Are online behavioural characteristics effective predictors of intrinsic motivation and user engagement in the online learning environment?

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This study aimed to investigate the predicted relationship among online behavioural characteristics, intrinsic motivation and user engagement. An online learning platform was used to collect data on the online reading time and the number of test attempts of 161 graduate students, as well as their post-learning motivation and user engagement levels. The data were processed based on the e-learning motivation and user engagement scales. The data structure was validated using structural equation modelling. The findings showed that online reading time positively predicts anxiety and negatively affects focused attention. A higher number of test attempts negatively affects effort expectancy, perceived usability, novelty, felt involvement and endurability, leading to reduced user interaction quality. The findings suggest designing online courses with multiple smaller units, each with controlled learning time.

Implications for practice or policy:

- Educators can integrate motivation and engagement measures with learning logs to better align instructional support with learners' psychological and behavioural patterns.
- Instructional designers can apply learning analytics evidence to optimise platform features that strengthen learner motivation and sustained engagement.
- Course designers should limit excessive online text reading and adopt multimodal materials to reduce anxiety and attention loss.
- Assessment designers may need to limit repeated test attempts, as frequent retries are linked to lower perceived ease of use and adaptability.

Keywords: online learning behaviour, online behavioural characteristics, motivation, user engagement, online learning, structural equation modelling (SEM)

Introduction

In the study of online learning environments, engagement in learning merits close inspection (Getenet et al., 2024; Martin & Borup, 2022; Sun & Rueda, 2012). Fredricks et al. (2004) found that engagement levels vary by learning environment; as one of the important variables affecting learning effectiveness, the engagement level is associated with learning behaviour, feelings or thoughts. Learning engagement is useful in assessing the quality of online learning activities, online courses and online learning (Bergdahl, 2022; Bond & Bergdahl, 2022; Ma et al., 2015). Ma et al. employed online learning system records to analyse the impact of teachers on student engagement and concluded that this method is more direct and comprehensive compared with self-report questionnaires. However, the association between records of online learning system behaviour and learning engagement requires further research. Studies have explored teacher-student and peer interaction in online learning. Such interactions were initially categorised by Moore (1989) as human interaction. In terms of human-computer interaction, O'Brien and

Toms (2008) believe that the design of the platform interface and its corresponding multimedia functions should facilitate user engagement in the learning and interaction processes, just as teachers guide students to participate in classroom-based education. User engagement is the process and result of human-computer interaction; thus, it is vital to understand the individual, systemic and contextual factors that shape user engagement (O'Brien & McKay, 2018). Relevant studies have further bridged user engagement into learning processes by demonstrating how interaction quality, perceived usability and cognitive load management influence learning satisfaction (Kok et al., 2024). These studies have also utilised various behavioural characteristics recorded through interaction with online learning platforms, to explore engagement levels and influencing variables (Lee et al., 2021; Ma et al., 2015; Shukor et al., 2014). Within Bandura's (1986) reciprocal determinism framework, individual characteristics, behaviours and environment affect and interact with one another. Individuals' behavioural engagement can predict their psychological engagement, while their psychological engagement can predict their behavioural engagement in future learning. O'Brien and McKay (2018) believe that future research may attempt to deconstruct and examine the design, content and user characteristics in shaping engagement. Therefore, this study investigated the impact of learning behaviour on user engagement based on logged behaviour records.

Motivation is widely regarded as a significant psychological variable that influences learning behaviour, learning effort and learning achievement (Bandura, 1977; Pintrich & Schunk, 1996; Sun & Rueda, 2012). In the self-determination theory, intrinsic motivation is considered as an individual's willingness to be engaged in activities. Compared with extrinsic motivation, intrinsic motivation is a more important variable that affects learning in the e-learning environment (Pintrich & Schunk, 1996). Learning through information technology improves motivation levels; however, in the digital environment of distance learning, a teacher cannot directly observe the actual learning behaviour of learners and may not grasp the impact of behavioural characteristics on post-learning motivation. In addition, in a learning environment with human-computer interaction, it is necessary to further analyse the differences in personal characteristics that could affect user engagement and how such differences influence system design and content (Liu & Pu, 2023; O'Brien & McKay, 2018). Therefore, after reviewing the log indicators of behavioural characteristics used in past studies, this study aimed to record online reading time and number of test attempts via a learning management system (LMS) to investigate their predicted relationship with intrinsic motivation in e-learning and user engagement (Alemayehu & Chen, 2023; Black et al., 2008; Ferrer et al., 2022; Hu et al., 2014; Hung & Zhang, 2008; Macfadyen & Dawson, 2010; Perera et al., 2009). This study employed structural equation modelling (SEM) to analyse the relationship between online learning, exam test frequency, intrinsic motivation and user engagement.

