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Social-psychological interventions in college: A meta-analysis of effects on academic outcomes and heterogeneity by study context and treated population

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1. Introduction

A college degree is crucial in today's competitive labor market, yet nearly half of all college students never graduate (Shapiro et al., 2017). Because of statistics such as this, policymakers and institutions of higher education have made college completion a national priority. Indeed, researchers, policymakers, and practitioners seek to better understand which factors are critical for student success at different points in students' college-to-degree trajectory. What is known is that the college completion puzzle is complex, including factors such as college readiness, institutional support, non-cognitive characteristics, financial considerations, and job opportunities.

Recently, attention has been paid to the powerful role social-psychological factors—such as student mindset and motives—can play in encouraging college student learning, success, and degree completion (Destin, 2018; Harackiewicz & Priniski, 2018). Indeed, correlational studies have concluded that social-psychological factors are critical for success in college, linking these factors to student engagement and positive behavior (Chemers, Hu, & Garcia, 2001). In addition, studies have found that these factors predict both academic achievement and college persistence (Robbins, Allen, Casillas, Peterson, & Le, 2006; Robbins et al., 2004). Further, a large number of interventions based on social-psychological and motivation theories have been developed over the past two decades in an effort to improve educational outcomes in higher education.

These interventions, commonly referred to as "social-psychological interventions," aim to target social-psychological processes that interfere with academic functioning.[1] Because most are low-cost and require few resources, they provide practitioners with a potential

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[1] The interventions discussed in the present meta-analysis are based on both social-psychological and motivation theories, so they have the potential to impact constructs from both disciplines. We lean towards using the term "social-psychological" because these interventions specifically target psychological processes occurring in a social environment—that is, the college classroom or university. Additionally, they are intended to influence behavior in a social environment. We acknowledge, however, that other scholars have used the term "motivation interventions" to describe them as well. Indeed, these interventions affect psychological processes and therefore explicitly impact motivation, often due to higher academic achievement. Take, for example, a sense of belonging intervention that improves academic achievement, such as the one studied in Walton et al. (2015) (see page 6 for more detail). Walton et al. (2015) study included two items to measure the impact of the social belonging intervention on self-efficacy and they found that the intervention improved women's confidence in their prospects of succeeding in engineering. This outcome is in line with other studies that have reported associations between students sense of belonging and academic motivation in both the K-12 and postsecondary context (e.g., Freeman, Anderman, and Jensen, 2007; Korpershoek, Canrinus, Fokkens-Bruinsma, and de Boer, 2019; Zumbrunn, McKim, Buhs, Hawley, 2012).

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way to enhance educational outcomes efficiently and without the interruption of normal classroom processes. Though all *narrative* reviews about these interventions are positive (see Harackiewicz & Priniski, 2018; NASEM, 2017; Yeager & Walton, 2011), evidence from systematic reviews and meta-analyses is limited, including mixed results. Additionally, the majority of systematic reviews estimate the effect of interventions in the K-12 context instead of in the higher education context. Thus, it remains relatively unclear whether social-psychological factors are useful points of intervention for promoting student success *in college*.

We attempt to fill this gap in research literature by examining whether interventions in college settings that incorporate social-psychological factors—namely, interventions that encourage a growth mindset, link classroom work to real-world aspirations, and/or use tools to activate students' motivation and sense of belonging—typically improve student success in higher education. Different from the narrative reviews that dominate education literature, this study uses a meta-analytic approach. The rapid growth of college motivation interventions over the past few years renders a meta-analysis in the college setting feasible and substantiates a focused review of this setting.

Our synthesis has four important strengths compared to prior reviews. First, we synthesize estimates from only primary studies that used random-assignment (experimental) procedures. This restriction to causal estimates from RCTs substantially increases the validity of our findings and should be more informative for institutional administrators who must decide which student success policies to support. Second, we consider institutional context and treatment delivery characteristics of each study to systematically advance our understanding of *when* interventions are effective. A third strength of our synthesis is that we also contribute to nuance in our empirical understanding of *for whom* social-psychological interventions are effective.

There have been calls for more research about moderator variables and context that are a result of findings about the impact of social-psychological interventions as context-dependent (Yeager & Walton, 2011). Specifically, what might work in a research-intensive university with high-performing, highly-motivated students may not be as effective at a more broad-access, less selective school. Researchers certainly consider it important to understand *where* effects are generated, and this is particularly important for institutional administrators and practitioners so that they do not implement interventions inappropriate for their student population. Overall, our synthesis has the potential to facilitate a better understanding of these interventions, thereby positively informing the decisions of institutions, educators, and policymakers.

The fourth strength of our synthesis is that for the types of interventions reflected in our inclusion criteria (i.e., interventions that directly and/or indirectly manipulate students' growth mindset, sense of belonging, utility value, or values affirmation), our synthesis includes more studies than the most recent review conducted on this topic (see Lazowski & Hulleman, 2016). Over one-third of our final sample is from 2016 or later, which is when the most recent meta-analysis was published. The additional data points help us arrive at a more precise estimate of intervention effects, increase our confidence in the external validity and generalizability of the conclusions, and provide evidence about the degree to which intervention effects can be replicated.

2. Social-Psychological interventions in higher education

The college context is a unique setting for motivational interventions. College is a time of transition that has the potential to amplify feelings of self-doubt, anxiety, and isolation (Center for Collegiate Mental Health (CCMH), 2019 , January; Eagan et al., 2017). These feelings, coupled with increased personal autonomy, position college students well to reap the benefits that social-psychological interventions can offer. Social-psychological interventions are based on social-psychological and motivation theories, targeting specific educational problems—such as the challenges students face during their first year in college—and the processes underlying them. For example, in one study, students were given an interactive module to watch during college orientation that explicitly conveyed the idea that intellectual ability can change and develop (i.e., a growth mindset). Students exposed to this module significantly improved their academic motivation and performance (Yeager et al., 2016). In another study, students were provided with opportunities to make concrete connections between what they were learning in a course and things that they cared about. This particular intervention increased final exam scores in the course, and the effects were largest for students who performed poorly on their initial exams (Hulleman, Kosovich, Barron, & Daniel, 2016).

Our synthesis includes three types of social-psychological interventions relevant to higher education, following the framework put forth by Harackiewicz and Priniski (2018). These interventions focus on students' perceived value of academic tasks ("task value interventions"), their framing of academic challenges ("framing interventions"), and their personal values ("personal value interventions"). In the section that follows, we provide examples of interventions in each category.

2.1. Theory-Based Categories of Social-psychological interventions in college

2.1.1. Task value interventions

"communicate the value and importance of course content either by providing examples of the relevance or usefulness of academic tasks for personal goals, or by encouraging students to ascertain the task's value for themselves through writing exercises" (Harackiewicz & Priniski, 2018, p. 411).

Utility value interventions are a common type of task value intervention in higher education. Utility value interventions typically involve asking students to write about why a particular aspect of their course was relevant or useful. For example, researchers in Canning et al. (2018) asked undergraduate biology students in the experimental group to write essays addressing the personal relevance of a topic from their course. They were encouraged to include concrete information covered in the unit and to explain why this information was relevant and useful, using personal examples. The experimental group earned significantly higher grades in a biology course compared to their peers in the control group (a difference equal to 0.19 on a 0 to 4 point scale), and 79.8% of students in the experimental group proceeded to the next semester of biology, compared to only 69.5% in the control condition.

