Exploring the Relationship Between Motivation and Academic Performance Among Online and Blended Learners: A Meta-Analytic Review

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Abstract

In higher education, motivational factors are considered one of "the strongest predictors of academic performance" (Honike et al., 2020, p. 1). A meta-analysis of face-to-face (f2f) courses (Richardson et al., 2012) supports these claims, finding a strong correlation between performance self-efficacy and academic performance ($r = 0.59$), as well as accounting for 14% of the variation in academic performance using locus of control, performance self-efficacy, and grade goal as predictors. These f2f results are compelling enough that self-efficacy is often used synonymously with online learning in primary research. However, the results of prior f2f meta-analytic reviews have yet to be extended to online and blended learning contexts. We explored student motivation, specifically subscales for attributional style, self-efficacy, achievement goal orientation, self-determination and task value in relation to student academic performance. Informed by 94 outcomes from 52 studies, our results diverge from f2f findings. The highest correlation was mastery avoidance goals ($r = 0.22$); academic self-efficacy ($r = 0.19$) was substantially lower than f2f findings ($r = 0.31$; $r = 0.59$) in Richardson et al. (2012). Using a parsimonious model (i.e., delivery mode, learning self-efficacy, and mastery approach goals), students' average academic performance failed to identify statistically significant predictors. These results call into question the assumption that student motivation is a strong predictor of academic performance in online and blended courses. The lack of strong relationships and the lack of predictive power hold clear implications for researchers, practitioners, and policymakers that assume these relationships are stronger.

Keywords: meta-analysis, online learning, blended learning, motivation

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Enrollment in online courses and degree programs has grown significantly in recent years. In 2012, more than 25% of college students in the United States were enrolled in at least one online course, a number that rose to 36% in 2019 (Hamilton & Freeman, 2023). By 2021, 60% of college students were taking some or all of their classes online. That is, roughly 8.5 million college students in the United States took online classes from public institutions (National Center for Education Statistics, 2022a). Increased enrollment in online courses or degree programs are likely due to a confluence of factors, including more positive perceptions of online learning. Changes in positive views of online learning may be due in part to evidence indicating that online students perform just as well academically as "traditional" face-to-face (f2f) learners (Bernard et al., 2004). However, there is wide variability in the results of studies that make these modality comparisons, with some studies showing a benefit of f2f attendance and others showing a benefit of online attendance.

One potential explanation for this variability in outcomes is student motivation, as illustrated in this quote by Allie Gasgreen (2012):

> It doesn't seem surprising that someone who can set goals, visualize paths to achieve them, and summon the motivation to start down those paths would be more likely to succeed than someone who can't do those things.

Strong evidence from studies of students learning in a f2f environment indicates that motivation matters for student success (Richardson et al., 2012). More current research with online students further indicates that online students exhibit lower intrinsic and extrinsic motivation, less interest, and less valuing of their courses than f2f students (Stark, 2019). Thus, students learning online might be more vulnerable to poorer academic outcomes if indeed the relationship between motivation and academic performance is similarly strong in online courses as it is in f2f courses. It is therefore not surprising that in online education, student motivation is of particular interest. Many measures of "readiness to learn online" include motivational constructs, such as self-efficacy and locus of control (e.g., Dray et al., 2011; Stritto et al., 2023; Tang et al., 2021). However, the number and quality of meta-analytic reviews examining the relationship between student motivation and academic performance in online contexts remains limited.

Given the proliferation of both online course offerings (Seaman et al., 2018) and online learner readiness instruments that link motivation to preparedness in online learning (Stritto et al., 2023), a rigorous review of research examining the relationship between student motivation and academic performance in online and blended courses is warranted. Therefore, in this meta-analysis, we investigated whether online students' motivational characteristics would predict their academic outcomes. In what follows, we briefly: (1) review the literature on the relationship between motivation and academic performance, (2) describe the motivational constructs relevant to current achievement motivation theories, and (3) report on our own meta-analysis of the relationship between a specific set of motivational constructs and online student performance.

Motivation and Academic Performance

Overall, research indicates that dimensions of motivation are positively correlated with college student outcomes (Howard et al., 2021; Huang, 2012; Multon et al., 1991; Richardson et al., 2012). For example, students who are intrinsically motivated to attend college tend to have higher GPAs and greater intentions to persist in college than students lacking that motivation

(Friedman & Mandel, 2011; Guiffrida et al., 2013). Other research indicates that motivational beliefs, like self-efficacy, can predict higher academic achievement (as measured by GPA; Bouih et al., 2021; Komarraju & Nadler, 2013). A more recent study shows that self-efficacy mediates the relationship between achievement goal orientation and academic achievement (Honicke et al., 2020).

Within the context of f2f learning, important meta-analytic work has tackled motivation research from several perspectives, including reviews of both intervention research and correlational studies. In a 2004 meta-analysis, the best predictors of GPA were academic self-efficacy and achievement motivation, while the best predictors of retention were academic goals and academic self-efficacy (Robbins et al., 2004). In 2012, a meta-analysis examining the relationship between a multitude of motivational constructs and academic performance found correlations anywhere from -0.14 (performance avoidance goal orientation) to much larger, positive values like 0.59 (performance self-efficacy). However, most effect sizes hovered around 0.10 (Richardson et al., 2012). In this same study, the researchers found that a model using locus of control, academic self-efficacy, and grade goal as predictors for GPA explained 14% of the variation in performance. After controlling for high school GPA and SAT/ACT scores, academic self-efficacy and grade goal were still significant predictors of GPA. In a meta-analytic review conducted by Lazowski and Hulleman in 2016, motivation theory informed interventions were generally effective ($d = 0.49$) within the full range of elementary to postsecondary education settings.

Based on this evidence, the academic community appears to agree that "motivational factors are [one of] the strongest predictors of academic performance" (Honike et al., 2020, p. 1). However, after nearly three decades of research, few careful systematic and meta-analytic reviews exist that can speak to the relationship between motivational factors and academic achievement in online or even blended courses. One exception is a recent systematic review of factors associated with academic performance in online classes (Chung et al., 2022). While motivation was not the stated focus, eight papers were found that intersected with motivation and academic performance. The review reported statistically significant correlations with self-efficacy, and an association with general motivation. However, no correlation values were reported as part of this systemic review.

In general, one issue with existing reviews is the variability in the quality of the reviews. Some reviews are grounded in established theoretical frameworks, pose specific research questions, delineate the search process, and set clear inclusion and exclusion criteria (Chung et al., 2022; Honicke & Broadbent, 2016; Tsai et al., 2011; Xu et al., 2021). Other reviews are not systematic (Artino & Stephens, 2009; Hodges, 2008; Kauffman, 2015; Meece et al., 2006; Miltiadou & Savenye, 2003) or vary in the extent to which important information about the search and inclusion process is disclosed (Alqurashi, 2016; Moos & Azevedo, 2009; Ng, 2019). Of the systematic or meta-analytic reviews that do exist, many focus exclusively on different facets of self-efficacy (e.g., Alqurashi, 2016; Hodges, 2008; Honicke & Broadbent, 2016; Moos & Azevedo, 2009), which is just one of several variables that make up student motivation (Wigfield et al., 2021).

Student Motivation

In psychological science, motivation is viewed as a complex, multidimensional latent construct consisting of several different dimensions including but not limited to: self-efficacy, achievement goal orientation, intrinsic and extrinsic motivation, task value, and attributional style. In this section, we briefly define each of these motivational constructs according to empirical research.

Self-Efficacy

Self-efficacy—a person's belief in their ability to organize and execute the tasks required to achieve a desired level of performance—is derived from Bandura's Social Cognitive Theory (1986, 1997). According to this definition, self-efficacy is domain specific. A student's self-efficacy for a particular academic task is influenced by several factors: (1) previous performance on a similar task, (2) observing others failing or succeeding at the task, (3) encouragement from instructors or peers, and (4) affective reactions to the task (e.g., anxiety; Wigfield et al., 2021). Generally, increased self-efficacy motivates engagement in a task and more specifically, academic self-efficacy has been positively correlated with a range of educational outcomes (Joo et al., 2013; Strawser et al., 2019). In the context of online learning, there is clear interest in both domain adaptations of self-efficacy, as well as modality specific adaptations of self-efficacy. This interest is manifested in the creation of measures like the Online Learning Self-Efficacy Scale (Zimmerman & Kulikowich, 2016).

Achievement Goal Orientation

Achievement goal orientation is "a future focused cognitive representation" (Hulleman et al., 2010, p. 423) that guides behavior either towards or away from a specific outcome or goal. In the literature, achievement goals are typically measured across two dimensions: (1) mastery vs. performance goals and (2) approach vs. avoidance goals (Bardach et al., 2020; Elliot & McGregor, 2001; Elliot & Murayama, 2008; Hulleman et al., 2010). Mastery goal orientation reflects learning for the sake of learning—to gain new knowledge of skills. Performance goal orientation instead represents a student's desire to learn only so that they appear competent (or avoid seeming incompetent) to others. Approach goals refer to a desire to learn, while avoidance goals refer to a desire to avoid failure. In general, mastery goal orientation (without regard to approach or avoidance) relates to positive academic outcomes (e.g., increased engagement, improved performance). The results of a performance goal orientation are more dependent upon the approach or avoidance orientation: performance approach goals are associated with better academic performance while performance avoidance goals are associated with worse performance. In a rigorous meta-analytic review published by Hulleman and colleagues (2010), the authors examined correlations between academic achievement, defined as class grades or test scores, and achievement goal constructs. They found small positive correlations for performance approach and mastery approach and inverse correlations for performance avoidance and mastery avoidance.

Intrinsic and Extrinsic Motivation

Self-Determination Theory (SDT; Deci & Ryan, 1985) outlines three classes of motives for human behavior: (1) autonomy, (2) competence, and (3) relatedness. Within this framework, Ryan and Deci distinguished between different reasons that people pursue a specific goal. The basic distinction made is between intrinsic and extrinsic motivation. Intrinsic motivation involves carrying out an action for its own sake or internal value (e.g., for interest or fun; Ryan, 2019; Ryan & Deci, 2000). Extrinsic motivation involves acting toward a goal that has consequences separate from the activity itself. That is, external rewards, punishments, or other factors outside of the individual influence the individual's motivation to act. Almost all empirical research shows that supporting students' intrinsic motivations has positive effects on their performance, while the use of extrinsic motivations has mixed effects on performance (Ryan & Deci, 2000). In more recent theorizing, there are varied types of extrinsic motivation that Ryan and Deci (2020) have categorized into four sub-types including: (1) external regulation (behaviors motivated by external rewards or punishments); (2) introjection regulation (behaviors motivated by internalized emotions like pride or shame); (3) identified regulation (behaviors motivated by the perceived value of a task); and (4) integrated regulation (behaviors motivated by the alignment of both the perceived value of a task and the inherent enjoyment experienced in completing the tasks).

Task Value

According to the situated expectancy-value theory of achievement motivation (Eccles & Wigfield, 2020), achievement related decisions depend on cultural, social, and psychological influences. The psychological influences are expectancies for success (very similar to self-efficacy) and subjective task values. Subjective task values have been further operationalized as attainment value (importance of doing well on a task), intrinsic value, utility value (how a task relates to current and future goals), and cost. Previous research has focused on measuring changes in motivation over time, how motivation is related to course and major selection, and motivational factors that influence retention and performance (Hulleman et al., 2016). Additionally, recent work has examined how interventions to strengthen these motivational beliefs impact achievement-related behaviors (Kosovich et al., 2019; Rosenzweig et al., 2020; Totonchi et al., 2022).

Attributional Style

Attributional style (Weiner, 1985; 2010) refers to how students perceive the causes of their academic successes and failures. A student's causal attribution comprises three components: (1) locus of causality, (2) stability, and (3) controllability. Locus refers to whether students' view the cause as internal (something about them) or external (something outside of themselves). Stability refers to whether the cause is constant (remains the same over time and in different situations) or whether it is variable. Controllability refers to whether the cause is under the student's volitional control. As an example, if a student receives a failing grade on a physics exam and attributes the failure to their ability to "do physics," the attribution is internal, unstable, and not under optional control. However, if the student were to attribute the failing grade to a lack of sleep because a fire alarm went off in the dorm the night before, this attribution is external, unstable, and uncontrollable. Different combinations of the components of causal attributions tend to motivate academic behavior in specific ways (Graham, 2020). In the first example, the student will be less motivated to improve moving forward while in the second example, they are likely to be more motivated.

