International Journal of Science and Mathematics Education
https://doi.org/10.1007/s10763-024-10456-4

Exploring the Effects of Technology-Related Informal Mathematics Learning Activities: A Structural Equation Modeling Analysis

Haozhe Jiang[1] · Ritesh Chugh[2] · Darren Turnbull[2] · Xiaoqin Wang[3] · Suting Chen[4]

Received: 18 August 2023 / Accepted: 15 February 2024

Abstract

Despite the burgeoning adoption of informal learning in people's daily lives, the actual effects of informal learning activities, especially technology-related informal learning activities, are much less reported than those of formal learning. Furthermore, there is a notable lack of research on the effects of technology-related informal mathematics learning activities (TRLA). This study aims to propose and validate a new model which illustrates the effects of TRLA on four constructs: mathematics self-efficacy (MSE), mathematics interest (MI), self-regulation in mathematics learning (SR), and teacher-student relationship (TSR). Adopting a quantitative cross-sectional survey approach, 460 students were investigated. The data were analyzed employing two-step structural equation modeling. Our findings demonstrate the direct effects of TRLA on MI and SR as well as the indirect effects on MI, MSE, and TSR. This study advances the understanding of technology-enhanced informal learning, which is an emerging perspective of technology-enhanced learning.

Keywords Effect · Informal mathematics learning · Structural equation modeling · Technology enhanced learning · Technology-related learning activities

Introduction

The way in which people learn and acquire new skills is rapidly evolving. Numerous information and communication technologies (ICTs) (e.g. mobile devices, wireless Internet) have made learning ubiquitous (Carreira et al., 2016; Hwang & Purba, 2022), and learning is becoming increasingly non-traditional, informal, spontaneous, open, and unintentional (Bitzenbauer et al., 2024; He & Li, 2019;

✉ Ritesh Chugh
r.chugh@cqu.edu.au

Extended author information available on the last page of the article

Published online: 15 March 2024

Jagušt et al., 2018; Shaby et al., 2023). According to Jagušt et al. (2018), at least 70% of learning happens outside formal learning settings. However, despite the burgeoning adoption of informal learning in people's daily lives, its actual effects are much less reported than those of formal learning (Morris et al., 2019; Walan & Gericke, 2021).

School mathematics is commonly perceived as difficult (Li & Schoenfeld, 2019). It is reported that many students are concerned about assessment-driven school mathematics learning environments (Jenßen et al., 2023; Yuan et al., 2023). Meanwhile, knowledge of science, technology, engineering, and mathematics (STEM) related knowledge can be acquired within different real-world contexts through non-assessment-driven informal learning experiences (Jiang et al., 2021; Marcus et al., 2018). Of possible concern is research indicating that students may be bound by the traditional teacher-led classroom experiences and could not easily adapt themselves to other learning forms of STEM fields (Jiang et al., 2021). This highlights the importance of exploring the real impact of informal STEM learning.[1] Particularly, as Acioly-Regnier (2020) claimed, informal learning is not a well-recognized or sufficiently explored area in mathematics educational research, and the effects of informal mathematics learning have rarely been examined. In addition, most existing studies regarding informal STEM activities focus on K-12 students (e.g. Hoffman et al., 2021; Maiorca et al., 2021; Roberts et al., 2018), while university students appear to be ignored. Hence, studies are needed to justify the effects of informal mathematics learning activities, particularly at the university level.

Technology-enhanced learning refers to the advantages and benefits of using ICTs in teaching and learning (Shen & Ho, 2020), and discussions on the subject have increased exponentially in higher education in recent years (Dunn & Kennedy, 2019; Zhao et al., 2022). However, a considerable percentage of studies are set in classroom or formal contexts (Viberg et al., 2021). Consequently, very little evidence elucidates the effects of technology-related informal learning activities on students. Considering the different characteristics of formal and informal learning (He & Zhu, 2017), do ICTs help students achieve similar benefits in informal learning as formal learning? Does the integration of ICTs enhance informal learning? Very few studies have addressed these concerns. He et al. (2021) called for more efforts to extend the current body of knowledge in technology-enhanced learning into informal learning contexts. Thus, more empirical research is needed to advance the understanding of technology-enhanced informal learning (He & Zhu, 2017; He et al., 2021).

Motivated by these gaps, this study aims to propose and validate a new model to illustrate some of the potential effects of technology-related informal mathematics learning activities (TRLA). Based on our new model, the larger goal is to explore other impacts of technology-related informal learning and further bridge the gaps between formal and informal learning. Focusing on an emerging perspective, namely technology-enhanced informal mathematics learning, this study contributes to the existing literature on technology-enhanced and informal learning.

[1] STEM learning can be viewed as individual science, technology, engineering and mathematics learning or interdisciplinary learning that focuses on integrating the individual STEM disciplines (Jiang et al., 2021; Li, 2018). Hence, informal STEM learning includes informal science, technology, engineering and mathematics learning. Accordingly, informal mathematics learning belongs to informal STEM learning, particularly as mathematics belongs to the STEM umbrella.

Literature Review and Hypotheses Development

We conceptualize our research model based on the control-value theory (Pekrun, 2006; Pekrun et al., 2011) and the self-determination theory (La Guardia & Patrick, 2008; Ryan & Deci, 2000). On the one hand, the control-value theory posits that students' learning environment (e.g. TRLA) can have effects on their interest and motivation to learn, control and value beliefs (e.g. self-efficacy) and self-regulation in learning (Pekrun, 2006). On the other hand, the self-determination theory postulates that self-determination (i.e. self-regulation) can affect people's social relationships with their important others (La Guardia & Patrick, 2008; Ryan & Deci, 2000). Drawing from these two theories, we include five constructs in our model, namely technology-related informal mathematics learning activities (TRLA) on mathematics self-efficacy (MSE), mathematics interest (MI), self-regulation in mathematics learning (SR) and teacher-student relationship (TSR).

Technology-Related Informal Mathematics Learning Activities (TRLA)

According to Livingstone (2001), all of the activities "involving the pursuit of understanding, knowledge or skill which occurs without the presence of externally imposed curricular criteria" could be regarded as informal learning (p. 4). Notably, these kinds of learner-led, non-assessment-driven, unstructured, voluntary activities are usually situated in out-of-school settings (He & Li, 2019; He & Zhu, 2017; Toh et al., 2017). The rapid development of ICTs has changed informal learning activities, and many such activities take place in technology-related environments (e.g. Amado et al., 2018; Carreira et al., 2016; Chugh & Turnbull, 2023; Chugh et al., 2023). Technology-related informal learning activities can be defined as activities that involve informal learning processes taking place with ICTs (He et al., 2021). Personal computers and smartphones with ubiquitous internet access are now commonplace and provide learners with numerous opportunities to search for the resources and information they need (Mehrvarz et al., 2021). As a new and emerging learning style, the effects of technology-related informal learning activities on students have not been fully explored. Specifically, most previous studies only detect the effects of technology-related informal learning activities on students' academic performance (Goff et al., 2018; Heidari et al., 2021; Mehrvarz et al., 2021), and to the best of our knowledge, their effects on other aspects such as learning attitudes and beliefs have rarely been investigated.

In the STEM fields, informal learning activities may have a significant potential impact on student achievement (Hurst et al., 2019), interest (Roberts et al., 2018) and self-efficacy (Hoffman et al., 2021; Maiorca et al., 2021), but such effects are much less reported than those in school settings (Morris et al., 2019; Walan & Gericke, 2021). Hence, research on informal STEM learning, especially informal mathematics learning, is strongly advocated (Morris et al., 2019; Pattison et al., 2016; Satyam et al., 2020; Walan & Gericke, 2021). Furthermore, studies on technology-related informal mathematics learning activities (TRLA) are minimal. Compared with traditional informal learning, it is also unclear whether technology-related informal STEM or mathematics learning can affect students equally or more.

