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Effects of group awareness support in CSCL on students' learning performance: A three-level meta-analysis

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Abstract

Group awareness (GA) is essential for computer-supported collaborative learning (CSCL), as it informs learners about other group members' activities, knowledge, and emotions. A key advantage of GA support is that it can collect, process, and visualize GA information, which provides a basis for students' reflection and adjustment during collaborative learning, thus facilitating their learning performance. However, empirical findings regarding the effectiveness of GA support have been inconsistent. The present study conducted the first three-level meta-analysis of 46 empirical studies to examine the effects of GA support on students' learning performance and further explore the possible moderating factors that may have contributed to the inconsistencies of primary studies. The results indicated the following: (1) GA support in CSCL had a moderate significant effect on students' learning performance (Hedges'$g = 0.46$, $p < 0.001$); (2) GA support in CSCL had the greatest influence on students' cognitive development (Hedges'$g = 0.49$, $p < 0.001$), followed by behavioral participation (Hedges'$g = 0.47$, $p < 0.001$), and then social emotion (Hedges'$g = 0.38$, $p < 0.001$); and (3) GA support type and group size were the only two significant moderating factors. Based on these findings, we propose several theoretical and pedagogical implications.

Keywords Group awareness · Computer-supported collaborative learning (CSCL) · Learning performance · Three-level meta-analysis

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Introduction

While computer-supported collaborative learning (CSCL) has been widely practiced in teaching because of its various pedagogical benefits, such as providing collaboration with flexible time and space boundaries, recent studies have also identified possible pitfalls when using CSCL (Järvelä & Hadwin, 2013; Järvelä et al., 2015; Kreijns et al., 2003; Zhang et al., 2023). There are three common manifestations described in the literature: (1) free-riding behavior and unequal participation, in which some members reduce their efforts because they assume their group members will compensate for their lack of contribution (Brooks & Ammons, 2003; Lipponen et al., 2003; Saqr et al., 2022); (2) off-topic and low-quality discussion, in which members stray from the core of the discussion because they lack an understanding of what opinions their group members hold (Munneke et al., 2007; Ollesch et al., 2021; Park et al., 2016; Yücel & Usluel, 2016); and (3) negative emotions during collaboration, such as low levels of group-process satisfaction, low levels of group cohesion, and collaborative learning attitude (Baltes et al., 2002; Ozaydın Ozkara & Cakir, 2018; Straus, 1997). Although these pitfalls are not unique to CSCL, they are more prevalent for CSCL in online learning environments due to the enhanced difficulty for students to perceive other group members' actions, attitudes, and emotions (Janssen & Bodemer, 2013; Li et al., 2021; Phielix et al., 2010). The pitfalls of CSCL highlight the importance of group awareness (GA) for coordinating collaboration, and many researchers have proposed that providing GA support is a significant method to promote high-performance collaboration (Janssen & Bodemer, 2013; Lin & Tsai, 2016; Schnaubert & Bodemer, 2022).

The concept of GA was established in the field of computer-supported collaborative work (CSCW) and defined as the "understanding of the activities of others, which provides a context for your own activity" (Dourish & Bellotti, 1992). Since 2000, researchers in the field of CSCL have applied the term to group activities related to knowledge (Ogata & Yano, 2000). GA in CSCL informs learners about other group members' activities, knowledge, and emotions (Bodemer & Dehler, 2011; Janssen & Bodemer, 2013; Ollesch et al., 2021). A key advantage of GA support is that it can collect, process, and visualize GA information, which provides the basis for self-observation and self-reflection (Lin, Lai et al., 2016a, Lin, Szu et al., 2016b). This can influence students' learning behavior and performance in an implicit way without using direct force or orders (Lin, Lai et al., 2016a, Lin, Szu et al., 2016b; Miller & Hadwin, 2015). Previous research has also identified the importance of GA support in promoting active behavioral participation (Liu et al., 2018; Ma et al., 2023), high level cognitive development (Buder & Bodemer, 2008; Li et al., 2021), and positive social emotion (Phielix et al., 2011; Jongsawat & Premchaiswadi, 2009).

However, despite broad agreement concerning the high potential of GA support for enhancing CSCL performance, existing research about its effectiveness yielded mixed results (Buder, 2011; Buder & Bodemer, 2008; Dehler et al., 2009; Kirschner et al., 2015; Li et al., 2021). The reason for this phenomenon may be related to different GA characteristics (e.g., GA support type), CSCL context (e.g., group size, disciplinary domain, and intervention duration), and participant characteristics (e.g., education level and self-regulation level) (Buder, 2011; Ollesch et al., 2021; Ollesch et al., 2022; Wang et al., 2019). Consequently, many educators consider providing GA support a promising way to improve CSCL performance. Nevertheless, the overall effectiveness of GA support lacks quantitative systematic evaluation, and the boundary conditions under which GA support functions remain largely unknown. Therefore, we conducted a three-level meta-analysis to investigate the effects of GA support in CSCL on students' learning performance based on the literature from 2000 to 2022. We also identified the possible differential effects of GA support through moderator analyses. The outcomes of this study can provide valuable insights for future research and teaching practice of CSCL.

Related work

Previous literature reviews in CSCL

Over the past decades, CSCL has long been the focus of educational research, and numerous meta-analyses have been published. These meta-analyses were either focused on the effects of CSCL or approaches that impact on CSCL performance. In terms of assessing the effectiveness of CSCL, Jeong et al. (2019) conducted a meta-analysis about the effects of CSCL in STEM education. CSCL was found to have the greatest impact on process outcomes, followed by cognitive outcomes, and affective outcomes. Additionally, the results indicated that CSCL outcomes were moderated by types of technology and pedagogy, educational levels, and disciplinary domains. Talan (2021) located 40 studies from 2010 to 2020 for a meta-analysis. The findings showed that CSCL had a moderate positive effect on academic achievement, and this effect was moderated by intervention duration.

Since the effectiveness of CSCL seems to be backed by rigorous literature reviews, researchers in recent years have begun to focus on various approaches to improve students' CSCL performance. Most meta-analyses that are concerned with a similar topic were focused on explicit approaches such as argumentation interventions and CSCL scripts. For example, Wecker and Fischer (2014) analyzed 12 studies on the role of argumentation intervention in CSCL and found that the intervention had a moderate effect on argumentation but no effect on domain-specific knowledge. Radkowitsch et al. (2020) examined the effects of CSCL scripts on K-12 students' learning performance. Their findings indicated that learning with CSCL scripts leaded to a non-significant positive effect on motivation, a small positive effect on domain learning and a medium positive effect on collaboration skills.

GA support is another implicit but essential approach suggested to improve students' learning performance in CSCL. Several qualitative reviews have been published to enhance our understanding of why and how GA support can contribute to CSCL. For example, Janssen and Bodemer (2013) explained the theoretical mechanisms by which GA support influence the effectiveness of collaboration from an educational psychology perspective (e.g., cognitive load theory, germane learning). Bodemer and Dehler (2011) described how GA is formed, processed and translated in action, and thereby affecting CSCL processes and outcomes. Buder (2011) attested the power of GA support in improving CSCL performance and suggested future directions in this research field. He suggested that there should be more attempts to systematically explore the mechanisms and boundary conditions under which GA supports are more effective.

While previous qualitative reviews have provided general hypotheses and viewpoints on the effects of GA support, they lacked evidences from objective statistical findings. Furthermore, we still lack an understanding of the boundary conditions under which GA support functions more effectively. Meta-analysis aims to draw a general conclusion and identify significant moderator variables from existing empirical research using quantitative methods, which is considered to be a more objective method for conducting reviews

(Guzzo et al., 1987). To our best knowledge, the current study is the first meta-analysis to examine the effects of GA support in CSCL on students' learning performance, contributing to the previous qualitative literature reviews.

Effects of GA support in CSCL

GA in CSCL refers to being informed about specific aspects of other group members, such as knowledge about group members' behavioral participation (e.g., which task they are working on?), their knowledge and skills (e.g., what do they know and what they are able to do?), and their social activities (e.g., how do they feel about the collaborative process?) (Bodemer & Dehler, 2011; Gross et al., 2005; Liu et al., 2018). The accessing and processing of GA information provides the basis for group members' reflection and coordination, which is a key prerequisite for effective collaboration.