Problem Statement and Research Questions

In summary, research with on-campus students indicates that motivation is associated with academic performance (e.g., Dokhykh, 2021; Friedman & Mandel, 2011; Guiffrida et al., 2013; Honicke et al., 2020), although a comprehensive meta-analytic review of well-established motivational constructs revealed considerable variability in this relationship (Richardson et al., 2012). To the best of our knowledge, only one systematic review focused on online students (Chung et al., 2022); only eight studies were found that intersect with motivation, as their focus was quite broad. Therefore, the aim of this meta-analysis was to examine the extent to which students' academic achievement in online or blended courses is related to their motivational characteristics. Our specific research questions were as follows:

***RQ$_1$*:** What is the relationship between students' motivational characteristics (specifically self-determination motivation, attributional style, task value, self-efficacy, and achievement goals) and academic performance in online or blended learning environments?

***RQ$_2$*:** Does the relationship between students' motivational characteristics and student academic performance differ between online and blended learning environments?

***RQ$_3$*:** What combination of instructional delivery mode (blended/online) and motivational characteristics best predicts positive student academic performance?

Methods

Search Strategy

Using Gusenabuer and Haddaway's (2020) recommendations for meta-analysis, we searched the following educational databases: Psychological and Behavioral Sciences, Education Source, Social & Behavioral Sciences, ERIC, PsycINFO, Education Full Text, Proquest, Science Direct, SCOPUS, Wiley Online Library, and Web of Science. We searched these databases using the following Boolean operators: (internality OR "internal locus of control" OR "external locus of control" OR globality OR stability OR "attributional style" OR "academic locus of control" OR optimism OR "self-efficacy" OR "intrinsic motivation" OR "extrinsic motivation" OR "goal orientation" OR "achievement goal" OR "task value") AND ALL= ("online learning" OR "distance learning" OR "web based learning" OR "blended learning"). To be comprehensive, we searched back to 1990, the year web browsers and the http protocol helped democratize information access (Berners-Lee et al., 1994). The earliest year of data collection for a study that met inclusion criteria was 1998. We also looked through existing systematic and narrative reviews, as well as included primary research studies to look for search referrals or "footnote chasing" (White, 2019).

Inclusion and Exclusion Criteria

After a scoping review, we determined that descriptive designs with correlations would yield the largest number of studies and outcomes. We included articles describing research studies that took place in the context of blended or online learning and measured one or more of the following motivational constructs: (1) attributional style (locus of control); (2) self-efficacy (general, domain-specific, or technology); (3) achievement goal orientation; (4) intrinsic or extrinsic motivation; (5) task value; or (6) "motivation" generally. We also included articles that reported performance-based outcomes (e.g., course or exam grades), provided sufficient data to derive a correlation between motivation and performance, and sampled college or vocational students.

We excluded articles if the reported studies were conducted in response to the COVID-19 pandemic. While many colleges and universities began offering remotely delivered courses in March of 2020, these courses do not represent intentionally designed online or blended courses. As pathways back to "a new normal" varied by university, we chose to treat Summer and Fall of 2020 as still containing potential COVID era classes, in part because social distancing and active pandemic management strategies were still in place. In the case of duplicate data or reporting, the write-up with the most thorough dataset was retained. See Appendix A for the full list of included articles. This appendix reports: (1) APA citations; (2) outcome names; (3) measures used for prediction; and (4) coded variables used in subsequent analyses (i.e., effect size estimates r, sample size, confidence intervals, modality *blended/online*, and the motivational construct measured).

Coding Procedures

Search Results and Screening Process

We conducted a two-phase screening process to determine inclusion or exclusion (see Figure 1). Members of the research team conducting the database searches carried out an independent first-pass screening of titles and abstracts to determine if a study included performance-based outcomes, motivational constructs, and an online or blended course modality. Database searches returned 10,946 potential articles and this initial screening resulted in a substantial reduction of studies. We added to the database results with an ancestral search of included articles, resulting in an additional 59 returns.

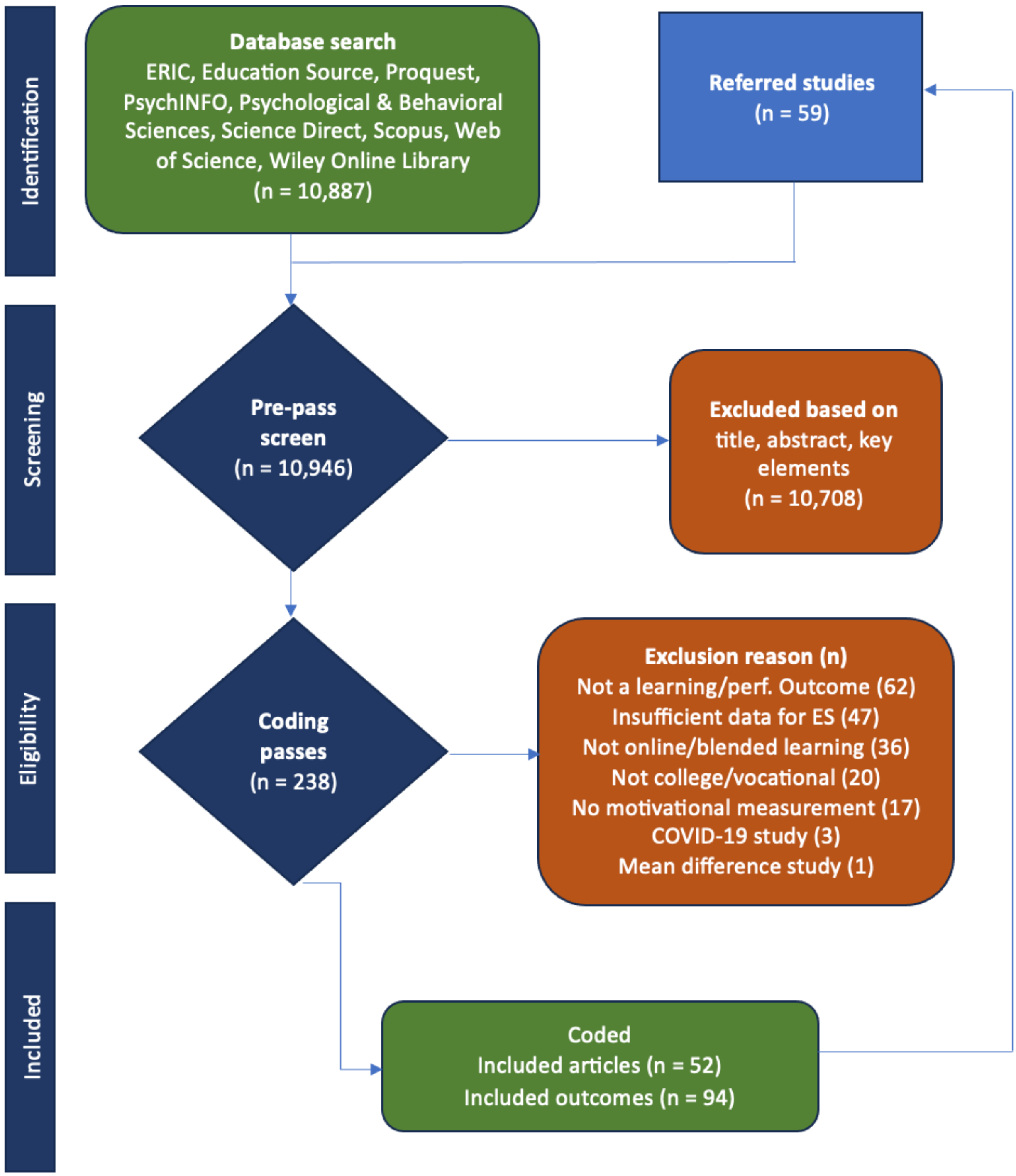
A total of 238 articles (2.8%) went through to the second phase of the screening process. During the second phase of screening, rotating pairs of researchers applied the inclusion criteria to the full text of the remaining articles. The final number of included articles was 52. At this stage, most promising studies were removed for presenting affective/motivational instruments as academic performance (e.g., satisfaction, self-efficacy), failing to report or provide enough information to calculate an effect size, falling outside of the college/vocational sphere, or using the phrase online or blended without meeting definitions for the terms as described by the Online Learning Consortium[1].

Coding Process

The coding team consisted of five researchers experienced in meta-analytic review processes and coding procedures. Each study went through an independent first and second pass followed by a consensus coding phase. Interrater reliability for each coded variable was assessed by means of Krippendorff's alpha (2004) which is robust to the full range of data types. Specific reliability results are presented in alongside the coded variables and type of data for each analysis. The full coding guide is available upon request.

[1] https://onlinelearningconsortium.org/updated-e-learning-definitions-2/

Figure 1
Literature Search Stages and Outcomes PRISMA



<u>Coding Scheme</u>

The following information was extracted from each study. We list this information alongside the inter-rater reliability from independent coding passes: (1) article citation information including year of data collection; (2) course delivery mode (α = 1.00, nominal); (3) motivational construct (α = 0.67, nominal); (4) sample size (α = 0.99, ratio); (5) type of correlation (α = 0.99, nominal); and (6) correlation (i.e., effect size, α = 0.99, ratio).

Results

By design, this meta-analytic review set out to cover a wide range of motivational constructs, across studies that reported different learning outcomes (such as test scores or grades), and were conducted in different disciplines. As a result, it is unreasonable to assume there was a single true effect size, and a random effects model was used in all relevant analyses. A Hunter-Schmidt correction was used for correlation coefficients (Schmidt & Hunter, 2015). This was selected primarily because the observed correlations were already normally distributed and because it allows the data to be kept, analyzed, and reported on in their original scale. The origins are rooted in adjusting based on reliability scores which were not widely available. Rather than impute reliability, we used a simple inverse variance weighting factor. All supporting and primary analyses were conducted in STATA MP version 17.

Supporting Analyses

Before addressing the research questions, an examination of the data for key decision points was conducted, including outlier detection, publication bias, and independence of outcomes and their study of origin. Each of these supporting analyses and any corresponding decisions could impact subsequent results, which is why they are presented first.

<u>Single outlier</u>

A quick examination revealed a single negative outlier, defined as an observation at least three standard deviation units above or below the mean. As a first step, a detailed look at the outlier outcome, from Stephen et al. (2020), showed no characteristics so different that it should be dropped from the study. Rather than lose the data, we trimmed the coefficient to the next lowest observed correlation (r = -0.58).

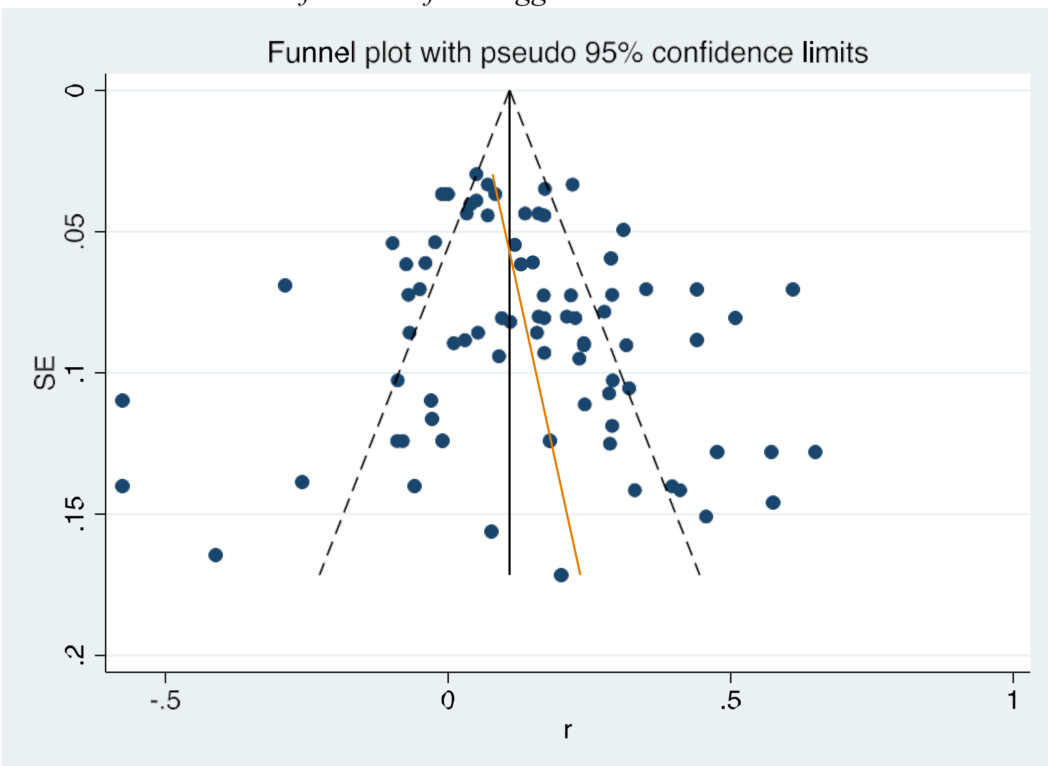
<u>No publication bias</u>

Publication bias was thus examined through multiple lenses as recommended (Bell, 2007) and with great care given known missing effect sizes. Visual inspection of a funnel plot does not show a consistent pattern of more correlations that are above the observed mean correlation with higher standard error (see Figure 2). Visual inspection aligns with the Egger's test, t (94) = 0.58, p = 0.20 ,which fails to lend support for publication bias even after trimming a negative outlier.

