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Multivariate meta-analysis of self-regulated learning and academic performance in higher education: Moderators, mediators, and methodological insights

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ABSTRACT

This meta-analysis examines the relationship between self-regulated learning (SRL) and academic performance in higher education, quantifying the overall effect size and exploring factors contributing to variability. A systematic review using Google Scholar and Scopus identified 62 studies (14 articles, N=6,991 participants) published between 2014 and 2024, involving undergraduate, medical, and EFL learners. Using a random-effects model, the analysis revealed a pooled moderate positive effect of SRL (Zr=0.239, 95% CI: 0.204–0.274, p<0.001) on academic performance. Subgroup analyses revealed higher effect sizes among medical students (Zr=0.326) compared to undergraduate (Zr=0.228) and EFL learners (Zr=0.284). Path analysis studies yielded larger effect sizes (Zr=0.312) compared to correlational designs (Zr=0.239), highlighting SRL's mediating role. No significant publication bias was detected (p=0.484, Egger's test). Practically, these findings suggest educators should design interventions tailored to academic contexts, incorporating explicit goal-setting, structured self-monitoring, and reflective practices. Future research should address methodological gaps by adopting longitudinal designs, diversifying samples, and standardizing SRL measurement frameworks.

1. Introduction

1.1 Background

Self-regulated learning (SRL) is an essential process in education, enabling learners to take active control of their learning through goal setting, self-monitoring, and self-evaluation. These processes are part of a cyclical model proposed by Zimmerman, which involves forethought, performance, and self-reflection phases. These phases allow learners to adapt and refine their strategies continuously, enhancing learning outcomes (Xu et al., 2022; Yu et al., 2022). In higher education, SRL has gained increasing recognition as a critical skill for fostering autonomy, sustaining motivation, and driving academic success (Dogu et al., 2022; Wang et al., 2023). Students with well-developed SRL abilities are better equipped to tackle academic challenges, including those presented by online learning environments, as evidenced during the COVID-19 pandemic (Hadwin et al., 2022; Men et al., 2023). Beyond its immediate benefits, SRL plays a pivotal role in lifelong learning, enabling students to become proactive, reflective, and adaptive in their educational pursuits (Sáez-Delgado et al., 2023; van der Graaf et al., 2023).

The theoretical basis of SRL highlights its multifaceted nature, encompassing cognitive, motivational, and metacognitive components. Zimmerman's framework, which includes forethought (planning and goal-setting), performance (self-monitoring), and self-reflection phases (Zimmerman, 2008), underscores how learners actively

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adapt their strategies based on continuous feedback and reflection (He et al., 2022; Yu et al., 2022). In contrast, Pintrich's model emphasizes motivation and the perceived value of tasks as core drivers influencing students' engagement in SRL (Pintrich, 2004). Metacognition involves awareness and control over cognitive processes, empowering learners to evaluate their understanding and adjust their strategies accordingly, leading to improved academic outcomes (Afrashteh & Rezaei, 2022; Pachón-Basallo et al., 2022). Motivation is another crucial element, as it drives learners to persist in the face of challenges and to engage in behaviors that enhance learning. Students with higher levels of motivation are more likely to employ self-regulation strategies effectively, thereby achieving better academic performance (Wang et al., 2023; Xu et al., 2022).

Self-efficacy, defined as the belief in one's ability to achieve specific goals, plays a vital role in SRL. High self-efficacy has been linked to greater persistence, higher academic goals, and adaptive learning strategies, all of which contribute to improved academic performance (Halmo et al., 2024; Miao & Ma, 2023). For instance, students with strong self-efficacy beliefs are more likely to tackle difficult tasks, monitor their progress effectively, and adjust their learning approaches when necessary. This interplay between self-efficacy and metacognition forms the foundation of SRL, enabling students to navigate complex academic environments with confidence and strategic awareness (Dahri et al., 2024; Siregar et al., 2024).

The relationship between SRL and academic performance has been the focus of extensive research, with numerous studies highlighting its positive impact. For example, Xu et al. (2022) demonstrated that effective SRL strategies significantly enhanced academic performance during online learning, particularly during the disruptions caused by the COVID-19 pandemic. Similarly, Wang et al. (2023) found that SRL mediates the relationship between mental health and academic performance, suggesting that students who manage their learning processes effectively are better able to cope with psychological challenges. Furthermore, Hadwin et al. (2022) emphasized the role of SRL in overcoming academic challenges, while Tadesse et al. (2022) identified SRL strategies as strong predictors of perceived learning gains among undergraduate students. Collectively, these studies underscore the critical role of SRL in fostering academic success and highlight the importance of developing these skills in educational settings.

Interventions aimed at improving SRL have also demonstrated significant benefits for academic performance. For instance, targeted SRL interventions during online learning not only addressed challenges posed by remote education but also enhanced students' long-term learning strategies and outcomes (Hadwin et al., 2022). Teacher-driven strategies, such as fostering a supportive learning environment and integrating SRL practices into instruction, have also been effective. Research by Cunha (2023) demonstrated that teacher-led SRL interventions improved students' classroom engagement and psychological well-being, particularly for those with lower prior achievement. Heikkinen et al. (2023) further highlighted the potential of learning analytics in supporting SRL, showing that data-driven feedback helps students monitor and adjust their learning processes effectively. Additionally, Miao and Ma (2023) emphasized the importance of teacher autonomy support in fostering SRL, which enhances students' self-efficacy and engagement, ultimately improving academic performance.