As it is difficult for students to access GA information directly in an online environment, a series of GA supports have been developed (Janssen & Bodemer, 2013). In the development of GA supports, learning analytics are often introduced to collect and record abundant data (e.g., login length, page revision history) generated by students in online collaborative platforms (e.g., Wikis, Facebook discussion), providing a rich resource of GA information (Hu et al., 2022). Then, by processing and visualizing this GA information, GA support can provide learners with feedback on collaboration and help them improve CSCL performance.

Several studies on the benefits of GA support have been published in recent years. Based on the current research, the effectiveness of GA support is mainly measured by behavioral participation, cognitive development, and social emotion. First, research has shown that GA support encouraged students' behavioral participation by triggering the mechanism of social evaluation and social comparison (Liu et al., 2018; Ollesch et al., 2021; Shepperd, 1993). For example, Janssen et al. (2011) adopted GA support to provide students with members' relative contributions and found that their behavioral participation was significantly motivated. Second, GA support has been found to benefit students' cognitive development by fostering shared understanding and the recognition of non-shared information. For example, according to Sangin et al. (2011), GA supports initiated learning activities that aim to gain missing knowledge, thereby promoting individual cognitive development. Studies conducted by Engelmann and colleagues (e.g., Engelmann & Hesse, 2010; Engelmann & Hesse, 2011; Engelmann et al., 2009) supported this conclusion. Third, studies have revealed that GA supports promoted positive social emotions such as satisfaction, trust, and cohesion among group members by reducing the likelihood of unequal participation and unequal access to information (Aggarwal & O'Brien, 2008; Capdeferro & Romero, 2012; Kimmerle et al., 2007; Le et al., 2018; Phielix et al. 2010; Strauß & Rummel, 2021).

While above-mentioned studies have identified the positive effects of GA support in CSCL, others have suggested that GA support does not always show obvious advantages, with some even hypothesizing it has negative effects. For instance, Lin et al. (2021) applied GA support in peer assessment and found that although GA support stimulated individuals to participate more actively in group interaction, there was no significant improvement in the quality of interactive messages and team production. Kirschner et al. (2015) found that Radar (GA support in the experiment) did not improve group satisfaction because it made learners become aware of dissatisfaction about the functioning of their peers or the group. Additionally, some researchers argued that students may experience disadvantages when provided GA support, as it could cause evaluation apprehension (Dehler et al., 2009). Furthermore, GA support may lead to "downward social comparisons," in which students compare themselves to poor performers, thereby undermining individual performance (Dehler et al., 2009).

To sum up, GA support offers considerable potential for promoting CSCL performance, including behavioral participation, cognitive development, and social emotion. However, the findings presented in the above studies are disparate and make it difficult for educators to decide whether to provide students in CSCL with GA support. Therefore, it is necessary and valuable to conduct a meta-analysis to evaluate the significant impacts of GA support on collaboration. Additionally, this paper's exploration of the boundary conditions under which GA supports work can provide valuable insights for the understanding of GA and the implementation of CSCL.

Possible moderator variables

The inconsistent findings in previous research on the effect of GA support in CSCL may be attributed to various factors. We first looked for theoretical support for the choice of moderator variables from existing reviews and empirical studies (e.g., Bodemer & Dehler, 2011; Janssen and Bodemer, 2013; Jeong et al., 2019; Lin & Tsai, 2016; Lin, Lai et al., 2016a, Lin, Szu et al., 2016b; Ollesch et al., 2021; Talan, 2021). The we conducted a preliminary literature search to determine which variables are frequently reported in GA support intervention studies. Finally, we identified three groups of possible moderator variables: GA support type, CSCL context (group size, disciplinary domain, and intervention duration), and educational level.

Group awareness support type

Previous studies have mentioned three essential types of GA information to improve students' learning performance in CSCL (Bodemer & Dehler, 2011): (1) behavioral awareness, which refers to the information about other members' activities in the group, such as what and how much they are contributing to the group task (Janssen et al., 2011; Pifarré et al., 2014); (2) cognitive awareness, which comprises the cognitive information of other members, such as their knowledge, opinions, or goals (Ollesch et al., 2021); and (3) social awareness, which indicates the functioning of the group as perceived by group members (Pifarré et al., 2014). This type of GA information mainly informs about the presence or availability of other members and assesses social patterns such as influence, friendliness, reliability, collaboration, and productivity (Phielix et al., 2011; Pifarré et al., 2014). Accordingly, based on the GA information provided, GA support can also be divided into behavioral, cognitive, and social categories.

While some studies have provided only one type of GA information, other studies have shown that single GA indicators hardly address all the challenges of CSCL (Ollesch et al., 2021). A study was coded "combined type" when a GA support provides more than one type of GA information. Some researchers suggested that different types of GA information may have varying functions and effectiveness, which can complement each other and thus better meet students' collaborative learning needs (Ollesch et al., 2021; Phielix et al., 2011). However, other researchers have argued that certain types of GA information may not play a role in supporting collaboration (Li et al., 2021). What's more, providing extra, useless information may distract learners and increase their cognitive load. Therefore, we consider GA support type as a potential moderator variable to explore whether combined types of GA support are more effective than individual types. Additionally, we intended to explore how different individual types of GA support affect learning performance in different dimensions.

CSCL context

In meta-analysis, disciplinary domain and intervention duration were the most common moderator variables associated with the research context (Wang et al., 2022). Furthermore, group size is closely related to collaborative learning, and has frequently been used in previous CSCL studies to examine heterogeneity of effect size differences (Lai & Wong, 2022; Luo et al., 2023; Sung et al., 2017). Therefore, in the current study, the moderator variables of group size, disciplinary domain, and intervention duration were selected as CSCL context characteristics.

First, group size is one of the important moderator variables. Researchers have suggested that group size is a significant factor influencing group interaction and performance in CSCL (Kim, 2013; Luo et al., 2023). In other meta-analyses related to collaborative learning, group size has typically been considered an important moderator variable that significantly moderates the findings (Lai & Wong, 2022; Sung et al., 2017). Although many of the existing studies related to GA adopted smaller groups (2–4 members), several researchers have proposed that the effects of GA support might be greater if the group size is increased (more than 4 members) (Janssen et al., 2011; Strijbos et al., 2004; Wang et al., 2019). Consequently, we investigated whether group size contributed to a difference in effect size and which group size would benefit more from GA support.

Second, disciplinary domain is another common moderator variable in meta-analyses (Jeong et al., 2019; Talan, 2020). Studies related to GA support were conducted in a variety of disciplinary domains, such as biology, physics, math, electronic commerce, computer science, and engineering. There are differences in task types, knowledge content, structure, and characteristics across different disciplines. Therefore, GA support may be more necessary and readily implemented in some disciplinary domains than in others. To better understand the inconsistent results across studies, it would be valuable to treat disciplinary domain in different studies as a potential moderator variable.

Third, the various lengths of interventions could also influence the effectiveness of GA support in CSCL (Janssen et al., 2011). On the one hand, the effectiveness of GA support may decrease as the intervention time extends due to the novelty effect (that is, learners' interest in something new can fade over time). On the other hand, researchers have argued that learners with GA support for a longer duration tend to be more engaged in CSCL. This is because groups are systems that continuously try to achieve equilibrium, a process that often requires an extended period (Ollesch et al., 2021; Strauß & Rummel, 2021). Therefore, we explored whether intervention duration moderates the effect of GA support, thereby providing insights into the timing of GA support.

Educational level

Another possible explanation for the inconclusive results in previous studies might be the differences in participants' educational levels. Students with varying levels of mental development may apply different learning strategies and behaviors according to the GA information at hand, which would affect the experiment's results (Lin, Lai et al., 2016a, Lin, Szu et al., 2016b; Lin & Tsai, 2016). It is crucial for researchers, educators, and developers to identify the educational levels that would most benefit from GA support, as this would allow them to make scientific and appropriate educational decisions based on student characteristics.

