Received: 20 September 2021 | Revised: 7 September 2022 | Accepted: 5 November 2022

DOI: 10.1111/jcal.12759

REVIEW ARTICLE

Journal of Computer Assisted Learning WILEY

The effects of mobile technology usage on cognitive, affective, and behavioural learning outcomes in primary and secondary education: A systematic review with meta-analysis

Jingxian Wang[1] | Dineke E. H. Tigelaar[2] | Tian Zhou[1] | Wilfried Admiraal[3]

[1]Center for Studies of Education and Psychology of Minorities in Southwest China of Southwest University, Southwest University, Chongqing, China

[2]ICLON, Leiden University Graduate School of Teaching, Leiden University, Leiden, The Netherlands

[3]Centre for the Study of Professions, Oslo Metropolitan University, Oslo, Norway

Correspondence
Jingxian Wang, Center for Studies of Education and Psychology of Minorities in Southwest China of Southwest University, Southwest University, No. 2 Tiansheng Road, BeiBei District, Chongqing 400715, China.
Email: j.wang@iclon.leidenuniv.nl

Funding information
Chongqing Social Science Planning Doctoral Project (Research on the Construction Mechanism of "Digital Pedestal" for the Integration of Urban and Rural Education), Grant/Award Number: 2021BS089

Abstract

Background: The impact of mobile technology usage on student learning in various educational stages has been the subject of ongoing empirical and review research. The most recent meta-analyses on various types of mobile technology use for potential benefits of learning covered the empirical studies up to about nine years ago. Since then, the use of mobile technology in primary and secondary education has increased tremendously, and numerous empirical studies have been conducted on this topic, but their conclusions were inconsistent.

Objectives: The purpose of this systematic review is to re-examine this issue by meta-analyzing the empirical research studies from the last nine years, with a focus on cognitive, affective, and behavioral learning outcomes in primary and secondary education, and to examine the potential moderators that may have contributed to the heterogeneity across findings.

Methods: Based on our inclusion and exclusion criteria, we found 85 studies of 78 peer-reviewed papers (N = 9157) from electronic databases and major journals in educational technology and mobile learning between 2014 and 2022. We then examined 15 moderators that were expected to affect student learning outcomes.

Results and Conclusions: Compared with traditional technology and non-technology groups, using mobile technology produced medium positive and statistically significant effects on primary and secondary students' learning, in terms of cognitive (g = 0.498, 95% CI [0.382, 0.614]), affective (g = 0.449, 95% CI [0.301, 0.598]) and behavioural (g = 0.339, 95% CI [0.051, 0.627]) learning outcomes. Further moderator analyses revealed that student factors (i.e., community type, students' socioeconomic status), learning process (i.e., hardware used, student-to-hardware ratio, teaching method) and study quality (i.e., learning topic/content equivalence, degree of technology use in the control group) were among the variables that moderated the summary effect sizes for at least one learning outcome dimension significantly. The findings and their implications for researchers, policymakers and practitioners are discussed.

KEYWORDS
learning outcomes, meta-analysis, mobile learning, primary education, secondary education

1 | INTRODUCTION

Mobile technology is characterized by wireless internet-connected devices that can influence student learning through specific affordances. For example, mobile devices with diverse functions such as instant feedback, speech recognition, and peer assessment enrich learning opportunities and meet students' demands, prompting higher learning achievement. While classroom lectures with traditional technologies (e.g., desktop computers, pen and papers) can address problem-solving in isolation, the traditional approach lacks possibilities for learners to apply what they have learned. Considering the rapid growth and affordability of mobile technology, mobile learning, known as 'learning across multiple contexts, through social and content interactions using personal electronic devices' (Crompton, 2013, p. 4), has become a fast-growing research field. Recent research shows that instantly gathering student data from mobile devices can help teachers monitor students' learning progress and deliver differentiated instruction (Lee et al., 2019). Beyond the importance to teachers, the potential benefits of mobile technology usage are related to different learning outcomes. Researchers found that allowing students to use mobile devices to conduct computer simulations improved subject achievement in the language (Alfadil, 2020) and science (Chang et al., 2020). Because students perceive mobile devices as exciting learning aids, they can be used to improve affective learning outcomes including lowering learning anxiety (Lee et al., 2019) and fostering attitude towards the course and mobile technology (Sahin & Yilmaz, 2020). The mobility of mobile devices facilitates social interaction (Hwang et al., 2018) and knowledge co-creation (Lim et al., 2019). Therefore, mobile technology affords students to learn individually and collectively (Koole, 2009). There are some minor concerns on mobile learning, however, regarding distractive effect (Zhai et al., 2019), self-control challenges (Troll et al., 2020), and heavy cognitive load (Chu, 2014).

Technology in itself does not result in higher learning outcomes until a user starts interacting with it. Therefore, different mobile technology usage may have different educational effects or affordances. Moreover, the overall effects of mobile technology usage on learning outcomes vary by population, intervention, and culture. Focusing on evaluating the effects of mobile technology usage in general and the specific moderator variables may thus provide some important insights into how best to design and use mobile technology to facilitate learning. To date, the pooled effects of mobile technology usage on learning have mainly been limited to cognitive learning. We argue that the targeted learning goals for '21st-century skills' include cognitive, affective, and behavioural goals. Recent highly cited articles on mobile learning have focused more on the affective and behavioural dimensions (Lai, 2020). It is yet to be known the overall effects of mobile technology on non-cognitive learning outcomes, which play a vital role in understanding students' learning from alternative perspectives. Besides, the diverse results for contextual factors of learning with mobile technology suggest that there is a need for further clarification regarding the impact of potential moderators, such as student factors, hardware affordances, duration of intervention, and teaching methods. To quantify the overall effects of mobile technology usage on cognitive, affective, and behavioural learning outcomes, and to identify potential moderators affecting the overall effect for each outcome, we employed a meta-analysis to compare mobile learning effects with traditional learning in primary and secondary education. Our results from an up-to-date meta-analytic synthesis may provide a rich overview of the current mobile-learning practices and their overall effects, informing researchers, policymakers and practitioners on how best to integrate mobile technology in teaching and learning.

1.1 | Previous narrative reviews of learning with mobile technologies

Narrative reviews regarding mobile learning published over the past 3 years have been performed in various educational contexts (e.g., Chung et al., 2019; Diacopoulos & Crompton, 2020; Lai, 2020; Suarez et al., 2018). These studies have examined various dimensions of learning outcomes such as Bloom's taxonomy of educational objectives (Chung et al., 2019), learners' agency (Suarez et al., 2018), thinking skills, engagement and collaboration (Diacopoulos & Crompton, 2020). Academics also constrained narrative reviews to school-aged students. Crompton et al. (2017) conducted a systematic review from 2010 to 2015, investigating the general characteristics of 113 mobile-learning studies conducted in PK-12 (students ages 2–18), such as research purposes, methodologies, and outcomes, domains, contexts, and learning activities. In 2019, Crompton and her colleagues (Crompton et al., 2019) published an up-to-date analysis of students' cognitive learning level as measured by Bloom's Taxonomy in PK-12 mobile learning research. They reviewed 101 articles from 2010 to 2016 and found that mobile devices were integrated into more subjects. Similarly, Crompton and Burke (2020) applied the Substitution, Augmentation, Modification, and Redefinition (SAMR) framework to examine PK-12 studies from 2014 to 2019. They found that mobile technologies were sometimes used to replicate activities without functional changes. Besides, Burden et al. (2019) systematically reviewed 57 studies from 2010 to 2017 focused on innovative mobile learning practices in K-12 education. However, these studies were limited as papers were identified through either the top journals or database searches, which may not represent all works published on mobile learning. Also, the included studies were often published before 2015 (Crompton et al., 2017), conducted in special education settings (Crompton et al., 2019; Crompton & Burke, 2020), or lack comparison groups (Crompton et al., 2017), which means they cannot generally reflect the current mainstream practice or makes it challenging to evaluate the interventions.

1.2 | Previous meta-analyses of effects of mobile technology usage on learning outcomes

Numerous experimental or quasi-experimental studies have been conducted to investigate the effects of mobile technology usage. The findings of these primary studies as listed in Table 1 have been synthesized in at least eight meta-analyses. However, most meta-analyses

TABLE 1 Eight meta-analyses of mobile learning research over the last 5 years, ordered by year of publication

Meta-analyses (year)	Inclusive dates	K	Average ES	Education levels	Subjects	Devices	Learning outcomes
Castillo-Manzano et al. (2016)	2008–2012	53	0.48	University, non-university	Various	Audience-response devices	Examination scores
Fabian et al. (2016)	2003–2012	14	0.48	Elementary education	Mathematics	Various	Student scores
Hunsu et al. (2016)	2001–2014	86 for cognitive; 25 for non-cognitive	0.05 for cognitive; 0.23 for non-cognitive	K-12, college	Various	Clicker-based technologies	Cognitive and non-cognitive learning outcomes (i.e., Attitudinal and behavioural learning outcome)
Sung et al. (2016)	1993–2013	108 articles for cognitive; 22 for affective	0.523 for cognitive; 0.433 for affective	Kindergarten, elementary school, middle school, high school, college, adults	Various	Various	Cognitive and affective learning outcomes
Sung, Yang, and Lee (2017)	2000–2015	163	0.516	Kindergarten, elementary school, junior high school, senior high school, college, graduate school, and adults	Various	Various	Learning achievement, learning attitude, and peer interaction for collaborative learning
Cho et al. (2018)	2008–2017	22	0.51	Primary, secondary, and post-secondary	Language	Various	Tests
Mahdi (2018)	2009–2015	16	0.67	Young and adult learners	Language	Various	Vocabulary tests
Yang et al. (2020)	2001–2017	87	0.803	Various	Various	Various	Cognitive and affective learning outcome for inquiry-based learning

had a limited scope, either to synthesize a single outcome variable (Castillo-Manzano et al., 2016; Cho et al., 2018; Fabian et al., 2016; Yang et al., 2020), or to centre on specific subjects (Castillo-Manzano et al., 2016; Cho et al., 2018; Mahdi, 2018), or particular mobile devices (Castillo-Manzano et al., 2016; Hunsu et al., 2016). We found three broader meta-analyses aimed at various mobile technology use for potential benefits of cognitive and non-cognitive learning in all grades and disciplines. Sung et al. (2016) investigated the effects of integrating mobile devices on learning in comparison with control groups that used traditional learning, that cut across all levels of learning stages from 1993 to 2013. They found a significant medium average effect size (ES) of $g = 0.523$ for learning achievement and $g = 0.433$ for affective outcome variables, compassing 110 journal articles. Besides, unlike other reviews, Sung and his colleagues focused on different teaching methods, for example, inquiry-based learning (Sung, Yang, & Lee, 2017) and collaborative learning (Yang et al., 2020).

Although the above meta-analyses have added academic understanding to the effects of mobile technology usage, they did not distinguish between affective and behavioural learning outcomes from non-cognitive outcomes, nor consider conducting moderator analyses related to these non-cognitive outcome variables. Moreover, it is hard to determine what happens to primary and secondary students and see how mobile devices boost their learning in various ways. To address these concerns, we have conducted this meta-analysis, which differs from previous studies for the following reasons. First, an addition from 2014 on is necessary because of the large number of studies. Secondly, the current study is not limited to cognitive learning outcomes but also includes non-cognitive learning outcomes. We examined the effects of mobile technology usage on three dimensions of learning outcomes. Cognitive, behavioural, and affective outcomes were used to categorize the learning outcomes (see e.g., Hunsu et al., 2016). Third, we considered a series of factors from both educational and methodological aspects, which are supposed to moderate the effectiveness of the mobile technology intervention.

1.3 | Potential moderator variables considered

We adopted the 3P (presage–process–product) model (Biggs, 2003) to determine the primary aspects of moderators that could reflect the full picture of teaching and learning within the mobile technology integration context. The 3P model provides us to comprehend the relationships among student and teaching context presage factors, learning process factors, and product factors (learning outcomes) within the context of mobile technology usage. Moreover, higher methodological quality studies could have provided substantially different results than less quality studies (Cheung & Slavin, 2016). Therefore, the potential moderators which were derived from relevant studies conducted earlier have been grouped into four categories: student factors, teaching context, learning process, and study quality. A total of 17 variables (i.e., two variables related to student factors, six variables related to teaching context, five variables related to learning process, and four variables related to study quality) were considered as potential moderators.

First, community type and student socioeconomic status (SES) have been considered as student factors. The socio-cultural background is crucial for ensuring adequate Internet access and use conditions. Much has been done in recent decades to address the digital divide, particularly the unequal distribution of educational technologies and 'hidden curriculum' among urban, suburban, and rural schools (Hess & Leal, 2001; Li & Ranieri, 2013). Empirical studies also indicated that the impact of online adaptive learning tools on primary school students' mathematics test scores increase as the socioeconomic status of students decreases (Perera & Aboal, 2019). In order to explore whether students from rural or suburban schools or those with low SES are more disadvantaged in mobile learning than their peers, community type and SES are considered potential moderators.

Second, teaching context factors include education level (including primary and secondary school, for example, Sung et al., 2016), school type (e.g., public and private school), learning environment (including formal, informal, and unrestricted settings, e.g., Sung et al., 2016; Yang et al., 2020), school subjects (including language arts, social studies, mathematics etc., e.g., Sung et al., 2016), and provision of teacher training on content and on technology before interventions (Hillmayr et al., 2020). Third, hardware used (including laptop, tablet PCs, mobile phone, classroom response systems, etc, e.g., Sung et al., 2016), student-to-hardware ratio (including own, pairwise, and in groups, et al., Hillmayr et al., 2020), software used (including general-purpose and learning-oriented software, e.g., Chauhan, 2017; Sung et al., 2016), teaching method (including lectures, cooperative learning, game-based learning, self-directed learning, computer-assisted testing/assessment, and mixed methods., e.g., Sung et al., 2016) and duration of intervention (including ≤4 h, >4 and ≤24 h, >1 and ≤7 days, >1 and ≤4 weeks, >1 month and ≤6 months, >6 months, e.g., Sung et al., 2016; Sung, Hwang, et al., 2017) are selected as the learning process factors. Fourth, we examine whether the different results between the studies could be explained by research design (including quasi-experimental and experimental design, e.g., Hillmayr et al., 2020), instructor equivalence (including same and different instructor for experimental and control groups, e.g., Schmid et al., 2014), degree of technology use in the control group (including pen-and-paper, traditional technology, e.g., Sung et al., 2016), and the procedure of ES extraction (including calculated from exact descriptive and calculated from inferential statistics, e.g., Schmid et al., 2014). Although researchers have constantly discussed the significance of the above variables (see e.g., Chauhan, 2017; Schmid et al., 2014; Sung et al., 2016; Zheng et al., 2016), below we go into detail on our rationale for the selected five moderator variables related to the learning process, which might provide a deeper insight in the implementation and evaluation of the interventions of interest.

The learning process factors can typically be described by three main aspects: human resources, technological resources, and intervention duration. First, human resources primarily refer to teachers, especially the type of pedagogy they adopted that supports students to acquire knowledge and their interaction processes. Several meta-analyses (see e.g., Sung, Hwang, et al., 2017; Yang et al., 2020) have shown that different teaching methods implemented in mobile learning context produce different effects. In Sung et al.'s (2016) study, the largest learning-achievement ES was found for inquiry-oriented learning, followed by mixed methods, while cooperative learning and game-based learning yielded insignificant ESs. Second, technological resources primarily relate to the degree of resource access and differences in resource usage that supports educational processes. Regarding technology access, a meta-analysis (Hillmayr et al., 2020) examining the potential of digital tools to enhance mathematics and science learning in secondary schools indicated that pairwise use of digital tools by students yielded larger ESs than if they use media on their own but no significant differences were found. The most common variables with regard to the differences of resource usage are hardware and software used for learning. Sung et al. (2016) found that the ESs differed significantly among the various hardware including handheld, laptops and mixed devices, and larger effects were reported for learning-oriented software than for general software designed for commercial purposes. In terms of function, mobile devices with multiple functions, including tablet PCs and mobile phones, appeared to produce larger ESs than single-function devices (e.g., classroom response systems, digital pen). Third, intervention duration refers to the duration between time prior intervention and time post intervention. Mobile learning interventions conducted for durations of >4 weeks and ≤6 moths had highest ESs (Sung et al., 2016). If the intervention duration is too long, the effects could decline because students feel less motivated (Lee et al., 2019) and received less support.

1.4 | The present study

Given the conflicting empirical research results on the effects of mobile technology usage on learning outcomes over the last decade, given the length of time after the previous broad meta-analyses of research on this issue, and given the fact that many new studies have been conducted in this area since the last meta-analysis, it is unclear if the previous findings (e.g., Sung et al., 2016) about this issue remain relevant and valid. Meta-analyses allow us to describe the current state of the research field, looking for overall effects and possible moderating effects (Borenstein et al., 2009), which could have implications on practice, policy, and future research. Hence, there is a need for an updated comprehensive meta-analysis of the effects of mobile technology usage on students' learning outcomes, particularly in primary and secondary education, which is not limited to cognitive learning outcomes, and which considers a number of educational and methodological factors.