<u>No dependence factor</u>

With an average of 1.8 and maximum of 6 outcomes per article, the independence assumption for many of the statistics employed in meta-analysis was violated. Using a robust variance estimation analysis, we tested six levels of assumed intra-class correlation between the observed correlation values and the study of origin. The difference in the modeled coefficient between an intra-class correlation of 0 and an intra-class correlation of .99 was .007. This narrow difference lends support to the idea that study of origin is not a factor in the effect sizes for this meta-analysis. As a result, outcomes were largely kept as separate effect sizes, combined only when outcomes from the same study were coded identically on all criteria.

Figure 2
Funnel Plot with Line of Best Fit from Egger's Test



Results reporting and magnitude

To provide a consistent point of reference, the overall effect size across all outcomes (r = 0.14) is reported any time all data points are summarized. This overall effect size should not be cited as there are substantial differences between these studies and outcomes, which is why a random effects model was used. The only meaningful summaries to cite are the effect sizes for the five motivational constructs and their subconstructs (see Table 1) or the blended vs online modality (see Table 2). In general, closer ties between outcomes yield more meaningful the summaries. Interpreting effect sizes using the context of prior research findings is recommended best practice (Durlak, 2009). In Richardson et al. (2012), the classroom equivalent to this meta-analysis of online learning relies on Cohen's guidelines of small (.10), medium (.30), and large (.50). Their findings encompass a wide range (r = 0.01 to r = 0.59) with most correlations being small. Hedges and Hedberg (2007) claim that educational researchers may find policymaker interest in a mean difference (d) effect size of .20, which is roughly equivalent to an r of 0.10 (Fritz et al., 2012). Using the Richardson et al. (2012) scale for both the magnitude and the significance, and using the adjusted Hedges and Hedberg (2007) threshold, our results indicated effect sizes clustered around the small range, and are of policy maker interest (r = 0.10).

All findings are reported alongside 95% confidence intervals and two measures of heterogeneity including Q with significance testing and I^2. With the sole exception of *optimism* all groupings show statistically significant heterogeneity (Q) that is based upon meaningfully large proportions (I^2) of observed variation in differences in effect sizes. This is best encapsulated in Appendix B, where a series of figures show a Funnel plot of all outcomes organized by motivational constructs and subconstructs. The funnel plots shows both variation in individual correlation values and variation in confidence intervals for outcomes.

RQ1—Motivational characteristics and performance

As shown in Table 1, almost half of the observed outcomes dealt with some form of *self-efficacy* including *technology* (n = 18) and *learning self-efficacy* (n = 28). Subscales are presented from inverse/lowest correlations to highest and grouped around theoretically aligned motivational constructs, which are also summarized together. Note that each scale was coded with the directionality that an increase in the motivational subscale would be associated with an increase in performance.

Table 1

Motivational Relationships, Grouped By Scale and Subscale With 95% Confidence Intervals

motivation (sub)scales	***n***	***r***	***CI[95%]***	***I2***	***Q***	***p***
self-determination motivation	16	0.13	[0.02, 0.18]	87.5%	135.6	0.01
relative autonomy index	1	-0.04	[-0.16, 0.08]	-	-	-
general motivation	5	0.12	[0.02, 0.22]	93.8%	64.8	0.01
intrinsic motivation	8	0.15	[0.08, 0.22]	83.9%	49.7	0.01
extrinsic motivation	3	0.15	[0.03, 0.28]	82.7%	11.58	0.03
attributional style	15	0.12	[0.08, 0.17]	73.9%	53.7	0.01
internal locus of control	6	0.10	[0.03, 0.16]	84.3%	31.9	0.01
optimism	4	0.08	[0.04, 0.12]	51.3%	6.2	0.10
external locus of control	5	0.18	[0.08, 0.29]	69.1%	12.9	0.01
task value	6	0.14	[0.09, 0.19]	66.4%	14.9	0.01
self-efficacy	46	0.14	[0.12, 0.17]	79.9%	223.7	0.01
technology self-efficacy	18	0.07	[0.03, 0.12]	79.6%	83.3	0.01
learning self-efficacy	28	0.19	[0.16, 0.23]	81.4%	145.5	0.01
achievement goals	10	0.16	[0.12, 0.20]	93.6%	141.6	0.00
performance avoidance	2	0.15	[-0.06, 0.09]	76.2%	4.21	0.04
performance approach	2	0.17	[0.21, 0.25]	96.7%	30.3	0.01
mastery approach	4	0.20	[0.14, 0.26]	95.6%	68.3	0.01
mastery avoidance	2	0.22	[0.14, 0.29]	97.9%	48.0	0.01
Overall	**94**	**0.14**	**[0.12, 0.16]**	**83.2%**	**554.5**	**0.01**

The variations between *technology* and *learning self-efficacy* back up theoretical claims that self-efficacy is situationally dependent. In the context of online learning, the results call into question the utility of assessing *technology self-efficacy*, given the poor relationship (r = 0.07) with student performance. While *learning self-efficacy* showed a stronger relationship ($r = 0.19$) than many of the subscales, it did not approach previous findings (Richardson et al, 2012) of medium *self-efficacy* relationships ($r = 0.31$) for face to face classes.

Achievement goals subscales were consistently among the largest correlations values peaking at *mastery avoidance* ($r = 0.22$) and essentially similar to *learning self-efficacy*. They reveal both promise and a need for replication work, as they were some of the fewest outcomes across all subscales. By way of contrast, the single point estimate for *relative autonomy index*, an effort to encapsulate intrinsic and extrinsic motivation in a single scale, may not be worth replicating ($r = -0.04$). *Optimism* ($r = 0.08$) was the only subgroup analysis to have support for homogeneous outcomes. Rather than indicating a single true effect size, this is most likely attributable to all outcomes ($n = 4$) coming from the same study. Much like achievement goals, additional research is needed.

RQ2—Motivation for online and blended learning

According to our coding criteria, online classes needed to be entirely online. Note that proctored in-person testing that are not part of the learning experience were not considered an in-person portion of the class (Behcekapili & Karaman, 2020). For a class to be considered "blended," at least 25% of the class needed to be online and the online content for blended classes needed to cover unique material.

The correlation between motivation and learning (see Table 2) for blended course experiences was slightly larger ($r = 0.21$) than online ($r = 0.12$) and this difference was statistically significant (ANOVA style Z test, $Z = 6.93$, $p = 0.01$). However, this difference is not practically significant. For blended courses, about 5% ($R^2 = 0.05$) of the variability in performance was explained by differences in motivation. For online courses, this dropped to 1% ($R^2 = 0.01$). In both delivery formats, there was at best a small relationship between motivation and learning.

Table 2
Motivational relationships by delivery mode with 95% confidence intervals

Delivery mode	*n*	*r*	*CI[95%]*	*I2*	*Q*	*p*
online	78	0.12	[0.10, 0.14]	82.8%	446.6	.01
blended	16	0.21	[0.16, 0.27]	85.5%	103.7	.01
Overall	**94**	**0.14**	**[0.12, 0.16]**	**83.2%**	**554.5**	**.01**

RQ 3—Predicting student performance

To address the combination of variables that predict students' academic performance, key variables for motivational construct and delivery mode were dummy coded with *online delivery* (as the lower correlation value) and *relative autonomy index* (as the closest correlation to zero) used as the reference groups. This aids in interpretation of the beta coefficients where positive values are associated with an increase in student performance (see Table 3).

Table 3
Meta Regression (Full and Final) Models Predicting Student Learning and Performance

model/variable	b	SE	t	P
full model				
blended delivery	0.08	0.07	1.30	0.20
general motivation	-0.03	0.18	-0.16	0.87
intrinsic motivation	0.00	0.17	0.02	0.98
extrinsic motivation	-0.01	0.20	-0.04	0.97
internal locus of control	-0.05	0.17	-0.27	0.79
optimism	-0.04	0.18	-0.25	0.80
external locus of control	0.04	0.18	0.25	0.80
task value	0.02	0.17	0.13	0.90
technology self-efficacy	-0.06	0.15	-0.42	0.68
learning self-efficacy	0.04	0.15	0.23	0.82
performance avoidance	-0.10	0.20	-0.51	0.61
performance approach	0.04	0.20	0.19	0.85
mastery approach	0.07	0.18	0.40	0.69
mastery avoidance	0.08	0.20	0.39	0.70
intercept	0.12	0.14	0.86	0.39
final model				
blended delivery	0.08	0.06	1.30	0.20
learning self-efficacy	0.06	0.05	1.20	0.23
mastery approach	0.09	0.10	0.92	0.36
intercept	0.10	0.03	3.87	0.00

Note: b = beta coefficient, *SE* = standard error

Put simply, no combination of variables reliably predicted student performance. Two meta-regression models were run, the first full model included all of the variables, the second final model removed those with lowest *t*-scores. Both the full model, F (14, 79) = 0.46, p = 0.95, adjusted R^2 = -15.21%, and the more parsimonious final model, F (3, 90) = 1.38 p = 0.25, adjusted R^2 = 0.71%, were a poor fit for the data. Using all available predictor variables failed to outperform a simple average of student performance, resulting in a negative R^2 value. The parsimonious model had no significant predictors and accounted for less than 1% of the variability in student performance. Both models are poor fits likely because of the low correlation values, as well as the sparse data in the meta-regression analysis. In short for online/blended students other factors seem to be more important than motivation. For instance, online students with high task value, high self-efficacy, and a mastery approach orientation to a course can still experience mental health emergencies, or abruptly lose access to childcare.

Conclusion and Discussion

One strength of meta-analysis is the ability to make recommendations, and our findings have implications for both practitioners and researchers. For practitioners, we agree with scholars who are calling on faculty to carefully consider how to support student success through course design (Jones, 2014) or providing support structures, including university counseling services for students experiencing anxiety or distress (Sulla et al., 2022). Practitioners may also want to explore or continue on-going partnerships with researchers to carefully examine the elements of course design that are strongly associated with academic performance in both online and blended modalities.

For researchers, more work is needed examining student factors and other contextual factors that may help explain the motivational relationship differences between f2f learners and learners in online and blended courses. These factors include but are not limited to: self-regulated learning; personality; learning preferences; demographics; employment status; student experience; enrollment; and instructors. Learning strategies, which form many of the subscales in the MSLQ (Pintrich, 1991), may also help explain these differences. Both primary research and review work investigating other student level, course level, and institutional level factors would encourage all stakeholder to move past reasonable assumptions and towards data-informed practices that are specific to online and blended learners (such as Chung et al., 2022; Jones, 2014; Sulla et al., 2022). A recent example of research in this area is a systematic review conducted by Chung and colleagues (2022), examining the correlates of academic performance in online courses. Based on their review and our meta-analysis, it is clear that focusing search efforts on predictors of academic performance yields more primary research; Chung et al. (2022) included eight studies examining motivational constructs whereas this meta-analysis included 52 (Chung et al., 2022; Jones, 2014).