Mathematics Interest (MI)

Mathematics interest (MI) is the learners' "predisposition to engage and reengage with" mathematics "over time, as well as the psychological state that accompanies this engagement" (Bohrnstedt et al., 2020, p. 173). Prior studies showed inconsistent results regarding the impact of informal STEM learning activities on STEM interest. Specifically, Roberts et al. (2018) concluded that informal STEM learning successfully developed students' STEM interests as students may have fun in those activities, while Lock et al. (2019) found that such an impact was insignificant statistically. According to the control-value theory (Pekrun, 2006), students' interest and motivation to learn will be influenced by their learning environment (e.g. TRLA). For instance, students may develop their interest and be motivated to learn when they find the learning materials pique curiosity and the learning environment is motivational (Pekrun, 2006; Pekrun et al., 2011). In TRLA, with the assistance of ICTs, there is no doubt that students will find it more manageable and enjoyable to obtain the mathematical resources they find interesting (Pierce et al., 2007). Hence, they are very likely to develop MI in TRLA. However, this has scarcely been verified. We hypothesize:

H1. MI is directly influenced by TRLA.

Mathematics Self-Efficacy (MSE)

Mathematics self-efficacy (MSE) can be defined as the "students' beliefs in terms of their capabilities to effectively deal with mathematics problems and get rid of difficulties" (Zhu & Meyer, 2022, p. 82). Based on Bandura's (1997) social cognitive theory, self-efficacy has four sources: enactive mastery experiences, vicarious experiences, verbal persuasion and emotional arousal. In terms of emotional arousal, if individuals experience joy, excitement and contentment in an activity, they are more likely to have high levels of self-efficacy (Bandura, 1997). In contrast, if individuals experience anxiety, sadness and dissatisfaction, they are more likely to have low levels of self-efficacy (Bandura, 1997). It is obvious that if students have strong mathematics interests, they will feel joyful in mathematics learning activities, and thus, they will be more likely to have high levels of self-efficacy. The effects of mathematics interest on mathematics self-efficacy have also been confirmed in Zhang and Wang's (2020) empirical study. We hypothesize:

H2. MSE is directly influenced by MI.

The control-value theory posits that students' control and value beliefs (e.g. self-efficacy) will be impacted by their learning environment (Pekrun, 2006). As Pekrun (2006) proposed, students' control and value beliefs (e.g. self-efficacy) are acquired during exposure to their learning settings. For instance, if students find the learning materials easy to understand, they will feel competent and develop self-efficacy (Pekrun, 2006). Hence, as a supportive learning environment, TRLA may help students develop their self-efficacy. Furthermore, it was found that technology-related informal learning activities can help students improve their academic performance (Goff et al., 2018; Heidari et al., 2021; Mehrvarz et al., 2021). Therefore, in the mathematics domain, it is reasonable to assume that students may be more confident in their mathematics capabilities or performance after TRLA. We hypothesize:

H3. MSE is directly influenced by TRLA**.**

Self-Regulation in Mathematics Learning (SR)

Self-regulation in mathematics learning (SR) refers to the "process whereby learners set goals for their" mathematics "learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features" in the mathematics learning environment (Pintrich, 2000, p. 453). The control-value theory proposes that students use different learning strategies in different learning settings (Pekrun, 2006). Moreover, a learning environment that can provide students with autonomy and support will promote self-regulated learning (Pekrun, 2006). A wealth of evidence has indicated that incorporating ICTs in learning activities can foster students' self-regulation (Bergamin & Hirt, 2018; Palalas & Wark, 2020; Seifert & Har-Paz, 2020). In TRLA, students rarely get any in-time guidance or support from their teachers, and have to apply a series of cognitive or non-cognitive strategies (e.g. goal-setting and planning, keeping records and monitoring, self-evaluation) to promote their self-learning (Ballouk et al., 2022). However, the association between technology-related informal learning and self-regulation has rarely been substantiated, especially during students' mathematics learning. We hypothesize:

H4. SR is directly influenced by TRLA.

Recent research has shown that self-regulation can impact interest (Callan et al., 2022). A meta-analysis showed that students' intrinsic motivation and interest were significantly enhanced after receiving self-regulated learning training (Theobald, 2021). Particularly, Carneiro et al. (2011) posited that self-regulation was an important mediator in the effects of technology-related informal learning environments on learners' interest. Research has also shown that learners' interest can be evoked by active participation and attractive learning environments (Neher-Asylbekov & Wagner, 2023). Carneiro et al. (2011) further argued that informal learning environments are less instructor-oriented and more learner-oriented, requiring learners to use self-regulatory skills to interact with the environments appropriately. In other words, if the informal learning environments are active and attractive, but learners cannot use self-regulatory skills to engage in the environments (e.g. learners cannot persist in the learning due to a lack of self-control), their interest in the subject matter might be limited. However, to the best of our knowledge, the relationship between self-regulation and interest has not been confirmed in the domain of mathematics education. We hypothesize:

H5. SR directly influences MI.

Self-regulation has been found to be significantly correlated to academic self-efficacy (Ziegler & Opdenakker, 2018). According to Müller and Seufert (2018), self-efficacy is one consequence of self-regulation. This is because self-regulation can be considered one kind of enactive mastery experience (Müller & Seufert, 2018), which is one powerful source of self-efficacy (Bandura, 1997). As Müller and Seufert (2018) explained, when learners perform their planned actions and achieve their goals in their self-regulation process, they will "interpret the results of these enactive mastery learning experiences and form beliefs about how capable they are in managing subsequent related learning activities" (p. 2). These arguments have also been justified in some empirical studies. For instance, Wang (2023) found that students who successfully apply self-regulated strategies in their learning may have more confidence in their academic performance. However, to the best of our knowledge, such a relationship has not been examined in the context of mathematics learning. We hypothesize:

H6. SR directly influences MSE.

Teacher-Student Relationship (TSR)

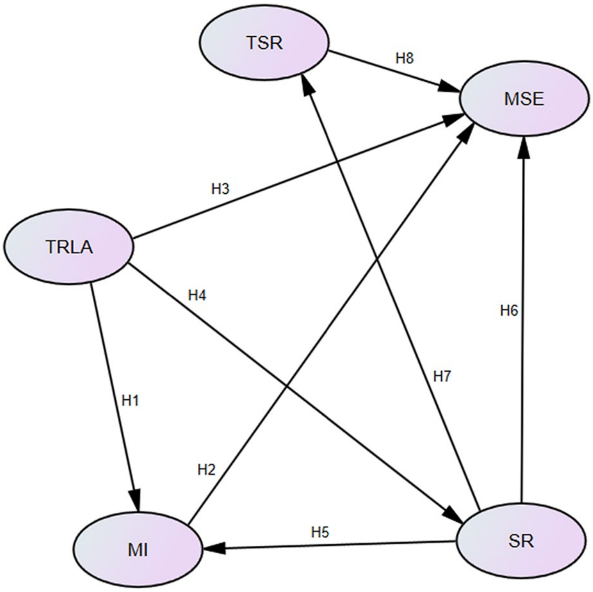
Based on Zhou et al.'s (2020) definition, the teacher-student relationship (TSR) can be regarded as a two-way interpersonal link between teachers and students "that takes place in proximal (e.g. interpersonal interactions) and distal systems (e.g. the classroom context)" (p. 474). Based on the self-determination theory (La Guardia & Patrick, 2008; Ryan & Deci, 2000), self-determination (i.e. self-regulation) plays a vital role in people's social relationships. Specifically, the more people are autonomously motivated or self-regulated, "the more they will experience the relationship to be fulfilling" (Legault, 2017, p. 6). Self-regulated people will try to have positive relationships with their important others who can support them in pursuing their goals (La Guardia & Patrick, 2008; Ryan & Deci, 2000).

