Uncertainty Avoidance Moderates the Relationship between Time Management Monitoring and Learning Engagement in Blended Learning Contexts among University Students in Beijing

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Abstract

The aim of this study was to investigate the relationship between time management monitoring and learning engagement in a blended learning environment among university students, as well as the moderating effect of uncertainty avoidance on this relationship. The subjects were 548 undergraduates from 6 universities in Beijing, with 467 valid responses received. The data was collected using the Time Management Monitoring Scale, Learning Engagement Scale, and Uncertainty Avoidance Scale, with confirmatory factor analysis and reliability tests confirming their validity and reliability. This was a field study examining blended learning courses combining online and offline instruction at universities in Beijing. Structural equation modeling revealed that time management monitoring positively influenced learning engagement. Uncertainty avoidance also had a positive effect on learning engagement and moderated the relationship between time management monitoring and learning engagement. Students with higher uncertainty avoidance exhibited a more significant positive association between their time management abilities and engagement in blended learning contexts.

Keywords: learning engagement, moderator, time management monitoring, uncertainty avoidance

1. Introduction

The COVID-19 pandemic enhanced the popularity of online open-learning courses. Although many students returned to class since the outbreak ended, the blended learning model remained a major trend (Guppy et al., 2022). In Europe, the number of universities conducting blended learning has been increasing annually. Kluijfhout et al. (2019) reported that over 70% of European universities conducted blended learning courses. The pan-European massive open online course initiative, which offers online instruction in numerous languages and disciplines, provides an excellent basis for universities to develop blended learning courses (European Commission, 2013).

Time management and engagement in learning are critical to student education. Students' time management skills are essential skills for blended learning (Talosa et al., 2021). According to Zhang et al. (2018) time management involves the psychological and operational characteristics involved in time use. Time management is a multidimensional and monitoring time management is most easily modified at the behavioral level of these dimensions. It refers to an individual's ability to plan and organize time. Learning engagement is a predictor of learning effort and academic achievement.

Hofstede (1986) described uncertainty avoidance as the degree of perceived danger experienced by members of different cultures when threatened by unknown positional states. Groups with high levels of uncertainty avoidance, who are concerned with stability and safety, tend to conservatively avoid risk by rigorous planning, avoiding ambiguity in learning, and seeking to control the outcome of future events (Geletkanycz, 1997). Individuals with low levels of uncertainty avoidance tend to exhibit more risk-taking behavior and are comfortable in unstructured and ambiguous situations (Swierczek, 2003). As a result, individuals with low uncertainty avoidance are more proactive and adaptable when dealing with risky situations. Uncertainty avoidance has a significant impact on people's behavior and learning. Those with low levels of uncertainty avoidance are more likely to take risks and are better equipped to handle uncertainty than those with high levels of uncertainty avoidance. According to Ying et al. (2021) uncertainty avoidance

played a significant role in determining university students' learning engagement and final outcomes in a blended learning environment during the COVID-19 pandemic. Following the pandemic, blended learning is now a prominent approach to university education.

Beijing's numerous universities, many of which are world class, use blended learning to promote the values required for effective and efficient learning (Bruggeman, 2021; Wang, 2021). Since 2020, universities in Beijing have established various online blended learning platforms.

This study, to explore the relationship between learners' time management strategies and active participation in blended learning environments, and the moderating role of cultural differences, was based on the theoretical framework of self-regulated learning theory (SRLT) (Harris, 2012). Self-regulation refers to learners' cognitive and motivational processes by which they actively plan, monitor, and evaluate their own learning to enhance their learning outcomes(Pintrich, 2000). Prior studies have shown that effective time management positively impacts on students' engagement and academic achievement (Zimmerman, 2011). However, research that investigates learners' self-regulatory strategies when adapting to new blended learning contexts, especially in contexts where there are differences across cultures, is required (Broadbent, 2015). This study set out to validate the association between time management monitoring and learning engagement, as well as the moderating effect of uncertainty avoidance on this association, with a view to provide empirical evidence to apply and expand SRLT, and offer important theoretical and practical implications for understanding and improving learners' participation and experiences in blended learning settings.