Aim of the current study

GA support is an important concept in CSCL that has been extensively researched, but there are still some issues to be addressed urgently in this area. The first key issue is that existing empirical studies on the effectiveness of GA support have been inconsistent. Moreover, we still lack an understanding of the boundary conditions under which GA support functions. To our best knowledge, this meta-analysis is the first study to conduct a quantitative synthesis of existing empirical research into the effects of GA support in CSCL. In addition, at the methodological level, conventional meta-analytic methods ignored the correlation of effect sizes within the same study, which can result in a biased result. In the current study, we used the cutting-edge three-level meta-analysis method to deal with the problem of non-independent effect sizes within a study (Cai & Fan, 2020; Cai et al., 2022). It could provide a more accurate estimate of the impact of GA support in CSCL.

We attempt to contribute to the field of CSCL by realizing two research objectives. The first aim was to conduct the first three-level meta-analysis to examine the average effect of GA support on students' learning performance. The second aim was to conduct moderator analyses to investigate if the variety of effects between studies can be explained by GA support type, CSCL context characteristics, or participants' educational level. Taking into account these objectives, we addressed the following questions:

RQ1: What is the overall effect of GA support in CSCL on students' learning performance?
RQ2: How do GA support type, CSCL context characteristics (i.e., group size, disciplinary domain, and intervention duration), and participants' educational level moderate the effect?

Method

Literature search and inclusion criteria

A literature search was conducted from 2000 to 2022 by means of Web of Science (WOS), Science Direct, Wiley, Springer, and Educational Resources Information Center (ERIC) databases. The search was restricted to the period from 2000 to 2022 since the concept of GA was introduced into CSCL since 2000. The following search terms were used: (group awareness OR behavioral awareness OR cognitive awareness OR knowledge awareness OR social awareness) AND (computer-supported collaborative learning OR CSCL). In order to include a comprehensive sample of studies, we also adopted the snowball method to conduct a supplementary review of the studies. Two researchers in this study completed the searching and screening process.

To be included in this meta-analysis, studies had to meet specific criteria (see Table 1). In terms of study design, we made reference to some existing meta-analysis practices (Radkowitsch et al., 2020; Wu et al., 2020). We excluded studies with pre-and-post designs

Table 1 Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Language	English	Non-English language
Study type	Quantitative studies	Review articles, theoretical articles, and qualitative studies were excluded.
Study design	Experimental or quasi-experimental design.	Studies not making use of a traditional control group.
Availability	The full-text of the study must be available to consult via university library systems or the Internet.	Studies of which the full-text was not available to consult.
Statistical information	Studies reporting sufficient statistical information to calculate the effect size (e.g., means, standard deviations, sample sizes of experimental groups and control groups, or other information such as *t* statistic or *F* statistic).	Studies not reporting sufficient statistical information (e.g., means, standard deviations, sample sizes of experimental groups and control groups, or other information such as *t* statistic or *F* statistic).

because the findings of such studies are susceptible to more factors other than the intervention itself. Every record was independently screened by two researchers to establish the reliability of the screening process. Any disagreement between the two was discussed within the research team to reach the final decision for inclusion. Figure 1 shows a visual overview of the literature search process in line with the PRISMA standards (Moher et al., 2009). Initially, 1642 seemingly relevant studies were located based on literature search. After initial screening based on each study's title and abstract by checking whether a study was about the effect of GA support in CSCL, we narrowed down the list to 98 studies. We re-read the full texts based on the inclusion and exclusion criteria. Finally, a total of 46 studies satisfied the inclusion criteria.

Coding of studies

All the articles were coded by two coders independently and the inter-rater reliability was 0.9, as measured by Cohen's Kappa. Any disagreement in coding was resolved through discussion within the research team. The overview of the coding scheme for the included studies is shown in Table 2. Some of the main encoding variables are as follow. It should

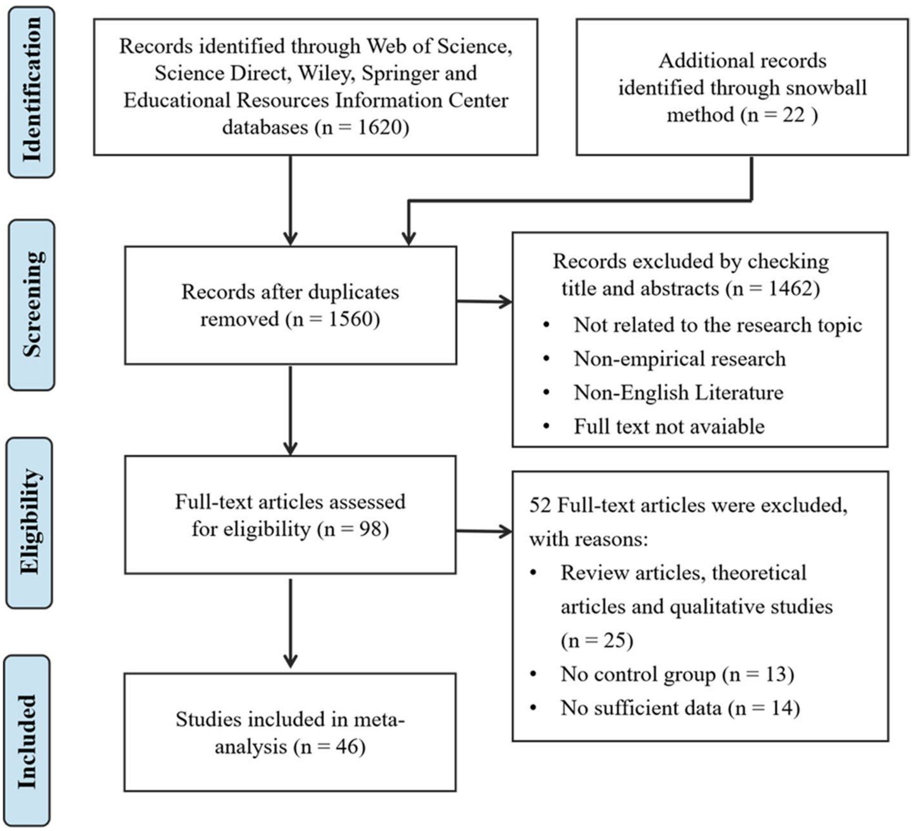


Fig. 1 PRISMA flow diagram of data collection

Table 2 Overview of the coding scheme for the included studies

Code	Category
Study characteristics	(1) authors; (2) publication year; (3) sample size (EG vs. CG)
GA support type	(1) individual-behavioral; (2) individual-cognitive; (3) individual-social; (4) combined type.
Group size	(1) smaller group (2–4 members); (2) larger group (more than 4 members.
Disciplinary domain	(1) humanities; (2) social science; (3) natural science; (4) engineering.
Intervention duration	(1) short (≤1 week); (2) medium (1–8 weeks); (3) long (>8 weeks).
Educational level	(1) primary education; (2) secondary education; (3) higher education; (4) professional training; (5) mixed (i.e., participants include both students and professionals).
Outcome measurement	(1) behavioral participation; (2) cognitive development; (3) social emotion.

be noted that in the following variables, if the article did not report the relevant content, it was coded as "not mentioned".

GA support type As we discussed above, GA support can be divided into four categories based on the type of GA information it provides: (1) individual-behavioral; (2) individual-cognitive; (3) individual-social; (4) combined type (that is, a GA support provides more than one type of GA information).

Group size The group size was divided according to the existing meta-analysis and previous GA empirical research (Janssen et al., 2011; Strijbos et al., 2004; Wang et al., 2019). In our meta-analysis, group size was divided into two categories: (1) smaller group (2-4 members); (2) larger group (more than 4 members).

Disciplinary domain Based on the discipline domains covered by the existing research, they were coded into four categories in this study: (1) humanities; (2) social science; (3) natural science; (4) engineering.