A final recommendation for scholars is to think critically about the measurement space for this work. It is clear that researchers, following the recommendations of Bandura (1986, 1997), have treated constructs like self-efficacy as domain/content specific. Established measures, such as the MSLQ, have been adapted to the content areas and sometimes within online settings. In some cases, new measures, coded as technology self-efficacy, were created to cover constructs like computer self-efficacy (Simmering et al., 2009) or internet self-efficacy (Panigrahi et al., 2021). In this meta-analysis, technology self-efficacy correlations were among the largest number of outcomes (n = 18) with the second lowest correlation value ($r = 0.07$). Based on this work, niche approaches like technology self-efficacy are likely of secondary importance to the content domain. In our view, a parsimonious approach that is focused on content rather than modality is a better way to measure motivation.

In conclusion, the results of this meta-analysis challenges existing assumptions about the relationship between student motivation and academic performance in online and blended courses. This relationship may vary considerably based on a number of factors, including the type of motivation, how it is measured, and the modality in which the learning is taking place. The recommendations offer here will hopefully galvanize both practitioners and researchers to carefully consider other factors that impact student motivation, academic performance, and their relationship, through additional systematic review work and primary research.

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References

Akin, A. (2007). Academic locus of control scale: A study of validity and reliability. *Çukurova University Journal of Educational Faculty*, *34*(3), 9–17. https://www.acarindex.com/dosyalar/makale/acarindex-1423874900.pdf

Alkış, N., & Temizel, T. T. (2018). The impact of motivation and personality on academic performance in online and blended learning environments. *Journal of Educational Technology & Society*, *21*(3), 35–47. https://doi.org/10.30191/ETS.201807_21(3).0004

Alqurashi, E. (2016). Self-efficacy in online learning environments: A literature review. *Contemporary Issues in Education Research (Online)*, *9*(1), 45–52.

Amin, E. A.-R. (2016). Using wikis in developing writing performance and motivation among EFL students at Majmaah University. *Journal of Faculty of Education—Benha University*, *352*(3502), 1–31. https://doi.org/10.12816/0028199

Amin, E. A.-R. (2019). A correlational study between some motivational constructs and EFL writing performance in a blended learning environment. *International Journal of English Linguistics*, *9*(3), 238–248. https://doi.org/10.5539/ijel.v9n3p238

Artino, A. R., Jr., & Stephens, J. M. (2009). Beyond grades in online learning: Adaptive profiles of academic self-regulation among naval academy undergraduates. *Journal of Advanced Academics*, *20*(4), 568–601. https://doi.org/10.1177/1932202X0902000402

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice Hall.

Bardach, L., Oczlon, S., Pietschnig, J., & Lüftenegger, M. (2020). Has achievement goal theory been right? A meta-analysis of the relation between goal structures and personal achievement goals. *Journal of Educational Psychology, 112*(6), 1197–1220. https://doi.org/10.1037/edu0000419

Baturay, M. H., & Yukselturk, E. (2015). The role of online education preferences on student's achievement. *Turkish Online Journal of Distance Education*, *16*(3), 3–12. https://doi.org/10.17718/tojde.47810

Bell, P. D. (2007). Predictors of college student achievement in undergraduate asynchronous web-based courses. *Education*, *127*(4), 523–533. https://doi.org/10.1016/j.compedu.2023.104776

Bernard, R. M., Abrami, P. C., Wade, A., Borokhovski, E., & Lou, Y. (2004). *The effects of synchronous and asynchronous distance education: A meta-analytical assessment of Simonson's "Equivalency Theory." 2004 AECT Convention- 27th Annual Proceedings, 1*, 102–109. https://eric.ed.gov/?id=ED485078

Bouih, A., Nadif, B., & Benattabou, D. (2021). Assessing the effect of general self-efficacy on academic achievement using path analysis: A preliminary study. *Journal of English Language Teaching and Applied Linguistics, 3*(4), 18–24. https://doi.org/10.32996/jeltal.2021.3.4.3

Cannon, J. P., Lohtia, R., & Paulich, B. J. (2023). Blended learning in principles of marketing: The effects of student differences on student performance. *Journal of Marketing Education*, *45*(1), 70–90. https://doi.org/10.1177/02734753211058357

Cassidy, S., & Eachus, P. (2002). Developing the Computer User Self-Efficacy (CUSE) scale: Investigating the relationship between computer self-efficacy, gender and experience with computers. *Journal of Educational Computing Research*, *26*(2), 133–153. https://doi.org/10.2190/JGJR-0KVL-HRF7-GCNV

Chang, C. S. (2000). *The effect of attitudes and self-efficacy on college student performance in online instruction* [Doctoral dissertation, University of Kansas]. ProQuest Dissertations and Theses. https://www.proquest.com/docview/304603922

Chang, C.-S., Liu, E. Z.-F., Sung, H.-Y., Lin, C.-H., Chen, N.-S., & Cheng, S.-S. (2014). Effects of online college student's Internet self-efficacy on learning motivation and performance. *Innovations in Education & Teaching International*, *51*(4), 366–377. https://doi.org/10.1080/14703297.2013.771429

Chang, M.-M., & Ho, C.-M. (2009). Effects of locus of control and learner-control on web-based language learning. *Computer Assisted Language Learning*, *22*(3), 189–206. https://doi.org/10.1080/09588220902920094

Chen, K.-C., & Jang, S.-J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior*, *26*(4), 741–752.

Cho, M.-H., & Shen, D. (2013). Self-regulation in online learning. *Distance Education*, *34*(3), 290–301. https://doi.org/10.1080/01587919.2013.835770

Chung, J., McKenzie, S., Schweinsberg, A., & Mundy, M. E. (2022, February). Correlates of academic performance in online higher education: A systematic review. *Frontiers in Education,* 7, 820567. https://doi.org/10.3389/feduc.2022.820567

Crandall, V. C., Katkovsky, W., & Crandall, V. J. (1965). Children's beliefs in their own control of reinforcements in intellectual-academic achievement situations. *Child Development*, *36*(1), 91–109. https://doi.org/10.2307/1126783

Deci, E. L., & Ryan, R. M. (1985). Conceptualizations of intrinsic motivation and self-determination. In *Intrinsic motivation and self-determination in human behavior* (pp. 11–40). Plenum Press.

DeTure, M. (2004). Cognitive style and self-efficacy: Predicting student success in online distance education. *American Journal of Distance Education*, *18*(1), 21–38.

Dokhykh, R. A. (2021). The impact of motivation on the academic performance of university students. *Journal of Humanities & Social Sciences, 5*(13), 103–113. https://doi.org/10.26389/AJSRP.R060221

Dray, B. J., Lowenthal, P. R., Miszkiewicz, M. J., Ruiz-Primo, M. A., & Marczynski, K. (2011). Developing an instrument to assess student readiness for online learning: A validation study. *Distance Education*, *32*(1), 29–47. https://doi.org/10.1080/01587919.2011.565496

Duncan, T. G., & McKeachie, W. J. (2005). The making of the Motivated Strategies for Learning Questionnaire. *Educational Psychologist*, *40*(2), 117–128. https://doi.org/10.1207/s15326985ep4002_6

Eastin, M. S., & LaRose, R. (2000). Internet self-efficacy and the psychology of the digital divide. *Journal of Computer-Mediated Communication*, *6*(1), JCMC611. https://doi.org/10.1111/j.1083-6101.2000.tb00110.x

Eccles, J., Adler, T., & Meece, J. L. (1984). Sex differences in achievement: A test of alternate theories. *Journal of Personality and Social Psychology, 46*(1), 26–43.

Elliot, A. J., & McGregor, H. A. (2001). A 2 × 2 achievement goal framework. *Journal of Personality and Social Psychology*, *80*(3), 501–519. https://doi.org/10.1037/0022-3514.80.3.501

Elliot, A. J., & Murayama, K. (2008). On the measurement of achievement goals: Critique, illustration, and application. *Journal of Educational Psychology*, *100*(3), 613–628. https://doi.org/10.1037/0022-0663.100.3.613

Ergul, H. (2004). Relationship between student characteristics and academic achievement in distance education and application on students of Anadolu University. *Turkish Online Journal of Distance Education*, *5*(2), 81-90.

Fadda, H. A. (2019). The relationship between self-regulations and online learning in an ESL blended learning context. *English Language Teaching*, *12*(6), 87–93. https://doi.org/10.5539/elt.v12n6p87

Finney, S. J., & Schraw, G. (2003). Self-efficacy beliefs in college statistics courses. *Contemporary Educational Psychology*, *28*(2), 161–186. https://doi.org/10.1016/S0361-476X(02)00015-2

Friedman, B. A., & Mandel, R. G. (2011). Motivation predictors of college student academic performance and retention. *Journal of College Student Retention: Research, Theory & Practice*, *13*(1), 1–15. https://doi.org/10.2190/CS.13.1.a

Gerlich, R., Mills, L., & Sollosy, M. (2009). An evaluation of predictors of achievement on selected outcomes in a self-paced online course. *Research in Higher Education, 4*, 1–14.

Goad, T., Jones, E., Bulger, S., Daum, D., Hollett, N., & Elliott, E. (2021). Predicting student success in online physical education. *American Journal of Distance Education*, *35*(1), 17–32. https://doi.org/10.1080/08923647.2020.1829254

Grasgreen, A. (2012, July 5). *Here's Hoping*. Inside Higher Ed. https://www.insidehighered.com/news/2012/07/06/researchers-apply-hope-theory-boost-college-student-success

Grolnick, W. S., & Ryan, R. M. (1987). Autonomy in children's learning: An experimental and individual difference investigation. *Journal of Personality and Social Psychology*, *52*(5), 890–898. https://doi.org/10.1037/0022-3514.52.5.890

Guamer Erickson, A. S., & Noonan, P. M. (2018). Self-efficacy formative questionnaire. In *The skills that matter: Teaching interpersonal and intrapersonal competencies in any classroom* (pp. 175–176). Corwin.

Guiffrida, D. A., Lynch, M. F., Wall, A. F., & Abel, D. S. (2013). Do reasons for attending college affect academic outcomes?: A test of a motivational model from a self-determination theory perspective. *Journal of College Student Development*, *54*(2), 121–139. https://doi.org/10.1353/csd.2013.0019

Goulão, M. (2014). The relationship between self-efficacy and academic achievement in adults' learners. *Athens Journal of Education*, *1*, 237–246.

Gusenbauer, M., & Haddaway, N. R. (2020). Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. *Research Synthesis Methods, 11*(2), 181–217. https://doi.org/10.1002/jrsm.1378

Hamilton, I., & Freeman, V. (2023, May 24). *By the numbers: The rise of online learning in the U.S.* Forbes Advisor.

Hamm, J. M., Perry, R. P., Chipperfield, J. G., Parker, P. C., & Heckhausen, J. (2019). A motivation treatment to enhance goal engagement in online learning environments: Assisting failure-prone college students with low optimism. *Motivation Science*, *5*(2), 116–134. https://doi.org/10.1037/mot0000107

Hobson, T. D., & Puruhito, K. K. (2018). Going the distance: Online course performance and motivation of distance learning students. *Online Learning*, *22*(4), 129–140. https://doi.org/10.24059/olj.v22i4.1516

Hodges, C. B. (2008). Self-efficacy, motivational email, and achievement in an asynchronous math course. *The Journal of Computers in Mathematics and Science Teaching*, *27*(3), 265–285. https://www.learntechlib.org/primary/p/25282/

Honicke, T., & Broadbent, J. (2016). The influence of academic self-efficacy on academic performance: A systematic review. *Educational Research Review*, *17*, 63–84. https://doi.org/10.1016/j.edurev.2015.11.002

Honicke, T., Broadbent, J., & Fuller-Tyszkiewicz, M. (2020). Learner self-efficacy, goal orientation, and academic achievement: Exploring mediating and moderating relationships. *Higher Education Research & Development*, *39*(4), 689–703. https://doi.org/10.1080/07294360.2019.1685941

Howard, J. L., Bureau, J. S., Guay, F., Chong, J. X. Y., & Ryan, R. M. (2021). Student motivation and associated outcomes: A meta-analysis from Self-Determination Theory. *Perspectives on Psychological Science, 16*(6), 1300–1323. https://doi.org/10.1177/1745691620966789

Hrastinski, S. (2019). What do we mean by blended learning? *TechTrends, 63*(5), 564–569. https://doi.org/10.1007/s11528-019-00375-5

Huang, C. (2012). Discriminant and criterion-related validity of achievement goals in predicting academic achievement: A meta-analysis. *Journal of Educational Psychology*, *104*(1), 48–73. https://doi.org/10.1037/a0026223

Hulleman, C. S., Barron, K. E., Kosovich, J. J., & Lazowski, R. A. (2016). Student motivation: Current theories, constructs, and interventions within an Expectancy-Value framework. In A. A. Lipnevich, F. Preckel, & R. D. Roberts (Eds.), *Psychosocial skills and school systems in the 21st Century* (pp. 241–278). Springer International Publishing.

