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Response Rates of Online Surveys in Published Research: A Meta-analysis

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Response rates of online surveys in published research: A meta-analysis☆

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ABSTRACT

The response rates of online surveys were often examined in the literature by comparing to other modes of surveys. Questions regarding what constitutes a respectable response rate for online surveys in research remained unanswered. To fill in the knowledge gap, we conducted a comprehensive search, screened 8672 studies, and examined 1071 online survey response rates reported in education-related research. Our analyses showed the number of online surveys in published research grew steadily across the years. The average online survey response rate is 44.1%. Our results indicate that sending an online survey to more participants did not generate a higher response rate. Instead, sending surveys to a clearly defined and refined population positively impacts the online survey response rate. In addition, pre-contacting potential participants, using other types of surveys in conjunction with online surveys, and using phone calls to remind participants about the online survey could also yield a higher response rate. The use of incentives did not show a significant impact on the response rate of online surveys. Other factors that impacted the rates included the funding status of a project, and the age and occupation of the participants. Concrete suggestions for reviewing and improving the online survey response rates are provided.

Response rates of online surveys in published research: a meta-analysis

The use of the internet by U.S. adults has increased from 52% in 2000 to 93% in 2021 (Pew Research Center 2021), opening a new channel for researchers to collect data. In 2017, for the first time, online surveys constituted the majority of all quantitative survey modes implemented worldwide (ESOMAR, 2018; Daikeler et al., 2020). In educational research, online surveys have also become one of the most popular methods for collecting data (Saleh & Bista, 2017). The proliferation of using online surveys may be due to several inherent advantages, such as reductions in research cost, shorter time required for implementation, fewer transcription errors, and ease of analysis (Andrews et al., 2003; Saleh & Bista, 2017).

While online surveys can be effective and efficient, they require a respectable response rate as the response rate is often viewed as an important criterion for judging the quality of a survey (Hox and De Leeuw 1994). As a newer method of surveys, online surveys have been compared to other traditional formats of surveys in terms of response rates through meta-analyses. For example, Shih and Fan (2008) synthesized 39 comparisons of the response rates between online surveys and mail surveys. They found that online surveys produced on average 11% lower response rate than mail surveys. Manfreda et al. (2008) conducted a broader comparison and included mail, e-mail, fax, and phone surveys. Based on 45 comparisons, they also reported an average 11% lower response rate of online surveys than the other modes examined in the study. In the latest meta-analysis, similar results were reported with newer evidence. Daikeler et al. (2020) examined 114 comparisons of the response rates between online surveys and mail, e-mail, telephone, and in-person surveys. They discovered that online surveys yielded an average 12% lower response rate than other modes of surveys. The same conclusion was made in the other meta-analysis that was also conducted by Daikeler but with different colleagues, in which they focused on examining the impact of country-level factors on the response rates (Daikeler et al., 2021). These comparative meta-analyses provide conclusive evidence that, in general, online surveys produce an 11%–12% lower response rate than other types of surveys. Since these syntheses focused on the relative response rates and calculated the

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differences in response rates between online and other modes of surveys, the information for the online survey response rates was usually not reported. In the conclusion of their meta-analysis, Daikeler et al. (2020) suggest that "[t]o gain further evidence about the absolute web response level and its moderators, we strongly recommend that meta-analytical research be carried out in this regard" (p. 531). This statement clearly points out the need to investigate online survey response rates and the factors that may impact the rates.

Among these comparative meta-analyses mentioned above, Shih and Fan (2008) reported a 34% averaged response rate of online surveys. Daikeler et al. (2021) reported the average rate as 36%. These estimated response rates are nowhere near the 80% suggested by the U.S. Office of Management and Budget (OMB), which reviews most federal evaluations and research projects and asserts minimum methodology requirements for federally funded projects (Office of Management and Budget, 2016). OMB's concern about surveys with response rates lower than 80% is that the responses might not represent the intended survey population, which could introduce nonresponse bias and impact the data quality. Nonetheless, researchers found no evidence suggesting an 80% or higher response rate is an optimum response rate (Hendra & Hill, 2019). On the contrary, Fosnacht et al. (2017) came up with different propositions by examining the data from one of the most widely used higher education assessment instruments, the National Survey of Student Engagement (NSSE). They found the estimates based on the data remained reliable even with a 5%–10% response rate with a sample size of at least 500. They also found that surveys with a smaller sample size (i.e., less than 500) need 20%–25% response rates to provide fairly confident estimates. The existing discrepancy of online survey response rate between the OMB's requirement and the empirical evidence from NSSE poses a critical question: What is a reasonable response rate for an online survey? A subsequent question that is practically important is: What factors can impact the rates? The answers to these questions can help online survey users and evaluators better plan and maintain the quality of online surveys.

Previous syntheses on online survey response rates

Since the origins of the World Wide Web in 1994 and the advent of online surveys, researchers have attempted to conduct meta-analyses to systematically examine online survey response rates and the factors that could impact these rates. More than 20 years ago, Cook et al. (2000) identified 49 studies across the fields of sociometric, psychometric, and public opinion research that reported 68 independent online survey response rates. They found the average response rate of these online surveys was 39.6% (SD = 19.6%). Seven years later, Archer (2007) examined 99 web surveys administered by a center at Ohio State University over the courses of 33 months. He found the average response rate of those surveys to be 48.3%. A more recent synthesis based on 207 online surveys reported in four counseling psychology journals uncovered an average response rate of 34.2% (Poynton et al., 2019). The latest synthesis conducted by Burgard et al. (2020) focused on the response rates of online surveys sent to adults with anxiety disorder or depression. They found the average response rate was 42.8% based on 20 identified studies. The findings of these meta-analyses are varied. The reasons for these inconsistent results could be the timeframe of the research carried out, the specific population studied in the syntheses, or both. To have an updated and a comprehensive understanding of online survey response rates, a meta-analysis that includes newer studies without limitations on specific topics or participants is needed.