Theoretical background

Learning analytics and the learning process

When traditional teaching activities gradually evolve into blended learning, the proliferation of LMS and virtual learning environment platforms enables researchers to obtain data on student interaction more conveniently (Agudo-Peregrina et al., 2014; Bessadok et al., 2023; Fahd et al., 2021; Thompson et al., 2013). Online learning platforms and LMSs (such as Blackboard and Moodle) automatically record learners' behaviour during the learning process and analyse the potential behavioural patterns accordingly (Black et al., 2008; He, 2013; Sun et al., 2017; Sun et al., 2018). Through data mining and extraction technology, researchers can formulate meaningful inferences on learning processes and experiences. Such methods, compared with traditional questionnaires or interviews, are less disruptive and intrusive to teaching activities, as data are analysed by back-end servers (Black et al., 2008; Juhaňák et al., 2019; Sáiz-Manzanares et al., 2021).

Recent studies on learning behaviour have made use of data collected from server logs or LMS logs. Through theoretical research on definition tracking and the modification of back-end learning database servers or self-designed data conversion programmes, researchers have obtained more streamlined data that reflect the relationship among behaviours over time. Thus, the time and effort required for analysis have been significantly reduced, leading to higher test validity (Agudo-Peregrina et al., 2014; Arizmendi et al., 2023; He, 2013; Hou, 2012; Hung & Zhang, 2008; Perera et al., 2009). This study aimed to utilise process record data to capture the behavioural characteristics during learning to investigate the predictability of behavioural characteristics in distance learning concerning post-course intrinsic motivation and user engagement levels.

In terms of indicators of online behavioural characteristics, Hung and Zhang (2008) suggested that both login frequency and frequency of accessing course materials can significantly explain learners' participation levels and are, therefore, attributed to learning performance. Hu et al. (2014) claimed that online reading time and frequency of accessing teaching materials could significantly predict learners' performance in end-of-term examinations. Ademi et al. (2019) analysed the Moodle logs of students and found that the total number of visits, number of course views and number of submitted assignments are all positively correlated with grades. Hung et al. (2020) used educational data mining to explore learners' LMS behaviour records, such as online time, the number of late submissions and the number of unsubmitted assignments to predict learning performance. That study showed that recent research on LMS behaviour records based on learning analysis has focused mostly on examining the relationship between learning behaviour and learning performance, while putting less emphasis on the relationship between learning behaviour and learning motivation. However, the course used for this study was research ethics, which was considered essential for all learners to master. Therefore, this study adopted online reading time and the number of test attempts, as opposed to exam results, to predict learners' intrinsic motivation and user engagement following learning activities.

Learning behaviour and online learning motivation

Motivation is one of the variables that significantly affects learning achievement. It influences learners' choices in learning tasks, level of effort as well as endurability and emotional state, eventually deciding academic achievement level (Pintrich & Schunk, 1996). Goopio and Cheung (2020) noted that the high drop-out rate in e-learning is a serious problem. Therefore, there is a need to investigate how learners maintain their motivation level in e-learning. The self-determination theory by Deci and Ryan (1985) categorises motivation into two types: intrinsic and extrinsic. Intrinsic motivation refers to engagement on the user's own accord: the willingness to carry out activities due to enjoyment and passion. Extrinsic motivation refers to participation in learning because of other external factors, such as rewards, incentives, or punishment avoidance. Related empirical research indicates that both types of motivation affect cognitive learning, learning attitude, independent or collaborative learning, learning self-efficacy, academic achievement and overall user acceptance of e-learning (Diwakar et al., 2023; Kong et al., 2012; Saadé et al., 2007; Tseng & Tsai, 2010; Yoo et al., 2012).

In the context of e-learning, learning motivation and intended use are significantly affected by the user acceptance level towards information technology such as digital materials or e-learning platforms. The unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) combines the technology acceptance model (TAM; Davis, 1986; Davis et al., 1989) with the study of intrinsic and extrinsic motivation by Davis et al. (1992), proposing a more comprehensive theoretical model for exploring user behaviour on information systems. The theories include an intrinsic motivation factor, namely, effort expectancy, and three extrinsic motivation factors, namely, performance expectancy, social influence and facilitating conditions (Venkatesh et al., 2003).

Empirical research on TAM and UTAUT has deemed enjoyment, playfulness and anxiety as intrinsic motivation variables (Abdullah et al., 2023; Alowayr, 2022; Lee et al., 2005; Yoo et al., 2012). As the UTAUT theoretical framework of Venkatesh et al. (2003), which explored the association between motivational factors and technology user behaviour, is similar to the research topics in this study, we used their framework as the theoretical basis for this work.

Studies have indicated the significant impact of intrinsic and extrinsic motivation on online learner behaviour (Alemayehu & Chen, 2023; Deci & Ryan, 1985; Pintrich et al., 1991; Yoo et al., 2012). Yoo et al. applied UTAUT to explore the link between intrinsic and extrinsic motivation and user behavioural intention; their findings showed that intrinsic motivation has a significant impact on user behavioural intention. However, an analysis by Chen and Jang (2010) based on the combination of learning motivation and online learning records revealed no significant correlation between motivation and hours per week studying, number of hits and participants' final grades.

Bandura (1986) stated that the interaction between a person, their behaviour and their environment affects their learning process and results. Studies have explored the impact of learning motivation on behaviour, but based on the perspective of interaction, the behavioural characteristics of learners during online learning could also be a pre-factor for post-course individual motivation. Therefore, the current work explored the predictability of learning behavioural characteristics based on learning motivation to shed light on the association between motivation and behaviour.