Following the population, intervention, comparison and outcome (PICO) framework, the population is composed of students in primary and secondary education. The intervention is the use of mobile technology for learning. The comparison is made with a non-technology (e.g., pen and paper) or traditional technology group (e.g., desktop computers and whiteboards). Learning outcomes were divided into three categories. Cognitive learning outcomes refer to knowledge retention or recall, and the development of intellectual abilities and skills (Bloom et al., 1956). This category of learning outcomes consists of six major categories: Knowledge, Comprehension, Application, Analysis, Synthesis, and Evaluation. Affective learning outcomes reflect learners' emotions (e.g., anxiety, nervous) and perceptions of their experience and benefits from mobile technology-based learning, including motivation, attitude, value, and satisfaction (Wei et al., 2021). Behavioural learning outcomes relate to learners' engagement and interactions in mobile learning (e.g., time spent conducting experiments, interactions with peers) and performance against learning tasks (e.g., passing a subject test) (Wei et al., 2021). Specifically, this meta-analysis seeks to answer the following research questions:

RQ1: When compared with traditional learning, what is the overall effectiveness of using mobile technologies in primary and secondary education on students' learning outcomes in terms of cognitive, affective, and behavioural dimensions?

RQ2: What, if any, factors based on 3P model, that is student factors, teaching context and learning process factors, moderate the relationship between mobile technology use and learning outcomes?

RQ3: For RQ1 above, what, if any, study quality characteristics explain the heterogeneity in results?

2 | METHOD

2.1 | Inclusion and exclusion criteria

Our criteria for the determination of coding studies and subsequent meta-analysis were developed based on a preliminary literature review on the use of mobile technology for educational purposes. A pre-defined criterion for identifying research samples was listed below:

(a) The study used an experimental or quasi-experimental research design.

(b) The results of the mobile technology intervention group were compared with non-technology (e.g., pen and paper) or traditional technology (e.g., desktop computers and whiteboards) groups.

(c) Learning outcomes were reported as the dependent variable, measured by either cognitive, affective, or behavioural learning outcomes.

(d) Reported original data and provided sufficient information to calculate ESs, such as means, standard deviations, the sample size in each group.

(e) The sample consisted of primary or secondary school students.

(f) Studies were published in peer-reviewed journals, and a full text was available.

(g) Studies were published between 2014 and 2022 and were written in English. The starting year was set in 2014 because we extended Sung et al. (2016) study to understand the mobile learning empirical field over recent years.

Several exclusion criteria were used. Conceptual analysis or research reviews, and qualitative research, pre-experimental studies, editorials and retracted articles were excluded. Moreover, studies on gifted education, special education, or disabilities learning were excluded. Studies involving any children with special educational needs were also excluded because this may have potential impacts on the entire group's performance. In cases where studies met all the inclusion criteria but lacked sufficient descriptive statistics or inferential statistics to calculate ESs were excluded.

2.2 | Literature search and data sources

A literature search was conducted in June 2020 and updated in June 2022. Studies were identified from two different sources. First, a database search was performed on all databases available at the library of Leiden University, such as Web of Science, Elsevier, ERIC, SAGE journals. Four sets of keywords were combined: (1) population (i.e., student); (2) mobile-technology related terms (i.e., mobile technology, mobile device, personal digital assistant, handheld, iPad, laptop, tablet, smart phone, mobile phone, response system); (3) learning-related keywords (i.e., learning outcome, achievement, performance); and (4) research-design related keywords (i.e., experimental, quasi-experimental). For the search, a Boolean OR operator first linked the keywords within each set; a Boolean AND operator was used to combine keywords across the four sets. The terms of mobile technology were searched within titles, and other terms were searched within any field. 1395 peer-reviewed articles were found, and 24 duplicate papers were then removed in Mendeley. In the next step, the title and abstract of each paper were read. Based on our criteria, the first author assessed these 1395 studies to determine 'yes,' 'maybe,' or 'no' (Liberati et al., 2009), and papers in the 'maybe' group were then assigned to the

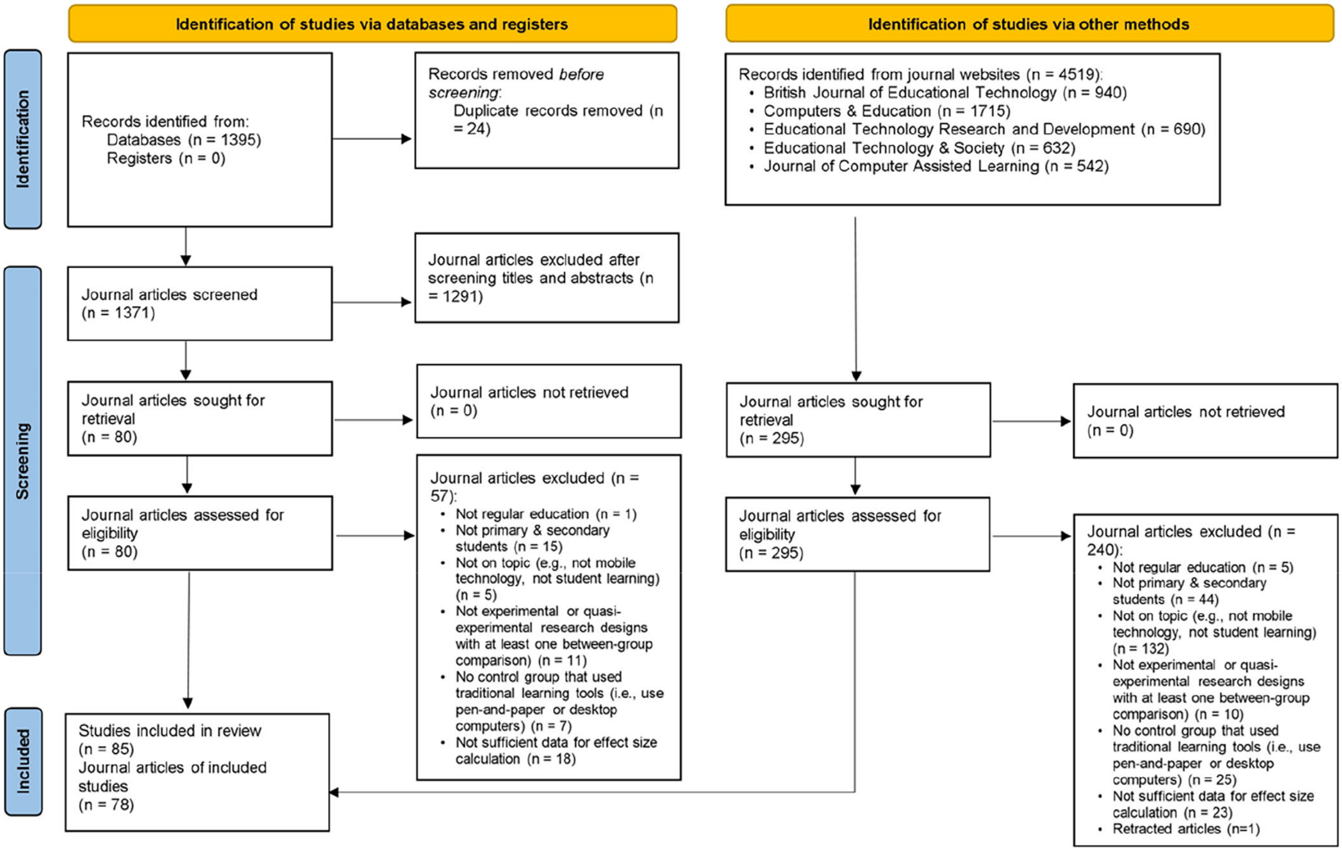

FIGURE 1 Flowchart of the study selection process following the guidelines of the PRISMA 2020 (Page et al., 2021).

other three authors for the final decision. A total of 80 eligible papers were obtained in this stage.

Moreover, we browsed five journals online in June 2020 and updated the search in June 2022, including the British Journal of Educational Technology, Computers & Education, Educational Technology Research and Development, Educational Technology & Society, Journal of Computer Assisted Learning. These journals were selected because they are major educational technology and mobile learning journals included in the Web of Science EDUCATION & EDUCATIONAL RESEARCH category with an impact factor of 3 or higher. The first author collected all the articles published from 2014 to 2022 on each journal website. After removing the 66 duplicates from the 4519 papers contained in the five journals, additional 295 studies were found after screening abstracts, resulting in 375 articles for full-text review. These articles were not found in the first stage and the main reason is that the terms of mobile technologies were searched within titles and these studies used other related terms (e.g., games, mobile learning, mobile application, online tools and clickers).

During the final full-text screening step, at least two authors screened the articles applying the inclusion and exclusion criteria to check for eligibility. There were minor disagreements mostly related to whether mobile technologies were used, and these were discussed among the four authors until they were resolved. This step limited these studies to the 85 studies of 78 journal articles that were included in this meta-analysis. Figure 1 provides a flowchart describing the inclusion process and describes the reasons why studies were excluded, following the guidance of The PRISMA 2020 (Page et al., 2021).

2.3 | Coding of potential moderators

First, a coding sheet was developed mainly based on the coding variables in recent meta-analysis articles (Schmid et al., 2014; Sung et al., 2016). Evidence produced by review, however, was used to assess relationships that primary researchers never examined (Cooper & Hedges, 1994). Thus, a strategy we used to adapt the original coding sheet was to search for possible moderators by evaluating a subset of studies (Brown et al., 2003). After the pilot testing on 22 articles, four variables (i.e., provision of student training on technology before interventions, provision of student training on content before interventions, learning topic/content equivalence, and software/tool equivalence) were added to the coding sheet. After completing the code sheet, a codebook was developed to guide the coding process for all eligible studies.

After coding all the studies, the first author collected all the doubts from 32 articles. Then the second author checked the doubts from the 11 articles, the third author checked doubts from 8 articles, and the fourth author checked the doubts from 13 articles. The second, third and fourth authors indicated when he/she had the same solution, when he/she had a different solution that he/she was quite certain about, and when he/she had a different solution or query which he/she thought the coding members needed to be discussed more. For example, in the study of Jere-Folotiya et al. (2014), the first and second authors had different solutions to software/tool equivalence, and disagreements were resolved through joint discussions among all authors. In this manner, nine disagreements in coding were discussed until a consensus was reached regarding how the variable should be coded during two online meetings.

In total, we coded for 21 variables (17 variables from previous studies introduced in the Section 1 and four variables from our new data) that were supposed to be used as moderators. The four new variables were learning topic/content equivalence, software/tool equivalence, provision of student training on technology before interventions, and provision of student training on content before interventions. Learning topic/content equivalence showed whether the experimental and control groups used the same set of textbook, assignments, subject matter content and topic (see e.g., Schmid et al., 2014). Similarly, software/tool equivalence related to whether the experimental and control groups used the same set of learning software or tools. However, not all were included in the moderator analyses. We excluded six moderators either because of low variability in the outcome (i.e., school type and software used), or because very few studies reported the relevant information (i.e., student and teacher training on technology and content). In the end, 15 variables served as moderators (see Table 3 for the final moderators and their categories).

2.4 | Effect size calculation

In the present meta-analysis, the standardized mean difference between the intervention and the control conditions on the posttest was the dependent variable. We chose the ES of Hedges' g over Cohen's d because it is more accurate for smaller samples (Borenstein et al., 2009). The intervention group outperformed the control group by showing a positive ES. Cohen (1992) indicated that the value of any pooled Hedges' g was viewed as following: small effect ($g = 0.2$), medium effect ($g = 0.5$), and large effect ($g = 0.8$).

Wherever applicable, the ESs were calculated based on the post-baseline means and standard deviations rather than scores reflecting changes from baseline to follow-up, as these are not independent (Cuijpers et al., 2017). If they were not available, we used other inferential statistics as long as they represent the difference between the intervention and the control condition on the posttest.

The cognitive learning outcome was the primary outcome and we also coded ESs based on affective and behavioural learning outcomes. When more than one appropriate outcome measure was reported in a study, we calculated ESs for all of those. The software Comprehensive Meta-Analysis (CMA), Version 2 was used to calculate the ES for each contrast.

2.5 | Statistical dependence of the samples

We included 10 studies with multiple comparisons. Since these comparisons are not independent of each other this may yield an artificial reduction of heterogeneity which can affect the pooled ES, we examined these possible effects by conducting sensitivity analyses in which we included only one of the comparisons per study. However, this did not result in a different result (for more details, see Section 3.3). The second case of dependent data was reporting multiple outcomes or time-points per study. A study may involve different measures for the same learning outcome variable. In this case, we created a synthetic ES for each study, which is a more conservative method for combining dependent outcomes than assuming completely independent outcomes (see Borenstein et al., 2009). When multiple time points of one dependent variable in one study could be calculated, we chose only to include the measurement that is closest to the end of the intervention that causes differences between experimental and control groups to rule out other possible explanations. Additionally, for those studies providing two or more independent experiments, and each experiment contributing independent information, we treated each experiment as a separate study, computed the effect within experiments, and then use these effects as the unit of analysis.

2.6 | Data analysis

We conducted three meta-analyses: one on the cognitive learning outcome, one on the affective learning outcome, and one on behavioural learning outcome. Because there was a wide range of different participants, interventions and outcome measures between studies, we used the random-effects model to calculate the average ESs. The random-effects model allows for between-study variance beyond random error (Borenstein et al., 2009).

The first method to examine heterogeneity is to look carefully at the forest plot. Forest plots were presented to examine ES distributions, and to assist in identifying outliers. Outliers were defined as studies in which the 95% CI was outside the 95% CI of the pooled studies and excluding outliers from a meta-analysis results in a considerable drop in the level of heterogeneity (Levy Berg et al., 2009). However, outlier tests are tools that help us to find certain studies that are worth examining in more detail but should not be taken as a justification of removal studies (Viechtbauer & Cheung, 2010).

Additionally, the Q-statistics was utilized to calculate the heterogeneity of the average ESs. As an indicator of heterogeneity, we calculated the I^2-statistic, which gives heterogeneity in percentages and it is assumed that a percentage of 25% indicates low heterogeneity, 50% moderate and 75% high heterogeneity (Higgins et al., 2003).

In order to assess the effects of differences between the primary studies that might have an influence on the results we tested the effects of a priori defined variables. Moderator analyses were conducted using a random effects model to compare the contrasts based on categorical moderator variables in all the meta-analyses. Only categorical moderator variables that had at least four contrasts in the categories were used (Bakermans-Kranenburg et al., 2003). Because very few studies were found in some categories, we merged these categories. For example, we assumed that the SES of students was not low if it was not reported in the study.

Publication bias was inspected in all sets of studies. Studies with significant results are more likely to be published and thus significant findings may be overrepresented in a meta-analysis which may lead to an overestimation of the average ES. The visual display of ESs against standard errors by a funnel plot is a popular way to evaluate publication bias and an asymmetrical distribution of the studies indicates the risk of missing studies (Card, 2012). We also conducted Egger's test of the intercept to quantify the bias captured by the funnel plot and to test whether it was significant (Egger et al., 1997). Furthermore, Rosenthal's fail-safe N was estimated to show the number of missing studies ($5k + 10$) with zero effect to be required to generate non-significant results (Rosenthal, 1979). Additionally, trim-and-fill method (Duval & Tweedie, 2000) was carried considering the aggregated effects.

3 | RESULTS

3.1 | Characteristics of included studies

The final dataset consisted of 85 studies from 78 articles with a total of $N = 9157$ students. Studies included in the present meta-analysis are marked with asterisk (*) in the reference list. Appendix A provides an overview of the studies. The most studied region was Taiwan ($n = 29$). Community types (i.e., urban, suburban and rural) were only reported in 25% of the studies. In a few studies ($n = 6$), students came to school with a low SES. More than half of the studies ($n = 44$) investigated primary school students and less than half of the studies ($n = 41$) investigated students from the secondary school level. For learning environment, 61 studies implemented in the formal settings. Science were the most studied subjects (n = 26), followed by Language arts ($n = 23$), Social studies ($n = 16$) and Mathematics ($n = 14$). Handheld devices with multiple functions (including laptops, tablet PCs, and mobile phones) were the most widely studied hardware ($n = 71$), followed by handheld devices with one specific function ($n = 12$, including classroom response systems, digital pen, etc.). In about half of the studies ($n = 49$), students owned and used a mobile device. With regard to teaching method, inquiry-oriented leaning ($n = 30$, including discovery and exploration, problem-solving, project-based learning, and cooperative learning) was the most frequently researched, followed by game-based learning ($n = 18$). The studied intervention duration were similar, that is, <1 day ($n = 22$), 1 day–4 weeks ($n = 33$), and >4 weeks ($n = 22$). Only 14 studies utilized a true experimental design. Some studies conducted well on equivalent instructor ($n = 41$), equivalent learning topic/content ($n = 70$), and equivalent software/tool ($n = 42$). Finally, pen-and-paper conditions ($n = 52$) were the most often studied control groups, followed by traditional technology condition ($n = 19$).