To further understand the online survey response rates, researchers have studied factors that may impact the rates. In a systematic review of literature, Fan and Yan (2010) developed a conceptual model to describe the web survey process and used the model to organize the discussion of the factors that impact survey response rate. Based on their model, the surveyor creates and implements a web survey, and the survey is completed and returned by the surveyee. Four steps take place in the process between surveyors and surveyees: The first step is web survey development, which concerns the process of designing a web survey. The second step is web survey delivery, which concerns the selection and contact of the potential participants as well as the delivery of the web survey. The third step is web survey completion, which concerns the process of the surveyee's completing and submitting the survey. The fourth step is web survey return, which concerns the process of handling the web survey data. For each step, Fan and Yan evaluated the impact of factors on the response rates. The factors they found that positively impacted the response rates include topic salience, invite personalization, selectivity, pre-notifications, reminders, and incentives. The factors that had a negative impact on the response rates include the length of the survey, poor visual presentation, and unstable internet coverage. Some factors referred to as "social level factors" (i.e., survey fatigue, public attitudes, and social cohesion) were also related to a decline in response rates worldwide.

Many of the factors discussed in Fan and Yan (2010) were empirically examined in the meta-analyses above. Cook et al. (2000) identified 15 factors from their collection of studies and calculated the correlation between each factor and the response rate. They found through a regression model that the factors together counted for 60.4% of the variation observed in the response rates. Archer (2007) examined 13 variables that are related to survey delivery and nine related to survey development. He used correlations and identified six factors that were significantly related to the response rates. He then created a regression model based on the two most significant factors (i.e., number of potential respondents and number of days the survey was left open) that accounted for 41.4% of the variation observed in response rates. Poynton et al. (2019) examined the factors related to recruitment strategies (i.e., online vs. mixed). They also expanded the investigation outside of the survey process described in Fan and Yan's model and focused on the response rates in different types of research (i.e., quantitative, qualitative, and mixed methods). Burgard et al. (2020) focused on the response rates of participants with affective disorder and investigated the impact of study design and time effects. Table 1 summarizes the factors and their relationships to the online survey response rates from the previous meta-analyses. Some factors were investigated in more than one synthesis, and the findings were inconsistent. For example, the length of online surveys appeared to have a negative relationship with the response rate in Burgard et al. (2020), but the relationship was found to be non-significant in Cook et al. (2000). Similar discrepancies were found in examining the factors related to the survey delivery.

To fill in the knowledge gap and expand from previous meta-analyses, we intended to conduct a thorough search and include a complete set of published research that used online surveys to collect data in one of the largest datasets in social science. We wanted to investigate the usage of online surveys and the response rates in more recent studies. We also wanted to explore the factors associated with the variation of the response rates observed in the studies.

The specific research questions we intended to answer in this meta-analysis are:

1. What is the average online survey response rate reported in educational research?
2. Do the number of studies that adopt online surveys change over time?
3. Do the average online survey response rates change over time?
4. What are the factors that have significant impacts on online survey response rates?

We hoped to provide concrete guidance for researchers to evaluate and improve their online survey response rates based on our analyses of the accumulated evidence.

Table 1
Factors and their relationship with online survey response rate examined in previous meta-analyses.

Factors	Cook et al. (2000)	Archer (2007)	Poynton et al. (2019)	Burgard et al. (2020)
Study-level characteristics				
Sponsorship with fund	+[b]			
Result promised	NS[b]			
Number of potential respondents		[a]		
Number opting out		–		
Number bounced		NS [d]		
Type of research methods			Qualitative>Mixed>Quantitative	
Recruitment method			Mixed>Online only	
Research topics				
Topic salience	+[a]			
Topic sensitive	+[b]			
Educational related topic	+[b]			
More than only attitude	NS[b]			
Survey Development				
Length of survey	NS[a]			–
Password requirement	NS[a]			
Number of open-ended questions		[a]		
Number of one-line open-ended questions		NS[c]		
Number of Y/N questions		NS		
Number of demographic questions		NS		
Number of headings		NS		
Length of rating scales		NS[c]		
Readability level of invitation		NS[d]		
Readability level of survey		NS[d]		
Survey Delivery				
Pre-contact	+[a]			
Personalization	+[a]			
Incentives	-[a]			NS
Number of contacts/reminders	*	NS		
Days between reminders		[a]		
Number of days left open		[a]		
Days between launch and reminder		[a]		
Length of subject line & invitation		NS		–
Time launched (Year/Month/Date)		NS[c]		–
E-mail Invitation				-[e]
Participant characteristics				
Professional population	-[b]			
Academic setting (faculty/students)	-[a]			

+The factor has a positive relationship with the response rate.
-The factor has a negative relationship with the response rate.
*After three contacts, response rates started to diminish.
NS Non-significant correlation.
[a] The results were based on the description in text. The univariate relationship between each factor and the response rate could be found in Table 1 in the original article. However, based on the graph, the relationship may not be statistically significant.
[b] Results were based on the correlation table. A correlation that is smaller or equal to .1 is marked as N·S.
[c] Positively correlate to the response rate but did not reach statistical significance due to the sample size.
[d] Negatively correlate to the response rate but did not reach statistical significance due to the sample size.
[e] Invite via e-mail yielded lower response rates than those invited via phone or mail.

Methods

In our synthesis, we followed PRISMA guidelines (Page et al., 2021) for conducting our meta-analysis. We also used their checklist to ensure all the aspects were carried out with accuracy and quality.

Search for the studies

To conduct a broad yet attainable synthesis, we focused on the response rates of online surveys reported in education-related fields. We conducted the keyword search in one of the most comprehensive databases, the Education Resources Information Center (ERIC). The primary keywords/phrases used for identified relevant studies are combinations of the following: online survey, web survey, electronic survey, e-mail survey, internet survey, and response rate. Our search aimed at the studies published in 2007 and after to avoid duplicating the efforts from the previous meta-analysis (Archer, 2007), where the online survey response rate and the extensive factors that may impact the rates were examined. The first round of search was conducted in 2015, and the follow-up searches were completed in 2016, 2017, 2019, and 2020. By comparing the search results across years, we noticed that earlier studies were still been added to the database in the later time. In our latest search in January 2020, we found no additional studies appeared to have been added for the period of 2007–2014. To ensure we have a complete collection of studies for this period, we spent four months after our last search randomly selecting ten journals where the studies were published. We manually went through each issue published between 2007 and 2014. We also randomly checked the references of 100 included studies in Google Scholar. No additional studies were identified through the manual and Google Scholar searches.

The original search identified 8672 potential studies. The studies qualified for this synthesis must have used an online survey as the data collection method, reported the response rate or provided the information for calculating the response rate, and been published in English. Through the initial screening and the coding process, we identified 1043 studies with 1071 independent response rate studies that met the criteria stated earlier. The detailed screening process and the reasons for excluding studies are outlined in Fig. 1.