While the relationship between SRL and academic performance is well-documented, it is not without complexities. Several factors mediate or moderate this relationship, influencing its outcomes. Self-efficacy serves as a critical mediator, shaping students' motivation and persistence, which in turn enhances SRL and academic success (Miao & Ma, 2023). For instance, Miao's research demonstrated that teacher autonomy support positively impacts self-efficacy, fostering more effective SRL strategies and improved academic engagement. Social support, defined here as emotional, informational, or practical assistance provided by teachers, peers, or family, is another important mediator, as it alleviates psychological distress and creates favorable conditions for effective SRL. Xu et al. (2022) found that supportive environments enhance students' ability to self-regulate their learning, particularly under stressful conditions. Moreover, intrinsic motivation—driven by internal factors such as interest, enjoyment, or inherent satisfaction in learning tasks—is a crucial moderator. Students who are intrinsically motivated are more likely to engage in SRL practices, leading to better academic outcomes (Hands & Limniou, 2023). These factors underscore the complex interplay of cognitive, emotional, and social elements in shaping the relationship between SRL and academic achievement.

1.2 Research Gap and Novelty

Despite the growing body of evidence, several gaps in the literature remain. One notable challenge is the inconsistent definition and operationalization of SRL across studies. While some researchers focus on metacognitive strategies as the core of SRL (Říčan et al., 2022; Xu et al., 2022), others emphasize motivational or environmental factors, leading to fragmented conclusions about its impact on academic performance (Hadwin et al., 2022; Navarro et al., 2023). Additionally, the mechanisms through which SRL influences academic outcomes are not fully understood. This theoretical ambiguity arises partly due to the overlapping but distinct frameworks proposed by Zimmerman, which prioritizes metacognitive regulation, and Pintrich, which integrates motivational aspects. While some studies highlight self-efficacy as a mediator (Wang et al., 2023; Xu et al., 2022), others point to social support or specific learning strategies as critical factors. This lack of consensus underscores the need for more comprehensive models that integrate these elements to provide a holistic understanding of SRL.

Furthermore, the generalizability of existing research is limited, as many studies focus on specific populations, such as nursing students or those in online learning environments (Ragusa et al., 2023; Yoo & Jung, 2022). Additionally, existing literature often disproportionately represents studies from Western or Anglophone contexts, limiting global generalizability. Greater inclusion of research from regions such as Asia, Africa, and Latin America would enhance cultural contextualization and applicability of findings. Longitudinal studies tracking the development of SRL over time and its long-term effects on academic achievement are also scarce (Bardach et al., 2023; Sáez-Delgado et al., 2023). Addressing these gaps is essential for advancing our understanding of SRL and its implications for educational practices.

1.3 Research Objective and Questions

In light of these considerations, this meta-analysis aims to address critical gaps in the literature and provide a comprehensive synthesis of the relationship between SRL and academic performance in higher education. Specifically, the objectives of this study are to (1) quantify the overall effect size of SRL on academic performance in higher education, providing a reliable estimate of its impact across diverse studies; (2) examine the sources of heterogeneity in the relationship between SRL and academic performance, identifying factors that influence variations in effect sizes; (3) evaluate the role of potential mediators and moderators, such as self-efficacy, social support, and motivation, in shaping the SRL-academic performance relationship; and (4) assess publication bias and the robustness of the findings using advanced statistical techniques.

The central research questions thus guiding this study are: *What is the overall effect of SRL on academic performance in higher education? What factors contribute to the heterogeneity observed in the relationship between SRL and academic performance? How do mediators such as self-efficacy and social support influence the impact of SRL on academic outcomes?* and *Is there evidence of publication bias in the studies analyzed, and how does it affect the reliability of the findings?*

This meta-analysis seeks to contribute to the growing body of research on SRL by addressing these questions, explicitly linking findings to instructional theories and practical curriculum design frameworks. By synthesizing findings from a diverse range of studies, this analysis aims to offer a comprehensive understanding of SRL and its critical role in academic success.

2. Method

This meta-analysis followed a rigorous methodology to synthesize findings from studies examining the relationship between self-regulated learning (SRL) and academic performance in higher education. The methods were guided by established frameworks such as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and the Meta-analysis of Observational Studies in Epidemiology (MOOSE), ensuring transparency and reproducibility throughout the process (Bafeta et al., 2013; Yeomans et al., 2018). The analytical approach adhered to best practices for systematic reviews and meta-analyses in psychology and education, emphasizing a structured, unbiased, and replicable process (Grant et al., 2013; Martínez-García, 2022). Inter-rater reliability was calculated using Cohen's Kappa ($\kappa = 0.84$), indicating high agreement between two independent reviewers during the study selection process.

2.1 Data Sources and Search Strategy

A comprehensive search was conducted across two major databases, Google Scholar and Scopus, covering publications from the last decade (2014–2024). This timeframe was selected to capture recent trends and advancements in SRL research. Keywords included "self-regulated learning," "self-efficacy," "academic achievement," "academic performance," and "metacognition." Boolean operators and search strings were utilized to enhance precision and comprehensiveness (Boulos et al., 2021; Marler et al., 2014). The search process prioritized peer-reviewed journal articles to ensure the quality and credibility of the studies included. To enhance global representation and citation diversity, additional manual searches were performed to specifically identify studies from underrepresented regions (e.g., Asia, Africa, Latin America).