3.2 | Evaluation of publication bias

Regarding the possibility of publication bias affecting our data, funnel plots for each dependent variable were examined for asymmetry, as presented in Figures 2, 3, and 4. Another test for the funnel plot asymmetry was Egger's regression test. Results shown that there was no indication for publication bias for cognitive learning (intercept = 1.175, 95% CI [−0.439, 2.788], $t(107) = 1.443$, $p = 0.152$) and behavioural learning (intercept = −1.141, 95% CI [−5.229, 2.947], $t(12) = 0.608$, $p = 0.554$), but the intercept for affective learning (intercept = 2.612, 95% CI [0.671, 4.553], $t(35) = 2.732$, $p = 0.010$) was significant. Finally, the fail-safe N was 3079, 1166, and 111, with

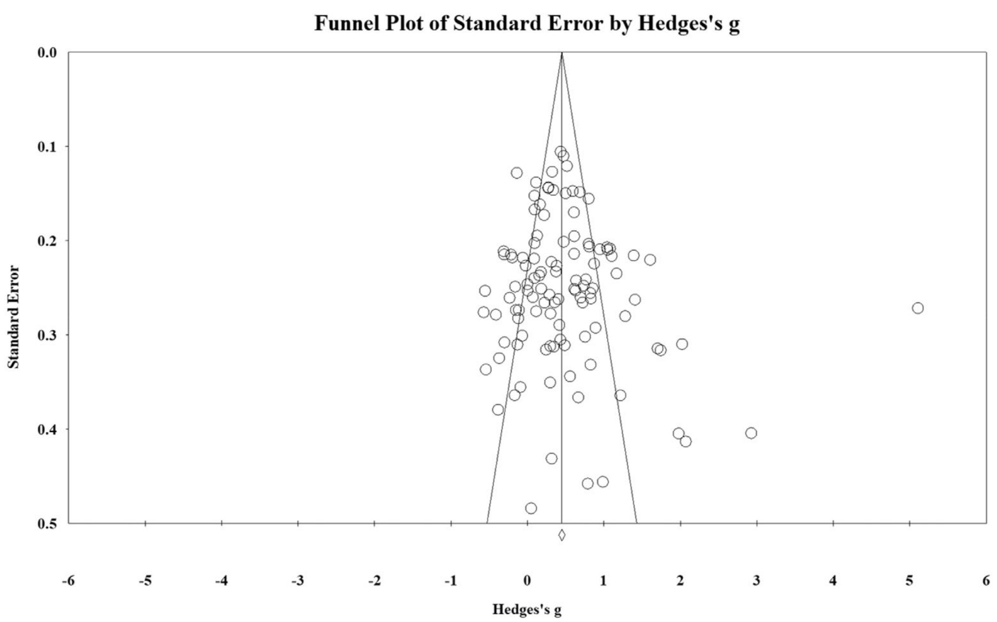

FIGURE 2 Funnel plot of the 109 effect sizes for cognitive outcomes.

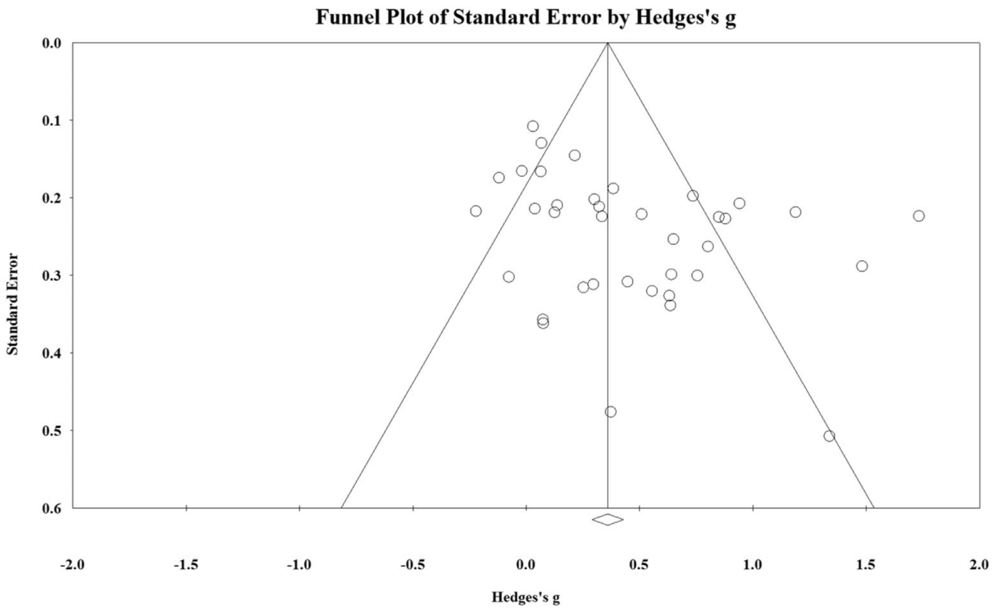

FIGURE 3 Funnel plot of the 37 effect sizes for affective outcomes.

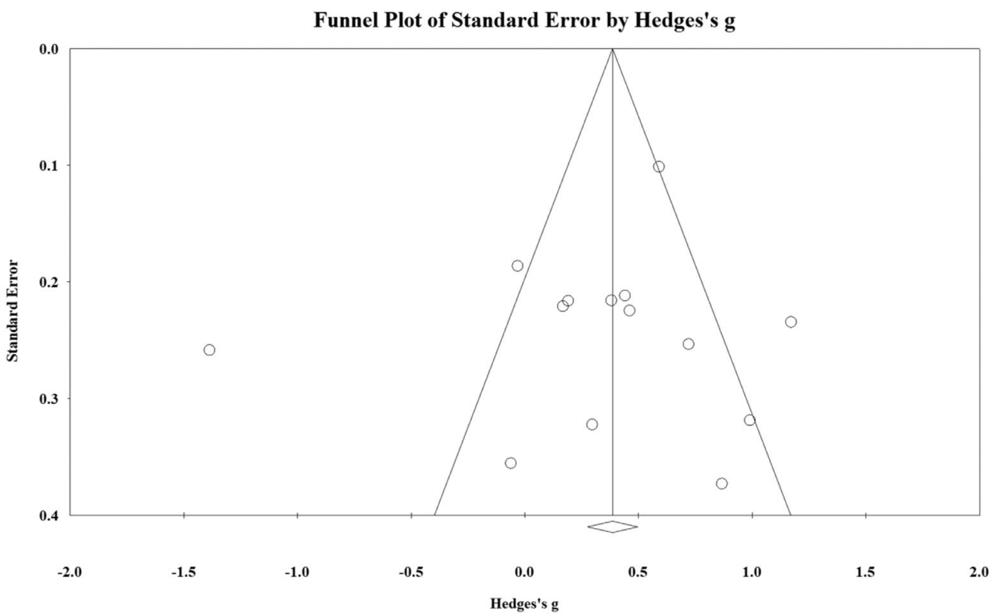

FIGURE 4 Funnel plot of the 14 effect sizes for behavioural outcomes.

cognitive, affective and behavioural learning outcomes, respectively, which is much larger than the tolerable number of studies with 555, 195 and 80, respectively.

The trim-and-fill method can further estimate any 'missing effect sizes' based on the assumption that ESs should follow an approximately normal distribution (Duval & Tweedie, 2000). With the trim-and-fill method, 26 imputed ESs are plotted on the right side of the plot for cognitive learning outcomes, indicating that if 26 missing studies were added to the random effects category, the overall effect would become 0.715, 95% CI [0.594, 0.835]. These results show that this meta-analysis was not substantially affected by publication bias. We further conducted trim and fill procedures on affective learning outcomes and behavioural learning outcomes and found that no missing studies were identified and needed to be added, resulting in the same adjusted point estimate and confidence interval as the main results ($g = 0.449$, 95% CI [0.301, 0.598]) and ($g = 0.339$, 95% CI [0.051, 0.628]) for affective and behavioural learning outcomes, respectively. All of the above may indicate publication bias was unlikely to be a concern for this meta-analysis.

3.3 | Overall effects of mobile technology usage compared with control groups

The first research question focused on the advantages of using mobile technologies on student learning outcomes correspondingly in

Study name	Statistics for each study: Hedges's g	Lower limit	Upper limit
Al-Balushi, Al-Musawi, Ambusaidi, and Al-Hajri (2017)	0.290	-0.215	0.795
Alcoholado, Diaz, Tagle, Nussbaum, and Infante (2016) Comp 1	-0.367	-1.003	0.269
Alcoholado, Diaz, Tagle, Nussbaum, and Infante (2016) Comp 2	-0.541	-1.201	0.119
Alfadil (2020)	0.631	0.135	1.128
Bhagat, Yang, Cheng, Zhang, and Liou (2021) Comp 1	0.050	-0.898	0.999
Bhagat, Yang, Cheng, Zhang, and Liou (2021) Comp 2	0.792	-0.106	1.689
Cai, Liu, Wang, Liu, and Liang (2021)	0.096	-0.302	0.494
Cavus and Ibrahim (2017)	2.074	1.264	2.884
Cetinkaya and Sütcü (2018) Comp 1	0.832	0.319	1.345
Cetinkaya and Sütcü (2018) Comp 2	2.026	1.418	2.633
Chang and Hwang (2018)	0.803	0.404	1.203
Chang et al. (2020)	-0.118	-0.672	0.436
Chen, Yang, Huang, and Yao (2020) Comp 1	-0.212	-0.634	0.210
Chen, Yang, Huang, and Yao (2020) Comp 2	-0.308	-0.723	0.106
Chen, Yang, Huang, and Yao (2020) Comp 3	-0.196	-0.623	0.232
Chen, Yang, Huang, and Yao (2020) Comp 4	-0.301	-0.723	0.120
Cheng, Su and Kinshuk (2021)	1.409	0.894	1.924
Chien, Tsai, Chen, Chang, and Chen (2015)	0.433	-0.165	1.031
Chu (2014)	-0.551	-1.048	-0.054
Danaei, Jamali, Mansourian, and Rastegarpour (2020)	0.560	-0.114	1.234
del Olmo-Muñoz, Cózar-Gutiérrez, and González-Calero (2020)	-0.059	-0.487	0.369
Ebadi and Bashir (2021) Comp 1	0.320	-0.526	1.165
Ebadi and Bashir (2021) Comp 2	0.989	0.095	1.883
Edwards, Rule, and Boody (2017)	0.829	0.179	1.479
Erbas and Demirer (2019)	-0.128	-0.736	0.480
Fidan & Tuncel (2019) Comp 1	0.699	0.188	1.210
Fidan & Tuncel (2019) Comp 2	1.281	0.731	1.830
Fokides, Atsikpasi and Karageorgou (2020) Comp 1	1.044	0.638	1.451
Fokides, Atsikpasi and Karageorgou (2020) Comp 2	0.477	0.082	0.872
Fokides, Atsikpasi and Karageorgou (2020) Comp 3	1.608	1.176	2.040
Fokides, Atsikpasi and Karageorgou (2020) Comp 4	1.050	0.639	1.462
Fokides, Atsikpasi and Karageorgou (2020) Comp5	1.392	0.968	1.815
Fokides, Atsikpasi and Karageorgou (2020) Comp6	0.811	0.406	1.216
Giasiranis and Sofos (2017)	0.490	-0.120	1.099
Huang and Lin (2017)	1.082	0.673	1.491
Huang, Chen, and Hsu (2019)	0.640	0.165	1.115
Huang, Shadiev, Sun, Hwang, and Liu (2017)	0.407	-0.107	0.921
Huang, Su, Yang, and Liou (2017) Comp 1	0.301	-0.310	0.913
Huang, Su, Yang, and Liou (2017) Comp 2	-0.067	-0.657	0.523
Huang, Yang, Chiang, and Su (2016)	0.384	-0.061	0.829
Hung and Young (2015)	-0.089	-0.786	0.607
Hwang, Zhao, Shadiev, Lin, Shih, and Chen (2020) Comp 1	0.304	-0.240	0.848
Hwang, Zhao, Shadiev, Lin, Shih, and Chen (2020) Comp 2	0.893	0.319	1.467
Jere-Folotiya et al. (2014) Comp 1	0.220	-0.119	0.560
Jere-Folotiya et al. (2014) Comp 2	-0.020	-0.465	0.424
Jere-Folotiya et al. (2014) Comp 3	0.097	-0.231	0.425
Jong, Chan, Hue, and Tam (2018) Sample 1	0.274	-0.009	0.558
Jong, Chan, Hue, and Tam (2018) Sample 2	0.690	0.398	0.981
Jong, Chan, Hue, and Tam (2018) Sample 3	0.804	0.499	1.109
Jong, Tsai, Xie and Wong (2020) Sample 1	0.277	-0.004	0.559
Jong, Tsai, Xie and Wong (2020) Sample 2	0.596	0.306	0.885
Jong, Tsai, Xie and Wong (2020) Sample 3	0.503	0.209	0.797
Joo-Nagata, Abad, Giner, & García-Peñalvo (2017)	0.611	0.278	0.945
Khan, Hwang, Azeem Abbas, and Rehman (2019) Sample 1	0.738	0.252	1.224
Khan, Hwang, Azeem Abbas, and Rehman (2019) Sample 2	0.949	0.538	1.360
Ku, Huang, and Hus (2015)	0.358	-0.162	0.879
Lai, Chen, and Lee (2019)	0.756	0.164	1.348
Lee and Choi (2020)	0.005	-0.492	0.501
Lee, Hao, Lee, Sim, and Huang (2019)	0.246	-0.373	0.865
Liang, Hsu and Hwang (2021)	-0.299	-0.902	0.305
Lin (2014)	1.169	0.708	1.630
Lin (2017)	0.167	-0.151	0.484
Liu, Lin, Wang, Yeh, and Kalyuga (2021) Comp 1	-0.410	-0.956	0.136
Liu, Lin, Wang, Yeh, and Kalyuga (2021) Comp 2	-0.110	-0.646	0.427
Liu, Lin, Wang, Yeh, and Kalyuga (2021) Comp 3	-0.148	-0.685	0.389
Liu, Lin, Wang, Yeh, and Kalyuga (2021) Comp 4	0.117	-0.422	0.657
Liu, Lin, Wang, Yeh, and Kalyuga (2021) Comp 5	0.129	-0.253	0.511
Liu, Wang, Lei, Wang, and Ren (2020)	0.613	0.193	1.033
Liu, Yu, Chen, Wang, and Xu (2021) Comp 1	0.003	-0.480	0.487
Liu, Yu, Chen, Wang, and Xu (2021) Comp 2	0.157	-0.308	0.622
Liyanawatta, Yang, Liu, Zhuang, and Chen (2022)	0.827	0.325	1.328
Mabuza and Osodo (2020)	0.180	-0.278	0.638
Nikou and Economides (2018)	0.614	0.231	0.998
Outhwaite, Gulliford, and Pitchford (2017) Study 1	-0.158	-0.646	0.330
Outhwaite, Gulliford, and Pitchford (2017) Study 4	-0.381	-1.124	0.363
Passig, Tzuriel, and Eshel-Kedmi (2016) Comp 1	0.073	-0.437	0.583
Passig, Tzuriel, and Eshel-Kedmi (2016) Comp 2	1.705	1.089	2.322
Passig, Tzuriel, and Eshel-Kedmi (2016) Comp 3	-0.230	-0.741	0.282
Passig, Tzuriel, and Eshel-Kedmi (2016) Comp 4	1.745	1.125	2.365
Potocki, Chailleux, Gimenes, and Pylouster (2021)	0.095	-0.204	0.394
Purba, Hwang, Pao, and Ma (2019)	1.219	0.505	1.933
Ruiz-Ariza, Casuso, Suarez-Manzano, and Martinez-López (2018)	0.341	0.053	0.628
Sahin and Yilmaz (2020)	1.105	0.680	1.529
Shadiev, Hwang, and Liu (2018)	-0.569	-1.111	-0.028
Shadiev, Hwang, Huang, and Liu. (2015)	0.724	0.203	1.246
Stanojević and Ranđelović (2018)	2.930	2.137	3.722
Su and Cheng (2015) Comp 1	0.857	0.365	1.348
Su and Cheng (2015) Comp 2	0.094	-0.376	0.564
Sung, Hwang, Lin, and Hong (2017)	0.421	-0.147	0.988
Uittert, Verhoeven, and Segers (2022)	0.326	0.077	0.575
Vanbecelaere, Van den Berghe, Cornillie, Sasanguie, Reynvoet, and Depaepe (2020)	-0.136	-0.387	0.116
Volk, Cotič, Zajc, and Starcic (2017)	5.110	4.577	5.643
Walczak and Taylor (2018)	0.116	-0.156	0.388
Wang (2016)	0.227	-0.295	0.748
Wang (2017a)	0.668	-0.050	1.386
Wang (2017b)	0.316	-0.120	0.753
Wollscheid, Sjaastad, Tømte, and Løver (2016) Comp 1	-0.164	-0.878	0.549
Wollscheid, Sjaastad, Tømte, and Løver (2016) Comp 2	0.300	-0.387	0.987
Yallihep and Kutlu (2020)	1.980	1.187	2.773
Yang, Chen, Zheng, and Hwang (2021)	0.348	-0.265	0.960
Yousef (2021)	0.183	-0.310	0.676
Zhang, Shang, Pelton, and Pelton (2020)	0.617	0.124	1.110
Zhang, Sung, Hou, and Chang (2014) Sample 1	0.376	-0.081	0.833
Zhang, Sung, Hou, and Chang (2014) Sample 2	0.767	0.293	1.240
Zhao, Hwang, Chang, Yang, and Nokkaew (2021) Comp 1	0.091	-0.339	0.521
Zhao, Hwang, Chang, Yang, and Nokkaew (2021) Comp 2	0.876	0.435	1.316
Zheng, Warschauer, Hwang, and Collins (2014)	0.437	0.229	0.645
Zhu and Urhahne (2018) Comp 1	0.519	0.281	0.756
Zhu and Urhahne (2018) Comp 2	0.475	0.258	0.691
	0.498	0.382	0.614

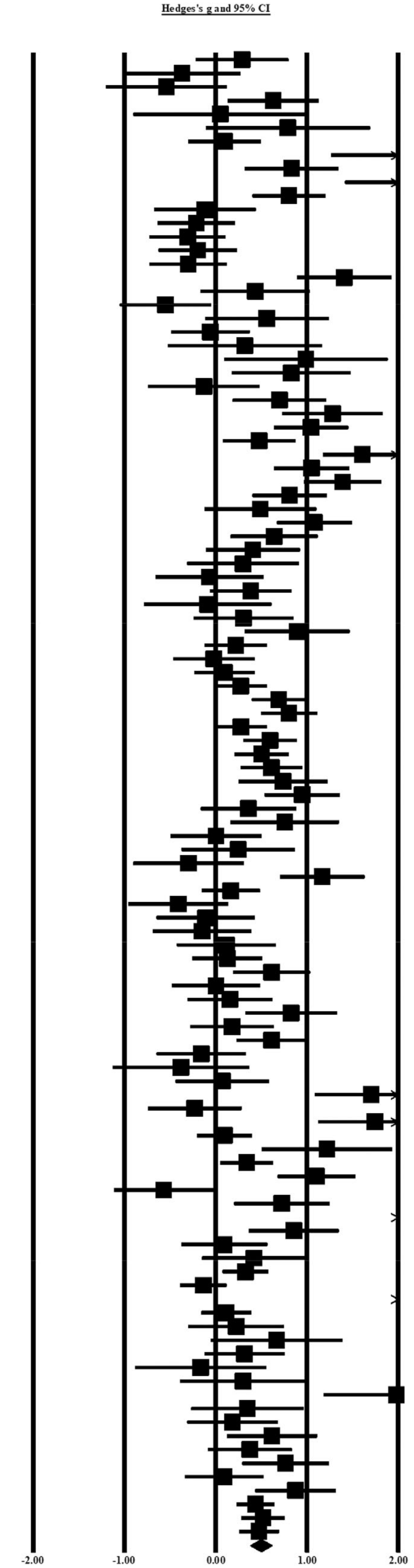

FIGURE 5 Forest plot of the 109 effect sizes for cognitive outcomes. Within one article, when multiple sample or studies were presented, the figure reports the result of each sample (sample 1, sample 2, etc.) or study (study 1, study 2, etc.) separately. Similarly, when studies used multiple comparisons, the figure reports the result of each comparison (comp 1, comp 2, etc.) separately.