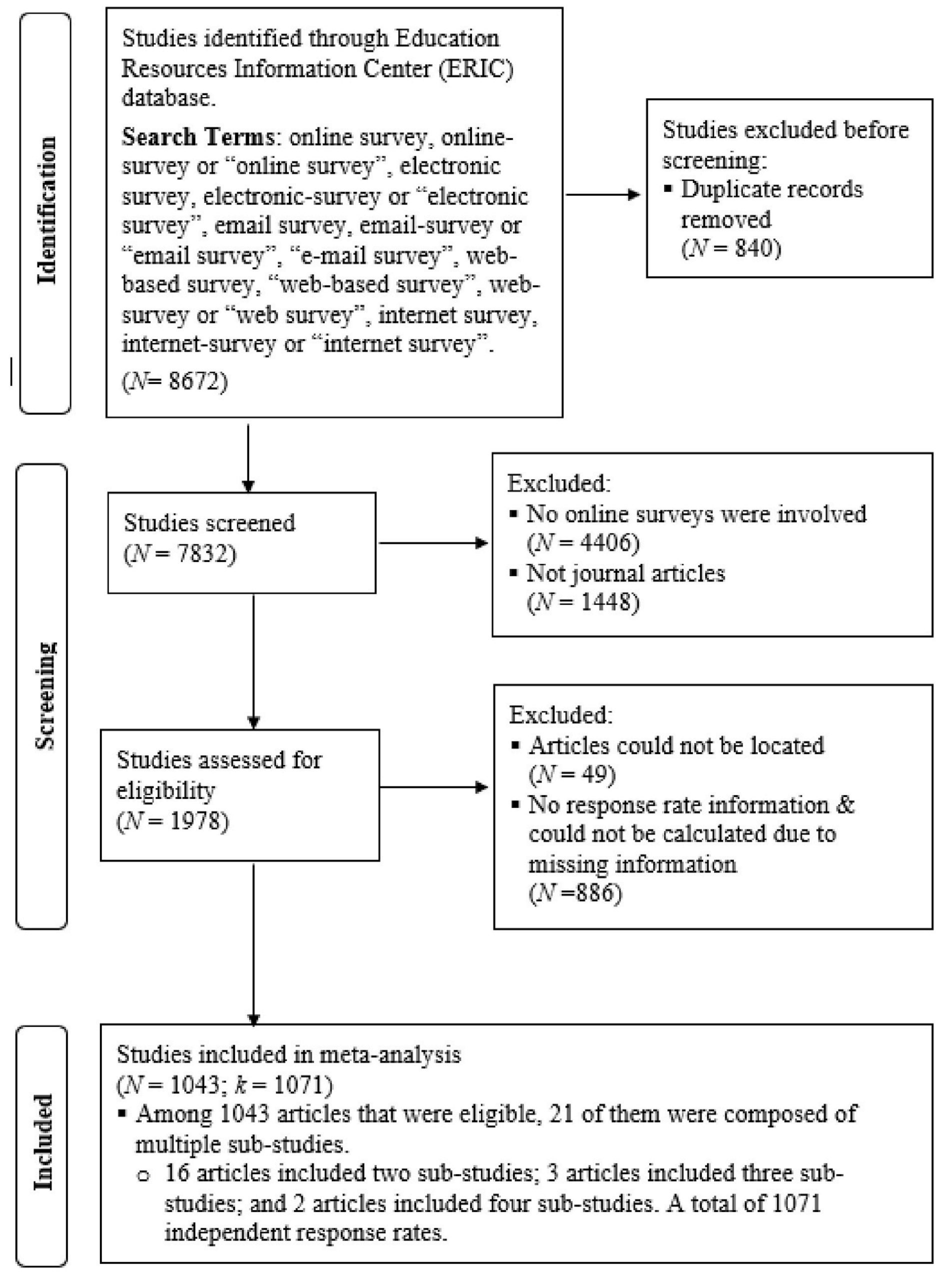

Fig. 1. Flow chart of the review and selection process.

Evaluation of the searched studies

A set of coding sheets and an associated codebook were developed to extract relevant information from the searched studies. We coded basic study features (e.g., year, funding status), research topics (e.g., survey focus, technology-related topic), survey implementation (e.g., random selection, incentive), and participant characteristics (e.g., age, education level). Several factors we coded were examined in the previous meta-analyses, but some of them were not. For example, we coded survey focus by identifying studies with a specific focus, such as online learning, non-online in-school learning, professional development, and special education. Those studies were grouped, and the response rate for each group was examined and compared. For domain, we coded the topic of the study based on one of the four domains proposed by Reynolds et al. (2007): online measures about offline phenomena (i.e., use online surveys to study activities that are *not* related to online activities); online measures about online phenomena (i.e., use online surveys to study activities that *are* related to online activities); online measures about online variations (e.g., use online surveys to compare various online activities); and online measures about online action (e.g., use online surveys to study online behavior). For the age of the participants, our code was based on the range of the age reported in the study. If a study has mixed ages of participants, the code is based on 80% of participants' age. If no sufficient information is provided to code the age, it falls into the N/I group. We also intended to code survey attributes, such as the length of the survey and the scales used in the survey. However, because the survey usually serves only as a tool for collecting the data and not many details are reported in the collected studies, we could not consistently extract the information from most studies. For the same reason, we also could not meaningfully extract the information regarding the geographical boundaries where the surveys were sent. The descriptive statistics of the major coded variables are provided in Table 2.

Five coders with educational research backgrounds were trained

Table 2
Descriptive statistics of the factors examined.