To address potential publication bias, the search strategy incorporated principles for identifying grey literature, such as reports and theses. However, only peer-reviewed studies indexed in Scopus were ultimately included, given the emphasis on ensuring high methodological rigor and standardization (Tsuji et al., 2020). Grey literature (e.g., theses, reports) was ultimately excluded due to variability in methodological rigor, inconsistent peer-review standards, and to maintain comparability and quality assurance across studies. This decision was explicitly acknowledged as a limitation of the review.

2.2 Study Selection

The selection process involved predefined inclusion and exclusion criteria to ensure relevance and quality. Studies were eligible for inclusion if they: (1) focused on higher education populations, specifically university or college students; (2) employed correlational, regression, or path analysis methodologies to examine the relationship between SRL and academic performance; (3) reported data in an international language, predominantly English; (4) were published in Scopus-indexed journals; and (4) included a sample size of more than 50 participants.

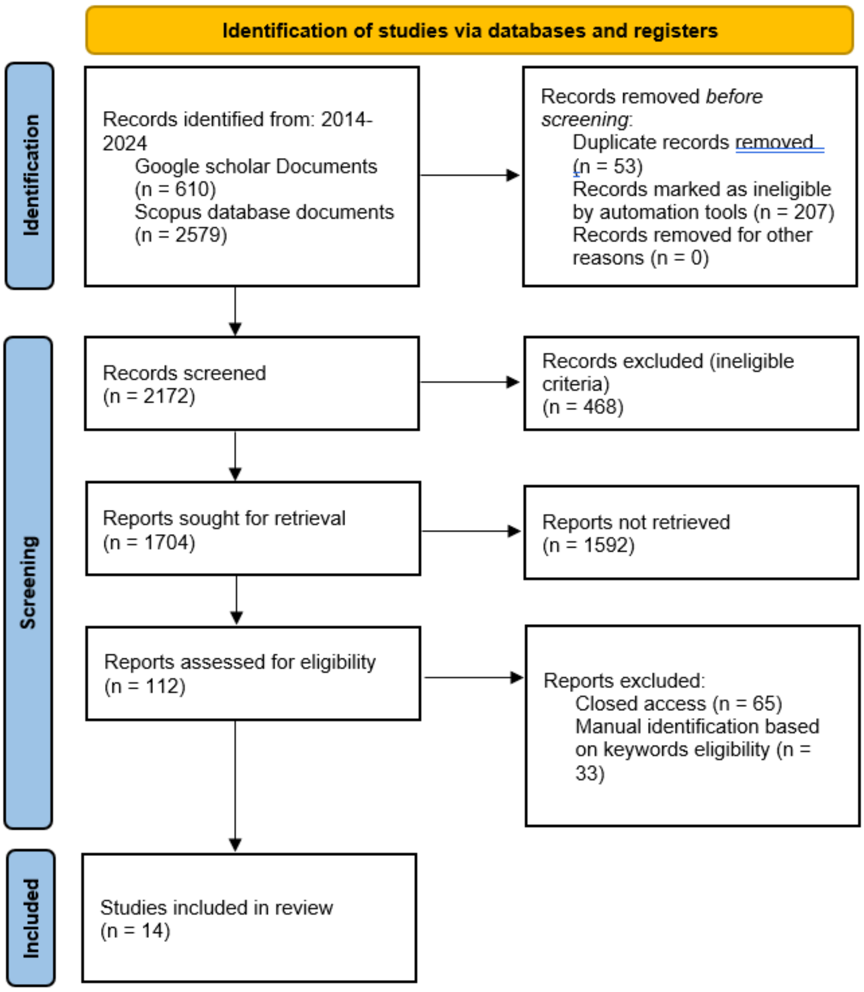

Figure 1. The selection process utilized

Regression analyses were standardized by converting regression coefficients to correlation coefficients (r), while path analysis studies were included if SRL (or its subscales) was treated as an independent or mediating variable. Studies were excluded if they did not provide sufficient data for effect size calculations or if SRL was found to have no direct or mediated effect on academic performance (Baziliansky & Cohen, 2021). Study quality was systematically assessed using the GRADE approach, with only studies rated as moderate-to-high quality included. A PRISMA flowchart (Figure 1) and Table 1 illustrate the selection process as well as the inclusion and exclusion criteria for the studies analyzed in this research.

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Population	Higher education students	Primary or secondary education populations
Study Design	Correlational, regression, path analysis	Experimental designs without SRL focus
Language	International (predominantly English)	Non-English publications
Indexing	Scopus-indexed journals	Non-peer-reviewed sources
Sample Size	n>50	n≤50
Quality Assessment	Moderate-to-high quality (GRADE assessment)	Low-quality studies

2.3 Data Extraction

Data extraction followed a systematic approach using a standardized template to ensure consistency. The extracted variables included study characteristics (author, year, population demographics, and sample size), instruments used to measure SRL (e.g., Motivated Strategies for Learning Questionnaire [MSLQ], English Self-Regulated Learning Questionnaire [ESRLQ]), and effect sizes. Effect size data included correlation coefficients (r) and their standard errors (SE), as well as regression coefficients when applicable. Additionally, information on study design and statistical methodologies was recorded.