Study name	Hedges's g	Lower limit	Upper limit
Bhagat, Yang, Cheng, Zhang, and Liou (2021) Comp 1	0.374	-0.559	1.306
Bhagat, Yang, Cheng, Zhang, and Liou (2021) Comp 2	1.338	0.344	2.333
Cai, Liu, Wang, Liu, and Liang (2021)	0.302	-0.095	0.698
Chang and Hwang (2018)	1.733	1.295	2.172
Chen, Yang, Huang, and Yao (2020) Comp 1	0.851	0.409	1.292
Chen, Yang, Huang, and Yao (2020) Comp 2	0.323	-0.092	0.737
Chen, Yang, Huang, and Yao (2020) Comp 3	0.510	0.076	0.944
Chen, Yang, Huang, and Yao (2020) Comp 4	0.039	-0.381	0.459
del Olmo-Muñoz, Cózar-Gutiérrez, and González-Calero (2020)	-0.221	-0.647	0.205
Erbas and Demirer (2019)	0.253	-0.366	0.872
Fidan & Tuncel (2019) Comp 1	0.803	0.287	1.318
Fidan & Tuncel (2019) Comp 2	1.483	0.917	2.048
Furió, Juan, Seguí, and Vivó (2015)	0.632	-0.008	1.272
Giasiranis and Sofos (2017)	0.448	-0.156	1.052
Huang and Lin (2017)	0.942	0.535	1.348
Huang, Su, Yang, and Liou (2017) Comp 1	0.297	-0.314	0.908
Huang, Su, Yang, and Liou (2017) Comp 2	-0.076	-0.668	0.517
Huang, Yang, Chiang, and Su (2016)	0.335	-0.105	0.774
Hung and Young (2015)	0.074	-0.626	0.774
Joo-Nagata, Abad, Giner, & García-Peñalvo (2017)	0.065	-0.261	0.391
Lai, Chen, and Lee (2019)	0.756	0.167	1.345
Lee, Hao, Lee, Sim, and Huang (2019)	0.556	-0.072	1.184
Lin (2014)	0.879	0.434	1.325
Liyanawatta, Yang, Liu, Zhuang, and Chen (2022)	0.650	0.153	1.147
Makransky, Petersen, and Klingenberg (2020) Study 2	-0.119	-0.461	0.223
Nikou and Economides (2018)	0.736	0.349	1.124
Papastergiou, Natsis, Vernadakis and Antoniou (2021)	-0.018	-0.343	0.306
Quintas, Bustamante, Pradas, and Castellar (2020)	0.031	-0.181	0.242
Ruiz-Ariza, Casuso, Suarez-Manzano, and Martínez-López (2018)	0.215	-0.070	0.501
Sahin and Yilmaz (2020)	1.189	0.760	1.618
Sung, Hwang, Lin, and Hong (2017)	0.641	0.055	1.227
Tapingkae, Panjaburee, Hwang, and Srisawasdi (2020)	0.385	0.016	0.754
Vanbecelaere, Van den Berghe, Cornillie, Sasanguie, Reynvoet, and Depaepe (2020)	0.068	-0.186	0.322
Wang (2017a)	0.076	-0.634	0.785
Yallihep and Kutlu (2020)	0.637	-0.028	1.301
Zhao, Hwang, Chang, Yang, and Nokkaew (2021) Comp 1	0.126	-0.304	0.555
Zhao, Hwang, Chang, Yang, and Nokkaew (2021) Comp 2	0.137	-0.274	0.548
	0.449	0.301	0.598

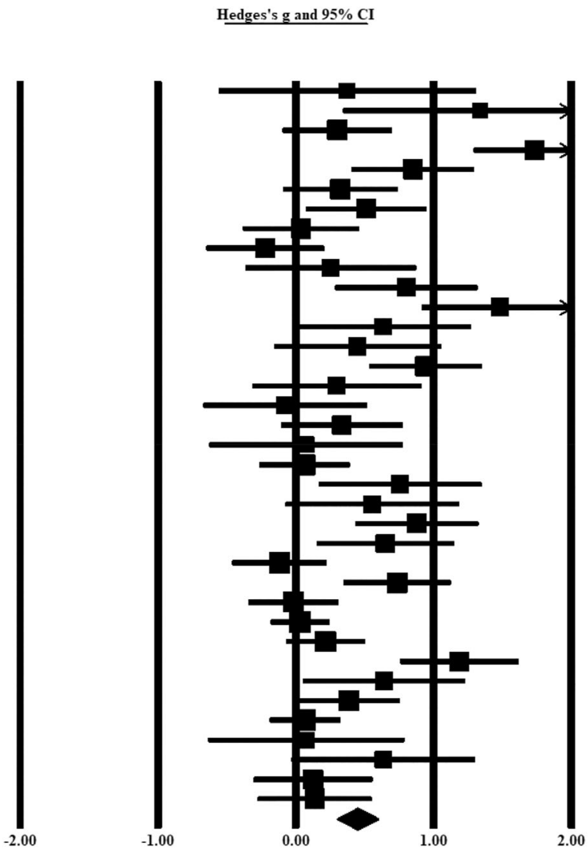

FIGURE 6 Forest plot of the 37 effect sizes for affective outcomes.

comparison to students learning without mobile technologies. We could compare the effects of mobile technologies with control groups on learning outcome in 109 cognitive comparisons from 80 journal articles, in 37 affective comparisons from 17 journal articles, and in 14 behavioural comparisons from 11 journal articles. Within each study set, ESs and 95% confidence intervals of each study are presented in Figures 5, 6 and 7.

With regard to the primary outcome variable, the overall effect shows that the use of mobile technologies had a medium positive and significant effect on cognitive learning ($g = 0.498$, 95% CI [0.382, 0.614]). Similar to the effects on cognitive learning, the combined effect on affective learning was medium ($g = 0.449$, 95% CI [0.301, 0.598]). For behavioural learning outcomes, a medium positive and significant ES ($g = 0.339$, 95% CI [0.051, 0.627]) was also found. Heterogeneity is large ($I^2 = 86.618$ for the cognitive dimension, $I^2 = 75.662$ for the affective dimension, $I^2 = 83.327$ for the behavioural dimension) for the effects on all three learning outcome dimensions and highly significant ($p < 0.001$) in these analyses.

Ten studies were special since they included multiple comparisons. We examined the possible effects of this by conducting analyses with only one ES (either the largest or the smallest ES) per study. As Table 2 reveals, the resulting ESs were roughly the same as in the overall analyses. Heterogeneity test was not significant for affective ($I^2 = 0$, $p = 0.743$), and behavioural ($I^2 = 0$, $p = 0.995$) learning outcome, indicating the observed differences might not be important. However, heterogeneity test was significant for cognitive learning outcome ($I^2 = 62.328$, $p = 0.047$), indicating these overall ESs should be interpreted cautiously.

3.4 | Moderator analyses

To answer RQ2 and RQ3, we performed moderator analyses. We calculated ESs and 95% CI for each level with at least four studies of all potential moderators. Results for cognitive learning outcomes are presented in Table 3, affective and behavioural learning outcome are presented in Tables B1 and B2 respectively in Appendix B, along with all between group heterogeneity tests.

For cognitive learning outcomes, as can be seen in Table 3, of all 15 variables tested, 6 moderators were found. We found indications that students from urban areas had higher ESs than others ($p = 0.003$), that low SES students had lower ESs than others ($p = 0.001$), that students using handheld device with multiple functions were significantly more effective than using device with one single function ($p = 0.001$), that each student having one mobile device was significantly associated with the higher ESs ($p < 0.001$), that equivalent learning topic/content between comparison groups resulted in a higher ESs ($p < 0.001$), and that the ESs differed significantly between the degree of technology use in the control group ($p = 0.015$).

Study name	Hedges's g	Lower limit	Upper limit
Chen, Yang, Huang, and Yao (2020) Comp 1	0.191	-0.233	0.615
Chen, Yang, Huang, and Yao (2020) Comp 2	0.381	-0.042	0.804
Chen, Yang, Huang, and Yao (2020) Comp 3	0.168	-0.265	0.601
Chen, Yang, Huang, and Yao (2020) Comp 4	0.461	0.021	0.901
Chien, Tsai, Chen, Chang, and Chen (2015)	0.991	0.366	1.615
Hung and Young (2015)	0.867	0.137	1.598
Lin (2014)	1.171	0.712	1.631
Liu, Wang, Lei, Wang, and Ren (2020)	0.441	0.026	0.856
Liyanawatta, Yang, Liu, Zhuang, and Chen (2022)	0.721	0.224	1.218
Quintas, Bustamante, Pradas, and Castellar (2020)	0.591	0.392	0.789
Tapingkae, Panjaburee, Hwang, and Srisawasdi (2020)	-0.031	-0.396	0.334
Wang (2017a)	-0.061	-0.757	0.636
Yang, Chen, Zheng, and Hwang (2021)	0.297	-0.335	0.929
Zhang, Sung, Hou, and Chang (2014) Sample 2	-1.386	-1.893	-0.880
	0.339	0.051	0.627

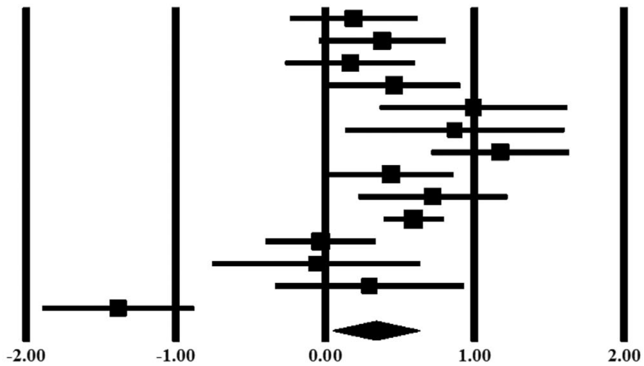

FIGURE 7 Forest plot of the 14 effect sizes for behavioural outcomes.

TABLE 2 Overall effect sizes of mobile technology usage

Dependent variable	Effect size and 95% confidence interval				Heterogeneity			
	N	g	SE	95% CI	Q(p)	Df(Q)	τ^2 (SE)	I^2 (%)
Cognitive learning outcome								
All studies	109	0.498	0.059	(0.382, 0.614)	813.006 (<0.001)	108	0.316 (0.059)	86.716
Possible outliers removed	83	0.378	0.036	(0.307, 0.448)	176.951 (<0.001)	82	0.052 (0.016)	53.659
One effect size per study (largest)	74	0.599	0.079	(0.444, 0.754)	648.333 (<0.001)	73	0.392 (0.089)	88.740
One effect size per study (smallest)	74	0.442	0.075	(0.295, 0.589)	586.158 (<0.001)	73	0.348 (0.080)	87.546
Affective learning outcome								
All studies	37	0.449	0.076	(0.301, 0.598)	147.916 (<0.001)	36	0.149 (0.053)	75.662
Possible outliers removed	32	0.376	0.061	(0.257, 0.494)	63.570 (0.001)	31	0.055 (0.029)	51.235
One effect size per study (largest)	30	0.486	0.089	(0.312, 0.660)	139.051 (<0.001)	29	0.173 (0.066)	79.144
One effect size per study (smallest)	30	0.407	0.083	(0.244, 0.569)	121.801 (<0.001)	29	0.145 (0.057)	76.191
Behavioural learning outcome								
All studies	14	0.339	0.147	(0.051, 0.627)	77.968 (<0.001)	13	0.239 (0.134)	83.327
Possible outliers removed	12	0.302	0.157	(−0.006, 0.609)	61.717 (<0.001)	11	0.229 (0.142)	82.177
One effect size per study (largest)	11	0.367	0.189	(−0.004, 0.738)	75.887 (<0.001)	10	0.325 (0.206)	86.823
One effect size per study (smallest)	11	0.339	0.190	(−0.034, 0.712)	77.016 (<0.001)	10	0.330 (0.208)	87.016

In the moderator analyses for affective learning outcomes (see Table B1 in Appendix B), we only found studies in which inquiry-oriented learning resulted in a higher differential ES than studies in which game-based learning were applied ($p = 0.039$). In the series of moderator analyses regarding behavioural learning effects, results in Table B2 in Appendix B showed that the effects size was not significantly associated with any of the eight variables tested.

4 | DISCUSSION

4.1 | Overall effects on learning outcomes

We conducted a systematic review with a meta-analysis of experimental and quasi-experimental studies comparing the effects of learning with and without mobile technology. Compared with traditional technology and non-technology groups, mobile technology produced medium positive and statistically significant effects on primary and secondary students' learning in terms of cognitive, affective, and behavioural learning outcomes. The current meta-analysis provides the converging 'best evidence' for the overall beneficial effects of using mobile technology in education.

4.2 | Moderator variables

The main effects of mobile technology mentioned above are not the same for all student groups and learning contexts. Therefore, moderator analyses have been performed with characteristics of the students and learning contexts as moderators. The results from a series of

TABLE 3 Moderator analyses and weighted mean effect sizes for cognitive outcome variables

Moderator category	Moderator variables	*N*	*g*	SE	95% CI	Q_B	*p*
Student factor	[a]Community type						
	Urban	14	0.567	0.138	(0.297, 0.837)	8.989	0.003
	Not urban	12	0.061	0.097	(−0.129, 0.252)		
	[a]SES						
	Low	7	0.059	0.122	(−0.180, 0.298)	11.994	0.001
	Not low	102	0.534	0.063	(0.410, 0.685)		
Teaching context	[a]Education level						
	Primary school	61	0.471	0.091	(0.293, 0.649)	0.189	0.664
	Secondary school	48	0.521	0.072	(0.381, 0.662)		
	[a]Learning environment						
	Formal settings	83	0.467	0.074	[0.323, 0.612)	2.047	0.359
	Informal settings	19	0.512	0.070	[0.375, 0.650)		
	Unrestricted	7	0.921	0.312	(0.310, 1.531)		
	[a]School subject						
	Language arts	30	0.475	0.079	(0.320, 0.630)	1.921	0.750
	Social studies	13	0.420	0.106	(0.213, 0.626)		
	Mathematics	21	0.557	0.231	(0.105, 1.010)		
	Science	39	0.459	0.087	(0.289, 0.629)		
	Professional subjects	4	1.305	0.674	(−0.015, 2.625)		
Learning process	[a]Hardware used in intervention group						
	Handheld devices with multiple functions	89	0.557	0.072	(0.417, 0.698)	10.469	0.001
	Handheld devices with one specific function	18	0.222	0.075	(0.076, 0.369)		
	[a]Student-to-hardware ratio						
	Own	68	0.595	0.084	(0.431, 0.760)	21.725	<0.001
	Shared	16	0.043	0.083	(−0.120, 0.207)		
	[a]Teaching method						
	Inquiry-oriented learning	43	0.4941	0.073	(0.349, 0.633)	2.501	0.776
	Game-based learning	19	0.458	0.104	(0.254, 0.662)		
	Self-directed learning	9	0.744	0.258	(0.239, 1.249)		
	Computer-assisted testing/assessment	15	0.475	0.159	(0.163, 0.787)		
	Lectures	4	0.519	0.286	(−0.042, 1.080)		
	Mixed	9	0.967	0.395	(0.192, 1.742)		
	[a]Duration of the intervention						
	<1 day	33	0.279	0.093	(0.097, 0.462)	4.518	0.104
	1 day–4 weeks	34	0.517	0.083	(0.354, 0.681)		
	>4 weeks	28	0.566	0.151	(0.269, 0.863)		
Study quality	[a]Research design						
	Quasi-experimental	86	0.530	0.067	(0.398, 0.662)	1.333	0.248
	Experimental	23	0.369	0.122	(0.129, 0.608)		
	[a]Instructor equivalence						
	Same	54	0.487	0.082	(0.326, 0.648)	0.065	0.799
	Different	41	0.521	0.104	(0.318, 0.726)		

(Continues)

TABLE 3 (Continued)

Moderator category	Moderator variables	N	g	SE	95% CI	Q_B	p
	[b]Learning topic/content equivalence						
	Same	88	0.574	0.071	(0.434, 0.713)	13.263	< 0.001
	Different	13	0.203	0.073	(0.061, 0.346)		
	[b]Software/tool equivalence						
	Same	48	0.519	0.109	(0.306, 0.731)	0.009	0.924
	Different	43	0.506	0.083	(0.342, 0.669)		
	[a]Degree of technology use in the control group						
	Pen-and-paper	67	0.607	0.087	(0.436, 0.777)	5.895	0.015
	Traditional technology	25	0.279	0.103	(0.077, 0.481)		
	[a]Procedure of effect size extraction						
	Calculated from exact descriptive	97	0.512	0.066	(0.382, 0.643)	2.498	0.114
	Calculated from inferential statistics	11	0.342	0.085	(0.176, 0.508)		

[a]The moderators considered from previous studies are designated by an asterisk.
[b]The moderators considered from new data are designated by two asterisks.

moderator analyses supported the importance of some variables from three categories, that is, student factors, learning process, and study quality, that explained differences in learning outcomes between mobile learning and traditional learning. From an educational perspective - as indicated in the 3P model, ESs varied significantly for cognitive learning outcomes according to community type, SES, hardware used, ratio, while teaching methods was the only significant moderator variable for affective learning outcomes. The mobile technology interventions benefited more for students from urban areas, not low SES backgrounds, using handheld devices with multiple functions, using mobile devices on their own and for inquiry-oriented learning. Nevertheless, because the number of included studies was small, these effects must be interpreted with caution. Furthermore, the three factors in the teaching context category (education level, learning environment, and school subject) were not significant moderators for all learning outcomes. Moreover, with regard to learning process, the results on cognitive learning outcomes identified two moderators (i.e., hardware used in intervention group, student-to-hardware ratio), on affective learning outcomes identified one moderator (i.e., teaching method). From the methodology perspective, the results on cognitive learning outcomes identified two moderators (i.e., learning topic/content equivalence, and degree of technology use in the control group), while on affective and behavioural learning outcomes no moderators were identified.