Moreover, Aldrup et al. (2018) and Evans et al. (2019) found that students' misbehavior negatively impacted the teacher-student relationship. As self-regulated students usually exhibit lesser misbehavior (Cole et al., 2019), they tend to have better relationships with their teachers. However, to the best of our knowledge, no prior studies have confirmed it. We hypothesize:

H7. TSR is directly influenced by SR.

Bandura (1997) claimed verbal persuasion is also a source of self-efficacy. Teachers are frequently considered the most important verbal persuaders of students, and students who have good relationships with their teachers are more likely to receive positive comments from their teachers (Smart, 2014). Zhou et al. (2020) further found that positive teacher-student relationships will contribute to high levels of mathematics self-efficacy. Hence, students' relationships with teachers indirectly facilitated by

Fig. 1 The conceptual research model. *Note*. Technology-related informal mathematics learning activities (TRLA), mathematics self-efficacy (MSE), mathematics interest (MI), self-regulation in mathematics learning (SR), teacher-student relationship (TSR)



TRLA may further enhance their mathematics self-efficacy. However, this relationship between TSR and MSE has seldom been examined in universities. We hypothesize:

H8. TSR directly influences MSE.

Figure 1 shows our conceptual research model, which illustrates that TRLA may have direct effects on MI, MSE, and SR as well as indirect effects on MI, MSE, and TSR. Our model integrates the control-value theory (Pekrun, 2006; Pekrun et al., 2011) and the self-determination theory (La Guardia & Patrick, 2008; Ryan & Deci, 2000). Specifically, the direct effects of TRLA on MI, MSE, and SR are supported by the control-value theory (Pekrun, 2006; Pekrun et al., 2011), while the direct impact of SR on TSR is supported by the self-determination theory (La Guardia & Patrick, 2008; Ryan & Deci, 2000). In addition, the effects of MI, SR and TSR on MSE are supported by Bandura's (1997) theory regarding the sources of self-efficacy.

Method

Participants

We adopted a quantitative cross-sectional survey study design, frequently used in science and mathematics education research (e.g. Guo et al., 2022; Jiang et al., 2024; Parviainen et al., 2023). A total of 460 students from two universities[2] in China were

[2] Both universities have a pronounced focus on nurturing STEM disciplines, with a mandatory component of advanced mathematics for all students.

recruited and invited to complete the survey instruments. Using the listwise deletion method (McNeish, 2016), we removed 21 incomplete responses. The final data set consists of 439 valid responses. Among them, 44% are male students, and 56% are female students. As for our participants' majors, 35.8% are science, technology, engineering, and mathematics (STEM), 44.6% are economics and management, and 19.6% are humanities and social sciences. Hence, to some extent, our participants can be considered representative, as the difference in the proportion of male and female students is only around 10%, and their majors cover almost all disciplines. In addition, 13.4% of students usually spend less than one hour per week in TRLA, 46.9% spend 1–2 h, 35.8% spend 2–3 h,[3] and 3.9% spend three hours or above.

Instrument Development and Data Collection

The process of instrument development involved five stages. To begin with, based on relevant literature, an English language instrument containing five constructs was developed (see Table 1). Next, we developed a Chinese version following the forward and back translation rules (Guillemin et al., 1993). Education researchers and language experts then reviewed the translated instrument. Based on their comments, related revisions were undertaken. Subsequently, following Slattery et al.'s (2011) guide, a pilot test was conducted on 139 university students. A few items were revised or deleted based on students' feedback (e.g. those items that could not be understood clearly). Items with low factor loadings were also removed after an initial statistical check (Hair et al., 2010). After the pilot test, seven items were removed (i.e. TRLA2, TRLA6, MI4, MI5, MSE1, MSE5 and TSR1). Finally, according to the results of our pilot test, we developed an improved seven-point Likert scale (see the Appendix) and employed it in the formal data collection. Students were informed of our recruitment information by their teachers. All participants voluntarily completed the questionnaires after knowing our privacy protection measures and their rights. After the data collection, we validated the formal research instrument using the data set containing 439 responses (see the Results section).

Data Analysis

Using AMOS 22 Graphics, we adopted a two-step structural equation modeling approach to analyze the "complex relationships between directly and indirectly observed (latent) variables" (Stein et al., 2012, p. 495). Before the first step, univariate normality tests were performed to test the assumption of normality in the structural equation modeling. In the first step, we employed the confirmatory factor analysis (CFA) technique to validate our instrument. In the second step, we examined the hypotheses and calculated the direct, indirect and total effects of TRLA on MI, MSE, SR, and TSR.

[3] The group of students spending 1–2 h encompasses those spending 1 h but excludes those spending 2 h. Similarly, the group of students spending 2–3 h comprises those spending 2 h but does not include students spending 3 h.

Table 1 The constructs of the initial instrument applied in the pilot test

Constructs	Number of items	Item Name	References for item development
TRLA	6	TRLA1, TRLA2, TRLA3, TRLA4, TRLA5, TRLA6,	Lock et al., 2019; Tang & Zhang, 2020; Xu & Jang, 2017
MI	5	MI1, MI2, MI3, MI4, MI5	Fiorella et al., 2021; Jiang et al., 2022; Jiang et al., 2023; Stevens & Olivarez, 2005
MSE	5	MSE1, MSE2, MSE3, MSE4, MSE5	Fiorella et al., 2021; Jiang et al., 2022; Jiang et al., 2023; Zhou et al., 2020
SR	5	SR1, SR2, SR3, SR4, SR5	Lee & Tsai, 2011; Liu et al., 2023; Villavicencio & Bernardo, 2016
TSR	4	TSR1, TSR2, TSR3, TSR4	Zhou et al., 2020

During the data analysis, several goodness-of-fit indices suggested by Hu and Bentler (1999) were used to assess the model fit, including the chi-square to the degree of freedom ratio (χ^2/df), the comparative fit index (CFI), the Tucker-Lewis index (TLI), the standardized root mean residual (SRMR), and the root mean square error of approximation (RMSEA). Specifically, Hu and Bentler (1999) recommended that χ^2/df should be lower than 5, CFI and TLI should not be lower than 0.95, and SRMR and RMSEA should be smaller than 0.08.

Results

The Results of the Measurement Model

Before the first step, we tested the univariate normality. According to Stevens (2009), this significance test on kurtosis is highly sensitive to the sample size and may not be practical in structural equation modeling. Hence, it is recommended to inspect the kurtosis values for individual variables (Kline, 2005; Stevens, 2009). To ensure that the model's fit remains unaffected, it is essential that all kurtosis values remain within a magnitude not exceeding 3.0. (Kline, 2005). The AMOS output showed that no absolute kurtosis values were greater than 3.0, indicating no severe deviations from normality.

