistence. Additionally, establishing study groups can enhance their learning perseverance, creating a supportive environment.
- Cluster 3: Persistent Interactive Learners: These learners persistently work toward their goals and actively participate in discussions. Despite high LA and lower concentration, they excel in discussions and benefit significantly from these interactions. Because this group heavily relies on communication for learning, various interactive activities such as group discussions, online forums, social media, and teacher guidance can enhance their learning experiences. Teachers should maintain real-time communication to address their anxieties promptly. During instructional discussions, engaging methods like questioning and quizzes can help maintain their focus.

For Art Universities

Personalized learning for art students is a complex and crucial task due to the higher demands on their creativity and expressive abilities. The following suggestions could enhance the personalized learning experience for art students:

- Understanding students’ interests and talents: An in-depth understanding of each student’s hobbies and talents would help to improve the students’ personalized learning experience. The collection of this information through personal interviews, surveys, or group discussions if the condition allows.
- Offering projects to meet students’ diverse needs: Design flexible course structures allowing students to choose projects aligning with their interests and goals. Personalized projects can include artwork in different mediums, independent research projects, or interdisciplinary collaborative efforts.
- Encouraging self-directed learning: Help students develop self-directed learning skills by encouraging them to explore, and learn new skills, to expand their artistic skill and knowledge. Provide resources and guidance while giving them enough space to unleash their creativity.
- Personalized assessment methods: Design diverse assessment methods, including art exhibitions, oral presentations, or written assignments. Allow students to choose assessment formats that match their talents and learning styles, enabling them to showcase their abilities effectively.
- Providing learning resources: Offer a wide range of art resources, including art libraries, studio facilities, and digital materials. Ensure students can easily access the materials and information they need.
- Encouraging collaboration and communication: Promote collaboration among students; create team projects; and encourage interactions with peers, teachers, and the artistic community. Such collaborations broaden perspectives and stimulate creative thinking.

- Personalized tutoring and guidance: Provide personalized tutoring and guidance services to help students create individualized learning plans and address academic and creative challenges.
- Encouraging practical experience and internships: Provide opportunities for students to participate in practical projects and internships, enhancing their hands-on skills and helping them build professional networks in the art industry.
- Continuous feedback and adjustments: Regularly engage in feedback sessions with students to understand their learning experiences and needs. Adjust and improve personalized learning plans based on feedback to ensure effectiveness.

By tailoring the learning environment to individual strengths and interests, these methods foster holistic development, encouraging students to explore diverse artistic expressions, instilling a love for lifelong learning, and showcasing their unique talents through various assessments. Access to comprehensive resources, collaboration, and community engagement enriches the social aspect of learning. Personalized support, practical experiences, and continuous feedback mechanisms contribute to individual growth and readiness for the professional art world. Together, these strategies create a dynamic educational framework, empowering art students to excel academically and cultivate innovative artistic talents.

Applications of the Study

Insights gained from this study provide revelations for a wide array of stakeholders in the field of art education. Specifically, art universities and institutions specializing in art majors stand to gain significantly. These findings can inform teaching methodologies and curricula for art majors, empowering educators to adapt their approaches to the distinct needs and learning styles of their students. Instructors can incorporate the study's outcomes into their teaching methods, cultivating a learning environment that is more conducive and responsive.

Academic advisors in these institutions can use the study's results to offer more targeted and effective guidance to art students. By understanding students' preferences, anxieties, and LB, advisors can provide personalized counseling and support, ensuring students navigate their academic journeys more smoothly. Understanding students' technological preferences and anxieties can enable these groups to create online platforms or events that are more engaging and conducive to participation.

Academic recruiters, both in universities and external agencies, can employ the insights from this study to attract potential art students. By emphasizing the institution's personalized learning approaches and understanding of students' individual needs, recruiters can effectively communicate the institution's student-centered environment to attract students seeking tailored educational experiences.