	Number of response rate (k)	Range of the sample size (n)	Range of the response rate
Year			
2007	40	41–9231	9.9%–100.0%
2008	59	28–36333	2.4%–100.0%
2009	81	10–26088	1.6%–100.0%
2010	88	27–9997	1.5%–100.0%
2011	110	12–36900	2.8%–100.0%
2012	213	9–30420	3.6%–100.0%
2013	225	5–67759	0.4%–100.0%
2014	255	9–62541	0.9%–100.0%
Funding			
Yes	233	9–60000	0.9%–100.0%
No	838	5–67759	0.4%–100.0%
Survey Focus			
General	736	9–67759	0.4%–100.0%
Online learning	114	5–9463	16.1%–100.0%
Professional development	67	12–8038	5.4%–100.0%
Non-online learning	132	8–46032	10.9%–100.0%
Special education	22	39–9825	16.8%–94.0%
Random Selection			
No	916	5–67759	0.4%–100.0%
Yes	155	10–62541	1.6%–100.0%
Age			
20 and below	52	15–51638	1.6%–100.0%
20–30	121	12–36900	2.9%–100.0%
30–40	61	18–13350	6.2%–100.0%
40 and above	126	9–6000	0.9%–100.0%
N/I	711	5–67759	0.4%–100.0%
Gender			
Both	1045	8–67759	0.4%–100.0%
Female	20	5–15891	14.4%–100.0%
Male	6	350–6000	9.4%–54.0%
Occupation			
Non-student	662	8–60000	0.9%–100.0%
Student	409	5–67759	0.4%–100.0%
Use other Survey			
No	932	8–67759	0.4%–100.0%
Yes	139	5–22880	6.2%–100.0%
Pre-contact			
N/I	784	5–67759	0.4%–100.0%
Yes	287	12–51638	2.9%–100.0%
Incentive			
N/I	852	5–67759	0.4%–100.0%
Yes	219	19–62541	1.6%–100.0%
Reminder Method			
E-mail	336	10–67759	3.3%–100.0%
Mail	16	45–29364	9.2%–71.1%
Other/no	713	5–62541	0.4%–100.0%
Phone	6	43–471	42.9%–100.0%
Technology-related Topic			
No	946	5–67759	0.9%–100.0%
Yes	125	10–50000	0.4%–100.0%
Survey Domain			
About off-line phenomena	853	8–67759	0.9%–100.0%
About online phenomena	24	10–7002	10.4%–100.0%
About online variations	147	10–62541	0.4%–100.0%
About online action	47	5–40000	2.1%–100.0%
Sample Size			
100 and below	196	5–100	5.7%–100.0%
101–300	232	101–300	11.0%–100.0%
301–700	221	301–700	1.1%–100.0%
701–2500	218	701–2500	4.8%–100.0%
2501 and above	204	2508–67759	0.4%–83.0%

before the formal coding started. Each of them coded the same set of five studies independently, and the results were compared and discussed. The process continued until the coding results were consistent across the coders. Following this initial process, each identified study was coded by one main coder. Additionally, every five studies in the dataset were coded by a second coder. Any discrepancies in the coding results between the two coders were resolved before the analyses started. Coding reliability, calculated as the percentage of coder agreement, ranges from 89% to 100%.

Effect size

The effect size (*ES*) for this study is the response rate of the online survey. It is a proportion defined as the number of people who responded divided by the total valid number of people contacted. When using proportions as the *ESs* in the meta-analysis, it is usually recommended to transform the proportions to have a sampling distribution that is closer to a normal distribution with a sample variance that can be better approximated. Two commonly used transformation methods are logit (Sutton et al., 2000) and double arcsine transformation (Freeman & Tukey, 1950). The sampling distribution of logit-transformed *ESs* is better approximated by a normal distribution, yet the corresponding sampling variance can still be problematic. The double-arcsine transformed *ESs* usually work well for both normalizing and variance-stabilizing the sample distribution, yet the computation is more complicated. In this meta-analysis, we performed the analyses based on all three forms of *ESs* (i.e., raw *ES*, logit transformed *ES*, double-arcsine transformed *ES*), and the results were similar. To avoid duplication, we only reported the results based on the double-arcsine transformed *ESs* as they usually produced the estimates that fell between the two other methods. The summary results based on the double-arcsine transformed *ES* were converted back to proportions using the formula proposed in Miller (1978) for easy interpretation.

Analytical models

Two models were commonly considered to summarize the overall *ESs* for meta-analysis: a fixed-effect model and a random-effects model. Since this synthesis comprises diverse participants in the included studies, the random-effects model that allows the true effect vary from study to study is more appropriate (Borenstein et al., 2021). The inversed-variance method was used as the weight for combining the *ESs* and for further modeling (Cooper et al., 2019). Because the variance of the *ESs* is calculated with the sample size information, a larger study is given more weight when applying this method.

We used the Q statistic (Cochran, 1954) to test for the significance of the variation of *ESs*. The degree of heterogeneity was further described by the I^2 index (Higgins & Thompson, 2002). An I^2 larger than 50% indicates a moderate variability among the *ESs*. When the variation of *ESs* is significant, we explore the sources of the variation through moderator analyses. ANOVA-like analyses were conducted to examine the relationship between coded factors and the *ESs*. The analyses were conducted using the meta-analysis package in R: metafor (Viechtbauer, 2010).

Publication bias

Publication bias is the tendency to decide to publish a study based on the study results rather than on the basis of its theoretical or methodological quality (Rothstein et al., 2005). It is a thorny issue for meta-analysis as the validity of meta-analysis depends heavily on having a complete collection of possible results disregard the significance level. In our synthesis, the *ESs* are response rates of online surveys used to collect data. They usually are not the focal results of the primary studies. Therefore, it is less likely that a study would not be published simply due to a low response rate. In Fig. 2, we presented the funnel plot that is

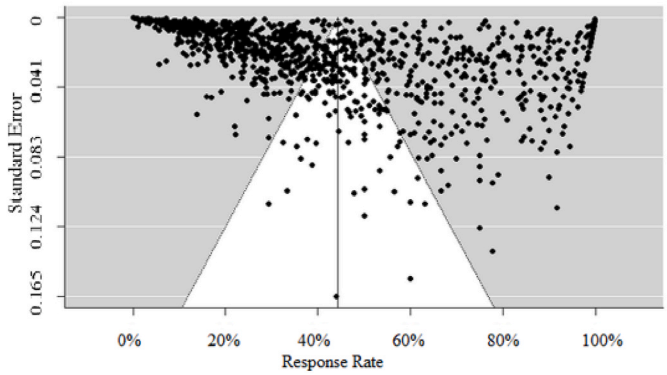

Fig. 2. The funnel plot of standard error by response rate.

typically shown to evaluate publication bias in meta-analysis. In this figure, the *ES*s left to the mean effect bar in the middle of the plot are clustered toward smaller standard errors than the right side of the plot. It showed the studies with lower response rates were based on studies with larger sample sizes (i.e., surveys were sent to more participants). The spread of *ES*s across a wide range of *ES*s indicated that both low and high *ES*s were found in our collection, which suggests the concern of the bias came from including only studies with high response rates may not be an issue in our synthesis.

