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Synchronous online learning supports cognitive and affective outcomes more than traditional face-to-face and asynchronous online education: A meta-analysis of webinars☆

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ABSTRACT

The COVID-19 pandemic led schools and universities worldwide to rapidly shift from traditional, in-person classes to synchronous online learning through webinar platforms such as Zoom, WebEx, and Microsoft Teams. This meta-analysis examined 31 randomized controlled trials (RCTs) involving 3823 learners to better understand how effective synchronous online programs are for supporting both affective outcomes (such as attitudes, satisfaction, self-efficacy, and interest) and cognitive outcomes (including declarative knowledge and procedural skills). Overall, the findings show that synchronous online learning is more effective than asynchronous online and face-to-face education in improving both learners' affect and their learning performance. The strongest positive effects of webinars appeared when they were compared to waitlist groups and asynchronous courses, and when affective outcomes focused on learners' self-efficacy beliefs. The study also found a significant link between affective and cognitive outcomes. Finally, we highlight practical implications for instructional design and suggest directions for future research on webinar-based learning.

Educational relevance and implications statement

This meta-analysis explored if synchronous online learning in webinars is more or less effective than other forms of education, such as traditional face-to-face education or asynchronous learning in the digital world. The findings of this study confirm that learners report higher levels of knowledge and skills and higher levels of motivation, self-efficacy, and interest when they participated in webinars compared to other forms of education.

1. Introduction

The COVID-19 pandemic forced many educational institutions around the world to change their mode of education from synchronous face-to-face classes to synchronous online instruction using webinar infrastructure from technical platforms such as Zoom, WebEx, or Teams. This change was sudden, yet offered the chance to examine the effectiveness of synchronous online learning environments (Gegenfurtner et al., 2020; Munjal & Zutshi, 2020; Pachankis et al., 2022). As a result, the number of studies grew considerably. Of course, synchronous online learning is not a novel concept and many studies have tested and explored its effectiveness long before the COVID-19 pandemic stopped face-to-face education (for meta-analytic reviews, see Ebner & Gegenfurtner, 2019; Gegenfurtner & Ebner, 2019), for example in the domains of medical education (Alnabelsi et al., 2015; Constantine, 2012), marketing education (Francescucci & Rohani, 2019), professional training (Gegenfurtner et al., 2018), religious education (Olson & McCracken, 2015), teacher education (Amirova et al., 2023), and science education (Prawestri et al., 2020).

Studies on the effective design of synchronous online learning often compare learners' affective or cognitive outcomes from webinars with other modes of education, particularly synchronous face-to-face education and asynchronous online learning. For example, Kim (2024) randomly assigned college students into synchronous face-to-face, synchronous online, and asynchronous online conditions to train students' juggling skills. Boekeloo et al. (2024) compared the effectiveness of synchronous face-to-face and online training programs for therapists working with lesbian, gay, bisexual, transgender, queer/questioning, and other sexual and gender diverse (LGBTQ+) people. Some studies also contrast affective and cognitive outcomes from learners in webinar programs with learners from a waitlist who have not received any

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training (Hepburn et al., 2022; Iannotta et al., 2024; McMahon-Howard & Reimers, 2013). The reported effect sizes vary significantly in size, with some studies favoring synchronous online learning (Compen et al., 2021; Rahmati et al., 2020) and other studies indicating that learning and motivation are higher when learners participate in face-to-face or asynchronous programs (Constantine, 2012; Kim, 2024).

Research on designing effective synchronous online learning often consider affective and cognitive outcomes as indicators of program effectiveness (Ebner & Gegenfurtner, 2019; Gegenfurtner et al., 2025). Across studies, different measures are used to operationalize affective and cognitive outcomes. First, affective outcomes can be approximated as more favorable attitudes after training (Khadivzadeh et al., 2021), as satisfaction reported on evaluation sheets (Calo et al., 2019), or as higher levels of self-efficacy beliefs (Hohmann et al., 2023) and learning motivation and interest (Alnabelsi et al., 2015; Francescucci & Rohani, 2019; Knogler et al., 2015; Laine et al., 2020). Second, cognitive outcomes can measure declarative knowledge (Amirova et al., 2023; Prawestri et al., 2020) or procedural skills (Hepburn et al., 2022; Kim, 2024). While it seems intuitive to assume that affective and cognitive outcomes are correlated because motivation is often considered a precursor of learning, Ebner and Gegenfurtner (2019) reported that learning and satisfaction in webinars were negatively associated; it is thus an interesting question to re-examine this correlation with a larger meta-analytic database, including studies that emerged since the COVID19-pandemic and accounting for the plethora of measures used to examine different affective and cognitive outcomes.