Beyond individual institutions, the relevance of this study extends to programs focused on designing personalized learning in art pedagogy. Educators and curriculum designers involved in these programs can incorporate the findings into their methodologies, ensuring future art educators are equipped with the knowledge and strategies to create inclusive and effective learning environments for their students. Ultimately, the study's impact ripples throughout the entire educational ecosystem, fostering a more responsive, supportive, and student-centered approach to art education.

Limitations and Future Research

The conclusions drawn from this study need to be approached with caution due to certain limitations. Firstly, the scope of this study was limited to students from Shanghai S University, which limits the generalizability of the research results. In addition, this study specifically targeted art students. Therefore, there may have been significant differences in learner characteristics observed among students from different universities or focusing on different disciplines. Therefore, it is necessary to carefully extrapolate the research results to a wider student group or different academic disciplines.

For future research, it would be suggested to expand the target population by including a more diverse range of students from nonart majors. This approach would facilitate comprehensive interdisciplinary comparisons. Such comparisons are instrumental in delving deeper into the similarities and differences in learning characteristics across various academic disciplines, providing a more detailed and comprehensive data foundation for educational research.

Secondly, this study delved into several factors in the learning characteristics of art students, including LB, SE, LA, and SOA. However, as highlighted in the literature review, learning characteristics constitute a vast and multidimensional domain, encompassing various dimensions and elements. Thus, the study's perspective was constrained, unable to cover all potential factors influencing learning characteristics comprehensively.

To gain a more comprehensive understanding of learning characteristics, future research could consider incorporating additional dimensions and factors, such as learning motivation, learning styles, social factors, and more. This approach would provide a richer and more comprehensive research perspective. Although this study explored a limited scope, the diversity and complexity of learning characteristics extend far beyond the current research boundaries. Future studies are suggested to further explore the diversity of learning characteristics, including but not limited to individuals' emotional attitudes, family educational backgrounds, and sociocultural environments. Additionally, the research findings on emotions and SE suggest the potential inclusion of psychophysiological factors and cognitive elements in understanding the mechanisms and roles during the learning processes of art students. By employing interdisciplinary research methods, researchers can delve deeper into the interrelationships among these factors, unveiling the underlying mechanisms and patterns behind learning characteristics.

Furthermore, although this study identified the role of technology in personalized learning, due to constraints in time, funding, and expertise, the research was limited to conducting a literature review and analyzing related technologies. Empirical studies assessing the effectiveness of these technologies in actual teaching, specifically their applicability to art students, were beyond the scope of the current study. Therefore, it is recommended that future researchers leverage advanced data analysis techniques and artificial intelligence algorithms to delve into the hidden learning characteristic patterns within extensive datasets. This data-driven research approach can help discover patterns that might be overlooked in traditional research, offering a fresh perspective and new possibilities for studying learning characteristics.

Additionally, this study did not comprehensively track the learning outcomes of students after the implementation of personalized learning, both quantitatively and qualitatively. This implies that researchers have not yet deeply understood the specific impacts of personalized learning on students' academic performance, self-development, and learning characteristics. Systematic evaluation of the implementation effects of personalized learning, including changes in academic performance, increased interest in subjects, and enhanced learning motivation, is a crucial direction for future research. Furthermore, the changes in students' learning characteristics after implementing personalized learning are also a matter of great interest. This kind of change analysis could provide valuable insights into the effectiveness of personalized learning, shaping students' attitudes and behaviors toward learning.

Therefore, future research can longitudinally track various indicators, such as academic performance, subject interests, and participation rates, after the implementation of personalized learning, and conduct quantitative analyses to obtain more specific and objective data. Moreover, qualitative research methods such as in-depth interviews and observations can be employed to explore students' subjective experiences and changes in the personalized learning environment. Such a comprehensive research design will contribute to a more in-depth understanding of the implementation effects of personalized learning and the changes in students' learning characteristics, providing a scientific basis and practical experience for personalized education.

