Examining the Impact of Fragmented Learning on Education: Empirical Evidence from SOR Theory Analysis

Jinqiao Zhou[1,a], Chengning Fang[2,b*]

[1]College of art, Zhejiang Normal University, Jinhua, Zhejiang, China
[2]NingBoTech University, Hangzhou, Zhejiang, China

[a]zhoujinqiao@zjnu.edu.cn,[b*]904125153@qq.com

Abstract. In recent years, the integration of technology and education has led to the emergence of a highly fragmented, flexible, and ubiquitous learning environment. Concurrently, the popularity of short videos has presented an opportunity to explore their potential for fragmented learning. This study aims to investigate the impact of several factors, including system quality, information quality, metacognition, perceived autonomy, perceived usefulness, motivation, and learning engagement, on fragmented learning among college students. A survey questionnaire was distributed to 297 college students, and a continuous intention model, based on the Stimulus-Organism-Response (S-O-R) theory, was constructed to analyze the factors influencing students' intent to continue using short videos for learning purposes. We conducted empirical research by using SPSS and AMOS software. The findings indicate that perceived usefulness, learning motivation, and learning input significantly influence continued intention, with learning input having the greatest impact. Moreover, system quality, information quality, metacognition, and perceived autonomy significantly affect perceived usefulness, motivation, and learning engagement, respectively. Among these factors, metacognition exerts the most significant influence on perceived usefulness, learning motivation, and learning engagement. This paper provides valuable insights and guidance for developing educational functions for short videos.

Keywords: fragmented learning; short videos; S-O-R theory; continuance intention

1 Introduction

Information technology, represented by the Internet, has become ubiquitous in all aspects of human life, work, and learning. The integration of technology and education, accompanied by the development process of education informatization, has expanded the channels through which people acquire knowledge, overcome the con

S. Zhu et al. (eds.), *Proceedings of the 3rd International Conference on Education, Language and Art (ICELA 2023)*, Advances in Social Science, Education and Humanities Research 831,
https://doi.org/10.2991/978-2-38476-214-9_60

straints of time, space, media, and means inherent in the traditional school and classroom model, and introduced a highly fragmented, flexible, and ubiquitous learning environment. However, although learning has become increasingly convenient, it also exhibits a degree of randomness and uncertainty in the timing of learning activities and significant variations in the duration of learning. The outbreak of the epidemic has greatly propelled the development of e-learning, online learning, and self-directed learning. Numerous scholars have conducted extensive studies on e-learning, online learning, and self-directed learning. Kumar et al. [1] think E-learning is considered an alternative to traditional education and can also complement it. Rossett [2] argues that the concept of e-learning has been revolutionary, offering new approaches to learning and performance improvement. Further studies can be consulted in [3]-[5]. Muilenburg [6] think that with the popularization of the Internet, the potential of online learning is also increasing. More study one consult [7]-[9].

Autonomous learning, also referred to as self-directed learning, is a contemporary educational theory that is grounded in principles of humanistic psychology and cognitive psychology. Holec [10] defines autonomy as "the ability to take charge of one's learning". Learners' independent learning based on the Internet and mobile terminals, tailored to their own needs, has given rise to a new learning mode known as microlearning or fragmented learning. Fragmented learning involves utilizing mobile Internet technology and wireless media devices to access learning resources and information, engaging in learning activities on specific or fragmented knowledge during spare moments, and enabling digital learning anytime and anywhere. Fragmented learning overcomes the limitations of time and space, while also meeting the psychological needs of modern fast-paced individuals [11]. It is characterized by small, fragmented content that promotes learner autonomy and independent learning [12].

Fragmented learning has become an important avenue for college students to engage in independent learning in the present day. Liang et al. [13] examined the characteristics of fragmented learning behaviors and the reshaping of knowledge in online education, tailored to individual learning needs. Wenxiu [14] proposed a well-founded approach to fragmented learning by analyzing its connotations, characteristics, advantages, and disadvantages. Song et al. [15] investigated the mediating role of the Internet in learning outcomes within the framework of constructivist knowledge, employing a classical questionnaire. Zhu and Geng [16] explored fragmented learning among college students in the Internet era and analyzed its influences and strategies for enhancing effectiveness. Li [17] analyzed the application of fragmented learning in online courses. However, e-learning or online learning, such as learning on MOOCs platforms, is not typically classified as fragmented learning. Firstly, courses on MOOCs platforms have time constraints and lack sufficient autonomy. Secondly, some courses are longer in duration. When college students switch back to MOOCs after attending offline classrooms, they may become bored, contradicting the original intent of fragmented learning. Nevertheless, the emergence of short videos has introduced a novel platform for fragmented learning. For example, Douyin, one of the most popular short video platforms in China, offers both website and mobile app access, enabling learners to access relevant content anytime and anywhere. However, few studies have focused on short videos and fragmented learning among college students.