Learning behaviour and user engagement

Engagement in learning refers to the cognitive process, active participation and emotional engagement during learning (Pellas, 2014). Engagement is gauged to assess the quality of online learning activities, online courses and learning experience (Ma et al., 2015; Pellas, 2014). Engagement in learning is a multidimensional concept; it includes behavioural engagement, emotional engagement and cognitive engagement and is associated with learners' behaviour, feelings and thoughts (Fredricks et al., 2005; Fredricks et al., 2004). Student engagement is mostly defined as learners investing resources such as time, effort and energy in learning activities to enhance their academic understanding and improve academic performance (Vytasek et al., 2020). According to Sun and Rueda (2012), the factors related to engagement in online learning situations comprise usage of course navigation, quality of information technology, as well as learning motivation.

On the other hand, in terms of human-computer interactions, O'Brien and Toms (2008) noted that user engagement represents the response to the usage of an information system. User engagement is defined in this study as it is in O'Brien and Toms (2008) – the quality of an individual's experience of using technology tools. Similar to teachers seeking to engage students in class, the information interface and multimedia design should engage users in interaction. O'Brien and Toms (2008) proposed a conceptual model of user engagement comprising the following phases of engagement: from the point of engagement, whereby users are attracted by the aesthetics of the interface or novel performance, to the promotion of interest and motivation. Subsequently, users are encouraged to engage in interactive situations, thus bringing about positive emotions and making them look forward to giving feedback on the system. In contrast, disengagement occurs in the following situations: poor usability, difficult challenges, negative emotions, long duration, as well as interruption.

In addition, O'Brien and Toms (2008) pointed out that the interface aesthetics, emotional expression, challenges, feedback, resistance and motivation, along with other factors, are key characteristics of user engagement. O'Brien and Toms (2012) later proposed perceived usability, novelty, felt involvement, endurability, aesthetic appeal and focused attention as the six dimensions of user engagement within the conceptual framework for system environment types and developed the User Engagement Scale. The concept and tools are in line with online materials and post-course assessment learning formats used in the online course under this study. Therefore, this study adopted the User Engagement Scale in exploring the engagement level of users during online learning activities.

Related studies have used the monitoring and recording function of online learning platforms to measure engagement as well as time and effort put in during the learning process; the measurement can be used as the index for learner engagement level (Ma et al., 2015; Shukor et al., 2014) and has also been applied in measuring user engagement on a comparatively larger scale (Lalmas et al., 2022). Shukor et al. used online learning platform records as indicators of behavioural engagement. Toro-Troconis et al. (2019) quantified engagement using metrics including webpage views, discussion forum posts and participation in online seminars. Ma et al. examined 16 behavioural indicators, ranging across individual logins, forum posts, learning material uploads, question postings, assignment submissions and the use of note-taking function. They concluded that a higher number of completed learning tasks leads to higher learning interaction. Vytasek et al. (2020) emphasised that the time spent on learning can be used as an indicator of behavioural engagement, as well as one of the visual indicators of behavioural processes that the platform often provides for learners to conduct self-examination. Lee et al. (2021) further highlighted that behavioural engagement is influenced by personal, systematic and environmental factors, where learners' expectations impact their initial motivation but not necessarily participation. Bandura's (1986) interactive decision theory suggests that learning behaviours influence post-course psychological engagement, which subsequently predicts future learning behaviour. This study explored behavioural characteristics as a pre-factor of user engagement.

Present study

As shown above, in an in-person learning environment, teachers have direct control over the association between learners' behaviours and their learning motivation, and promote their post-course learning motivation through instructional interventions. However, concerning personal autonomy in distant learning, studies have explored only the predictive relations between LMS records and learning performance (Ademi et al., 2019; Hung et al., 2020), ignoring the impact of LMS learning behaviours on post-course learning motivation. Furthermore, when evaluating the utility of learning platforms, it is important to understand how learners' behavioural history affects the quality of their experience with platform use (O'Brien & McKay, 2018). Therefore, this study used time spent for reading and online learning and number of test attempts to predict intrinsic learning motivation and user engagement. The research questions were as follows.

1. Can online reading time and the number of test attempts be used as significant precedence factors for intrinsic motivation?
2. Can online reading and the number of test attempts be used as significant precedence for user engagement?

Studies have shown that online reading time is a positive predictor of post-course performance (Ademi et al., 2019; Hu et al., 2014; Hung et al., 2020). This study, therefore, assumed that online reading time may have the same predictive effect on motivation and user engagement. However, frustration may grow as the number of test attempts increases. Therefore, it also assumed that the number of test attempts is a negative predictor of learning motivation and user engagement.