In summary, the ability of students to manage and allocate their time positively affects their engagement in blended learning. Therefore, this study investigated the time management monitoring, uncertainty avoidance, and learning engagement of university students engaged in blended learning in Beijing.

2. Literature Review

2.1 Time Management, Learning Engagement, and Self-Regulated Learning Theory

Self-regulated learning theory (SRLT) offers an important framework for understanding learners' active and constructive processes that direct their motivation and cognition (Pintrich, 2000). Key self-regulatory processes include goal setting, self-monitoring, self-instruction, and self-reinforcement (Zimmerman, 2011). From an SRLT viewpoint, effective time management exemplifies learners' self-directed efforts to intentionally structure and manage different resources to optimize their academic success because better time management tendencies positively influence student behavior such as regularly attending classes, persisting on carrying out learning tasks, and participating more in learning activities (Zimmerman, 2011). Published literature also illustrates that learners' time management skills and self-regulatory competence can facilitate their active engagement in blended and online learning contexts (Broadbent, 2015).

However, there are notable gaps in understanding the nuances of how learners' time management strategies are related to their participation and achievements within newer digitally enhanced blended instruction models, especially as regards cross-cultural differences in self-regulation. For instance, previous cross-cultural comparisons narrowly focus on static time attitudes and not the enactment of time management strategies for goal-driven learning tasks(Zampetakis, 2010). Thus, this research assessed the effects of university students' time management monitoring strategies on their blended learning engagement, while considering potential cultural variations.

2.2 Time Management Monitoring and Learning Engagement

Learning engagement is a measure of students' involvement in the learning process. Kuh (2009) states that engagement is the result of an interaction between student learning behaviors and environmental support. Astin's(1984) theory, that supports this idea, states that the more time and attention students devote to effective learning activities, the better their learning outcomes. Recent discussions among researchers have focused on students' motivation to engage in learning with a focus on students' effective time management and self-monitoring behaviors in improving academic performance. Students can enhance their learning outcomes through flexible learning and adapting to their learning tasks and personal circumstances (Pan et al., 2011).

The Self-System Model of Motivational Development (SSMMD) proposed by Skinner et al. (2008) suggests that individual factors have an impact on learning outcomes. According to the model, students who effectively manage their time develop a positive academic self-concept which in turn enhances their engagement in learning and academic performance. Recent research by Sorella et al. (2002) demonstrates that time management habits are influenced by personality traits. Effective time management habits, which are closely tied to positive coping styles,

significantly enhance students' engagement in learning activities (Skinner et al., 2008). But individuals may have varying perceptions, attitudes, and behaviors when it comes to managing the same amount of time which often motivate them to work towards their goals (Zimmerman, 2011). Consequently, skillful time management can significantly impact on actual participation in learning activities.

Existing literature suggests that effective time management, which is strongly linked to improvements in personal motivation and coping style, can motivate university students to actively participate in learning activities (Sorella et al., 2002). An optimal attitude towards time management and the appropriate allocation of time to learning tasks can influence learners' use of their own time and energy expenditure to sustainably participate in school learning practices. Talib and Sansgiry (2012) report a positive correlation between university students' time management skills and their learning engagement level from the results of a questionnaire survey. Therefore, optimal time management skills promote higher learning engagement.

Considering the research studies and inferences discussed above, this study posits that effective time management monitoring can predict the level of learning engagement exhibited by university students in blended learning environments. Consequently, the study puts forth the following hypothesis: H1: Time management monitoring of university students in blended learning has a significant impact on their learning engagement.

2.3 Uncertainty Avoidance and Learning Engagement

Hofstede's (1980) seminal work showed that cultures high in uncertainty avoidance, where instructors are seen as authority figures with standard answers and learning tends to be structured, students rely more on teachers for guidance and explicit guidelines. In response, blended instruction was conceived to increase engagement by integrating technology-enhanced components with flexible social features (Walker, 2020). However, blended models can also introduce uncertain learning outcomes and paths for students. To mitigate such risks in implementation, university policies often aim to provide a clear framework and expectations around blended learning courses (Bruggeman, 2021). Given high uncertainty avoidance, Chinese students frequently prefer structured regulations and plans when directing their own education (Muflih et al., 2021). Learners uncomfortable with ambiguous instructional scenarios tend to adhere more closely to established rules. Thus, Chinese students may feel more assured and motivated to engage in blended learning behaviors, as long as clear teacher-set expectations reinforce the process. In this cultural context, certainty around blended design and guidelines can facilitate greater acceptance and participation.