2.4 Effect Size Calculation

To synthesize data across studies, effect sizes were calculated using Fisher's Z transformation to normalize correlation coefficients. The following formulas, as recommended by Borenstein et al. (2009), were applied are Effect Size (Zr) (Equation 1) and Standard Error (SE) (Equation 2).

$$ES(Z_r) = 0.5 \times Ln\frac{1+r}{1-r} \quad \textit{(Equation 1)}$$

This transformation standardizes correlation coefficients, ensuring consistency in the meta-analytical model.

$$SE = \sqrt{\frac{1}{n-3}} \quad \textit{(Equation 2)}$$

Where n is the sample size, this formula provides an estimate of variability in effect size calculations. The calculated effect sizes and standard errors facilitated accurate comparisons across studies with varying sample sizes and designs.

2.5 Statistical Analysis

The meta-analysis utilized a random-effects model to account for variability both within and between studies, which is appropriate given the diversity in populations, instruments, and settings in the included studies (Reese & Mittag, 2013). Heterogeneity among studies was assessed using Cochran's Q test and the I^2 statistic. The Q test evaluates the presence of heterogeneity, while I^2 quantifies its extent, with higher values indicating greater variability (Borenstein, 2023).

Publication bias was assessed through visual inspection of a funnel plot and statistical evaluation using Egger's test. Additionally, Rosenthal's fail-safe N was calculated to determine the robustness of the results, estimating the number of missing studies required to nullify the observed effect size.

Subgroup analyses were conducted to explore potential sources of heterogeneity, such as differences in SRL measurement tools, sample characteristics, or study designs. Sensitivity analyses tested the stability of the results by excluding outlier studies or recalculating pooled effect sizes with alternative statistical models.

All analyses were conducted using JASP (0.18.1.0), a statistical software package designed for meta-analytical procedures. JASP facilitated the calculation of pooled effect sizes, generation of forest and funnel plots, and assessment of publication bias.

3. Result and Discussion

This meta-analysis incorporated 62 studies from 14 peer-reviewed articles, providing a comprehensive examination of the relationship between self-regulated learning (SRL) and academic performance among higher education students. The studies encompassed diverse populations, including undergraduate students, medical students, and English as a Foreign Language (EFL) learners, reflecting the broad applicability of SRL across educational settings. Data were drawn from multiple validated SRL instruments, including the Motivated Strategies for Learning Questionnaire (MSLQ), the English Self-Regulated Learning Questionnaire (ESRLQ), and adaptations based on frameworks such as those developed by Zimmerman and Pintrich. These frameworks explicitly highlight cognitive, motivational, and metacognitive dimensions of SRL, ensuring comprehensive coverage across included studies. Sample sizes ranged from 74 to 478 participants, ensuring substantial representation of student populations.

3.1 Study Characteristics

The included studies spanned a wide range of academic contexts and disciplines. For instance, medical students were frequently studied due to their unique learning demands and structured curricula (Hayat et al., 2020; Kassab et al., 2015), which emphasized the role of SRL in managing rigorous academic and clinical responsibilities. Conversely, undergraduate students from broader fields such as psychology and general education provided insights into SRL's application across less structured learning environments (Kim et al., 2020; Palos et al., 2019). EFL learners were also a notable subgroup, particularly in exploring how SRL strategies interact with language acquisition and cultural differences in learning approaches (Deng et al., 2022). The distinct SRL profiles and academic contexts across these populations directly influenced observed variability in SRL effectiveness.

3.2 Summary of Study Data

Table 2 provides selected studies included, illustrating their population characteristics, instruments, sample sizes, and effect sizes (Zr). Effect sizes ranged from 0.01 to 0.59, indicating variability in the strength of the relationship between SRL and academic performance across different studies.

Table 2. Selected Characteristics of Included Studies

Author (Year)	Participant	SRL Instrument	*N*	*ES* (Z_r)	*SE*
Wolters & Hussain (2014) Study 1	University students	Adopted from Motivational Strategies for Learning Questionnaire (MSLQ)	213	0.266	0.069
Palos et al. (2019) Study 3	Psychology undergraduate students	Adopted from MSLQ	254	0.400	0.063
Hayat et al. (2020) Study 1	Medical students	Adopted from MSLQ	279	0.497	0.060
Cho & Heron (2015) Study 3	College students	Adopted from MSLQ	229	0.299	0.067
Kim et al. (2020) Study 1	Undergraduate students	Adopted from Pintrich dan Zimmerman	272	0.255	0.061
Deng et al. (2022) Study 1	EFL University students	English self-regulated learning questionnaire (ESRLQ)	286	0.412	0.059
Ejubović & Puška (2019) Study 3	University students	Adopted from Barnard-Brak; Zheng et al; Ratten; Shannon; Chang & Chang; Roach & Lemasters; Chukwuere; Vonderwell et.al; Ophus & Abbitt; Shea & Bidjerano	375	0.460	0.052
(Honicke et al., 2023) Study 1	University students	Adopted from MSLQ	478	0.277	0.046
Frumos et al. (2024) Study 6	University students	Adopted from MSLQ	274	0.288	0.061