In another example, Harackiewicz, Canning, Tibbetts, Priniski, and Hyde (2015) implemented a brief writing intervention in a college biology course. Students in the treatment group were asked on three separate occasions to answer a question using course material and to discuss the relevance of the concept or issue to their own life or the lives of others. Those receiving treatment saw a statistically significant but relatively small overall improvement in biology course grades ($d = .06$). However, the effect was particularly pronounced for first-generation URM students, whose average grades were higher by more than half a letter grade (slightly over 2.5 versus slightly under 2.1 on a 0 to 4 point scale) compared with the grades of the control group.

2.1.2. Framing interventions

"focus on the challenges students face during academic transitions and help students cope with adversity by encouraging them to frame challenges as common and improvable" (Harackiewicz & Priniski, 2018, p. 412).

Social belonging interventions are a type of framing intervention. Interventions targeting social belonging—that is, the feeling of connectedness and relatedness to one's institution and peers—typically involve making students aware that uncertainty about their place in college is both common and temporary. Walton, Logel, Peach, Spencer, and Zanna (2015) utilized a social belongingness intervention targeting freshmen engineering students. Participants in the intervention group read a brief report and listened to audio recordings of upperclassmen who confirmed that both male and female engineering majors worried about belonging and representation in engineering, but experienced the fading of these feelings with time. The intervention resulted in impressive treatment effects, as the GPA of women in male-dominated majors rose, on average, more than a full letter grade higher than the GPA of otherwise-similar women in the control group. In addition to the effect on GPA, this intervention improved women's perceived experience of their engineering major—as measured by a sense of belonging, self-efficacy, and enjoyment—relative to women in the control condition (a moderate-to-large effect size equal to a standardized mean difference of .67).

Growth mindset interventions are a second type of framing intervention. A growth mindset is the belief that intelligence is not fixed and is, instead, a malleable quality that can be improved. Mindset theory suggests that students with stronger growth mindsets have more adaptive psychological traits and behaviors (e.g., a positive response to failure), which lead to greater academic achievement (Dweck, 2007; Rattan, Savani, Chugh, & Dweck, 2015). Studies suggest that students with a fixed mindset can be taught that intelligence is in fact malleable and therefore can be improved by interventions. For example, Aronson, Fried, and Good (2002) used a pen-pal paradigm intervention in which students were encouraged to view intelligence as malleable. Participants were presented with fictitious letters from at-risk youth; those in the experimental condition were asked to write responses that would encourage their pen pals to work hard even though they were experiencing difficulties. They were further encouraged to talk about how research showed that the brain is like a muscle that will grow stronger through effort. Not only did the intervention measurably improve growth mindset beliefs, but it also improved educational enjoyment and first-year GPA.

Attribution retraining interventions are similar, conceptually, to growth mindset interventions, as their goal is to link success to effort rather than to inherent ability. Theoretically, attribution retraining should engender the belief in students that they can succeed if they try harder or perhaps study more effectively (Menec et al., 1994). Researchers in Perry, Stupnisky, Hall, Chipperfield, and Weiner (2010), for example, presented college students with the message that poor performance can be improved through effort, accompanying this message with an activity as reinforcement. This typical attribution retraining intervention resulted in statistically-and practically-significant treatment effects, with attribution-retraining participants earning first-year GPAs that were approximately .26 grade points higher than those of control participants.

2.1.3. Personal values interventions

Focus on students' core values. As described in Harackiewicz and Priniski (2018), these interventions require students to articulate their personal values rather than merely contemplate the value of course material. This approach aims to highlight the *indirect* value of a course. For example, students may be asked to select from a list of values (e.g., independence, creativity, relationships with family) and then be asked to elaborate on why those values are important to them.

As one example of this intervention type, Harakciewicz et al.'s (2014) values affirmation intervention targeted students taking an introductory biology class. In a brief writing exercise, twice during the semester, students wrote about the values most important to them. Control group students wrote about why values least important to them might be important to someone else. The values-affirmation intervention had important effects for first-generation students: both a significant effect on course grade and, furthermore, increased likelihood of continued enrollment in the biology course sequence. First-generation students in the values affirmation group were more likely to enroll in the next biology course than continuing-generation students, representing a difference in enrollment of roughly 10%. They were also more likely to enroll in the next course in a relevant sequence than were their counterparts in the control group, representing a difference in enrollment of roughly 20%.

Brady et al. (2016) found heterogeneous effects by race for another values affirmation intervention. In this study, first- and second-year college students completed a brief writing exercise in which those in the affirmation condition wrote about their most important values and control group students wrote about a value relatively unimportant to them, also exploring why this value might be important to someone else. Brady et al.'s (2016) intervention effect size was null overall, but positive and moderate for Latinx students. For Latinx participants, though, the benefits persisted: GPAs collected two years after the end of the intervention were significantly higher for students in the affirmation condition than for those in the control group. This affirmation intervention also resulted in a large (effect size equal to 0.94) positive impact for Latinx students regarding "adaptive adequacy"—a measure of self-integrity, self-esteem, and hope.

2.2. Design features of social-psychological interventions in college

The studies outlined above indicate that social-psychological interventions differ in their theoretical bases, but reveal a pattern of larger effects for subgroups of students. They also demonstrate that the interventions show promise in helping students perform better in college. It is also important to note that these interventions differ regarding their characteristics. These differences, discussed below, have the potential to moderate the relationship between interventions and academic outcomes. Two main differences are (1) whether an intervention includes an interactive component and (2) intervention setting.

Passive versus interactive intervention. An interactive element, in the context of social-psychological interventions, means that after participants read materials about the targeted motivation factor, they then write a relevant reflective essay. A writing component has the potential to enhance treatment effects because it can help students internalize positive messages about success through a 'saying is believing' effect (Higgins & Rholes, 1978). For college students, engaging with messages in this way has greater potential to foster an attitude change than passively receiving a message alone.

Intervention setting. Motivation interventions can take place in a variety of settings, particularly in laboratories or in a classroom. Although a laboratory setting can promote internal validity by controlling for extraneous factors, laboratory interventions run the risk of lacking ecological validity. In fact, Lazowski and Hulleman (2016) found that average intervention effect sizes dropped from .63 to .46 when only studies conducted in the educational context (i.e., excluding laboratory-based studies) were considered, suggesting that what is effective in the laboratory may be less effective in contextualized settings. In contrast, classroom-based interventions are more difficult to control but have the advantage of being situated in the learning context—findings from these studies therefore have greater external validity for future social-psychological interventions.

2.3. Review of previous narrative reviews and meta-analyses

The past decade has seen three narrative reviews of social-psychological interventions across school levels, two narrative reviews focused on higher education, and two related meta-analysis. Although these syntheses provide useful information on such interventions, they do not provide comprehensive causal evidence for social-psychological interventions on college academic outcomes. The seven reviews are one or more of narrative (instead of meta-analytic), K-20 (instead of focused on college), outdated, subject to bias (by allowing designs other than RCTs), and calculating effects for merged academic and non-academic outcomes (note that Table 3 reviews key pieces of literature). Because the prior reviews informed our work, though, we review them in some detail.