In the first step of the structural equation modeling approach, we applied the CFA technique to test the measurement model and validate the instrument. The CFA results showed that the five-factor measurement model of TRLA, MI, MSE, SR and TSR fitted to the data well with the following goodness-of-fit indices: $\chi^2=402.222$, $df=125$, $\chi^2/df=3.218$, RMSEA = 0.071, CFI = 0.977, TLI = 0.972, SRMR = 0.031. The values of composite reliability (CR) and average variance extracted (AVE) for all constructs respectively exceed the threshold of 0.70 and 0.50 (see the Appendix), indicating that convergent validity was assured (Hair et al., 1998). The coefficients of interrelationships among the constructs are smaller than the square root of AVEs (see Table 2). Hence, the Fornell-Larcker criterion is achieved, and the discriminant validity is assured (Fornell & Larcker, 1981). The coefficients of Cronbach's alpha (α) are also higher than the threshold of 0.70 (see the Appendix), suggesting the construct reliability was assured.

The Results of the Structural Model

In the second step of the structural equation modeling approach, the structural model was tested, and the hypotheses were examined. The results are shown in Table 3. The structural model fitted to the data well with the following goodness-of-fit indices: $\chi^2=403.568$, $df=127$, $\chi^2/df=3.178$, RMSEA = 0.071, CFI = 0.977, TLI = 0.972, SRMR = 0.032. It was found that TRLA significantly impacted MI ($\beta=0.322$, $p=0.000$) and SR ($\beta=0.668$, $p=0.000$). However, the influence of TRLA on MSE ($\beta=-0.052$, $p=0.154$) was not significant. Meanwhile, SR significantly impacted MI ($\beta=0.540$, $p=0.000$), MSE ($\beta=0.525$, $p=0.000$) and TSR

Table 2 Fornell-Larcker discriminant validity

Construct	TRLA	MI	MSE	SR	TSR
TRLA	**0.931**				
MI	0.683	**0.973**			
MSE	0.609	0.795	**0.956**		
SR	0.668	0.756	0.849	**0.889**	
TSR	0.422	0.440	0.576	0.609	**0.965**

Note. Bold numbers on the diagonal are the square roots of the AVEs

Table 3 Summary of the hypothesis examining results

Hypotheses	Paths	Standardized coefficients (β)	C.R	Results
H1	TRLA → MI	0.322***	7.416	Accepted
H2	MI → MSE	0.386***	9.238	Accepted
H3	TRLA → MSE	-0.052	-1.424	Rejected
H4	TRLA → SR	0.668***	15.442	Accepted
H5	SR → MI	0.540***	12.231	Accepted
H6	SR → MSE	0.525***	11.046	Accepted
H7	SR → TSR	0.608***	14.713	Accepted
H8	TSR → MSE	0.108***	3.441	Accepted

Note. *$p<0.05$; **$p<0.01$; ***$p<0.001$

($\beta=0.608$, $p=0.000$). Besides, the significant influence of MI on MSE ($\beta=0.386$, $p=0.000$) was also exhibited. Therefore, H1, H2 and H4-H8 could be accepted, while H3 was not supported.

As H3 could not be confirmed, we revised our hypothesized research model by removing its path (i.e. TRLA → MSE). The revised model with standardized coefficients is shown in Fig. 2.

After removing the insignificant path, the standardized direct, indirect, and total effects of TRLA on MI, MSE, SR, and TSR were also calculated (see Table 4). Notably, the mediating roles of MI, SR, and TSR were verified. Specifically, MI played a mediating role in the effects of TRLA on MSE (TRLA → MI → MSE, $\beta=0.118$, $p=0.000$). SR played a mediating role in the effects of TRLA on MI (TRLA → SR → MI, $\beta=0.360$, $p=0.000$), the effects of TRLA on MSE (TRLA → SR → MSE, $\beta=0.338$, $p=0.000$), and the effects of TRLA on TSR (TRLA → SR → TSR, $\beta=0.405$, $p=0.000$). TSR and SR had chain mediating effects between TRLA and MSE (TRLA → SR → TSR → MSE, $\beta=0.043$, $p=0.000$). MI and SR had chain mediating effects between TRLA and MSE (TRLA → SR → MI → MSE, $\beta=0.131$, $p=0.000$). Although the direct impact of TRLA on MSE and TSR was not significant, the indirect effects of TRLA on MSE[4]

[4] There were four indirect paths between TRLA and MSE: TRLA → MI → MSE, TRLA → SR → MSE, TRLA → SR → TSR → MSE and TRLA → SR → MI → MSE.

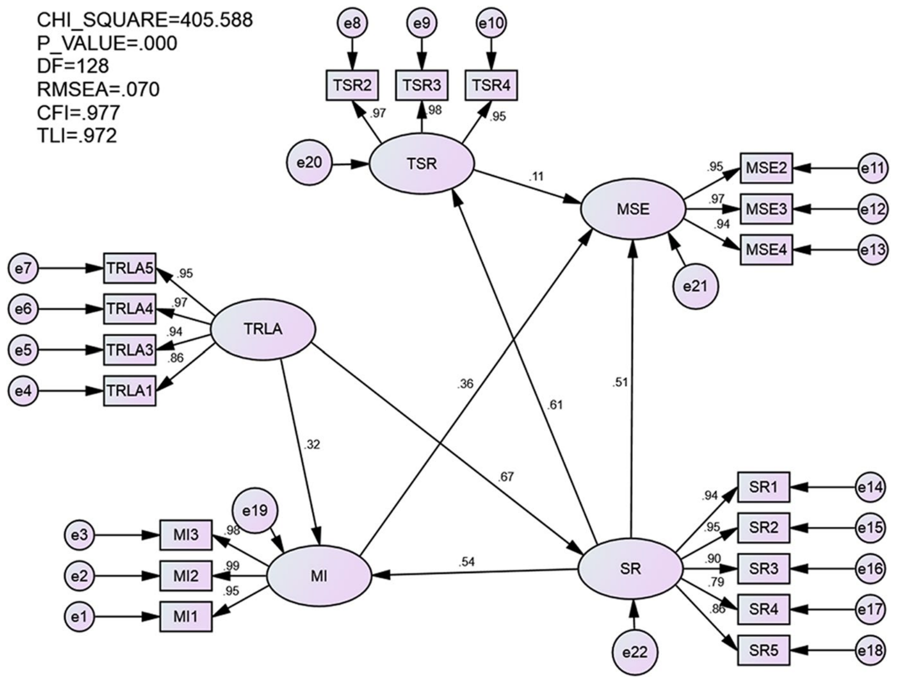


Fig. 2 The revised model with standardized coefficients

Table 4 Standardized direct, indirect, and total effects of TRLA on MI, MSE, SR and TSR

Effect	TRLA on MI	TRLA on MSE	TRLA on SR	TRLA on TSR
Direct effect	0.323***	–	0.666***	–
Indirect effect	0.360***	0.630***	–	0.405***
Total effect	0.682***	0.630***	0.666***	0.405***

Note. $^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

and TSR[5] were significant. In addition, TRLA significantly influenced MI both directly and indirectly.[6]

Discussion and Conclusions

Theoretical Contributions

This study successfully integrates the control-value theory (Pekrun, 2006; Pekrun et al., 2011) and the self-determination theory (La Guardia & Patrick, 2008; Ryan & Deci,

[5] The indirect path between TRAL and TSR was: TRLA → SR → TSR.
[6] The indirect path between TRAL and MI was: TRLA → SR → MI.

2000), and proposes and validates a novel model exhibiting the direct and indirect impact of TRLA on MSE, MI, SR, and TSR. To the best of our knowledge, this is the first empirical-based model depicting the effects of TRLA on a series of variables. Our findings demonstrate the direct effects of TRLA on MI and SR and the indirect effects on MI, MSE, and TSR. These effects, especially indirect ones, have rarely been discussed in previous educational research and practice. Most importantly, this study helps extend the current body of knowledge in technology-enhanced learning into informal learning contexts. It also contributes to the emerging research field of technology-enhanced learning (i.e. technology-enhanced informal learning).