Several conceptual frameworks and models offer theoretical reasons as to how affective and cognitive processes interact in digital learning environments (Baker et al., 2013; Gegenfurtner et al., 2021; Mayer, 2020). First, the cognitive-affective theory of learning with media (CATML; Moreno & Mayer, 2007) holds that motivation and affect influence how learners select, organize, and integrate information in working memory; in this theory, essential and generative processing of information is high when learners' motivation is high. Second, the cognitive-affective-social theory of learning in digital environments (CASTLE; Schneider et al., 2022) assumes that social cues in the digital material activate social schemata in long-term memory; these schemata influence learners' motivation, emotion, and metacognition which, in turn, support the cognitive processes of selecting, organizing, integrating, and retrieving information in memory. Third, the attention, relevance, confidence, and satisfaction (ARCS) model (Keller, 2010; Li & Keller, 2018) argues that to promote deep learning, digital environments need to include a motivational design that help learners believe they can master the material (self-efficacy), fulfill their curiosity (interest), and promote feelings of being an enjoyable and fair learning experience (satisfaction). Fourth and finally, the community of inquiry (CoI) framework (Garrison, 2017) suggests that cognitive presence and particularly the social presence of teachers and peers can fulfill the need of relatedness, supporting deep learning and motivation in online environments (Adam et al., 2025; Kovanović et al., 2015; Kreijns et al., 2024; Martin et al., 2022). The first three theories CATML, CASTLE, and ARCS are very useful to understand how affective and cognitive processes are associated in synchronous online, asynchronous offline, and face-to-face classroom learning; it is an interesting research question for meta-analytic synthesis to examine if cognitive and affective variables are similar or different across these learning modalities. The latter theory CoI (Garrison, 2017) is particularly prevalent in face-to-face and synchronous online learning environments in which learners typically have direct social interaction with peers and teachers; in contrast, asynchronous online education does not always include social exchange processes, but social cues can be incorporated there as well to stimulate cognitive, affective, and social learning processes (Baker et al., 2013; Gegenfurtner et al., 2021; Schneider et al., 2022). Still, because social and teacher presence are a natural part of synchronous online and face-to-face education, we can assume that cognitive and affective processes in synchronous programs may be stronger compared to those in asynchronous programs. Without further empirical evidence, however, the extent to which cognitive and affective processes differ across online and offline learning remains unclear. Accordingly, a primary aim of this meta-analytic synthesis is to elucidate how various instructional modes elicit comparable (or different) demands on learners' cognitive and affective processing.

When reflecting on previous research on synchronous online learning, then (a) the heterogeneity in direction and size of favorable or unfavorable effects, (b) the variety in control conditions to which synchronous online learning is compared, and (c) the range of measures used to operationalize cognitive and affective outcomes tend to blur clear answers as to how effective webinars are. Furthermore, studies still use small sample sizes per experimental condition, sometimes with participant numbers smaller than ten or twelve per group (Munjal & Zutshi, 2020; Olson & McCracken, 2015), which increases the likelihood of bias induced by sampling error, even if participants are randomly assigned to conditions. As a remedy to this reported heterogeneity in the original studies, a meta-analysis can account for the artifactual variance of sampling error and compare aggregated effect sizes in homogeneous subgroups (Chernikova, Jansen, et al., 2024; Gegenfurtner & Kollar, 2025; Schmidt & Hunter, 2015). Such a meta-analytic comparison might provide robust answers on the effects of webinars for learning and motivation.

Consequently, this meta-analysis aimed to answer three research questions. The first research question was: How effective is synchronous online learning in promoting learners' affective outcomes? The second question was: How effective is synchronous online learning in promoting learners' cognitive outcomes? Finally, the third question was: To what extent are affective and cognitive outcomes associated?

2. Methods

To answer these three research questions, (a) we performed a systematic search of relevant publications, (b) extracted and coded a number of variables from the identified publications, and (c) meta-analyzed the coded information with corrections for sampling error. This section includes all details of our methods for search, coding, and analysis.

