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Research

The mediating effect of engagement in the relationship between self-efficacy and perceived learning in the online mathematics environment among Chinese students

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Abstract
Perceived learning is seen as a key measure of actual learning and an essential element of course assessment. This research investigated how learning engagement mediates the relationship between learning self-efficacy and perceived learning in online mathematics courses. Using a predictive correlational approach, the study analyzed the impact of three aspects of learning engagement on the link between learning self-efficacy and perceived learning. A survey was conducted with a randomly selected sample of 605 students enrolled in online mathematics classes in Guangzhou. Structural Equation Modeling (SEM) with AMOS version 24.0 was employed to test the proposed model. The results from the maximum likelihood estimation showed that the measurement model for learning self-efficacy, engagement, and perceived learning fit well. The findings revealed that learning self-efficacy directly influences all three aspects of learning engagement in an online mathematics setting. Additionally, there was a direct relationship between learning self-efficacy and perceived learning, with all three dimensions of learning engagement partially mediating this connection. Overall, these results underscore the significance of improving student self-efficacy and engagement to enhance online learning experiences and outcomes.

Article highlights

- How confident students feel in their learning abilities influences their level of engagement in online math classes.
- This self-confidence also affects their perception of how much they are learning from the course.
- Improving both students' confidence and engagement is essential for achieving more effective online learning experiences and outcomes.

Keywords Engagement · Mathematics education · Perceived learning · Self-efficacy · SEM

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1 Introduction

With the advancement of communication technology and the extensive reach of the Internet, online education has become more accessible and is expanding globally [1]. Ensuring equal access to technology is becoming widely acknowledged as essential for advancing sustainable education [2]. The use of information technology enables cross-cultural interactions [3]. Educational technology offers a vast array of resources and supports ongoing professional development for educators.

The COVID-19 pandemic has notably accelerated the growth of the online education market in China. Since 2017, the number of online users has grown each year, reaching 377 million in 2020, which represents 40.5% of all users [4]. China's online education sector now includes five key areas: preschool education, K-12 education, higher education, vocational education, and other types of education [5]. Of these, K-12 education is the largest segment, with the Smart Education of China platform for K-12 reporting 72.51 million registered users and over 700 million cumulative views [6]. Nevertheless, with the relaxation of COVID-19 restrictions and the introduction of China's 'Double Reduction' policy and other measures affecting online education, K-12 student registrations have been affected [5]. Considering the developmental stages of teenagers, it is important to focus on optimizing online education for this age group. Thus, investigating factors that impact effective online course organization is crucial.

Previous studies have highlighted that student learning outcomes are key indicators of the success of online education [7]. When evaluating traditional versus online learning, achievement is viewed as a critical factor. Perceived learning is a predictor of students' academic performance [8]. Moreover, Stein and Wheaton [9] argued that perceived learning might be a better predictor of success than course outcomes or final grades. As such, perceived learning is seen as a crucial measure of learning and a fundamental component of course evaluation [10].

Perceived learning offers instructors valuable insights from the learner's perspective, aiding in the enhancement of online course design, delivery, and assessment, and ultimately improving the online learning experience for students [11]. It also acts as a reflective evaluation of the learning experience [12]. Students who feel they have thoroughly engaged with course materials are more likely to participate actively in online sessions [13, 14]. Thus, perceived learning can be a useful metric for assessing a course's effectiveness. By understanding the factors that influence perceived learning, instructors can refine the quality of online courses in terms of design, delivery, and assessment, thus enriching the learning experience for students [15]. Evaluating students' perceptions of their learning is essential for educators and instructional designers seeking to enhance online course quality and improve the overall learning experience.

Self-efficacy for online learning is a crucial factor influencing learning outcomes. Higher self-efficacy is vital for encouraging technology acceptance, improving learning experiences, and boosting students' academic performance and perceived learning in online environments [16]. Students frequently find asynchronous activities—such as reading materials, assignments, exercises, and quizzes—difficult to evaluate, teach, and consult [17]. The challenges students face in problem-solving often stem from an inability to effectively utilize their existing knowledge, rather than a deficiency in mathematical understanding. Moreover, student engagement is viewed as an indicator of learning quality because it contributes to positive outcomes, deep learning, critical thinking, retention rates, and overall satisfaction [18, 19]. It plays a key role in understanding and enhancing student learning [20, 21]. Research has demonstrated that engagement in online classes significantly improves retention rates and alleviates feelings of isolation [22, 23]. Online learning engagement, which involves meaningful interaction and communication, reflects the time, effort, energy, thought, and emotions students invest in their learning, and is considered a valid measure of online education quality [24, 25].

The existing literature on online self-efficacy and engagement has revealed several factors affecting students' learning outcomes. However, the specific interactions between learners' perceptions of self-efficacy, learning engagement, and mathematical factors, especially within online mathematics education, remain insufficiently explored. This study, therefore, sought to examine how learning engagement mediates the relationship between self-efficacy and perceived learning in the context of online mathematics. It aimed to answer the following research questions: a) Does learning self-efficacy predict the components of learning engagement (vigor, dedication, absorption)? b) Do these components of learning engagement (vigor, dedication, absorption) predict perceived learning? c) Do these components of learning engagement mediate the relationship between learning self-efficacy and perceived learning? By addressing these questions, the study aimed to provide a deeper understanding of how self-efficacy and engagement affect learning outcomes in online mathematics education.

2 Literature review

2.1 Learning self-efficacy

In the growing field of online learning, researchers have examined how self-efficacy can influence students' perceived learning outcomes [11]. Learning self-efficacy, rooted in self-efficacy theory [26] and locus of control theory [27], reflects an individual's confidence in their ability to tackle specific learning tasks, activities, or challenges [26]. Essentially, if students lack confidence in their capabilities, they are less likely to put forth the effort needed to achieve their goals [11]. Those with high self-efficacy view complex tasks as opportunities for growth, maintaining a positive perspective that enhances their skills and boosts the likelihood of successful outcomes [28–30]. When they encounter failure, they attribute it to insufficient effort or knowledge, which they believe they can improve upon [26], leading to greater satisfaction, reduced stress, and improved overall well-being [28, 31]. In contrast, individuals with low self-efficacy see complex tasks as threats and tend to avoid them [28].

In mathematics education, self-efficacy plays a crucial role in shaping learners' self-concept and academic success [32, 33]. Alqurashi [11, 31] found that self-efficacy is a strong predictor of perceived learning in online environments, significantly supporting students in achieving their learning objectives. Students with high self-efficacy are known for their greater perseverance and resilience when confronting mathematical challenges [32]. Recent research underscores the importance of psychological factors, like self-efficacy, in boosting learning capabilities and improving academic performance and perceived learning in online contexts [16, 34]. Yunusa and Umar's review [35] highlights that self-efficacy and academic engagement are crucial predictors of perceived learning in e-learning environments. However, further research is needed to fully grasp the nuances of the relationship between self-efficacy and perceived learning in online settings [11]. This relationship is complex and influenced by various factors, including previous online learning experiences, technology anxiety, instructor feedback, and class preparation [36]. Studies in mathematics education have shown how learners' self-efficacy in their abilities affect their mathematical success, especially in asynchronous online learning environments. Ongoing investigation into the dynamics between self-efficacy and perceived learning outcomes is vital for understanding what drives successful learning experiences for secondary students in the digital era. In an online mathematics setting, the perceived effectiveness of the learning platform is affected by self-efficacy. According to Çiğdem [75], the interactivity of online learning environments, along with students' self-efficacy, improves their perceptions of the platforms' usefulness.