Understanding the impact of short videos on college students' engagement with fragmented learning and elucidating the relationship between various factors and note-taking during fragmented learning are crucial for enhancing college students' attention to fragmented learning and optimizing their fragmented learning practices. In this paper, we developed a user profile based on the learning behavior characteristics of short video users, analyzed learners' individual learning needs, and provided recommendations and guidance for college students to utilize short videos for fragmented learning. Specifically, we examined the factors influencing the continuous use of short videos by college students in the context of fragmented learning. We administered questionnaires to a sample of 297 college students and employed the S-O-R theory to construct a model of the factors influencing college students' intention to continue using short videos. We conduct empirical study by using SPSS 26.0 and Amos 28.0 software.

2 Theoretical foundation

2.1 Structural Equation Modeling and S-O-R theory

In recent years, empirical methods have gained increasing recognition in educational research, prompting educational researchers to employ mathematical statistical tools for quantitative empirical investigations. Among these analytical tools, Structural Equation Modeling (SEM) holds considerable importance. At the methodological level, SEM has become a prominent statistical analysis paradigm in social science research. For instance, SEM has found widespread application in studying various topics published in Computers & Education, a top international journal in educational technology included in the SSCI. These studies include investigations on the efficacy of programming learning in computational thinking development [18], learning behavior of MOOCs learners [19], teachers' capacity for integrating information technology [20], learning strategies and motivation in online foreign language learning [21], asynchronous discussion behaviors and engagement of online learners [22], among others. In comparison to international studies, the utilization of SEM in education-related fields in China started relatively later. However, as educational research paradigms evolve, researchers in the field of education in China are gradually becoming acquainted with SEM and applying it to locally-relevant research.

The S-O-R theory evolved from the S-R theory and consists of three components: stimulus, impact, and response [23]. Cognitivism argues that people's behavior (R) is not directly produced by stimuli (S), but is mediated by consciousness (O) and governed by it. Current academic research on the stimuli of this theoretical model has been extensive. Jun et al. [24] investigated how peer-to-peer monitoring affects team satisfaction with teamwork as well as cognitive and affective appraisal processes compared to centralized monitoring. In terms of student learning, Yang [25] et al. investigated the relationship between peer references, perceived closeness and perceived control and learning engagement based on the S-O-R theoretical model. Chang [26] investigated the factors affecting students' mobility experience and satisfaction using Technology Acceptance Modeling (TAM) theory and the S-O-R theory. Zhang Second et al. [27] combined the Social Cognitive Career Theory (SCCT) and the SOR model to study the

psychological cognitions and attitudes that students develop during the learning process. Yang et al. [28] study drew on the Stimulus Organism Response (SOR) framework and the autonomy theory to examine the factors influencing the persistence of college students' m-learning by taking into account the need for autonomy and learning engagement. The author believes that this kind of research is also applicable to short videos. Therefore, based on the "S-O-R" theory, this paper takes the features of short video recommendations as stimuli (S), and investigates their effects on perceived usefulness, learning engagement, learning motivation (O), and continuance intention (R). On the basis of this, we study the role of perceived usefulness, learning input and learning motivation.

2.2 Some hypotheses

Information quality, encompassing both the source and content of information, plays a crucial role in information utilization [29]. In the realm of e-learning, information quality has been found to significantly impact the use of information systems [30], particularly within e-learning systems [31]. Saeed et al. [32] posited that information quality has a positive influence on users' online behavior. Furthermore, Li et al. [33] discovered that information quality has positive influence to the intention of reuse e-learning systems. In the context of MOOCs, users' perceptions of information quality may be shaped by the instructor's expertise and the credibility of the course content. Therefore, this study presents the following hypothesis:

H1: Information quality is positively related to perceived usefulness.

H5: Information quality is positively related to learning engagement.

H9: Information quality is positively related to learning motivation.

According to DeLone and McLean [34], system quality has an influence on system usage and satisfaction [35]. In this study, we define system quality as the user's perception of the integration of system functionality and operational reliability in AI tools. Wang et al. [36] explored the impact of e-learning system quality on usage and satisfaction during its implementation. Lin and Lu [37] validated the positive effect of system quality on learners' intention to use it, using the Internet as an example. They argued that despite the Internet's popularity, various system quality factors can still lead to discontinuation of its use. Saeed et al. [38] posited that system quality is a primary determinant of consumers' perceived online behaviors and subsequent actions. Therefore, this study presents the following hypothesis:

H2: System quality is positively related to perceived usefulness.

