Meta-Analytically Exploring the Learning Outcomes Assisted With Twitter in the Pandemic Time

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ABSTRACT

The use of social media such as Twitter has gained popularity in education during the COVID-19 pandemic. This study included 22 high-quality peer-reviewed journal articles for the meta-analysis. The authors reveal that there are no significant differences in teaching effectiveness between the Twitter and non-Twitter-assisted learning approaches. Twitter-assisted learning outcomes are significantly higher than the non-Twitter-assisted whether Twitter is used as a supplementary or an integrated tool. Twitter-assisted learning can lead to significantly higher learning outcomes than non-Twitter-assisted learning in the USA, Greece, and Sweden, but no significant difference is revealed in Spain. Swedish users hold significantly positive attitudes towards the use of Twitter in education, but no significant difference is found in the USA. Twitter-assisted learning can cause significantly more engagement than non-Twitter-assisted in the USA, and male learners have significantly higher learning outcomes than females in both the USA and Spain.

KEYWORDS

Countries, Gender Differences, Learning Outcomes, Meta-Analysis, Twitter

INTRODUCTION

Since the outbreak of COVID-19, billions of learners have been forced to acquire knowledge through social media such as Twitter and Facebook since the majority of them are required to keep social distance with peers or teachers. Consequently, learners are forced to learn knowledge through the use of social media and teachers have to deliver knowledge through mobile applications where social media are important tools. Social media-assisted learning outcomes have thus become a serious concern of educators and learners. Therefore, the first important thing for this study to clarify is both positive and negative Twitter-assisted learning outcomes.

POSITIVE FINDINGS

The COVID-19 pandemic has forced people to receive education through social media such as Twitter and Facebook (Yu, 2021). Twitter-assisted learning could improve learners’ engagement in learning...
activities and communities. Active engagement in learning could improve learning outcomes although the link between them proved weak. Tips through Twitter were useful to learners in Spain because they deem Twitter a tool for educational purposes (Fouz-Gonz tool 2017). With Twitter, Spanish students could actively participate in learning activities although they could hardly integrate the use of Twitter into learning interactions. Guidance should, therefore, be provided for students to improve the interaction. The restriction on the length of a message could encourage users to think and decide what to type next. The training schedule could focus on the design of learning activities (Feliz, Ricoy, & Feliz, 2013). With social media such as Twitter, American students, who consider Twitter a useful tool, could actively join in large learning communities and enhance their learning interest (Hitchcock & Young, 2016). Greek Students’ learning attitudes towards Twitter were positive, leading to their active engagement in learning activities (Katrimpoza, Tselios, & Kasimati, 2019). Therefore, this study will focus on learning attitudes, learning achievements, and learning engagement in both Twitter and non-Twitter-assisted learning methods.

The use of Twitter could improve users’ learning outcomes due to various factors. Integrating Twitter into a course coupled with teacher participation could greatly improve students’ learning outcomes in the USA (Junco, Michael Elavsky, & Heiberger, 2013). Twitter-assisted learning approaches could greatly improve students’ learning outcomes by enhancing their engagement (Junco, Heiberger, & Loken, 2010). Twitter use could greatly improve Greek students’ laboratory performance although it is not found significantly correlated with their personality traits. The use of Twitter could improve Greek students’ learning outcomes and social presence and enhance their self-efficacy (Loutou, Tselios, & Altanopolou, 2018). In a classroom, American students who used Twitter frequently obtained significantly higher learning outcomes than those who seldom used Twitter (Webb, Dugan, & Burchett et al., 2015). Broadcast journalism majors could perform excellently assisted with Twitter in terms of the degree of learning activity engagement and interactivity in the USA (Cozma & Hallaq, 2019). Other smart learning tools such as interactive webinars and podcasts may also improve learning outcomes (Campi, Amparore, Checcucci, Claps, & Zhuang, 2021).

The use of Twitter could positively improve users’ psychological status such as engagement and memory. Engagement Twitter Support could improve American breast cancer patients’ gain of knowledge by reducing their anxiety (Attai, Cowher, & Al-Hamadani, Schoger, Staley, & Landercasper, 2015). Students were in general satisfied with the mobile learning system-assisted with Twitter since it could improve knowledge gain and provide cooperative opportunities in Sri Lanka (Dissanayake, Hewagamage, Ramberg, & Wikramanayake, 2016). Caring through Twitter dialogues rather than one-way communication could improve Swedish Twitter users’ learning attitudes and intentions (Collander, Dahl communication cou. American students held positive learning attitudes toward the Twitter integrated classroom and actively participated in the learning activities (Luo & Xie, 2018). American students positively evaluated Twitter use in a classroom and reported increased social presence with peers although Twitter use might not improve their memory of academic contents (Smith & Tirumala, 2012). Social media tools such as Twitter could improve information retention through their visual input function, especially in American post-secondary education (Arceneaux & Dinu, 2018). The use of Twitter could improve American students’ memory and enables them to keep more important concepts in their mind (Blessing, Blessing, & Fleck, 2012).

Some studies reported gender differences in the use of Twitter. For example, American men were more likely to examine tweets to share resources and criticize other tweets while women tended to write tweets and positively evaluated other tweets. This indicates that the teacher could use different teaching strategies toward different genders in the USA (Kerr & Schmeichel, 2018). Females’ contributions to Twitter seemed significantly larger than males (Davidson-Shivers, Muilenburg, & Tanner, 2001). Males could produce significantly more voice messages than females (McConnell, 1997). Therefore, this study will focus on teaching effectiveness and gender differences in both Twitter and non-Twitter-assisted learning methods in different countries.
NEGATIVE FINDINGS

Despite many studies revealed positive findings regarding the educational effect of Twitter use, there are also many studies reporting negative results. For example, it was reported that the use of Twitter could not improve learning outcomes in the USA (Al-Bahrani, Patel, & Sheridan, 2017). Even Twitter messages were related to lecture notes; they failed to improve American users’ learning outcomes in terms of multiple-choice grades and free-recall performance. Worse, when learners create and send tweets frequently, the quality of their lecture notes will be reduced (Kuznekoff, Munz, & Titsworth, 2015). The use of Twitter in class could not significantly influence American users’ interest in politics and news reading although it might positively influence their learning outcomes (Feezell, 2019).