Intervention duration Intervention duration in experimental studies generally ranges from a few hours to several months. Among them, 1 week and 8 weeks are commonly used as interval standards in meta-analysis (Guo, 2022; Lai & Wong, 2022). One week was selected as it provided an early assessment of the intervention's immediate effects, while eight weeks usually means half a semester, allowing for a more comprehensive evaluation of the intervention's long-term impact. The choice of these interval standards aimed to capture the short-term, medium-term, and long-term effects of the intervention. Therefore, intervention duration was coded as three categories: (1) short (≤1 week); (2) medium (1-8 weeks); (3) long (>8 weeks).

Educational level Different studies involved participants of different ages. We did not include kindergarten children, in part because the existing literature did not address this group, and in part because kindergartners are too young for computer-supported collaborative learning. Therefore, educational level was coded as a categorical variable with five levels: (1) primary education; (2) secondary education; (3) higher education; (4) professional training; (5) mixed (that is, participants include both students and professionals).

Outcome measurement Learning performance used in previous studies can be divided into three categories: (1) Behavioral participation. If a study focused on students' behavioral contributions in collaboration, such as the number of comments, word count of comments, on-task behaviors, system retention duration, cooperative rate, and equality of participation, it was coded as "behavioral participation". (2) Cognitive development. A study was coded as having cognitive development as learning performance if a test or an examination was administered to measure students' knowledge mastering and the quality of work. Additionally, students' knowledge construction and learning strategy level also often appeared in GA-related studies and were considered to be the indicators of cognitive development. (3) Social emotion. Studies that recorded students' self-efficacy, group cohesion, collaborative learning attitude, well-being, team development, and group-process satisfaction were coded as "social emotion".

Data analysis

Calculation of effect sizes

In the current study, the standardized mean difference (mean difference between GA support groups and non-GA support groups divided by the pooled standard deviation) was adopted as the measure of effect size (Borenstein et al., 2021). Moreover, Hedges' *g* was calculated by R software (Version 4.3.1). In most cases, Hedges' *g* was calculated by using means and standard deviations. When raw outcome data was not reported in a study, we transformed the inferential statistics (e.g., *t* or *F* value) into Hedges' *g* (Wouters et al., 2013).

In the process of calculating effect sizes, the following rules for complex cases were applied: (1) For the selected studies with more than one experimental or control groups, we formed multiple pairwise comparisons and then calculate multiple effect sizes (Hu et al., 2022). (2) When the selected studies reported multiple dimensions of learning performance, one effect size was extracted for each dimension (Wu et al., 2020). (3) When the behavioral performance goal of a study is to address the equality of participation, the gini coefficient (ranging from 0 to 1) was usually reported in this study (Strauß & Rummel, 2021). Larger values of the gini coefficient indicated more unequal distribution of participation. In this case, we did a reverse calculation of the value and then calculated the Hedges' *g*. For other measurements of behavioral participation (e.g., the number of comments and word count of comments), the more means the better. In terms of outcome variables related to social emotions, since the included variables are all positive, a larger value indicates a better outcome. For cognitive development variables, lager values also imply better performance, so the reverse calculation is not required and Hedges' *g* can be calculated directly.

Finally, from these 46 studies, we extracted 98 effect sizes because several studies included more than one effect size.

Three-level meta-analysis model

Since some studies reported multiple dimensions of outcome variables or multiple comparisons, multiple effect sizes could arise per study and they are dependent within studies. The conventional meta-analytic methods ignored the dependence of effect sizes within a study, which would lead to overestimation of the variance of the pooled effect sizes and biased estimates (Cai & Fan, 2020; Cai et al., 2022). In response to this problem, the recommended approach is to use three-level meta-analysis approach. The three-level meta-analytic model includes three sources of variance: sampling variation (level 1), within-study variance (level 2), and between-study variance (level 3). The statistical software package R (Version 4.3.1) and the "metafor" package were used for the following statistical analyses (Viechtbauer, 2010).

First, in terms of the overall analyses, we used the maximum likelihood estimation method to compute the parameter estimates, standard errors, and the 95% confidence intervals (CI). Effect sizes of 0.2, 0.5, and 0.8 were treated as small, medium, and large, respectively (Cohen, 1992).

Second, a heterogeneity analysis was performed to investigate the variance in effect sizes across studies. We calculated the Cochran's Q-statistic to test whether variability in the observed effect sizes was caused by study attributes. A statistically significant Q-statistic indicates the heterogeneity in the studies. To further examine heterogeneity, another statistic, I^2, was also computed, which describes the percentage of variation across studies resulting from true heterogeneity rather than from sampling error (Higgins & Thompson, 2002). In the current three-level meta-analysis, three different variance components were all examined. Significant heterogeneity test results indicate the necessity of moderator analyses to identify variables that might account for the variability in effect sizes (Guo, 2022; Wu et al., 2020).

Then, we conducted moderator analyses to examine how GA support type, CSCL context characteristics (i.e., group size, disciplinary domain, and intervention duration), and participants' educational level influence the effectiveness of GA support on students' learning performance.

Publication bias

Publication bias refers to the potential bias that research papers with statistically significant and/or larger effect sizes are more likely to be published than those with smaller and/or non-significant effect sizes (Rosenthal, 1979). In the current study, one study with an effect size greater than 12 among the 46 included studies was tested to be significantly higher than the other studies (Liu et al., 2018). Therefore, it was detected as an outlier and excluded from future analysis. For the remaining 45 studies (with 96 effect sizes), we used two methods to assess the potential impact of publication bias: the multilevel extension of funnel plot test and the classic fail-safe N test. A symmetrical, inverted funnel suggests that publication bias is not present (Egger et al., 1997). The classic fail-safe N test is also an important method to evaluate whether publication bias can be ignored (Rosenthal, 1979). It is suggested that the fail-safe N value should be larger than 5k + 10, where k is the number of effect sizes included in the meta-analysis (Rosenberg, 2005; Rosenthal, 1979).

Results

Descriptive findings

After removing one outlier (Liu et al., 2018), the current meta-analysis included 45 articles reporting on 58 independent studies and comprising 96 effect sizes. Table 8 (Appendix) shows the sample characteristics, with an overview of the authors, publication year, sample size, GA support type, group size, disciplinary domain, intervention duration, educational level, and outcome measured for each included study.

According to the descriptive analysis, most studies adopted an individual type of GA support (62.1%, No. Studies = 36), whereas only 37.9% (No. Studies = 22) adopted combined types. Among the studies providing an individual type of GA support, most explored the effectiveness of cognitive GA support (No. Studies = 22), followed by behavioral GA support (No. Studies = 9), and then social GA support (No. Studies = 5).

We also conducted a descriptive analysis of CSCL context characteristics. In terms of group size, more studies were conducted in smaller groups (62.1%, No. Studies = 36) than larger groups (20.7%, No. Studies = 12). Additionally, in a small number of studies, we cannot obtain the group size from the available information (17.2%, No. Studies = 10). Regarding disciplinary domain, natural sciences was the most frequently studied disciplines (41.4%, No. Studies =24), followed by social sciences (25.9%, No. Studies = 15) and engineering (25.9%, No. Studies = 15). Humanities are the least studied (3.4%, No. Studies = 2). Two studies did not report discipline domains (3.4%). For intervention duration, most studies lasted 1 week or less (53.4%, No. Studies = 31), followed by more than 8 weeks (20.7%, No. Studies = 12), and 1-8 weeks (15.5%, No. Studies = 9). About 10.3% (No. Studies = 6) of the studies did not report intervention duration.

As for participants' educational level, the results indicated that higher education (65.5%, No. Studies = 38) was the most frequently studied educational level, followed by secondary education (15.5%, No. Studies = 9), mixed sample (10.3%, No. Studies = 6), and professional training (6.9%, No. Studies = 4). Primary educational learners were the least studied, with only one study (1.7%) (Gijlers et al., 2013).

Overall analyses and heterogeneity test

Based on the three-level meta-analytic model, the results in Table 3 showed that GA support in CSCL had a moderate significant effect on students' learning performance (g = 0.46, SE = 0.06, 95% CI [0.34; 0.58], $p < 0.001$). We then analyzed the effects of GA support on different dimensions of learning performance. The results showed that GA support in CSCL had the greatest influence on students' cognitive development (g = 0.49, SE = 0.08, 95% CI [0.33; 0.65], $p < 0.001$), followed by behavioral participation (g = 0.47, SE = 0.11, 95% CI [0.24; 0.69], $p < 0.001$), and then social emotion (g = 0.38, SE = 0.07, 95% CI [0.23; 0.53], $p < 0.001$).