Results

Overall summary of the response rates

Following the selection criteria, we identified 1071 independent *ES*s (k) from 1043 studies for this meta-analysis. The total sample size for this meta-analysis is 4,425,708. Compared to a normal distribution, the *ES*s spread with a slightly positive skew and a median of 39.3% (see Fig. 3). The test of homogeneity of the *ES*s was significant ($Q = 5778.58$, $p < .001$, $I^2 = 99.94\%$), which indicated that not all the *ES*s are from the same population. The random-effects model was adopted to calculate the weighted mean response rate, and the moderator analyses were conducted to explore the source of variation. The estimated mean response rate was 44.1%, with a 95% confidence interval (*CI*) 42.3%–46.0%.

Moderator analysis

We identified several potential sources (i.e., the moderators) that may contribute to the significant variation among the *ES*s based on our coding. The mean *ES* for each group within each moderator was calculated, and the between-group variation was estimated and tested based on the Q statistics. We presented the results by organizing the moderators into four categories: Study features (i.e., year of publication, funding status, and sample size), research topics (i.e., survey focus, tech-related topic, and domain), survey implementations (i.e., random selection, use of other types of survey, pre-contact, incentive, and reminder method), and participant characteristics (i.e., age, gender, and occupation). A forest plot that shows the estimated mean response rates and the *CI*s for the moderators is presented. A vertical dashed line representing the overall mean is marked in the plot as a reference line.

Study features. The number of studies that adopted online surveys increased steadily from the *year* 2007 ($k = 40$) to 2014 ($k = 255$). The mean response rates fluctuated significantly ($p < .001$) and did not follow a monotone trend across years. The highest mean response rate (52.6%) occurred in 2008; the lowest mean response rate (39.0%) occurred in 2010. *Funding status* had a significant impact on the response rates ($p < .001$). About one-fifth of the *ES*s ($k = 233$) came from surveys supported with funds, and those surveys yielded a higher mean response rate (48.0%) comparing to the surveys supported with no funding support or no funding information provided (43.1%). However, the *CI*s of this moderator overlapped in the forest plot, which suggests funding status did not impact the response rates. The discrepancy between the statistical test and the visual inspection could be attributed to the unbalanced number of studies for the funding status groups. The *sample size* of the survey significantly contributed to the variation of the mean response rates ($p < .001$). The smaller the sample size, the higher the mean response rates. The highest response rate (72.7 %) occurred when less than 100 participants were surveyed. When the surveys were sent to

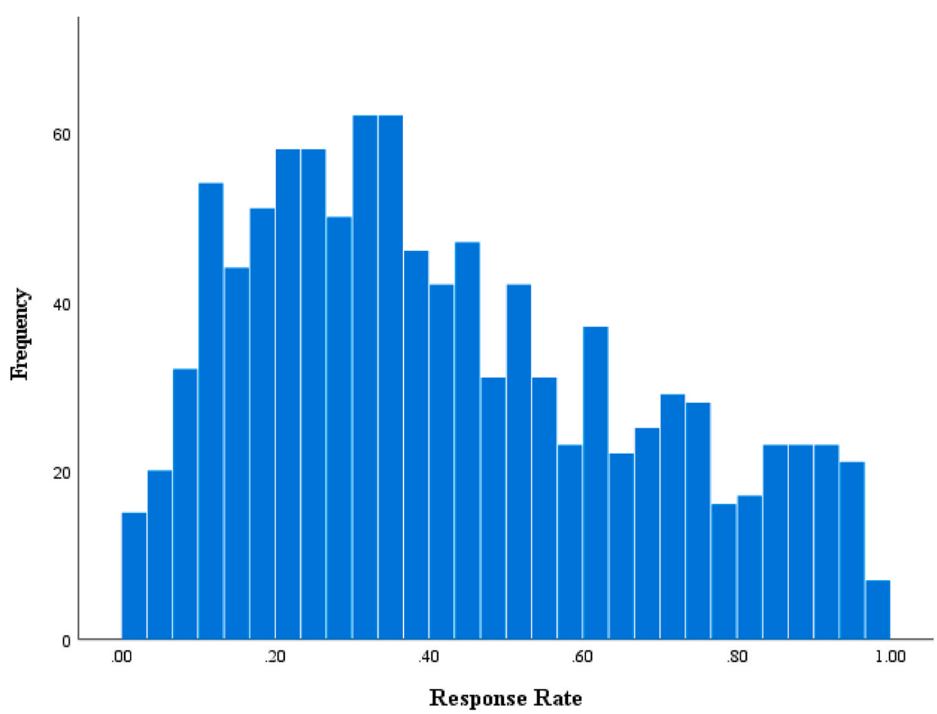

Fig. 3. Distribution of response rates (k = 1071).

samples that were larger than 2500, the mean response rate became the lowest (20.3%). The descriptive statistics and the forest plot for factors related to the study features can be found in Fig. 4.

Research topics. The impact of research topics on the online survey response rates was examined through three moderators. All of them contributed significantly to the variation in online survey response rates ($p < .001$). When examining the impact of *survey focus*, we found the studies focused on online learning yielded the highest mean response rate (62.8%). Studies focused on non-online learning in schools, professional training, or special education also reported higher mean response rates of around 60%. When examining the surveys topics based on whether they were *tech-related*, the mean response rate was significantly higher for the studies related to technology (53.0%) than the non-technology-related studies (42.9%). In terms of *domain*, most of the studies in our collection used online survey to study-offline phenomena ($k = 853$), which yielded the lowest mean response rate (41.9%) when compared to other studies focused on online phenomena (66.6%), online variations (50.2%), and online action (56.2%). The descriptive statistics and the forest plot for factors related to the research topics can be found in Fig. 5.

Survey implementations. Four of five moderators related to the survey implementations showed significant contribution to the variation of the response rates ($p < .01$). When the *random selection* of samples was reported in the studies, the mean response rate was lower (36.7 %) compared to the studies with no indication of random selection (45.4%). When studies offered *other formats of the same survey* along with the online survey, the mean response rate was higher (53.1%) compared to studies that used only online surveys (42.8 %). Using the *pre-contact* to the potential participants yielded a higher mean response rate (54.6%) than without the pre-contact. Sending a *reminder* of the online survey in different forms had different impacts on the response rates. Studies that sent out reminders using either e-mail (37.8%) or mail (26.9%) showed average lower response rates than the studies without reporting the reminder information (47.3%). The highest average response rate (79.0%) was found when using phone calls to remind the survey participants. It is important to note that this finding was based on only six *ESs*. The *incentive* is the only factor that did not relate to the online response rates. When studies noted that they provided *incentives*, the mean response rate was higher (45.6%) than those without noting the usage of incentives (44.1%). The difference was not significant ($p = .362$). The descriptive statistics and the forest plot for factors related to the survey implementations can be found in Fig. 6.