H6: System quality is positively related to learning engagement.

H10: System quality is positively related to learning motivation.

Riyan et al. [39] investigated the positive impact of achievement goals and metacognition on mathematical modeling ability. Hayat et al. [40] studied the mediating role of metacognitive learning strategies and learning-related emotions in the relationship between academic self-efficacy and academic performance among medical students. Kaplan et al. [41] examined the association between students' mathematical metacognitive awareness and their perceived problem-solving skills. Khodabakhshzadeh et al. [42] explored the role of metacognition in foreign language achievement.

Wang et al. [43] utilized the Chinese version of the Index of Scientific Reading Awareness (ISRA) to explore the relationship between metacognitive awareness and scientific reading comprehension among Taiwanese students. Therefore, this study presents the following hypothesis:

H3: Metacognition is positively related to perceived usefulness.

H7: Metacognition is positively related to engagement in learning.

H11: Metacognition is positively related to motivation to learn.

Perceived autonomy refers to users' inherent psychological need to experience a sense of autonomy when utilizing AI tools for learning. According to self-determination theory, intrinsic motivation is fortified when individuals perceive a sense of autonomy in their activities. This means that users can engage in autonomous learning based on their own interests and preferences, which is reflected through their intrinsic motivation [44]. Furthermore, autonomy is a defining characteristic of fragmented learning. A supportive environment that nurtures autonomy empowers users to effectively utilize fragmented time for independent learning, thereby enhancing learning efficiency and fostering a perception of usefulness [45]. Therefore, this study presents the following hypothesis:

H4: Perceived autonomy is positively related to perceived usefulness.

H8: Perceived autonomy is positively related to engagement in learning.

H12: Perceived autonomy is positively related to motivation to learn.

Perceived usefulness is defined as an individual's belief regarding the extent to which using a specific system will enhance their job performance. It is an original variable in the Technology Acceptance Model (TAM) that influences technology acceptance [46]. Perceived usefulness serves as a significant motivator for user satisfaction and intention to continue utilizing information systems [47]. It is a strong and direct determinant of continuance intention [48] and also positively impacts satisfaction [49]. Additionally, Lee [50] has examined the impact of perceived usefulness. Therefore, if users perceive short videos as highly useful, their continuance intention will increase, motivating them to continue using them. If users experience a decline in performance after engaging with short videos, it may lead to negative feelings and affect their willingness to persist with their use. Therefore, this study presents the following hypothesis:

H13: Perceived usefulness is positively correlated with continuance intention.

Learning engagement refers to the sustained effort that learners invest in the learning process with the aim of achieving their learning goals. It has been widely utilized as a metric for assessing MOOC learning outcomes [51]. Learning engagement encompasses various multidimensional variables, such as motivation, awareness, and attitudes, rather than being confined to a single dimension like action [52]. Hoi and Hang [53] argued that enhancing student engagement is crucial for reducing dropout rates in online learning. Subsequently, Yuan and Powell [54] explored the elements of MOOCs that motivate learners to engage. Additionally, Xiong et al. [55] examined the relationships among student motivation, engagement, and retention using a structural equation model. Therefore, this study presents the following hypothesis:

H14: Learning engagement is positively related to continuance intention.

H15: Learning motivation is positively related to continuance intention.

In the field of information system continuance theory, the continuous intention to use a system is primarily driven by satisfaction gained from its utilization [56]. Continuance intention, as defined in the ECM model, signifies the intent to persist in using the information system [56]. Basak and Calisir [57] report that an individual's decision to continue using an information system can also be influenced by psychological motivation that emerges during initial system use. Therefore, if individuals effectively employ short video fragmentation learning, they are more likely to continue utilizing it. For more details, one refer to Figure 1.

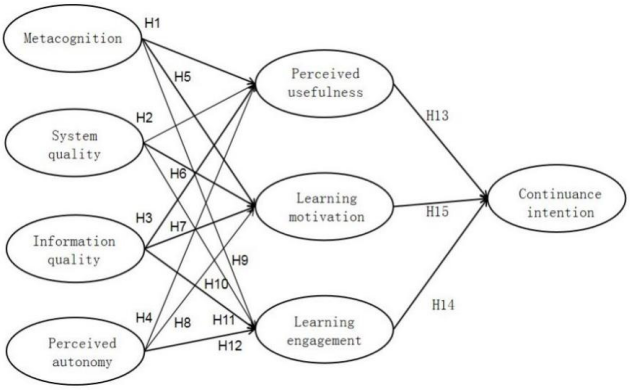

Fig. 1. Research framework

3 Empirical analysis

3.1 Reliability and validity analysis

This paper utilizes reliability analysis to assess the effectiveness of the scale, primarily employing Cronbach's coefficient to measure the internal consistency. Typically, a Cronbach's coefficient above 0.7 indicates good consistency, while values within the range of 0.6 to 0.7 are considered acceptable. If the coefficient falls below 0.6, revising the questionnaire may be necessary.