Hulleman, C. S., Schrager, S. M., Bodmann, S. M., & Harackiewicz, J. M. (2010). A meta-analytic review of achievement goal measures: Different labels for the same constructs or different constructs with similar labels? *Psychological Bulletin*, *136*(3), 422–449. https://doi.org/10.1037/a0018947

Hung, M.-L., Chou, C., Chen, C.-H., & Own, Z.-Y. (2010). Learner readiness for online learning: Scale development and student perceptions. *Computers & Education*, *55*(3), 1080–1090. https://doi.org/10.1016/j.compedu.2010.05.004

Husman, J., Derryberry, W. P., Crowson, H. M., & Lomax, R. (2004). Instrumentality, task value, and intrinsic motivation: Making sense of their independent interdependence. *Contemporary Educational Psychology*, *29*(1), 63–76.

Hwang, G.-J., Yang, L.-H., & Wang, S.-Y. (2013). A concept map-embedded educational computer game for improving students' learning performance in natural science courses. *Computers & Education*, *69*, 121–130. https://doi.org/10.1016/j.compedu.2013.07.008

Jacobs, G., Opdenacker, L., & Waes, L. V. (2005). A multilanguage online writing center for professional communication: Development and testing. *Business Communication Quarterly*, *68*(1), 8–22. https://doi.org/10.1177/1080569904273330

Jadric, M., Bubas, G., & Hutinski, Z. (2010). Dispositional predictors of student success in e-learning courses. *Proceedings of the ITI 2010, 32nd International Conference on Information Technology Interfaces*, 361–366.

Joo, Y. J., Lim, K. Y., & Kim, J. (2013). Locus of control, self-efficacy, and task value as predictors of learning outcome in an online university context. *Computers & Education*, *62*, 149–158. https://doi.org/10.1016/j.compedu.2012.10.027

Kauffman, H. (2015). A review of predictive factors of student success in and satisfaction with online learning. *Research in Learning Technology*, *23,* 26507. https://doi.org/10.3402/rlt.v23.26507

Kim, J.-Y. (2012). A study on learners' perceptional typology and relationships among the learner's types, characteristics, and academic achievement in a blended e-Education environment. *Computers & Education*, *59*(2), 304–315. https://doi.org/10.1016/j.compedu.2012.01.010

Krippendorff, K. (2004). Reliability in content analysis: Some common misconceptions and recommendations. *Human Communication Research*, *30*(3), 411–433. https://doi.org/10.1111/j.1468-2958.2004.tb00738.x

Lantolf, J. P., & Thorne, S. L. (2006). *Sociocultural theory and the genesis of second language* d*evelopment*. Oxford University Press.

Berners-Lee, T., Cailliau, R., Luotonen, A., Nielsen, H. F., & Secret, A. (1994). The World-Wide Web. *Communications of the ACM*, *37*(8), 76–82. https://doi.org/10.1145/179606.179671

Lee, Y., & Choi, J. (2013). A structural equation model of predictors of online learning retention. *The Internet and Higher Education*, *16*, 36–42. https://doi.org/10.1016/j.iheduc.2012.01.005

Lefcourt, H. M., Von Baeyer, C. L., Ware, E. E., & Cox, D. J. (1979). The multidimensional-multiattributional causality scale: The development of a goal specific locus of control scale. *Canadian Journal of Behavioural Science*, *11*(4), 286–304. https://doi.org/10.1037/h0081598

Levenson, H. (1981). Differentiating among internality, powerful others, and chance. In H. M. Lefcourt (Ed.), *Research with the* locus *of control construct* (pp. 1–15). Academic Press.

Levy, Y. (2007). Comparing dropouts and persistence in e-learning courses. *Computers & Education*, *48*(2), 185–204. https://doi.org/10.1016/j.compedu.2004.12.004

Liu, C., Sands-Meyer, S., & Audran, J. (2019). The effectiveness of the student response system (SRS) in English grammar learning in a flipped English as a foreign language (EFL) class. *Interactive Learning Environments*, *27*(8), 1178–1191. https://doi.org/10.1080/10494820.2018.1528283

Lynch, R., & Dembo, M. (2004). The relationship between self-regulation and online learning in a blended learning context. *International Review of Research in Open and Distributed Learning*, *5*(2), 1–16. https://doi.org/10.19173/irrodl.v5i2.189

Marakas, G., Johnson, R., & Clay, P. F. (2007). The evolving nature of the computer self-efficacy construct: An empirical investigation of measurement construction, validity, reliability and stability over time. *Journal of the Association for Information Systems*, *8*(1). https://doi.org/10.17705/1jais.00112

Martin, F., Tutty, J. I., & Su, Y. (2010). Influence of learning management systems self-efficacy on e-learning performance. *Journal on School Educational Technology*, *5*(3), 26–35.

McPhaul-Moore, E. (2013). Predictors of online learning success in a rural community college [Doctoral dissertation, Northcentral University]. ProQuest Dissertations and Theses. https://www.proquest.com/docview/1444627614

Meece, J. L., Anderman, E. M., & Anderman, L. H. (2006). Classroom goal structure, student motivation, and academic achievement. *Annual Review of Psychology*, *57*, 487–503. https://doi.org/10.1146/annurev.psych.56.091103.070258

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E. M., Freeman, K. E., & Urdan, T. (2000). *Manual for the Patterns of Adaptive Learning Scales (PALS)*. University of Michigan.

Miltiadou, M., & Savenye, W. C. (2003). Applying social cognitive constructs of motivation to enhance student success in online distance education. *AACE Review*, *11*(1), 78–95. https://www.learntechlib.org/primary/p/17795/

Miltiadou, M., & Yu, C. H. (2000). Validation of the Online Technologies Self-Efficacy Scale (OTSES). https://eric.ed.gov/?id=ED445672

Moos, D. C., & Azevedo, R. (2009). Learning with computer-based learning environments: A literature review of computer self-efficacy. *Review of Educational Research*, *79*(2), 576–600. https://doi.org/10.3102/0034654308326083

Morris, L. V., Wu, S.-S., & Finnegan, C. L. (2005). Predicting retention in online general education courses. *American Journal of Distance Education*, *19*(1), 23–36. https://doi.org/10.1207/s15389286ajde1901_3

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of Counseling Psychology*, *38*(1), 30–38. https://doi.org/10.1037/0022-0167.38.1.30

National Center for Education Statistics. (2022a, March). *Digest of Education Statistics, 2021*. U.S. Department of Education, National Center for Education Statistics. https://nces.ed.gov/programs/digest/d21/tables/dt21_311.33.asp

National Center for Education Statistics. (2022b, December). *Digest of Education Statistics, 2022*. U.S. Department of Education, National Center for Education Statistics. https://nces.ed.gov/programs/digest/d22/tables/dt22_311.15.asp

Neroni, J., Meijs, C., Kirschner, P. A., Xu, K. M., & de Groot, R. H. M. (2022). Academic self-efficacy, self-esteem, and grit in higher online education: Consistency of interests predicts academic success. *Social Psychology of Education*, *25*, 951–975. https://doi.org/10.1007/s11218-022-09696-5

Ng, C. (2019). Shifting the focus from motivated learners to motivating distributed environments: A review of 40 years of published motivation research in Distance Education. *Distance Education*, *40*(4), 469–496. https://doi.org/10.1080/01587919.2019.1681892

Noe, R. A., & Schmitt, N. (1986). The influence of trainee attitudes on training effectiveness: Test of a model. *Personnel Psychology*, *39*(3), 497–523. https://doi.org/10.1111/j.1744-6570.1986.tb00950.x

Pajares, F., & Graham, L. (1999). Self-efficacy, motivation constructs, and mathematics performance of entering middle school students. *Contemporary Educational Psychology*, *24*(2), 124–139. https://doi.org/10.1006/ceps.1998.0991

Pajares, F., Hartley, J., & Valiante, G. (2001). Response format in writing self-efficacy assessment: Greater discrimination increases prediction. *Measurement and Evaluation in Counseling and Development*, *33*(4), 214–221. https://doi.org/10.1080/07481756.2001.12069012

Peng, H., Wang, Y., Huang, R., & Chen, G. (2006). Self-efficacy of distance learning: Structure and related factor. *Open Education Research*, *2*, 41–45.

Pintrich, P. R. (1991). *A manual for the* u*se of the Motivated Strategies for Learning Questionnaire (MSLQ)*. National Center for Research to Improve Postsecondary Teaching and Learning.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *82*(1), 33. https://doi.org/10.1037/0022-0663.82.1.33

Remedios, R., & Richardson, J. T. E. (2013). Achievement goals in adult learners: Evidence from distance education. *British Journal of Educational Psychology*, *83*(4), 664–685. https://doi.org/10.1111/bjep.12001

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353–387. https://doi.org/10.1037/a0026838

Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., & Carlstrom, A. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. *Psychological Bulletin*, *130*(2), 261–288. https://doi.org/10.1037/0033-2909.130.2.261

Roblyer, M. D., Davis, L., Mills, S. C., Marshall, J., & Pape, L. (2008). Toward practical procedures for predicting and promoting success in virtual school students. *American Journal of Distance Education*, *22*(2), 90–109. https://doi.org/10.1080/08923640802039040

Rosenzweig, E. Q., Wigfield, A., & Hulleman, C. S. (2020). More useful or not so bad? Examining the effects of utility value and cost reduction interventions in college physics. *Journal of Educational Psychology*, *112*(1), 166–182. https://doi.org/10.1037/edu0000370

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, *80*(1), 1–28. https://doi.org/10.1037/h0092976

Runyon, J. M. (2013). *The first-time online learner: Readiness and successful course completion* [Doctoral dissertation, Northcentral University]. ProQuest Dissertations and Theses. https://eric.ed.gov/?id=ED556388

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, *25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology, 61*, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Sankaran, S. R., & Bui, T. (2001). Impact of learning strategies and motivation on performance: A study in web-based instruction. *Journal of Instructional Psychology*, *28*(3), 191–198. https://www.learntechlib.org/p/95445/

Seaman, J., Allen, E., & Seaman, J. (2018). *Grade increase: Tracking distance education in the United States*. Babson Survey Research Group. https://www.bayviewanalytics.com/reports/gradeincrease.pdf

Scheier, M. F., & Carver, C. S. (1985). Optimism, coping, and health: Assessment and implications of generalized outcome expectancies. *Health Psychology*, *4*(3), 219–247. https://doi.org/10.1037/0278-6133.4.3.219

Schmidt, F. L., & Hunter, J. E. (2015). *Methods of meta-analysis: Correcting error and bias in research findings* (3rd ed.). Sage.

Schwarzer, R., & Jerusalem, M. (1995). Generalized Self-Efficacy scale. In J. Weinman, S. Wright, & M. Johnston (Eds.), *Measures in health psychology: A user's portfolio. Causal and control beliefs* (pp. 35–37). NFER-Nelson. http://userpage.fu-berlin.de/~health/selfscal.htm

Shell, D. F., Murphy, C. C., & Bruning, R. H. (1989). Self-efficacy and outcome expectancy mechanisms in reading and writing achievement. *Journal of Educational Psychology*, *81*(1), 91–100. https://doi.org/10.1037/0022-0663.81.1.91

Shen, D., Cho, M.-H., Tsai, C.-L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *The Internet and Higher Education*, *19*, 10–17. https://doi.org/10.1016/j.iheduc.2013.04.001

Simmering, M. J., Posey, C., & Piccoli, G. (2009). Computer self-efficacy and motivation to learn in a self-directed online course. *Decision Sciences Journal of Innovative Education*, *7*(1), 99–121. https://doi.org/10.1111/j.1540-4609.2008.00207.x

Spence, D. J. (2004). Engagement with mathematics courseware in traditional and online learning environments: Relationship to motivation, achievement, gender, and gender orientation. *Dissertation Abstracts International Section A: Humanities and Social Sciences, 65*(2-A), 480.