We should try to see both sides of a coin when exploring the use of Twitter in education. Professional contents on the Twitter platform, as well as American students’ learning attitudes, could greatly influence the teachers’ credibility. Twitter could be both an advantage of and an obstacle to learning and teaching (DeGroot, Young & VanSlette, 2015). There were several drawbacks, e.g. technical issues, limitation to higher-order skill acquisition, and limited learning opportunities, in the Twitter integrated mobile learning system in Sri Lanka (Dissanayeke, Hewagamage, Ramberg, & Wikramanayake, 2016).

It was also found that Twitter may not be suitable for educational use. American Twitter users are younger and wealthier than those in other regions, leading to under-representativeness of Twitter population. This causes the claim that Twitter may be more properly used by corporations than by social science researchers in the USA (Blank, 2016). This argument may dampen the enthusiasm of Twitter use for educational purposes. Twitter may be not appropriate for educational purposes since tweets have numerous problems, e.g. lack of relational cues in tweets, limitation to contents, no hint of communicative behavior, and insufficient timeline (Yoshida, 2021).

A RESEARCH GAP

Little is known about the effect of different Twitter usages on learning outcomes. Some studies adopted Twitter as an integrated learning tool (e.g. Feezell, 2019; Loutou et al., 2018; Feliz et al., 2013; Dissanayeke et al., 2016), while others as a supplemental learning tool (e.g. Al-Bahrani et al., 2017; Arceneaux & Dinu, 2018; Blank, 2016; Blessing et al., 2012). Very few studies have been committed to the differences in the effect of both usages. Although there are some studies meta-analytically reviewing the effect of Twitter use on educational outcomes (e.g. Yu & Yu, 2021), very few of them analyzed the effect of Twitter across different countries. There is also a study committed to new strategies to improve learning engagement assisted with Twitter (He et al., 2022), but it does not examine the effect of Twitter on learning engagement across various countries or areas. This study will thus focus on the effect of Twitter usages on learning outcomes across different countries. We tabulated the comparison between the proposed study and state of the art (Table 1).

Research Questions

Considering the research gap and inconsistent findings regarding the use of Twitter for educational purposes, we proposed several research questions as follows:

RQ1: Can Twitter-assisted approaches improve learning outcomes such as learning attitudes, learning achievements, learning engagement, and teaching effectiveness?
RQ2: Can Twitter-assisted approaches improve learning outcomes in different countries?
RQ3: Are there any gender differences in Twitter-assisted learning outcomes in different countries?
RQ4: Can different usages of Twitter lead to different learning outcomes?
METHODS

This meta-analysis and systematic review will follow the framework of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher, Liberati, Tetzlaff, Altman, & Group, 2009). The methods include protocol and registration, eligibility criteria, information sources, literature search and selection, quality assessment, data extraction, and statistical analysis.

Protocol and Registration

This study focuses on Twitter-assisted learning outcomes in terms of country, gender, and usage, which is not required to be registered. It is conducted based on PRISMA (Moher, Liberati, Tetzlaff, Altman, & Group, 2009) and approved by the institutional review board which waives a review protocol.

Eligibility Criteria

We selected and excluded studies based on inclusion and exclusion criteria. The studies will be included if they (1) focus on Twitter-assisted learning outcomes in terms of country, gender, and Twitter usage; (2) are of higher quality; (3) divide participants into both control and treatment groups for a comparative analysis; (4) adopt a randomized controlled design through a comparative analysis between both control and treatment groups; and (5) are peer-reviewed academic works.

The studies will be excluded if they (1) focus on Twitter technology itself rather than Twitter use in education; (2) belong to reviews rather than empirical studies; (3) cannot provide enough information for meta-analysis even after contacting authors including number of participants, means, and standard deviations across both groups; or (4) are written in a language other than English.

Information Sources

The information sources from multiple online databases, i.e. EBSCOhost, Taylor & Francis Online, Wiley Online Library, and Sage. We also obtained information through corresponding with the authors in case the full-text does not provide enough data for meta-analysis. We searched the above databases on January 27, 2021. The coverage of dates ranges from the commencement year until January 2021.

| N  | This study                                           | State of the art                                      |
|----|------------------------------------------------------|-------------------------------------------------------|
| 1  | Twitter as both an integrated and a supplemental learning tool | Twitter as an integrated learning tool (e.g. Feezell, 2019; Loutou et al., 2018; Feliz et al., 2013; Dissanayake et al., 2016), |
| 2  | The effect of Twitter use on educational outcomes and gender differences across different countries | The effect of Twitter use on educational outcomes (e.g. Yu & Yu, 2021) |
| 3  | Strategies to improve Twitter-assisted learning attitudes, achievements, engagement, and teaching effectiveness | Strategies to improve Twitter-assisted learning engagement (He et al., 2022) |
| 4  | The effect of Twitter use on learning outcomes and gender differences | The effect of Twitter on learning outcomes (Feezell, 2019) |
Literature Search and Selection

The literature search and selection involve four steps based on the PRISMA flowchart (Yang, Yen, McGowan, Chen, Chiang, & Mancini, et al., 2012). All the literature was searched from online databases, i.e. EBSCOhost, Taylor & Francis Online, Wiley Online Library, and Sage. In the first step, we searched the online databases using corresponding terms to obtain literature before we removed the duplicated results. In the second step, we invited two independent reviewers to screen the irrelevant results by perusing abstracts and titles. In the third step, two independent reviewers evaluated the eligibility of the full texts. In the fourth step, both reviewers presented the results of evaluation and negotiated on any disagreements. A third experienced reviewer would join and determine the selection if both reviewers could not persuade each other on any specific literature selection. After the four-step selection process, we finally determined 22 peer-reviewed journal articles for the meta-analysis (Figure 1).

Quality Assessment

We evaluated the quality of the selected studies based on the University of West England Framework for Critically Appraising Research Articles (Moule et al., 2003). The selected articles are evaluated in terms of each section, i.e. The Introduction, The Methods Section, Data Collection and Analysis, The Results/Findings, and The Conclusions. Each section is assessed based on a certain criterion. For example, the introduction section should include a clear statement about the topic being investigated and a clear rationale for the research. The research design should be clearly described and the research methods should be appropriate for the topic being investigated. Two reviewers scored each selected article. The average score will be considered. We selected the top-scored 22 articles. The Inter-rater Cohen’s kappa coefficient is 0.82.