Based on the data analysis results presented in Table 1, it is evident that the Cronbach's alpha values for each construct (system quality, information quality, socialized interaction, perceived autonomy, perceived competence, intrinsic motivation, perceived usefulness, satisfaction, continuance intention) and the entire questionnaire are 0.199, 0.779, 0.790, 0.782, 0.789, 0.807, 0.839, 0.855, and 0.961, respectively. All of these coefficients exceed 0.7, indicating a high level of reliability. Thus, the overall measurement scale demonstrates good internal consistency and stability, indicating strong reliability. In this paper, the structural validity of the questionnaire is primarily evaluated using principal component analysis and factor analysis.

Table 1. Results of confidence analysis

Construct	Sample size	Item count	Cronbach's Alpha	Standardized Cronbach's Alpha
System quality	297	3	0.799	0.801
Information quality	297	4	0.779	0.782
Metacognition	297	4	0.790	0.793
Perceived autonomy	297	3	0.782	0.783
Perceived usefulness	297	4	0.789	0.789
Learning engagement	297	5	0.807	0.807
Learning motivation	297	3	0.839	0.840
Continuance intention	297	5	0.855	0.855
All	297	31	0.961	0.961

Before conducting factor analysis, it is crucial to assess the appropriateness of the analysis using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. The KMO values for each variable determine the suitability of factor analysis in different situations. Generally, a KMO > 0.9 indicates high suitability, 0.8 < KMO < 0.9 suggests suitability, 0.7 < KMO < 0.8 indicates moderate suitability, 0.6 < KMO < 0.7 implies lower suitability, and KMO < 0.6 means factor analysis is unsuitable. Additionally, Bartlett's test of sphericity assesses the validity of the factor analysis. If the significance value (Sig.) of Bartlett's test is less than 0.05, it confirms a correlation between variables, supporting the validity of the factor analysis.

After conducting the factor analysis (as demonstrated in Table 2), the KMO values indicate good structural validity, affirming the suitability of factor analysis for the variables. Furthermore, the questionnaire passing the validity test suggests a correlation between variables, supported by Bartlett's test significance value being below 0.05. In conclusion, based on the results of the factor analysis, the variables exhibit satisfactory structural validity, and the questionnaire has successfully passed the validity test.

Table 2. Validity analysis results

Construct	KMO	Ballett sphericity test			Structural validity of the questionnaire
		Chi-Square	*Degrees of freedom*	*Significant level*	
System quality	0.703	281.697	3	0.000	Favorable
Information quality	0.739	331.514	6	0.000	Favorable
Metacognit-ion	0.826	776.124	6	0.000	Favorable
Perceived autonomy	0.705	248.183	3	0.000	Favorable
Perceived usefulness	0.784	325.260	6	0.000	Favorable
Learning engagement	0.822	429.431	10	0.000	Favorable
Learning motivation	0.837	851.590	6	0.000	Favorable
Continuance intention	0.859	593.367	10	0.000	Favorable

3.2 Structural model evaluation

In this study, the AMOS 26.0 software was employed to test the aforementioned model and hypotheses. As depicted in Table 3, the results reveal that the chi-square value is 872.191 with 413 degrees of freedom. The ratio of the chi-square value to the degree of freedom is calculated as 2.112, falling within the acceptable range of 1-3 and indicating a good model fit.

The goodness-of-fit index measures 0.836, slightly below the desired value of 0.9 but still greater than 0.8. This indicates a fitting value close to the evaluation standard, falling within an acceptable range. The Tucker Lewis index, at 0.925, exceeds the desired value of 0.9, meeting the criteria for an ideal fit. The adjusted fit index is computed at 0.803, lower than 0.9 but higher than 0.8. This value is in proximity to the evaluation standard and falls within an acceptable range. The comparative fit index measures 0.933, surpassing 0.9 and aligning with the evaluation standard. Moreover, the root-mean-square error is 0.061, below the ideal value of 0.08.

Together, these statistics indicate a good fit between the model and the data. In summary, the findings of this study suggest that the model employed in the analysis effectively adapts to the collected data.