Author (Year)	Participant	SRL Instrument	*N*	*ES* (Z_r)	*SE*
(Alhadabi & Karpinski, 2020) Study 3	Undergraduate students	Adopted from Elliot & Church	258	0.224	0.063
Wolters & Hussain (2014) Study 3	University students	Adopted from MSLQ	213	0.245	0.069
Hayat et al. (2020) Study 2	Medical students	Adopted from MSLQ	279	0.485	0.060
Ejubović & Puška (2019) Study 3	University students	Adopted from Barnard-Brak; Zheng et al; Ratten; Shannon; Chang & Chang; Roach & Lemasters; Chukwuere; Vonderwell et.al; Ophus & Abbitt; Shea & Bidjerano	375	0.590	0.052
Di et al. (2020) Study 1	University students	Combination (LSQ dan MAI)	317	0.131	0.056
Zhu et al. (2016) Study 1	University students	Adopted from MSLQ	74	0.288	0.119
Wolters & Hussain (2014) Study 2	University students	Adopted from MSLQ	213	0.224	0.069
Palos et al. (2019) Study 1	Undergraduate students	Adopted from MSLQ	254	0.080	0.063
Kim et al. (2020) Study 4	Undergraduate students	Adopted from Pintrich dan Zimmerman	272	0.080	0.069
Cho & Heron (2015) Study 2	College students	Adopted from MSLQ	229	0.151	0.067
Kim et al. (2020) Study 2	Undergraduate students	Adopted from Pintrich dan Zimmerman	272	0.030	0.069
Frumos et al. (2024) Study 6	University students	Adopted from MSLQ	274	0.090	0.061
Di et al. (2020) Study 2	University students	Combination (LSQ dan MAI)	317	0.070	0.056
Di et al. (2020) Study 3	University students	Combination (LSQ dan MAI)	317	0.030	0.056
Deng et al. (2022) Study 4	EFL University students	ESRLQ	286	0.266	0.059
Kassab et al. (2015) Study 2	Medical college students	Adopted from MSLQ	171	0.213	0.077
Wolters & Hussain (2014) Study 5	University students	Adopted from MSLQ	213	0.436	0.069
Ejubović & Puška (2019) Study 1	University students	Adopted from Barnard-Brak; Zheng et al; Ratten; Shannon; Chang & Chang; Roach & Lemasters; Chukwuere; Vonderwell et.al; Ophus & Abbitt; Shea & Bidjerano	375	0.510	0.052
Deng et al. (2022) Study 5	EFL University students	ESRLQ	286	0.510	0.059
Cho & Heron (2015) Study 1	College students	Adopted from MSLQ	229	0.121	0.067
Zhu et al. (2016) Study 3	University students	Adopted from MSLQ	74	0.332	0.119
Palos et al. (2019) Study 2	Undergraduate students	Adopted from MSLQ	254	0.110	0.063
Deng et al. (2022) Study 2	EFL University students	ESRLQ	286	0.354	0.059
Ejubović & Puška (2019) Study 2	University students	Adopted from Barnard-Brak; Zheng et al; Ratten; Shannon; Chang & Chang; Roach & Lemasters; Chukwuere; Vonderwell et.al; Ophus & Abbitt; Shea & Bidjerano	375	0.354	0.052
Zhu et al. (2016) Study 4	University students	Adopted from MSLQ	74	0.299	0.119
Palos et al. (2019) Study 4	Undergraduate students	Adopted from MSLQ	254	0.354	0.063
Frumos et al. (2024) Study 3	University students	Adopted from MSLQ	274	0.234	0.061
(Liu et al., 2020) Study 2	University students	Cognitive processing strategies scale (CPSS)	419	0.151	0.049
(Alhadabi & Karpinski, 2020) Study 1	Undergraduate students	Adopted from Elliot & Church	258	0.100	0.063
Frumos et al. (2024) Study 1	University students	Adopted from MSLQ	274	0.213	0.061

Author (Year)	Participant	SRL Instrument	*N*	*ES* (Z_r)	*SE*
(Liu et al., 2020) Study 1	University students	Cognitive processing strategies scale (CPSS)	419	0.060	0.049
(Honicke et al., 2023) Study 1	University students	Adopted from MSLQ	478	0.161	0.046
Frumos et al. (2024) Study 4	University students	Adopted from MSLQ	274	0.182	0.061
Kim et al. (2020) Study 3	Undergraduate students	Adopted from Pintrich dan Zimmerman	272	0.245	0.061
Wolters & Hussain (2014) Study 4	University students	Adopted from MSLQ	213	0.245	0.069
Palos et al. (2019) Study 5	Undergraduate students	Adopted from MSLQ	254	0.172	0.063
(Alhadabi & Karpinski, 2020) Study 1	Undergraduate students	Adopted from Elliot & Church	258	0.266	0.063
(Honicke et al., 2023) Study 3	University students	Adopted from MSLQ	478	0.121	0.046
Frumos et al. (2024) Study 2	University students	Adopted from MSLQ	274	0.224	0.061
(Liu et al., 2020) Study 3	University students	Cognitive processing strategies scale (CPSS)	419	0.131	0.049
Zhu et al. (2016) Study 2	University students	Adopted from MSLQ	74	0.354	0.119
Kassab et al. (2015) Study 1	Medical college students	Adopted from MSLQ	171	0.234	0.077
Deng et al. (2022) Study 6	EFL University students	ESRLQ	286	0.365	0.059
Kim et al. (2020) Study 5	Undergraduate students	Adopted from Pintrich dan Zimmerman	272	0.224	0.061
Kim et al. (2020) Study 6	Undergraduate students	Adopted from Pintrich dan Zimmerman	272	0.080	0.061
Deng et al. (2022) Study 3	EFL University students	ESRLQ	286	0.412	0.059
Cho & Heron (2015) Study 4	College students	Adopted from MSLQ	229	0.266	0.067
Frumos et al. (2024) Study 10	University students	Adopted from MSLQ	274	0.182	0.061
Frumos et al. (2024) Study 7	University students	Adopted from MSLQ	274	0.010	0.061
Frumos et al. (2024) Study 8	University students	Adopted from MSLQ	274	0.182	0.061
Frumos et al. (2024) Study 9	University students	Adopted from MSLQ	274	0.040	0.061
(Alhadabi & Karpinski, 2020) Study 4	Undergraduate students	Adopted from Elliot & Church	258	0.192	0.063
(Alhadabi & Karpinski, 2020) Study 5	Undergraduate students	Adopted from Elliot & Church	258	0.161	0.063