Methodology

Participants

This study used a cross-sectional survey to recruit graduate students as participants. The objectives and process of the research were clearly stated on the registration system, along with the request for the participants to sign an informed consent document. Thereafter, the participants formally enrolled in the online research ethics course. Through convenience sampling, participants were recruited from Taiwan's three national universities via a range of modes (e.g., campus bulletins, email and social websites). This course was an online self-learning course, and data collection spanned three months. A total of 249 participants registered, of whom 170 completed the course. A total of 161 valid responses were collected. Of these, 64 and 97 were completed by female and male participants, respectively. The average age of the participants was 23.46 years (M = 23.46, SD = 2.46). All participants were informed of the study's purpose and procedures and provided written consent. Their involvement was voluntary and had no impact on course evaluations or grading. The study followed institutional ethical standards to ensure confidentiality and protect participants' rights.

Instruments

Measurement scales

The E-learning Motivation Scale used in this study was adapted from Yoo et al.'s (2012) Staff E-Learning Acceptance Scale, which is based on the UTAUT scale proposed by Venkatesh et al. (2003). Yoo et al.

(2012) adapted Venkatesh et al.'s scale and operationalised intrinsic and extrinsic motivation using 23 questionnaire items. We translated the original scale into traditional Chinese and refined into six dimensions comprising 20 questions. As Yoo et al.'s scale was originally designed for a workplace e-learning context, we excluded three items from the scale because they were not applicable to the current e-learning environment. The six dimensions are anxiety, attitude towards e-learning, effort expectancy, facilitating conditions, performance expectancy and social influence. The first three fall under intrinsic motivation, whereas the latter three, under extrinsic motivation. This scale uses a five-point Likert scale, with 1 representing *very unconfident* and 5, *very confident*. Participants responded to the questionnaire on the online platform.

After confirmatory factor analysis, questions 1, 14, 17, 18, 19 and 20 were removed owing to lower factor loadings. Hence, 14 questions remained. The social influence dimension was also removed, as it did not apply to this study (no teacher-student or student-student interactions in this study's learning environment). Therefore, only five dimensions were retained. Three questions on anxiety remained, with factor loadings ranging from .77 to .83. An example is, "I feel anxious about e-learning". There were four questions under attitude towards e-learning, with factor loadings ranging from .55 to .80. An example is, "E-learning makes the learning process more interesting". There were three questions under effort expectancy, with factor loadings ranging from .59 to .81. An example is, "It was easy for me to operate the e-learning platform". There were two questions under facilitating conditions, with factor loadings ranging from .71 to .77. An example is, "I have enough knowledge to use e-learning tools". There were two questions under performance expectancy, with factor loadings ranging from .41 to .93. An example is, "Using e-learning tools can speed up learning".

Each dimension remained stable after the deletion of questions. The dimensions also revealed good model fit indices (χ^2 = 127.05, *df* = 67, *p* < .001), including the comparative fit index (CFI = 0.96), root-mean-square error of approximation (RMSEA = 0.08) and standardised root-mean-square residual (SRMR = 0.05). According to the good indicative standard of Hu and Bentler (1999) at CFI ≥ .90, RMSEA < .08 and SRMR < .08, this motivation scale showed a good degree of adaptation. The total scale Cronbach's alpha was .89, which is in line with the .7 higher reliability standard recommended by Nunnally and Bernstein (1994).

We adapted the User Engagement Level Scale from the User Engagement Scale by O'Brien and Toms (2012). The original scale consisted of six dimensions: perceived usability, novelty, felt involvement, endurability, aesthetic appeal and focused attention. We translated the original scale, consisting of 23 questions, into traditional Chinese. The scale uses a five-point Likert scale, with 1 representing *very unconfident* and 5, *very confident*. A total of 161 valid questionnaires were collected. After confirmatory factor analysis, questions 1, 8, 9, 11, 12, 18, 19 and 21 were removed owing to lower factor loadings. Hence, 15 questions remained.

There were five questions on perceived usability on the scale, with factor loadings ranging from .64 to .83. An example is, "I was frustrated". There were five questions on novelty, felt involvement, endurability, with factor loadings ranging from .53 to .76. An example is, "I would recommend this course to my peers". There were two questions on aesthetic appeal, with factor loadings ranging from .76 to .79. An example is, "The interface looks elegant and appealing". There were three questions on focused attention, with factor loadings ranging from .74 to .79. An example is, "I was so engrossed in learning that I lost track of time". Each dimension remained stable after the deletion of questions, with the fit index of χ^2 = 167.88, *df* = 84, *p* <.001 and adapted indicators of CFI = 0.94, RMSEA = 0.08 and SRMR = 0.06 (Hu & Bentler, 1999). The Cronbach's alpha was .92, which is in line with the high-reliability standard of .7 recommended by Nunnally and Bernstein (1994).

Online learning platform and materials

This study utilised Research Ethics, a course hosted on a university-based online learning platform. The course materials used in this study were drawn from the Taiwan Research Ethics Education Program developed by the Ministry of Education in Taiwan (Center for Taiwan Academic Research Ethics Education, n.d.). The online course was designed for new doctorate and master's students and did not restrict students’ study time and location.

For research purposes, we developed an online learning platform based on the resources provided by the Center for Taiwan Academic Research Ethics Education (n.d.). Unit-level and post-course assessments were implemented systematically. The platform has back-end functions that automatically captured records on user clicks, page view statistics and metrics for behavioural information analysis. The platform uses Microsoft Visual Studio 2013 as development tools, ASP.NET 4.5 C# as programming language structure, and Microsoft SQL Server 2008 R2 as a database. It was constructed on a Microsoft Internet Information Service server, with Microsoft Windows Server 2008 R2 as the operating system. A screenshot of the system is shown in Figure 1.