Table 3. Goodness of fit indices

Norm	Reference Indicators	Actual results
CMIN/DF	1-3 is excellent, 3-5 is good	2.112
RMSEA	<0.05 is excellent, <0.08 is good	0.061
TLI	>0.9 is excellent, >0.8 is good	0.925
CFI	>0.9 is excellent, >0.8 is good	0.933
GFI	>0.9 is excellent, >0.8 is good	0.836
AGFI	>0.9 is excellent, >0.8 is good	0.803
CMIN	\	872.191
DF	\	413

The results of path analysis and hypothesis testing are presented in Table 4 and Figure 2. The findings indicate that perceived usefulness, learning engagement, and learning motivation positively influence continuance intention, highlighting their significance in promoting continuance intention of short videos among university students. Therefore, hypotheses H13, H14, and H15 are supported. Interestingly, learning engagement demonstrates the strongest positive influence on continuance intention among university students, followed by perceived usefulness and learning motivation. This suggests that university students prioritize enhancing learning engagement to

strengthen their continuance intention of short videos, over perceived usefulness and learning motivation.

Furthermore, the results reveal that information quality, system quality, metacognition, and perceived autonomy positively influence perceived usefulness, confirming hypotheses H1, H2, H3, and H4. Notably, metacognition and information quality exert the strongest positive influence on perceived usefulness, followed by system quality and perceived autonomy. This suggests that students recognize the importance of metacognition and information, particularly in ways that enhance perceived usefulness, thereby improving their continuance intention.

Additionally, the results indicate that information quality, system quality, metacognition, and perceived autonomy positively influence learning engagement, supporting hypotheses H5, H6, H7, and H8. Interestingly, metacognition demonstrates the strongest positive influence on learning engagement, followed by information quality, system quality, and perceived autonomy. This suggests that university students acknowledge the significance of metacognition, especially in ways that enhance learning engagement to improve their continuance intention.

Moreover, the results show that information quality, system quality, metacognition, and perceived autonomy positively influence learning motivation, substantiating hypotheses H9, H10, H11, and H12. Interestingly, metacognition exerts the strongest positive influence on learning motivation, followed by information quality, system quality, and perceived autonomy. However, the differences in their influence are not significant.

Table 4. Hypotheses testing results

Hypo-thesis	**Estimate**	S. **E.**	**Standa-rd error**	**C.R.**	**P**	**Outcome**
H1	0.319	0.284	0.039	8.159	***	Supported
H2	0.181	0.175	0.037	4.938	***	Supported
H3	0.422	0.313	0.05	8.432	***	Supported
H4	0.137	0.141	0.033	4.211	***	Supported
H5	0.262	0.280	0.033	8.025	***	Supported
H6	0.161	0.187	0.029	5.552	***	Supported
H7	0.344	0.307	0.042	8.194	***	Supported
H8	0.144	0.178	0.026	5.526	***	Supported
H9	0.285	0.233	0.037	7.755	***	Supported
H10	0.286	0.254	0.040	7.183	***	Supported
H11	0.341	0.232	0.046	7.387	***	Supported
H12	0.227	0.215	0.036	6.396	***	Supported
H13	0.286	0.310	0.073	3.935	***	Supported
H14	0.652	0.588	0.109	5.966	***	Supported
H15	0.135	0.159	0.06	2.238	0.025	Supported

Table footnote: In the table, "***" indicates that the number is less than 0.001, "→" indicates that the variable has an effect on the variable pointed to by the arrow.