Prior studies confirmed that integrating ICTs into mathematics teaching and learning could increase students' MI (e.g. Demir & Önal, 2021). Meanwhile, there are some inconsistencies among previous results regarding the impact of informal STEM learning on students' interests. Some research indicated positive effects existed (e.g. Roberts et al., 2018), while others did not detect significant effects (e.g. Lock et al., 2019). For the first time, our findings confirm that TRLA can impact MI directly and indirectly. This means the influences of technology-related mathematics learning activities on MI occur not only in formal learning settings, but also in informal learning contexts, giving further credence to technology-enhanced informal learning. As such, the control-value theory, which claims that interest will be impacted by learning settings, is confirmed in our study (Pekrun, 2006; Pekrun et al., 2011).

The direct effects of technology-related classroom learning activities on MSE were detected in prior studies (e.g. Fowler et al., 2022). Simultaneously, it was found that informal STEM learning activities affected students' self-efficacy, including MSE (Hoffman et al., 2021; Maiorca et al., 2021). Moreover, previous research also certified that students' academic performance could be improved after participating in technology-related informal learning as students had more access to different subject knowledge during these activities (Goff et al., 2018; Heidari et al., 2021; Mehrvarz et al., 2021). Based on these previous conclusions, students may be more confident in their mathematics performance and capabilities after TRLA. Surprisingly, contrary to our hypothesis, the direct effects of TRLA on MSE are not significant. Despite this, significant indirect effects of TRLA on MSE, where MI, SR, and TSR are mediators, have been verified in this study. This is indirect evidence of technology-enhanced informal learning. In addition, our findings imply that the direct effects of technology-related learning activities in formal and informal settings may be different.

Our findings echo that incorporating ICTs in learning activities can foster students' self-regulation (Bergamin & Hirt, 2018; Palalas & Wark, 2020; Seifert & Har-Paz, 2020). As self-regulation involves cognition (Pintrich, 2000), the association between technology-related learning activities and self-regulation is very important in understanding technology-enhanced informal learning. In other words, ICTs can potentially improve students' cognitive and affective outcomes. In particular, we confirm such an association in the context of informal mathematics learning at the university level, a frequently neglected research area (Acioly-Regnier, 2020). Our findings also support the relationship between the learning environment and self-regulation in learning, as posited by the control-value theory (Pekrun, 2006; Pekrun et al., 2011). More importantly, our study goes beyond previous studies and reveals that SR is an indispensable mediator in the indirect path between TRLA and TSR.

This study may be the first to obtain the results that TRLA exerts indirect effects on TSR. The indirect impact of TRLA on TSR is based on the integration of the control-value theory (Pekrun, 2006; Pekrun et al., 2011) and the self-determination theory (La Guardia & Patrick, 2008; Ryan & Deci, 2000) as the former theory supports the direct impact of TRLA on SR and the latter theory supports the direct impact of SR on TSR. To the best of our knowledge, no prior studies of technology-enhanced learning have examined the effects on TSR. Notably, TSR is very helpful in supporting and improving students' classroom learning (Zhou et al., 2020). This indicates that if students positively participate in TRLA, their relationships with teachers may be better, and they are more likely to achieve better classroom learning outcomes. Daguš et al. (2018) have claimed many gaps between formal and informal technology-related learning. We argue that TSR can play essential roles in bridging the gaps between formal and informal learning and increasing the transferability of the effects of formal and informal learning.

Practical Implications

Nowadays, informal learning is much less emphasized than school learning in educational practice (Petkovic, 2018). Considering the effects of TRLA, much more attention should be paid to them. Policymakers, parents, and teachers can provide students with various TRLA and encourage them to participate. For instance, parents and teachers can organize out-of-school discussions or debates on specific mathematics problems through the Internet. In addition, parents and teachers can regularly share reading materials or stories about mathematics and mathematicians with students through social media. TRLA also provides good opportunities to develop TSR, further supporting students' formal learning. In those activities, where the pressure of assessment or examinations is removed, teachers tend to be more easygoing and friendly. Thus, we suggest that teachers make the most of those informal activities, listen to their students and chat with students more freely.

Limitations and Future Directions

This study is not without limitations. Firstly, based on this proposed and validated model, we only examined the effects of TRLA on MI, MSE, SR, and TSR, while some other possible aspects were ignored. Based on this model, we are going to establish a more comprehensive model in the future to help understand other effects of TRLA. Secondly, as a quantitative cross-sectional survey study, our data were collected in a single time frame. Therefore, future studies can adopt longitudinal approaches to capture the dynamic and long-term effects of TRLA. Thirdly, in our forthcoming expanded project, we will further investigate the interaction between technology, formal learning, and informal learning to identify opportunities for their synergistic deployment to improve student knowledge acquisition.

Appendix

Table 5 Summary of the CFA results

Construct	Item	Description	Mean	SD	Std	α	CR	AVE
TRLA	TRLA1	I browse content about mathematics or mathematicians on the Internet	5.187	1.575	0.861	0.962	0.963	0.867
	TRLA3	I try to find some online resource related to mathematics problem-solving in my spare time	5.148	1.587	0.941			
	TRLA4	I discuss some topics related to mathematical learning through social media	5.057	1.631	0.967			
	TRLA5	I always follow news from mathematics organizations via online blogs or microblogging	5.100	1.582	0.951			
MI	MI1	I enjoy learning mathematics	5.253	1.646	0.947	0.981	0.982	0.947
	MI2	I am interested in mathematics courses	5.317	1.558	0.992			
	MI3	I find learning mathematics interesting	5.296	1.558	0.980			
MSE	MSE2	I am confident I will do well on mathematics assignments and tasks	5.681	1.441	0.955	0.969	0.970	0.915
	MSE3	I believe I can master the knowledge and skills in the mathematics course	5.651	1.455	0.973			
	MSE4	I am confident I will do well on mathematics tests	5.513	1.518	0.941			
SR	SR1	I will set my own mathematics learning goals	5.811	1.247	0.936	0.948	0.949	0.790
	SR2	I can recognize the inadequacy of my mathematical knowledge and skills	5.729	1.295	0.949			
	SR3	I use appropriate strategies that ensure I learn mathematics well	5.519	1.383	0.902			
	SR4	I will evaluate or review my learning effectiveness	5.715	1.280	0.792			
	SR5	I improve my learning approaches when it is necessary	5.731	1.347	0.855			
TSR	TSR2	The mathematics teacher is very concerned about my physical and mental health	6.011	1.372	0.972	0.976	0.976	0.931
	TSR3	The mathematics teacher would like to hear my truth	5.991	1.388	0.977			
	TSR4	The mathematics teacher gives extra help when I need it	6.109	1.301	0.946			

Note. Std. refers to standardized factor loadings

Acknowledgements This work is supported by the Humanities and Social Sciences Research Youth Program of the Ministry of Education of the People's Republic of China (20YJC880117).

Funding Open Access funding enabled and organized by CAUL and its Member Institutions

Data Availability The datasets collected and analyzed during the current study are not available per constraints from East China Normal University.

Declarations

Ethical Statement This research obtained ethical endorsement for this research before distributing the questionnaires among university students.

Conflict of Interest There is no conflict of interest between the authors and respondents.