Figure 1. Research Ethics course platform home page

The digital course materials comprise four units that are presented in Flash multimedia animation format, each lasting 30 to 40 minutes. Every unit begins with a situational skit to attract learners’ attention and stimulate their motivation. Following the content structure, a unit is then divided into several sub-sections with pages. Based on students’ cognitive load and content allocation, each page contains a 30- to 90-second video animation explaining the learning content. The system provides "Next" and "Previous" buttons for learners to pace their viewing. The interface also provides a navigation list; learners can freely switch pages.

Data collection and analysis

The experimental design is as shown in Figure 2. The platform guided users in completing the online reading tasks and exams in sequence. Thereafter, the users completed a post-exam questionnaire. The behaviour record function embedded in the platform enabled us to view the actual learning behaviour of individual users. The responses of the learning motivation, user engagement and learners’ data (e.g., background information, number of log-ins, online reading time, number of test attempts) were recorded on the system. SEM analysis was conducted using Mplus7 package software to verify the prediction model used in this research.

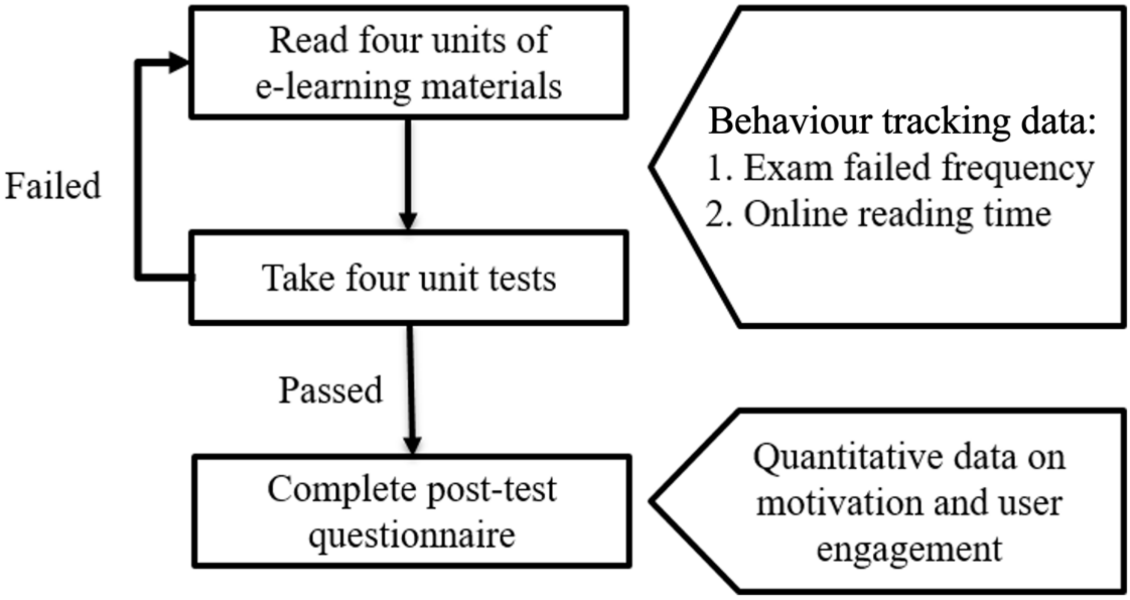

Figure 2. Test implementation flowchart

Results

Structural model of learning motivation

This study used online reading time and the number of test attempts as behavioural predictors of five dimensions of intrinsic and extrinsic motivation. Findings from the initial SEM showed that online reading time and the number of test attempts were unable to significantly predict post-course attitude towards e-learning, facilitating conditions and performance expectancy. However, they significantly predicted anxiety and effort expectancy. Therefore, the study retained only the last two motivation dimensions for analysis.

The final model of motivation is shown in Figure 3. The product-moment correlation of behavioural characteristics and learning motivation is shown in Table 1. Figure 3 illustrates the standardised path coefficients of the structural model. Regarding the structural paths, online reading time positively predicted anxiety (γ = .19, p < .001), whereas number of test attempts significantly predicted effort expectancy (γ = -.18, p = .03), although the value of χ^2 (17) = 30.78, p = .02 was significant. Three other fit indices suggested an acceptable fit of data: CFI = .98, RMSEA = .07 and SRMR = .11 (only SRMR falls slightly short of the standard (< .08)) (Hu & Bentler, 1999). Since effort expectancy and anxiety are dimensions of the same scale, there was a significant positive correlation observed between the two. A significant negative correlation between online reading time and the number of test attempts was observed, indicating that the greater the amount of time spent reading online, the lower the number of test attempts.