Figure 1. A flowchart of literature inclusion
Data Extraction

The data were extracted by both reviewers from the eligible studies. To fulfill the meta-analysis, they extracted data such as authors, publication years, the total number of participants, means, and standard deviations of both groups.

They also extracted data regarding country, e.g., USA, UK, Sri Lanka, Sweden, Spain, and Greece, learning outcomes, and Twitter usage. Learning outcomes are classified into learning achievements, attitude, gender differences in learning outcomes, engagement, and teaching effectiveness. Twitter usage is classified into Twitter as a supplemental learning tool and Twitter as an integrated learning tool.

Similarly, both reviewers met together to decide on the final extracted data after they finished data extraction. In case they could not reach an agreement on any data, a third reviewer would be invited to make a decision.

Statistical Analysis

Stata MP/14.0 was used to analyze the extracted data and fulfill the meta-analysis. Z-statistics were adopted to analyze the effect of meta-analytical outcomes. Since the data type is continuous, we entered the numbers of participants, means, and standard deviations of both groups into Stata MP/14.0, labeled the data by authors and publication years, and selected country, learning outcome, and Twitter usage as a variable. The pooling model was either random (I-V heterogeneity) or fixed (Inverse Variance). The effect size was expressed as Cohen $d$ or standardized mean differences (SMD). $d$ is considered very small if the value is 0.1, small if 0.2, medium if 0.5, large if 0.8, very large if 1.2, and huge if the value is 2.0 (Sawilowsky, 2009). SMD was calculated through the formula: $SMD = \frac{\text{difference in mean outcome between groups}}{\text{standard deviation of outcome among participants}}$.

Due to various situations, different characteristics of participants, and different interventions, different studies tend to cause different effect sizes. Statistical heterogeneity occurs immensely and is unavoidable (Higgins & Green, 2011). We, therefore, quantify heterogeneity using $I^2$ through the formula below:

$$I^2 = \left( \frac{Q - df}{Q} \right) \times 100\%$$  \hspace{1cm} (1)

where $Q$ indicates the chi-squared result and $df$ means the degree of freedom (Higgins & Green, 2011). The heterogeneity will be considered not important if $F = 0\% - 40\%$, moderate if $30\% - 60\%$, substantial if $50\% - 90\%$, considerable if $75\%$ to $100\%$. Roughly, we will use a random-effect model to conduct the meta-analysis if $F$ is larger than 50% and a fixed-effect model if it is smaller than 50%. If the value of $F$ is large, we will test the sensitivity using the influence analysis in Stata MP/14.0. We will also test the publication bias using Begg’s (Begg & Mazumdar, 1994) and Egger’s (Egger, Smith, Schneider, & Minder, 1997) tests.

Results

This results section will present the findings based on the research questions, including characteristics of included studies, risk of bias within studies, results for individual and synthetic analysis, followed by answers to research questions. The organization of the results is presented based on the protocol of PRISMA.

Characteristics of Included Studies

Table 2 pools the characteristics of included studies, involving author, publication year, sample size, country, learning outcome, and Twitter usage. The specific data such as means and standard deviations of both control and treatment groups are provided in the data file.
Both Egger’s and Begg’s tests were used to detect the publication bias. The data input format \( \theta \ se_\theta \) was assumed for both tests. Figure 2 presents an Egger’s plot of publication bias. A dot in Figure 2 indicates an individual study. The uneven distribution of the dots along either side of the middle no-effect line indicates the presence of publication bias \( (t = 4.70, p < .01) \). Begg’s test examines the publication bias through rank correlation between standardized intervention effect and its standard error, which also indicate the presence of publication bias \( (z = 3.15, p = 0.002) \).

### Table 2. Characteristics of included studies

| N  | Author/year                | Sample size | Country | Learning outcome                                                | Twitter usage                                |
|----|----------------------------|-------------|---------|-----------------------------------------------------------------|-----------------------------------------------|
|    |                            | Treatment   | Control |                                                                 |                                               |
| 1  | Al-Bahrani et al., 2017    | 130         | 130     | USA Learning achievements and their gender differences          | Twitter as a supplemental learning activity  |
| 2  | Arceneaux & Dini, 2018     | 390         | 390     | USA Learning achievements                                         | Twitter as a supplemental learning activity  |
| 3  | Attai et al., 2015        | 189         | 189     | USA Learning achievements                                         | Twitter integrated learning                  |
| 4  | Blank, 2016               | 94          | 78      | USA/UK Learning achievements and attitude                        | Twitter as a supplemental learning activity  |
| 5  | Blessing et al., 2012     | 30          | 33      | USA Learning achievements                                         | Twitter as a supplemental learning activity  |
| 6  | Collander et al., 2015    | 66          | 92      | Sweden Attitude                                                  | Twitter integrated learning                  |
| 7  | Cozma & Hallaq, 2019      | 18110       | 18110   | USA Attitude                                                     | Twitter integrated learning                  |
| 8  | DeGroot et al., 2015      | 16          | 22      | USA Attitude                                                     | Twitter integrated learning                  |
| 9  | Dissanayake et al., 2016  | 13          | 13      | Sri Lanka Teaching effectiveness                                 | Twitter integrated learning                  |
| 10 | Fezzell, 2019             | 71          | 71      | USA Attitude                                                     | Twitter integrated learning                  |
| 11 | Feliz et al., 2013        | 3026        | 3026    | Spain Male-female                                                | Twitter integrated learning                  |
| 12 | Fouz-González, 2017       | 44          | 24      | Spain Learning achievements and teaching effectiveness           | Twitter integrated learning                  |
| 13 | Hitchcock & Young, 2016   | 30          | 30      | USA Learning achievements                                         | Twitter as a supplemental learning activity  |
| 14 | Junco et al., 2010        | 19          | 53      | USA Learning achievements and engagement                         | Twitter as a supplemental learning activity  |
| 15 | Junco et al., 2013        | 65          | 53      | USA Learning achievements                                         | Twitter as a supplemental learning activity  |
| 16 | Katrimpouza et al., 2019  | 80          | 152     | Greece Learning achievements                                      | Twitter as a supplemental learning activity  |
| 17 | Kerr & Schmeichel, 2018   | 657         | 696     | USA Gender differences in learning outcomes                      | Twitter as a supplemental learning activity  |
| 18 | Kuznekoff et al., 2015    | 30          | 32      | USA Learning achievements                                         | Twitter as a supplemental learning activity  |
| 19 | Loutou et al., 2018       | 17          | 17      | Greece Learning achievements and engagement                      | Twitter integrated learning                  |
| 20 | Luo & Xie, 2019           | 22          | 16      | USA Learning achievements                                         | Twitter integrated learning                  |
| 21 | Smith & Tirumala, 2012    | 41          | 35      | USA Attitude                                                     | Twitter as a supplemental learning activity  |
| 22 | Webb et al., 2015         | 2           | 66      | USA Learning achievements                                         | Twitter integrated learning                  |