Although research has indicated the influence of social support from both school and family on technology access and usage among children (Li & Ranieri, 2013), previous meta-analyses of mobile technology interventions failed to examine this moderator effect due to lacking relevant information. According to the subgroup analysis, students with low SES background and from rural schools benefited less than their peers. This finding is perhaps due to the fact that these students are living in different conditions compared to their urban counterparts with fewer digital opportunities, and therefore they acquire less knowledge, experience, and support about mobile learning. The finding is of particular importance in understanding the new digital divide and offering a valuable direction to explore differences among subgroups, for example, ethnicity and migration status.

Furthermore, in line with previous meta-analysis (Sung et al., 2016), handheld devices with multiple functions often induced better cognitive learning outcomes. This result provides insights for designing features for mobile devices and shows the possibility of finding a balance between cost and benefit in mobile learning. For example, clickers that allow students to quickly and anonymously respond to questions presented in class are much less complex and costly than tablets, which enable students to do more things and involve strategies that include student-centred, dynamic, interactive techniques that could promote cognitive development. However, a clicker is much less costly than a tablet, which is particularly critical for economically disadvantaged schools and students. Besides, in contrast to the assumption of Haßler et al. (2016), the current meta-analysis proved the higher learning gains in a student–device ratio of one-to-one environment than the shared-device learning environment. A possible explanation is that individual student mobile device supported student-centered and individualized learning (Zheng et al., 2016) and enabled teachers or computer systems to provide immediate feedback to individual students (Castillo-Manzano et al., 2016).

No significant effects were found in variables in the teaching context category. An important implication of these findings is that mobile technology interventions can have an equally powerful effect on students' learning across teaching contexts. In terms of the learning process, students who adopted inquiry-oriented learning showed better affective learning outcomes than those who adopted game-based learning, although both produced significant overall effects in mobile learning. In contrast to Sung et al. (2016) study, the current study found that game-based learning significantly affected cognitive learning outcomes, possibly due to game-based learning being more closely related to the curriculum and learning objectives than 10 years ago. Additionally, Borovay (2007) examined the impact of inquiry-classroom environments on flow and found that all students reported higher flow states in inquiry settings than students' experiences in traditional and occasional inquiry classrooms. He also noted that during the inquiry process, students could pursue questions of their own interest and approach their tasks based on the knowledge they had previously acquired with little teacher involvement. Nevertheless, in game-based learning, the game is often not about inquiry but provides the storyline or context upon which the inquiry is structured (Istance & Kools, 2013), and high performance in a game does not necessarily indicate effective learning (Papamitsiou & Economides, 2016). Altogether, inquiry-oriented learning may improve learners' affective outcomes more effectively than game-based learning.

With regard to the research methodology category, the finding that instructor equivalence was not found to be a significant moderator is in accordance with previous meta-analysis on college students' learning outcomes in technology-enabled active learning environments (Shi et al., 2020). The influence of other features of the study quality, such as learning topic/content equivalence, tool/software equivalence, and procedure of ES extraction, have not been investigated as potential moderators in past meta-analyses. However, in this study, learning topic/content equivalence (whether the learning topic/content was the same in both the experimental and control groups) served as a significant moderator for cognitive learning outcomes, and the ES was larger when the same topic/content was employed. The findings are biased by the use of different learning topic/content, supporting the claim that methodological rigour needs to be enhanced in research on mobile learning. Besides, degree of technology use in the control group were significant moderators with regard to cognitive learning outcomes. This difference may suggest that using mobile technology has larger effects than not using technology or using traditional technology, perhaps because mobile technology allows students greater flexibility in learning and seamlessly integrate the learning experiences across various dimensions. In sum, this calls for future research to consider the features of study quality to explore whether the moderator effects exist and might contribute to the observed differences.

4.3 | Limitations and future research

Many studies were not included in this meta-analysis because the necessary information was not reported. Out of 375 potentially relevant journal articles found in the databases and journal websites, only 85 studies could finally be used for the analyses. Studies were excluded not only because they lacked statistical data but also because of other missing information that is important for meta-analyses. Because of time constraints, we only have one reviewer collecting data and did not contact study authors to clarify unclear information, which may result in missing relevant studies. On the other hand, As stated by Sung et al. (2019), mobile-learning research has suffered from methodological shortcomings that might hinder the ability of mobile-learning research to obtain reliable evidence for sustaining innovative practices and creating valid theories. To this end, Sung et al. (2019) suggest mobile-learning researchers should utilize valid designs for their research tools, procedures, and statistical methods and focus on presenting their research results more clearly by applying the checklist for the Rigour of Education-Experiment Designs (CREED). Owing to the limited number of empirical mobile-learning studies, the quality of experimental research was not used as a criterion for the inclusion or exclusion of research samples, except that these studies were peer-reviewed; instead features of study quality were analysed as potential moderators. Furthermore, we had few studies examining differential effects on affective and behavioural learning outcomes. We recommend that outcomes beyond cognitive learning outcomes are given more attention in research designs to fully explore the complex array of student outcomes in a learning situation. Other factors, such as training of teachers and students on technology/content, software used, and school type, could provide more practical and theoretical insights into the effects of using mobile technologies on school students' learning. These variables were not included in the moderator analyses of the present study due to low variability in categories or missing information in the studies. Moreover, the majority of experimental treatments suffer from the limitation of short-term mobile technology interventions; in our study, about two-thirds of interventions lasted less than 4 weeks. Studies indicated that researchers might create artificial environments for a brief duration (Cheung & Slavin, 2013). Therefore, we argue the need for longitudinal research to discard the novelty effect of mobile technology. Lastly, because all included studies were written in English, we suggest that future meta-analyses could consider adding more articles written in different languages to yield more robust findings than using an English single language. However, because of these limitations, readers should take the findings with caution because they may have limited generalizability in different situations and contexts.

4.4 | Implications for policymakers and practitioners

The findings above may provide insight into the optimal arrangement of mobile learning regarding the presage (e.g., community type, SES), process (e.g., student-to-hardware ratio, hardware used, teaching method), study quality (e.g., learning topic/content equivalence, degree of technology use in the control group), and product (e.g., cognitive, affective and behavioural learning) variables, which are the central concerns of mobile learning policymakers, practitioners, and parents.

First, the study is timely given the current debates by policymakers and politicians, about the use of mobile devices in schooling. There is a focus in the media and much professional commentary on the adverse effects of school-aged students' use of mobile devices, including health problems like eyesight (China), potentially ethical issues (Indonesia), cyber-safety (Japan), classroom management concerns (Malaysia), and technology addiction (South Korea) (Churchill et al., 2018). The current meta-analysis provides a clear indication for policymakers on the effectiveness of mobile technology usage and evidence-based guidance on the use of mobile devices in schooling that provides a counterpoint to some of the current concerns. For example, some people believed that the use of mobile devices is not good for students' eyes, but in fact, the individual device helps students with poor eyesight see the learning content more clearly compared with look up at the backboards or whiteboards, especially those sitting in the back rows in a large classroom. For children, a mobile device is fast becoming a must-have not a nice-to-have, and it extends learning time and space (Norris & Soloway, 2015) and may sometimes serve as an unavoidable alternative for online learning (Dhawan, 2020). We recognize that hardware alone does not fulfil its potential in education and change teaching and learning fundamentally. However, different from traditional classroom learning and supported by mobile technologies' innovative features and their educational affordances, student-centred and active learning will become the new norm in tomorrow's education systems. More importantly, while the academic success of students historically determines the quality of school learning, the quality of the 'learning process' has increased in importance and extends the understanding of learning outcomes (OECD, 2019). Therefore, policymakers who hesitate to scale up the use of mobile devices in education are encouraged to take actions either for improving educational quality or for bridging the digital divide. And before approving all actions under a given policy, there is an urgent need to articulate strategic intentions supplemented by established decision-making mechanisms and support.

Second, educational practitioners and parents may need to be convinced of the value of mobile learning to better prepare and support student learning. Long-term educational technology integration with appropriate supporting logistics may increase teachers' readiness to use digital technology (Christensen & Knezek, 2017) and the level of commitment to integrating their teaching with the students' learning (Khlaif, 2018). For example, if there is a lack of targeted teacher training in the preparation stage, and insufficient technical and pedagogical support during the phases of implementation, teachers might not be able to provide innovative teaching methods, and they might even reduce the time available for students to use mobile devices. Moreover, these conditions should include removing the negative effects, such as distraction, increased cognitive load, and mobile phone addiction. One way to solve these problems is to strengthen learners' self-regulation skills, as they are especially important for informal learning like homework performance (Nikou & Economides, 2018). Besides, the role of parents is important, as researchers pointed out that students' view of parental support is not only related to their learning motivation but also to their actual behaviours in self-regulating their learning (Sha et al., 2012).

4.5 | Conclusions

As interest in the tendencies of mobile learning and the affordances of mobile technologies, it is not only crucial of reimagining teaching and learning with mobile technology in primary and secondary education, but also valuable of reassessing the effectiveness of mobile technology usage on different learning outcomes as well as how to use mobile technologies for learning effectively, enjoyably, and engagingly. This study using the best evidence from experimental or quasi-experimental studies aimed to answer whether school students learn better with mobile technology and which factors explain the differences in results. Although the results of our meta-analyses of 109 cognitive comparisons from 80 journal articles, 24 affective comparisons from 17 journal articles, and 14 behavioural comparisons from 11 journal articles, indicated that mobile technology usage was positively and significantly associated with cognitive, affective, and behavioural learning outcomes, we cannot be certain the difference was influenced by mobile technology usage and not by other variables. We also found that from both educational and methodological perspectives, the impacts of mobile technology usage were moderated by multiple factors, especially the student factors, learning process, and study quality factors. Again, while these associations are promising, we cannot make firm claims about the differences in effects of various types of mobile technology usage. Hence, given the limited number of studies included in the meta-analyses, especially the fact that studies with negative results are published fewer than those with positive results, and the considerable heterogeneity in reported mobile learning studies, we urge policymakers and researchers to interpret these results with caution. More importantly, in the near future, researchers need to optimize the quality of experimental studies, and educational stakeholders need to take responsibility and get ready to adopt and support mobile technology usage in educational practices based on evidence-based endeavours.

ACKNOWLEDGEMENTS

This work was supported by Chongqing Social Science Planning Doctoral Project Research on the Construction Mechanism of "Digital Pedestal" for the Integration of Urban and Rural Education (grant number 2021BS089) .

CONFLICT OF INTEREST

There is no conflict of interest associated with this research study.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/jcal.12759.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Jingxian Wang https://orcid.org/0000-0003-2156-0966

REFERENCES

References marked with an asterisk indicate studies included in the meta-analysis.

Al-Balushi, S. M., Al-Musawi, A. S., Ambusaidi, A. K., & Al-Hajri, F. H. (2017). The effectiveness of interacting with scientific animations in chemistry using mobile devices on grade 12 students' spatial ability and scientific reasoning skills. *Journal of Science Education and Technology*, *26*, 70–81. https://doi.org/10.1007/s10956-016-9652-2

Alcoholado, C., Diaz, A., Tagle, A., Nussbaum, M., & Infante, C. (2016). Comparing the use of the interpersonal computer, personal computer and pen-and-paper when solving arithmetic exercises. *British Journal of Educational Technology*, *47*(1), 91–105. https://doi.org/10.1111/bjet.12216

Alfadil, M. (2020). Effectiveness of virtual reality game in foreign language vocabulary acquisition. *Computers & Education*, *153*, 103893. https://doi.org/10.1016/j.compedu.2020.103893

Bakermans-Kranenburg, M. J., van IJzendoorn, M. H., & Juffer, F. (2003). Less is more: Meta-analyses of sensitivity and attachment interventions in early childhood. *Psychological Bulletin*, *129*(2), 195–215.

Bhagat, K. K., Yang, F. Y., Cheng, C. H., Zhang, Y., & Liou, W. K. (2021). Tracking the process and motivation of math learning with augmented reality. *Educational Technology, Research and Development*, *69*(6), 3153–3178.

Biggs, J. (2003). *Teaching for quality learning at university: What the student does* (2nd ed.). Open University Press.

Bloom, B. S., Englehart, M. D., Furst, E. J., Hill, W. H., & Krathwohl, D. R. (1956). *Taxonomy of educational objectives. Handbook I: Cognitive domain*. David McKay Company.

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. Wiley.

Borovay, L. A. (2007). Inquiry education as a context for the experience of flow (doctoral dissertation, McGill University). eScholarship@McGill. https://escholarship.mcgill.ca/concern/theses/b27740146

Brown, S. A., Upchurch, S. L., & Acton, G. J. (2003). A framework for developing a coding scheme for meta-analysis. *Western Journal of Nursing Research*, *25*(2), 205–222.

Burden, K., Kearney, M., Schuck, S., & Hall, T. (2019). Investigating the use of innovative mobile pedagogies for school-aged students: A systematic literature review. *Computers & Education*, *138*, 83–100.

Cai, S., Liu, C., Wang, T., Liu, E., & Liang, J. C. (2021). Effects of learning physics using augmented reality on students' self-efficacy and conceptions of learning. *British Journal of Educational Technology*, *52*(1), 235–251.

Card, N. A. (2012). *Applied meta-analysis for social science research*. Guilford Press.

Castillo-Manzano, J. I., Castro-Nuño, M., López-Valpuesta, L., Sanz-Díaz, M. T., & Yñiguez, R. (2016). Measuring the effect of ARS on academic performance: A global meta-analysis. *Computers & Education*, *96*, 109–121.

Cavus, N., & Ibrahim, D. (2017). Learning English using children's stories in mobile devices. *British Journal of Educational Technology*, *48*(2), 625–641. https://doi.org/10.1111/bjet.12427

Cetinkaya, L., & Sütçü, S. S. (2018). The effects of Facebook and WhatsApp on success in English vocabulary instruction. *Journal of Computer Assisted Learning*, *34*(5), 504–514. https://doi.org/10.1111/jcal.12255

*Chang, C. J., Liu, C. C., Wen, C. T., Tseng, L. W., Chang, H. Y., Chang, M. H., Chiang, S. H. F., Hwang, F. K., & Yang, C. W. (2020). The impact of light-weight inquiry with computer simulations on science learning in classrooms. *Computers & Education*, *146*, 103770. https://doi.org/10.1016/j.compedu.2019.103770

Chang, S. C., & Hwang, G. J. (2018). Impacts of an augmented reality-based flipped learning guiding approach on students' scientific project performance and perceptions. *Computers & Education*, *125*, 226–239. https://doi.org/10.1016/j.compedu.2018.06.007

Chauhan, S. (2017). A meta-analysis of the impact of technology on learning effectiveness of elementary students. *Computers & Education*, *105*, 14–30.

Chen, C. H., Yang, C. K., Huang, K., & Yao, K. C. (2020). Augmented reality and competition in robotics education: Effects on 21st century competencies, group collaboration and learning motivation. *Journal of Computer Assisted Learning*, *36*(6), 1052–1062.

Cheng, M., Su, C.-Y., & Kinshuk. (2021). Integrating smartphone-controlled paper airplane into gamified science inquiry for junior high school students. *Journal of Educational Computing Research*, *59*(1), 71–94.

Cheung, A. C., & Slavin, R. E. (2013). The effectiveness of educational technology applications for enhancing mathematics achievement in K-12 classrooms: A meta-analysis. *Educational Research Review*, *9*, 88–113.