2.3.1. Narrative reviews

2.3.1.1. Narrative reviews across school levels. Karabenick and Urdan (2014) is an exemplar discussion of the value of social-psychological and motivation interventions, including: the importance of empirical evidence in these types of interventions (Walkington & Bernacki, 2014), examining attribution retraining (Perry, Chipperfield, Hladkyj, Pekrun, & Hamm, 2014), expectancy-value theory (Harackiewicz, Tibbetts, Canning, & Hyde, (2014), and identity and interest theories (Kaplan, Sinai, & Flum, 2014). The numerous studies and projects outlined in this cross-grade narrative research synthesis further emphasize the effectiveness of motivation interventions in promoting positive student outcomes – such as improved academic performance and persistence – at all grade levels. One particularly salient take away from this review was that motivation interventions are most effective when they target a specific group of students at a specific point in their educational careers. This reasoning substantiates our focus on college-level interventions, as college is a unique educational period in which many students experience autonomy for the first time, face new academic and social opportunities, and must manage a new set of responsibilities. These changes have the potential to alter students' motivation for learning, and therefore they also require institutions to incorporate engagement techniques that are different from those used in the K-12 context.

In a cross-grade narrative review, Yeager and Walton (2011) emphasized the theoretical underpinnings and efficacy of motivation interventions. They reviewed laboratory-based motivation intervention studies that communicated a social-psychological message, utilized random assignment, and estimated effects of interventions on students' grades in a course or institution over time. The authors concluded that such interventions are effective because they affect how students learn and thereby result in recursive self-reinforcing messages.

Casad et al. (2018) reviewed six social-psychological interventions that specifically improved gender and/or race inequality in STEM education. Similar to Yeager and Walton (2011), they provided information on the psychological processes that these interventions address, but also discussed their limitations. For example, they noted that growth mindset interventions seem to work particularly well in lab settings but that replication is needed to see if they work equally well in classrooms. They also noted the limited evidence on long-term effects. Lastly, similar to other reviews, they included a discussion about the degree to which these interventions are context- and sample-dependent, and concluded that values affirmation interventions are particularly sensitive in this regard.

2.3.1.2. Narrative reviews in higher education. A recent narrative review provided further support for motivation interventions (NASEM, 2017), and focuses only on higher education. The report highlighted the role of intrapersonal competencies in students' college success, including qualities such as a strong sense of belonging, growth mindset, and academic self-efficacy. As part of this effort, the report reviewed interventions that have helped students develop these competencies, reporting that interventions based on these qualities seem particularly effective for students most at risk for college attrition, such as URM students. NASEM concluded by encouraging replication of the interventions.

In another narrative review, Harackiewicz and Priniski (2018) discussed interventions in college that aim to change students' perceived value of academic tasks, re-frame students' interpretation of academic challenges, and help students tap into sources of self-worth. The scope of the review resulted in the analysis of 20 studies, though the authors only discussed a subset in detail. A contribution of this review was that it provided a theoretical discussion about the relationship between intervention type and student learning outcomes. For example, utility value interventions engage students with the content of a course and the content of a particular field. In other words, these interventions have the potential to stimulate interest in a field and therefore could be related to more distal outcomes, such as students' educational and career choices. Echoing previous work, Harackiewicz and Priniski (2018) concluded that theoretically-driven motivation interventions are effective because they target specific educational problems and the processes underlying them. Further, they stressed that these interventions are context-dependent and encouraged replication to better understand the mechanisms by which and conditions under which these interventions are most effective. They also noted the importance of replication given that some interventions have inconsistent findings across studies, particularly for personal values interventions.

2.3.2. Meta-analytic reviews

The narrative reviews discussed above are informative. Each review treats the empirical context, sample, and treatment conditions delicately, and provides the reader with a detailed account of interventions and their potential benefits for student learning outcomes. However, narrative reviews include only a small subset of studies in a field, and may suffer from selection bias (Cooper & Rosenthal, 1980; Lipsey & Wilson, 2001). Compared to narrative reviews, systematic reviews encompass all studies that are publicly available. They also have the benefit of providing a meta-analytic effect size measuring the strength of the intervention effect. As mentioned earlier, this type of information is particularly important for institutional administrators and policymakers who have limited resources and must decide between a number of approaches for supporting student success in college.

Sisk, Burgoyne, Sun, Butler, and Macnamara (2018) completed a meta-analysis focusing solely on the impact of growth mindset interventions and academic achievement (as measured by standardized test scores, course grades, and GPA) across the K-20 school spectrum.[2] They concluded that overall effects were weak; on average, the academic achievement of students receiving a growth mindset intervention relative to students in control groups was $d = 0.08$. Further, they found minimal variation in effect size by developmental stage. However, subsequent moderator analyses showed that socio-economic status (SES) was a significant moderator. For students from low-SES households, the effect size for academic achievement was much larger ($d = 0.34$, 95% CI = [0.07, 0.62], $p = .013$). This particular finding echoes the narrative reviews discussed above. Lastly, Sisk et al. (2018) found that mode of intervention was a significant moderator. Specifically, growth-mindset interventions were not effective when administered via computer programs instead of via hard-copy reading materials.

The Lazowski and Hulleman (2016) meta-analysis is the only quantitative review to date that includes a comprehensive dataset of theoretically-driven motivation interventions. Lazowski and Hulleman (2016) encompassed 92 intervention studies and 16 related theoretical frameworks of student motivation spanning all educational stages.

Because Lazowski and Hulleman's (2016) inclusion criteria were less conservative than ours, their final sample included a wide range of studies, and it is therefore difficult to determine the implications of this meta-analysis for higher education. Indeed, it reported an effect size of $d = 0.47$ (95% CI [0.38 to 0.57]) for studies conducted in the postsecondary context. This effect size, however, included both RCTs and quasi-experimental studies; we cannot interpret the effect size estimate as a causal effect. Perhaps more importantly, the reported effect size reflected both academic (e.g., course grade-related) and non-academic (e.g., self-efficacy-related) outcome measures. The degree to which these interventions are effective for bottom-line college outcomes, such as course grades, GPA, and persistence is difficult to determine from this meta-analysis.

Further, the difference in effect size estimates between the Lazowski and Hulleman (2016) and the Sisk et al. (2018) meta-analyses suggests that an updated analysis could be informative. Lazowski and Hulleman (2016) reported an effect size equal to 0.56, whereas Sisk et al. (2018) reported an effect size equal to 0.08.[3] Even accounting for the differences in inclusion criteria, the large disparity in effect size estimate for growth mindset interventions between these two studies suggests that the additional studies included in Sisk et al. (2018) are mainly responsible for their different conclusion. This emphasizes the need to examine whether effect size estimates for other intervention types, such as utility value and social belonging, experience the same type of decline in effect size estimate with the inclusion of additional studies. We are able to address this in our analyses.

2.4. Present study

Existing literature about social-psychological interventions suggests that they have the potential to improve student learning outcomes. Our meta-analysis enhances this body of work, by providing an up-to-date meta-analysis of their effects on college students' academic outcomes and examining whether effect size estimates differ by outcome measure, study context, intervention design, and subgroup populations of students. Overall, our analyses synthesize 111 unique effect size estimates from a final sample of 41 college-level randomized interventions. We focus on random assignment designs since they are best suited to address questions of cause and effect (Shadish, Cook, & Campbell, 2002).

[2] This was meta-analysis 2 in Sisk et al., 2018.

[3] The effect size for Lazowski and Hulleman (2016) ($d = 0.56$) refers to growth mindset studies, labeled implicit theories of intelligence. See Table 2 in Lazowski and Hulleman (2016).