2.1. Search

Table 1 shows a list of inclusion and exclusion criteria that we applied for our search. To be included, a study had to randomize learners in a synchronous online and a control condition and report an effect size between conditions on cognitive and affective outcomes. Studies were excluded if they assigned learners non-randomly to conditions or if they reported affective outcomes only, cognitive outcomes only, or neither affective nor cognitive outcomes. We also omitted studies if they used only recoded webinars in the form of a video, not live webinars, and if studies compared live webinars to other types of synchronous online education, for example contrasting two instructional designs. To minimize publication bias, we deliberately included all studies, independent of publication type, publication language, age group, and educational field. We used 01 January 2019 as the starting point of our search to continue and update the meta-analysis of Ebner and Gegenfurtner (2019), who ended their literature search in 31 December 2018. Using these inclusion criteria, a total of twenty studies with 31 independent data sources were identified and subsequently coded (Fig. 1).

2.2. Coding

Table 2 presents the coding scheme two trained raters used to code information from the included studies. Each study was coded for publication, effect size, study, and learner characteristics. Effect size characteristics included sample size information in the webinar and control condition as well as Cohen's d and Hedges' g as standardized mean

Table 1
Criteria for inclusion and exclusion in the meta-analytic review.

Criterion	Inclusion	Exclusion
Study design	Randomized controlled trials	Studies without randomization
Type of control	Traditional face-to-face education, asynchronous online education, no-training waitlist condition	Another synchronous online learning condition
Measures	Studies reporting affective **and** cognitive outcomes	Studies reporting affective outcomes only, cognitive outcomes only, or neither affective nor cognitive outcomes
Effect size	Studies reporting an effect size and the sample size in both the webinar and any control groups	Studies not reporting an effect size or sample size information
Publication date	January 01, 2019 to September 01, 2024	Prior to 2019
Publication types	Original research, including journal articles and unpublished theses	Meta-analyses, trial registrations
Publication language	All languages	–
Age group of learners	All age groups	–
Educational field	All fields	–

difference between conditions at immediate posttest. Study characteristics included the type of control condition used (traditional face-to-face, asynchronous online, waitlist), the type of the affective measure (satisfaction, attitudes, self-efficacy, motivation / interest), and the type of the cognitive measure (knowledge, skills). Operational definitions for knowledge were: knowledge test scores and course grade; for skills: outcomes in a performance test. The affective measures were measured with items in self-report questionnaires; their operational definitions were for satisfaction: satisfaction, acceptability, enjoyment; for attitudes: attitudes; for self-efficacy: self-efficacy, confidence; and for motivation / interest: motivation, interest. Studies were coded as separate reports when they reported multiple affective or cognitive measures. For example, when a study reported outcomes in form of a knowledge test and in form of a procedural skills test, two effect sizes were coded (e.g., Joshi et al., 2013; Pachankis et al., 2022); similarly, when a study reported, for example, attitudes and self-efficacy, two effect sizes were coded (e.g., Boekeloo et al., 2024; Hohmann et al., 2023). Finally, learner characteristics were coded as age (in years) and gender (percentage of female learners) in the webinar and control conditions.

2.3. Analysis

Based on a random-effects model, the meta-analytic calculations were performed following Schmidt and Hunter's (2015) recommendations for meta-analyses of experimental effects. We calculated Cohen's d and Hedges' g based on the mean, standard deviation, and sometimes standard error estimates reported in the included studies. When these estimates were not reported, we converted F or β into Hedges' g using the practical meta-analysis effect size calculator (Lipsey & Wilson, 2001; Wilson, 2023). We then corrected Hedges' g for sampling error using formulae provided by Schmidt and Hunter (2015) to get the corrected Hedges' g_c. Finally, we computed standard deviations and 95 % confidence intervals of g_c. These calculations were performed separately for the affective and cognitive outcomes in our primary meta-analysis based on the full data set of aggregated effect sizes. Because our analyses are based on aggregated effect sizes, individual participant data cannot be identified; hence, human subject approval from an institutional review board was not required (Higgins et al., 2024). Following the primary