Conclusion

This chapter discussed learner characteristics in art education, focusing on SE, LA, and SOA. The study highlighted the significant impact of SE on LB and the moderating effect of LA. It emphasized the crucial role of SOA in personalized learning. Cautious technological integration and considerations for social aspects in art pedagogy were also addressed. Recommendations for schools and teachers included understanding student interests, offering personalized projects, encouraging self-directed learning, implementing varied assessments, providing excellent resources, promoting collaboration, offering personalized tutoring, encouraging practical experiences, and collecting continuous feedback for adjustments.

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APPENDICES

Appendix A. Coding for Scales and Variable

Scale/ Variable	Sub variable	Question label	Question	Various type	Value coding
Learning Behavior(LB) Scale	**LB_ engagement**	LB_paticipation_1	I regularly study the relevant materials provided by the course according to the requirements of the course.	Scale	1=completely disagree; 2=disagree; 3=uncertain; 4=agree; 5=completely agree
		LB_paticipation_2	I try to participate in every learning activity organized by the course.	Scale	
		LB_paticipation_3	I leave enough time to complete the course learning task.	Scale	
		LB_paticipation_4	Even if I don't have requirements, I also actively participate in some learning activities that contribute to the course learning (e.g., doing self-test questions and homework, discussing with peers).	Scale	
		LB_paticipation_5	I check the announcements, information, and discussion replies of the course regularly.	Scale	

LB_ persistence	LB_persistence_1	During course learning, I often can't study according to my learning plan.	Scale	5=completely disagree; 4=disagree; 3=uncertain; 2=agree; 1=completely agree
	LB_persistence_2	When learning the course, once other things are affecting me, I can't persist on completing my study.	Scale	
	LB_persistence_3	During course learning, I always give up halfway through.	Scale	
LB_ focus	LB_focus_1	During course learning, I try not to be interrupted by external things.	Scale	1=completely disagree; 2=disagree; 3=uncertain; 4=agree; 5=completely agree
	LB_focus_2	During course learning, I am not doing things unrelated to learning.	Scale	
	LB_focus_3	During course learning, I can immediately adjust if I find I am distracted.	Scale	
	LB_focus_4	During course learning, I can study the relevant content for a long time.	Scale	
LB_ interaction	LB_interaction_1	During course learning, I take the initiative to share my views or useful resources with my classmates and teachers.	Scale	

	LB_interaction_2	During course learning, I actively respond to the questions, help, or posts of teachers or students.	Scale	
	LB_interaction_3	During course learning, I actively participate in the discussion in the discussion area.	Scale	
	LB_interaction_4	When I encounter problems or confusion in course learning, I take the initiative to ask my classmates or teachers for help through the network.	Scale	
	LB_interaction_5	The exchange of online course discussion helps me regulate my mood.	Scale	
	LB_interaction_6	Online communication with teachers and students makes me feel more relaxed.	Scale	
	LB_interaction_7	Browsing the online course discussion area, I feel very productive.	Scale	

	LB_ flexibility	LB_flexibility_1	During course learning, I can take the initiative to complete the learning tasks and broaden my learning.	Scale	
		LB_flexibility_2	During course learning, I can use the new technology and tools I have mastered for learning.	Scale	
		LB_flexibility_3	During course learning, I can take the initiative to explore some new tools or methods.	Scale	
		LB_flexibility_4	During course learning, I can clearly express my views through the network.	Scale	
Spatial Orientation Ability (SOA)Scale	**SOA**	SOA_1	I often get lost in online course learning (such as disorientation and loss in the face of many networks of information)	Scale	5=completely disagree; 4=disagree; 3=uncertain; 2=agree; 1=completely agree
		SOA_2	In online course learning, due to too many link levels, I can't go back to the original learning content.	Scale	

		SOA_3	In online course learning, the amount of network information is so complex that I can't find the information I need.	Scale	
		SOA_4	In online course learning, the information is so rich and colorful that I always attracted to the content beyond my learning objectives.	Scale	
		SOA_5	In online course learning, there are too many sites that match the learning objectives, and jumping back and forth between them consumes time in the selection process.	Scale	
Self-efficacy (SE) Scale	**SE_ general**	SE_general_1	I am confident to deal with most of the problems while learning.	Scale	1=completely disagree; 2=disagree; 3=uncertain; 4=agree; 5=completely agree
		SE_general_2	It is easy for me to persist in completing course studies.	Scale	