As technology advances and internet usage becomes more prevalent, students are increasingly eager to utilize technology for communication. This trend has prompted researchers to explore context-specific self-efficacy within virtual learning environments, leading to the development of distinct constructs such as computer self-efficacy, internet self-efficacy, and online learning self-efficacy [31]. Recent studies have examined the relationship between learning self-efficacy and other constructs, particularly focusing on learning engagement in online settings [23, 37, 38]. For example, Wu [38] investigated how learning self-efficacy, engagement, and social presence interact among Chinese EFL students, finding that online learning self-efficacy predicts and enhances engagement through increased social presence. Similarly, Derakhshan and Fathi [37] discovered that online learning self-efficacy has a significant positive effect on engagement among 578 EFL learners. Martin and colleagues [23] found that students with high online learning self-efficacy were more engaged in their studies and that this self-efficacy was associated with higher achievement.

In online mathematics education, students who have higher self-efficacy are more inclined to actively engage with course materials, participate in discussions, and complete assignments, which enhances their learning outcomes [76]. Spence and Usher [39] compared traditional and online students regarding the impact of computer self-efficacy on courseware engagement, concluding that computer self-efficacy significantly influenced engagement in online environments but not in traditional settings. In a conventional secondary mathematics classroom setting, Ozkal [40] found that students' mathematics self-efficacy significantly predicted their learning engagement and mathematical performance. Investigating self-efficacy in online education is crucial, as it provides insights into factors influencing learners' engagement and success. As research deepens, understanding the role of online self-efficacy in promoting engagement and achievement in online learning environments will help optimize learners' experiences in online mathematics education.

2.2 Learning engagement

The overarching construct of engagement remains pertinent in both online and traditional classrooms, although its conceptualization has evolved over time. Engagement can be defined as the extent of an individual's productive participation and persistence in various activities [41]. In the educational context, it refers to a positive, fulfilling state of mind marked by vigor, dedication, and absorption, encompassing students' aspirations, a sense of belonging, and productivity [42]. This construct is characterized by three core dimensions: vigor, dedication, and absorption, and is widely recognized as the learners' enthusiasm, motivation, and determination to actively participate and succeed in their own learning [41, 42]. As a key indicator of students' positive psychological engagement in learning, it reflects their positive and healthy mental state. Engagement helps cultivate qualities such as optimism, resilience, a sense of meaning, and creativity, thereby promoting students' development and preparing them for future societal integration [43].

Research on learning inputs has evolved from a uni-dimensional to a multi-dimensional approach, with existing studies on learning inputs broadly categorized into two-dimensional, three-dimensional, and four-dimensional structures [44]. Initially, researchers defined learning engagement as learners actively participating in school-provided activities [45], focusing primarily on the behavioural dimension, which includes positive attitudes and learning behaviours while excluding negative experiences during learning activities. However, this concept has been criticized for its narrow focus on behavioural variables, though it paved the way for further discussions in the educational field [43]. Later, Schaufeli and colleagues [42, 46], from a psychological perspective, described learning engagement as students' involvement in learning tasks and activities akin to "work." In this view, students are engaged in mandatory, structured tasks (e.g., completing assignments, attending class) and activities aimed at specific goals. As a result, following the concept of learning engagement introduced by scholars, this study characterizes learning engagement in terms of three dimensions: vigor, dedication, and absorption. Collectively, these dimensions offer a comprehensive insight into student engagement within digital learning settings. Through prioritizing vigor, dedication, and absorption, educators can enhance their ability to formulate and execute strategies that enhance student involvement, leading to enhanced academic achievements and heightened satisfaction in online learning environments.

Vigor is characterized by high energy and mental resilience when working on study-related tasks, along with a willingness to exert effort even in the face of difficulties. Dedication involves deep engagement in one's studies, marked by feelings of significance, enthusiasm, inspiration, pride, and challenge. Absorption refers to being fully concentrated and joyfully engaged in learning to the extent that time seems to pass quickly, making it difficult to disengage from studies [41]. Each of these dimensions has unique qualities and significantly influences students' engagement levels in educational settings [44, 47]. These dimensions align with Fredrick's constructs of behavioural, cognitive, and emotional engagement, illustrating that academic engagement now encompasses individuals' feelings, behaviours, and thought processes [43]. However, engagement in schoolwork and the experience of flow share conceptual similarities [42], indicating that engagement can operate on different timescales.

Research consistently shows that students exhibiting high levels of vigor, dedication, and absorption tend to perform well academically, experience high life satisfaction, and show fewer depressive symptoms [48]. When students have confidence in their abilities (self-efficacy), they are more inclined to engage actively, commit to their studies, and effectively absorb the material. This increased engagement subsequently improves their perceived learning, as they feel more competent and successful in their academic efforts [77]. Luo et al. [78] found that learning engagement acts as a mediator between self-efficacy and academic achievement, indicating that engaged students are more likely to view their learning positively. For instance, Tuominen-Soini and Salmela-Aro [49] identified four groups among high school students: dedicated, dedicated-exhausted, cynical, and burned-out. Despite higher stress levels, engaged students were more academically successful and more likely to attend college. The patterns of engagement and burnout remained stable from adolescence to early adulthood. Additionally, a cross-sectional study by Teuber et al. [50] found that the three dimensions of learning engagement (vigor, dedication, and absorption) were inversely correlated with emotional exhaustion and positively associated with self-efficacy, perseverance, teacher-student relationships, and life satisfaction. This study also highlighted the strong psychometric properties of this framework within the Chinese educational context. Although multiple studies have demonstrated the correlation between learning engagement and academic performance, literature examining the relationship between learning engagement and perceived learning is limited, particularly in online learning. Thus, addressing this gap is crucial for enhancing our understanding of online learning dynamics and improving educational methods in the digital age.

In online learning, engagement is typically measured through tools that evaluate behavioural, cognitive, and affective aspects. Effective online education depends on creating activities that engage students on various levels [51]. These activities might include linking learning to real-world issues and promoting enjoyable discussions [52]. In contrast, tools designed for physical classrooms often focus on direct interactions and visible behaviours. For example, engagement measures for traditional settings assess student participation and interaction, which differ from digital interactions in online environments. To measure engagement in online learning, we adapted the instrument by Schaufeli et al. [41], which includes the dimensions of vigor, dedication, and absorption. This tool is well-suited for online contexts because it offers a comprehensive framework for assessing engagement. By evaluating these three dimensions—vigor, dedication, and absorption—educators can pinpoint areas where students may need support and apply targeted strategies to improve engagement. For instance, creating a strong sense of community and providing meaningful experiences can boost students' dedication and vigor, leading to greater absorption in their studies [53]. This approach aligns with our context, where online mathematics courses are designed to offer foundational learning opportunities and enhance understanding of secondary school-level mathematics. The program aims to support students in improving their academic performance by reinforcing key concepts and addressing individual learning needs, focusing on engagement throughout the online learning experience.