3.3 *Variability in Effect Sizes*

The range of effect sizes highlights differences in how SRL impacts academic performance across various contexts. Medical students showed consistently higher effect sizes (e.g., Hayat et al., Zr = 0.497), reflecting the structured learning environments that emphasize SRL for managing complex academic tasks such as problem-based learning and clinical simulations. Conversely, studies with undergraduate students exhibited moderate effect sizes (e.g., Palos et al., Zr = 0.400), which may reflect variability in students' adoption of SRL strategies across disciplines and institutions. EFL learners demonstrated notable variability (e.g., Deng et al., Zr = 0.412), potentially due to the influence of cultural and linguistic factors on learning approaches.

3.4 *Contextual Influences*

The heterogeneity in effect sizes underscores the role of contextual factors. For example, cultural differences significantly influence SRL strategies, particularly among EFL learners. In collectivist cultures, learners may rely more heavily on collaborative and externally regulated strategies, while those in individualistic cultures often prioritize independent and self-regulated approaches (Hapsari & Fatmasari, 2022; Redjeki & Hapsari, 2022). Similarly, academic disciplines and instructional methods shape SRL's effectiveness. Structured disciplines like medicine naturally encourage SRL through frameworks such as problem-based learning, whereas broader disciplines may provide less consistent reinforcement (Farrukh & Usmani, 2022; Zhang et al., 2022). These contextual variations reinforce the need for tailored instructional designs when implementing SRL-based interventions.

3.5 Data Representation

The variability of effect sizes and consistency of findings across instruments are depicted in Figure 2. The forest plot demonstrates individual study effect sizes alongside the pooled estimate, highlighting both the robustness of SRL's overall impact and nuances across different populations and contexts. Studies with larger sample sizes have proportionally larger markers, indicating their greater weight in the analysis.