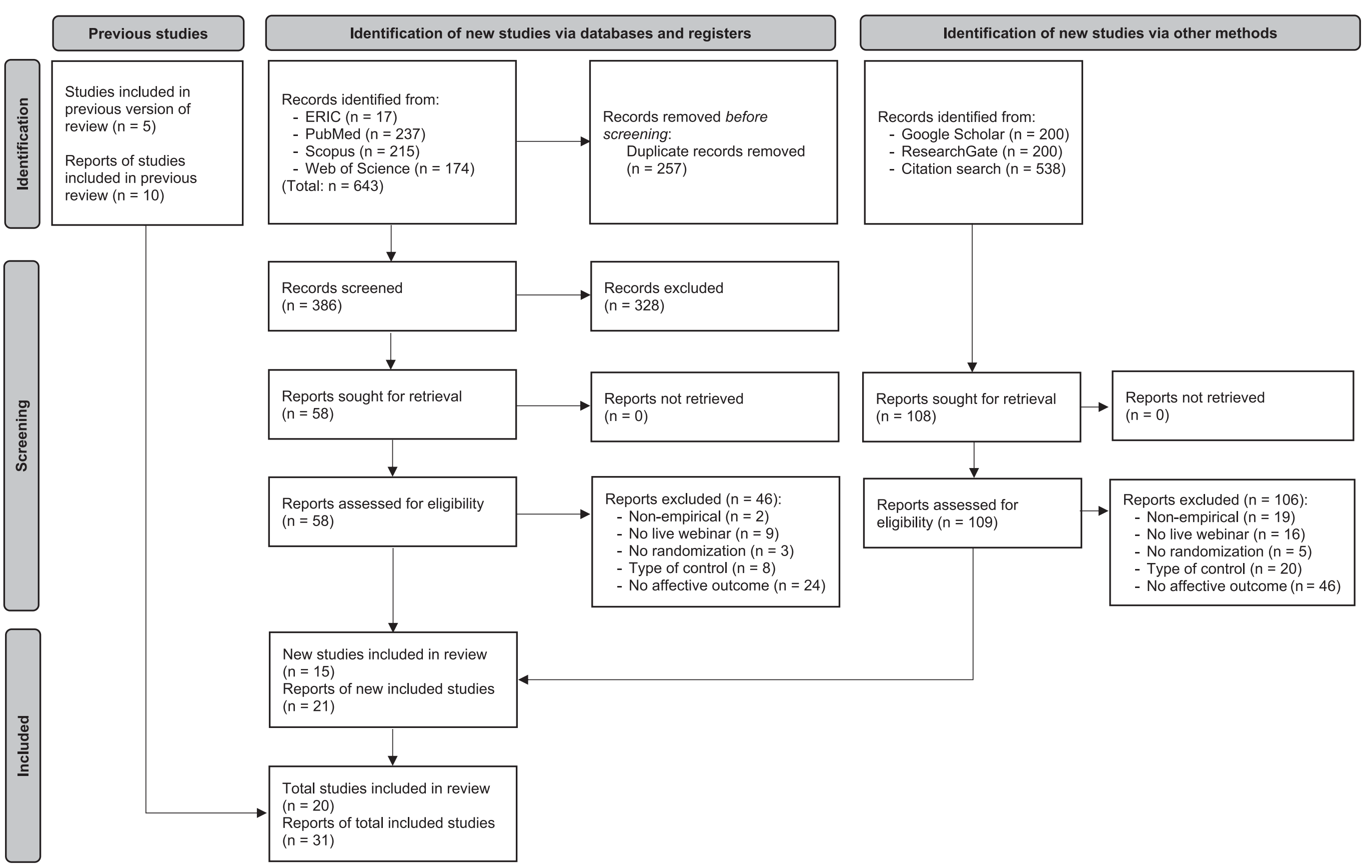

Fig. 1. PRISMA 2020 flow diagram for updated systematic reviews which included searches of databases, registers and other sources.

Table 2
Coding scheme.

Characteristics	Main category	Sub-category
Publication characteristics	Author	Last name of first author
	Publication year	Coded as year
Effect size estimates	Sample size	Sample size N in the webinar condition
		Sample size N in the control condition
	Cohen's d	Cohen's d of the affective posttest difference between conditions
		Cohen's d of the cognitive posttest difference between conditions
	Hedges' g	Hedges g of the affective posttest difference between conditions
		Hedges g of the cognitive posttest difference between conditions
Study characteristics	Type of control	1 = Traditional face-to-face education
		2 = Asynchronous online education
		3 = No training / waitlist condition
	Affective measure	1 = Satisfaction
		2 = Attitudes
		3 = Self-efficacy
		4 = Motivation / interest
	Cognitive measure	1 = knowledge
		2 = skills
Learner characteristics	Age	Mean age coded as years for learners in the webinar condition
		Mean age coded as years for learners in the control condition
	Gender	Percentage of female learners in the webinar condition
		Percentage of female learners in the control condition