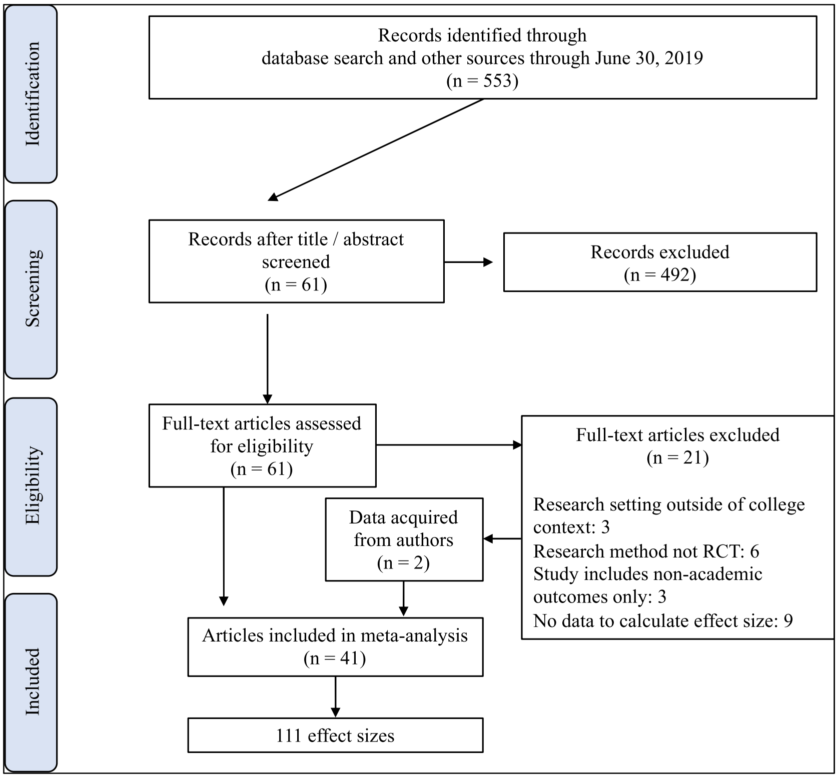

Fig. 1. PRISMA flow chart, Adapted from Moher, Liberati, Tetzlaff, and Altman (2009).

In addition, our synthesis investigates factors—such as type of intervention, study context, type of outcome measure, and intervention design features—that may moderate the relationship between social-psychological interventions and academic achievement. We focus on two research questions: (1) what is the average effect of social-psychological interventions on college students' academic outcomes? and (2) what characteristics of interventions and participants best predict differences in average effect size?

3. Method

3.1. Literature search

We conducted a comprehensive literature search using *Google Scholar* and *PsychInfo* to locate peer-reviewed journal articles, conference papers, doctoral dissertations, and other published and unpublished materials ('grey literature'). We retrieved studies through the end of June 2019. We used the following search terms: *motivation interventions, motivation interventions college, growth mindset interventions, sense of belonging interventions, utility value interventions, attribution retraining, academic self-efficacy interventions, goal-setting interventions, positive future-self, positive future-self interventions,* and *intrinsic motivation interventions.* We also reviewed the reference lists of pertinent chapters in Karabenick and Urdan (2014), prior educational reviews in the same field (e.g., Lazowski & Hulleman, 2016; Yeager & Walton, 2011), and relevant empirical studies found in the database search. We also contacted authors known in the motivation field to request access to their unpublished work. Our literature search yielded 553 results in total.

3.2. Inclusion criteria

Results were only eligible for inclusion if they reported empirical results from an intervention (i.e., they came from a study). Intervention studies meeting the following eight criteria were included in this meta-analysis:

(1) The intervention targeted students attending a college or university,
(2) The intervention that the study presented aimed at directly and/or indirectly manipulating students' growth mindset, sense of belonging, utility value, or values affirmation,
(3) The study included a clearly defined treatment and control/comparison group,
(4) The study used random assignment,
(5) The study included a collegiate academic outcome variable,
(6) The study reported sufficient information so that effect sizes could be calculated,

(7) The study was published in English, and
(8) The study was published between 1980 and 2019.[4]

These inclusion criteria reduced the number of qualifying studies to 41 (see Fig. 1), from which we computed 111 effect sizes (see the Calculation of Effect Size section for details).

3.3. Coding procedure

A code sheet and codebook were developed to record information about effect sizes and potential moderator variables. Coded variables included (1) type of intervention (i.e., utility value, social belonging, growth mindset, values affirmation), (2) outcome measure, (3) institutional context, (4) design elements, and (5) publication status. We also included an indicator for whether the effect size reflected estimates for a particular subgroup population of students. The first and third authors independently coded each study, and the coding agreement across all dimensions was 97%. We resolved all disagreements via discussion.

Intervention type. Each study was coded following the classification system outlined in Harackiewicz and Priniski (2018), where targeted interventions in higher education are divided into three types: task-value, framing, and personal values. Using these distinctions and the examples provided for each (see detailed discussion in Theory-Based Categories of Social-Psychological Interventions in College), we further categorized studies in our analysis into the following four categories: (1) utility value, (2) social belonging, (3) growth mindset/attribution retraining, and (4) values affirmation.

Outcome measure. We categorized each individual effect size as measuring one of the following five student outcomes: (1) competency (e.g., assessments of critical thinking), (2) course exam, (3) course grade, (4) GPA, and (5) persistence measure. The following outcomes were categorized as a measure of persistence: first-year retention, retention at year 2, number of courses in a similar field, total credits accumulated during the study window, enrollment in subsequent course.

Study context. We coded each study for whether the intervention was conducted at a selective institution. Selectivity is a binary measure based on the institution's acceptance rate and the institution's 4-year graduation rate.[5]

Design elements. We coded interventions for whether or not they included an active component and more specifically a writing component. Interventions were also coded for their setting; that is, whether they were administered in a lab or in a non-lab setting, such as in a class.

Student demographic characteristics. We coded each individual effect size for whether they represented a mean difference only for Black students, Hispanic/Latinx students, first-generation college students, or women in a male-dominated major.

Publication status. We coded the variables related to publication status as follows: (1) the study's year of publication and (2) whether it was published in a peer-reviewed journal (1 = published; 0 = unpublished). We did not find non-peer-reviewed published studies that satisfied our inclusion criteria.

3.3.1. Missing data

The majority of studies that met inclusion criteria reported sufficient information to calculate an effect size. When a study did not provide enough information to calculate the ES, we contacted the authors for the appropriate statistics. We contacted five authors, and two responded to our request. For the coding of study characteristics such as the inclusion of a writing component, interventions were coded as 1 if they clearly stated that a writing component was present, and otherwise coded as 0. We did not contact study authors to differentiate between studies with no writing component and studies with a writing component that was not mentioned in the primary study documents, for example.

3.4. Calculation of Effect Size

Hedges' *g*, which adjusts the standardized mean difference Cohen's *d* to correct for upward bias for small samples (Hedges, 1981), is the standardized effect size (ES) used in our meta-analysis, to indicate the difference in outcome variable (e.g., academic achievement) in standard deviation units between the treatment and control groups. ES values were calculated using the Comprehensive Meta-Analysis (CMA) software program (Borenstein, Hedges, Higgins, & Rothstein, 2005). These values are based on a variety of statistical information provided by each study: means, standard deviations, *p*-values, and *t*-values, for example. Positive ES values indicate a more favorable result for students receiving the intervention than for students in the control group.