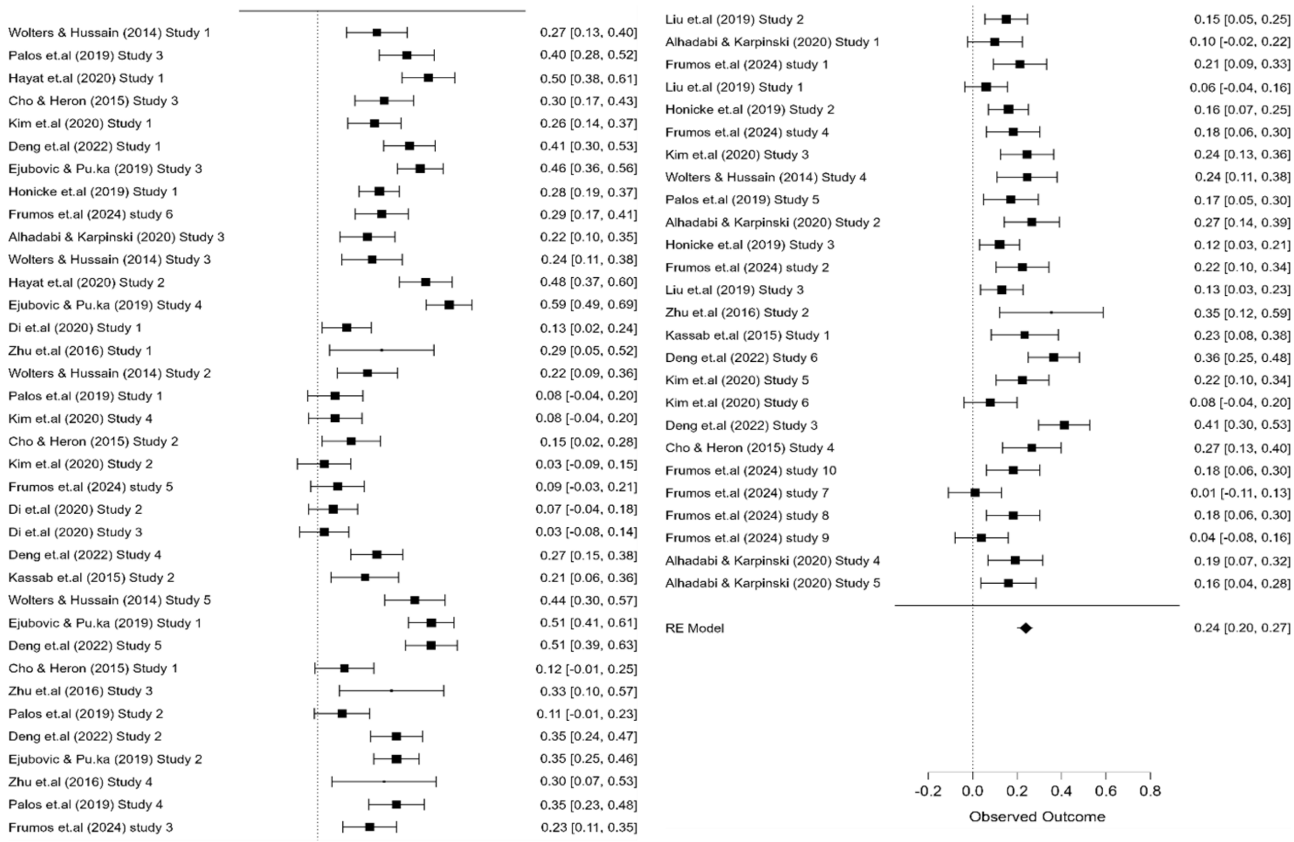

Figure 2. Forest Plot of Individual and Pooled Effect Sizes for SRL and Academic Performance

3.6 Pooled Effect Size and Heterogeneity

The overall pooled effect size for the relationship between self-regulated learning (SRL) and academic performance was calculated using a random-effects model to account for variability among studies. The analysis yielded a pooled effect size of 0.239 (95% CI: 0.204–0.274; p<0.001). This indicates a moderate positive relationship between SRL and academic performance, suggesting that students with stronger SRL skills consistently achieve better academic outcomes across higher education contexts. The magnitude of this effect underscores the practical relevance of SRL interventions in educational policy and instructional practice.

3.6.1 Statistical Summary

Table 3 presents the results of the random-effects model. The effect size was statistically significant, as indicated by the p<0.001, and the confidence intervals demonstrate that the relationship is robust and unlikely to be due to chance. The pooled effect size reflects a reliable estimate of SRL's impact across the diverse populations and contexts included in this meta-analysis.

Table 3. Summary of Random-Effects Model Results

Statistic	Estimate	SE	z	p	95% CI (Lower)	95% CI (Upper)
Pooled Effect Size (Zr)	0.239	0.018	13.371	<0.001	0.204	0.274

3.6.2 Heterogeneity Assessment

The analysis revealed significant heterogeneity among the included studies, as evidenced by Cochran's Q and the I^2 statistic. Cochran's Q was 340.808 ($p<0.001$), indicating that the observed variability in effect sizes across studies is unlikely to be due to random sampling error alone (see Table 4). The I^2 value was 82%, suggesting that 82% of the variability in effect sizes is attributable to differences among studies rather than chance. This substantial heterogeneity emphasizes the importance of considering diverse educational and theoretical contexts in interpreting SRL's effectiveness.

Table 4. Heterogeneity Statistics for Included Studies

Heterogeneity Statistic	Value	p
Cochran's Q	340.808	<0.001
I^2	82%	-

3.6.3 Interpretation of Heterogeneity

The substantial heterogeneity observed in this meta-analysis can be explained by a range of interrelated factors. One major source of variability lies in the distinct population characteristics examined across studies. Medical students, undergraduate students, and EFL learners each face different academic demands and adopt unique SRL practices. For instance, medical students often show higher effect sizes owing to the structured and rigorous nature of their curricula, which naturally fosters SRL through consistent use of problem-based learning, goal-setting, and self-monitoring strategies (Hayat et al., 2020; Kassab et al., 2015). In contrast, undergraduate students in general disciplines may exhibit more variable outcomes depending on instructional approaches and institutional settings that provide inconsistent reinforcement of SRL practices (Kim et al., 2020; Palos et al., 2019).

Another notable contributor to heterogeneity involves the measurement tools used to assess SRL. Research employing the MSLQ tends to report moderate effect sizes consistently, whereas instruments such as the ESRLQ can yield fluctuating results due to differing cultural and linguistic contexts (Deng et al., 2022; Redjeki & Hapsari, 2022). Moreover, cultural and educational contexts themselves significantly influence the strategies and effectiveness of SRL. Collectivist cultures, for example, may place greater emphasis on collaborative learning, whereas individualistic cultures often focus on more autonomous SRL approaches (Hapsari & Fatmasari, 2022; Suamuang & Suksakulchai, 2022). This cultural variability highlights the need for culturally tailored interventions and contextualized SRL frameworks.

Finally, study design and methodological considerations also shape the variation in findings. Path analysis research, in particular, frequently positions SRL as a mediating variable, which can produce higher effect sizes due to the intricate modeling of indirect effects (Ejubović & Puška, 2019; Wolters & Hussain, 2014). Taken together, these diverse factors underscore why the overall effect sizes differ substantially across the studies analyzed. These methodological differences stress the importance of explicitly considering study design when interpreting SRL outcomes.