Participant characteristics. All three moderators related to the participation characteristics showed significant contribution to the variation of the response rates ($p < .001$). The *age* of the respondents appeared to have a negative relationship with the response rates. The highest mean response rate was found in the studies where the participants were mostly below 20 years old (57.6%); the lowest mean response rate was found in the 40 years old and above group (38.0%). The effect of *gender* was tested based on a smaller number of studies ($k = 26$). The male-only studies yielded a lower mean response rate (28.8 %) than female-only studies (49.3%). However, the difference was not significant ($p = .37$) due to the smaller number of *ESs* for each group (6 and 20 respectively). When examining the impact of *occupation* of the participants on the response rates, studies that focused on the student population yielded a higher mean response rate (48.5%) than studies that focused on the non-student population (41.4%). The descriptive statistics and the forest plot for factors related to the participant characteristics can be found in Fig. 7.

Discussion

The trend of the online survey response rates

In this meta-analysis, we examined 1071 independent online surveys response rates reported in studies in education-related fields and investigated the factors that may impact the rates. Evidence shows the use of online surveys in published research grew steadily from 40 surveys in 2007 to 255 surveys in 2014. The growth is expected as the medium for conducting online surveys has become more mature and as it becomes easier to adopt online surveys to collect data. Following this trend, it is very likely that using such form of surveys in research will keep increasing. In terms of the response rates across years, instead of the gradual decline suggested by survey researchers across social science disciplines in America and abroad (Brick & Williams, 2013; National Research Council, 2013), we observed a significant variation. We also observed a wide range of response rates reported in the published studies in our collection. This finding addresses the concern Cook et al. (2000) had that "meta-analyses of only published studies may result in an overestimation of typical response rates because studies with lower responses rates may not be submitted for publication in some disciplines or they may not be published when they are submitted" (p. 826). It is

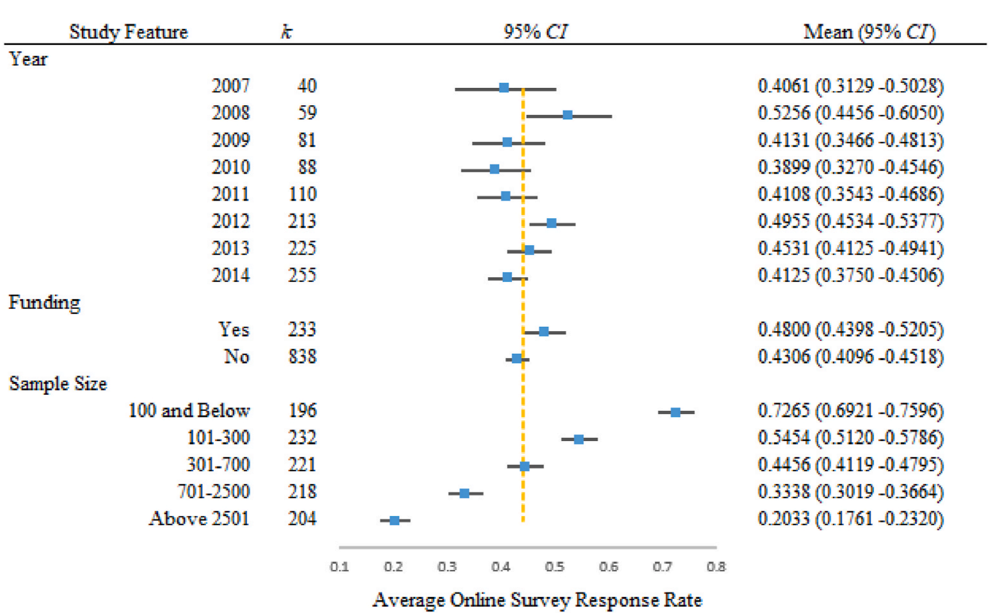

Fig. 4. Forest plot for factors related to the study features.

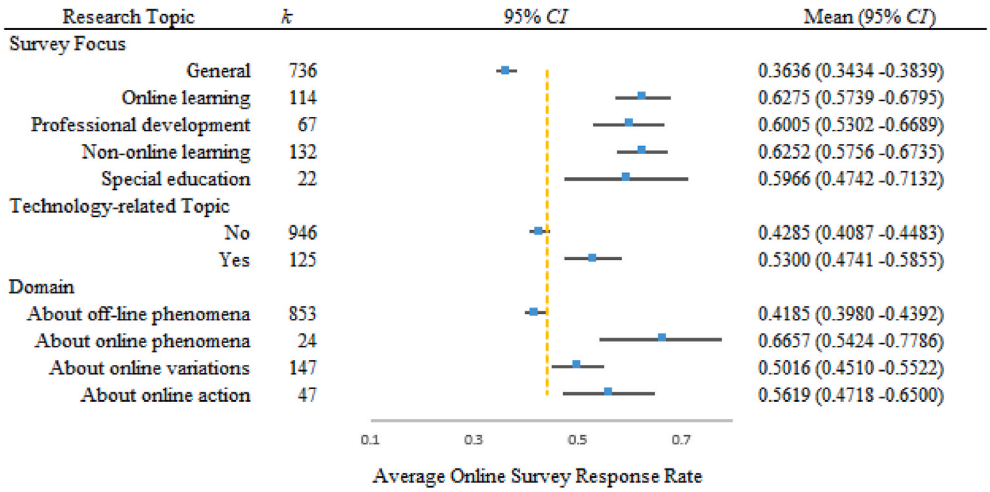

Fig. 5. Forest plot for factors related to the research topics.