As for the heterogeneity analysis, the statistically significant Q values revealed that there was considerable heterogeneity across the effect sizes (Q (95) = 374.18, $p < 0.001$). Furthermore, the estimated variance values at level 2 (within-study level) and level 3 (between-study level) were both 0.10. Both level 2 and level 3 explained moderate degrees of heterogeneity, with I^2_{level2} = 37.31% and I^2_{level3} = 38.22%, respectively. Taken together, the results showed the presence of statistical heterogeneity and suggested the need for a moderator analysis that could inspect sources for heterogeneity for learning performance.

Moderator analysis

In addition to determining that GA support positively affects students' learning performance, this study also aims to examine possible moderator variables that influence the effectiveness of GA support. We analyzed the GA support type, CSCL context

Table 3 Results for the overall analysis

Outcome classification	No. studies	No. ES	*g (SE)*	*t* value (sig)	95%CI	*Q* (df)	% var. at level 1	Level 2 variance	% var. at level 2	Level 3 variance	% var. at level 3
Learning performance	58	96	0.46 (0.06)	7.62***	[0.34; 0.58]	374.18 (95)***	24.47%	0.10	37.31%	0.10	38.22%

(1) No. studies: number of studies. (2) No. ES: number of effect sizes (3) g: Hedges' g. (4) SE: standard error. (5) CI: confidence interval. (6) Q: homogeneity test of all effect sizes. (7) df: degrees of freedom. (8) var.: variance. (9) Level 2 variance: variance between effect sizes extracted from the same study (heterogeneity of within-study) (10) Level 3 variance: variance between studies (heterogeneity of between-study)

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

characteristics, and educational level as moderators. If a study was coded "not mentioned" in any subgroup, it was excluded from the moderator analysis for the corresponding subgroup.

GA support types as moderators

For GA support types, we first explored whether it is more effective to provide combined type (i.e., a GA support provides more than one type of GA information) or an individual type (i.e., behavioral, cognitive or social GA support). The results presented in Table 4 suggested that the effect sizes significantly differed between combined and individual types (F (1, 94) = 7.57, $p < 0.01$). Moreover, the effect size for combined type ($g = 0.65$, $p < 0.001$) was significantly greater than that for an individual type ($g = 0.34$, $p < 0.001$), indicating that students could benefit more from combined types of GA support.

Moreover, we combined three types of individual GA support and three types of learning performance to enrich this meta-analysis in several ways. As shown in Table 5, for behavioral participation, there was no significant difference between the studies adopting behavioral, cognitive, and social GA support (F (2, 16) = 0.48, $p = 0.63$). Although all three types of individual GA support showed positive effects on students' behavioral participation, the effect size of behavioral GA support was the largest and only it showed statistical significance ($g = 0.53$, $p < 0.05$).

In terms of cognitive development, the results also suggested no significant difference in the effect sizes for the different types of GA support (F (2, 30) = 0.16, $p = 0.85$). The effect size of behavioral GA support ($g = 0.45$, $p < 0.05$) was higher than that of cognitive GA support ($g = 0.32$, $p < 0.01$). However, the effect size of social GA support was not statistically significant ($g = 0.31$, $p = 0.18$).

As for social emotion, GA support type was also found no significant moderating effect. Cognitive GA support showed the largest effect size and only it had a statistically significant positive effect on students' social emotion ($g = 0.37$, $p < 0.05$).

CSCL context as moderators

As shown in Table 6, the moderating effect of group size was evident in the current sample (F (1, 73) = 4.89, $p < 0.05$). In studies that had reported group size, the effect size was significantly greater for larger groups ($g = 0.71$, $p < 0.001$) than for smaller groups ($g = 0.38$, $p < 0.001$), which indicates that larger groups can benefit more from GA support in CSCL.

For disciplinary domain as a potential moderator, a statistically non-significant moderating effect was found (F (3, 88) = 1.55, $p = 0.206$). GA support had positive effects on all four disciplinary domains and the largest effect size was at humanities ($g = 070$, $p < 0.05$). The second greatest is the effect size of engineering ($g = 0.65$, $p < 0.001$), followed by natural sciences ($g = 0.38$, $p < 0.001$) and social sciences ($g = 0.38$, $p < 0.01$).

With respect to intervention duration, results in Table 6 suggested no significant difference in the effect sizes for different duration levels (F (2, 84) = 2.47, $p = 0.087$). This finding suggested that the effectiveness results may not have been significantly influenced by the novelty effect. However, an interesting finding was that the intervention duration of more than 8 weeks had the largest effect size ($g = 0.75$, $p < 0.001$). The effect sizes of 1-8 weeks ($g = 0.41$, $p < 0.05$) and 1week or less ($g = 0.41$, $p < 0.001$) were essentially equal.

Table 4 Effects of GA support types on effect size (combined type vs. individual type)

Moderator	No. studies	No. ES	*g (SE)*	*t* value (sig)	95%CI	F (df1, df2)	Level 2 variance	Level 3 variance
GA support types								
Individual type	36	60	0.34 (0.07)	4.85***	[0.20, 0.48]	F (1, 94) = 7.57**	0.10	0.06
Combined type	22	36	0.65 (0.09)	7.25***	[0.47, 0.83]	$p = 0.007$		

(1) No. studies: number of studies. (2) No. ES: number of effect sizes (3) g: Hedges'g. (4) SE: standard error. (5) CI: confidence interval. (6) F (df1, df2): omnibus test of regression coefficient in the model. (7) p: p value of the omnibus test. (8) Level 2 variance: variance between effect sizes extracted from the same study (heterogeneity of within-study) (9) Level 3 variance: variance between studies (heterogeneity of between-study)

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

Table 5 Effects of individual GA support types (behavioral vs. cognitive vs. social) on three types of learning performance

Outcome classification	Moderator	No. studies	No. ES	*g (SE)*	*t* value (sig)	95%CI	F (df1, df2)	Level 2 variance	Level 3 variance
	Individual GA support types								
Behavioral participation	behavioral	5	7	0.53 (0.24)	2.26*	[0.03, 1.03]	F (2, 16) = 0.48	0.15	0.15
	cognitive	5	9	0.23 (0.21)	1.13	[-0.21, 0.67]	$p = 0.63$		
	social	1	3	0.27 (0.36)	0.74	[-0.50, 1.04]			
	Individual GA support types								
Cognitive development	behavioral	3	6	0.45 (0.21)	2.14*	[0.02, 0.87]	F (2, 30) = 0.16	0.07	0.07
	cognitive	16	22	0.32 (0.10)	3.24**	[0.12; 0.52]	$p = 0.85$		
	social	3	5	0.31 (0.23)	1.36	[-0.16; 0.78]			
	Individual GA support types								
Social emotion	behavioral	1	3	-0.04 (0.20)	-0.22	[-0.55; 0.47]	F (2, 5) = 1.69	0.00	0.00
	cognitive	1	3	0.37 (0.13)	2.79*	[0.03; 0.71]	$p = 0.28$		
	social	1	2	0.27 (0.36)	0.74	[-0.50; 1.04]			

(1) No. studies: number of studies. (2) No. ES: number of effect sizes (3) *g*: Hedges'*g*. (4) SE: standard error. (5) CI: confidence interval. (6) F (df1, df2): omnibus test of regression coefficient in the model. (7) *p*: *p* value of the omnibus test. (8) Level 2 variance: variance between effect sizes extracted from the same study (heterogeneity of within-study). (9) Level 3 variance: variance between studies (heterogeneity of between-study)