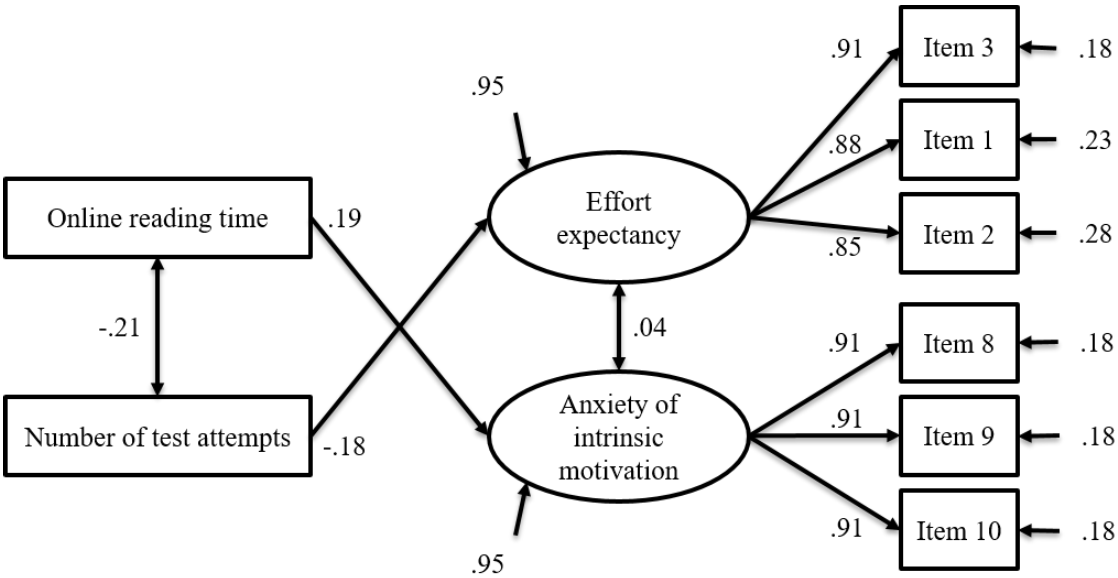

Figure 3. Structural model of learning motivation

Table 1
Behavioural characteristics and learning motivation product-moment correlation table

Variables	ORT	NTA	EE	ANX
Online reading time (ORT)	1.00	-.21**	.10	.20*
Number of test attempts (NTA)		1.00	-.17*	-.09
Effort expectancy (EE)			1.00	.33**
Anxiety (ANX)				1.00

*p < .05. **p < .01

Structural model of user engagement level

This study used online reading time and the number of test attempts as behavioural predictors to investigate whether they could be used to predict the four dimensions of user engagement level. Findings from the initial SEM showed that online reading time and the number of test attempts were unable to significantly predict post-course aesthetic appeal. However, they could significantly predict perceived usability, novelty, felt involvement, endurability and focused attention. Therefore, the study retained the last three engagement dimensions for analysis.

The final model of motivation is shown in Figure 4. The product-moment correlation of behavioural characteristics and learning motivation is shown in Table 2. Figure 4 illustrates the standardised path coefficients of the structural model. Regarding the structural paths, online reading time significantly negatively predicted focused attention (γ = -.22, p < .01), whereas number of test attempts significantly negatively predicted perceived usability (γ = -.20, p = .02) and novelty, felt involvement, endurability (γ = -.28, p < .01). The value of χ^2 (83) = 178.17, p < .01 was significant. Three other fit indices suggested a good fit of data: CFI = .92, RMSEA = .08 and SRMR = .11 (only SRMR falls slightly short of the standard (< .08)) (Hu & Bentler, 1999). Since perceived usability, novelty, felt involvement, durability, and focused attention are constructs of the same scale, there was a significant positive correlation among the three engagement dimensions. A significant negative correlation between online reading time and the number of test attempts was observed, indicating that the greater the amount of time spent reading online, the lower the number of test attempts.