Risk of Bias Within Studies

Both Egger’s and Begg’s tests were used to detect the publication bias. The data input format \( \theta \ se_\theta \) was assumed for both tests. Figure 2 presents an Egger’s plot of publication bias. A dot in Figure 2 indicates an individual study. The uneven distribution of the dots along either side of the middle no-effect line indicates the presence of publication bias \( (t = 4.70, p < .01) \). Begg’s test examines the publication bias through rank correlation between standardized intervention effect and its standard error, which also indicate the presence of publication bias \( (z = 3.15, p = 0.002) \).
Results for Individual and Synthetic Analysis

This result section presents the findings regarding pooled learning outcomes, their differences in different countries and, different usages of Twitter.

RQ1: Can Twitter-assisted approaches improve learning outcomes such as learning attitudes, learning achievements, learning engagement, and teaching effectiveness?

To determine whether a random-effect or fixed-effect model we should adopt, we tested the heterogeneity of the effect sizes for learning achievements. The result shows that the effect sizes are heterogeneous ($Q = 2129.93$, $df = 73$, $p < .01$, $I^2 = 96.6$) (Table 3). We, therefore, adopted a random-effect model to conduct the meta-analysis of learning achievements.

Through Stata MP/14.0, we obtained 74 effect sizes (SMD) in terms of learning outcomes, so we analyze learning outcomes independently to show them clearer in a forest plot (Figure 3). As shown in Figure 3, the horizontal line indicates the 95% confidence interval. The middle line is referred to as a no-effect line because if the horizontal line crosses it, the effect will be considered not significant. The diamond indicates the pooled result of effect sizes. If the diamond crosses the no-effect line, the result will be considered not significant. Since the diamond does not cross the no-effect line and is located to the right of the no-effect line, we conclude that Twitter-assisted learning outcomes are significantly higher than the non-Twitter-assisted ($d = 0.380$, 95% CI: 0.16-0.60, $z = 3.31$, $p = 0.001$) (Table 3).

The effect sizes are also heterogeneous for other learning outcomes such as attitude ($Q = 518.43$, $df = 17$, $p < .01$, $I^2 = 96.7$), gender difference ($Q = 5965.96$, $df = 7$, $p < .01$, $I^2 = 99.9$), teaching effectiveness ($Q = 15.13$, $df = 5$, $p = .01$, $I^2 = 67$), and overall learning outcomes ($Q = 14131.53$, $df = 111$, $p < .01$, $I^2 = 99.2$), but not for engagement ($Q = 1.03$, $df = 5$, $p = 0.96$, $I^2 = 0$) (Table 3). To
Table 3. Meta-analysis results for Twitter-assisted learning outcomes

| Learning outcomes       | SMD    | 95% CI      | % weight | Heterogeneity statistic | df    | p   | F (%) | z     | p    |
|-------------------------|--------|-------------|----------|-------------------------|-------|-----|-------|-------|------|
| Attitude                | 0.302  | 0.110       | 0.495    | 518.43                  | 17    | <.01| 96.7  | 3.08  | 0.002|
| Learning achievement    | 0.380  | 0.155       | 0.604    | 2129.93                 | 73    | <.01| 96.6  | 3.31  | 0.001|
| Gender difference       | 2.174  | 0.842       | 3.505    | 5965.96                 | 7     | <.01| 99.9  | 3.20  | 0.001|
| Engagement              | 0.408  | 0.181       | 0.635    | 1.03                    | 5     | 0.96| 0     | 3.52  | <.01 |
| Teaching effectiveness  | -0.140 | -0.523      | 0.243    | 15.13                   | 5     | 0.01| 67.0  | 0.72  | 0.474|
| Overall                 | 0.483  | 0.269       | 0.697    | 14131.53                | 111   | <.01| 99.2  | 4.43  | <.01 |

Figure 3. A forest plot of effect sizes of learning achievements
keep the analysis method consistent, we adopted a random-effect model to conduct the meta-analysis regarding other learning outcomes.

As shown in Figure 4, the diamonds for attitude, engagement, gender differences, and overall learning outcomes do not cross the no-effect line and they are all located to the right of the no-effect line. We, therefore, report that Twitter-assisted learning attitude ($d = 0.302$, 95% CI: 0.11-0.50, $z = 3.08$, $p = 0.002$), engagement ($d = 0.408$, 95% CI: 0.18-0.64, $z = 3.52$, $p < .01$), and overall learning outcomes ($d = 0.48$, 95% CI: 0.27 - 0.70, $z = 4.43$, $p < .01$) are significantly larger than the non-Twitter-assisted (Table 3). Males obtain significantly better learning outcomes than females in the context of Twitter-assisted learning ($d = 2.17$, 95% CI: 0.84 - 3.51, $z = 3.20$, $p = .001$) (Table 3). However, the diamond for teaching effectiveness (Figure 5) crosses the no-effect line ($d = -0.14$, 95% CI: -0.52 - 0.24, $z = 0.72$, $p = 0.47$) (Table 3). Thus, we report that there are no significant differences in teaching effectiveness between the Twitter and non-Twitter-assisted learning approaches.