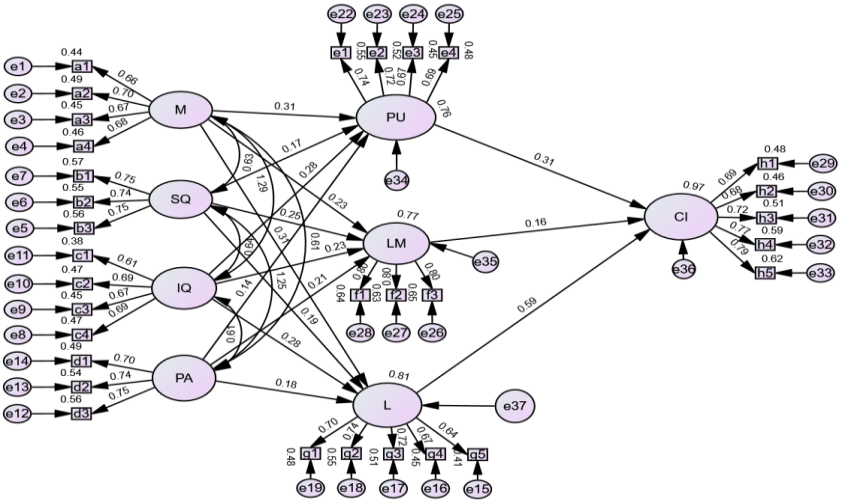

Fig. 2. Path analysis results

4 Conclusions

Through this study, we have investigated the factors influencing the continuous use of short videos for fragmented learning among college students and explored their interrelationships. Additionally, we have gained insights into the extent of the effects and the pathways of influence of each factor on the continuous use of short videos.Our analysis reveals that information quality, system quality, metacognition, and perceived autonomy positively influence learning input. By intervening in these factors, we can directly affect perceived usefulness, learning input, and learning motivation, consequently influencing continuous use. Therefore, this analysis primarily focuses on strategies to enhance college students' sustained use of short videos for fragmented learning. These strategies involve improving metacognitive abilities, enhancing the system quality and information quality of short videos, and fostering perceived autonomy.

1. Emphasizing the cultivation of metacognitive ability of college students.

Improving the quality of the platform system can help college students develop their metacognitive abilities. Metacognition plays a vital role in guiding and regulating the entire learning process. As shown in Figure 2, metacognition exerts the most direct and strongest influence on perceived usefulness, learning engagement, and learning motivation, thereby impacting continuous use. Therefore, short video platforms should prioritize attention to and support the development of college students' metacognitive abilities. Furthermore, the platform's system quality directly affects perceived usefulness, learning engagement, and learning motivation. Hence, the platform can embed metacognitive cues in short videos to facilitate learners' fragmented learning. For instance, the platform can guide learners between different videos on the same topic,

recommend related videos after learners complete questions, and design prompt questions to prompt college students in various learning stages. These strategies encourage further study, self-monitoring, and self-regulation of the learning process. Additionally, formative learning evaluation and feedback enable learners to regularly evaluate their learning methods, progress, and outcomes, facilitating continuous adjustment and improved self-regulation. Thus, short video platforms should consider incorporating effective evaluation methods and tools, such as post-video questionnaires or real-time evaluations by other learners. Cultivating college students' metacognitive abilities in their daily learning, including establishing clear learning goals and maintaining learning process records, is also essential. Overall, the platform should develop a learner model to create an optimal learning environment for students.

2. Optimize the development of fragmented learning platforms and learning resources

Optimizing the design and development of short video resources can stimulate college students' learning motivation. Both information quality and perceived autonomy directly impact perceived usefulness, learning engagement, and learning motivation. As fragmented learning becomes a prominent mode of learning for college students, it is crucial to focus on the information quality and learner autonomy of short videos. Firstly, Designing short video presentations that integrate multimedia elements: Text-only presentations may lead to learner anxiety and impatience, hindering the generation and retention of learning motivation. Integrating multimedia features such as graphical interfaces, dynamic simulations, and animations can engage learners' multiple senses, providing enjoyment and effectively stimulating interest and motivation. This approach prevents attention lapses and promotes sustained attention.furthermore, Emphasizing learner autonomy in design: Platforms can adopt a "notebook" format to allow learners to mark learning points and make notes, promoting interaction between learners and the content. This design element enhances learning input and maintains stable attention.

References

1. S. Basak, M. Wotto, P. Belanger, “E-learning, M-learning and D-learning: Conceptual definition and comparative analysis,” E-learning and Digital Media, vol. 15, pp. 191-216, 2018.
2. A. Rossett. The ASTD e-learning handbook. 2002.
3. J. Moore, C. Dickson-Deane, K. Galyen, “E-Learning, online learning, and distance learning environments: Are they the same?” The Internet and higher education, vol. 14, pp. 129-135, 2011.
4. R. Derouin, B. Fritzsche, E. Salas, “E-learning in organizations,” Journal of management, vol. 31, pp. 920-940, 2005.
5. K. Pituch, Y. Lee, “The influence of system characteristics on e-learning use,” Computers & Education, vol. 47, pp. 222-244, 2006.
6. L. Muilenburg, Z. Berge, “Student barriers to online learning: a factor analytic study,” Distance Education, vol. 26, pp. 29-48, 2005.
7. H. Huang, “Toward constructivism for adult learners in online learning environment,” British Journal of Educational Technology, vol. 33, pp. 27-37, 2002.