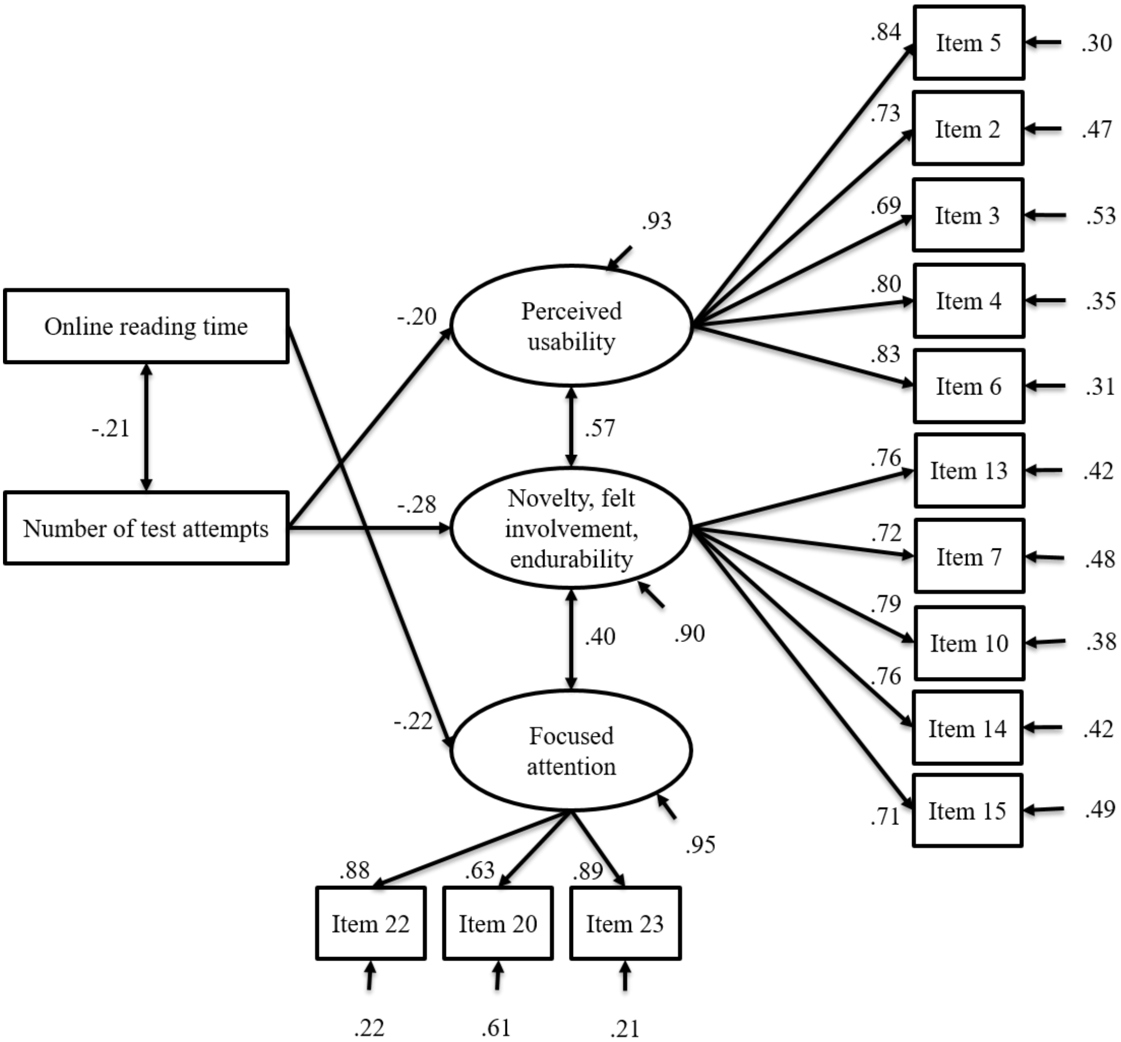

Figure 4. Structural model of user engagement level

Table 2
Behavioural characteristics and user engagement level product-moment correlation table

Variables	ORT	NTA	PU	NFE	FA
Online reading time (ORT)	1.00	-.21**	.20*	.14	-.20**
Number of test attempts (NTA)		1.00	-.22**	-.25**	-.04
Perceived usability (PU)			1.00	.60**	.29**
Novelty, felt involvement, endurability (NFE)				1.00	.48**
Focused attention (FA)					1.00

**p* < .05. ***p* < .01.

Discussion

The number of test attempts in online learning predicts effort expectancy, perceived usability, novelty, felt involvement and endurability.

The findings showed that the number of test attempts can significantly predict effort expectancy (dimension of intrinsic motivation), aligning with the study's expectation. Efforts expectancy has been confirmed as a key dimension of intrinsic motivation in e-learning; before the start of a task, learners expect the required amount of effort (Alemayehu & Chen, 2023; Bessadok et al., 2023; Deci & Ryan, 1985;

Fahd et al., 2021; Pintrich et al., 1991; Venkatesh et al., 2003; Yoo et al., 2012). The results showed that the e-learning system would prompt the learners to reread materials and retake the exam when their number of test attempts increases. This function may help lower learners' effort expectancy in e-learning as well as their expectations when they are required to reread or retake exams. Hence, the frequency of failed exam behaviour becomes a negative behavioural predictor of effort expectancy.

In addition, findings on user engagement level also showed that the number of test attempts can negatively predict the perceived usability and novelty, felt involvement, endurability of online learning, which meets the study's expectation. In the conceptual framework of O'Brien and Toms (2008), negative feedback by information systems interferes with learners' engagement. Both UTAUT and TAM have noted that the system should minimise redundant interfaces and procedures to reduce negative feedback from the system to the user (Davis et al., 1989; O'Brien & McKay, 2018; Venkatesh et al., 2003). This study showed that messages and prompts on failed exams, re-reading and re-taking of exams might lead to users perceiving the learning process as lengthy, hence reducing perceived usability and novelty, felt involvement, endurability, as well as lowering learners' engagement level of using the system, in close alignment with research focused on optimising system feedback design (Agudo-Peregrina et al., 2020; Hong, 2024; Lee et al., 2021).

However, failing in exams may happen sometimes in online learning environments. Thus, the online course should strive to understand users' preferences and provide personalised encouraging feedback to reduce negative emotions caused by the negative feedback from the system. This would help promote higher intrinsic motivation and increased enjoyment in e-learning (Chen & Jang, 2010). The study suggests that online courses be designed with fewer negative feedback prompts when users fail their exams. Systems could increase positive messages to avoid a decrease in user engagement levels.