Based on the previously mentioned studies and their corresponding inferences, the study proposed the following hypothesis (H2): Uncertainty avoidance among college students in blended learning affects learning engagement.

2.4 Time Management Monitoring, Learning Engagement, and Uncertainty Avoidance

Recent research indicates that uncertainty avoidance impacts psychological and attitudinal changes associated with adapting to new learning models (Jin et al., 2013; Yi et al., 2013). Cultures high in uncertainty avoidance resist change overall, fear conflict and instability, and desire clear structure and directions to methodically achieve aims (AI-Adwan et al., 2018; Cummings et al., 1987). In contrast, those comfortable with uncertainty and ambiguity can better adjust to uncertain environments, but may also hesitate more in attempting to avoid mistakes(Zaman et al., 2020; O'Connor et al., 2022).

In the context of blended learning transitions, students routinely plan study time to meet goals, but this process itself may cause hesitation, especially for uncertainty-avoidant learners. However, those focused on high-quality, precise work can leverage time management skills to self-monitor progress effectively (Xu et al., 2019). Uncertainty-avoidant students likely exhibit more blended learning anxiety but may also manage time more efficiently, stay assertive in seeking help, and commit to engagement goals. Alternatively, students low in uncertainty avoidance depend on teacher guidance for answers(Eringa et al., 2015).

Given these differences, college students' uncertainty avoidance is hypothesized to moderate the link between time management monitoring abilities and learning engagement in blended instruction. Students high in uncertainty avoidance can potentially translate strong time management skills more effectively into actual participation and focus. H3: Uncertainty avoidance moderates the relationship between time management monitoring and learning engagement in the blended learning context among college students.

3. Methods

3.1 Research Framework

Based on the research hypotheses, time management monitoring influences learning engagement, and uncertainty

avoidance moderates the association between time management monitoring and learning engagement (Figure 1).
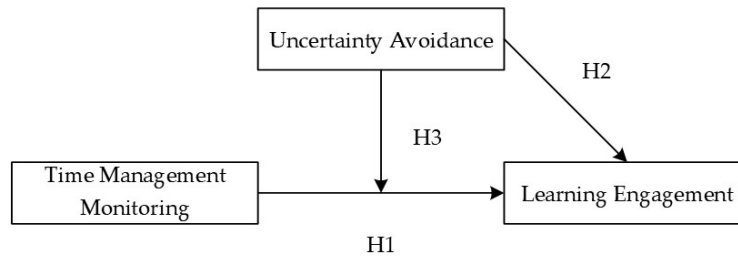

Figure 1. Hypothetical Model

3.2 Participants

The participants were Chinese university students enrolled in undergraduate institutions. After obtaining approval from the Academic Committee of the International College of K University (approval number: No. 2022-0218) and informed consent from the respondents. In 2022, Beijing's 67 universities had a total of 595,700 students, with each institution having an average of 6,475 students, according to the Beijing Education Development Statistical Bulletin for the academic year 2021–2022(Beijing Municipal Education Commission, 2022). Because of the large student population, a stratified sampling method based on the overall size and the level of university was used to select six universities: two top universities, two provincial (municipal) general public universities, and two general private universities.

Gorsuch (1983) suggested that a questionnaire recovery sample size should be 5–10 times the number of study questions, and the sample size should be greater than 100(Qiu, 2013). Therefore, a total of 548 questionnaires were distributed to students among the 6 universities, and 467 valid questionnaires were returned.