	SE_general_3	It is easy for me to use courses for learning.	Scale	
	SE_general_4	I think I have a strong ability for independent learning.	Scale	1=completely disagree; 2=disagree; 3=uncertain; 4=agree; 5=completely agree
	SE_general_5	I'm very confident in my course learning.	Scale	
	SE_special_1	I believe that I have the network skills needed for the course learning.	Scale	
	SE_special_2	I believe that I can achieve good learning results through the course study.	Scale	
SE_ special	SE_special_3	I believe that I can quickly find the learning resources I need on the Internet.	Scale	
	SE_special_4	I believe that I can use E-mail, QQ, forums, and other ways to communicate with teachers and students in course learning.	Scale	
	SE_special_5	The basic skills required for course learning are easy to master.	Scale	

		SE_special_6	I believe I can master most of the knowledge in the course.	Scale
Learning Anxiety (LA) Scale	**LA_ delay**	LA_delay_1	In online courses, I feel anxious when the internet speed of online courses slows down, I feel anxious.	Scale
		LA_delay_2	In online courses, I feel anxious when I couldn’t complete the learning task due to the lack of network connection.	Scale
		LA_delay_3	In online courses, I feel impatient when the webpage jumps, or the resource download is slow.	Scale
	LA_ search	LA_search_1	In online courses, I feel anxious when I can’t search for the information I need for a long time.	Scale
		LA_search_2	In online courses, I feel anxious when I can’t think of the right search keywords.	Scale

	LA_search_3	In online courses, I feel anxious when I can’t extract the information I need from a large amount of information.	Scale
LA_ terminology	LA_terminology_1	In online courses, I feel anxious when the knowledge in online courses is difficult to understand.	Scale
	LA_terminology_2	In online courses, I feel anxious about abstract or difficult words.	Scale
	LA_terminology_3	In online courses, I feel anxious about knowledge I’m not interested in.	Scale
LA_ general	LA_general_1	In online courses, I feel anxious when the learning effect of online courses is not good.	Scale
	LA_general_2	In online courses, I feel anxious when I’m not focused.	Scale

		LA_general_3	In online courses, I feel anxious when my self-control becomes poor.	Scale	
Background information	**Gender**	Gender	What is your gender?	Nominal	1 = male; 2 = female
	Grade	Grade	What is your grade?	Ordinal	1 = Freshman 2 = Sophomore 3 = Junior &Senior
	Year of art learning	YAL	How long did you study art before you came to university?	Ordinal	1 = 1-5years; 2 = more than 5years
	School	School	which school you comes form?	Nominal	
	*****1=School of design;2=School of New Media Art;3= School of fashion design;4=school of Fine Arts;5=School of Performing Art;6=School of Cultural and Creative Industries;7=School of Management;8=School of pop music and dance				
Open end Question	**Open End**	OE	In which areas do you think the school should provide personalized support for students majoring in arts?	String	

Appendix B. Reliability Statistics (Cronbach Alpha)