Stephen, J. S., Rockinson-Szapkiw, A. J., & Dubay, C. (2020). Persistence model of non-traditional online learners: Self-efficacy, self-regulation, and self-direction. *American Journal of Distance Education*, *34*(4), 306–321. https://doi.org/10.1080/08923647.2020.1745619

Strawser, M. G., Gaffney, A. L. H., Kercsmar, S. E., & Pennell, M. (2019). A blended basic course examination of communication apprehension and self-efficacy: A comparative analysis. *Basic Communication Course Annual*, *29*, 53–73. https://ecommons.udayton.edu/bcca/vol29/iss1/6

Stritto, M. E. D., Aguiar, N. R., & Andrews, C. (2023). From online learner readiness to life-long learning skills: A validation study. *Online Learning*, *27*(4).

Sulla, F., Aquino, A., & Rollo, D. (2022). University students' online learning during COVID-19: The role of grit in academic performance. *Frontiers in Psychology*, *13*.

Sun, Y., & Rogers, R. (2021). Development and validation of the Online Learning Self-efficacy Scale (OLSS): A structural equation modeling approach. *American Journal of Distance Education*, *35*(3), 184–199. https://doi.org/10.1080/08923647.2020.1831357

Tai, H.-C. (2016). Effects of collaborative online learning on EFL learners' writing performance and self-efficacy. *English Language Teaching*, *9*(5), 119–133. http://dx.doi.org/10.5539/elt.v9n5p119

Tang, Y. M., Chen, P. C., Law, K. M., Wu, C., Lau, Y., Guan, J., He, D., & Ho, G. (2021). Comparative analysis of student's live online learning readiness during the coronavirus (COVID-19) pandemic in the higher education sector. *Computers & Education, 168*, 104211. https://doi.org/10.1016/j.compedu.2021.104211

Tladi, L. S. (2017). Perceived ability and success: Which self-efficacy measures matter? A distance learning perspective. *Open Learning: The Journal of Open, Distance and e-Learning*, *32*(3), 243–261. https://doi.org/10.1080/02680513.2017.1356711

Torun, E. D. (2020). Online distance learning in higher education: E-learning readiness as a predictor of academic achievement. *Open Praxis*, *12*(2), 191–208. https://search.informit.org/doi/10.3316/informit.352722164544178

Totonchi, D., Huelskoetter, E., Ferrer, B., & Hulleman, C. (2022, June 26-29). *Improving community college students' STEM motivation and achievement by implementing utility-value interventions*. [Conference Paper] 2022 ASEE Annual Conference & Exposition. https://peer.asee.org/improving-community-college-students-stem-motivation-and-achievement-by-implementing-utility-value-interventions

Trice, A. D. (1985). An academic locus of control scale for college students. *Perceptual and Motor Skills*, *61*(3, Pt 2), 1043–1046. https://doi.org/10.2466/pms.1985.61.3f.1043

Tsai, C.-C., Chuang, S.-C., Liang, J.-C., & Tsai, M.-J. (2011). Self-efficacy in internet-based learning environments: A literature review. *Journal of Educational Technology & Society*, *14*(4), 222–240. https://www.jstor.org/stable/jeductechsoci.14.4.222

Urdan, T., & Kaplan, A. (2020). The origins, evolution, and future directions of achievement goal theory. *Contemporary Educational Psychology*, *61*, 101862. https://doi.org/10.1016/j.cedpsych.2020.101862

Vallerand, R. J., Pelletier, L. G., Blais, M. R., Briere, N. M., Senecal, C., & Vallieres, E. F. (1992). The Academic Motivation Scale: A measure of intrinsic, extrinsic, and amotivation in education. *Educational and Psychological Measurement*, *52*(4), 1003–1017. https://doi.org/10.1177/0013164492052004025

Wadsworth, L., Husman, J., Duggan, M., & Pennington, N. (2007). Online mathematics achievement: Effects of learning strategies and self-efficacy. *Journal of Developmental Education*, *30,* 6–14.

Wang, A. Y., & Newlin, M. H. (2000). Characteristics of students who enroll and succeed in psychology Web-based classes. *Journal of Educational Psychology*, *92*(1), 137–143. https://doi.org/10.1037/0022-0663.92.1.137

Wang, A. Y., & Newlin, M. H. (2002). Predictors of web-student performance: The role of self-efficacy and reasons for taking an on-line class. *Computers in Human Behavior*, *18*(2), 151–163. https://doi.org/10.1016/S0747-5632(01)00042-5

Wang, Y., Peng, H., Huang, R., Hou, Y., & Wang, J. (2008). Characteristics of distance learners: Research on relationships of learning motivation, learning strategy, self-efficacy, attribution and learning results. *Open Learning: The Journal of Open, Distance and e-Learning*, *23*(1), 17–28. https://doi.org/10.1080/02680510701815277

Warren, L., Reilly, D., Herdan, A., & Lin, Y. (2020). Self-efficacy, performance and the role of blended learning. *Journal of Applied Research in Higher Education*, *13*(1), 98–111. https://doi.org/10.1108/JARHE-08-2019-0210

White, H. (2019). Scientific communication and literature retrieval. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The handbook of research synthesis and meta-Analysis* (3rd ed., pp. 51–72). Russell Sage Foundation.

Wigfield, A., Muenks, K., & Eccles, J. S. (2021). Achievement motivation: What we know and where we are going. *Annual Review of Developmental Psychology*, *3*(1), 87–111. https://doi.org/10.1146/annurev-devpsych-050720-103500

Wipawayangkool, K., Lilly, J., & Grogan, A. (2022). Knowledge management strategy-based learning preferences and self-efficacy on academic performance: An online vs. face-to-face study. *International Journal of Knowledge and Learning*, *15*(2), 165–184.

Wuellner, M. R. (2015). Student success factors in two online introductory-level natural resource courses. *Natural Sciences Education*, *44*(1), 51–59. https://doi.org/10.4195/nse2014.12.0029

Xu, J., Lio, A., Dhaliwal, H., Andrei, S., Balakrishnan, S., Nagani, U., & Samadder, S. (2021). Psychological interventions of virtual gamification within academic intrinsic motivation: A systematic review. *Journal of Affective Disorders*, *293*, 444–465. https://doi.org/10.1016/j.jad.2021.06.070

Yurdugul, H., & Alsancak Sarikaya, D. (2013). The scale of online learning readiness: A study of validity and reliability. *Education and Science*, *38*(169), 391–406. https://www.proquest.com/openview/c6b0a56d9385205d7bf3759a9bedd68d/1

Yurdugul, H., & Demir, O. (2017). An investigation of pre-service teachers' readiness for e-learning at undergraduate level teacher training programs: The case of Hacettepe University. *Hacettepe Üniversitesi Eğitim Fakültesi Dergisi*, *32*(4), 896–915.

Zhang, J., Li, F., Duan, C., & Wu, G. (2001). Research on self-efficacy of distance learning and its influence to learners' attainments. In C. H. Lee (Ed.), *Proceedings of the International Conference on Computers in Education (ICEE)*. Incheon National University of Education. https://www.semanticscholar.org/paper/Research-on-Self-Efficacy-of-Distance-Learning-and-Zhang-Li/b297555da2325e320eebbc1640c62ad849530a92

Zhou, Y., & Wang, J. (2019). Goal orientation, learning strategies, and academic performance in adult distance learning. *Social Behavior and Personality: An International Journal*, *47*(7), 1–20. https://doi.org/10.2224/sbp.8195

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American Educational Research Journal*, *29*(3), 663–676. https://doi.org/10.2307/1163261

Zimmerman, W. A. (2017). Predicting success in an online course using expectancies, values, and typical mode of instruction. *International Journal of E-Learning & Distance Education*, *32*(1). https://eric.ed.gov/?id=EJ1155812

Zimmerman, W. A., & Kulikowich, J. M. (2016). Online learning self-efficacy in students with and without online learning experience. *American Journal of Distance Education*, *30*(3), 180–191. https://doi.org/10.1080/08923647.2016.1193801

Appendix—A Studies, Outcomes, and Coding

Citation	Delivery Mode	Motivational Construct	Measure (Citation)	Sample Size	Effect Size (*r*)	95% CI for *r*	Type of Correlation
Fadda (2019)	blended	learning SE	MSLQ (Lantolf & Thorne, 2006)	70	0.29	[0.06, 0.05]	Pearson's *r*
Alkis & Temizel (2018)	blended	learning SE	MSLQ (Pintrich, 1991)	127	0.03	[-0.14, 0.20]	Pearson's *r*
		intrinsic motivation		189	0.44	[0.27, 0.61]	Pearson's *r*
	online	learning SE		189	0.22	[0.08, 0.36]	Pearson's *r*
		intrinsic motivation		127	0.17	[0.03, 0.31]	Pearson's *r*
Amin (2019)	blended	extrinsic motivation	Writing Motivation Questionnaire (Amin, 2016)	60	0.48	[0.23, 0.73]	Pearson's *r*
		learning SE			0.57	[0.32, 0.82]	Pearson's *r*
		intrinsic motivation			0.65	[0.40, 0.90]	Pearson's *r*
Bahçekapili & Karaman (2020)	online	external LoC	Academic external locus of control scale (Akin, 2007)	525	0.16	[0.08, 0.25]	Pearson's *r*
		internal LoC	Academic internal locus of control scale (Akin, 2007)		0.03	[-0.05, 0.12]	Pearson's *r*
		learning SE	GSES (Schwarzer & Jerusalem, 1995)		0.14	[0.05, 0.22]	Pearson's *r*
Baturay & Yukselturk (2015)	online	technology SE	Internet self-efficacy scale (Y.-J. Joo et al., 2000)	148	0.11	[-0.05, 0.27]	Pearson's *r*

Citation	Delivery Mode	Motivational Construct	Measure (Citation)	Sample Size	Effect Size (*r*)	95% CI for *r*	Type of Correlation
Cannon et al. (2023)	blended	learning SE	Self-efficacy formative questionnaire (Guamer Erickson & Noonan, 2018)	656	0.05	[-0.03, 0.13]	Pearson's *r*
Chang & Ho (2009)	online	internal LoC	Intellectual Achievement Responsibility and Control of Learning Beliefs (Crandall et al., 1965; Pintrich, 1991)	115	0.17	[-0.01, 0.35]	Point biserial
Chang et al. (2014)	online	technology SE	Online Computer Technology Survey (C. S. Chang, 2000)	80	0.24	[0.02, 0.46]	Point biserial
Chen & Jang (2010)	online	relative autonomy index	Relative Autonomy Index (Grolnick & Ryan, 1987; Vallerand et al., 1992)	267	-0.04	[-0.16, 0.08]	other
Cheng et al. (2023)	online	academic SE	PALS (Midgley et al., 2000)	168	0.10	[-0.06, 0.25]	Combined
	online	task value	MSLQ (Pintrich, 1993)	168	0.07	[-.08, 0.22]	Combined
Cho & Shen (2013)	online	intrinsic motivation	MSLQ (Duncan & McKeachie, 2005)	64	-0.09	[-0.33, 0.15]	Pearson's *r*
		extrinsic motivation			-0.08	[-0.32, 0.16]	Pearson's *r*
		learning SE			0.18	[-0.06, 0.42]	Pearson's *r*
Cigdem & Ozturk (2016)	blended	general motivation	OLRS (Hung et al., 2010; Yurdugul & Alsancak Sarikaya, 2013)	155	0.16	[0.00, 0.32]	Pearson's *r*
		technology SE			0.21	[0.05, 0.37]	
Gulao (2014)	online	learning SE	MSLQ (Pintrich et al., 1991)	63	0.29	[0.04, 0.53]	Pearson's *r*
DeTure (2004)	online	technology SE	OTSES (Miltiadou & Yu, 2000)	73	-0.03	[-0.26, 0.20]	other
Ergul (2004)	online	mastery approach goals	PALS (Midgley et al., 2000)	124	0.01	[-0.17, 0.19]	Pearson's *r*
		learning SE	MSLQ (Pintrich & De Groot, 1990)		0.24	[0.07, 0.42]	Pearson's *r*