Cheung, A. C., & Slavin, R. E. (2016). How methodological features affect effect sizes in education. *Educational Researcher*, *45*(5), 283–292. https://doi.org/10.3102/0013189X16656615

Chien, K. P., Tsai, C. Y., Chen, H. L., Chang, W. H., & Chen, S. (2015). Learning differences and eye fixation patterns in virtual and physical science laboratories. *Computers & Education*, *82*, 191–201. https://doi.org/10.1016/j.compedu.2014.11.023

Cho, K., Lee, S., Joo, M. H., & Becker, B. J. (2018). The effects of using mobile devices on student achievement in language learning: A meta-analysis. *Education Sciences*, *8*(3), 105.

Christensen, R., & Knezek, G. (2017). Readiness for integrating mobile learning in the classroom: Challenges, preferences and possibilities. *Computers in Human Behavior*, *76*, 112–121.

Chu, H. C. (2014). Potential negative effects of mobile learning on students' learning achievement and cognitive load—A format assessment perspective. *Educational Technology & Society*, *17*(1), 332–344.

Chung, C. J., Hwang, G. J., & Lai, C. L. (2019). A review of experimental mobile learning research in 2010–2016 based on the activity theory framework. *Computers & Education*, *129*, 1–13.

Churchill, D., Pegrum, M., & Churchill, N. (2018). The implementation of mobile learning in Asia: Key trends in practices and research. In J. Voogt, G. Knezek, R. Christensen, & K.-W. Lai (Eds.), *Second handbook of information technology in primary and secondary education* (pp. 817–858). Springer.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159.

Cooper, H., & Hedges, L. V. (1994). Potentials and limitations of research synthesis. In H. Cooper & L. V. Hedges (Eds.), *The handbook of research synthesis*. Russell Sage.

Crompton, H. (2013). A historical overview of mobile learning: Toward learner-centered education. In Z. L. Berge & L. Y. Muilenburg (Eds.), *Handbook of mobile learning* (pp. 3–14). Routledge.

Crompton, H., & Burke, D. (2020). Mobile learning and pedagogical opportunities: A configurative systematic review of PreK-12 research using the SAMR framework. *Computers & Education*, *156*, 103945.

Crompton, H., Burke, D., & Gregory, K. H. (2017). The use of mobile learning in PK-12 education: A systematic review. *Computers & Education*, *110*, 51–63.

Crompton, H., Burke, D., & Lin, Y. C. (2019). Mobile learning and student cognition: A systematic review of PK-12 research using Bloom's taxonomy. *British Journal of Educational Technology*, *50*(2), 684–701.

Cuijpers, P., Weitz, E., Cristea, I. A., & Twisk, J. (2017). Pre-post effect sizes should be avoided in meta-analyses. *Epidemiology and Psychiatric Sciences*, *26*(4), 364–368.

Danaei, D., Jamali, H. R., Mansourian, Y., & Rastegarpour, H. (2020). Comparing reading comprehension between children reading augmented reality and print storybooks. *Computers & Education*, *153*, 103900. https://doi.org/10.1016/j.compedu.2020.103900 del Olmo-Muñoz, J., Cózar-Gutiérrez, R., & González-Calero, J. A. (2020). Computational thinking through unplugged activities in early years of primary education. *Computers & Education*, *150*, 103832. https://doi.org/10.1016/j.compedu.2020.103832

Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, *49*(1), 5–22.

Diacopoulos, M. M., & Crompton, H. (2020). A systematic review of mobile learning in social studies. *Computers & Education*, *154*, 103911.

Duval, S., & Tweedie, R. (2000). Trim and fill: A simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis. *Biometrics*, *56*(2), 455–463.

*Ebadi, S., & Bashir, S. (2021). An exploration into EFL learners' writing skills via mobile-based dynamic assessment. *Education and Information Technologies*, *26*(2), 1995–2016.

Edwards, C. M., Rule, A. C., & Boody, R. M. (2017). Middle school students' mathematics knowledge retention: Online or face-to-face environments. *Educational Technology & Society*, *20*(4), 1–10.

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal*, *315*, 629–634. https://doi.org/10.1136/bmj.315.7109.629

Erbas, C., & Demirer, V. (2019). The effects of augmented reality on students' academic achievement and motivation in a biology course. *Journal of Computer Assisted Learning*, *35*(3), 450–458. https://doi.org/10.1111/jcal.12350

Fabian, K., Topping, K. J., & Barron, I. G. (2016). Mobile technology and mathematics: Effects on students' attitudes, engagement, and achievement. *Journal of Computers in Education*, *3*(1), 77–104.

Fidan, M., & Tuncel, M. (2019). Integrating augmented reality into problem based learning: The effects on learning achievement and attitude in physics education. *Computers & Education*, *142*, 103635. https://doi.org/10.1016/j.compedu.2019.103635

Fokides, E., Atsikpasi, P., & Karageorgou, D. (2020). Tablets, plants, and primary school students: A study. *Technology, Knowledge and Learning*, *25*(3), 621–649.

Furió, D., Juan, M. C., Seguí, I., & Vivó, R. (2015). Mobile learning vs. traditional classroom lessons: A comparative study. *Journal of Computer Assisted Learning*, *31*(3), 189–201. https://doi.org/10.1111/jcal.12071

Giasiranis, S., & Sofos, L. (2017). Flow experience and educational effectiveness of teaching informatics using AR. *Educational Technology & Society*, *20*(4), 78–88.

Haßler, B., Major, L., & Hennessy, S. (2016). Tablet use in schools: A critical review of the evidence for learning outcomes. *Journal of Computer Assisted Learning*, *32*(2), 139–156.

Hess, F. M., & Leal, D. L. (2001). A shrinking "digital divide"? The provision of classroom computers across urban school systems. *Social Science Quarterly*, *82*(4), 765–778.

Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ*, *327*, 557–560.

Hillmayr, D., Ziernwald, L., Reinhold, F., Hofer, S. I., & Reiss, K. M. (2020). The potential of digital tools to enhance mathematics and science learning in secondary schools: A context-specific meta-analysis. *Computers & Education*, *153*, 103897. https://doi.org/10.1016/j.compedu.2020.103897

Huang, C. S., Su, A. Y., Yang, S. J., & Liou, H. H. (2017). A collaborative digital pen learning approach to improving students' learning achievement and motivation in mathematics courses. *Computers & Education*, *107*, 31–44. https://doi.org/10.1016/j.compedu.2016.12.014

Huang, C. S., Yang, S. J., Chiang, T. H., & Su, A. Y. (2016). Effects of situated mobile learning approach on learning motivation and performance of EFL students. *Educational Technology & Society*, *19*(1), 263–276.

Huang, T. C., Chen, M. Y., & Hsu, W. P. (2019). Do learning styles matter? Motivating learners in an augmented geopark. *Educational Technology & Society*, *22*(1), 70–81.

Huang, Y. M., & Lin, P. H. (2017). Evaluating students' learning achievement and flow experience with tablet PCs based on AR and tangible technology in u-learning. *Library Hi Tech*, *35*(4), 602–614. https://doi.org/10.1108/lht-01-2017-0023

Huang, Y. M., Shadiev, R., Sun, A., Hwang, W. Y., & Liu, T. Y. (2017). A study of the cognitive diffusion model: Facilitating students' high level cognitive processes with authentic support. *Educational Technology Research and Development*, *65*(3), 505–531. https://doi.org/10.1007/s11423-016-9475-0

Hung, H. C., & Young, S. S. C. (2015). An investigation of game-embedded handheld devices to enhance English learning. *Journal of Educational Computing Research*, *52*(4), 548–567.

Hunsu, N. J., Adesope, O., & Bayly, D. J. (2016). A meta-analysis of the effects of audience response systems (clicker-based technologies) on cognition and affect. *Computers & Education*, *94*, 102–119.

Hwang, G. J., Lai, C. L., Liang, J. C., Chu, H. C., & Tsai, C. C. (2018). A long-term experiment to investigate the relationships between high school students' perceptions of mobile learning and peer interaction and higher-order thinking tendencies. *Educational Technology Research and Development*, *66*, 75–93.

Hwang, W. Y., Zhao, L., Shadiev, R., Lin, L. K., Shih, T. K., & Chen, H. R. (2019). Exploring the effects of ubiquitous geometry learning in real situations. *Educational Technology Research and Development*, *68*(3), 1–27. https://doi.org/10.1007/s11423-019-09730-y

Istance, D., & Kools, M. (2013). OECD work on technology and education: Innovative learning environments as an integrating framework. *European Journal of Education*, *48*(1), 43–57.

*Jere-Folotiya, J., Chansa-Kabali, T., Munachaka, J. C., Sampa, F., Yalukanda, C., Westerholm, J., Richardson, U., Serpell, R., & Lyytinen, H. (2014). The effect of using a mobile literacy game to improve literacy levels of grade one students in Zambian schools. *Educational Technology Research and Development*, *62*(4), 417–436. https://doi.org/10.1007/s11423-014-9342-9

Jong, M. S. Y., Chan, T., Hue, M. T., & Tam, V. W. (2018). Gamifying and mobilising social enquiry-based learning in authentic outdoor environments. *Educational Technology & Society*, *21*(4), 277–292.

Jong, M. S. Y., Tsai, C. C., Xie, H., & Kwan-Kit Wong, F. (2020). Integrating interactive learner-immersed video-based virtual reality into learning and teaching of physical geography. *British Journal of Educational Technology*, *51*(6), 2064–2079.

Joo-Nagata, J., Abad, F. M., Giner, J. G. B., & García-Peñalvo, F. J. (2017). Augmented reality and pedestrian navigation through its implementation in m-learning and e-learning: Evaluation of an educational program in Chile. *Computers & Education*, *111*, 1–17. https://doi.org/10.1016/j.compedu.2017.04.003

Khan, S., Hwang, G. J., Azeem Abbas, M., & Rehman, A. (2019). Mitigating the urban–rural educational gap in developing countries through mobile technology-supported learning. *British Journal of Educational Technology*, *50*(2), 735–749. https://doi.org/10.1111/bjet.12692

Khlaif, Z. (2018). Teachers' perceptions of factors affecting their adoption and acceptance of mobile technology in K-12 settings. *Computers in the Schools*, *35*(1), 49–67.

Koole, M. L. (2009). A model for framing mobile learning. In M. Ally (Ed.), *Mobile learning: Transforming the delivery of education and training* (pp. 25–47). AU Press, Athabasca University.

Ku, D. T., Huang, Y. H., & Hus, S. C. (2015). The effects of GBL and learning styles on Chinese idiom by using TUI device. *Journal of Computer Assisted Learning*, *31*(6), 505–515. https://doi.org/10.1111/jcal.12085

Lai, A. F., Chen, C. H., & Lee, G. Y. (2019). An augmented reality-based learning approach to enhancing students' science reading performances from the perspective of the cognitive load theory. *British Journal of Educational Technology*, *50*(1), 232–247. https://doi.org/10.1111/bjet.12716

Lai, C. L. (2020). Trends of mobile learning: A review of the top 100 highly cited papers. *British Journal of Educational Technology*, *51*(3), 721–742.

Lee, C. C., Hao, Y., Lee, K. S., Sim, S. C., & Huang, C. C. (2019). Investigation of the effects of an online instant response system on students in a middle school of a rural area. *Computers in Human Behavior*, *95*, 217–223. https://doi.org/10.1016/j.chb.2018.11.034

*Lee, H. K., & Choi, A. (2020). Enhancing early numeracy skills with a tablet-based math game intervention: A study in Tanzania. *Educational Technology Research and Development*, *68*(6), 3567–3585.

Levy Berg, A., Sandell, R., & Sandahl, C. (2009). Affect-focused body psychotherapy in patients with generalized anxiety disorder: Evaluation of an integrative method. *Journal of Psychotherapy Integration*, *19*, 67–85.

Li, Y., & Ranieri, M. (2013). Educational and social correlates of the digital divide for rural and urban children: A study on primary school students in a provincial city of China. *Computers & Education*, *60*(1), 197–209.

Liang, H. Y., Hsu, T. Y., & Hwang, G. J. (2021). Promoting children's inquiry performances in alternate reality games: A mobile concept mapping-based questioning approach. *British Journal of Educational Technology*, *52*(5), 2000–2019.

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P., Clarke, M., Devereaux, P.J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *Journal of Clinical Epidemiology*, *62*(10), e1–e34.

Lim, G., Shelley, A., & Heo, D. (2019). The regulation of learning and co-creation of new knowledge in mobile learning. *Knowledge Management & E-Learning: An International Journal*, *11*(4), 449–484.

Lin, C. C. (2014). Learning English reading in a mobile-assisted extensive reading program. *Computers & Education*, *78*, 48–59. https://doi.org/10.1016/j.compedu.2014.05.004

Lin, C. C. (2017). Learning English with electronic textbooks on tablet PCs. *Interactive Learning Environments*, *25*(8), 1035–1047. https://doi.org/10.1080/10494820.2016.1242505

Liu, Q., Yu, S., Chen, W., Wang, Q., & Xu, S. (2021). The effects of an augmented reality based magnetic experimental tool on students' knowledge improvement and cognitive load. *Journal of Computer Assisted Learning*, *37*(3), 645–656.

Liu, R., Wang, L., Lei, J., Wang, Q., & Ren, Y. (2020). Effects of an immersive virtual reality-based classroom on students' learning performance in science lessons. *British Journal of Educational Technology*, *51*(6), 2034–2049.

Liu, T. C., Lin, Y. C., Wang, T. N., Yeh, S. C., & Kalyuga, S. (2021). Studying the effect of redundancy in a virtual reality classroom. *Educational Technology, Research and Development*, *69*(2), 1183–1200.

Liyanawatta, M., Yang, S. H., Liu, Y. T., Zhuang, Y., & Chen, G. D. (2022). Audience participation digital drama-based learning activities for situational learning in the classroom. *British Journal of Educational Technology*, *53*(1), 189–206.

Mabuza, M. Q., & Osodo, J. (2020). Effects of mobile phones on students' academic performance in religious education. *The Journal of Technology Studies*, *46*(1), 32–42.

Mahdi, H. S. (2018). Effectiveness of mobile devices on vocabulary learning: A meta-analysis. *Journal of Educational Computing Research*, *56*(1), 134–154.

Makransky, G., Petersen, G. B., & Klingenberg, S. (2020). Can an immersive virtual reality simulation increase students' interest and career aspirations in science? *British Journal of Educational Technology*, *51*(6), 2079–2097.

Nikou, S. A., & Economides, A. A. (2018). Mobile-based micro-learning and assessment: Impact on learning performance and motivation of high school students. *Journal of Computer Assisted Learning*, *34*(3), 269–278. https://doi.org/10.1111/jcal.12240

Norris, C., & Soloway, E. (2015). Mobile technology in 2020: Predictions and implications for K–12 education. *Educational Technology*, *55*(1), 12–19.

OECD. (2019). OECD future of education and skill 2030. A series of concept notes. https://www.oecd.org/education/2030-project/contact/OECD_Learning_Compass_2030_Concept_Note_Series.pdf.

Outhwaite, L. A., Gulliford, A., & Pitchford, N. J. (2017). Closing the gap: Efficacy of a tablet intervention to support the development of early mathematical skills in UK primary school children. *Computers & Education*, *108*, 43–58. https://doi.org/10.1016/j.compedu.2017.01.011

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery*, *88*, 105906.

Papamitsiou, Z., & Economides, A. A. (2016). Learning analytics for smart learning environments: A meta-analysis of empirical research results from 2009 to 2015. In M. J. Spector, B. B. Lockee, & M. D. Childress (Eds.), *Learning, design, and technology: An international compendium of theory, research, practice, and policy* (pp. 1–23). Springer.

*Papastergiou, M., Natsis, P., Vernadakis, N., & Antoniou, P. (2020). Introducing tablets and a mobile fitness application into primary school physical education. *Education and Information Technologies*, *26*(1), 799–816.

Passig, D., Tzuriel, D., & Eshel-Kedmi, G. (2016). Improving children's cognitive modifiability by dynamic assessment in 3D immersive virtual reality environments. *Computers & Education*, *95*, 296–308. https://doi.org/10.1016/j.compedu.2016.01.009

Perera, M., & Aboal, D. (2019). The impact of a mathematics computer-assisted learning platform on students' mathematics test scores. Maastricht Economic and social Research institute on Innovation and Technology (UNU- MERIT). https://www.merit.unu.edu/publications/wppdf/2019/wp2019-007.pdf.

Potocki, A., Chailleux, M., Gimenes, M., & Pylouster, J. (2021). ProVoc: An app to train vocabulary depth in order to foster children's reading comprehension. *Journal of Computer Assisted Learning*, *37*(5), 1324–1335.

Purba, S. W. D., Hwang, W. Y., Pao, S. C., & Ma, Z. H. (2019). Investigation of inquiry behaviors and learning achievement in authentic contexts with the ubiquitous-physics app. *Educational Technology & Society*, *22*(4), 59–76.

Quintas, A., Bustamante, J. C., Pradas, F., & Castellar, C. (2020). Psychological effects of gamified didactics with exergames in physical education at primary schools: Results from a natural experiment. *Computers & Education*, *152*, 103874. https://doi.org/10.1016/j.compedu.2020.103874

Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological Bulletin*, *86*(3), 638–641.