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

Table 6 Effects of CSCL context on effect size

Moderator	No. studies	No. ES	*g (SE)*	*t* value (sig)	95%CI	F (df1, df2)	Level 2 variance	Level 3 variance
Group size								
Smaller group	36	53	0.38 (0.08)	4.90***	[0.23, 0.54]	F (1, 73) = 4.89* $p = 0.030$	0.11	0.08
Larger group	12	22	0.71 (0.13)	5.67***	[0.46, 0.96]			
Disciplinary domain								
Humanities	2	4	0.70 (0.32)	2.16*	[0.06, 1.34]	F (3, 88) = 1.55 $p = 0.206$	0.10	0.09
Social sciences	15	23	0.38 (0.12)	3.15**	[0.14, 0.63]			
Natural sciences	24	37	0.38 (0.09)	4.05***	[0.19, 0.56]			
Engineering	15	28	0.65 (0.11)	5.86***	[0.43, 0.87]			
Intervention duration								
Short (≤ 1 week)	31	54	0.41 (0.08)	4.95***	[0.24, 0.57]	F (2, 84) = 2.51 $p = 0.087$	0.10	0.10
Medium (1-8 weeks)	9	12	0.41 (0.18)	2.30*	[0.06, 0.76]			
Long (> 8 weeks)	12	21	0.75 (0.13)	5.66***	[0.48, 1.01]			

(1) No. studies: number of studies. (2) No. ES: number of effect sizes (3) *g*: Hedges'*g*. (4) SE: standard error. (5) CI: confidence interval. (6) F (df1, df2): omnibus test of regression coefficient in the model. (7) *p*: *p* value of the omnibus test. (8) Level 2 variance: variance between effect sizes extracted from the same study (heterogeneity of within-study). (9) Level 3 variance: variance between studies (heterogeneity of between-study)

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

Educational levels as moderators

Regarding educational levels, the results presented in Table 7 suggest no statistically significant difference in the effect sizes (F (4, 91) = 0.51, p = 0.725). The largest effect size was at secondary education (g = 0.54, p < 0.01), followed by higher education (g = 0.49, p < 0.001), professional training (g = 0.46, p < 0.05), mixed sample (g = 0.31, p = 0.078), and primary education (g = -0.07, p = 0.888). Evidently, GA support had a significant positive impact on secondary education, higher education and professional training students. However, the influence on primary education students and mixed sample was in comparison not significant.

Publication bias

Publication bias was assessed through funnel plot and the classic fail-safe N test. The funnel plot is a scatter plot of each study's effect size against its standard error (Sterne & Egger, 2001). It typically has the following components: (1) Vertical line: The vertical line at the center of the plot represents the overall estimated effect size. (2) Dots or points: Each dot or point on the plot represents an individual study. The horizontal position of a dot represents the effect size estimate from that study, and the vertical position represents some measure of study precision, often the standard error or sample size. In a well-balanced scenario with no publication bias, we would expect to see smaller studies scattered widely at the bottom, and larger studies with more precise estimates clustered at the top. Generally speaking, a symmetrical, inverted funnel suggests the absence of publication bias in the meta-analysis (Egger et al., 1997). As shown in Fig. 2, the funnel plot is symmetrical, and most of the studies are in the middle and upper part of it, suggesting a general absence of the publication bias.

However, visual inspection alone is insufficient. Therefore, we also adopted the classic fail-safe N test. It is suggested that the fail-safe N value should be larger than 5k + 10, where k is the number of effect sizes included in the meta-analysis (Rosenberg, 2005; Rosenthal, 1979). According to the results, the classic fail-safe N test estimate was 9,955 (p < 0.0001), which exceeds the critical value of 490 (i.e., 5 × 96 + 10). Therefore, consensus among the results of inspection of funnel plot and the classic fail-safe N test provide evidence that publication bias does not pose a serious threat to the validity of the meta-analysis.

Discussion

The effectiveness of GA support on students' learning performance

Regarding RQ1, although previous empirical studies have produced mixed results, the present meta-analysis indicates a moderate, positive effect of GA support in CSCL. According to our results, GA support can improve students' learning performance by enhancing behavioral participation, promoting cognitive development, and improving social emotion.

These findings are in agreement with prior research and can be explained from educational psychology perspectives (Bodemer & Dehler, 2011; Buder, 2011; Janssen & Bodemer, 2013). First, according to the theory of social facilitation, the actual or

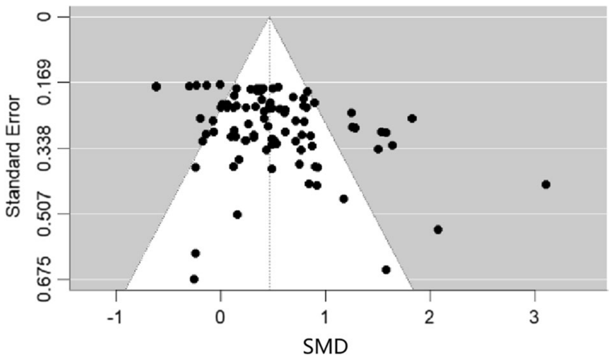
Table 7 Effects of educational level on effect size

Moderator	No. studies	No. ES	*g (SE)*	*t* value (sig)	95%CI	F (df1, df2)	Level 2 variance	Level 3 variance
Educational level								
Primary education	1	1	-0.07 (0.52)	-0.14	[-1.12, 0.97]	F (4, 91) = 0.51 $p = 0.725$	0.10	0.11
Secondary education	9	16	0.54 (0.16)	3.34**	[0.22, 0.85]			
Higher education	38	57	0.49 (0.08)	6.27***	[0.33, 0.64]			
Professional training	4	9	0.46 (0.23)	2.00*	[0.00, 0.92]			
Mixed	6	13	0.31 (0.18)	1.79	[-0.04, 0.67]			

(1) No. studies: number of studies. (2) No. ES: number of effect sizes (3) *g*: Hedges'*g*. (4) SE: standard error. (5) CI: confidence interval. (6) F (df1, df2): omnibus test of regression coefficient in the model. (7) *p*: *p* value of the omnibus test. (8) Level 2 variance: variance between effect sizes extracted from the same study (heterogeneity of within-study). (9) Level 3 variance: variance between studies (heterogeneity of between-study)

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

Fig. 2 Funnel plot of effect sizes



implied presence of others is an important factor to facilitate students' active behavioral participation (Little, 1998). GA support creates opportunities for learners to perceive the presence and contributions of their peers, thereby encouraging them to actively engage in collaborative learning activities (Bond & Titus, 1983; Little, 1998; Ma et al., 2023). Second, referring to the terminology of cognitive load theory, GA support can reduce extraneous cognitive load (e.g., the amount of effort and time required for group coordination), thereby enabling students to devote more efforts to activities related to higher cognitive levels (Janssen & Bodemer, 2013). Finally, GA support can facilitate social comparison and social referencing, which can influence students' social emotions. GA support provides opportunities for positive modeling and peer influence, leading to positive social emotions such as admiration, inspiration, and empathy. This social referencing also helps students regulate their own emotions and behaviors in a socially appropriate manner.

Although GA supports show significant positive effects on all three dimensions of learning performance, an interesting finding is that GA supports have the smallest effect on students' social emotion compared to the other two dimensions (with essentially equal effect sizes for behavioral participation and cognitive development). On the one hand, this phenomenon can be attributed to the evaluation apprehension caused by GA support (Dehler et al., 2009). When members' contributions become transparent, learners may worry excessively about how their work is perceived by both their instructors and peers. On the other hand, it may be due to the fact that GA supports are often designed to improve information sharing, communication, and task allocation, which have the most direct impact on students' cognitive development and behavioral participation. However, changes in the social-emotional performance takes more time.

Significant moderator variables

As for RQ2, in order to gain a deeper understanding of the conditions under which GA support is more effective, our study investigated five moderator variables that pertain to how GA support implemented: GA support type, group size, disciplinary domain, intervention duration, and educational level. The results indicated that GA support type and group size were the only two significant moderator variables that have influences on the effect size heterogeneity.