The sample for this study included a total of 467 participants, consisting of 228 (48.9%) males and 239 (51.1%) females. The age range of participants was between 18 and 25 years old, with a mean age of 20.3 years. Participants were classified into four academic levels, including 61 (13.1%) freshmen, 147 (31.5%) sophomores, 173 (37.0%) juniors, and 86 (18.4%) seniors. The sample was well-balanced in terms of gender. The sample size and diversity of academic levels and majors ensured the representativeness of the sample and the generalizability of the study findings.

3.3 Research Tools

A study questionnaire with all question items adapted from the literature was used in this study. Questions were presented in the form of a 5-point Likert scale. The questionnaire had relatively good reliability and validity. The questionnaire used had three sections: the Time Management Monitoring Scale, the Learning Engagement Scale and the Uncertainty Avoidance Scale.

The Time Management Monitoring Scale: Time Management Monitoring Scale for Adolescents was developed by Zhang et al. (2001) based on the cultural background and actual conditions in China. This scale is divided into five constructs: setting goals, planning, prioritization, ability to receive feedback, and time allocation. Its Likert scale ranges from 1 (not at all compliant) to 5 (fully compliant). Higher scores indicate better time management skills.

The Learning Engagement Scale: The online Learning Engagement Scale is a 16-item scale developed by Li (20021) divided into four constructs: behavioral engagement, cognitive engagement, affective engagement, and social interaction engagement.

The Uncertainty Avoidance Scale was developed by Jung and Kellaris (2004). It contains a single construct. The construct is scored on seven items that indicate students' level of adaptation to uncertainty.

3.4 Reliability and Validity

This study used descriptive analysis, reliability and validity analysis, path analysis, and structural equation modeling (SEM) for multigroup analyses. All analyses were conducted using SPSS (IBM, Armonk, NY, USA) and AMOS (IBM). After reliability validity analysis, time management monitoring had a skewness value of −0.060, kurtosis value of −1.079, skewness values ranging from −0.452 to 0.435, and a Mardia value of 21.499 [less than P × (P + 2)

= 35; P is the number of observed variables]; Learning engagement had a skewness value of 0.050, a kurtosis value of −1.066, SK values from −0.335 to 0.404, and a Mardia value of 21.499 [less than P × (P + 2) = 24]; and Uncertainty aversion had a skewness value of 0.082, a kurtosis value of −1.173, SK values from −0.210 to −0.049, and a Mardia value of 21.499 [less than P × (P + 2) = 3]. All these tests met the reliability criteria indicating that the data for all three scales were normally distributed (Kline, 1998).

Confirmatory factor analysis of the scales yielded a model fit index of $\chi2/df = 1.118$, a standardized root mean square residual (SRMR) of 0.027, a root mean square error of approximation of 0.016, a normative fit index (NFI) of 0.970, a comparative fit index (CFI) of 0.997, a parsimony-corrected index (PNFI) of 0.817, and a resolution corrected CFI (PCFI) of 0.839. These results suggest that the model had good fit (Hair et al., 1998; Lomax & Schumacker, 2004).

The internal consistency of the scales in this study was deemed to be adequate based on Cronbach's alpha values of .931, .904, and .922 for time management monitoring, learning engagement, and uncertainty avoidance, respectively.

The factor loadings for each of the three scales were greater than 0.5 [43, 44], the combined reliability values were all greater than 0.6, and the mean extraction for each latent variable was less than 0.5. These results suggested good convergent validity for the latent variables (Hair et al., 1998).

4. Results

4.1 Path Analysis

A direct effects model was developed using structural equation modelling to evaluate the effects of time management monitoring on learning engagement based on the following correlation index values: $\chi2/df = 1.146(\chi2/df<5)$ (Fornell & Larcker, 1981), SRMR = 0.022(SRMR<0.08) (Schumacker & Lomax,2004), CFI = 0.997(CFI≥0.90,)(Hu & Bentle, 1999), IFI = 0.997(IFI≥0.90)(Hu & Bentle, 1999), PNFI = 0.723(PNFI≥0.50) (Hu & Bentle, 1999), and PCFI = 0.706(PCFI≥0.50) (Hu & Bentle, 1999). These results suggest that the model had a reasonable fit (Kline, 1998; Hair et al., 1998).