References

Acioly-Regnier, N. (2020). Informal learning in mathematics education. In S. Lerman (Ed.), *Encyclopedia of mathematics education* (pp 373–380). Springer. https://doi.org/10.1007/978-3-030-15789-0_164

Aldrup, K., Klusmann, U., Lüdtke, O., Göllner, R., & Trautwein, U. (2018). Student misbehavior and teacher well-being: Testing the mediating role of the teacher-student relationship. *Learning and Instruction, 58*, 126–136. https://doi.org/10.1016/j.learninstruc.2018.05.006

Amado, N., Carreira, S., & Jones, K. (2018). *Broadening the scope of research on nathematical problem solving*. Springer. https://doi.org/10.1007/978-3-319-99861-9

Ballouk, R., Mansour, V., Dalziel, B., McDonald, J., & Hegazi, I. (2022). Medical students' self-regulation of learning in a blended learning environment: A systematic scoping review. *Medical Education Online, 27*(1), 2029336. https://doi.org/10.1080/10872981.2022.2029336

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman and Company.

Bergamin, P., & Hirt, F. S. (2018). Who's in charge?—Dealing with the self-regulation dilemma in digital learning environments. In K. North, R. Maier, & O. Haas (Eds.), *Knowledge management in digital change* (pp. 227–245). Springer. https://doi.org/10.1007/978-3-319-73546-7_14

Bitzenbauer, P., Höfler, S., Veith, J. M., Winkler, B., Zenger, T., & Kulgemeyer, C. (2024). Exploring the relationship between surface features and explaining quality of YouTube explanatory videos. *International Journal of Science and Mathematics Education, 22*(1), 25–48. https://doi.org/10.1007/s10763-022-10351-w

Bohrnstedt, G. W., Zhang, J., Park, B. J., Ikoma, S., Broer, M., & Ogut, B. (2020). Mathematics identity, self-efficacy, and interest and their relationships to mathematics achievement: A longitudinal analysis. In R. T. Serpe, R. Stryker, & B. Powell (Eds.), *Identity and symbolic interaction* (pp. 169–210). Springer. https://doi.org/10.1007/978-3-030-41231-9_7

Callan, G. L., DaVia Rubenstein, L., Barton, T., & Halterman, A. (2022). Enhancing motivation by developing cyclical self-regulated learning skills. *Theory into Practice, 61*(1), 62–74. https://doi.org/10.1080/00405841.2021.1932153

Carneiro, R., Lefrere, P., Lefrere, K., & Underwood, J. (2011). *Self-regulated learning in technology enhanced learning environments: A European perspective*. Sense Publishers. https://doi.org/10.1016/j.ssaho.2022.100381

Carreira, S., Jones, K., Amado, N., Jacinto, H., & Nobre, S. (2016). *Youngsters solving mathematical problems with technology: The results and implications of the Problem@Web Project*. Springer. https://doi.org/10.1007/978-3-319-24910-0

Chugh, R., & Turnbull, D. (2023). Gamification in education: A citation network analysis using CitNetExplorer". *Contemporary Educational Technology, 15*(2), 1–21. https://doi.org/10.30935/cedtech/12863

Chugh, R., Turnbull, D., Cowling, M. A., Vanderburg, R., & Vanderburg, M. A. (2023). Implementing educational technology in higher education institutions: A review of technologies, stakeholder perceptions, frameworks and metrics. *Education and Information Technologies, 28*, 16403–16429. https://doi.org/10.1007/s10639-023-11846-x

Cole, P. M., Ram, N., & English, M. S. (2019). Toward a unifying model of self-regulation: A developmental approach. *Child Development Perspectives, 13*(2), 91–96. https://doi.org/10.1111/cdep.12316

Demir, C. G., & Önal, N. (2021). The effect of technology-assisted and project-based learning approaches on students' attitudes towards mathematics and their academic achievement. *Education and Information Technologies, 26*(3), 3375–3397. https://doi.org/10.1007/s10639-020-10398-8

Dunn, T. J., & Kennedy, M. (2019). Technology enhanced learning in higher education: Motivations, engagement and academic achievement. *Computers & Education, 137*, 104–113. https://doi.org/10.1016/j.compedu.2019.04.004

Evans, D., Butterworth, R., & Law, G. U. (2019). Understanding associations between perceptions of student behaviour, conflict representations in the teacher-student relationship and teachers' emotional experiences. *Teaching and Teacher Education, 82*, 55–68. https://doi.org/10.1016/j.tate.2019.03.008

Fiorella, L., Yoon, S. Y., Atit, K., Power, J. R., Panther, G., Sorby, S., Uttal, D. H., & Veurink, N. (2021). Validation of the mathematics motivation questionnaire (MMQ) for secondary school students. *International Journal of STEM Education, 8*, Article 52. https://doi.org/10.1186/s40594-021-00307-x

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Fowler, S., Cutting, C., Kennedy, J., Leonard, S. N., Gabriel, F., & Jaeschke, W. (2022). Technology enhanced learning environments and the potential for enhancing spatial reasoning: A mixed methods study. *Mathematics Education Research Journal, 34*, 887–910. https://doi.org/10.1007/s13394-021-00368-9

Goff, E. E., Mulvey, K. L., Irvin, M. J., & Hartstone-Rose, A. (2018). Applications of augmented reality in informal science learning sites: A review. *Journal of Science Education and Technology, 27*, 433–447. https://doi.org/10.1007/s10956-018-9734-4

Guillemin, F., Bombardier, C., & Beaton, D. (1993). Cross-cultural adaptation of health-related quality of life measures: Literature review and proposed guidelines. *Journal of Clinical Epidemiology, 46*(12), 1417–1432. https://doi.org/10.1016/0895-4356(93)90142-N

Guo, M., Hu, X., & Leung, F. K. (2022). Culture, goal orientations, and mathematics achievement among Chinese students. *International Journal of Science and Mathematics Education, 20*, 1225–1245. https://doi.org/10.1007/s10763-021-10202-0

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis*. Prentice Hall.

Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

He, T., & Li, S. (2019). A comparative study of digital informal learning: The effects of digital competence and technology expectancy. *British Journal of Educational Technology, 50*(4), 1744–1758. https://doi.org/10.1111/bjet.12778

He, T., & Zhu, C. (2017). Digital informal learning among Chinese university students: The effects of digital competence and personal factors. *International Journal of Educational Technology in Higher Education, 14*, Article 44. https://doi.org/10.1186/s41239-017-0082-x

He, T., Huang, Q., Yu, X., & Li, S. (2021). Exploring students' digital informal learning: The roles of digital competence and DTPB factors. *Behaviour & Information Technology, 40*(13), 1406–1416. https://doi.org/10.1080/0144929X.2020.1752800

Heidari, E., Mehrvarz, M., Marzooghi, R., & Stoyanov, S. (2021). The role of digital informal learning in the relationship between students' digital competence and academic engagement during the COVID-19 pandemic. *Journal of Computer Assisted Learning, 37*(4), 1154–1166. https://doi.org/10.1111/jcal.12553

Hoffman, A.J., McGuire, L., Rutland, A., Hartstone-Rose, A., Irvin, M.J., Winterbottom, M., ... & Mulvey, K.L. (2021). The relations and role of social competencies and belonging with math and science interest and efficacy for adolescents in informal STEM programs. *Journal of Youth and Adolescence, 50*(2), 314–323. https://doi.org/10.1007/s10964-020-01302-1

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hurst, M. A., Polinsky, N., Haden, C. A., Levine, S. C., & Uttal, D. H. (2019). Leveraging research on informal learning to inform policy on promoting early STEM. *Social Policy Report, 32*(3), 1–33. https://doi.org/10.1002/sop2.5