2.3 Perceived learning

The purpose of any education, traditional or online, is to learn. The level of learning achieved, which is frequently measured by academic grades or perceived learning, can be used to evaluate the quality of a course. Student learning is an important indication of educational results and is frequently used to assess the quality of courses. Learning has two subconstructs: actual achievement, which relates to the grades students obtain, and perceived learning, which is based on students' self-reported learning experiences [7]. Perceived learning is the learner's self-evaluation of whether the course helped achieve its learning goals [54]. According to Rovai [54], student grades are not necessarily a good indicator of what a student has learned because students may come to class with prior knowledge, and grades may also represent class participation, timely submission of work, or attendance. Perceived learning is an important aspect of online education because if students report that their learning is inadequate, the instructor must consider improving the course design to increase learning [55].

Many other aspects of learning need to be considered when assessing what a student has learned [56]. Previous research has demonstrated the validity of self-reports of students' cognitive learning, and evidence from these studies suggests consistency of results over time and across populations [57]. For example, Stein and Wheaton [9] contended that perceived learning may be a greater predictor of achievement than course accomplishments or final grades. Perceived learning has been considered an indicator of learning and is one of the core elements of course evaluation [10].

On the one hand, perceived learning provides instructors with useful insights from the learner's perspective, which improves the quality of online courses in terms of design, delivery, and assessment, eventually increasing students' online learning experiences [11]. On the other hand, perceived learning provides a retrospective evaluation of the learning experience [12]. Students who believe they have mastered course materials are more likely to actively participate in online classes [13]. Therefore, student-perceived learning helps measure the success or failure of any course. Understanding the factors influencing perceived learning can empower instructors to enhance the quality of online courses, encompassing course design, delivery, and assessment, thereby enriching the learning experience for students [15]. Thus, educators and instructional designers must evaluate how students perceive their learning to improve the quality of online courses in terms of course design, delivery, evaluation, etc., as well as improve the student's learning experience.

2.4 Learning engagement as the mediator of the relationship between self-efficacy and perceived learning in the online mathematics environment

Previous research has consistently demonstrated the linkage between self-efficacy and engagement, self-efficacy and perceived learning, and engagement and perceived learning. Despite the limited number of prior studies in various educational settings, investigating the mediating effect of learning engagement in the relationship between learning self-efficacy and perceived learning in the online learning environment of mathematics is relatively non-existent. As such, this present study is relevant to studies in the subsequent discussion.

Panigrahi et al. [58] found that all dimensions of learning engagement fully explain the positive association between internet self-efficacy and perceived learning effectiveness in online education among Indian postgraduates. In line with the findings, Nia et al. [59] conducted a cross-sectional study to evaluate how student acceptance and satisfaction with online learning and self-efficacy influenced university student participation during the COVID-19 pandemic in nine different countries. Both study models indicated that student engagement as an indicator can modulate the relationship between self-efficacy and achievement in the online learning environment. According to Bandura's self-efficacy theory, students' motivation, learning state, and learning outcomes are all affected by their subjective perception of their ability to perform and succeed [60]. Furthermore, learning self-efficacy is a proximate element regulating the level of involvement in learning and can accurately predict engagement in learning [61].

As a result, it is reasonable to conclude that online learners' confidence in their abilities to manage and conduct internet-related tasks improves their perceived learning outcomes. This enhancement is mediated through various dimensions of learning engagement, such as vigor, which is characterized by high levels of energy and mental resilience while learning; dedication, which involves a sense of significance, enthusiasm, and pride in one's learning tasks; and absorption, where students are entirely concentrated and happily engrossed in their learning activities. In conclusion, understanding the interplay between self-efficacy, engagement, and perceived learning is crucial for optimizing online learning environments, especially in subjects like mathematics, where engagement can be particularly challenging. Future research should continue to explore these relationships in diverse educational settings and consider interventions that can boost self-efficacy and engagement to improve learning outcomes.

Based on the above empirical research, this study considers the possible mediation roles of online learning engagement to explore the relationship between learning self-efficacy and perceived learning in an online mathematics environment. The following conceptual model is shown in Fig. 1. Only some prior studies have examined the complex relationships between learning self-efficacy, learning engagement, and perceived learning in online learning environments. The current study has the following hypothesis:

Ha1: Learning self-efficacy is positively related to vigor

Ha2: Learning self-efficacy is positively related to dedication

Ha3: Learning self-efficacy is positively related to absorption

Ha4: Learning self-efficacy is positively related to perceived learning

Ha5: Vigor is positively related to perceived learning

Ha6: Dedication is positively related to perceived learning

Ha7: Absorption is positively related to perceived learning

Ha8: Vigor mediates the relationship between learning self-efficacy and perceived learning

Ha9: Dedication mediates the relationship between learning self-efficacy and perceived learning

Ha10: Absorption mediates the relationship between learning self-efficacy and perceived learning

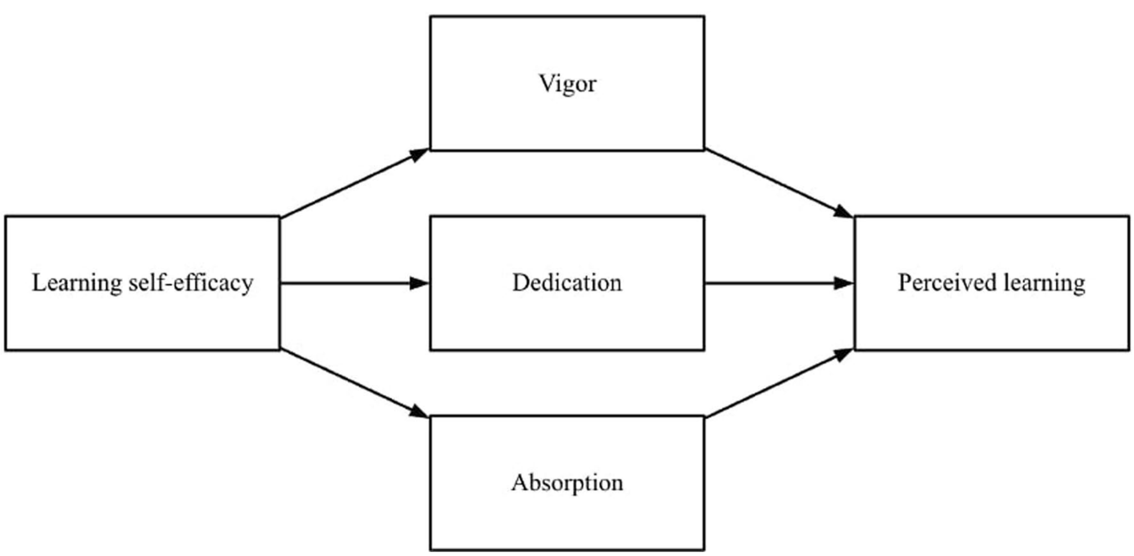

Fig. 1 The conceptual model

3 Methodolog

3.1 Participants and design

This study employed a quantitative approach and a predictive correlational research design, which explores the mediating effect of all three dimensions of learning engagement in the relationship between learning self-efficacy and perceived learning using structural equation modelling (SEM) [62, 63]. Predictive correlational research design is essential for comprehending and forecasting the relationships between variables across different fields. This design enables researchers to investigate the relationships among these variables and identify predictive patterns that can guide educational practices. Researchers can make well-informed predictions about outcomes based on these identified associations by employing statistical analyses to assess the connections between variables. The current study sample consisted of 9th-grade secondary school students from various schools within a district of Guangzhou City, Guangdong Province, China. This study conducted an online survey in the spring semester of 2024.