After the model was tested for fitness, the values of the parameters in the model were used to evaluate of H1 and H2. The results indicated that the path coefficient of time management monitoring on learning engagement was 0.651 with a t-value of 5.024, which was a statistically significant difference (p < 0.05). The path coefficient of uncertainty avoidance on learning engagement was 0.200 with a t-value of 15.380, which was a statistically significant difference (p < 0.05). The overall explanatory power was 61.4%. Thus, H1 and H2 were supported, which suggests that time management monitoring and uncertainty avoidance among college students can significantly and positively influence their learning engagement behavior (Table 1).

Table 1. Verifying the Influence of Time Management Monitoring (TMM) and Uncertainty Avoidance (UA) on Learning Engagement (LE).

Path	+/-	γ	t	Whether it is supported
TMM←LE	+	.651	5.024[*]	H1 supported
UA←LE	+	.200	15.380[*]	H2 supported

[*]p < .05.

4.2 SEM Multigroup Analysis

The present study hypothesized that uncertainty avoidance may influence the relationship between time management monitoring and learning engagement. Uncertainty avoidance was analyzed as a moderating variable. SEM multigroup analysis was used to evaluate the moderating effect related to H3. Score split on uncertainty avoidance was conducted as done by Paulssen et al. (2014) and Rodríguez et al. (2014), and high-score and low-score groups were divided into the restriction model (the high-score group's path coefficient was equal to the low-score's group path coefficient) and unrestricted model (freely estimating path coefficient). The chi-square values of the two models were compared for significant differences (Zhang, 2011).

The mean of uncertainty avoidance was determined to be 3.05 (standard deviation = 0.891). Participants with a mean score equal to or greater than 3.05 were categorized into the high uncertainty avoidance group, and those with a mean score less than or equal to 3.05 into the low uncertainty avoidance group. The high and low uncertainty avoidance groups had 226 and 241 participants, respectively. Independent sample t-tests were used to test the

validity of the groups. A t-value of -38.224 was obtained (p < 0.001), indicating that the two groups were well differentiated (Gorsuch, 1983).

The results for the unrestricted model were as follows: χ2/df = 3.761(χ2/df<5)(Fornell & Larcker,1981), AGFI = 0.921(AGFI<0.90)(Schumacker & Lomax,2004), NFI = 0.990(NFI≥0.90) (Gorsuch,1983), CFI = 0.992(CFI≥0.90) (Hu & Bentle,1999), CN = 324. The results for the unrestricted model were: χ2/df = 2.148, AGFI = 0.955, NFI = 0.988, CFI = 0.994, CN = 456. The unrestricted model outperformed the restricted model in all metrics and was therefore deemed to have good fit (Kline, 1998; Hair et al., 1998).

Table 2 shows that the unconstrained model had 202 degrees of freedom 2 and an χ2 value of 248.160, whereas the constrained model had 203 degrees of freedom and an χ2 value of 252.446. A direct comparison could be made between χ2 values because the difference in degrees of freedom was 1. The difference in χ2 value between the two models was 4.286 (p < 0.01), indicating that a significant difference existed between the unrestricted and restricted models (Zhang, 2011; Ranellucci, 2015). That the moderating effect of uncertainty avoidance differs between time management monitoring and learning engagement (Table 2).

Table 2. Multi-group Analysis of Moderating Model.

Model	χ^2	DF	χ^2difference
Unrestricted model	248.160	202	
Restricted model	252.446	203	4.286[**]

[**]*p* < .01.

If the cardinality difference between the two models reached significance, the equal path coefficients test one model would be rejected, indicating that the main effects have different path coefficients at different levels of time management than in the default case, as presented in Table 2. Thus, the moderating effect of H3 was supported; college students' uncertainty avoidance had a moderating effect on the relationship between time management monitoring and learning engagement behavior. The results of the interference path coefficients indicated that both low and high uncertainty avoidance significantly and positively influenced the relationship between time management monitoring and learning engagement behaviors as presented in Table 3. Overall, as the level of time management monitoring increased, college students with high uncertainty avoidance were more likely to increase their learning engagement than those with low uncertainty avoidance. Uncertainty avoidance exerted a positive moderating role on the relationship between time management monitoring and learning engagement.