8. V. Singh, A. Thurman, “How many ways can we define online learning? A systematic literature review of definitions of online learning (1988-2018),” American Journal of Distance Education, vol. 33, pp. 289-306, 2019.
9. L. Song, E. Singleton, J. Hill, M. Koh, “Improving online learning: Student perceptions of useful and challenging characteristics,” The internet and higher education, vol. 7, pp. 59-70, 2004.
10. S. Hoi, D. Sahoo, J. Lu, P. Zhao, “Online learning: A comprehensive survey,” Neurocomputing, vol. 459, pp. 249-289, 2021.
11. X. Xianqiao, “Fragmentation Learning of College English from the Perspective of Big Data,” Journal of Bengbu University, vol. 5, pp. 95-98, 2016.
12. I. Buchem, H. Hamelmann, “Microlearning: a strategy for ongoing professional development,” eLearning papers, vol. 21, pp. 1-15, 2010.
13. K. Liang, C. Wang, Y. Zhang, W. Zou, “Knowledge aggregation and intelligent guidance for fragmented learning,” Procedia computer science, vol. 131, pp. 656-664, 2018.
14. P. Wenxiu, “Analysis of fragmented learning features under the new media environment,” International Journal of Learning, Teaching and Educational Research, vol. 13, pp. 55-63, 2015.
15. Y. Song, T. Huang, “Influence of students’ online fragmented learning on learning effect: the mediating effect of the Internet,” International Journal of Emerging Technologies in Learning (IJET), vol. 17, pp. 179-190, 2022.
16. Y. Zhu, J. Geng, “Influencing factors of fragmented learning of college students in the Internet era and strategies for improving their effects,” Times Finance, vol. 5, pp. 146-147, 2020.
17. D. Li. Applied principles of fragmented learning for college online courses, Wireless Internet Technology, vol. 16, pp. 78-80, 2019.
18. S. Kong, M. Chiu, M. Lai, “A study of primary school students' interest, collaboration attitude, and programming empowerment in computational thinking education,” Computers & Education, vol. 127, pp. 178-189, 2018.
19. Y. Jung, J. Lee, “Learning engagement and persistence in Massive Open Online Courses (MOOCS),” Computers & Education, vol. 122, pp. 9-22, 2018.
20. S. Hsu, “Developing and validating a scale for measuring changes in teachers' ICT integration proficiency over time,” Computers & Education, vol. 111, pp. 18-30, 2017.
21. C. Lin, Y. Zhang, B. Zheng, “The roles of learning strategies and motivation in online language learning: A structural equation modeling analysis,” Computers & Education, vol. 113, pp. 75-85, 2018.
22. S. Goggins, W. Xing, “Building models explaining student participation behavior in asynchronous online discussion,” Computers & Education, vol. 94, pp. 241-251, 2016.
23. A. Mehrabian, J. Russell, “An approach to environmental psychology,” the MIT Press, 1974.
24. Y. Jung, B. Choi, W. Cho, “Group satisfaction with group work under surveillance: the stimulus-organism-response (SOR) perspective,” Telematics and Informatics, vol. 58, 101530, 2021.
25. J. Yang, M. Peng, S. Wong, W. Chong, “How E-Learning Environmental Stimuli Influence Determinates of Learning Engagement in the Context of COVID-19? SOR Model perspective,” Frontiers in Psychology, Vol. 12, 584976, 2021.
26. C. Chang, “Factors affecting m-learning continuance–From the perspectives of flow theory and stimulus-organism-response theory. European Conference on Knowledge Management,” vol. 23, pp. 1396-1402, 2022.