[4] The most comprehensive meta-analysis on this topic to date (i.e., Lazowski & Hulleman, 2016) did not limit their search to a specific time span and the majority of studies in their analysis (all but 2 studies) were conducted after 1980. Therefore, we included a time span to make the search process more efficient. Further, there was a slow but steady growth in these types of interventions starting in 2000 and more rapidly in 2010, therefore, going further back in time did not seem to make much sense.

[5] See Appendix Table 1 for acceptance rates and graduation rates and corresponding selectivity category. We also use a selectivity variable that comprised of three categories. The conclusions made about selectivity and average ESE remains the same. It should be noted that we include private, for-profit institutions in category three (broad-access) because we include one institution that fit this category. We acknowledge, however, that these types of institutions deserve their own category.

Table 1
Studies included in meta-analysis

Study	Intervention Type	# of Effect Size Estimates	Study Effect Size Estimate	Study Standard Error
Boese, Stewart, Perry, and Hamm (2013)	Attribution retraining	4	0.240	0.306
Hamm, Perry, Clifton, Judith, and Boese (2014)	Attribution retraining	4	0.168	0.224
Perry and Magnusson (1989)	Attribution retraining	4	−0.390	0.337
Perry et al. (2010)	Attribution retraining	9	0.617	0.173
Ruthig, Perry, Hall, and Hladkyj (2004)	Attribution retraining	4	0.426	0.210
Struthers and Perry (1996)	Attribution retraining	4	−0.003	0.259
Wilson and Linville (1985)	Attribution retraining	2	0.333	0.275
Aronson et al. (2002)	Growth mindset	2	0.466	0.236
Bostwick and Becker-Blease (2018)	Growth mindset	4	0.234	0.247
Broda et al. (2018)	Growth mindset	6	0.051	0.054
Burnette et al. (2019)	Growth mindset	1	0.073	0.090
Eskreis-Winkler et al. Study 3 (2016)	Growth mindset	1	0.381	0.189
Fabert (2014)	Growth mindset	1	0.289	0.124
Gripshover et al. Study 3 (2017)	Growth mindset	2	0.010	0.034
Gripshover et al. Study 7 (2017)	Growth mindset	2	−0.020	0.051
Gripshover et al. Study 9 (2017)	Growth mindset	2	0.000	0.046
Sriram (2013)	Growth mindset	1	−0.311	0.197
Wilson Study 2 (2009)	Growth mindset	1	1.479	0.328
Broda et al. Study 2 (2018)	Social belonging	6	0.022	0.054
Murphy, Carter, Gopalan, Walton, and Bottoms (2017)	Social belonging	6	0.142	0.091
Stephens, Hamedani, and Destin (2014)	Social belonging	2	0.337	0.252
Walton and Cohen (2011)	Social belonging	2	0.082	0.299
Walton & Cohen Study 2 (2007)	Social belonging	2	0.033	0.466
Walton et al. Study 2 (2015)	Social belonging	1	0.360	0.150
Yeager et al. Study 3 (2016)	Social belonging	1	0.250	0.082
Acee and Weinstein (2010)	Utility value	2	0.298	0.311
Canning et al. (2018)	Utility value	1	0.260	0.082
Durik et al. Study 1 (2015)	Utility value	2	0.082	0.268
Durik et al. Study 2 (2015)	Utility value	1	0.459	0.174
Harackiewicz et al. (2015)	Utility value	1	0.143	0.063
Hulleman et al. (2016)	Utility value	2	0.246	0.112
Hulleman and An (2017)	Utility value	1	0.260	0.295
McPartlan et al. (2019)	Utility value	4	0.003	0.190
Brady et al. (2016)	Values-affirmation	2	0.017	0.157
Gripshover et al. Study 4 (2017)	Values-affirmation	2	−0.130	0.077
Harackiewicz et al. (2014)	Values-affirmation	4	0.017	0.100
Layous et al., (2017)	Values-affirmation	2	0.407	0.207
Miyake et al. (2010)	Values-affirmation	6	−0.067	0.146
Tibbetts et al. (2016)	Values-affirmation	2	0.008	0.101
Walton et al. Study 1 (2015)	Values-affirmation	2	0.020	0.150
Woolf, McManus, Gill, and Dacre (2009)	Values-affirmation	4	0.115	0.155

Note. McPartlan et al. (2019) study includes first-year pilot study.

3.5. Publication bias

Publication bias occurs when some results are systematically less likely to be published than others (e.g., studies that find small or null effects; Rosenthal, 1979). We first investigated publication bias by comparing the magnitude of effect sizes from published studies to those from unpublished studies, both descriptively and statistically. We also investigated publication bias visually, by examining a funnel plot for any asymmetries in ES distribution, and furthermore via a targeted statistical test, by conducting an Egger's regression test for publication bias (Egger, Smith, Schneider, & Minder, 1997). Funnel plots are scatterplots of ES estimates plotted against a measure of study size (and thereby essentially standard error). Asymmetric funnel plots indicate potential publication bias (Harbord & Harris, 2009).

3.6. Analytic strategy

Many of the studies in our final sample included more than one outcome estimate; we therefore have multiple effect sizes (with

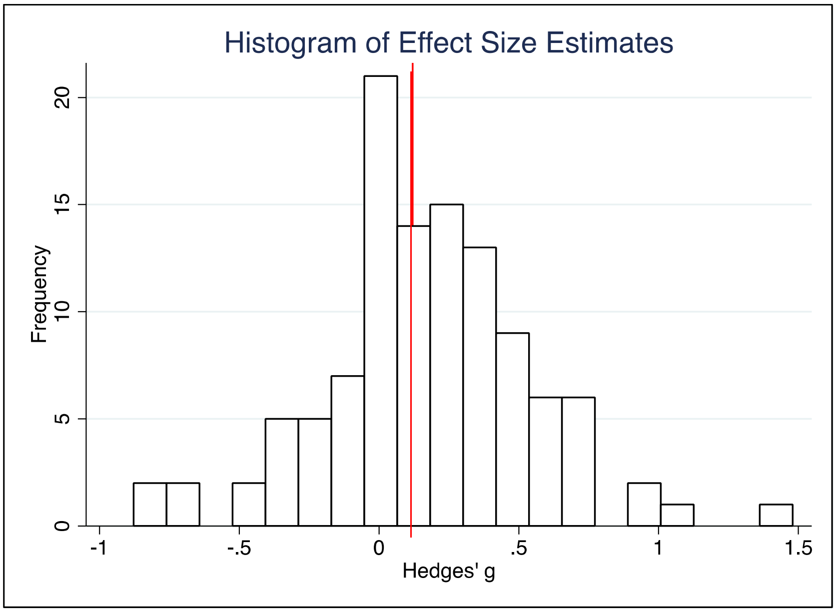

Fig. 2. Histogram of effect size estimates.

hierarchical dependencies) extracted from each of those studies. Almost half of meta-analyses combine multiple estimates within a study by a simple or weighted average (Ahn, Ames, & Myers, 2012). However, doing so does not account for the correlation of within-study estimates (Becker, Hedges, & Pigott, 2004; Gleser & Olkin, 2009; Kim & Becker, 2010; Raudenbush, Becker, & Kalaian, 1988). One avenue for correctly accounting for dependence among estimates is multivariate meta-analysis (see Gleser & Olkin, 2009; Hedges & Olkin, 1985; Raudenbush et al., 1988), but that approach requires within-study correlation statistics (Becker et al., 2004; Jackson, Riley, & White, 2011) which are usually not available.