Ruiz-Ariza, A., Casuso, R. A., Suarez-Manzano, S., & Martínez-López, E. J. (2018). Effect of augmented reality game Pokémon GO on cognitive performance and emotional intelligence in adolescent young. *Computers & Education*, *116*, 49–63. https://doi.org/10.1016/j.compedu.2017.09.002

Sahin, D., & Yilmaz, R. M. (2020). The effect of augmented reality technology on middle school students' achievements and attitudes towards science education. *Computers & Education*, *144*, 103710. https://doi.org/10.1016/j.compedu.2019.103710

Schmid, R. F., Bernard, R. M., Borokhovski, E., Tamim, R. M., Abrami, P. C., Surkes, M. A., Wade, A., & Woods, J. (2014). The effects of technology use in postsecondary education: A meta-analysis of classroom applications. *Computers & Education*, *72*, 271–291.

Sha, L., Looi, C. K., Chen, W., Seow, P., & Wong, L. H. (2012). Recognizing and measuring self-regulated learning in a mobile learning environment. *Computers in Human Behavior*, *28*(2), 718–728.

Shadiev, R., Hwang, W. Y., Huang, Y. M., & Liu, T. Y. (2015). The impact of supported and annotated mobile learning on achievement and cognitive load. *Educational Technology & Society*, *18*(4), 53–69.

Shadiev, R., Hwang, W. Y., & Liu, T. Y. (2018). Investigating the effectiveness of a learning activity supported by a mobile multimedia learning system to enhance autonomous EFL learning in authentic contexts.

Educational Technology Research and Development, *66*(4), 893–912. https://doi.org/10.1007/s11423-018-9590-1
Shi, Y., Yang, H., MacLeod, J., Zhang, J., & Yang, H. H. (2020). College students' cognitive learning outcomes in technology-enabled active learning environments: A meta-analysis of the empirical literature. *Journal of Educational Computing Research*, *58*(4), 791–817.
Stanojević, L., & Ranđelović, M. (2018). The effect of web-based classroom response system on students learning outcomes: Results from programming course. *Megatrend Revija*, *15*(2), 213–232. https://doi.org/10.5937/megrev1802213s
Su, C. H., & Cheng, C. H. (2015). A mobile gamification learning system for improving the learning motivation and achievements. *Journal of Computer Assisted Learning*, *31*(3), 268–286. https://doi.org/10.1111/jcal.12088
Suarez, A., Specht, M., Prinsen, F., Kalz, M., & Ternier, S. (2018). A review of the types of mobile activities in mobile inquiry-based learning. *Computers & Education*, *118*, 38–55.
Sung, H. Y., Hwang, G. J., Lin, C. J., & Hong, T. W. (2017). Experiencing the analects of Confucius: An experiential game-based learning approach to promoting students' motivation and conception of learning. *Computers & Education*, *110*, 143–153. https://doi.org/10.1016/j.compedu.2017.03.014
Sung, Y. T., Chang, K. E., & Liu, T. C. (2016). The effects of integrating mobile devices with teaching and learning on students' learning performance: A meta-analysis and research synthesis. *Computers & Education*, *94*, 252–275.
Sung, Y. T., Lee, H. Y., Yang, J. M., & Chang, K. E. (2019). The quality of experimental designs in mobile learning research: A systemic review and self-improvement tool. *Educational Research Review*, *28*, 100279.
Sung, Y. T., Yang, J. M., & Lee, H. Y. (2017). The effects of mobile-computer-supported collaborative learning: Meta-analysis and critical synthesis. *Review of Educational Research*, *87*(4), 768–805.
Tapingkae, P., Panjaburee, P., Hwang, G. J., & Srisawasdi, N. (2020). Effects of a formative assessment-based contextual gaming approach on students' digital citizenship behaviours, learning motivations, and perceptions. *Computers & Education*, *159*, 103998.
Troll, E. S., Friese, M., & Loschelder, D. D. (2020). How students' self-control and smartphone-use explain their academic performance. *Computers in Human Behavior*, *117*, 106624.
van Uittert, A., Verhoeven, L., & Segers, E. (2022). Responsiveness to a game-based intervention to enhance reading efficiency in first graders. *Journal of Computer Assisted Learning*, *38*(1), 178–191.
Vanbecelaere, S., Van den Berghe, K., Cornillie, F., Sasanguie, D., Reynvoet, B., & Depaepe, F. (2020). The effects of two digital educational games on cognitive and non-cognitive math and reading outcomes. *Computers & Education*, *143*, 103680. https://doi.org/10.1016/j.compedu.2019.103680
Viechtbauer, W., & Cheung, M. W. L. (2010). Outlier and influence diagnostics for meta-analysis. *Research Synthesis Methods*, *1*(2), 112–125.
Volk, M., Cotič, M., Zajc, M., & Starcic, A. I. (2017). Tablet-based cross-curricular maths vs. traditional maths classroom practice for higher-order learning outcomes. *Computers & Education*, *114*, 1–23. https://doi.org/10.1016/j.compedu.2017.06.004
Walczak, S., & Taylor, N. G. (2018). Geography learning in primary school: Comparing face-to-face versus tablet-based instruction methods. *Computers & Education*, *117*, 188–198. https://doi.org/10.1016/j.compedu.2017.11.001
Wang, Y. H. (2016). Could a mobile-assisted learning system support flipped classrooms for classical Chinese learning? *Journal of Computer Assisted Learning*, *32*(5), 391–415. https://doi.org/10.1111/jcal.12141
Wang, Y. H. (2017a). Exploring the effectiveness of integrating augmented reality-based materials to support writing activities. *Computers & Education*, *113*, 162–176. https://doi.org/10.1016/j.compedu.2017.04.013
Wang, Y. H. (2017b). The effectiveness of using cloud-based cross-device IRS to support classical Chinese learning. *Educational Technology & Society*, *20*(2), 127–141.
Wei, X., Saab, N., & Admiraal, W. (2021). Assessment of cognitive, behavioral, and affective learning outcomes in massive open online courses: A systematic literature review. *Computers & Education*, *163*, 104097.
Wollscheid, S., Sjaastad, J., Tømte, C., & Løver, N. (2016). The effect of pen and paper or tablet computer on early writing–a pilot study. *Computers & Education*, *98*, 70–80. https://doi.org/10.1016/j.compedu.2016.03.008
Yallihep, M., & Kutlu, B. (2020). Mobile serious games: Effects on students' understanding of programming concepts and attitudes towards information technology. *Education and Information Technologies*, *25*(2), 1237–1254. https://doi.org/10.1007/s10639-019-10008-2
Yang, G., Chen, Y. T., Zheng, X. L., & Hwang, G. J. (2021). From experiencing to expressing: A virtual reality approach to facilitating pupils' descriptive paper writing performance and learning behavior engagement. *British Journal of Educational Technology*, *52*(2), 807–823.
Yang, J. M., Sung, Y. T., & Chang, K. E. (2020). Use of meta-analysis to uncover the critical issues of Mobile inquiry-based learning. *Journal of Educational Computing Research*, *58*(4), 715–746.
Yousef, A. M. F. (2021). Augmented reality assisted learning achievement, motivation, and creativity for children of low-grade in primary school. *Journal of Computer Assisted Learning*, *37*(4), 966–977.
Zhai, X., Zhang, M., Li, M., & Zhang, X. (2019). Understanding the relationship between levels of mobile technology use in high school physics classrooms and the learning outcome. *British Journal of Educational Technology*, *50*(2), 750–766.
Zhang, J., Sung, Y. T., Hou, H. T., & Chang, K. E. (2014). The development and evaluation of an augmented reality-based armillary sphere for astronomical observation instruction. *Computers & Education*, *73*, 178–188. https://doi.org/10.1016/j.compedu.2014.01.003
*Zhang, L., Shang, J., Pelton, T., & Pelton, L. F. (2020). Supporting primary students' learning of fraction conceptual knowledge through digital games. *Journal of Computer Assisted Learning*, *36*(4), 540–548.
*Zhao, J., Hwang, G. J., Chang, S. C., Yang, Q. F., & Nokkaew, A. (2021). Effects of gamified interactive e-books on students' flipped learning performance, motivation, and meta-cognition tendency in a mathematics course. *Educational Technology Research and Development*, *69*(6), 3255–3280.
Zheng, B., Warschauer, M., Hwang, J. K., & Collins, P. (2014). Laptop use, interactive science software, and science learning among at-risk students. *Journal of Science Education and Technology*, *23*(4), 591–603. https://doi.org/10.1007/s10956-014-9489-5
Zheng, B., Warschauer, M., Lin, C. H., & Chang, C. (2016). Learning in one-to-one laptop environments: A meta-analysis and research synthesis. *Review of Educational Research*, *86*(4), 1052–1084.
Zhu, C., & Urhahne, D. (2018). The use of learner response systems in the classroom enhances teachers' judgment accuracy. *Learning and Instruction*, *58*, 255–262. https://doi.org/10.1016/j.learninstruc.2018.07.011

How to cite this article: Wang, J., Tigelaar, D. E. H., Zhou, T., & Admiraal, W. (2022). The effects of mobile technology usage on cognitive, affective, and behavioural learning outcomes in primary and secondary education: A systematic review with meta-analysis. *Journal of Computer Assisted Learning*, 1–28. https://doi.org/10.1111/jcal.12759

APPENDIX A: OVERVIEW OF STUDIES INCLUDED IN THE META-ANALYSIS

Study	Region	Community type	SES	Education level	Learning environment	School subjects	Mobile technologies used in intervention group	Student-to-hardware ratio in intervention group	Teaching method in intervention group	Duration of the intervention	Research design	Instructor equivalence	Learning topic/content equivalence	Software/tool equivalence	Degree of technology use in control group	Procedure of effect size extraction
Al-Balushi et al. (2017)	Oman	Not reported	Not low	Secondary school	Formal setting	Science	Handheld devices with multiple functions	Own	Mixed	>4 weeks	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Alcoholado et al. (2016)	Chile	Not reported	Low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	[a] Shared: comparison 1; own: comparison 2	Computer-assisted testing/assessment	>4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Alfadil (2020)	Saudi Arabia	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Shared	Game-based learning	1 day–4 weeks	Quasi-experimental	Same	Same	Not reported	Pen-and-paper	Calculated from exact descriptive
Bhagat et al. (2021)	Taiwan of China	Urban	Not low	Secondary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Inquiry-oriented learning	Not reported	True experimental design	Not reported	Same	Different	Pen-and-paper	Calculated from exact descriptive
Cai et al. (2021)	Mainland of China	Not reported	Not low	Secondary school	Formal setting	Science	Handheld devices with one specific function	Shared	Inquiry-oriented learning	1 day–4 weeks	Quasi-experimental	Same	Same	Same	Traditional technology	Calculated from exact descriptive
Cavus and Ibrahim (2017)	Cyprus	Not reported	Not low	Secondary school	Unrestricted	Language arts	Handheld devices with multiple functions	Own	Self-directed learning	1 day–4 weeks	Experimental	Not reported	Same	Same	Pen-and-paper	Calculated from exact descriptive
Cetinkaya and Sütçü (2018)	Turkey	Not reported	Not low	Secondary school	Unrestricted	Language arts	Handheld devices with multiple functions	Own	Self-directed learning	>4 weeks	Quasi-experimental	Same	Same	Different	Not reported	Calculated from exact descriptive
Chang and Hwang (2018)	Taiwan of China	Not reported	Not low	Primary school	Formal setting	Science	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	1 day–4 weeks	Quasi-experimental	Same	Same	Not reported	Pen-and-paper	Calculated from exact descriptive
Chang et al. (2020)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Science	Handheld devices with multiple functions	Shared	Mixed	<1 day	Quasi-experimental	Same	Same	Different	Traditional technology	Calculated from exact descriptive
Chen et al. (2020)	Taiwan of China	Not urban	Not low	Secondary school	Formal setting	Science	Handheld devices with multiple functions	Shared	Inquiry-oriented learning	<1 day	Quasi-experimental	Same	Same	Same	Traditional technology	Calculated from exact descriptive
Cheng et al. (2021)	Mainland of China	Not reported	Not low	Secondary school	Formal setting	Science	Handheld devices with multiple functions	Not reported	Game-based learning	<1 day	Quasi-experimental	Same	Same	Different	Traditional technology	Calculated from exact descriptive
Chien et al. (2015)	Taiwan of China	Urban	Not low	Secondary school	Formal setting	Science	Handheld devices with one specific function	Shared	Inquiry-oriented learning	<1 day	Experimental	Different	Same	Same	Traditional technology	Calculated from inferential statistics
Chu (2014)	Taiwan of China	Not reported	Not low	Primary school	Unrestricted	Social studies	Handheld devices with one specific function	Not reported	Computer-assisted testing/assessment	<1 day	Experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Danaei et al. (2020)	Iran	Not reported	Not low	Primary school	Informal setting	Language arts	Handheld devices with multiple functions	Own	Self-directed learning	Not reported	Quasi-experimental	Not reported	Same	Same	Pen-and-paper	Calculated from inferential statistics

(Continues)

Study	Region	Community type	SES	Education level	Learning environment	School subjects	Mobile technologies used in intervention group	Student-to-hardware ratio in intervention group	Teaching method in intervention group	Duration of the intervention	Research design	Instructor equivalence	Learning topic/content equivalence	Software/tool equivalence	Degree of technology use in control group	Procedure of effect size extraction
del Olmo-Muñoz et al. (2020)	Spain	Not reported	Not low	Primary school	Formal setting	Professional subjects	Handheld devices with multiple functions	Own	Inquiry-oriented learning	<1 day	Quasi-experimental	Different	Different	Different	Not reported	Calculated from exact descriptive
Ebadi and Bashir (2021)	Iran	Not reported	Not low	Secondary school	Formal setting	Social studies	Handheld devices with multiple functions	Own	Inquiry-oriented learning	Not reported	True experimental design	Same	Same	Different	Pen-and-paper	Calculated from inferential statistics
Edwards et al. (2017)	USA	Not urban	Not low	Secondary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Lectures	Not reported	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from inferential statistics
Erbas and Demirer (2019)	Turkey	Not reported	Not low	Secondary school	Formal setting	Science	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	>4 weeks	Quasi-experimental	Same	Same	Different	Pen-and-paper	Calculated from exact descriptive
Fidan and Tuncel (2019)	Turkey	Not reported	Not low	Secondary school	Formal setting	Science	Handheld devices with multiple functions	Own	Inquiry-oriented learning	>4 weeks	Quasi-experimental	Same	Same	[a]Same: comparison 1; Different: comparison 2	Traditional technology	Calculated from exact descriptive
Fokides et al. (2020)	Greece	Not reported	Not low	Primary school	Formal setting	Science	Handheld devices with multiple functions	Own	Inquiry-oriented learning	Not reported	Quasi-experimental	Different	Same	Different	Pen-and-paper	Calculated from exact descriptive
Furió et al. (2015)	Spain	Not reported	Not low	Primary school	Formal setting	Social studies	Handheld devices with multiple functions	Own	Game-based learning	Not reported	Experimental	Not reported	Same	Not reported	Not reported	Calculated from exact descriptive
Giasiranis and Sofos (2017)	Greece	Not reported	Not low	Secondary school	Formal setting	Professional subjects	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	<1 day	Quasi-experimental	Not reported	Same	Same	Traditional technology	Calculated from exact descriptive
Huang and Lin (2017)	Taiwan of China	Not reported	Not low	Primary school	Informal setting	Science	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	<1 day	Experimental	Same	Same	Different	Pen-and-paper	Calculated from exact descriptive
Huang et al. (2019)	Taiwan of China	Not reported	Not low	Primary school	Informal setting	Social studies	Handheld devices with multiple functions	Own	Inquiry-oriented learning	<1 day	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from inferential statistics
Huang, Shadiev, et al. (2017)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Inquiry-oriented learning	>4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Huang, Su, et al. (2017)	Taiwan of China	Not reported	Not low	Primary school	Formal setting	Mathematics	Handheld devices with one specific function	Own	[a]Inquiry-oriented learning: comparison 1; Lectures: comparison 2	1 day–4 weeks	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Huang et al. (2016)	Taiwan of China	Not reported	Not low	Primary school	Informal setting	Language arts	Handheld devices with multiple functions	Not reported	Self-directed learning	<1 day	Quasi-experimental	Same	Different	Different	Pen-and-paper	Calculated from exact descriptive
Hung and Young (2015)	Taiwan of China	Not reported	Not low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Inquiry-oriented learning	<1 day	Quasi-experimental	Not reported	Same	Same	Pen-and-paper	Calculated from exact descriptive