Figure 4. A forest plot of effect sizes of learning outcomes except learning achievements

*1: Experimental Group*Control Group
To determine the type of analysis model, we measure the heterogeneity of effect sizes. The values of heterogeneity are all significant in the USA (\(Q = 12740.86, df = 83, p < .01, I^2 = 99.3\)), Greece (\(Q = 41.54, df = 8, p < .01, I^2 = 80.7\)), Spain (\(Q = 74.17, df = 7, p < .01, I^2 = 90.6\)), and Sweden (\(Q = 12.48, df = 5, p = .029, I^2 = 59.9\)) (Table 4). We, therefore, adopted a random-effect model to conduct the meta-analysis regarding learning outcomes in different countries.

As shown in Table 4, Twitter-assisted learning outcomes in the USA (\(d = 0.488, 95\% CI: 0.218 - 0.758, z = 3.54, p < .01\)), Greece (\(d = 0.716, 95\% CI: 0.361 - 1.071, z = 3.95, p < .01\)), Sweden (\(d = 0.404, 95\% CI: 0.194 - 0.614, z = 3.77, p < .01\)), and overall regions (\(d = 0.489, 95\% CI: 0.269 - 0.697, z = 4.43, p < .01\)) are significantly higher than the non-Twitter-assisted. However, in Spain, there are no significant differences between Twitter and non-Twitter-assisted learning outcomes (\(d = -0.16, 95\% CI: -0.589 - 0.269, z = 0.73, p = 0.465\)). We, therefore, conclude that Twitter-assisted learning can lead to significantly higher learning outcomes than non-Twitter-assisted learning in the USA, Greece, and Sweden but no significant difference is revealed in Spain.

**RQ2:** Can Twitter-assisted approaches improve learning outcomes in different countries?
Results for Learning Achievements in Different Countries

To meta-analytically examine learning achievements in different countries, we obtained a total of 73 effect sizes. We finally selected 69 effect sizes after removing 4 results due to the confusing research venue (USA and UK mixed).

As shown in Table 5, the effect sizes in the USA ($Q = 1976.39, p < .01, F = 96.9$), Greece ($Q = 41.38, p < .01, F = 83.1$), and overall regions ($Q = 2129.93, p < .01, F = 96.6$) are significantly heterogeneous although the effect size in Spain is not significantly heterogeneous ($Q = 1.73, p = .189, F = 42.1$). To keep analytical methods consistent, we adopted random-effect models to analyze different learning achievement in different countries.

As for learning achievements, Twitter-assisted learning results are significantly higher than the non-Twitter-assisted in the USA ($d = 0.305, 95\%CI = 0.052 - 0.558, z = 2.36, p = 0.018$), Greece ($d = 0.739, 95\%CI = 0.353 - 1.126, z = 3.75, p < .01$), and overall regions ($d = 0.380, 95\%CI = 0.155 - 0.604, z = 3.31, p = 0.001$). However, it is not significantly different in Spain ($d = -0.236, 95\%CI = -0.701 - 0.230, z = 0.99, p = 0.321$). Thus, we conclude that Twitter-assisted learning could lead to significantly higher learning achievements in the USA and Greece than the non-Twitter-assisted but no significant difference is found in Spain.

Results for Learning Attitudes in Different Countries

We obtained 6 effect sizes for learning attitudes in Sweden and 10 in the USA. A total of 16 effect sizes are pooled for the analysis of learning attitudes in different countries.

As shown in Figure 6, the effect sizes in Sweden ($F = 59.9, p = .029$) and the USA ($F = 95.8, p < .01$) are all significantly heterogeneous. We, therefore, adopted a random-effect model to conduct the meta-analysis. In Sweden, students hold significantly more positive learning attitudes toward Twitter-assisted learning than the non-Twitter-assisted ($d = 0.40, 95\%CI = 0.19 - 0.61$) (Table 4) since the diamond is located to the right of the no-effect line. In the USA, there are no significant differences in learning attitudes towards both Twitter and non-Twitter-assisted approaches ($d = 0.13, 95\%CI = -0.07 - 0.34$) (Table 4) since the diamond crosses the no-effect line. The overall results indicate that

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Table 4. Meta-analysis results in different countries

| Region  | SMD   | 95% CI   | %weight | Heterogeneity statistic | df | p   | F (%) | z          | p   |
|---------|-------|----------|---------|------------------------|----|-----|-------|------------|-----|
| USA     | 0.488 | 0.218    | 0.758   | 74.99                  | 83 | <.01| 99.3  | 3.54       | <.01|
| Greece  | 0.716 | 0.361    | 1.071   | 7.87                   | 41 | <.01| 80.7  | 3.95       | <.01|
| Spain   | -0.160| -0.589   | 0.269   | 7.16                   | 7  | <.01| 90.6  | 0.73       | 0.465|
| Sweden  | 0.404 | 0.194    | 0.614   | 5.49                   | 12 | 0.029| 59.9  | 3.77       | <.01|
| Overall | 0.489 | 0.269    | 0.697   | 100                    | 0  | <.01| 99.3  | 4.43       | <.01|

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Table 5. Meta-analytical results for learning achievements in different countries

| Country | SMD   | 95% CI   | %weight | Heterogeneity statistic | df | p   | F (%) | z          | p   |
|---------|-------|----------|---------|------------------------|----|-----|-------|------------|-----|
| USA     | 0.305 | 0.052    | 0.558   | 83.97                  | 61 | <.01| 96.9  | 2.36       | 0.018|
| Greece  | 0.739 | 0.353    | 1.126   | 10.54                  | 41 | <.01| 83.1  | 3.75       | <.01|
| Spain   | -0.236| -0.701   | 0.230   | 2.69                   | 1  | 0.189| 42.1  | 0.99       | 0.321|
| Overall | 0.380 | 0.155    | 0.604   | 100.00                 | 73 | <.01| 96.6  | 3.31       | 0.001|
students hold significantly more positive learning attitudes towards Twitter-assisted learning than the non-Twitter-assisted ($d = 0.29$, 95%CI = 0.10 - 0.49) (Table 4) since the diamond is located on the right side of the no-effect line. Therefore, we conclude that in Sweden users hold significantly positive attitudes towards the use of Twitter in education but no significant difference is found in the USA.