605 students from a specific region in Guangzhou were chosen randomly to take part in an online mathematics course survey. The online mathematics course is part of the mathematics teaching offer for free to all students with foundational mathematics learning opportunities to enhance their understanding and mastery of secondary school-level knowledge of mathematics. The program was specifically developed to support students in achieving better academic outcomes in mathematics by reinforcing core concepts and addressing individual learning needs. Prior to completing the questionnaire, students received information about the study's objectives, and their participation was voluntary. The survey included questions about demographic details and assessments on interaction, self-efficacy in online learning, academic emotions, and learning engagement. All questionnaires were presented in Chinese.

3.2 Instruments

3.2.1 Learning self-efficacy scale

The instrument utilized in this research measures student online learning self-efficacy. The instrument was adapted from Li et al. [64], providing four Likert scales for each question. The instrument was selected because it has been validated by Chinese scholars, including Li et al. [64], in the educational field within the Chinese educational environment. However, the research will use five Likert scales since research showed that past researchers mainly used five Likert scales to measure self-efficacy among respondents [65]. Some adaptations have been made from the sources. The instrument is a unidimensional scale comprising 14 items to assess learners' perception of their learning self-efficacy toward their online mathematics learning. An example of the question was, "*I have clear learning goals in the online mathematics course.*" Respondents must select their answer for every question on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

3.2.2 Learning engagement scale

The instrument used in this research is the Utrecht Work Engagement Scale developed by Schaufeli et al. [46]. This questionnaire was chosen because it has been validated for effectively measuring online learning engagement in secondary education contexts. It has demonstrated reliability and validity in similar studies [50, 64], capturing various dimensions of student engagement in online settings. Its simple design also ensures that secondary students can easily understand and complete it, reducing response bias and enhancing the accuracy of the data collected. This instrument consisted of 18 items to assess learners' learning engagement during online mathematics learning, among which six items were used to measure vigor, six were used to measure dedication, and six were used to measure absorption. Examples of the three subscales were: "*When I get up in the morning, I feel like going to the online mathematics class*," "*To me, online mathematics learning is challenging*," and "*When I am online mathematics learning, I forget everything else around me.*" The score for the negative item is reversed during data analysis. This questionnaire used the Likert scale to measure the level of learning engagement in the online learning environment. There are five scale choices from 1 to 5.

3.2.3 Perceived learning scale

The perceived learning questionnaire has been used to measure the level of student-perceived learning in the online education setting. The instrument was developed by Gray and DiLoreto [66]. This questionnaire was used because it is the most used to measure student-perceived learning within the online learning environment. This section consists of 6 questions regarding student online learning perceived learning. A sample item was "*I am pleased with what I learned in the online mathematics course.*" The score for the negative item is reversed during data analysis. The items will be graded on a five-point Likert scale, with one denoting "strongly disagree," 2 denoting "disagree," 3 denoting "neutral," 4 denoting "agree," and five denoting "strongly agree.".

3.3 Data analysis

In the initial analysis, we used SPSS 22.0 to perform descriptive statistics for all sub-constructs, accounting for missing data and outliers (using boxplots), and calculated means, standard deviations, skewness, and kurtosis. Pearson correlations were used to determine the relationships between latent variables and check for multicollinearity, ensuring that the relationships between latent variables were below 0.900 to avoid multicollinearity [67]. For assessing univariate normality, we used skewness values within ± 2.0 [68] and kurtosis values within ± 8.0 [67]. Following this, we employed SEM using AMOS version 24.0 to evaluate the hypothesized model. Initially, a measurement model (Confirmatory Factor Analysis—CFA) was calculated for each variable to confirm the dimensional structures of the instruments for the sample. We sequentially assessed the vigor, dedication, and absorption models for learning engagement, followed by evaluating two unidimensional constructs: learning self-efficacy and perceived learning.

We then established the hypothetical model to test the mediating effect of the three sub-constructs of learning engagement (vigor, dedication, and absorption) between learning self-efficacy and perceived learning. Model fit was assessed using various indices: standardized root mean residual (SRMR) (< 0.080), chi-square values ($P > 0.05$), comparative fit index (CFI) (> 0.900), Tucker-Lewis index (TLI) (> 0.900), root mean square error of approximation (RMSEA) (< 0.080), and the goodness-of-fit index (GFI) (> 0.900) [69]. According to Hu and Bentler [70], a model is considered acceptable if $\chi 2/df \leq 5$, RMSEA and SRMR < 0.08, and CFI and TLI > 0.9. A model is considered a good fit if RMSEA < 0.05 and CFI and TLI > 0.95. Additionally, the Bootstrap regression path analysis method was used to test the significance of the model's mediating effects.

4 Results

4.1 Descriptive results

The descriptive statistics are divided into two parts. The first part, presented in Table 1, includes the basic demographic information of the respondents, such as gender and whether they are the only child in their family. The second part, shown in Table 2, presents the mean, standard deviation, skewness, and kurtosis of the primary constructs in this study—learning self-efficacy, perceived learning, and the sub-constructs of learning engagement (vigor, dedication, and absorption).

As show in Table 1 data analyzed reveals that 282 students (46.6%) are male, while 323 students (53.4%) are female. This result indicates a relatively even distribution of male and female students in the study. From Table 4.7 the data analyzed

Table 1 Demographic information

Gender	Frequency	Percentage
Male	282	46.6%
Female	323	53.4%
Only Child	**Frequency**	**Percentage**
Yes	184	30.4%
No	421	69.6%

Table 2 Descriptive output of each construct

Construct	Sub-construct	Mean	Std	Skewness	Kurtosis
Learning self-efficacy	/	3.68	1.01	-0.96	-0.85
Learning engagement	Vigor	3.61	1.02	-0.71	-0.91
	Dedication	3.51	1.01	-0.41	-1.27
	Absorption	3.62	1.00	-0.73	-0.93
Perceived learning	/	3.52	1.14	-0.68	-1.10

reveals that 184 respondents (30.4%) are only children in family, whereas 421 respondents (69.6%) are not. This suggests that the majority of the study's respondents consists of non-only children.

As indicated in Table 2, the mean scores for the learning self-efficacy and perceived learning constructs were moderate (M = 3.68, M = 3.52, respectively). Learning engagement, vigor, dedication, and absorption were also moderate (M = 3.61, M = 3.51, M = 3.62, respectively).

Subsequently, Table 3 shows the correlation matrix for the sub-construct of learning engagement (vigor, dedication and absorption). As indicated in Table 3, statistically significant correlations were found between absorption and dedication ($\gamma = 0.65$), absorption and vigor ($\gamma = 0.65$), and dedication and vigor ($\gamma = 0.59$). The research findings indicate that the learning engagement sub-constructs are free from multicollinearity issues, thus fulfilling the discriminant validity for learning engagement variables.