We use robust variance estimation (RVE) to correctly account for the hierarchical dependencies of within-study estimates. RVE was developed to estimate meta-regression coefficients in models with dependent effect sizes and properly account for those statistical dependencies when the structure of their dependence is unknown (Hedges, Tipton, & Johnson 2010a, 2010b; Tanner-Smith & Tipton, 2014). In order to reduce the Type I error rate, our analyses also made use of a small sample correction to both residuals and degrees of freedom (Tipton, 2014). RVE performs at least as well as other approaches and is robust to variations in the intraclass correlation value *p*, for estimating both the effect size and heterogeneity statistics (Moeyaert et al., 2017; Scammacca, Roberts, & Stuebing, 2014). The meta-regression can be conducted with as few as 10 studies, has nominal estimation properties with 50 estimates from 10 studies, and has nearly nominal results for less evenly-balanced distributions of estimates (Hedges et al., 2010a). RVE is increasingly the technique of choice used to account for within-study dependencies in education meta-analyses (e.g., Aksayli, Sala, & Gobet, 2019; Conn, 2017; Dessemontet, Martinet, de Chambrier, Martini-Willemin, & Audrin, 2019; Dietrichson, Bøg, Filges, & Klint Jørgensen, 2017; Fitzpatrick & Burns, 2019). Our synthesis of ESs is via RVE meta-regression calculation of the coefficient only, using the small sample correction and hierarchical weights.

4. Results

Our final sample includes 41 studies, from which we extracted 111 unique effect sizes. Table 1 lists all studies included in the analysis and the respective study-level ESE.

4.1. Overall mean effect size estimate (ESE)

Fig. 2 presents a histogram of the 111 ESs extracted from our final sample. As shown in Fig. 2, the ESs range from −0.88 to 1.45. This figure suggests, descriptively, a positive relationship between motivation interventions and academic outcomes, as the majority (70.8%) of these estimates show that students in treatment groups outperformed students in control groups. The overall mean ESE from our RVE calculations (across not just all studies but also all moderator variables that we examine), indicated by the red line on the histogram, is 0.12 for social-psychological interventions on college academic outcomes.

4.1.1. Publication bias

The results comparing effect sizes for published and unpublished studies are shown in Table 2 (Column 3). The mean ES estimate is 0.14 for published and .07 for unpublished studies. The difference in these estimates, however, is not statistically significant ($p = .48$). The funnel plot in Fig. 3 shows symmetry at the top of the funnel, but less towards the middle and bottom: ESs appear to be positively

Table 2
Mean effect size estimates, Overall, by study characteristics and by student population.

	(1) N of ESEs	(2) N of studies	(3) Mean ESE	(4) SE
Overall Mean Estimate	111	41	0.120**	(0.037)
Intervention Type				
Utility value	14	8	0.182***	(0.053)
Sense of belonging	19	6	0.097	(0.051)
Growth mindset/AR	55	19	0.155*	(0.069)
Values affirmation	23	8	0.024	(0.037)
Outcome Measure				
Competency test	13	–	0.277	(0.258)
Course exam	14	–	0.110	(0.059)
Course grade	20	–	0.144**	(0.054)
GPA	45	–	0.171***	(0.038)
Persistence measure	19	–	0.024	(0.022)
Institutional Setting				
Selective	72	26	0.159**	(0.058)
Not-selective	28	10	0.048	(0.034)
Design Elements				
Passive intervention	43	15	0.147	(0.097)
Active intervention	68	26	0.104***	(0.022)
Intervention administered in a lab setting = No	70	27	0.078***	(0.020)
Intervention administered in a lab setting = Yes	41	14	0.281*	(0.120)
Subgroup Population				
At risk group in college or within major = No	74	–	0.050	(0.027)
At risk group in college or within major = Yes	37	–	0.300***	(0.076)
Publication Status				
Published = No	23	9	0.073*	(0.037)
Published = Yes	88	32	0.140**	(0.050)
Publication Date				
Publication date: 1985–2009	22	8	0.185	(0.124)
Publication date: 2010–2014	35	10	0.227	(0.134)
Publication date: 2015–2019	54	23	0.076***	(0.021)

Note. Robust variance estimation was used to retrieve average effect size estimates. Column 3 ESE calculated via meta-regression of the coefficient only for the pertinent study-level estimates, using the small sample correction and hierarchical weights. Asterisks indicate whether the coefficient is significantly different from zero. *p < .05; **p < .01; ***p < .001.

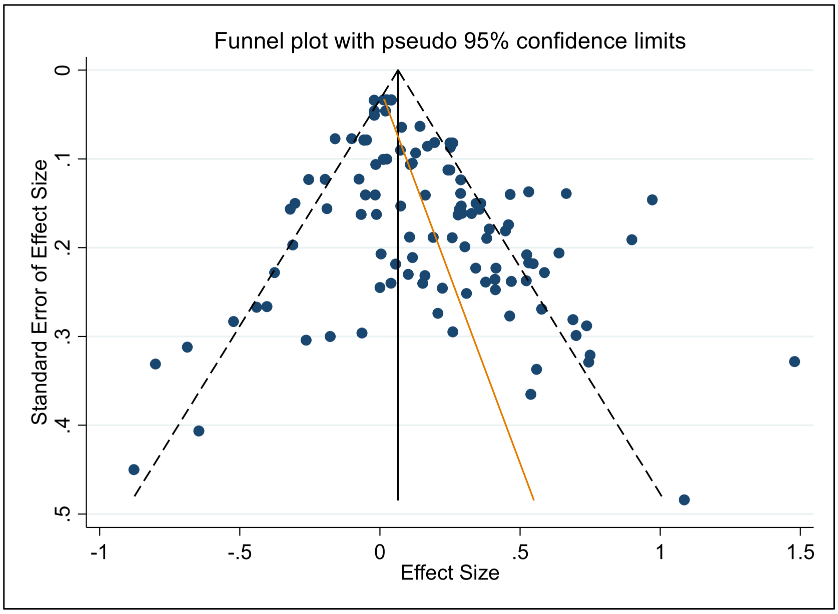

Fig. 3. Funnel Plot: Distribution of effect size estimates with regression line.

skewed. Visually, there appears to be a degree of publication bias. The Egger's (1997) regression test is a regression-based method that provides a *p*-value associated with publication bias. In our case, the *p*-value is significant. Taken together, the distribution of ESs supports an inference of publication bias; studies with smaller sample sizes are associated with more positive ESs than one would expect by chance. As a result, we calculated an adjusted overall average ES to account for publication bias using the "trim and fill" approach (Duval & Tweedie, 2000a; 2000b). The trim and fill approach builds on the key idea behind the funnel plot: in the absence of publication bias driven by statistical significance standards, the funnel plot would be symmetric around the meta-analytic mean effect. If the plot contains more small studies on the right than on the left, this may be due to publication bias, where smaller samples were only published if they reported the larger effects required to achieve statistical significance. Conversely, the concern is that studies may be missing on the left, where non-significant studies were suppressed from the literature. The trim and fill method attempts to impute ESs into a funnel plot to achieve symmetry, adds these ESs into the meta-analysis, and then re-computes the meta-analytic mean (Borenstein, Higgins, & Rothstein, 2009). The mean estimate based on trim and fill falls to 0.08 but is still statistically significant (95% CI 0.04 to 0.13).