GA support type as a significant moderator variable

Our results showed that studies adopting combined types of GA support (i.e., a GA support provides more than one type of GA information) had much larger effect sizes than those adopting an individual type of GA support (i.e., behavioral, cognitive or social GA support). A possible explanation for this finding is that collaboration is a complex coordination process involving both content space (i.e., group activities that are related to the task itself) and relational space (i.e., group activities that are related to interpersonal relationships) (Barron, 2003; Slof et al., 2010). Single GA indicators may not be able to fully address all the challenges of CSCL (Ollesch et al., 2021). Various types of GA information can be combined so as to complement each other, thereby better meeting students' collaborative learning needs and improving students' learning performance.

Moreover, we also analyzed the impact of individual GA support types on the different dimensions of learning performance and made some interesting findings. First, we are surprised to find that not every individual type of GA support shows a significant effect. Our results indicates that social GA support has no significant effect on all three types of learning performance. On the one hand, this may be related the design characteristics of existing social GA support. Since most of the information provided by existing social GA support was derived from students' self-reported data, it may not reflect learners' real collaboration status, which in turn may affect the effectiveness of social GA support (Phielix et al., 2010; Phielix et al., 2011; Kirschner et al., 2015). On the other hand, this could be attributed to the limited number of studies. Only five studies explored the impact of social GA support, so there may be an element of chance in the results. The role of social GA support cannot be ignored and more research related to social GA support needs to be considered.

Second, it was interesting to find that a strict corresponding relationship between GA support types and learning performance types does not exist. For example, behavioral GA support promotes learners' cognitive development better than cognitive GA support. This may be due to the fact that behavioral GA support provides more concrete and observable information than the other two types of GA support, and therefore has the most intuitive motivational effect on students' cognitive development. Additionally, deeper knowledge construction is based on more collaborative behaviors (Daspit & D'Souza, 2012; Galikyan & Admiraal, 2019). By facilitating behavioral participation, behavioral GA support triggers more elaborative discussions, which in turn leads to higher levels of cognitive development.

Group size as a significant moderator variable

In studies reporting group size, we found that it is more beneficial for larger groups (more than 4 members) than for smaller groups (2-4 members) to learn with the assistance of GA support. This finding is consistent with the views presented in previous research (Janssen et al., 2011; Liu et al., 2018; Wang et al., 2019). In smaller groups, each individual's obligation to participate is greater, and their level of engagement is more noticeable to other group members. This heightened visibility can make any lack of participation more apparent (Bonito, 2000; Janssen et al., 2011). However, in larger groups, it is difficult for learners to focus on the collaborative information of each member because the increased group size results in the generation of too much information. Therefore, GA support is more necessary and helpful for students under this circumstance.

Non-significant moderator variables

Of the moderators analyzed in our study, we found no significant differences in effect sizes across disciplinary domains, intervention durations, and educational levels. However, there are still some interesting findings that deserve to be taken into account.

First, in terms of disciplinary domain, while GA support proved to be helpful across the coded disciplinaries, the effect size in humanities is the largest. However, since the number of studies conducted in the humanities is very limited (with only two studies), more research is needed.

Second, as for educational level, it is unsurprising to find that GA support shows no significant effect on primary school students. An important reason may be that GA support provides implicit guidance for students without using direct advice, which means that learners need to process the information provided by GA support based on their own understanding (Lin, Lai et al., 2016a, Lin, Szu et al., 2016b; Miller & Hadwin, 2015). Due to the cognitive development level, primary school students may have difficulty in interpreting GA information in a reasonable way, which in turn affects the effectiveness of GA support. Another interesting finding regarding educational level is that the impact of GA support decreases in descending order from secondary, to higher education, to professional training. This may be due to the fact that learners' tendency to make social comparisons becomes lower as they get older, which in turn affects the role of GA support (Lin & Tsai, 2016; Little, 1998; Ma et al., 2023).

Finally, regarding intervention duration, although GA support shows significant effects at short (≤1 week), medium (1–8 weeks), and long (>8 weeks) intervention durations, we find that the effect size of long is much larger than the other two categories. According to Soller et al. (2005), it requires a long time for a group to reach equilibrium. GA information over a short period of time may not reflect the actual situation of individuals or groups, as learners' cooperative status has not reached a stable state. As a result, this information may not be convincing to students, and they may ignore it, which leads to a smaller impact.

Theoretical and pedagogical implications

Based on these findings, several implications could be drawn from the current meta-analysis.

From a theoretical point of view, the results of this meta-analysis support some cognitive and psychological theories (e.g., the cognitive load theory and social comparison theory), which in turn deepen our understanding of these theories as well as the field of GA (Bodemer & Dehler, 2011; Buder, 2011; Janssen & Bodemer, 2013; Little, 1998). For example, the results reveal that the coordination of group in collaborative learning increases extraneous cognitive load and GA support can reduce such cognitive load (Janssen & Bodemer, 2013). Additionally, referring to the terminology of social comparison theory, our findings suggest that providing students with GA support is more likely to stimulate upward social comparisons than downward comparisons (Little, 1998). Overall, these findings not only justify existing theories, but also extend them to some extent.

From a practical point of view, the findings of this meta-analysis provide valuable insights on the boundary conditions under which GA support functions, which provided experience and methods on how GA support can be used more effectively in CSCL. First, since the results showed that combined types of GA support significantly outperformed individual types, it is recommended that educational practitioners provide students with multiple types of GA information in CSCL to improve their learning performance. Additionally, for designers and developers of GA support, they should consider gathering as many types of collaborative information (behavioral, cognitive, and social) from students as possible. Second, since GA support is more effective for larger groups (more than 4 members), educational practitioners should weigh the costs and benefits of providing GA support according to the actual class size and planned group size.

Conclusions

This three-level meta-analysis is the first to conduct a quantitative synthesis of existing empirical research into the effects of GA support in CSCL. It makes valuable contributions that enhance our understanding about the effects of GA support in CSCL under different study conditions. First, the results of this study suggest that GA support can effectively improve students' learning performance in CSCL, as well as behavioral participation, cognitive development, and social emotion. Second, we conducted extensive moderator analyses and identified GA support type and group size as significant moderating factors.

However, we have to acknowledge that there are still some limitations in the current study. First, some empirical studies lacked sufficient statistical information for effective size calculation. As a result, they should be excluded from the meta-analysis, which may have influenced the results. Second, the moderator variables listed in the current study may not be comprehensive enough. There could be other study features or factors, such as the frequency of updating GA information that may affect the effectiveness of GA supports in CSCL. We did not consider some variables because there were too few empirical research reporting information about them. Finally, this meta-analysis was time-limited, as additional studies may have been published in the course of completing the current meta-analysis, as is the case with most review articles. Therefore, it should be noted that these limitations need to be considered when interpreting the findings of this study.

Appendix

Table 8 Overview of the characteristics of the included studies

Authors (Year)	Sample size (EG vs. CG)	GA support type	Educational context			Educational level	Outcome measurement
			Group size	Academic domain	Intervention duration		
Bodemer (2011)	40 (20 vs. 20)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	C
Buder & Bodemer (2008)	64 (32 vs. 32)	Individual-social	Smaller group	Natural sciences	Short	Higher education	C
Chen et al. (2023)	50 (26 vs. 24)	Combined type	Not mentioned	Humanities	Short	Secondary education	C
Dehler et al. (2009)	76 (38 vs. 38)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	C
Dehler et al. (2011)	76 (38 vs. 38)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	B, C
Dehler Zufferey et al. (2010)	42 (21 vs. 21)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	B, C
Engelmann & Hesse (2010)	120 (60 vs. 60)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	C, S
Engelmann & Hesse (2011)	120 (60 vs. 60)	Individual-cognitive	Smaller group	Natural sciences	Not mentioned	Higher education	C
Engelmann et al. (2009)	90 (45 vs. 45)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	B, C
Engelmann, Kolodziej et al. (2014a)1	120 (60 vs. 60)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	C
Engelmann, Kozlov et al. (2014b)2	120 (60 vs. 60)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	C
Farrokhnia et al.(2019)	40 (20 vs. 20)	Individual-cognitive	Smaller group	Natural sciences	Medium	Secondary education	C
Gijlers & de Jong (2009), study1	44 (22 vs. 22)	Individual-cognitive	Smaller group	Natural sciences	Short	Secondary education	B, C
Gijlers & de Jong (2009), study2	44 (22 vs. 22)	Individual-cognitive	Smaller group	Natural sciences	Short	Secondary education	B, C
Gijlers et al. (2013)	58 (34 vs. 24)	Individual-cognitive	Smaller group	Natural sciences	Short	Primary education	C
Hadwin et al. (2018), study1	113 (53 vs. 60)	Combined type	Smaller group	Social sciences	Long	Higher education	C