4.2 Evidence supporting reliability and validity

Table 4 presents Cronbach's Alpha values, composite reliability (CR), and average variance extracted (AVE) for self-efficacy, engagement, and perceived learning.

Table 4 displays the analysis results for the reliability indices of the constructs in this study, including self-efficacy, engagement, and perceived learning. The findings show that all reliability index values are at an excellent level. Specifically, the Cronbach's alpha values are as follows: learning self-efficacy (α = 0.96), perceived learning (α = 0.93), and engagement (α = 0.93). These figures indicate a high degree of internal consistency for each construct. Additionally, the CR values for all constructs exceed the acceptable threshold of 0.6, with the overall composite reliability exceeding 0.7, demonstrating strong internal consistency and reliability. The AVE values for self-efficacy, engagement, and perceived learning also meet the necessary criteria, supporting both convergent validity and overall construct validity. These results confirm that each dimension exhibits sufficient internal consistency and validity.

Table 3 Multicollinearity output for learning engagement

Sub-constructs of learning engagement	1	2	3
1. Absorption	1.00		
2. Dedication	0.65	1.00	
3. Vigor	0.65	0.59	1.00

Table 4 Reliability and validity analysis for all constructs

Construct	Sub-Construct	Cronbach's Alpha	CR	AVE	Overall Cronbach's Alpha
Learning Self-Efficacy		0.96	0.61	0.95	0.96
Perceived Learning		0.93	0.68	0.92	0.93
Engagement	Vigor	0.90	0.90	0.59	0.93
	Dedication	0.89	0.89	0.61	
	Absorption	0.90	0.90	0.60	

Table 5 Examination of the measurement model

Goodness-of-fit	Measurement standard	Results	
		Learning self-efficacy	**Perceived learning**
χ2	*P* > 0.05	83.087	9.445
χ2/df	< 5.00	1.079	1.049
RMSEA	< 0.080	0.011	0.009
CFI	> 0.950	0.980	0.987
GFI	> 0.900	0.981	0.995
TLI	> 0.950	0.989	0.950

Table 6 Examination of the measurement model for learning engagement

Goodness-of-fit	Measurement standard	Results	
		Model 1	**Model 2**
χ2	*P* > 0.05	406.083	116.927
χ2/df	< 5.00	3.076	1.008
RMSEA	< 0.080	0.059	0.004
CFI	> 0.950	0.957	0.981
GFI	> 0.900	0.936	0.977
TLI	> 0.950	0.950	0.980

4.3 Measurement models

The measurement model was employed to ensure that the observed variables accurately represented the latent variables before assessing the hypothetical structural model. Confirmatory Factor Analysis (CFA) was utilized to evaluate the adequacy of the latent variables, including learning self-efficacy (14 indicators), perceived learning (6 indicators), and learning engagement comprising vigor (6 indicators), dedication (6 indicators), and absorption (6 indicators). The outputs from the maximum likelihood estimation revealed that the measurement model for learning self-efficacy indicated an acceptable fit: $\chi 2 = 83.087$, $\chi 2/\mathrm{df} = 1.079$, RMSEA = 0.011, CFI = 0.980, GFI = 0.981, TLI = 0.989 (Table 5). The measurement model for learning engagement also indicated an acceptable fit: $\chi 2 = 116.927$, $\chi 2/\mathrm{df} = 1.008$, RMSEA = 0.04, CFI = 0.981, GFI = 0.977, TLI = 0.980. Furthermore, the measurement model for perceived learning demonstrated a good fit to the data: $\chi 2 = 9.445$, $\chi 2/\mathrm{df} = 1.049$, RMSEA = 0.009, SRMR = 0.0087, CFI = 0.987, GFI = 0.995, TLI = 0.950. Despite the significance of the chi-square result, the $\chi 2$/df, RMSEA, SRMR, CFI, GFI, and TLI values recommended that the a priori model had an adequate factor structure.

All types of assessments indicate that the model is suitable for the learning engagement construct, as the fit indices for χ^2, χ^2/df, *CFI*, and *RMSEA* show acceptable values. However, one item (Q26) of the dedication sub-construct exhibits low factor loadings (0.56). Therefore, items with low factor loadings were excluded to improve the model fit in this study. Referring to Table 7, there is one item with low factor loadings: item Q26 (sub-construct dedication) with a factor loading of 0.56. Consequently, model 2 was tested by removing item Q26. After conducting the *CFA* test estimation again by removing item Q26, the result indicates that the goodness-of-fit also meets the criteria (Table 6). Model 1 showed the following fit indices: $\chi 2 = 406.083$, $\chi 2/df = 3.076$, *RMSEA* = 0.059, *CFI* = 0.957, *GFI* = 0.936, *TLI* = 0.950. In comparison, Model 2, after removing item Q26, showed improved fit indices: $\chi^2 = 116.927$, $\chi^2/df = 1.008$, *RMSEA* = 0.04, *CFI* = 0.981, *GFI* = 0.977, and *TLI* = 0.980.

In Table 7, the factor loadings and coefficients of SEM regression are presented. All factor loadings for learning self-efficacy ranged from 0.770 to 0.810, for perceived learning from 0.810 to 0.860, and for the sub-constructs of learning engagement (vigor: 0.740–0.790, dedication: 0.760–0.820, absorption: 0.760–0.800) were found to be statistically significant ($P < 0.001$). Each item within these sub-constructs demonstrated strong factor loadings, confirming the consistency among items for each respective sub-construct. The standardized estimates for factor loadings exceeded 0.50 for all items, meeting the recommended criteria [71].

Table 7 Factor loadings of variables

Construct	Sub-construct	Item	Factor loading	P
Learning self-efficacy	/		0.793	***
			0.788	***
			0.783	***
			0.787	***
			0.767	***
			0.769	***
			0.791	***
			0.778	***
			0.788	***
			0.783	***
			0.779	***
			0.812	***
			0.784	***
			0.755	***
Learning engagement	Vigor		0.736	***
			0.749	***
			0.786	***
			0.795	***
			0.785	***
			0.764	***
	Dedication		0.766	***
			0.773	***
			0.76	***
			0.816	***
			0.776	***
			0.563	***
	Absorption		0.798	***
			0.777	***
			0.756	***
			0.757	***
			0.763	***
			0.794	***
Perceive learning	/		0.829	***
			0.806	***
			0.813	***
			0.862	***
			0.819	***
			0.814	***

***Significant

4.4 Testing the hypothesized models

We established a direct effect model to explore the predictive effects of learning self-efficacy on perceived learning (see Fig. 2). Like examining the measurement model, various goodness-of-fit values were also considered for each measurement to test the structural model: $\chi 2/df < 5.00$, RMSEA < 0.080, SRMR < 0.080, CFI > 0.950, GFI > 0.900, TLI > 0.950. The results of SEM indicated a highly satisfactory fit to data, $\chi 2 = 159.400$, $\chi 2/df = 0.943$, RMSEA = 0.000, SRMR = 0.0159, CFI = 0.989, GFI = 0.975, TLI = 0.998 (see Fig. 2). The results showed that learning self-efficacy [β = 0.580, P < 0.01] could significantly predict perceived learning.