**Results for Learning Engagement in Different Countries**

We retrieved 1 effect size in Greece and 5 effect sizes in the USA and adopted a fixed-effect model to conduct the meta-analysis since the results are not significantly heterogeneous ($I^2 = 0, p = 0.942$ for USA and no result for Greece). One effect size in Greece and 5 effect sizes in the USA were obtained for the meta-analysis of learning engagement in different countries (Figure 7). As shown in Figure 7, the diamond regarding the effect size in Greece crosses the no-effect line. We, therefore, conclude that there is no significant difference in learning engagement between Twitter and non-Twitter-assisted learning ($d = 0.58$, 95%CI = -0.11 - 1.26). On the contrary, in the USA, the pooled diamond does not cross the no-effect line and is located on the right side of the no-effect line, so we report that Twitter-assisted learning can cause significantly more engagement than non-Twitter-assisted in the USA ($d = 0.39$, 95%CI = 0.15 - 0.63).

**Results for Teaching Effectiveness in Different Countries**

We retrieved 5 effect sizes for meta-analysis of teaching effectiveness in Spain and 1 effect size in Sri Lanka. Considering the significantly heterogeneous result in Sri Lanka ($I^2 = 57.0\%, p = 0.01$) and the insignificantly heterogeneous results in Spain ($I^2 = 29.5\%, p = 0.225$), we adopt the same random-effect model to conduct the meta-analysis. We report that teaching effectiveness of the Twitter-assisted approach is significantly ($d = -0.30$, 95%CI = -0.56 - -0.03) (Figure 5) lower than the non-Twitter-assisted since the pooled diamond does not cross the no-effect line and located to the left of it in Spain. In Sri Lanka, Twitter-assisted teaching effectiveness is significantly higher than the non-Twitter-assisted ($d = 1.05$, 95%CI = 0.22 - 1.87) (Figure 5). The overall effect reports that there is no significant difference in teaching effectiveness between the Twitter and non-Twitter-assisted approaches ($d = -0.14$, 95%CI = -0.52 - 0.24) (Figure 5) because the pooled diamond crosses the no-effect line.

**RQ3:** Are there any gender differences in Twitter-assisted learning outcomes in different countries?

To determine gender differences in learning outcomes in different countries, we retrieved 7 effect sizes in the USA and 1 effect size in Spain. The results in the USA are significantly heterogeneous ($I^2 = 99.9\%, p < .01$, no result for Spain). We, therefore, adopted a random-effect model to conduct the meta-analysis. Male learners have significantly higher learning outcomes than females in both the USA ($d = 2.41$, 95%CI = 0.53 - 4.25) and Spain ($d = 0.54$, 95%CI = 0.49 - 0.59) because neither of the pooled diamonds in both countries crosses the no-effect line and they both are located to the right of the no-effect line (Figure 8).

**RQ4:** Can different usages of Twitter lead to different learning outcomes? We firstly measured the heterogeneity of effect sizes of different Twitter usages. Effect sizes of learning outcomes via different Twitter are also highly heterogeneous in both Twitter as a supplementary tool ($Q = 6995.91, df = 66, p < .01, F = 99.1$) and Twitter as an integrated tool ($Q = 14775.03, df = 44, p < .01, F = 99.1$). We, therefore, adopted a random-effect model to conduct the meta-analysis.

As shown in Table 6, either when Twitter is used as a supplementary tool ($d = 0.501$, 95% CI: 0.095 - 0.907, $z = 2.42, p = 0.015$) or as an integrated tool ($d = 0.459$, 95% CI: 0.216 - 0.702, $z = 3.70, p < .01$), the learning outcomes are significantly improved than the non-Twitter-assisted learning
Thus, we concluded that Twitter-assisted learning could lead to significantly higher learning outcomes than the non-Twitter-assisted whether it is used as a supplementary or an integrated tool. To facilitate reading, we included a table with lessons learned in the work (Table 7).

### A Sensitivity Analysis

To determine whether or not the results were stable, we conducted a sensitivity analysis through Stata MP/14.0. Extreme estimates of effect sizes tend to skew the average estimated values and remain out of the confidence interval (Borenstein, Hedges, Higgins & Rothstein, 2009). Consequently, it is necessary to determine whether any estimate of an individual study can greatly influence the pooled result (Borenstein, Hedges, Higgins & Rothstein, 2009). As shown in Figure 9, a dot indicates an individual study. The lower confidence interval limit is 0.27, and the upper confidence interval limit

| Twitter usage | SMD    | 95% CI | %weight | Heterogeneity statistic | df | p     | F (%) | z    | p    |
|---------------|--------|--------|---------|-------------------------|----|-------|-------|------|------|
| As a supplementary tool | 0.501  | 0.095  | 0.907   | 6995.91                 | 66 | <.01  | 99.1  | 2.42 | 0.015|
| As an integrated tool    | 0.459  | 0.216  | 0.702   | 14775.03                | 44 | <.01  | 99.1  | 3.70 | <.01 |
| Overall            | 0.483  | 0.269  | 0.697   | 14131.53                | 111| <.01  | 99.2  | 4.43 | <.01 |

### Table 6. Meta-analysis results for different usages of Twitter

### Table 7. Research questions and lessons learned in the work

| N   | Research questions                                                                 | Lessons learned in the work                                                                                                                                                                                                 |
|-----|-----------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1   | Can Twitter-assisted approaches improve learning outcomes such as learning attitudes, learning achievements, learning engagement, and teaching effectiveness? | Twitter-assisted learning outcomes are significantly higher than the non-Twitter-assisted; there are no significant differences in teaching effectiveness between the Twitter and non-Twitter-assisted learning approaches. |
| 2   | Can Twitter-assisted approaches improve learning outcomes in different countries? | Twitter-assisted learning can lead to significantly higher learning outcomes than non-Twitter-assisted learning in the USA, Greece, and Sweden but no significant difference is revealed in Spain; Twitter-assisted learning could lead to significantly higher learning achievements in the USA and Greece than the non-Twitter-assisted but no significant difference is found in Spain; in Sweden users hold significantly positive attitudes towards the use of Twitter in education but no significant difference is found in the USA; Twitter-assisted learning can cause significantly more engagement than non-Twitter-assisted in the USA; there is no significant difference in teaching effectiveness between the Twitter and non-Twitter-assisted approaches. |
| 3   | Are there any gender differences in Twitter-assisted learning outcomes in different countries? | Male learners have significantly higher learning outcomes than females in both the USA and Spain.                                                                                                                                 |
| 4   | Can different usages of Twitter lead to different learning outcomes?               | Twitter-assisted learning could lead to significantly higher learning outcomes than the non-Twitter-assisted whether it is used as a supplementary or an integrated tool.                                                                 |
is 0.70. All the meta-analysis estimates remain between the upper and lower confidence interval given a named study is omitted. We, therefore, conclude that the meta-analytical results are stable.