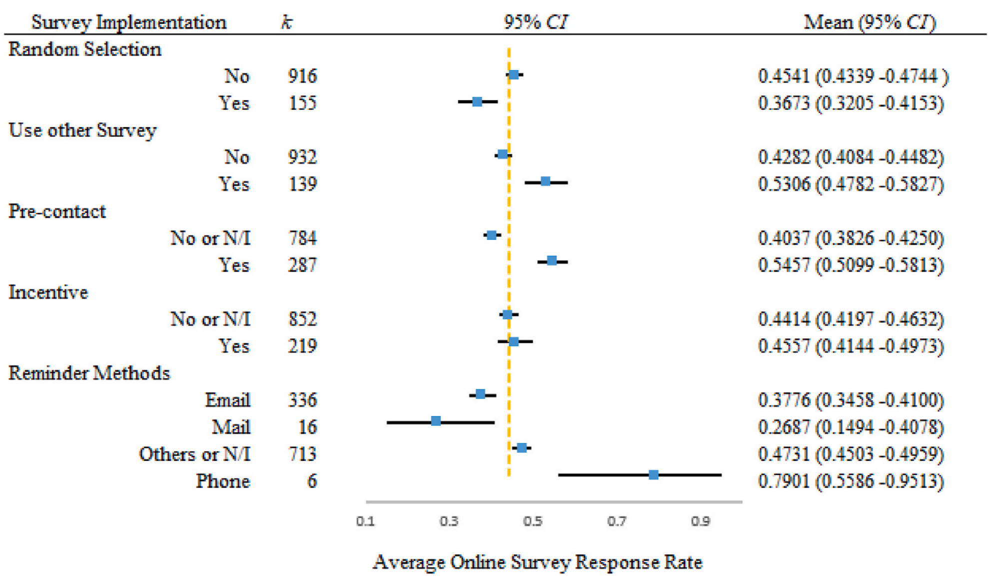

Fig. 6. Forest plot for factors related to the survey implementation.

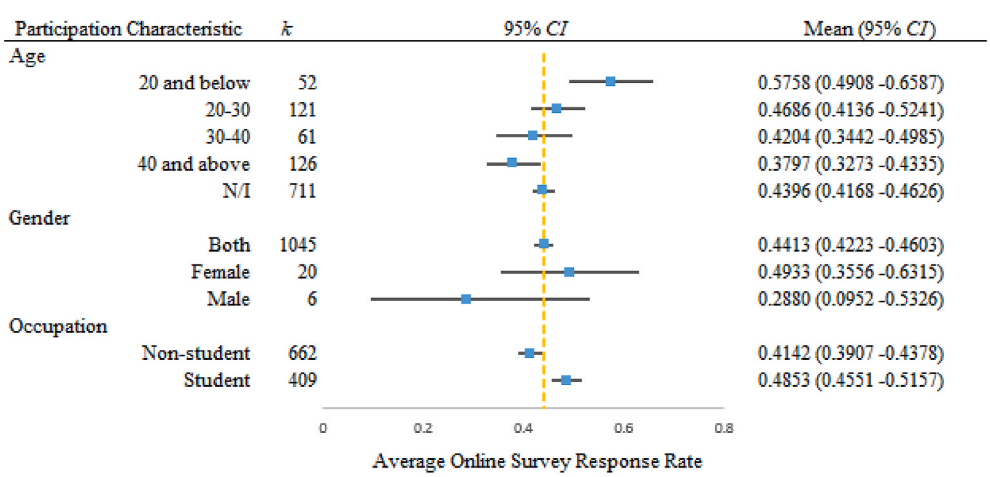

Fig. 7. Forest plot for factors related to the participant characteristics.

possible that having a reasonable number of representative respondents is more important than having a high response rate. When a survey was conducted on a large sample, a low response rate still yielded a good number of respondents for the study. The trend can be seen when we examined the sample size as one of the moderators. More discussion is provided in the next section.

Our synthesis showed the weighted mean of the online survey response rate in education-related fields is 44.1%. Compared to previous meta-analyses, it is lower than the mean response rate of 48.3% based on 99 surveys conducted by one institute from 2004 to 2006 (Archer, 2007). It is higher than the 34% based on 39 surveys reported in 37 studies (Shih & Fan, 2008) and the 39.6% based on 68 surveys reported in 49 studies (Cook et al., 2000). Note that the mean response rates in those aforementioned meta-analyses were calculated without mentioning the application of weight, so the sample size of the individual studies was not considered when pooling all the *ES*s together. Compared to the meta-analysis conducted with the application of weight, our mean response rate is higher than the 34.2% based on 207 response rates in the articles published in the similar timeframe as our study in four counseling journals (Poynton et al., 2019). Our finding is similar to Burgard et al. (2020), who found the weighted mean response rate to be 42.8% based on 20 studies focusing on adults with anxiety disorder or depression. It is worth noting that the heterogeneity index for our research (I^2= 99.94) is very similar to Burgard and colleagues' sample (I^2= 99.92%), which showed high variability among the response rates. The significant variation observed in *ES*s is expected as the surveys were used in various scenarios, and we followed up with the moderator analyses to explore the sources of variation.

Factors impacting the online survey response rates

One factor that had a negative relationship with the online survey response rates is the sample size. Evidence showed that sending a survey to more potential participants did not seem to generate higher rates. Instead, surveys sent to smaller samples reported higher response rates. The same trend was observed in the National Survey of Student Engagement (NSSE) reports, where the surveys were distributed to over 1600 colleges in the United States and Canada (Indiana University Center for Postsecondary Research and Planning, 2021). Their 2019 and 2020 reports discovered that higher average response rates were observed for smaller institutions. The same pattern was also held for other modes of surveys. Uhlig et al. (2014) found paper or mail surveys can also be more appropriate for smaller populations when looking at the response rates. Interestingly, when they compared the response rates for online surveys to other types of surveys, they found that online surveys are particularly time- and cost-efficient for populations larger than 300. This evidence suggests that, even though we found that online survey works better when the sample size is small, online surveys remain a more effective and efficient method for collecting data when the sample size is large compared to other survey modes.

The research topics of the studies are also related to the response rates. We found that when the online surveys focused on learning (both online and offline), special education, and professional development, the mean response rates were above 60%. To rule out the confounding effect that the high response rates were contributed by the studies with smaller sample sizes, which tends to show a higher response rate as discussed above, we investigated the relationship between survey focus (general vs. special topics) and the sample size. The point-biserial correlation was weak ($r = -.098$), which rules out the confounding impact of sample size on the relationship between study focus and response rate.