Online reading time can be used as a pre-factor to predict anxiety and focused attention.

This study showed that online reading time can significantly and positively predict anxiety in intrinsic motivation, which is consistent with the relationships proposed in the research questions, while its negative prediction of focused attention in user engagement was inconsistent with the study's research expectations and prior findings (Kok et al., 2024; Sun et al., 2021). To learners, e-learning and traditional teaching environment differ, as the former requires completing tasks on their own. Hence, they need to have self-discipline and intrinsic motivation in e-learning environments (Pintrich & Schunk, 1996). The study found that a longer reading time leads to a higher anxiety level. Anxiety is one of the dimensions of intrinsic motivation; it can negatively predict users' attitudes towards e-learning (perceived playfulness) (Venkatesh et al., 2003; Yoo et al., 2012). Online courses in this study were carried out sequentially. Learners were asked to read four units of the reading materials and then pass the exam. The assumption is that a longer time spent on the units and repeated learning tasks leads to a higher post-course anxiety level. Online reading time negatively affected post-course anxiety. That is, longer online reading time spent on the course was associated with higher learner anxiety and lower post-course motivation levels. Post-course motivation is not significantly correlated with weekly online time (Chen and Jang, 2010); this is inconsistent with the findings of this study. This study suggests that the learners were provided with teachers and assistants, so that they could seek assistance in case of difficulties (Chen and Jang, 2010). In this study, the learners could use the basic online learning functions to facilitate their self-directed learning, and the extended learning time (if any) increased personal stress, thus arousing their post-course anxiety.

Hu et al. (2014) pointed out that course duration is the most significant variable predicting learning effectiveness. The findings of this study show that online reading time can significantly predict anxiety and focused attention, contradicting those in Macfadyen and Dawson's (2010) study. They found only a weak correlation between time spent online and engagement in learning, whereas this study determined online reading time to be a significant pre-factor that can negatively predict focused attention in engagement level. Further, the more time the learner spent on online reading, the lower their focused attention and the weaker their post-course focused attention.

Focused attention refers to the level of psychological and emotional engagement of the learner during their interaction with the materials in the learning process (O'Brien & Toms, 2008). The user engagement model by O'Brien and Toms (2008) states that the engagement level has four phases, namely, point of engagement, engagement, disengagement and re-engagement. The findings of this study are aligned with the theory of O'Brien and Toms (2008): long reading time tends to lower learners' attention levels. This study suggests that in an online self-directed learning environment, if learners lack system-provided learning assistance and spend long hours perusing the learning content, they can hardly advance from disengagement to re-engagement, leading to a gradual decline in their focused attention.

Conclusion, limitations and future research

This study aimed to investigate the predictive relationships of online reading time and the number of test attempts in LMS with intrinsic motivation and user engagement level in e-learning. The study found that online reading time positively predicts learning anxiety while negatively predicting focused attention. Moreover, the number of test attempts negatively predicts efforts expectations, perceived usability, novelty, felt involvement and endurability. According to the findings, the unit duration (time) in online learning should be shortened appropriately and designed as multiple short sections to promote focused attention and reduce anxiety. The system feedback mechanisms for online exams should provide positive feedback during failed exam situations to reduce learners' frustration. This would promote intrinsic motivation and lead to a willingness to put in continuous effort in e-learning.

The LMS recording used in the study accurately captured different user behaviours. However, given the technical restrictions, the platform was unable to track data when learners clicked the "Back" or "Next" on the browser, resulting in potential data distortions (Black et al., 2008). Therefore, this study has inherent limitations in the recording of behavioural characteristics. Additionally, the behaviour records of reading time may have also been affected when users opened more than one browser window to read and take the exam concurrently. This study used a server session control mechanism to control exam pages; however, users with advanced web programming knowledge may have been able to bypass these controls, potentially affecting the behavioural data. Thus, caution should be practised in the interpretation of results. On the other hand, the measurement model had good fit indices, but the fit indices of the structural model were slightly less satisfactory (Hu & Bentler, 1999). The poor fit indices of the structural model may be attributable to two factors: (a) the predicted values of several constructs of the structural model were insignificant, and these constructs were thus excluded; and (b) the measurement error of online reading time could not be estimated by the model. Both factors affected overall model fitness, necessitating careful interpretation of the statistical results.

The study recommends that future research should gather more information on online learner behaviour as a basis for analysis, including the number of logins, login time, materials, exams, clicks and peer interaction time. Empirical data on behavioural records, motivation and engagement data at multiple time points (repeated measures) are also suggested, which are useful in any in-depth investigation on the interactive relationship between individual behavioural and psychological variables. Finally, future research should design and explore different functions for this system platform, such as an intelligent feedback function (Hong, 2024; Sun et al., 2019), and explore the impact of system functions on learning motivation and user engagement.

Author contributions

Jerry Chih-Yuan Sun: Conceptualisation, Investigation, Writing – original draft, Writing – review and editing; **Che-Tsun Lin:** Data curation, Investigation, Formal analysis, Writing – original draft; **Wen-Li Chang:** Writing – review and editing.

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