**DISCUSSION**

**Summary of Evidence**

We reveal that there are no significant differences in teaching effectiveness between the Twitter and non-Twitter-assisted learning approaches; Twitter-assisted learning outcomes are significantly higher than the non-Twitter-assisted whether Twitter is used as a supplementary or an integrated tool; Twitter-assisted learning can lead to significantly higher learning outcomes than non-Twitter-assisted learning in the USA, Greece, and Sweden but no significant difference is revealed in Spain; Sweden users hold significantly positive attitudes towards the use of Twitter in education but no significant difference is found in the USA; Twitter-assisted learning can cause significantly more engagement than non-Twitter-assisted in the USA; and Male learners have significantly higher learning outcomes than females in both the USA and Spain.

Generally, positive evidence has been revealed regarding the use of Twitter in education. This meta-analysis reports that the Twitter-assisted learning approach can lead to significantly higher learning outcomes than the non-Twitter-assisted in terms of learning achievements, learning attitudes, and learning engagement. But the former cannot lead to significantly higher teaching effectiveness than the latter possibly because many teachers, especially those who have been accustomed to traditional teaching, are resistant against radical changes of their traditional pedagogical approach. They, who prefer pencil-paper teaching, may have failed to skillfully teach students using social media such as Twitter. However, students tend to try new learning tools and use social media much more frequently than teachers, which has caused the results revealed above. It is thus reasonable to find that Twitter-assisted approaches improve learning outcomes such as learning attitudes, learning achievements, and learning engagement rather than teaching effectiveness.

The use of Twitter can improve learning outcomes in the USA and Sweden rather than Spain. In Sweden, Twitter-assisted learning is more positively evaluated than the non-Twitter-assisted while no significant difference was found in the USA. Twitter can significantly improve learning engagement in the USA but not in Greece. Surprisingly, Twitter can decrease the teaching effectiveness in the USA but significantly improve it in Sri Lanka. Males tend to show significantly higher learning outcomes than females in the Twitter-assisted learning context. Males assisted with Twitter significantly outperform females in both the USA and Spain. Whether Twitter is used as a supplementary or as an integrated tool, it can significantly improve learning outcomes including learning achievements, learning attitudes, learning engagement, and teaching effectiveness. It is thus reasonable to find that Twitter-assisted approaches can exert different influences on learning outcomes in different countries.

The findings are consistent with previous studies. For example, a Twitter-based mobile approach was used in Agriculture knowledge pedagogy, where students generally obtained satisfactory learning outcomes. However, the teaching effectiveness, as well as the higher-order skills, was not highly evaluated due to limitations of Tweet language on the Twitter platform such as the word number limit and unfamiliar English technical terms for Sri Lankan students (Dissanayeke, Hewagamage, Ramberg, & Wikramanayake, 2016). Online interactions through social media greatly vary across different countries, which may have caused different educational outcomes such as reading literacy and comprehension (Luyten, 2022).

Another support regarding the lower teaching effectiveness sources from Spain. In the teaching period, Tweets’ remaining tractable for students to review may cause the difficulty of checking whether students finish the assignment in time or not. It also becomes difficult to obtain the information regarding the time and its span students have learned based on the tweets. The limitation to training stimuli, merely 22 tweets, may have exacerbated Twitter-assisted teaching effectiveness. Rewarding the participants may have also drawn some participants who are interested in rewards rather than
learning, leading to poor teaching effectiveness (Fouz-González, 2017). Consequently, Twitter-assisted teaching effectiveness may have been weakened, which requires a rigid teaching design based on Twitter. Due to confusion between Spanish and English, Spanish learners of English tend to insert epenthetic vowels prior to consonant clusters (Fouz-González, 2017), which may have negatively influenced their learning outcomes.

Previous studies also support that men tend to achieve more success in Twitter-assisted learning. For example, males tend to produce slightly more tweets than females (Feliz, Ricoy, & Feliz, 2013). Females tend to be less engaged in Twitter-assisted learning compared with males, who may be more interested in technology-based learning. Consequently, females obtained significantly lower learning achievements than males in terms of the final course grade, gap-closing measure, and post- and pre-test scores (Al-Bahrani, Patel, & Sheridan, 2017). Men seem to more readily share resources with peers through tweets, where they like to show off their academic, professional, or other personal success via critical languages while women tend to affirm other tweets (Kerr & Schmeichel, 2018). The different language style requires men to invest more time and energy in tweet production, while it requires women to invest more time in message browsing. Obviously, production needs more knowledge and creativeness than browsing. Unsurprisingly, men tend to obtain more knowledge through Twitter-assisted learning compared with women. It is thus reasonable to find significant gender differences in Twitter-assisted learning outcomes in different countries.

It is also found that Twitter can greatly improve students’ learning enthusiasm, promote students’ interaction and reflection, train students’ skills of producing concise sentences, and build a real learning environment through learning feedback (Zhu, 2010). In Twitter-assisted teaching, teachers can record students’ feedback, trace students’ learning progress, and obtain their learning performance. In Twitter-assisted learning, students can discuss with peers to solve difficult problems, share their own opinions, and retrieve a sea of information from the platform. This will definitely improve their engagement in learning, intensify their interest, cultivate their positive attitudes toward Twitter use in learning, and finally greatly improve students’ learning achievements and enhance the teaching effectiveness.