Items	Corrected Item-Total Correlation(CITC)	Cronbach Alpha if Item Deleted	Cronbach α
LB_paticipation_1	0.789	0.89	
LB_paticipation_2	0.826	0.883	
LB_paticipation_3	0.794	0.889	**0.912**
LB_paticipation_4	0.732	0.905	
LB_paticipation_5	0.76	0.897	
LB_persistence_1	0.782	0.844	
LB_persistence_2	0.814	0.815	**0.889**
LB_persistence_3	0.755	0.868	
LB_focus_1	0.681	0.819	
LB_focus_2	0.684	0.825	**0.851**
LB_focus_3	0.755	0.786	
LB_focus_4	0.684	0.814	
LB_interaction_1	0.753	0.896	
LB_interaction_2	0.765	0.894	
LB_interaction_3	0.786	0.892	
LB_interaction_4	0.68	0.904	**0.911**
LB_interaction_5	0.757	0.895	
LB_interaction_6	0.663	0.906	
LB_interaction_7	0.726	0.899	
LB_flexibility_1	0.773	0.867	
LB_flexibility_2	0.836	0.845	**0.896**
LB_flexibility_3	0.803	0.854	
LB_flexibility_4	0.679	0.899	
SOA_1	0.84	0.917	
SOA_2	0.857	0.913	
SOA_3	0.819	0.92	**0.934**
SOA_4	0.808	0.922	
SOA_5	0.802	0.924	
SE_general_1	0.819	0.925	
SE_general_2	0.823	0.923	
SE_general_3	0.836	0.921	**0.936**
SE_general_4	0.822	0.924	
SE_general_5	0.862	0.916	
SE_special_1	0.776	0.918	
SE_special_2	0.817	0.912	
SE_special_3	0.818	0.912	**0.929**
SE_special_4	0.726	0.924	
SE_special_5	0.802	0.914	
SE_special_6	0.812	0.913	
LA_delay_1	0.886	0.899	
LA_delay_2	0.857	0.922	**0.938**
LA_delay_3	0.873	0.909	
LA_search_1	0.91	0.953	
LA_search_2	0.923	0.943	**0.963**
LA_search_3	0.928	0.94	
LA_terminology_1	0.848	0.831	
LA_terminology_2	0.839	0.837	**0.904**
LA_terminology_3	0.745	0.92	
LA_general_1	0.858	0.94	**0.945**

Items	Corrected Item-Total Correlation(CITC)	Cronbach Alpha if Item Deleted
LA_general_2	0.901	0.907
LA_general_3	0.896	0.911

Appendix C. Validity Check

Table C.1

Validity Analysis LB (Learning Behavior) , Factor = 4

Items	Factor Loadings				Communalities
	Factor 1	Factor 2	Factor 3	Factor 4	
LB_interaction_1	**0.792**	0.198	0.212	0.061	0.715
LB_interaction_2	**0.814**	0.241	0.135	0.062	0.744
LB_interaction_3	**0.836**	0.199	0.151	0.099	0.771
LB_interaction_4	**0.719**	0.257	0.153	0.146	0.628
LB_interaction_5	**0.730**	0.159	0.313	0.034	0.658
LB_interaction_6	**0.634**	0.135	0.349	-0.027	0.542
LB_interaction_7	0.675	0.184	0.350	0.015	0.613
LB_paticipation_1	0.187	**0.826**	0.201	0.069	0.762
LB_paticipation_2	0.220	**0.852**	0.181	0.065	0.812
LB_paticipation_3	0.144	**0.825**	0.245	0.137	0.781
LB_paticipation_4	0.424	**0.704**	0.162	0.059	0.705
LB_paticipation_5	0.230	**0.811**	0.115	0.082	0.730
LB_focus_1	0.319	0.239	**0.676**	0.180	0.649
LB_focus_2	0.239	0.211	**0.795**	0.054	0.737
LB_focus_3	0.286	0.235	**0.772**	0.102	0.743
LB_focus_4	0.418	0.175	**0.651**	0.160	0.655
LB_persistence_1	0.044	0.082	0.097	**0.891**	0.812
LB_persistence_2	0.069	0.091	0.144	**0.900**	0.844
LB_persistence_3	0.089	0.099	0.059	**0.879**	0.793
Eigenvalues (Initial)	8.353	2.300	1.888	1.153	-
% of Variance (Initial)	43.963%	12.104%	9.939%	6.068%	-
% of Cum. Variance (Initial)	43.963%	56.067%	66.006%	72.073%	-
Eigenvalues (Rotated)	4.664	3.736	2.768	2.526	-
% of Variance (Rotated)	24.547%	19.663%	14.570%	13.293%	-
% of Cum. Variance (Rotated)	24.547%	44.210%	58.781%	72.073%	-
KMO	**0.913**				-
Bartlett's Test of Sphericity (Chi-Square)	6073.678				-
df	171				-
p value	0.000				-

Note: Blue indicates that the absolute value of loading is greater than 0.4.