4.2. Moderator analyses

In addition to the overall mean ESE of 0.12, Table 2 Column 3 shows the mean ESE for each moderator variable. Each estimate was calculated as its own RVE coefficient-only model that again correctly accounts for statistical dependencies among estimates when studies produced more than one effect size. As shown, all ESEs are positive, and most are significantly different from zero.

In terms of intervention type, we find that utility value and growth mindset interventions are particularly effective. The mean ESE is 0.18 and 0.16 respectively. The mean ESE is lowest for studies categorized as 'values affirmation' ($d = 0.02$). We also estimate the mean ESE for each outcome measure. The mean ESE is largest for those generated from competency test scores ($d = 0.28$), but it is not statistically significant, and for GPA ($d = 0.17$), the latter of which includes the largest number of ESEs.

We also calculated mean ESEs for variables related to study context. We find that institutional context matters. Specifically, studies conducted at institutions coded as selective have a mean ESE equal to 0.16. Studies conducted at moderately-selective/broad-access institutions (labeled non-selective) have a much lower mean ESE equal to 0.05. A joint test of significance shows that the ESEs are statistically different from one another ($p = .03$).[6] We also calculated the mean ESE for studies that took place in a laboratory context. The mean ESEs for studies that took place in a laboratory ($d = 0.28$) is much larger than those for studies that did not take place in a lab ($d = 0.08$).

Regarding design characteristics, we find that – counter to prior conclusions – studies including a writing component ($d = 0.10$) report average ESs smaller than those that do not include a writing component ($d = 0.15$). Lastly, we also calculated mean ESE for a subset of effects that reflected students at risk in college or within a major. The mean ESE for this particular group is $d = .30$, which differs significantly from the mean ESE calculated for a subset of effects for students not at risk ($d = 0.05$).

4.2.1. Heterogeneity

In RVE meta-analysis with hierarchical weights it is appropriate to conduct two tests of heterogeneity in estimates. Omega squared is a measure of variation in within-study or within-cluster estimates of effect size. Tau squared ($\tau 2$) estimates variance between clusters (between studies), and is more similar to heterogeneity measures that readers may be familiar with from other meta-analytic approaches.

For both the overall effect size estimate and all analyses by study or student characteristics, the value of omega squared was 0.000, revealing no problematic within-study heterogeneity. For 20 of the 23 effect size estimates in Table 2, Tau squared was also 0.000, but 3 estimates exhibit at least minimal between-study heterogeneity. For studies conducted in a lab setting ($\tau 2 = 0.0028$) and studies published before 2009 ($\tau 2 = 0.0399$), the extent of between-study variance in effect size is still quite small. In other words, these values still indicate a precise estimate resulting from a narrow range of values in effect size estimate matching those characteristics (Borenstein, Higgins, & Rothstein, 2009). The much larger value of Tau squared (0.1977) reveals much less stability (and greater variation) in the true effect of college social-psychological interventions for the studies whose outcome measure was a competency test. Although outside the scope of this meta-analysis, it would be useful for future research to further examine both the causes of the greater variation in estimates for test outcomes and what is illuminated by examining test outcomes restricted by other study or student characteristics.

5. Discussion & conclusion

In this study, the primary goal has been to synthesize evidence regarding the efficacy of social-psychological interventions in the college context. Our choice to focus on college-level interventions stems from the fact that college is a unique setting in which students become particularly autonomous. Unlike primary school and high school, during which parents and teachers often drive and incentivize students' motivation to succeed, college facilitates student responsibility and motivation. This fact, informed by the recent growth of social-psychological interventions in the college context, motivates our inquiry.

Narrative reviews (Harackiewicz & Priniski, 2018; NASEM, 2017) and the most recent systematic review (Lazowski & Hulleman,

[6] When institutional selectivity includes three categories—selective, moderately selective, broad access—the mean ESE is still larger among selective and moderately selective institutions as compared to broad access institutions. The joint test of significance p-value in this case is equal to 0.07.

2016) suggest that social-psychological interventions are an effective way to improve student academic outcomes in college. Consistent with this body of work, we found a positive relationship between this type of intervention and academic outcomes. It is important to note, however, that although our results are consistent in *direction* with extant knowledge, our ESE is one-third the magnitude of Lazowski and Hulleman's (2016). This is not surprising when one considers our narrow focus on college-level *randomized* interventions. In doing so, we included a small subset of Lazowski and Hulleman's (2016) studies—all of which fall within the interventions with academic-related outcome measures that are most relevant to the college context: utility value, sense of belonging, growth mindset, and values affirmation (Harackiewicz & Priniski, 2018). Given the increasing popularity of these types of interventions, our final sample includes 31 additional studies unavailable to Lazowski and Hulleman (2016).

Our synthesis addresses a more specific question than prior meta-analytic and narrative reviews: are social-psychological interventions effective in postsecondary education in terms of academic outcomes? This said, we acknowledge, of course, that academic outcomes are not the only markers of success in college. For example, Brown, Smith, Thoman, Allen, and Muragishi (2015) found that an intervention emphasizing the communal utility value of biomedical research increased student motivation to pursue a biomedical research career in the future. This is an important study with practical implications. We do not capture outcomes such as this in our analysis; we focus on bottom-line academic outcomes because they are highly relevant to institutional administrators and policymakers trying to understand the college-to-degree pipeline. We know from prior literature that how well students do academically is a strong predictor of college degree attainment (Gershenfeld, Ward Hood, & Zhan, 2016; Stewart, Lim, & Kim, 2015).

In our synthesis, we find that social-psychological interventions in college improve academic outcomes with a mean ESE of 0.12. To interpret this ESE, we follow the framework provided by Kraft (2020) developed for education interventions. As compared to traditional benchmarks for interpreting ESEs (Cohen, 1988), the Kraft (2020) framework takes into consideration program cost and scalability, in addition to effect size estimate, and is more aligned with empirical evidence about what magnitude of effects are replicable from education interventions specifically. Given that social-psychological interventions are low-cost and easy to scale, the ESE of 0.12 is considered moderate. This moderate effect (Kraft, 2020) is comparable to ESs often found in higher education research. For example, Sneyers and De Witte (2017) examined mentoring interventions in higher education through a meta-analytic review of 25 studies, finding that student-faculty mentoring has a positive impact on both retention and graduation ($d = 0.15$ and 0.10, respectively). Comparing the average ES from our meta-analysis to practical benchmarks in higher education may provide incentive for colleges and universities to implement social-psychological interventions and test their efficacy, especially since they are cost-effective. In fact, a typical social-psychological intervention costs only dollars per student (Paunesku, 2013; Yeager & Walton, 2011).

5.1. Key findings from moderator analyses

5.1.1. Particular benefits for at-risk students

We want to highlight three findings from our moderator analyses that have clear implications for institutional administrators and future research. Social-psychological interventions seem to be particularly beneficial for students least likely to persist in college overall or within specific majors. In our study, we refer to these students as "at risk" and report an average ESE for these students ($d = 0.30$) that is substantial in comparison to effects typically found in education research; it is also 0.25 standard deviation units greater than the ES for students not designated "at-risk." This finding is consistent with the findings of prior literature that emphasize social-psychological interventions are most beneficial when they target specific groups of students for specific reasons (Harackiewicz & Priniski, 2018).

This finding is also in line with Sisk et al. (2018), who found evidence that academically high-risk students and economically disadvantaged students may benefit the most from growth mindset interventions. This is a promising outcome given that addressing the achievement gap between advantaged and disadvantaged students is a priority. Social-psychological interventions may offer a low-cost approach for doing so.