meta-analysis of the aggregated data, we estimated the moderating effects of type of control and measure in theory-driven subgroup analyses (Schmidt & Hunter, 2015) and examined the influence of affective on cognitive outcomes using an unrestricted weighted least squares meta-regression (Stanley & Doucouliagos, 2017). Publication bias was analyzed visually and statistically using the Egger test (Egger et al., 1997) on funnel plot asymmetry as recommended by Higgins et al. (2024).

3. Results

3.1. Description of included studies

The twenty studies included in this meta-analysis offered a total of 31 independent data sources. Total sample size was 3823 learners with 1648 in the webinar condition and 1635 in the control condition, indicating a relatively equal distribution of learners across conditions. Mean sample size in all $k = 31$ reports was 105.9 (±131.2), with 53.2 (±63.3) learners in the webinar condition and 52.7 (±68.5) in the control condition. These relatively small sample sizes tend to warrant meta-analytic correction of effect sizes for the artifactual variance induced by sampling error. On average, learners in the webinar condition were 35.5 (±13.3) years old and learners in the control condition were 34.6 (±12.6) years old. The percentage of female participants was 69.9 (±16.6) in the webinar and 68.5 (±10.4) in the control condition. Age and gender differences between conditions were statistically non-significant and thus excluded from further moderator analyses.

3.2. Publication bias for affective and cognitive outcomes

To estimate the presence of publication bias post-hoc in our meta-analysis, we performed the Egger test (Egger et al., 1997). Results signaled funnel plot asymmetry to be statistically non-significant, with $\beta = 0.53$, SE = -1.17, $p = .182$ for the affective outcomes and $\beta = -0.51$, SE = -3.90, $p = .279$ for the cognitive outcomes. These analyses suggest that publication bias was not an issue in our meta-analysis. In addition to these post-hoc analyses, we aimed to minimize the presence of publication bias at the start of our systematic literature search by employing deliberately wide inclusion criteria, for example with regard to publication type, publication language, and educational field (as detailed in Table 1).

3.3. Affective and cognitive outcomes of webinar-based learning

The mean differences across the included studies varied greatly. For affective outcomes, Hedges' g_c ranged from −1.04 to +1.69. For cognitive outcomes, Hedges' g_c ranged from −0.54 to +4.27. This heterogeneity in effect sizes tends to warrant meta-analytic synthesis. Table 3 presents the psychometric properties of the primary meta-analysis. In the table, the corrected Hedges' g_c coefficient is particularly interesting because this effect size signals the extent to which webinars have positive or negative outcomes for learners. When interpreting g_c, Higgins et al. (2024) propose to interpret values of 0.1 as trivial effects, values of 0.2 as small effects, values of 0.5 as medium effects, values of 0.8 as large effects, and values of 1.3 as very large effects. Results of the primary meta-analysis reported in Table 3 suggest that webinars are effective in promoting affective and cognitive outcomes of learners. Compared to control conditions, k = 31 reports with a total sample size of 3283 learners show a g_c of 0.24 for affective outcomes, signaling a small positive effect, and a g_c of 0.50 for cognitive outcomes, signaling a medium positive effect.

3.4. Subgroup analyses of affective and cognitive outcomes

These effect sizes represent aggregate estimates. More detailed subgroup analyses can unveil the extent to which the type of the control condition and different measures used to assess affective and cognitive learner outcomes can moderate the findings. First, Table 4 shows affective and cognitive outcomes of synchronous online learning compared differentially to three control conditions: traditional face-to-face learning, asynchronous online learning, and a no-training waitlist condition. The results suggest that effect sizes did not differ significantly for affective outcomes. For cognitive outcomes, Hedges' g_c differed significantly, $F(2,28) = 4.04$, $p = .029$, $\eta^2 = 0.22$: Reports that compared webinars to traditional face-to-face education showed lower positive effects (g_c = 0.19) than did reports that compared webinars to asynchronous online education (g_c = 0.25) and waitlist conditions (g_c = 1.16).