Using the direct effect model as a basis, we conducted a multiple mediating effect model incorporating the three sub-constructs of learning engagement (vigor, dedication, and absorption) as mediators to explore the relationship

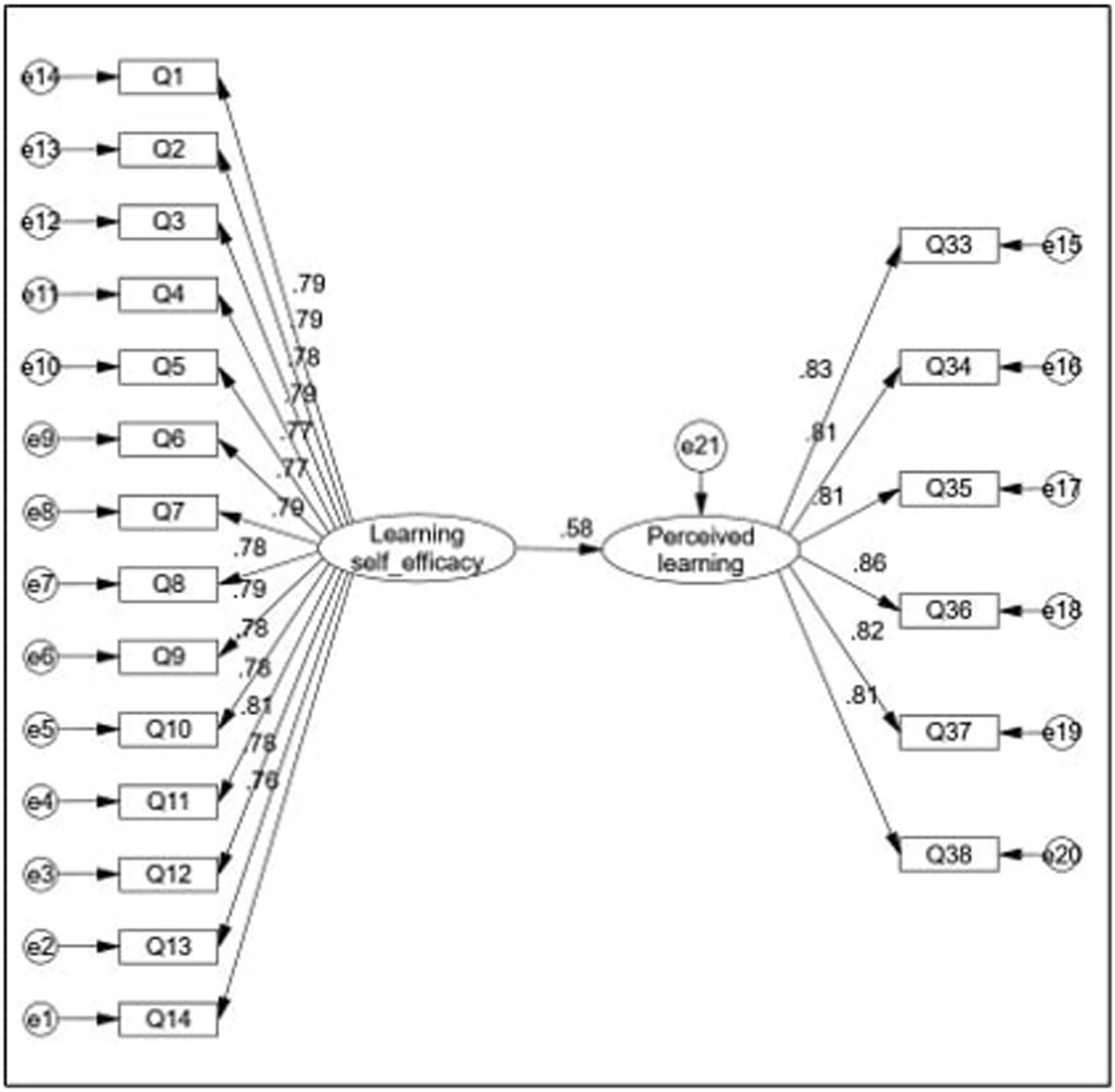

Fig. 2 The direct effects model

between learning self-efficacy and perceived learning (see Fig. 3). The fit indices for the multiple indirect effects model were satisfactory: $\chi 2 = 1028.814$, $\chi 2/df = 1.654$, RMSEA = 0.033, CFI = 0.973, GFI = 0.916, TLI = 0.971 (see Fig. 3). The results indicated that learning self-efficacy [$\beta = 0.360$, $P < 0.01$] predicted vigor, which in turn predicted perceived learning [$\beta = 0.150$, $P < 0.01$]; secondly, learning self-efficacy [$\beta = 0.470$, $P < 0.01$] predicted dedication, which also predicted perceived learning [$\beta = 0.210$, $P < 0.01$]. Thirdly, learning self-efficacy [$\beta = 0.150$, $P < 0.01$] predicted absorption, with the indirect path coefficient from absorption to perceived learning being significant [$\beta = 0.090$, $P = 0.027 < 0.05$].

This study utilized Baron and Kenny's [72] method to investigate whether all three constructs of learning engagement (vigor, dedication, and absorption) mediated the relationship between learning self-efficacy and perceived learning. Based on the bias-corrected bootstrapping test results (Table 8), the indirect effects of learning self-efficacy on perceived learning through vigor (indirect effect = 0.063, 95% CI = [0.029, 0.113]), dedication (indirect effect = 0.114, 95% CI = [0.063, 0.182]), and absorption (indirect effect = 0.044, 95% CI = [0.002, 0.095]) were significant. The results indicated that all three constructs of learning engagement (vigor, dedication, and absorption) mediated the relationship between learning self-efficacy and perceived learning.

Based on Table 9 and the multiple mediating effect model (Fig. 3), the study indicates that when both the direct relationship between the independent variable (learning self-efficacy) and the dependent variable (perceived learning) and the indirect relationships through vigor, dedication, and absorption are significant, partial mediation occurs [72].