5.1.2. Effectiveness at highly-selective institutions

Compared to narrative reviews, meta-analytic reviews are often criticized for stripping away context. Indeed, context is very important for generalizability in our study since most students in the United States attend non-selective colleges and universities; the factors that affect student achievement and persistence may differ across contexts. In our meta-analysis, we have attempted to capture context, finding that studies conducted at more-selective institutions have larger ESEs than studies conducted at less-selective institutions. This finding makes sense when considering the forces that social-psychological interventions are, according to research literature, operating against. At a broader-access institution, a student may have many high school classmates. A "belonging" intervention will likely be countering greater feelings of *not* belonging at a highly-selective institution. Similarly, the stereotype threat faced by URM students and women in STEM fields is more prevalent at higher-selectivity institutions because, in most cases, the proportion of racial minority and low-income students is small at these institutions (Inzlicht & Ben-Zeev, 2000; Walton, Spencer, & Erman, 2013).

In our study, less-selective institutions include broad access institutions and community colleges. Given that these types of colleges enroll more than half of college students–many of whom are often underprepared for college-level coursework (Bailey, 2009) in addition to being from low-SES families and often the first in the family to attend college–the finding about selectivity has implications for how researchers should conceptualize student support (Deil-Amen, 2011). In other words, the majority of students in most colleges may need more than "light touch" social-psychological interventions to successfully progress through college. Indeed, persistence models for community college students stress the importance of strong student-faculty interactions and the need for these interactions to be nurtured *in the classroom* given that most community college students commute to school. High-quality interactions and the

Table 3
Review of literature & comparison of ESEs.

	Our findings		Lazowski and Hulleman (2016), Review of Educational Research[a]		Harackiewicz and Priniski (2018), Annual Review of Psychology[b]		Sisk et al. (2018), Psychological Science[c]	
	Meta-analysis		Meta-analysis		Narrative review		Meta-analysis	
	N	ES	N	ES	N	ES	N	ES
Overall ES estimate	41	0.120 (0.037)	10	0.205 (0.067)	15	0.150 (0.057)	–	–
Intervention Type:								
Utility value	8	0.182 (0.053)	1	–	3	–	–	–
Social belonging	6	0.097 (0.051)	3	0.232 (0.078)	5	–	–	–
Growth mindset/AR	19	0.155 (0.069)	5	0.313 (0.112)	2	–	–	–
Growth mindset	12	0.127 (0.054)	1	–	1	–	13	0.080 (0.045)
Values affirmation	8	0.024 (0.037)	1	–	5	–	–	–

Note. N = number of studies in postsecondary context. Standard error in parentheses.
[a] N includes randomized control trial studies. They include 16 studies in the postsecondary context; however, 5 do not report an academic outcome and we can not retrieve ESE from one.
[b] Harackiewicz and Priniski (2018) include 21 studies; we were unable to retrieve ESE for 5 of them.
[c] The effect size estimate is not going to be the same as that reported in Sisk et al. for the following reasons: 1. We use the most updated version of each manuscript, see Bostwick (2015) for an example; 2. We use Hedges' *g*, not Cohen's *d*; and 3. We include studies not included in their analysis.

experiences they help create in the classroom are important for community college student success (Deil-Amen, 2011).

Social-psychological interventions may still be appropriate in these contexts, but institutional administrators and practitioners need to consider how to tailor them to fit their students. For example, there are qualitative studies that have discussed the importance of cultivating the development of a "college-going identity" for non-traditional students (Collatos, Morell, Nuno, & Lara, 2004; Saunders & Serna, 2004). As a result, interventions based on identity frameworks could prove to be more impactful. Also, institutional administrators and practitioners may want to consider dosage effects. It could very well be the case that students attending relatively less-selective institutions would benefit from repeated messages throughout the semester. Social-psychological interventions, for the most part in their current form, provide messages at a single time point during the semester. Whether students benefit from repeated messages is an empirical question that future research could easily test.

5.1.3. *Smaller effects in classroom settings*

Further, the finding about selectivity, coupled with the low ESE for studies conducted in non-lab settings ($d = 0.08$, as compared to .28 for studies conducted in a lab setting), has implications regarding generalizability, scalability, and research. Most importantly, this large split in ESE indicates that the expected effects from future social-psychological interventions in non-lab college settings account for only about half of our overall estimate. Second, the split provides an important opportunity for research on program design; in other words, are there elements of lab delivery that can be applied with more universal delivery in order to increase the effectiveness of future non-lab interventions?

To address these types of questions, we encourage future work to take place in classrooms rather than in a lab setting, so that our field can start exploring under what conditions—and with what instructor behaviors—social-psychological interventions are most effective in field settings. Indeed, instructor characteristics could make a nontrivial difference in how intervention messages are interpreted, and our findings therefore motivate further exploration. A sense of belonging intervention in a male-dominated engineering class, for example, could send a stronger message to females if the intervention is administered by a female engineering instructor.

Lastly, we must be cognizant of the fact that future findings from social-psychological interventions in college may change our conclusions. Table 3 presents a review of ESs across key literature syntheses. As shown in Table 3, Sisk et al. (2018) reports a much lower ESE for growth mindset interventions than Lazowski and Hulleman (2016) does (0.08 versus 0.31).[7] We speculated that this was largely due to the increase in study sample size and questioned whether the ESE for other types of interventions would be diminished in a similar fashion in our updated syntheses. This seems to be true—although to a lesser degree—for social belonging interventions. Lazowski and Hulleman (2016) include 3 social belonging studies in the college context; we include 6, and the ESEs between these studies differ by 0.13 (0.23 versus 0.10).

Social-psychological interventions show an average effect that is large enough to make a difference for students. The results of our study are therefore relevant for any institutional administrator who works to help students succeed in terms of development, retention, engagement, achievement, and graduation. A good approach moving forward may be to build on the identified heterogeneity in social-psychological interventions to further improve them so that they can benefit a broader group of students.

[7] 31 was calculated by the author. The point estimate was retrieved using randomized control studies only as an attempt to make the two studies more comparable.

CRediT authorship contribution statement

Sabrina Solanki: Formal analysis, Visualization, Data curation, Writing - original draft, Project administration, Conceptualization. **Dan Fitzpatrick:** Methodology, Formal analysis, Writing - review & editing, Conceptualization. **Masha R. Jones:** Writing - review & editing, Conceptualization, Validation. **Hansol Lee:** Writing - review & editing, Conceptualization.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.edurev.2020.100359.

Appendix

Table 1
Institutional Selectivity Categories.

Acceptance Rate	Graduation-Rate	Selectivity Category
0.05	0.95	1 = Selective University
0.30	0.94	1 = Selective University
0.41	0.86	1 = Selective University
0.53	79.6	2 = Moderately Selective
0.53	79.6	2 = Moderately Selective
0.66	0.84	2 = Moderately Selective
0.66	0.79	2 = Moderately Selective
0.70	0.59	2 = Moderately Selective
0.72	0.82	2 = Moderately Selective
Competitive	0.80	2 = Moderately Selective

Note. Each institution was categorized as 1 = selective or 2 = moderately selective if it had both the designated acceptance rate and graduation rate. Institutions accepting the majority of students, such as community colleges, were categorized as 3 = broad access. In the main model that uses a two-category selectivity variable, we include broad-access in category 2.

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