Hwang, W. Y., & Purba, S. W. D. (2022). Effects of ubiquitous-physics app on students' inquiry behaviors and learning achievements. *The Asia-Pacific Education Researcher, 31*, 439–450. https://doi.org/10.1007/s40299-021-00585-7

Jagušt, T., Botički, I., & So, H. J. (2018). A review of research on bridging the gap between formal and informal learning with technology in primary school contexts. *Journal of Computer Assisted Learning, 34*(4), 417–428. https://doi.org/10.1111/jcal.12252

Jenßen, L., Roesken-Winter, B., & Blömeke, S. (2023). Measuring pre-service primary teachers' shame in mathematics—a comprehensive validation study. *International Journal of Science and Mathematics Education, 21*, 463–488. https://doi.org/10.1007/s10763-022-10253-x

Jiang, H., Wang, K., Wang, X., Lei, X., & Huang, Z. (2021). Understanding a STEM teacher's emotions and professional identities: A three-year longitudinal case study. *International Journal of STEM Education, 8*, Article 51. https://doi.org/10.1186/s40594-021-00309-9

Jiang, H., Turnbull, D., Wang, X., Chugh, R., Dou, Y., & Chen, S. (2022). How do mathematics interest and self-efficacy influence coding interest and self-efficacy? A structural equation modeling analysis. *International Journal of Educational Research, 115*, 102058. https://doi.org/10.1016/j.ijer.2022.102058

Jiang, H., Chugh, R., Turnbull, D., Wang, X., & Chen, S. (2023). Modeling the impact of intrinsic coding interest on STEM career interest: Evidence from senior high school students in two large Chinese cities. *Education and Information Technologies, 28*, 2639–2659. https://doi.org/10.1007/s10639-022-11277-0

Jiang, H., Islam, A. Y. M. A., Gu, X., & Guan, J. (2024). How do thinking styles and STEM attitudes have effects on computational thinking? A structural equation modeling analysis. *Journal of Research in Science Teaching, 61*(3), 645–673. https://doi.org/10.1002/tea.21899

Kline, R. B. (2005). *Principles and practices of structural equation modeling*. Guilford Press.

La Guardia, J. G., & Patrick, H. (2008). Self-determination theory as a fundamental theory of close relationships. *Canadian Psychology/Psychologie Canadienne, 49*(3), 201–209. https://doi.org/10.1037/a0012760

Lee, S. W. Y., & Tsai, C. C. (2011). Students' perceptions of collaboration, self-regulated learning, and information seeking in the context of Internet-based learning and traditional learning. *Computers in Human Behavior, 27*(2), 905–914. https://doi.org/10.1016/j.chb.2010.11.016

Legault, L. (2017). Self-determination theory. In V. Zeigler-Hill & T. Shackelford (Eds.), *Encyclopedia of personality and individual differences* (pp. 1–9). Springer. https://doi.org/10.1007/978-3-319-28099-8_1162-1

Li, Y. (2018). Journal for STEM education research—Promoting the development of interdisciplinary research in STEM education. *Journal for STEM Education Research, 1*(1–2), 1–6. https://doi.org/10.1007/s41979-018-0009-z

Li, Y., & Schoenfeld, A. H. (2019). Problematizing teaching and learning mathematics as "given" in STEM education. *International Journal of STEM Education, 6*, Article 44. https://doi.org/10.1186/s40594-019-0197-9

Liu, C., Hou, J., Tu, Y. F., Wang, Y., & Hwang, G. J. (2023). Incorporating a reflective thinking promoting mechanism into artificial intelligence-supported English writing environments. *Interactive Learning Environments, 31*(9), 5614–5632. https://doi.org/10.1080/10494820.2021.2012812

Livingstone, D. W. (2001). *Adults' informal learning: Definitions, findings, gaps and future research.* Centre for the Study of Education and Work, OISE/UT.

Lock, R. M., Hazari, Z., & Potvin, G. (2019). Impact of out-of-class science and engineering activities on physics identity and career intentions. *Physical Review Physics Education Research, 15*(2), 020137. https://doi.org/10.1103/PhysRevPhysEducRes.15.020137

Maiorca, C., Roberts, T., Jackson, C., Bush, S., Delaney, A., Mohr-Schroeder, M. J., & Soledad, S. Y. (2021). Informal learning environments and impact on interest in STEM careers. *International Journal of Science and Mathematics Education, 19*(1), 45–64. https://doi.org/10.1007/s10763-019-10038-9

Marcus, M., Haden, C. A., & Uttal, D. H. (2018). Promoting children's learning and transfer across informal science, technology, engineering, and mathematics learning experiences. *Journal of Experimental Child Psychology, 175*, 80–95. https://doi.org/10.1016/j.jecp.2018.06.003

McNeish, D. (2016). Missing data methods for arbitrary missingness with small samples. *Journal of Applied Statistics, 44*(1), 24–39. https://doi.org/10.1080/02664763.2016.1158246

Mehrvarz, M., Heidari, E., Farrokhnia, M., & Noroozi, O. (2021). The mediating role of digital informal learning in the relationship between students' digital competence and their academic performance. *Computers & Education, 167*, 104184. https://doi.org/10.1016/j.compedu.2021.104184

Morris, B. J., Owens, W., Ellenbogen, K., Erduran, S., & Dunlosky, J. (2019). Measuring informal STEM learning supports across contexts and time. *International Journal of STEM Education, 6*, Article 40. https://doi.org/10.1186/s40594-019-0195-y

Müller, N. M., & Seufert, T. (2018). Effects of self-regulation prompts in hypermedia learning on learning performance and self-efficacy. *Learning and Instruction, 58*, 1–11. https://doi.org/10.1016/j.learninstruc.2018.04.011

Neher-Asylbekov, S., & Wagner, I. (2023). Effects of out-of-school STEM learning environments on student interest: A critical systematic literature review. *Journal for STEM Education Research, 6*(1), 1–44. https://doi.org/10.1007/s41979-022-00080-8

Palalas, A., & Wark, N. (2020). The relationship between mobile learning and self-regulated learning: A systematic review. *Australasian Journal of Educational Technology, 36*(4), 151–172. https://doi.org/10.14742/ajet.5650

Parviainen, P., Eklund, K., Koivula, M., Liinamaa, T., & Rutanen, N. (2023). Teaching early mathematical skills to 3-to 7-year-old children—Differences related to mathematical skill category, children's age group and teachers' characteristics. *International Journal of Science and Mathematics Education, 21*, 1961–1983. https://doi.org/10.1007/s10763-022-10341-y

Pattison, S., Rubin, A., & Wright, T. (2016). *Mathematics in informal learning environments: A summary of the literature.* http://www.informalscience.org/mathematics-informal-learning-environments-summary-literature. Accessed 15 May 2023.

Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review, 18*(4), 315–341. https://doi.org/10.1007/s10648-006-9029-9

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The achievement emotions questionnaire (AEQ). *Contemporary Educational Psychology, 36*(1), 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Petkovic, S. (2018). *Desk study on the value of informal education, with special attention to its contribution to citizenship education, civic participation and intercultural dialogue and learning, European citizenship, peace-building and conflict transformation*. The European Union and the Council of Europe Youth Partnership, 1–21. Retrieved from https://pjp-eu.coe.int/documents/42128013/47261707/Desk-Study-Value-of-INFED.pdf/05fd448e-6e01-23cf-03ca-010c982cdf8a. Accessed 1 Aug 2023.