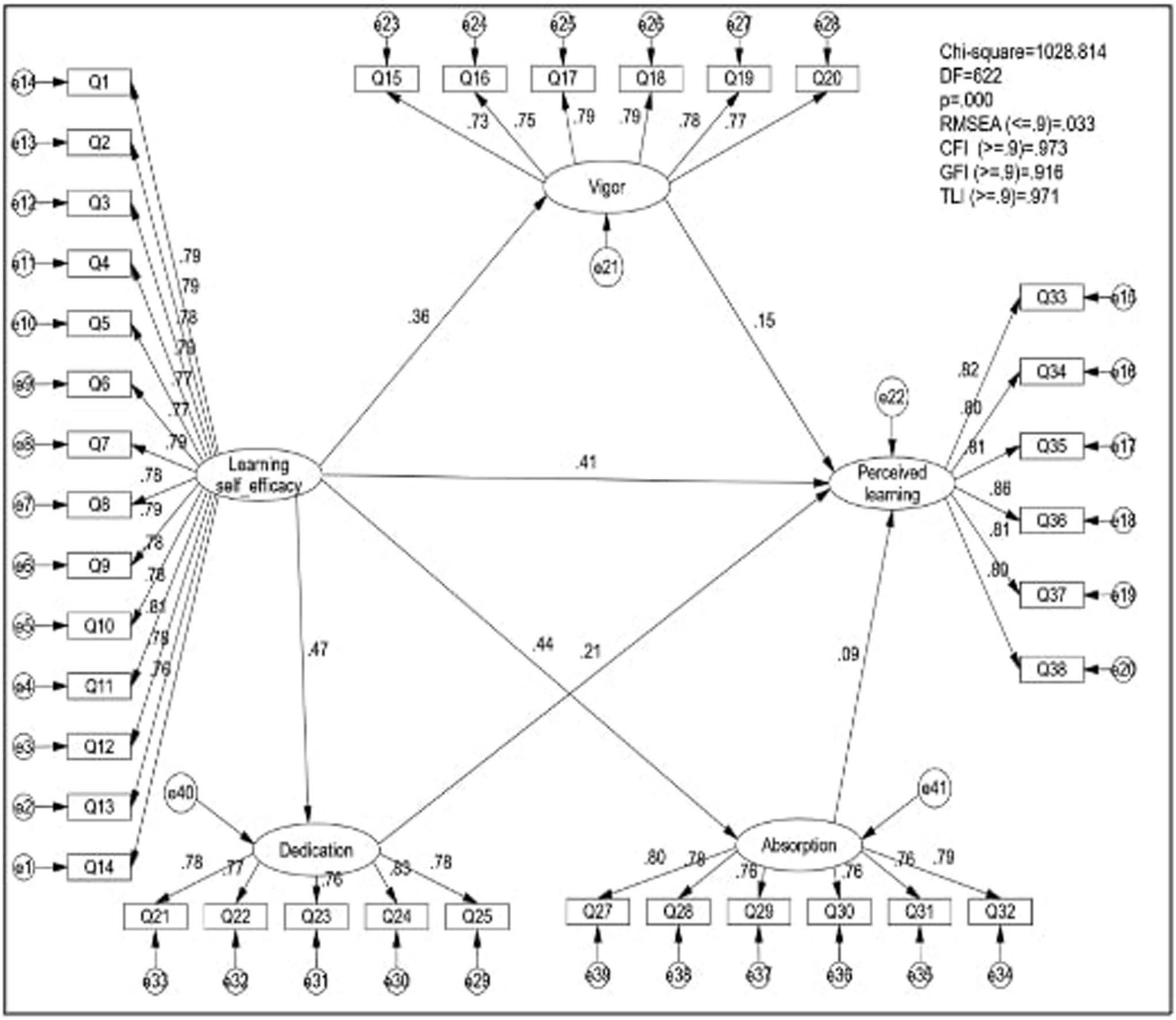

Fig. 3 The multiple mediating effect model

Table 8 Bias-corrected bootstrap test

Model pathways	Estimate	95% CI		P
		Lower	**Upper**	
LSE–- > vigor–- > perceived learning	0.064	0.029	0.113	0.001
LSE–- > dedication–- > perceived learning	0.114	0.063	0.182	0.000
LSE–- > absorption–- > perceived learning	0.044	0.002	0.095	0.039

Note: LSE = learning self-efficacy

Table 9 Distinguishing direct and indirect effects of the mediating model

Mediator	Direct effect	Indirect effect	Decision
Vigor	0.36 ($p < 0.05$)	0.054 ($p < 0.05$)	Partial Mediation
Dedication	0.47 ($p < 0.05$)	0.0987 ($p < 0.05$)	Partial Mediation
Absorption	0.44 ($p < 0.05$)	0.0396 ($p < 0.05$)	Partial Mediation

In this study, the direct effect of learning self-efficacy on perceived learning was significant, as were the indirect effects through vigor, dedication, and absorption. Therefore, vigor, dedication, and absorption collectively partially mediate the relationship between learning self-efficacy and perceived learning.

5 Discussion

Building on theoretical frameworks and previous empirical research, this study investigated the mediation role of learning engagement in the relationship between learning self-efficacy and perceived learning within the context of online mathematics education. Specifically, the study explored whether the sub-constructs of learning engagement (vigor, dedication, and absorption) mediate this relationship. The results underscored the significance of learning engagement in elucidating the association between self-efficacy and perceived learning. Furthermore, the study identified distinct predictive and mediating mechanisms among the three types of engagement in influencing perceived learning outcomes. These findings contribute to existing theories and offer practical insights for enhancing online educational practices.

Firstly, the results of our study indicated that learning self-efficacy directly predicts all three sub-constructs of learning engagement in the online mathematics environment which fully supports Hypothesis a1 to a3. The finding is in line with previous research [37–39], where their result demonstrated that learning self-efficacy has a direct significant positive contribution to learning engagement in the online learning environment. Specifically, the result also revealed that learning self-efficacy directly predicts all three sub-construct of learning engagement (vigor, dedication and absorption). This finding aligns with self-efficacy theory [26], suggesting that confident individuals are more likely to approach difficult tasks with more effort and determination. Student in the online mathematics environment might be more satisfied with the online learning environment regarding their learning process and feel more confident in their mathematics learning ultimately improving their learning engagement for learning mathematics. Therefore, students should be provided with appropriate resources and training to enhance their online learning self-efficacy beliefs and generate online learning engagement regarding vigor, dedication and absorption. This perspective has been proved by Wu [38], who found that Chinese online learners found the online learning environment to be effective in motivating them to learn and were satisfied with and engaged in the online learning process.

Secondly, our study confirmed a direct relationship between learning self-efficacy and perceived learning in the online mathematics environment, supporting Hypothesis a4. This finding aligns with previous studies by Navarro et al. [16] and Alqurashi [11, 31], which suggest that online learners' perceptions of their own learning efficacy significantly influence their capacity for self-directed learning. Online learners who possess high levels of learning confidence are more likely to perceive their learning experiences positively. They demonstrate confidence in their ability to achieve good grades, handle challenging topics, manage their study schedules effectively, plan and assess assignments using rubrics, and meet course expectations [11]. It can be inferred that the increase in self-efficacy, often derived from prior successful experiences, significantly enhances their perception of learning outcomes. Besides that, when faced with difficulties, they are more likely to remain calm and believe in their ability to find solutions, exhibiting greater perseverance and resilience when encountering challenges. Therefore, students with high levels of self-efficacy for learning are more likely to perceive more excellent learning outcomes. This corroborates the review made by Alqurashi [31], who argued that online learners with high self-efficacy are more likely to believe in their abilities, leading to greater motivation to engage in the online learning process. Confidence in the online environment empowers learners learning outcomes, thus enhancing their perceived learning. Furthermore, our findings align with those of Prabhu M et al.'s findings [34], which also reported a positive predictive relationship between online self-efficacy and perceived learning.