Table 8 (continued)

Authors (Year)	Sample size (EG vs. CG)	GA support type	Educational context			Educational level	Outcome measurement
			Group size	Academic domain	Intervention duration		
Hadwin et al. (2018), study2	127 (67 vs. 60)	Combined type	Smaller group	Social sciences	Long	Higher education	C
Hayashi (2020)	80 (40 vs. 40)	Individual-behavioral	Smaller group	Engineering	Short	Higher education	C
Janssen, Erkens & Kanselaar et al. (2007a)1	69 (52 vs. 17)	Individual-behavioral	Smaller group	Humanities	Medium	Secondary education	B, C, S
Janssen, Erkens, Kanselaar & Jaspers et al. (2007b)2	40 (20 vs. 20)	Individual-behavioral	Smaller group	Not mentioned	Medium	Secondary education	C
Jongsawat & Premchaiswadi (2009)	30 (15 vs. 15)	Individual-behavioral	Larger group	Engineering	Long	Higher education	B, C, S
Jongsawat & Premchaiswadi (2011)	60 (30 vs. 30)	Combined type	Larger group	Engineering	Short	Higher education	B, C, S
Jongsawat & Premchaiswadi (2014)	60 (30 vs. 30)	Combined type	Larger group	Engineering	Short	Higher education	B, C, S
Kimmerle & Cress (2008), study1	82 (39 vs. 43)	Individual-behavioral	Larger group	Natural sciences	Not mentioned	Higher education	B
Kimmerle & Cress (2008), study2	80 (37 vs. 43)	Individual-behavioral	Larger group	Natural sciences	Not mentioned	Higher education	B
Kimmerle et al. (2007)	82 (39 vs. 43)	Individual-behavioral	Larger group	Natural sciences	Not mentioned	Higher education	B
Kozlov et al. (2015)	60 (30 vs. 30)	Individual-cognitive	Smaller group	Natural sciences	Short	Higher education	C
Kwon et al. (2013)	53 (28 vs. 25)	Individual-social	Smaller group	Engineering	Not mentioned	Higher education	C, S
Lai (2021)	50 (22 vs. 28)	Individual-cognitive	Smaller group	Social sciences	Long	Higher education	C
Lin (2018)	84 (43 vs.41)	Combined type	Larger group	Engineering	Long	Higher education	B, C
Lin & Tsai (2016)	83 (42 vs. 41)	Combined type	Smaller group	Engineering	Long	Higher education	B
Lin, Lai et al. (2016a)1	99 (46 vs. 53)	Combined type	Larger group	Engineering	Medium	Higher education	B
Lin, Szu et al. (2016b)2	113 (57 vs. 56)	Combined type	Larger group	Engineering	Medium	Higher education	C

Table 8 (continued)

Authors (Year)	Sample size (EG vs. CG)	GA support type	Educational context			Educational level	Outcome measurement
			Group size	Academic domain	Intervention duration		
Lin et al. (2021)	115 (56 vs. 59)	Combined type	Smaller group	Engineering	Medium	Higher education	B
Liu et al. (2018) (removed as an outlier)	120 (72 vs. 48)	Individual-behavioral	Smaller group	Engineering	Short	Higher education	B, C
Ma et al. (2023), study1	97 (51 vs. 46)	Combined type	Larger group	Engineering	Long	Higher education	C, S
Ma et al. (2023), study2	119 (51 vs. 68)	Combined type	Larger group	Engineering	Long	Higher education	C, S
Michinov & Primois (2005)	27 (14 vs. 13)	Individual-behavioral	Not mentioned	Not mentioned	Not mentioned	Professional training	B, C, S
Ollesch et al. (2021), study1	79 (41 vs. 38)	Individual-behavioral	Not mentioned	Natural sciences	Short	Mixed	B, C
Ollesch et al. (2021), study2	79 (41 vs. 38)	Individual-cognitive	Not mentioned	Natural sciences	Short	Mixed	C
Ollesch et al. (2021), study3	76 (38 vs. 38)	Combined type	Not mentioned	Natural sciences	Short	Mixed	C
Ollesch et al. (2022), study1	74 (37 vs. 37)	Individual-cognitive	Not mentioned	Natural sciences	Short	Mixed	B, C, S
Ollesch et al. (2022), study2	74 (37 vs. 37)	Individual-social	Not mentioned	Natural sciences	Short	Mixed	B, C, S
Ollesch et al. (2022), study3	74 (37 vs. 37)	Combined type	Not mentioned	Natural sciences	Short	Mixed	B, C, S
Phielix et al. (2010)	39 (19 vs. 20)	Combined type	Smaller group	Social sciences	Short	Secondary education	C, S
Phielix et al. (2011), study1	79 (54 vs. 25)	Combined type	Smaller group	Social sciences	Short	Secondary education	C, S
Phielix et al. (2011), study2	47 (22 vs. 25)	Combined type	Smaller group	Social sciences	Short	Secondary education	C, S
Pifarré et al. (2014)	47 (24 vs. 23)	Combined type	Smaller group	Social sciences	Long	Higher education	B, C
Puhl et al. (2015), study1	43 (24 vs. 19)	Individual-social	Not mentioned	Engineering	Long	Professional training	B, C
Puhl et al. (2015), study2	39 (20 vs. 19)	Individual-social	Not mentioned	Engineering	Long	Professional training	B, C
Yilmaz & Karaoglan Yilmaz (2020)	42 (22 vs. 20)	Individual-cognitive	Smaller group	Engineering	Long	Higher education	C, S
Schnaubert & Bodemer (2019), study1	128 (64 vs. 64)	Individual-cognitive	Smaller group	Social sciences	Short	Higher education	B, C
Schnaubert & Bodemer (2019), study2	131 (67 vs. 64)	Individual-cognitive	Smaller group	Social sciences	Short	Higher education	B, C

Table 8 (continued)

Authors (Year)	Sample size (EG vs. CG)	GA support type	Educational context			Educational level	Outcome measurement
			Group size	Academic domain	Intervention duration		
Schnaubert & Bodemer (2019), study3	128 (64 vs. 64)	Individual-cognitive	Smaller group	Social sciences	Short	Higher education	B, C
Schreiber & Engelmann (2010)	90 (45 vs. 45)	Individual-cognitive	Smaller group	Social sciences	Short	Higher education	C
Stegmann et al. (2012)	48 (24 vs. 24)	Combined type	Smaller group	Social sciences	Short	Higher education	C
Strauß & Rummel (2021), study1	43 (20 vs. 23)	Combined type	Smaller group	Social sciences	Medium	Higher education	B
Strauß & Rummel (2021), study2	37 (17 vs. 20)	Combined type	Smaller group	Social sciences	Medium	Higher education	B
Wang et al. (2019)	24 (12 vs. 12)	Combined type	Larger group	Social sciences	Medium	Professional training	B, C

(1) Simple size (EG: experimental group; CG: control group). (2) Outcome measurement (B: behavioral participation; C: cognitive development; S: social emotion). (3) Since some studies conducted more than one experiment, we listed them separately and numbered them study1, study2, and etc. (4) If a researcher has more than one paper in the same year, add the number after the citation. For example, Janssen, Erkens & Kanselaar et al. (2007a)1, Janssen, Erkens, Kanselaar & Jaspers et al. (2007b)2, and etc. (5) Regarding the coding of group size, it is important to note that of the included studies, a small number included groups of both 2-4 and more than 4 members. These studies were coded according to the proportion of group size. For example, in Lin et al.' study, students were randomly assigned to teams of 3-5 members. However, the vast majority of the groups were smaller than five people, so this study was coded as smaller group

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* = study included in the meta-analysis

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