Citation	Delivery Mode	Motivational Construct	Measure (Citation)	Sample Size	Effect Size (*r*)	95% CI for *r*	Type of Correlation
Gerlich et al. (2009)	online	external LoC	Rotter's Internal-External Locus of Control Scale (1966)	40	0.08	[-0.23, 0.38]	Pearson's *r*
Goad et al. (2021)	online	mastery approach goals	ESPRI-2 (Roblyer et al., 2008)	821	0.17	[0.10, 0.24]	Transformed β
Hamm et al. (2019)	online	optimism	Life Orientation Test (Scheier & Carver, 1985)	617	0.04	[-0.04, 0.12]	Pearson's *r*
				617	0.04	[-0.04, 0.12]	Pearson's *r*
				509	0.07	[-0.02, 0.16]	Pearson's *r*
				509	0.17	[0.08, 0.26]	Pearson's *r*
Hobson & Puruhito (2018)	online	learning SE	Self-efficacy and outcome expectancy measure (Shell et al., 1989)	409	0.31	[0.21, 0.41]	Pearson's *r*
Hodges (2008)	online	learning SE	Novel (drawn from Miltiadou & Yu, 2000; Pintrich & De Groot, 1990; Spence, 2004; Zimmerman et al., 1992)	86	0.29	[0.07, 0.50]	other
Jadric, Bubas, Hutinski (2010)	online	technology SE	Novel (none)	269	0.15	[0.03, 0.27]	Pearson's *r*
Joo, Lim, & Kim (2013)	online	internal LoC	Internal, Powerful Others and Chance Scale (Levenson, 1981)	897	0.07	[0.00, 0.14]	Pearson's *r*
		learning SE	MSLQ (Pintrich & De Groot, 1990)	897	0.22	[0.16, 0.29]	Pearson's *r*
		task value (before)	Eccles, Adler, and Meece (1984)	897	0.25	[0.19, 0.32]	Pearson's *r*
		Task value (after)	Eccles, Adler, and Meece (1984)	897	0.19	[0.13, 0.26]	Pearson's *r*
Kim (2012)	blended	learning SE	Novel (None)	50	0.40	[0.12, 0.67]	Pearson's *r*

Citation	Delivery Mode	Motivational Construct	Measure (Citation)	Sample Size	Effect Size (*r*)	95% CI for *r*	Type of Correlation
Lee & Choi (2013)	online	internal LoC	internal academic locus of control scale (Levy, 2007)	282	0.29	[0.17, 0.40]	Combined
Liu et al. (2019)	blended	general motivation	Learning Motivation (Hwang et al., 2013)	50	-0.58	[-0.85, -0.30]	Point biserial
		learning SE	MSLQ variant (Pintrich et al., 1991)		-0.06	[-0.33, 0.22]	Point biserial
Lynch & Dembo (2004)	blended	technology SE	Internet self-efficacy scale (Eastin & LaRose, 2000)	94	-0.09	[-0.29, 0.11]	Pearson's *r*
		learning SE	MSLQ (Pintrich et al., 1991)		0.29	[0.09, 0.49]	Pearson's *r*
Martin et al. (2010)	online	technology SE	Novel (None)	33	0.20	[-0.14, 0.54]	Pearson's *r*
McPhaul-Moore (2013)	online	intrinsic motivation	MSLQ (Pintrich et al., 1991)	112	0.09	[-0.09, 0.27]	Pearson's *r*
		learning SE		110	0.23	[0.05, 0.42]	Pearson's *r*
Morris et al. (2005)	online	internal LoC	Rotter's Internal-External Locus of Control Scale (1966)	51	-0.26	[-0.53, 0.01]	Point biserial
Neroni et al. (2022)	online	learning SE	MSLQ (Pintrich et al., 1991)	1133	0.05	[-0.00, 0.11]	Pearson's *r*
Noteborn et al. (2012)	online	task value	MSLQ (Pintrich et al., 1991)	139	0.14	[-0.03, 0.31]	Pearson's *r*
Parker et al. (2021)	online	perceived academic locus of control	PAC (Perry et al., 2001)	327	0.29	[0.18, 0.39]	Combined
	online	task value	Course value (Perkrun & Meier, 2011)	327	0.07	[-0.04, 0.18]	Combined
Remedios & Richardson (2013)	online	mastery avoidance	Achievement Goal Questionnaire (Elliot & McGregor, 2001)	740	-0.01	[-0.08, 0.06]	Point biserial
		performance approach			-0.01	[-0.08, 0.06]	Point biserial

Citation	Delivery Mode	Motivational Construct	Measure (Citation)	Sample Size	Effect Size (*r*)	95% CI for *r*	Type of Correlation
		mastery approach			0.00	[-0.07, 0.07]	Point biserial
		performance avoidance			0.08	[0.01, 0.16]	Point biserial
Runyon (2013)	online	technology SE	Computer user self-efficacy (Cassidy & Eachus, 2002)	162	0.28	[0.12, 0.43]	Pearson's *r*
Sankaran & Bui (2001)	online	general motivation	Novel (None)	46	0.58	[0.29, 0.86]	Pearson's *r*
Savoji (2013)	online	intrinsic motivation	MSLQ (Pintrich et al., 1991)	187	0.06	[0.29, 0.86]	Transformed β
	online	extrinsic motivation	MSLQ (Pintrich et al., 1991)		0.06	[-0.09, 0.20]	Transformed β
	online	task value	MSLQ (Pintrich et al., 1991)		0.13	[-0.01, 0.28]	Transformed β
	online	learning SE	MSLQ (Pintrich et al., 1991)		0.29	[0.14, 0.43]	Transformed β
Simmering, Posey, & Piccoli (2009)	online	general motivation	initial motivation to learn (Noe & Schmitt, 1986)	190	-0.07	[-0.21, 0.07]	Pearson's *r*
		technology SE	CSES (Compeau & Higgins, 1995)		0.29	[0.15, 0.43]	Pearson's *r*
Stephen et al. (2020)	online	technology SE	OLSES (W. A. Zimmerman & Kulikowich, 2016)	82	-0.58	[-0.79, -0.36]	Point biserial
		learning SE			-0.03	[-0.25, 0.19]	Point biserial
Tai (2016)	online	learning SE	Writing Self-Efficacy Questionnaire (Jacobs et al., 2005; Pajares et al., 2001)	209	-0.29	[-0.42, -0.15]	Transformed β
Tladi (2017)	online	technology SE	OTSES variant (Miltiadou & Yu, 2000)	263	-0.07	[-0.20, 0.05]	Pearson's *r*
		learning SE	Distance Learning Self-Efficacy Scale (Zhang et al., 2001)		0.13	[0.01, 0.25]	Pearson's *r*

Citation	Delivery Mode	Motivational Construct	Measure (Citation)	Sample Size	Effect Size (*r*)	95% CI for *r*	Type of Correlation
Torun (2020)	online	technology SE	E-Learning Readiness Scale (Yurdugul & Demir, 2017)	153	0.10	[-0.06, 0.25]	Pearson's *r*
					0.17	[0.01, 0.33]	Pearson's *r*
		learning SE			0.23	[0.07, 0.38]	Pearson's *r*
		general motivation			0.51	[0.35, 0.67]	Pearson's *r*
Wadsworth et al. (2007)	online	learning SE	Novel (drawn from Bandura, 2006; Pajares & Graham, 1999)	89	0.32	[0.11, 0.53]	Transformed β
Wang & Newlin (2000)	online	external LoC	Rotter's Internal-External Locus of Control Scale (1966)	49	0.33	[0.05, 0.61]	Pearson's *r*
		external LoC	Academic locus of control scale (Trice, 1985)		0.41	[0.13, 0.69]	Pearson's *r*
Wang & Newlin (2002)	online	technology SE	Novel (None)	122	0.24	[0.06, 0.42]	Other
		learning SE	Novel (None)		0.32	[0.14, 0.49]	Other
Wang et al. (2008)	online	technology SE	Self-efficacy of distance learning (Peng et al., 2006)	135	0.05	[-0.12, 0.22]	Pearson's *r*
		external LoC	Multidimensional multiattributional causality scale (Lefcourt et al., 1979)		0.07	[-0.24, 0.10]	Combined
		intrinsic motivation	Novel (drawn from Wang et al., 2006)		0.16	[-0.01, 0.33]	Pearson's *r*
Warren et al. (2020)	blended	learning SE	Novel (None)	43	0.46	[0.16, 0.75]	Pearson's *r*
Wipawayangkool et al. (2022)	online	technology SE	Computer and internet self-efficacy (Marakas et al., 2007)	64	-0.01	[-0.25, 0.23]	Combined

Citation	Delivery Mode	Motivational Construct	Measure (Citation)	Sample Size	Effect Size (*r*)	95% CI for *r*	Type of Correlation
Wuellner (2015)	online	intrinsic motivation	MSLQ (Pintrich et al., 1991)	36	-0.41	[-0.73, -0.09]	Combined
Zhang et al. (2023)	blended	technology SE	TISQ (Wang et al., 2004)	202	0.13	[-0.01, 0.27]	Pearson's *r*
Zhou & Wang (2019)	online	performance avoidance	AGQ (Elliot & McGregor, 2001)	201	-0.05	[-0.19, 0.09]	Pearson's *r*
		performance approach			0.35	[0.21, 0.49]	Pearson's *r*
		mastery avoidance			0.44	[0.30, 0.58]	Pearson's *r*
		mastery approach			0.61	[0.47, 0.75]	Pearson's *r*
Zimmerman (2017)	online	technology SE	OLSES variant (Zimmerman & Kulikowich, 2016)	341	-0.10	[-0.20, 0.01]	Pearson's *r*
	online	learning SE		345	-0.02	[-0.13, 0.08]	Pearson's *r*
	online	learning SE	SELS (Finney & Schraw, 2003)	334	0.12	[0.01, 0.23]	Pearson's *r*