Second, Table 5 presents the results of the meta-analytic moderator estimation for the measures used to assess learners' affective and cognitive outcomes. Affective outcomes were measured as attitudes, satisfaction, self-efficacy, and motivation / interest. Hedges' g_c differed significantly, $F(3,27) = 3.93$, $p = .019$, $\eta^2 = 0.31$, with a trivial positive effect for satisfaction ($g_c = 0.07$), a medium positive effect for attitudes ($g_c = 0.40$), and a medium to large positive effect for self-efficacy (g_c = 0.66). Studies that measured affective outcomes as learners' motivation/ interest reported a small to medium negative effect ($g_c = -0.38$).

Third, Table 6 shows the results of the meta-analytic subgroup

Table 3
Meta-analytic results of affective and cognitive outcomes of webinar-based learning.

	k	N	d	g	g_c	SD_{gc}	95 % CI
Affective outcomes	31	3283	0.25	0.24	0.24	0.24	0.23; 0.25
Cognitive outcomes	31	3283	0.50	0.50	0.49	0.25	0.48; 0.50

Note. k = number of reports, N = total sample size; d = Cohen's d; g = Hedges' g; g_c = Hedges' g corrected for sampling error; SD_{gc} = standard deviation of g_c; *95 % CI* = 95 % confidence interval around g_c.

Table 4
Meta-analytic results of affective and cognitive outcomes per type of control.

	k	N	d	g	g_c	SD_{gc}	95 % CI	*Difference between subgroups*
Affective outcomes								$F(2,28) = 2.29$, $p = .12$, $\eta^2 = 0.14$
Face-to-face	12	1339	−0.04	−0.04	−0.04	0.26	−0.05; −0.02	
Asynchronous	10	1075	0.39	0.38	0.38	0.25	0.37; 0.40	
Waitlist	9	869	0.46	0.46	0.46	0.22	0.44; 0.47	
Cognitive outcomes								$F(2,28) = 4.04$, $p = .029$, $\eta^2 = 0.22$
Face-to-face	12	1339	0.20	0.19	0.19	0.26	0.17; 0.20	
Asynchronous	10	1075	0.26	0.26	0.25	0.25	0.24; 0.27	
Waitlist	9	869	1.19	1.17	1.16	0.24	1.15; 1.18	

Note. k = number of reports, N = total sample size; d = Cohen's d; g = Hedges' g; g_c = Hedges' g corrected for sampling error; SD_{gc} = standard deviation of g_c; *95 % CI* = 95 % confidence interval around g_c.

Table 5
Meta-analytic results of affective and cognitive outcomes per measure.

	k	N	d	g	g_c	SD_{gc}	95 % CI	*Difference between dimensions*
Affective outcomes								$F(3,27) = 3.93$, $p = .019$, $\eta^2 = 0.31$
Attitudes	9	645	0.41	0.41	0.40	0.24	0.38; 0.42	
Satisfaction	11	774	0.07	0.07	0.07	0.28	0.05; 0.09	
Self-efficacy	7	1016	0.67	0.66	0.66	0.20	0.65; 0.67	
Motivation/interest	4	848	−0.40	−0.39	−0.38	0.23	−0.40; −0.37	
Cognitive outcomes								$F(1,29) = 1.06$, $p = .312$, $\eta^2 = 0.04$
Knowledge	19	1969	0.64	0.63	0.63	0.26	0.62; 0.64	
Skills	12	1314	0.28	0.28	0.28	0.24	0.26; 0.29	

Note. k = number of reports, N = total sample size; d = Cohen's d; g = Hedges' g; g_c = Hedges' g corrected for sampling error; SD_{gc} = standard deviation of g_c; *95 % CI* = 95 % confidence interval around g_c.

analyses when type of control and measures are used as combined moderators. Differences between subgroups were statistically non-significant for affective and cognitive outcomes. On a descriptive level, we can note a large heterogeneity in effect sizes and a number of small cell sizes, possibly biased by second-order sampling error, indicating the need for more original empirical studies.