Table 3. Comparison of High and Low Grouping Path Coefficients.

Path	Low group γ (*N*=241)	High group γ (*N*=226)
LE←TMM	.669[**]	.761[**]

[**]*p* < .01.

TMM: Time Management Monitoring; LE: Learning Engagement.

5. Discussion and Conclusion

5.1 Discussion

This study verified H1: time management positively and significantly influences learning engagement, consistent with the findings of Talib and Sansgiry (2012) and Zimmerman's (1990) self-regulated learning theory. Wang et al. (2014) also found that middle school students' time management predicted their level of learning engagement. Learning is a student's primary task, and students who are good time managers are usually more willing to engage in learning activities to achieve learning goals, acquire knowledge, overcome difficulties, and gain satisfaction and happiness in the learning process than their peers who possess inferior time management skills.

This study verified H2: there is a positive relationship between uncertainty avoidance and learning engagement. In cultures with high levels of uncertainty, where learning is structured and the instructor is seen as having all the answers, students are more dependent on their instructor for rules and instructions (Talib & Sansgiry, 2012). Blended instruction was incepted to promote learning engagement mainly using technological developments and social features as opposed to relying on learning instructors as was done in classroom learning approaches. However, blended instruction can also lead to uncertain learning outcomes that university planning policies' attempt to reduce by providing learners with

clear guidelines and structure (Bruggeman et al., 2021). Chinese students prefer explicit regulations and plans when managing their own learning (Walker, 2022). Students with high uncertainty avoidance tend to closely follow established rules as they are motivating to engage in learning behaviors within rule-based expectations. Therefore, such students may feel more comfortable with the dynamic blended learning process.

The present study confirmed that uncertainty avoidance moderates the relationship between time management monitoring and learning engagement. Time management monitoring refers to the ability of students to continually self-regulate their use of time in response to changes in an online learning setting (Sorella, 2022). Effective time management monitoring helps shape students' time perception and has a significant impact on their learning engagement (Zimmerman, 1990). Given that students need to constantly plan their time during the blended learning process, students with superior time management skills will be more focused and committed to their study goals (Zimmerman & Schunk, 2011). However, students' uncertainty avoidance levels also affect how their time management monitoring is translated into actual learning engagement. Thus, students with higher uncertainty avoidance can effectively leverage their time management skills to attain higher engagement levels. A moderating role of uncertainty avoidance was observed. The degree of uncertainty avoidance of college students represents their cognitive attitudes toward the risks, changes, and ambiguities that they may face while using online teaching platforms. Students with high uncertainty avoidance make more rational decisions than students with low uncertainty avoidance. Students with high uncertainty avoidance can learn with high engagement and search for information about learning models when making judgments. Learning through an online environment requires a high level of time management to adhere to the rules and plans required for success at blended instruction. Students with high uncertainty avoidance are more likely to follow rules to avoid risk.

Additionally, time management monitoring has a positive effect on learning engagement among university students who are exposed to blended learning. Moreover, uncertainty avoidance has a positive effect on learning engagement and actively moderates the relationship between time management monitoring and learning engagement. Thus addressing uncertainty avoidance could promote learning engagement among university students. Similarly, time management monitoring can be an effective tool to enhance learning engagement in a blended learning environment.

5.2 Conclusion

This study confirms that the time management monitoring ability of university students has a positive impact on their learning engagement in a blended learning environment. Furthermore, uncertainty avoidance also has a positive effect on learning engagement, and plays a moderating role between time management monitoring and learning engagement. This suggests that paying attention to uncertainty avoidance can help enhance the university students' participation in blended learning. Similarly, cultivating good time management monitoring abilities is also an effective way of improving engagement in blended learning.

The research findings provide empirical support for self-regulated learning theory, and extend the theory's application in explaining cultural differences. The incorporation of the cultural dimension of uncertainty avoidance allows the theory's application to involve richer cultural characteristics, which helps better explain the differences in individual self-regulated learning across different cultural backgrounds.