Appendix B—Forrest Plot of Outcomes by Motivational Construct

Figure B1

Forrest Plot of Self-Determination Motivation Outcomes

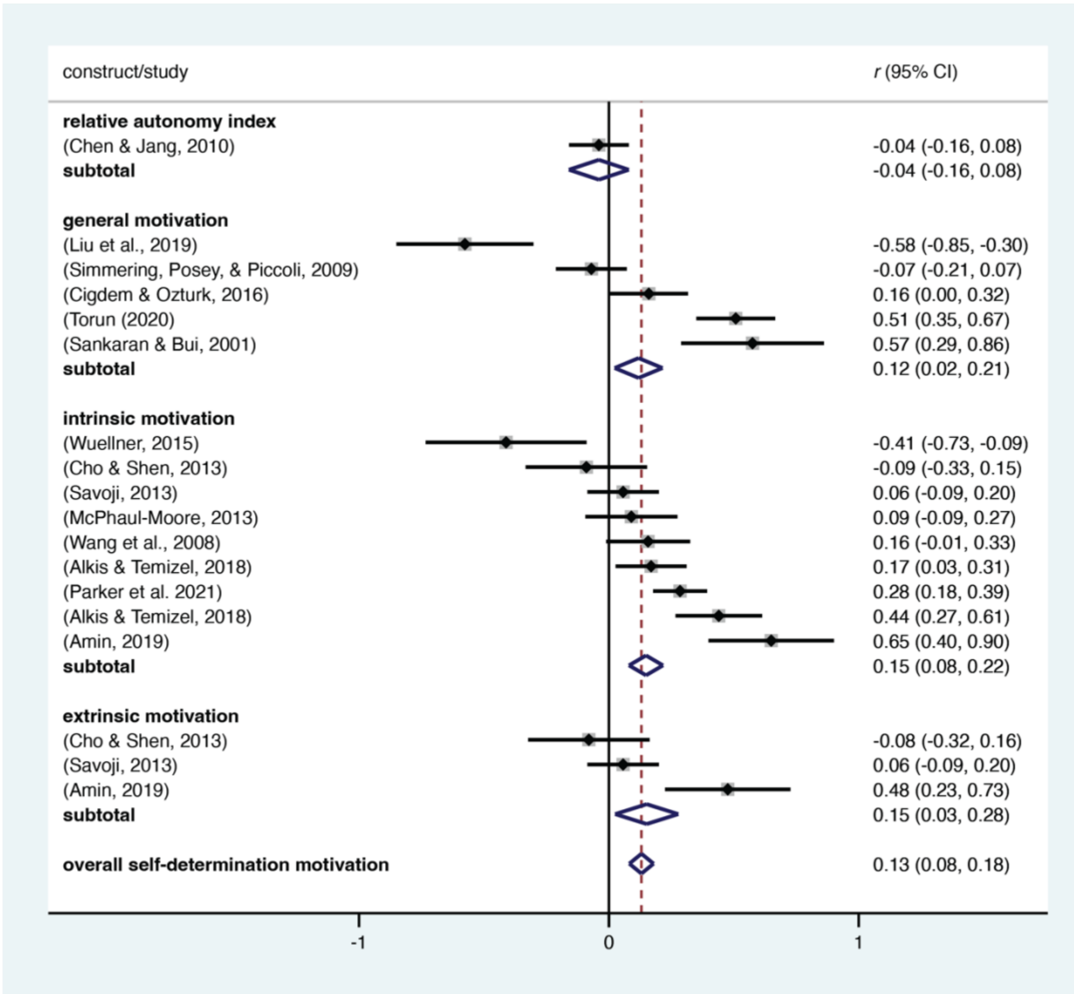

Figure B2

Forrest Plot of Attributional Style Outcomes

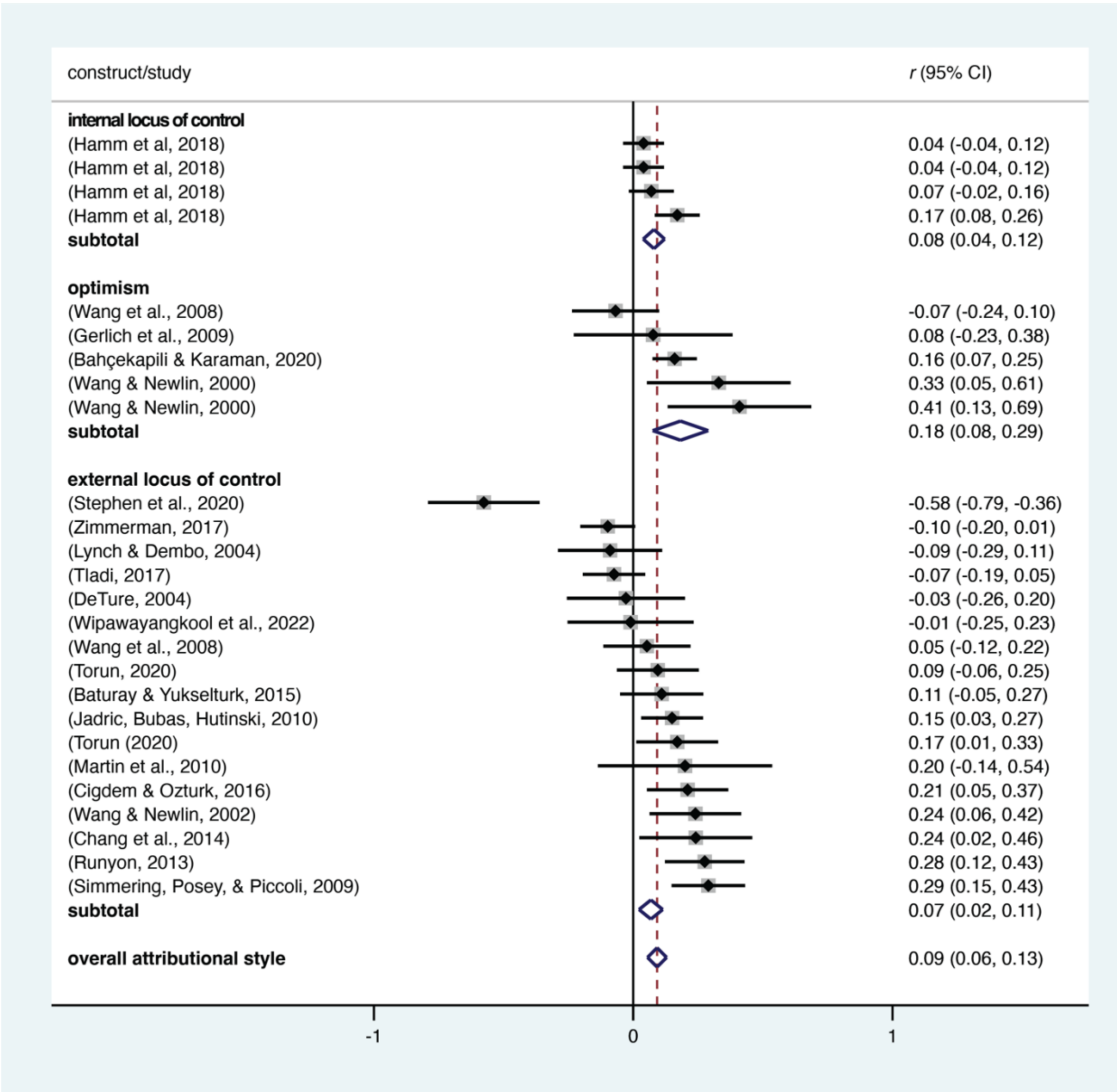

Figure B3

Forrest Plot of Task Value Outcomes

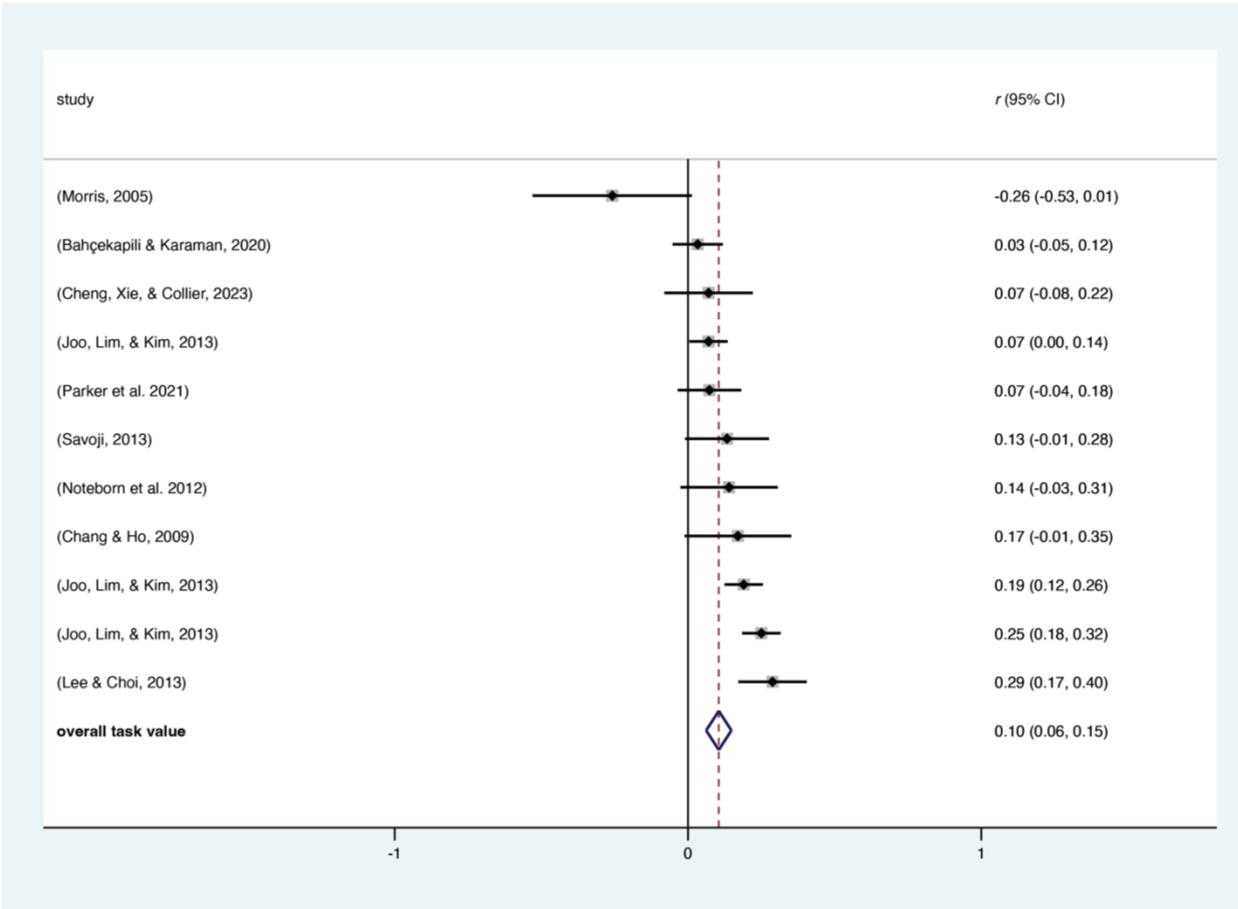

Figure B4

Forrest Plot of Self-Efficacy Outcomes

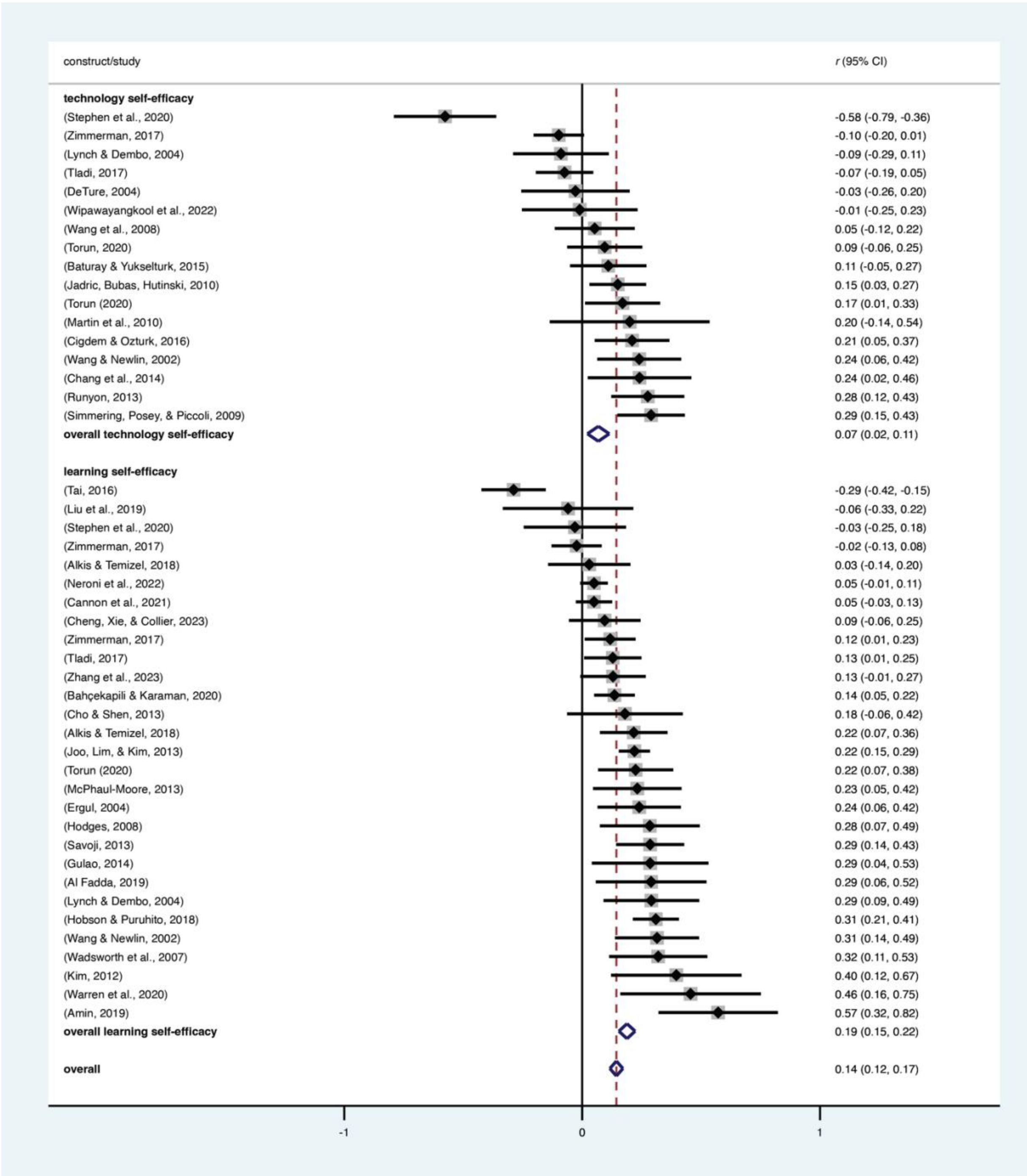

Figure B5

Forrest Plot of Achievement Goals Outcomes