3.5. Associations between affective and cognitive outcomes

Two-tailed bivariate correlation analyses were performed to determine the extent to which affective and cognitive learner outcomes were associated. For the overall dataset (k = 31), the Pearson correlation coefficient between Hedges' g_c for the affective and Hedges' g_c for the cognitive outcomes was r = 0.48, p = .006. A sample-size weighted regression analysis with affective g_c as the independent and cognitive g_c as the dependent variable reached statistical significance, with a

Table 6
Meta-analytic results of affective and cognitive outcomes per type of control and measure.

	k	N	d	g	g_c	SD_{gc}	95 % CI	*Difference between dimensions*
Affective outcomes								
Attitudes								$F(2,6) = 0.01$, $p = .992$, $\eta^2 = 0.00$
Face-to-face	3	207	0.38	0.38	0.37	0.24	0.34; 0.41	
Asynchronous	2	116	0.43	0.42	0.41	0.26	0.37; 0.46	
Waitlist	4	322	0.43	0.42	0.42	0.24	0.39; 0.44	
Satisfaction								$F(1,9) = 0.43$, $p = .527$, $\eta^2 = 0.05$
Face-to-face	6	338	−0.04	−0.04	−0.04	0.29	−0.07; −0.01	
Asynchronous	5	436	0.21	0.21	0.21	0.26	0.18; 0.23	
Waitlist	–	–	–	–	–	–	–	
Self-efficacy								$F(1,5) = 1.37$, $p = .295$, $\eta^2 = 0.22$
Face-to-face	–	–	–	–	–	–	–	
Asynchronous	2	469	1.11	1.09	1.08	0.20	1.07; 1.10	
Waitlist	5	547	0.49	0.49	0.49	0.20	0.47; 0.50	
Motivation/interest								$F(1,2) = 0.56$, $p = .533$, $\eta^2 = 0.22$
Face-to-face	3	794	−0.45	−0.44	−0.44	0.22	−0.45; −0.42	
Asynchronous	–	–	–	–	–	–	–	
Waitlist	–	–	–	–	–	–	–	
Cognitive outcomes								
Knowledge								$F(2,16) = 2.26$, $p = .137$, $\eta^2 = 0.22$
Face-to-face	7	1015	0.49	0.48	0.47	0.27	0.45; 0.49	
Asynchronous	6	392	0.42	0.41	0.41	0.28	0.38; 0.44	
Waitlist	6	562	1.05	1.04	1.03	0.23	1.01; 1.05	
Skills								$F(2,9) = 1.92$, $p = .202$, $\eta^2 = 0.30$
Face-to-face	5	324	−0.22	−0.22	−0.21	0.26	−0.24; −0.19	
Asynchronous	4	683	0.02	0.02	0.02	0.20	0.01; 0.03	
Waitlist	3	307	1.47	1.45	0.143	0.27	1.41; 1.46	

Note. Meta-analyses are not performed if $k < 2$. k = number of reports, N = total sample size; d = Cohen's d; g = Hedges' g; g_c = Hedges' g corrected for sampling error; SD_{gc} = standard deviation of g_c; *95 % CI* = 95 % confidence interval around g_c.

standardized $\beta = 0.52$, $SE = 0.16$, $p = .003$. These estimates tend to signal significant associations between affective and cognitive consequences in webinar-based learning.

4. Discussion

This meta-analysis examined the extent to which affective and cognitive outcomes of learners differ in synchronous online, asynchronous online, and face-to-face education. Such a comparison is timely because studies on digital learning in webinars proliferate since the COVID19-pandemic (Munjal & Zutshi, 2020; Pachankis et al., 2022) and have been extensively studied even before (Constantine, 2012; Gegenfurtner et al., 2018; Joshi et al., 2013; McMahon-Howard & Reimers, 2013). In light of our research questions, we can conclude that synchronous online learning is more effective than control conditions in promoting affective ($g_c = 0.24$) and cognitive ($g_c = 0.50$) learner outcomes. The positive effect of webinars was most pronounced when compared to waitlist conditions and asynchronous education programs and when affective outcomes were measured as self-efficacy beliefs. The results reported here also suggest that affective and cognitive outcomes were significantly associated ($\beta = 0.52$)—a finding that is particularly interesting when compared to the findings reported in a previous meta-analysis by Ebner and Gegenfurtner (2019) who reported a negative association between learning and satisfaction. One reason for this difference could be the fact that their meta-analysis considered learner satisfaction only, while the present meta-analysis included three more affective measures. Another reason is the limited meta-analytic database in their publication—five studies with ten independent data sources—might have led to second-order sampling error, which is less likely to the present meta-analysis with triple the number of data sources.