The only moderator that did not significantly relate to the online survey response rate in our meta-analysis was the use of the incentive. A similar finding was reported in another meta-analysis based on four studies (Burgard et al., 2020), and we confirmed the non-significant relationship with our extensive collection of studies. Neal et al. (2020) also demonstrated the lack of significant effect of incentives on the online survey response rate through their newest experimental research conducted in the educational setting. Nonetheless, it is worth mentioning that few studies that specifically focused on offering incentives had suggestions on how the incentives might work. For example, research has shown that the effectiveness of incentives for increasing response rates depends on the timing and type of incentive (Church, 1993; Pforr et al., 2015). Specifically, the pre-paid incentives increased response rates (Mercer et al., 2015; Porter, 2004), while post-paid incentives did not influence response rates (Goritz, 2006; Porter & Whitcomb, 2003). In addition, cash incentives (Dykema et al., 2013) and lotteries for tangible incentives (Heerwegh, 2006) have been shown to increase response rates for web-survey. Even though we were able to examine only the general effects of incentives in our meta-analysis, the more specific findings on the timing and type of incentives in the empirical studies could provide insights for survey researchers to plan their use of incentives to boost the response rates.

When investigating the factors related to the survey implementation, we found pre-contacting the potential respondents yielded higher response rates. This finding is in line with the recent synthesis (Burgard et al., 2020) as well as the earlier meta-analysis (Cook et al., 2000), in which they further suggested using more personal forms of contact such as face-to-face or phone contacts. We also discovered that using phone surveys as an alternative method to accompany online surveys resulted in a high average response rate that was above 80%. Previous studies have also discussed several types of mixed-mode survey approaches. Millar and Dillman (2011) focused on the mix of online and mail surveys in their experiment and found that offering a simultaneous choice of response modes did not improve the online response rate. However, they found that the timing of providing the alternative matters. When different survey modes are delivered sequentially, such as offering an online survey first and following with a mail option, online survey response rates are improved. Another factor that impacted the response rate is the reminder of the surveys. Two commonly seen methods, mail and e-mail reminder, turned out to yield lower response rates for online surveys than the studies that did not report information on using reminders. On the other hand, we found the phone reminder yielded a high response rate. However, this finding was based on six surveys sent to smaller samples, making it an efficient way to reach out to the participants and convince them to respond to the surveys.

When investigating the impact of participant characteristics, we found that the student population yielded higher response rates than the non-student population. Previous studies pointed out that students have more access to the internet, which provides more opportunities to respond to an online survey (Shih & Fan, 2008). Other researchers also found that college students are more responsive than doctors, school teachers, and the general population, who tend to prefer mail surveys (Shawver et al., 2016; Shih & Fan, 2008). When we examined the impact of gender on the online survey response rate, we found that male participants showed much lower response rates than female participants. However, the difference was not statistically significant based on only 26 *ES*s. On the other hand, a larger study based on 167,375 students in 321 institutions had demonstrated a significant gender gap in the online survey response rates (Porter & Umbach, 2006). A possible explanation for the observed gap is the difference between how males and females make decisions and value actions in the online environment (Smith, 2008). If the topic of survey is gender sensitive, researchers may want to pay more attention on recruiting representation sample for their research.

Suggestions for the consumers of online surveys

Finding the average response rate for funded studies is 48% in published studies implies the OMB's recommendation for 80% or higher response rate for federally funded projects is not practical. OMB's reason for requesting a high response rate is to reduce the nonresponse bias by surveying a high proportion of the sample. However, Hendra and Hill (2019) demonstrated that pursuing a high response rate may offer little or no reduction of nonresponse bias based on their investigation of the survey data from a large-scale evaluation. They further suggested the pursuit of high response rates lengthens the fielding period, which can create measurement problems. Based on the evidence from our synthesis and suggestions from other empirical studies discussed earlier, we posit the following recommendations for to the users and evaluators of online surveys to consider:

- When considering a reasonable response rate of an online survey, keep in mind that the average rate in the education-related field is 44%.
- Sending surveys to more participants does not necessarily yield a higher response rate. It is more critical to have a clearly defined and refined population to send the surveys to.
- When planning an online survey, consider the following actions associated with higher response rates: pre-contact the potential participants, use other types of surveys in conjunction with online surveys, and use phone calls to remind the participants about the survey.
- Incentives do not guarantee a boost in the online survey response rates. However, if resources allow, pre-paid incentives using cash or lotteries might increase the response rate.
- When evaluating the response rates of a project using online surveys, the following factors related to the study and participant characteristics should be considered: the funding status of the studies, and the age and occupation (i.e., students vs. non-student) of the participants.
- Even though some factors can be manipulated to increase the online survey response rate, the researchers should consider their resources and determine whether it is worth pursuing a higher rate.

Limitations and recommendations for future research

To broadly examine the online survey response rate in research, we included all the studies that adopted the online survey as a tool to collect data published in the education-related fields. Since the survey itself is usually not the focus of the studies and the description of the survey is usually scarce in the primary studies, we could not extract some of the information related to the survey characteristics (e.g., survey length and type of questions) and the survey implementation (e.g., survey open period and follow-up methods). However, the impact of these factors can be effectively studied using experimental designs. A few good examples are Deutskens et al. (2004) and Sauermann and Roach (2013).

This study is also limited by the inclusion of studies published prior to 2014 to ensure a complete set of evidence for the period of studies. To continue monitoring the trend of the response rates for online surveys, researchers should continue the efforts by examining newer studies. It will be particularly interesting to see if the recent pandemic impacts the usage of online surveys, especially when the human resources and physical contacts are limited and online surveys become an optimal choice for collecting data. We encourage synthesists in other fields to investigate their online survey response rates. The accumulated evidence can help to set up reasonable expectations when using online surveys.

From the methodology perspective, meta-analyzing proportions is an understudied area. We conducted our analyses using three types of effect sizes (the raw and two transformed response rates). We observed some degree of discrepancies among the results, and there is no consensus on the type of *ES*s that should be used. In addition, the estimate of variation (e.g., I^2) tends to be much larger when synthesizing proportions, which may require adjustment to reflect the true variation among the proportions. Furthermore, the procedure of combining proportions using meta-analysis has not been well laid out, and some previous meta-analyses failed to apply weight when pooling the response rates. Future exploration on the choices of transformation and the procedure of synthesizing proportions will benefit the researchers who investigate proportions. It will help to improve the quality of meta-analysis in education as the proportion is often reported in educational research.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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