Pierce, R., Stacey, K., & Barkatsas, A. (2007). A scale for monitoring students' attitudes to learning mathematics with technology. *Computers & Education, 48*(2), 285–300. https://doi.org/10.1016/j.compedu.2005.01.006

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic Press.

Roberts, T., Jackson, C., Mohr-Schroeder, M.J., Bush, S.B., Maiorca, C., Cavalcanti, M., ... & Cremeans, C. (2018). Students' perceptions of STEM learning after participating in a summer informal learning experience. *International Journal of STEM Education, 5*(1), 1–14. https://doi.org/10.1186/s40594-018-0133-4

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Satyam, V. R., Simpson, A., DiNapoli, J., & Yao, X. (2020). Building a robot: Making mathematics visible in a non-formal STEM learning environment. In A. I. Sacristán, J. C. Cortés-Zavala, & P. M. Ruiz-Arias (Eds.), *Mathematics education across cultures: Proceedings of the 42nd annual meeting of the North American chapter of the international group for the psychology of mathematics education* (pp. 2353–2354). PME-NA. https://doi.org/10.51272/pmena.42.2020

Seifert, T., & Har-Paz, C. (2020). The effects of mobile learning in an EFL class on self-regulated learning and school achievement. *International Journal of Mobile and Blended Learning, 12*(3), 49–65. https://doi.org/10.4018/IJMBL.2020070104
Shaby, N., Assaraf, O. B. Z., & Koch, N. P. (2023). Students' interactions during laboratory group activity in a science museum. *International Journal of Science and Mathematics Education*. https://doi.org/10.1007/s10763-023-10404-8
Shen, C. W., & Ho, J. T. (2020). Technology-enhanced learning in higher education: A bibliometric analysis with latent semantic approach. *Computers in Human Behavior, 104*, 106177.https://doi.org/10.1016/j.chb.2019.106177
Slattery, E. L., Voelker, C. C., Nussenbaum, B., Rich, J. T., Paniello, R. C., & Neely, J. G. (2011). A practical guide to surveys and questionnaires. *Otolaryngology-Head and Neck Surger, 144*(6), 831–837. https://doi.org/10.1177/0194599811399724
Smart, J. B. (2014). A mixed methods study of the relationship between student perceptions of teacher-student interactions and motivation in middle level science. *RMLE Online, 38*(4), 1–19. https://doi.org/10.1080/19404476.2014.11462117
Stein, C. M., Morris, N. J., & Nock, N. L. (2012). Structural equation modeling. In R. Elston, J. Satagopan, & S. Sun (Eds.), *Statistical human genetics* (pp. 495–512). Springer. https://doi.org/10.1007/978-1-61779-555-8_27
Stevens, J. P. (2009). *Applied multivariate statistics for the social sciences*. Routledge.
Stevens, T., & Olivarez, A. (2005). Development and evaluation of the mathematics interest inventory. *Measurement and Evaluation in Counseling and Development, 38*(3), 141–152. https://doi.org/10.1080/07481756.2005.11909775
Tang, X., & Zhang, D. (2020). How informal science learning experience influences students' science performance: A cross-cultural study based on PISA 2015. *International Journal of Science Education, 42*(4), 598–616. https://doi.org/10.1080/09500693.2020.1719290
Theobald, M. (2021). Self-regulated learning training programs enhance university students' academic performance, self-regulated learning strategies, and motivation: A meta-analysis. *Contemporary Educational Psychology, 66*, 101976. https://doi.org/10.1016/j.cedpsych.2021.101976
Toh, Y., So, H. J., Seow, P., & Chen, W. (2017). Transformation of participation and learning: Three case studies of young learners harnessing mobile technologies for seamless science learning. *The Asia-Pacific Education Researcher, 26*, 305–316. https://doi.org/10.1007/s40299-017-0350-5
Viberg, O., Andersson, A., & Wiklund, M. (2021). Designing for sustainable mobile learning–re-evaluating the concepts "formal" and "informal." *Interactive Learning Environments, 29*(1), 130–141. https://doi.org/10.1080/10494820.2018.1548488
Villavicencio, F. T., & Bernardo, A. B. I. (2016). Beyond math anxiety: Positive emotions predict mathematics achievement, self-regulation, and self-efficacy. *The Asia-Pacific Education Researcher, 25*(3), 415–422. https://doi.org/10.1007/s40299-015-0251-4
Walan, S., & Gericke, N. (2021). Factors from informal learning contributing to the children's interest in STEM–experiences from the out-of-school activity called Children's University. *Research in Science & Technological Education, 39*(2), 185–205. https://doi.org/10.1080/02635143.2019.1667321
Wang, C. J. (2023). Learning and academic self-efficacy in self-regulated learning: Validation study with the BOPPPS model and IRS methods. *The Asia-Pacific Education Researcher, 32*, 37–51. https://doi.org/10.1007/s40299-021-00630-5
Xu, Z., & Jang, E. E. (2017). The role of math self-efficacy in the structural model of extracurricular technology-related activities and junior elementary school students' mathematics ability. *Computers in Human Behavior, 68*, 547–555. https://doi.org/10.1016/j.chb.2016.11.063
Yuan, Z., Tan, J., & Ye, R. (2023). A cross-national study of mathematics anxiety. *The Asia-Pacific Education Researcher, 32*, 295–306. https://doi.org/10.1007/s40299-022-00652-7
Zhang, D., & Wang, C. (2020). The relationship between mathematics interest and mathematics achievement: Mediating roles of self-efficacy and mathematics anxiety. *International Journal of Educational Research, 104*, 101648. https://doi.org/10.1016/j.ijer.2020.101648
Zhao, G., Wang, Q., Wu, L., & Dong, Y. (2022). Exploring the structural relationship between university support, students' technostress, and burnout in technology-enhanced learning. *The Asia-Pacific Education Researcher, 31*, 463–473. https://doi.org/10.1007/s40299-021-00588-4
Zhou, D., Du, X., Hau, K. T., Luo, H., Feng, P., & Liu, J. (2020). Teacher-student relationship and mathematical problem-solving ability: Mediating roles of self-efficacy and mathematical anxiety. *Educational Psychology, 40*(4), 473–489. https://doi.org/10.1080/01443410.2019.1696947

Zhu, S., & Meyer, P. (2022). A comparative study of mathematics self-beliefs between students in Shanghai-China and the USA. *The Asia-Pacific Education Researcher, 31*(1), 81–91. https://doi.org/10.1007/s40299-020-00540-y

Ziegler, N., & Opdenakker, M. C. (2018). The development of academic procrastination in first-year secondary education students: The link with metacognitive self-regulation, self-efficacy, and effort regulation. *Learning and Individual Differences, 64*, 71–82. https://doi.org/10.1016/j.lindif.2018.04.009

Authors and Affiliations

Haozhe Jiang[1] · **Ritesh Chugh**[2] · **Darren Turnbull**[2] · **Xiaoqin Wang**[3] · **Suting Chen**[4]

Haozhe Jiang
jianghaozhe_ecnu@foxmail.com

Darren Turnbull
d.turnbull@cqu.edu.au

Xiaoqin Wang
wangxiaoqin_ecnu@163.com

Suting Chen
gench_math@163.com

1 College of Education, Zhejiang University, Zhejiang Province, Hangzhou 310058, People's Republic of China

2 School of Engineering and Technology, CML-NET & CREATE Research Centres, Central Queensland University, North Rockhampton, QLD 4702, Australia

3 College of Teacher Education, Faculty of Education, East China Normal University, Shanghai 200062, People's Republic of China

4 Shanghai Jian Qiao University, Shanghai 201306, People's Republic of China