27. G. Zhang, X. Yue, Y. Ye, M. Peng, "Understanding the impact of the psychological cognitive process on student learning satisfaction: combination of the social cognitive career theory and sor model," Frontiers in psychology, Vol.12, 712323, 2021.
28. S. Yang, S. Zhou, X. Cheng, "Why do college students continue to use mobile learning? learning involvement and self-determination theory," British Journal of Educational Technology, Vol.50, pp. 626-637, 2019.
29. A. Bhattacherjee, C. Sonford, "Influence processes for information technology acceptance: An elaboration likelihood model," MIS Quarterly, Vol. 30, pp. 805-825, 2006.
30. Y. Wang, H. Wang, D. Shee, "Measuring e-learning systems success in an organizational context: scale development and validation," Computers in Human Behavior, Vol. 23, pp. 1792-1808, 2007.
31. A. Molla, P. Licker, "E-commerce systems success: An attempt to extend and respecify the DeLone and McLean model of IS success," Journal of Electronic Commerce Success, Vol. 2, pp. 131-141, 2001.
32. K. Saeed, Y. Hwang, M. Yi, "Toward an integrative framework for online consumer behavior research: A meta-analysis approach," Journal of End User Computing, Vol. 15, pp. 1-26, 2003. 15(4): 1-26.
33. Y. Li, Y. Duan, Z. Fu, P. Alford, "An empirical study on behavioral intention to reuse e-learning systems in rural China," British Journal of Educational Technology, Vol. 43, pp. 933-948, 2012.
34. W. DeLone, E. McLean, "The DeLone and McLean model of information systems success: a Ten-year update," Journal of management information systems, Vol. 19, pp. 9-30, 2003.
35. S. Petter, W. DeLone, E. RMcLean, "The past, present, and future of 'IS Success'," Journal of the Association for Information Systems, Vol. 13, pp. 2, 2012.
36. Y. Wang, H. Wang, D. Shee, "Measuring e-learning systems success in an organizational context: scale development and validation," Computers in Human Behavior, Vol. 23, pp. 1792-1808, 2007.
37. J. Lin, H. Lu, "Towards an understanding of the behavioral intention to use a web site." International Journal of Information Management, Vol. 20, pp. 197-208, 2000.
38. K. Saeed, Y. Hwang, M. Yi, "Toward an integrative framework for online consumer behavior research: A meta-analysis approach," Journal of End User Computing, Vol. 15, pp. 1-26, 2003.
39. R. Hidayat, H. Zulnaidi, S. Syed Zamri, "Roles of metacognition and achievement goals in mathematical modeling competency: a structural equation modeling analysis," Plos One, Vol. 13, e0206211, 2018.
40. A. Hayat, K. Shateri, M. Amini, N. Shokrpour, "Relationships between academic self-efficacy, learning-related emotions, and metacognitive learning strategies with academic performance in medical students: a structural equation model," BMC Medical Education, Vol. 20, pp. 1-11, 2020.
41. A. Kaplan, M. Duran, G. Bas, "Examination with the structural equation modeling of the relationship between mathematical metacognition awareness with skill perception of problem solving of secondary school students," Journal of the Faculty of Education, Vol. 17, pp. 01-16, 2016.
42. H. Khodabakhshzadeh, M. Hosseinnia, S. Rahimian, "Learning Style, Metacognition and Creativity as Predictors of the Foreign Language Achievement: A Structural Equation Modeling Approach," Psychological Studies, Vol. 62, pp. 377-385, 2017.

43. J. Wang, S. Chen, "Exploring mediating effect of metacognitive awareness on comprehension of science texts through structural equation modeling analysis," Journal of Research in Science Teaching, Vol. 51, pp. 175-191, 2014.
44. O. Sorebo, H. Halvari, V. Gulli, R. Kristiansen, "The role of self-determination theory in explaining teachers' motivation to continue to use e-learning technology," Computers & Education, Vol. 53, pp. 1177-1187, 2009.
45. J. Roca, M. Gagné, "Understanding e-learning continuance intention in the workplace: A self-determination theory perspective," Computers in Human Behavior, Vol. 24, pp. 1585-1604, 2008.
46. F. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, Vol. 13, pp. 319-3400, 1989.
47. A. Bhattacherjee, "Understanding information systems continuance: An expectation-confirmation model," MIS Quarterly, Vol. 25, pp. 351-370, 2001.
48. S. Mouakket, "Factors influencing continuance intention to use social network sites: The Facebook case," Computers in Human Behavior, Vol. 53, pp. 102-110, 2015.
49. K. Lin, H. Lu, "Why people use social networking sites: An empirical study integrating network externalities and motivation theory," Computers in Human Behavior, Vol. 27, pp. 1152-1161, 2011.
50. Y. Lee, K. Kozar, K. Larsen, "The Technology Acceptance Model: Past, Present and Future," Communications of the Association for Information Systems, Vol. 12, pp. 752-780, 2003.
51. H. Coates, "Student Engagement in campus-based and online education," University Connections. Routledge, 2006.
52. J. Fredricks, P. Blumenfeld, A. Paris, "School engagement: Potential of the concept, state of the evidence," Review of educational research, Vol. 74, pp. 59–109, 2004.
53. V. Hoi, H. Hang, "The structure of student engagement in online learning: a bi-factor exploratory structural equation modelling approach," Journal of Computer Assisted Learning, Vol. 37, pp. 1141-1153, 2021.
54. L. Yuan, S. Powell, "MOOCs and open education: Implications for higher education," Centre for Educational Technology & Interoperability Standards, 2013.
55. Y. Xiong, H. Li, M. Kornhaber, H. Suen, B. Pursel, D. Goins, "Examining the relations among student motivation, engagement, and retention in a MOOC: A structural equation modeling approach," Global Education Review, Vol. 2, pp. 23-33, 2015.
56. A. Bhattacherjee, "Understanding information systems continuance: An expectation-confirmation model," MIS Quarterly, Vol. 25, pp. 351-370, 2001.
57. E. Basak, F. Calisir, "An empirical study on factors affecting continuance intention of using Facebook," Computers in Human Behavior, Vol. 48, pp. 181–189, 2015.