However, Twitter use in education may also bring about negative results. Plentiful information and advertisements on the Twitter platform may distract students and teachers. They may also be indulged in non-academic information. They may also feel it hard to concentrate on a given topic in case they are confronted with excessive information. They may pursue the effect of entertainment rather than knowledge acquisition. Pieces of knowledge carried by Twitter may not benefit the higher-order thinking skills and the organization of structured knowledge, resulting in easy attrition of acquired knowledge and disorganized knowledge stored in learners’ brain. Teachers may be reluctant to change their teaching styles and methods when they are required to teach via Twitter. They may also feel it awkward to deliver knowledge and difficult to focus on a topic if they are passively required to apply Twitter to their teaching practice. This may be an important reason for the decreased teaching effectiveness in some studies (e.g. Fouz-González, 2017).

Whether Twitter is used as a supplemental or as an integrated learning tool, it can exert a positive influence on learning outcomes to a certain degree. Besides, teachers and students should attempt to use Twitter to (1) build up a powerful learning community, (2) facilitate communication and discussion, (3) present students’ opinions and creativeness, (4) promote collaboration between peers and teachers, and (5) arrange and organize various kinds of learning activities. As learning activity organizers, teachers may carefully design Twitter-assisted learning activities to meet these goals. As technology developers, Twitter engineers may pay much attention to educational purposes when designing the functions of Twitter. It is thus reasonable to conclude that different usages of Twitter can lead to different learning outcomes.

In the future, designers or developers could integrate serious games into Twitter with an aim to improving Twitter-assisted learning outcomes. They could post recreational or educational videos on Twitter to enhance learning engagement, e.g. question answers, peer feedback, and opinion sharing.
Serious games through Twitter could improve collaborative learning and thus increase the engagement in learning activities (He et al., 2022). The serious games could also focus learners on the academic issues rather than the entertainment since their nature is education. The difficulty is how to design serious games and how to integrate them into Twitter to attract learners’ attention.

LIMITATIONS

There are several limitations to this study. Firstly, both Egger’s and Begg’s tests indicate the presence of publication bias, which may have caused result bias. Future research may include more studies of variety. Secondly, the study may not include all studies in the meta-analysis. Those written in a language other than English are excluded. Thirdly, the included studies themselves may have limitations. Fourthly, we may not include all eligible studies due to the limitation to library resources.

CONCLUSION

In general, Twitter use in education has been widely accepted and produced positive learning outcomes although there are still controversies in some countries regarding some aspects. Males tend to obtain more positive learning outcomes than females. Future research may adopt more interdisciplinary methods and include more literature to pool the effect of Twitter on educational outcomes especially during the COVID-19 pandemic. Future research could adopt topological nodes via the adaptive control on the basis of 9-D to address the issue of COVID-19 (Hamad et al., 2021). Future research could also consider the use of other social media such as Whatsapp and ubiquitous learning (Klein et al., 2018), as well as learning strategies in ubiquitous environments (Ferreira et al., 2020).

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APPENDIX

Tables and Figures

Figure 6. A forest plot of meta-analytical results for learning attitudes in different countries

| Study ID | SMD (95% CI) | Weight |
|----------|--------------|--------|
| Sweden   |              |        |
| Collander et al., 2015 | 0.71 (0.38, 1.03) | 7.15  |
| Collander et al., 2015 | 0.29 (-0.05, 0.60) | 7.22  |
| Collander et al., 2015 | 0.19 (-0.14, 0.53) | 7.08  |
| Collander et al., 2015 | 0.39 (0.07, 0.71) | 7.21  |
| Collander et al., 2015 | 0.11 (-0.23, 0.44) | 7.08  |
| Collander et al., 2015 | 0.74 (0.41, 1.06) | 7.14  |
| Subtotal (I² squared = 59.9%, p = 0.026) | 0.40 (0.19, 0.61) | 42.87 |

USA
| Study ID | SMD (95% CI) | Weight |
|----------|--------------|--------|
| Cozma & Hallaq, 2019 | -0.32 (-1.71, 1.06) | 1.61  |
| Fezzella, 2019 | 0.54 (0.20, 0.87) | 7.07  |
| Cozma & Hallaq, 2019 | -0.66 (-1.37, 0.06) | 4.09  |
| Smith & Trumala, 2012 | 1.06 (0.58, 1.54) | 5.79  |
| DeOroop et al., 2015 | 0.39 (-0.26, 1.04) | 4.50  |
| DeOroop et al., 2015 | 0.91 (0.18, 1.64) | 3.98  |
| Cozma & Hallaq, 2019 | -0.61 (-0.66, -0.57) | 6.87  |
| Smith & Trumala, 2012 | 2.01 (1.45, 2.55) | 5.20  |
| Fezzella, 2019 | 0.02 (-0.31, 0.34) | 7.12  |
| Cozma & Hallaq, 2019 | -0.60 (-0.62, -0.58) | 8.90  |
| Subtotal (I² squared = 95.8%, p = 0.000) | 0.13 (-0.07, 0.34) | 57.13 |

Overall (I² squared = 95.6%, p = 0.000) | 0.29 (0.10, 0.49) | 100.00 |

Figure 7. A forest plot of meta-analytical results for learning engagement in different countries

| Study ID | SMD (95% CI) | Weight |
|----------|--------------|--------|
| USA      |              |        |
| Jesse, 2012 | 0.40 (0.23, 0.56) | 30.49 |
| Jesse et al., 2010 | 0.50 (0.19, 1.10) | 10.92 |
| Jesse et al., 2010 | 0.20 (0.33, 0.07) | 18.73 |
| Jesse et al., 2010 | 0.47 (0.21, 1.15) | 11.21 |
| Jesse et al., 2010 | 0.51 (0.22, 1.24) | 9.70  |
| Subtotal (I² squared = 47.5%, p = 0.942) | 0.39 (0.15, 0.63) | 59.09 |

Greece
| Study ID | SMD (95% CI) | Weight |
|----------|--------------|--------|
| Lektel et al., 2015 | 0.55 (-0.11, 1.26) | 10.94 |
| Subtotal (I² squared = 47.5%, p = 0.942) | 0.55 (-0.11, 1.26) | 10.94 |

Heterogeneity between groups: p = 0.510
Overall (I² squared = 47.5%, p = 0.942) | 0.41 (0.18, 0.64) | 100.00 |
Figure 8. A forest plot for meta-analytical results for gender differences in different countries

Figure 9. A plot of sensitivity analysis results
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