The present meta-analysis was based on randomized controlled trials, which is often considered the gold standard in terms of methodological rigor and can thus provide robust answers learning and individual differences in digital learning (Chernikova, Jansen, et al., 2024; Gegenfurtner & Kollar, 2025). Still, this meta-analysis is not without limitations. One limitation is its focus on randomized trials; had we also considered quasi-experimental work, then we might have had an even larger meta-analytic database, but at the expense of producing inflated effect sizes because randomized controlled trials have been found to produce smaller and more conservative effects (Cheung & Slavin, 2016; de Boer et al., 2014; Means et al., 2009; Salcher-Konrad et al., 2024). Cheung and Slavin (2016, p.288) state that, if it is true that quasi-experiments overstate effects, "this implies that mean effect sizes from reviews that average randomized and quasi-experimental effect sizes are likely to be reporting inflated mean effect sizes". This evidence motivated our meta-analysis to prioritize randomized controlled trials. Future research may wish to engage in systematic comparisons of RCTs and quasi-experimental work on webinar-based learning. A second limitation is the examination of learner outcomes without considering different instructional design features—such as breakout rooms, the use of webcams, or quizzes (Gegenfurtner et al., 2025; Raes et al., 2020; Wagner et al., 2021)—within the different synchronous and asynchronous learning modalities. Furthermore, a number of different pedagogical models can be applied to synchronous (and asynchronous; Testers et al., 2020; Testers et al., 2024) online learning, such as flipped classrooms (Wagner et al., 2025), simulation-based learning (Chernikova, Holzberger, et al., 2024), game-based learning (Siewiorek & Gegenfurtner, 2010), and gamification (Schlag et al., 2025), among many others. It is valid to assume that differences in the instructional design can shape affective and cognitive (and social) processing (Garrison, 2017; Keller, 2010; Li & Keller, 2018), resulting in differences in effect sizes. Such analyses were beyond the scope of the present meta-analysis. Future work can engage in such exploration into how we can design effective webinars to promote learning and motivation, including the use of artificial intelligence (Jaldemark et al., 2025). A third limitation concerns the correlation analysis of the affective and cognitive outcomes: it should be noted that these correlation values are an aggregated meta-analytic correlation of standardized mean differences because single correlation coefficients between affective and cognitive outcomes are hardly reported in the included original studies.

In terms of theoretical implications, the meta-analytic evidence seems to suggest that synchronous online learning tends to support cognitive and affective processes more than other modes of instruction, possibly due to its high levels of social and teacher presence (Adam et al., 2025; Baker et al., 2013; Gegenfurtner et al., 2021; Kreijns et al., 2024; Martin et al., 2022; Mayer, 2020), particularly compared to asynchronous and waitlist conditions. This evidence tends to be in line with the CoI framework (Garrison, 2017). Future theory development can focus on conceptual models specifically for synchronous online learning environments to help understand how exactly social presence and other pedagogical features of the instructional design and motivation design (Keller, 2010) promote motivation, affect, and learning. Such a theory is currently missing and can be inspired by ample conceptual considerations on affective, cognitive, and social processes in digital education (Gegenfurtner et al., 2021; Hämäläinen, 2025; Li & Keller, 2018; Mayer, 2020; Moreno & Mayer, 2007; Schneider et al., 2022).

In terms of educational implications, it seems safe to recommend educators and educational policy makers to rely on synchronous online learning modalities because the meta-analytic parameter estimates favored webinars over face-to-face and asynchronous education. Of course, it can be speculated that particular instructional design features can further enhance (or even hamper) the benefits of webinars for learning and motivation. Still, our findings reported here signal that synchronous online learning has its place in the kaleidoscope of digital learning scenarios across the diversity of domains and disciplinary fields, including marketing, medical, professional, religious, science, and teacher education (Alnabelsi et al., 2015; Amirova et al., 2023; Francescucci & Rohani, 2019; Gegenfurtner et al., 2018; Olson & McCracken, 2015; Prawestri et al., 2020). To conclude, synchronous online instruction using webinar infrastructure from technical platforms such as Zoom, WebEx, or Teams seems an effective intervention to promote learning and motivation also now in post-pandemic education.

CRediT authorship contribution statement

Andreas Gegenfurtner: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Aldin Alijagic:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Sylvia Gabel:** Writing – review & editing, Conceptualization. **Özün Keskin:** Writing – review & editing, Conceptualization.

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[1] Studies preceded by an asterisk are included in the meta-analysis.

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