Table C.2

Validity Analysis SOA, Factor = 1

Items	Factor Loadings Factor 1	Communalities
SOA_1	**0.901**	0.812
SOA_2	**0.913**	0.833
SOA_3	**0.886**	0.785
SOA_4	**0.878**	0.771
SOA_5	**0.873**	0.762
Eigenvalues (Initial)	3.964	-
% of Variance (Initial)	79.278%	-
% of Cum. Variance (Initial)	79.278%	-
Eigenvalues (Rotated)	3.964	-
% of Variance (Rotated)	79.278%	-
% of Cum. Variance (Rotated)	79.278%	-
KMO	**0.898**	-
Bartlett's Test of Sphericity (Chi-Square)	1864.305	-
df	10	-
p value	0.000	-

Note: Blue indicates that the absolute value of loading is greater than 0.4.

Table C.3

Validity Analysis SE , Factor = 2

Items	Factor Loadings		Communalities
	Factor 1	Factor 2	
SE_general_1	**0.760**	0.448	0.779
SE_general_2	**0.821**	0.349	0.795
SE_general_3	**0.814**	0.376	0.804
SE_general_4	**0.814**	0.351	0.786
SE_general_5	**0.810**	0.414	0.828
SE_special_1	0.310	**0.817**	0.764
SE_special_2	0.540	**0.694**	0.773
SE_special_3	0.306	**0.848**	0.813
SE_special_4	0.344	**0.736**	0.660
SE_special_5	0.478	**0.711**	0.734
SE_special_6	0.553	**0.671**	0.756
Eigenvalues (Initial)	7.655	0.837	-
% of Variance (Initial)	69.590%	7.613%	-
% of Cum. Variance (Initial)	69.590%	77.203%	-
Eigenvalues (Rotated)	4.369	4.123	-
% of Variance (Rotated)	39.717%	37.486%	-
% of Cum. Variance (Rotated)	39.717%	77.203%	-
KMO	**0.943**		**-**
Bartlett's Test of Sphericity (Chi-Square)	4592.462		-
df	55		-
p value	0.000		-

Note: Blue indicates that the absolute value of loading is greater than 0.4.

Appendix D. Factor Analysis

Table D.1

Total Variance Explained

Factor	Eigen values			% of variance (Initial)			% of variance (Rotated)		
	Eigen	% of Variance	Cum. % of Variance	Eigen	% of Variance	Cum. % of Variance	Eigen	% of Variance	Cum. % of Variance
1	14.805	31.501	31.501	14.805	31.501	31.501	8.598	18.294	18.294
2	9.222	19.622	51.123	9.222	19.622	51.123	8.509	18.103	36.397
3	3.055	6.501	57.624	3.055	6.501	57.624	4.369	9.295	45.692
4	2.522	5.367	62.991	2.522	5.367	62.991	3.945	8.394	54.086
5	1.825	3.884	66.875	1.825	3.884	66.875	3.826	8.141	62.227
6	1.613	3.431	70.306	1.613	3.431	70.306	2.470	5.256	67.483
7	1.216	2.587	72.892	1.216	2.587	72.892	2.301	4.895	72.377
8	1.060	2.256	75.148	1.060	2.256	75.148	1.302	2.770	75.147
9	0.985	2.095	77.243	-	-	-	-	-	-
10	0.800	1.701	78.945	-	-	-	-	-	-
11	0.657	1.397	80.342	-	-	-	-	-	-
12	0.596	1.269	81.610	-	-	-	-	-	-
13	0.551	1.173	82.783	-	-	-	-	-	-
14	0.505	1.074	83.857	-	-	-	-	-	-
15	0.470	1.001	84.858	-	-	-	-	-	-
16	0.430	0.915	85.773	-	-	-	-	-	-
17	0.420	0.893	86.666	-	-	-	-	-	-
18	0.382	0.813	87.479	-	-	-	-	-	-
19	0.360	0.766	88.244	-	-	-	-	-	-
20	0.346	0.737	88.981	-	-	-	-	-	-
21	0.332	0.706	89.687	-	-	-	-	-	-
22	0.320	0.682	90.368	-	-	-	-	-	-
23	0.309	0.658	91.026	-	-	-	-	-	-