Study	Region	Community type	SES	Education level	Learning environment	School subjects	Mobile technologies used in intervention group	Student-to-hardware ratio in intervention group	Teaching method in intervention group	Duration of the intervention	Research design	Instructor equivalence	Learning topic/content equivalence	Software/tool equivalence	Degree of technology use in control group	Procedure of effect size extraction
Hwang et al. (2019)	Taiwan of China	Not reported	Not low	Primary school	Informal setting	Social studies	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	>4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Jere-Folotiya et al. (2014)	Zambian	Not reported	Not low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Not reported	Game-based learning	1 day–4 weeks	Quasi-experimental	Different	Different	Different	Not reported	Calculated from exact descriptive
Jong et al. (2018) Sample 1	Hongkong	Not reported	Not low	Secondary school	Informal setting	Social studies	Handheld devices with multiple functions	Not reported	Mixed	<1 day	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Jong et al. (2018) Sample 2	Hongkong	Not reported	Not low	Secondary school	Informal setting	Social studies	Handheld devices with multiple functions	Not reported	Mixed	<1 day	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Jong et al. (2018) Sample 3	Hongkong	Not reported	Not low	Secondary school	Informal setting	Social studies	Handheld devices with multiple functions	Not reported	Mixed	<1 day	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Jong et al. (2020)	Hongkong	Not reported	Not low	Secondary school	Formal setting	Social studies	Handheld devices with one specific function	Own	Inquiry-oriented learning	1 day–4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Joo-Nagata et al. (2017)	Chile	Urban	Not low	Primary school	Informal setting	Social studies	Handheld devices with multiple functions	Not reported	Computer-assisted testing/assessment	<1 day	Quasi-experimental	Not reported	Same	Same	Traditional technology	[c]Calculated from exact descriptive/Calculated from inferential statistics
Khan et al. (2019) Sample 1	Pakistan	Not urban	Not low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Game-based learning	1 day–4 weeks	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Khan et al. (2019) Sample 2	Pakistan	Not urban	Not low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Game-based learning	1 day–4 weeks	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Ku et al. (2015)	Taiwan of China	Not reported	Not low	Primary school	Informal setting	Social studies	Handheld devices with one specific function	Not reported	Game-based learning	Not reported	Quasi-experimental	Same	Same	Not reported	Traditional technology	Calculated from exact descriptive
Lai et al. (2019)	Taiwan of China	Not reported	Not low	Primary school	Formal setting	Science	Handheld devices with multiple functions	Own	Mixed	1 day–4 weeks	Quasi-experimental	Same	Same	Same	Traditional technology	Calculated from exact descriptive
Lee and Choi (2020)	Tanzania	Not urban	Not low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Game-based learning	>4 weeks	True experimental design	Same	Different	Different	Not reported	Calculated from exact descriptive
Lee et al. (2019)	Taiwan of China	Not urban	Low	Secondary school	Formal setting	Science	Handheld devices with one specific function	Own	Computer-assisted testing/assessment	>4 weeks	Quasi-experimental	Same	Different	Different	Traditional technology	Calculated from exact descriptive
Liang et al. (2021)	Taiwan of China	Urban	Not low	Primary school	Formal setting	Science	Handheld devices with multiple functions	Not reported	Game-based learning	<1 day	Quasi-experimental	Different	Same	Different	Not reported	Calculated from exact descriptive

(Continues)

Study	Region	Community type	SES	Education level	Learning environment	School subjects	Mobile technologies used in intervention group	Student-to-hardware ratio in intervention group	Teaching method in intervention group	Duration of the intervention	Research design	Instructor equivalence	Learning topic/content equivalence	Software/tool equivalence	Degree of technology use in control group	Procedure of effect size extraction
Lin (2014)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Inquiry-oriented learning	>4 weeks	Quasi-experimental	Same	Same	Same	Traditional technology	Calculated from exact descriptive
Lin (2017)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Inquiry-oriented learning	1 day–4 weeks	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Liu, Lin, et al. (2021)	Taiwan of China	Not reported	Not low	Primary school	Formal setting	Science	Handheld devices with one specific function	Own	Not reported	<1 day	True experimental design	Different	[a]Same: comparison 1,4,5; Different: comparison 2,3	Different	Traditional technology	Calculated from exact descriptive
Liu et al. (2020)	Mainland of China	Urban	Not low	Primary school	Formal setting	Formal setting	Handheld devices with multiple functions	Shared	Inquiry-oriented learning	>4 weeks	Quasi-experimental	Same	Same	Same	Traditional technology	Calculated from exact descriptive
Liu, Yu, et al. (2021)	Mainland of China	Not reported	Not low	Secondary school	Formal setting	Science	Handheld devices with multiple functions	Shared	Inquiry-oriented learning	<1 day	True experimental design	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Liyanawatta et al. (2022)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Game-based learning	1 day–4 weeks	Quasi-experimental	Different	Different	Different	Pen-and-paper	Calculated from exact descriptive
Mabuza and Osodo (2020)	the Kingdom of Eswatini	Not reported	Not low	Secondary school	Formal setting	Social studies	Handheld devices with multiple functions	Shared	Lectures	1 day–4 weeks	Quasi-experimental	Not reported	Same	Different	Pen-and-paper	Calculated from exact descriptive
Makransky et al. (2020)	Copenhagen	Not reported	Not low	Secondary school	Informal setting	Science	Handheld devices with multiple functions	Own	Inquiry-oriented learning	1 day–4 weeks	Quasi-experimental	Not reported	Same	Different	Traditional technology	Calculated from exact descriptive
Nikou and Economides (2018)	Europe	Not reported	Not low	Secondary school	Informal setting	Science	Mixed	Own	Computer-assisted testing/assessment	>4 weeks	Experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Outhwaite et al. (2017) Study 1	UK	Not reported	Low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Not reported	>4 weeks	Quasi-experimental	Different	Not reported	Not reported	Not reported	Calculated from inferential statistics
Outhwaite et al. (2017) Study 4	Uk	Not reported	Not low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Not reported	>4 weeks	Quasi-experimental	Same	Not reported	Not reported	Traditional technology	Calculated from exact descriptive
Papastergiou et al. (2020)	Greece	Urban	Not low	Primary school	Formal setting	Professional subjects	Handheld devices with multiple functions	Shared	Not reported	1 day–4 weeks	Quasi-experimental	Different	Same	Same	Traditional technology	Calculated from exact descriptive
Passig et al. (2016)	Israel	Urban	Not low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Computer-assisted testing/assessment	<1 day	Experimental	Same	Same	Not reported	Pen-and-paper	Calculated from exact descriptive
Potocki et al. (2021)	France	Not urban	Low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Not reported	Computer-assisted testing/assessment	1 day–4 weeks	Quasi-experimental	Different	Same	Different	Not reported	Calculated from exact descriptive
Purba et al. (2019)	Taiwan of China	Not reported	Not low	Secondary school	Unrestricted	Science	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	1 day–4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive

Study	Region	Community type	SES	Education level	Learning environment	School subjects	Mobile technologies used in intervention group	Student-to-hardware ratio in intervention group	Teaching method in intervention group	Duration of the intervention	Research design	Instructor equivalence	Learning topic/content equivalence	Software/tool equivalence	Degree of technology use in control group	Procedure of effect size extraction
Quintas et al. (2020)	Spain	Urban	Not low	Primary school	Formal setting	Science	Handheld devices with multiple functions	Own	Game-based learning	1 day–4 weeks	Quasi-experimental	Same	Same	Different	Pen-and-paper	Calculated from exact descriptive
Ruiz-Ariza et al. (2018)	Spain	Not reported	Not low	Secondary school	Informal setting	Not reported	Handheld devices with multiple functions	Own	Game-based learning	>4 weeks	Experimental	Not reported	Different	Different	Not reported	[b]**Calculated from exact descriptive/Calculated from inferential statistics**
Sahin and Yilmaz (2020)	Turkey	Not reported	Not low	Secondary school	Formal setting	Science	Not reported	Not reported	Lectures	1 day–4 weeks	Quasi-experimental	Different	Same	Different	Pen-and-paper	Calculated from exact descriptive
Shadiev et al. (2018)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Not reported	Self-directed learning	1 day–4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Shadiev et al. (2015)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Not reported	Self-directed learning	>4 weeks	Quasi-experimental	Not reported	Same	Same	Pen-and-paper	Calculated from exact descriptive
Stanojević and Ranđelović (2018)	Serbia	Not reported	Not low	Secondary school	Formal setting	Professional subjects	Handheld devices with multiple functions	Own	Computer-assisted testing/assessment	1 day–4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive
Su and Cheng (2015)	Taiwan of China	Not reported	Not low	Primary school	Informal setting	Science	Handheld devices with multiple functions	Own	[a]Mixed: comparison 1; Inquiry-oriented learning: comparison 2	1 day–4 weeks	Quasi-experimental	Same	Not reported	Not reported	Pen-and-paper	Calculated from exact descriptive
Sung, Hwang, et al. (2017)	Taiwan of China	Urban	Not low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Not reported	Game-based learning	<1 day	Quasi-experimental	Not reported	Same	Not reported	Traditional technology	Calculated from exact descriptive
Tapingkae et al. (2020)	Thailand	Not reported	Not low	Secondary school	Formal setting	Social studies	Handheld devices with multiple functions	Own	Mixed	1 day–4 weeks	Quasi-experimental	Different	Same	Different	Pen-and-paper	Calculated from exact descriptive
van Uittert et al. (2022)	Netherlands	Mixed	Not low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Shared	Game-based learning	>4 weeks	Quasi-experimental	Different	Different	Different	Not reported	Calculated from exact descriptive
Vanbecelaere et al. (2020)	Belgium	Not reported	Not low	Primary school	Formal setting	[b]Language arts/Mathematics	Handheld devices with multiple functions	Own	Game-based learning	>4 weeks	Quasi-experimental	Not reported	Same	Same	Pen-and-paper	Calculated from exact descriptive
Volk et al. (2017)	Slovenian	Not reported	Not low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Mixed	>4 weeks	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Walczak and Taylor (2018)	USA	Not urban	Low	Primary school	Formal setting	Social studies	Handheld devices with multiple functions	Shared	Mixed	1 day–4 weeks	Experimental	Different	Same	Different	Pen-and-paper	Calculated from inferential statistics
Wang (2016)	Taiwan of China	Not reported	Not low	Secondary school	Informal setting	Language arts	Handheld devices with multiple functions	Own	Self-directed learning	1 day–4 weeks	Quasi-experimental	Same	Same	Same	Pen-and-paper	Calculated from exact descriptive

(Continues)

Study	Region	Community type	SES	Education level	Learning environment	School subjects	Mobile technologies used in intervention group	Student-to-hardware ratio in intervention group	Teaching method in intervention group	Duration of the intervention	Research design	Instructor equivalence	Learning topic/content equivalence	Software/tool equivalence	Degree of technology use in control group	Procedure of effect size extraction
Wang (2017a)	Taiwan of China	Urban	Not low	Secondary school	Unrestricted	Language arts	Handheld devices with multiple functions	Own	Self-directed learning	1 day–4 weeks	Quasi-experimental	Not reported	Same	Same	Pen-and-paper	Calculated from exact descriptive
Wang (2017b)	Taiwan of China	Not reported	Not low	Secondary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Computer-assisted testing/assessment	1 day–4 weeks	Quasi-experimental	Same	Not reported	Not reported	Pen-and-paper	Calculated from inferential statistics
Wollscheid et al. (2016)	Oslo	Not urban	Not low	Primary school	Formal setting	Language arts	Handheld devices with multiple functions	Own	Not reported	>4 weeks	Quasi-experimental	Different	Not reported	Not reported	Pen-and-paper	Calculated from exact descriptive
Yallihep and Kutlu (2020)	Turkey	Not reported	Not low	Primary school	Formal setting	Professional subjects	Handheld devices with multiple functions	Not reported	Game-based learning	1 day–4 weeks	Quasi-experimental	Same	Same	Different	Not reported	Calculated from exact descriptive
Yang et al. (2021)	Mainland of China	Not reported	Not low	Primary school	Formal setting	Language arts	Handheld devices with one specific function	Own	Not reported	1 day–4 weeks	Quasi-experimental	Same	Same	Different	Traditional technology	Calculated from exact descriptive
Yousef (2021)	Egypt	Not reported	Not low	Primary school	Informal setting	Mathematics	Handheld devices with multiple functions	Own	Inquiry-oriented learning	1 day–4 weeks	Quasi-experimental	Not reported	Different	Different	Pen-and-paper	Calculated from exact descriptive
Zhang et al. (2020)	Mainland of China	Not reported	Not low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Game-based learning	Not reported	Quasi-experimental	Same	Different	Different	Not reported	Calculated from exact descriptive
Zhang et al. (2014) sample 1	Taiwan of China	Not reported	Not low	Primary school	Formal setting	Science	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	<1 day	Quasi-experimental	Different	Same	Same	Pen-and-paper	Calculated from exact descriptive
Zhang et al. (2014) Sample 2	Taiwan of China	Not reported	Not low	Primary school	Informal setting	Science	Handheld devices with multiple functions	Not reported	Inquiry-oriented learning	<1 day	Quasi-experimental	Different	Same	Same	Pen-and-paper	[c]Calculated from exact descriptive/Calculated from inferential statistics
Zhao et al. (2021)	Mainland of China	Not reported	Not low	Primary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Game-based learning	1 day–4 weeks	Quasi-experimental	Same	Same	Different	Pen-and-paper	Calculated from exact descriptive
Zheng et al. (2014)	USA	Urban	Low	Primary school	Unrestricted	Science	Handheld devices with multiple functions	Own	Inquiry-oriented learning	>4 weeks	Quasi-experimental	Different	Not reported	Not reported	Not reported	Calculated from inferential statistics
Zhu and Urhahne (2018)	Germany	Not reported	Not low	Secondary school	Formal setting	Mathematics	Handheld devices with multiple functions	Own	Computer-assisted testing/assessment	>4 weeks	Quasi-experimental	Different	Same	Not reported	Not reported	Calculated from exact descriptive

[a] Variables were different in the comparison groups for the same outcome variable.

[b] Both variables were presented in one comparison group for the same outcome variable.

[c] Both variables were presented in one comparison group for the different outcome variables.

APPENDIX B: MODERATOR ANALYSES FOR AFFECTIVE AND BEHAVIOURAL OUTCOME VARIABLES

TABLE B1 Moderator analyses and weighted mean effect sizes for affective outcome variables

Moderator category	Moderator variables	N	g	SE	95% CI	Q_B	p
Student factor	Community type						
	Urban	7	0.174	0.116	(−0.053, 0.401)	2.150	0.143
	Not urban	5	0.442	0.142	(0.164, 0.720)		
Teaching context	Education level						
	Primary school	17	0.346	0.116	(0.120, 0.573)	1.666	0.197
	Secondary school	20	0.539	0.094	(0.354, 0.723)		
	Learning environment						
	Formal settings	30	0.484	0.089	(0.309, 0.659)	0.554	0.457
	Informal settings	6	0.349	0.158	(0.038, 0.659)		
	School subjects						
	Language arts	6	0.503	0.130	(0.248, 0.758)	7.484	0.058
	Mathematics	6	0.222	0.137	(−0.046, 0.489)		
	Science	16	0.637	0.139	(0.365, 0.909)		
	Professional subjects	4	0.133	0.179	(−0.218, 0.483)		
Learning process	Hardware used in intervention group						
	Handheld devices with multiple functions	31	0.435	0.083	(0.273, 0.597)	1.080	0.299
	Handheld devices with one specific function	4	0.271	0.134	(0.008, 0.534)		
	Student-to-hardware ratio						
	Own	22	0.372	0.088	(0.200, 0.544)	0.122	0.727
	Shared	6	0.317	0.130	(0.063, 0.572)		
	Teaching method						
	Inquiry-oriented learning	18	0.560	0.135	(0.294, 0.826)	4.254	0.039
	Game-based learning	9	0.234	0.081	(0.076, 0.393)		
	Duration of the intervention						
	<1 day	11	0.361	0.115	(0.136, 0.587)	1.444	0.486
	1 day–4 weeks	15	0.400	0.134	(0.137, 0.664)		
	>4 weeks	8	0.596	0.163	(0.277, 0.915)		
Study quality	Research design						
	Quasi-experimental	31	0.413	0.084	(0.250, 0.577)	1.580	0.209
	Experimental	6	0.649	0.168	(0.320, 0.977)		
	Instructor equivalence						
	Same	19	0.589	0.113	(0.369, 0.810)	1.512	0.219
	Different	7	0.317	0.191	(−0.057, 0.691)		
	Learning topic/content equivalence						
	Same	32	0.478	0.085	(0.310, 0.645)	1.539	0.215
	Different	5	0.271	0.143	(−0.009, 0.551)		
	Software/Tool equivalence						
	Same	17	0.355	0.084	(0.190, 0.520)	0.378	0.539
	Different	17	0.442	0.114	(0.219, 0.665)		
	Degree of technology use in the control group						
	Pen-and-paper	16	0.521	0.137	(0.252, 0.789)	0.345	0.557
	Traditional technology	17	0.421	0.099	(0.228, 0.615)		

TABLE B2 Moderator analyses and weighted mean effect sizes for behavioural outcome variables

Moderator category	Moderator variables	*N*	*g*	SE	95% CI	Q_B	*p*
Student factor	Community type						
	Urban	4	0.528	0.145	(0.244, 0.813)	1.591	0.207
	Not urban	4	0.299	0.110	(0.084, 0.514)		
Teaching context	Education level						
	Primary school	5	0.156	0.363	(−0.554, 0.867)	0.515	0.473
	Secondary school	9	0.436	0.141	(0.159, 0.712)		
	School subjects						
	Language arts	5	0.635	0.217	(0.210, 1.060)	1.822	0.177
	Science	8	0.233	0.204	(−0.167, 0.633)		
Learning process	Student-to-hardware ratio						
	Own	7	0.514	0.165	(0.190, 0.838)	0.425	0.515
	Shared	6	0.389	0.099	(0.196, 0.582)		
	Duration of the intervention						
	<1 day	7	0.222	0.271	(−0.309, 0.753)	0.132	0.716
	1 day–4 weeks	5	0.338	0.169	(0.007, 0.670)		
Study quality	Instructor equivalence						
	Same	8	0.475	0.103	(0.274, 0.677)	0.676	0.411
	Different	4	0.065	0.488	(−0.892, 1.022)		
	Software/Tool equivalence						
	Same	10	0.317	0.215	(−0.105, 0.739)	0.087	0.768
	Different	4	0.400	0.180	(0.047, 0.754)		
	Degree of technology use in the control group						
	Pen-and-paper	6	0.113	0.310	(−0.495, 0.72)	1.307	0.253
	Traditional technology	8	0.496	0.127	(0.248, 0.744)		