5.3 Theoretical Contributions: Extending SRLT and Cross-Cultural Implications

Initially, our research empirically supports and extends Self-Regulated Learning Theory (SRLT), particularly in its application within blended learning environments. Our findings confirm the positive impact of time management monitoring on learning engagement, aligning with the SRLT emphasis on learners consciously organizing and planning their study time to enhance learning effectiveness. Additionally, our study explores how uncertainty avoidance serves as a cultural dimension influencing the learners' self-regulated learning strategies, offering a new perspective for understanding learner behavior across different cultural backgrounds.

Subsequently, this research provides practical insights for higher education institutions who are designing and implementing blended learning strategies. By identifying the crucial role of time management monitoring in enhancing student learning engagement, educators can develop more effective teaching methods and interventions to foster active participation among students in blended learning environments. Furthermore, our findings underscore the importance of considering the students' levels of uncertainty avoidance in instructional design, facilitating teachers to better meet their students' learning needs and provide appropriate support.

Finally, the research reveals the role of cultural values in shaping learning behaviors and experiences through an exploration of the impact of uncertainty avoidance on learning engagement. This finding holds significant implications for cross-cultural research and practice in the global educational landscape, particularly concerning the

need to account for cultural differences when designing and evaluating technology-enhanced learning environments.

5.4 Recommendations

The present study demonstrates that effective time management monitoring in blended teaching has a positive impact on learning engagement. The findings suggest that time management is a potential intervention for improving learning engagement. Teachers using learning platforms for blended teaching must develop suitable plans, set a course open time, and provide feedback on the students' progress to promote time management. Furthermore, teachers should provide reasonable arrangements for offline classes and optimize the management of such classes to avoid online learning delays. Colleges and universities should focus on cultivating the students' time management and self-control. Student can develop their own learning plans, reflect on the content of their courses, evaluate their approaches to studying, assess the deficiencies of their learning behaviors, prevent threats to learning caused by uncertain risks, learn to effectively relieve the stress of learning, and implement effective time management.

In this study, we found that students with higher levels of uncertainty avoidance tended to exhibit more rational decision-making, higher levels of learning engagement, and stronger information search behavior (Wang et al., 2014). However, this trait hinders the students' willingness to take risks and embrace challenges.

Based on these findings, schools and teachers should consider the potential benefits and drawbacks of cultivating their students' uncertainty avoidance. On the one hand, uncertainty avoidance may facilitate the students' learning participation and enhance their academic performance. On the other, it may also hinder their willingness to take risks and pursue new opportunities (Pintrich, 2003). Therefore, it is crucial to strike a balance between promoting the students' certainty and comfort and encouraging them to take risks and embrace challenges. Schools and teachers can incorporate strategies that foster a growth mindset and encourage students to view challenges as opportunities for growth and development (Ryan & Deci, 2000). For instance, teachers can provide students with feedback that emphasizes effort and progress rather than just grades and test scores (Schnitzler, 2021). Additionally, schools can offer opportunities for students to engage in extracurricular activities that promote risk-taking and creativity, such as entrepreneurship programs and innovation competitions.

In conclusion, while uncertainty avoidance may have positive effects on the students' learning participation, it has some drawbacks. Schools and teachers can promote a growth mindset and provide opportunities for students to take risks and embrace challenges to strike a balance between certainty and innovation.

5.5 Limitations and Future Research

This study had some limitations. First, the sample only included universities in Beijing due to difficulties in the collection of data during the COVID-19 pandemic. Therefore, future studies should collect data from more Chinese universities from students of various majors to verify these findings. Second, this study only used a single quantitative approach which may have been influenced by social desirability or common methodological biases (Wang, 2014). Future research could use a variety of methods, including qualitative methods, to triangulate the study findings.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

The participants had the study purpose explained to them first, and then they were asked to provide informed consent. Participation was voluntary, and all data were handled confidentially. This study did not accept any sponsorship funds. All authors state that there are no conflicts of interest.

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Data sharing statement

No additional data are available.

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