Thirdly, our finding revealed that all three dimensions of learning engagement significantly predict learners' online perceived learning outcomes, supporting Hypothesis a5 to a7 in this study. To our knowledge, no research is specific on the relationship between learning engagement and perceived learning in the context of online learning. However, these findings support prior research on the importance of learning engagement, including vigor, dedication, and absorption [48–50]. For instance, research by Teuber et al. [50] indicated that students with high levels of vigor, dedication, and absorption are associated with a solid ability to persevere, overcome challenges, and maintain high life satisfaction in their studies. Therefore, in the online learning environment, students with high vigor typically exhibit positive emotions and attitudes, making them more optimistic and confident when facing learning tasks. Additionally, students with high dedication have clear direction and purpose in their learning activities, allowing them to focus and effectively utilize learning resources and strategies, enhancing their perception of learning outcomes. Lastly, when students fully absorb their learning tasks, they are more likely to engage in deep information processing and critical thinking. Previous research supports this statement, which argues that fulfilling basic psychological needs, a major driver of engagement, may occur outside the work context [41].

Finally, our study confirmed hypotheses a8 to a10, indicating that all three dimensions of learning engagement—vigor, dedication, and absorption—partially mediate the relationship between learning self-efficacy and perceived learning in the online mathematics environment. This finding is consistent with prior research, particularly the work of Panigrahi et al. [58], which similarly demonstrated that all dimensions of learning engagement fully mediate the positive relationship between internet self-efficacy and perceived learning effectiveness among Indian postgraduate students. Bandura [73] suggests that self-efficacy serves as a psychological state influencing academic outcomes indirectly rather than directly. In essence, students with high vigor remain positive and energized when faced with learning tasks, leading to better engagement in the learning process [42]. Similarly, they are more likely to demonstrate a sense of significance, enthusiasm, inspiration, pride, and readiness to embrace the challenges of online learning, which may lead to more significant effort and engagement in their online learning activities. Students with high self-efficacy, supported by their vigor, dedication, and absorption, can better cope with the various pressures and challenges of online learning. This ability to cope helps them maintain a positive learning experience, enhancing their learning outcomes.

Moreover, self-efficacy can be strengthened or weakened when interacting with others in learning activities. The learning self-efficacy of online learners is correlated with their state of study concerning assigned tasks and activities. In other words, students possess a stronger self-efficacy of being able to fully be absorbed in accomplishing the given tasks related to mathematics learning, which is characterized by focused attention, a clear mind, mind and body unison, effortless concentration, complete control, loss of self-consciousness, distortion of time, and intrinsic enjoyment. At the same time, those who are low self-efficacious may experience negative affective states such as stress, anxiety, and depression that disengage them in the online mathematics learning environment. In other words, students with a stronger self-efficacy are fully absorbed in accomplishing the given tasks related to mathematics learning. Focused attention, a clear mind, mind and body unity, effortless concentration, complete control, loss of self-consciousness, distortion of time, and intrinsic enjoyment characterize this absorption [74]. In other words, students with stronger self-efficacy can fully engage in completing tasks related to mathematics learning, characterized by these positive states. Conversely, those with lower self-efficacy may experience negative affective states such as stress, anxiety, and depression, which disengage them from the online mathematics learning environment.

6 Conclusion

This study underscores the critical role of learning engagement as a mediating factor in the relationship between learning self-efficacy and perceived learning in an online mathematics environment. The findings affirm that students with higher self-efficacy are more likely to engage vigorously, dedicatedly, and absorbingly in their learning tasks, enhancing their perceived learning outcomes. Specifically, our results indicate that learning self-efficacy directly influences all three sub-constructs of learning engagement—vigor, dedication, and absorption—each of which partially mediates the relationship between self-efficacy and perceived learning. This aligns with the self-efficacy theory, which posits that individuals confident in their abilities are better equipped to tackle challenging tasks with more significant effort and persistence. Furthermore, the study highlights the importance of fostering a supportive online learning environment that enhances students' self-efficacy. Providing appropriate resources and training can help students feel more confident in their online learning capabilities, ultimately improving their engagement and learning outcomes. The empirical evidence from this research supports previous theories and offers practical insights for educators and policymakers aiming to improve online education quality. By understanding and leveraging the dynamics between self-efficacy, engagement, and perceived learning, stakeholders can better support students in achieving optimal educational outcomes in the digital age. The intricate interplay between these factors demonstrates that enhancing student self-efficacy and engagement is paramount for fostering compelling online learning experiences and outcomes.

According to our research, students' perceptions of learning in an online math environment and their level of engagement are highly influenced by their level of self-confidence. Learners' engagement and academic performance improve when their confidence grows, underscoring the need of sustainable teaching strategies. Building self-confidence improves resilience and adaptability, two qualities that are essential for academic success and lifetime learning. The goal of sustainable education is to give students the skills and mentality needed for ongoing professional and personal development. Thus, creating online learning settings that increase student engagement and self-assurance promotes success in a variety of learning scenarios. This tactic promotes the formation of productive study habits and long-term academic success.

7 Limitations and suggestions

Acknowledging limitations is crucial in research, and our study is no exception. Firstly, while all hypotheses were supported by the findings, one item (Q26) within the sub-construct of dedication exhibited a relatively low loading factor. This could potentially be attributed to the cognitive development stage of secondary school students. At this stage, students are still developing their cognitive abilities and self-regulation skills, which may affect their understanding of learning purposes and long-term goals. Future research should consider these developmental factors when designing and interpreting studies involving secondary school students in educational contexts. Compared to more concrete and immediate motivations (such as test scores or teacher praise), the concept of learning being "full of purpose" may seem more abstract and complex. Further research is needed to make the question more specific, which makes the concept of "full of purpose" more concrete by adding items such as "I believe learning math helps me solve real-world problems" or "I feel that online math learning enhances my logical thinking skills." Moreover, given the disparity in cognitive levels, future studies may need to expand the sample population to include adult students. Secondly, it is essential to note that this study was surveyed in May 2024 to investigate the academic impact of online learning as of December 2023. However, the online mathematics courses the respondents took were asynchronous, meaning that the online learning occurred outside their regular face-to-face school classes. This suggests that their in-school mathematics learning behaviors influenced the study results. Therefore, future research in foundational online education should take measures to eliminate this potential confounding factor and strive to maintain consistency between online learning and learning assessments.

Thirdly, while our study identified correlations among variables, it's important to note that correlational studies cannot establish causality. Future research should consider employing experimental designs or other methods that allow for the investigation of causal relationships among variables. Experimental designs could involve interventions or manipulations of the independent variable to directly observe its effects on the dependent variable. These approaches would provide clearer insights into how various factors influence the outcomes studied. Additionally, a potential limitation of our study is its reliance on self-reported measures, which may introduce bias or error. Future research could enhance validity by incorporating objective measurements or using multiple data sources. Objective measures might include direct observation or physiological assessments, which can offer more accurate and reliable data. Furthermore, integrating multiple data sources can provide a more comprehensive understanding of the phenomenon under study, as different sources may capture different aspects of the constructs being measured. By employing these methodological improvements, researchers can strengthen the validity and reliability of their findings, thereby advancing our understanding of the relationships between variables in educational contexts.

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Data availability The datasets are available upon reasonable request from the corresponding author.

Declarations

Ethics approval and consent to participate This study was approved by the school administration and the ethics committee of Universiti Putra Malaysia (JKEUPM) ref no. "UPM.TNCPI.800-2/1/7". Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Competing interests The authors declare no competing interests.

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