Total Variance Explained

Factor	Eigen values			% of variance (Initial)			% of variance (Rotated)		
	Eigen	% of Variance	Cum. % of Variance	Eigen	% of Variance	Cum. % of Variance	Eigen	% of Variance	Cum. % of Variance
24	0.302	0.642	91.668	-	-	-	-	-	-
25	0.290	0.617	92.285	-	-	-	-	-	-
26	0.259	0.551	92.837	-	-	-	-	-	-
27	0.257	0.548	93.384	-	-	-	-	-	-
28	0.249	0.529	93.913	-	-	-	-	-	-
29	0.243	0.517	94.430	-	-	-	-	-	-
30	0.224	0.477	94.907	-	-	-	-	-	-
31	0.217	0.462	95.369	-	-	-	-	-	-
32	0.205	0.437	95.806	-	-	-	-	-	-
33	0.191	0.407	96.212	-	-	-	-	-	-
34	0.181	0.385	96.597	-	-	-	-	-	-
35	0.172	0.365	96.962	-	-	-	-	-	-
36	0.168	0.358	97.321	-	-	-	-	-	-
37	0.157	0.334	97.655	-	-	-	-	-	-
38	0.146	0.311	97.966	-	-	-	-	-	-
39	0.142	0.302	98.268	-	-	-	-	-	-
40	0.129	0.275	98.543	-	-	-	-	-	-
41	0.125	0.266	98.808	-	-	-	-	-	-
42	0.119	0.254	99.062	-	-	-	-	-	-
43	0.108	0.230	99.292	-	-	-	-	-	-
44	0.101	0.214	99.506	-	-	-	-	-	-
45	0.090	0.191	99.697	-	-	-	-	-	-
46	0.078	0.167	99.864	-	-	-	-	-	-
47	0.064	0.136	100.000	-	-	-	-	-	-

Table D.2

Factor Loading

Items	Factor1 Learning Anxiety	Factor2 Self-efficacy	Factor3 Interaction	Factor4 Spatial orientation ability	Factor5 Participation	Factor6 Persistence	Factor7 Focus	Factor8 Delay
LA_delay_1								0.537
LA_delay_2								0.496
LA_delay_3								0.470
LA_search_1	0.832							
LA_search_2	0.849							
LA_search_3	0.872							
LA_terminology_1	0.859							
LA_terminology_2	0.842							
LA_terminology_3	0.789							
LA_general_1	0.868							
LA_general_2	0.867							
LA_general_3	0.869							
SE_general_1		0.762						
SE_general_2		0.737						
SE_general_3		0.755						
SE_general_4		0.738						
SE_general_5		0.768						
SE_special_1		0.815						
SE_special_2		0.821						
SE_special_3		0.819						
SE_special_4		0.724						
SE_special_5		0.816						
SE_special_6		0.829						
LB_interaction_1			0.688					
LB_interaction_2			0.715					
LB_interaction_3			0.729					
LB_interaction_4			0.613					
LB_interaction_5			0.74					
LB_interaction_6			0.651					
LB_interaction_7			0.677					
SOA_1				0.846				
SOA_2				0.87				
SOA_3				0.839				
SOA_4				0.795				

Items	Factor1 Learning Anxiety	Factor2 Self-efficacy	Factor3 Interaction	Factor4 Spatial orientation ability	Factor5 Participation	Factor6 Persistence	Factor7 Focus	Factor8 Delay
SOA_5				0.81				
LB_paticipation_1					0.809			
LB_paticipation_2					0.843			
LB_paticipation_3					0.801			
LB_paticipation_4					0.69			
LB_paticipation_5					0.793			
LB_persistence_3						0.842		
LB_persistence_1						0.832		
LB_persistence_2						0.861		
LB_focus_1							0.623	
LB_focus_2							0.694	
LB_focus_3							0.700	
LB_focus_4							0.583	