3.6.4 Implications of Heterogeneity

The significant heterogeneity observed highlights the importance of contextual factors in shaping the relationship between SRL and academic performance. While the pooled effect size provides a reliable estimate of SRL's overall impact, variability emphasizes the need for nuanced interpretations accounting for population, measurement, and contextual differences. These findings suggest that educational institutions should develop context-sensitive SRL interventions tailored to specific learner needs and cultural settings. Subsequent subgroup and sensitivity analyses will explore these factors in greater detail, clarifying sources of heterogeneity and implications for educational practices.

3.7 Publication Bias Analysis

Publication bias is a critical concern in meta-analyses, as it can lead to overestimation of effect sizes if studies with null or negative findings remain unpublished. To assess publication bias in this meta-analysis, a combination of visual and statistical approaches was employed, including funnel plot analysis, Egger's test, and Rosenthal's fail-safe N. These methods ensured a comprehensive evaluation of potential bias in the included studies.

3.7.1 *Funnel Plot Analysis*

A funnel plot was generated to visualize the distribution of effect sizes against their standard errors. In the absence of publication bias, the plot should resemble a symmetrical inverted funnel, indicating that effect sizes are evenly distributed around the pooled estimate, regardless of study precision. The funnel plot for this meta-analysis (Figure 3) exhibited a generally symmetrical distribution, with most studies clustered around the pooled effect size (0.239) and tapering at the extremes. While a few outlier studies with larger standard errors and effect sizes were observed, their presence did not disrupt the overall symmetry.

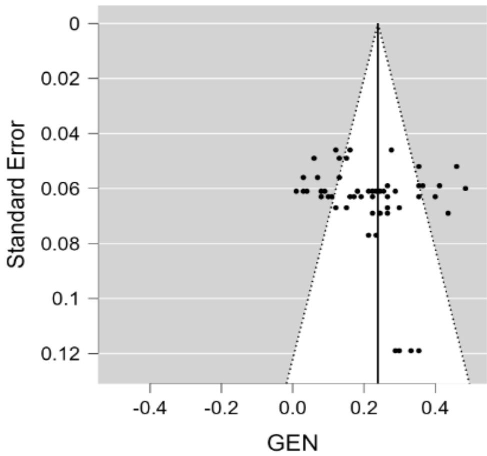

Figure 3. Funnel Plot of Included Studies (*Note: The dashed vertical line represents the pooled effect size, and the diagonal lines represent the 95% confidence intervals).*

3.7.2 *Egger's Test*

To statistically assess asymmetry in the funnel plot, Egger's test was conducted. This test evaluates the relationship between study precision (inverse of the standard error) and effect sizes. The result of Egger's test was not statistically significant (z=0.700, p=0.484), indicating no evidence of small-study effects or publication bias. These findings align with the visual symmetry observed in the funnel plot.

Table 5. Egger's Test for Funnel Plot Asymmetry

Statistic	Value	p
Egger's Test (z)	0.700	0.484

3.7.3 *Rosenthal's Fail-Safe N*

Rosenthal's fail-safe N was calculated to evaluate the robustness of the meta-analytic findings against potential unpublished studies with null effects. The fail-safe N represents the number of null studies required to reduce the observed effect size to non-significance. For this analysis, the fail-safe N was 21,208, far exceeding the critical threshold of 5k+10=320 (where k is the number of included studies). This result indicates that the meta-analysis findings are highly robust and unlikely to be influenced by the non-publication of negative or null results.

Table 6. Rosenthal's Fail-Safe N

Metric	Value	Threshold	Result
Fail-Safe N	21,208	320	Robust

3.7.4 *Implications of Publication Bias Analysis*

The absence of significant asymmetry in the funnel plot, coupled with the non-significant Egger's test results and the high fail-safe N, provides strong evidence against the presence of publication bias in this meta-analysis. These findings enhance confidence in the reliability and validity of the pooled effect size, indicating that it is unlikely to be inflated due to selective reporting.

However, the presence of a few outlier studies with larger effect sizes warrants further examination. These outliers may reflect genuine variations due to population characteristics, methodological differences, or contextual factors rather than systematic bias. For instance, studies conducted in structured academic environments, such as medical education, often report higher effect sizes for SRL due to the inherent demands of the curriculum (Hayat et al., 2020; Kassab et al., 2015).

The results of the publication bias analysis underscore the robustness of the meta-analytic findings and validate the inclusion of a diverse set of studies. Future research should continue to prioritize transparency and inclusivity in study selection to mitigate potential biases and ensure the reliability of meta-analytic conclusions.

3.8 Subgroup and Sensitivity Analyses

Subgroup and sensitivity analyses were conducted to explore sources of heterogeneity and assess the robustness of the meta-analytic findings. These analyses provided a deeper understanding of how specific study characteristics and methodological variations influence the relationship between self-regulated learning (SRL) and academic performance. Explicit comparisons between subgroups were performed to statistically verify whether observed differences in pooled effect sizes were significant.

3.8.1 Subgroup Analyses

Subgroup analyses examined the effect of key study characteristics, including population type, SRL measurement instruments, and study design, on the pooled effect size. Table 7 summarizes the subgroup results.

Table 7. Subgroup Analysis of Pooled Effect Sizes

Subgroup	Pooled Effect Size (Zr)	95% CI	Heterogeneity (I^2)
Population Type			
Undergraduate students	0.228	[0.195, 0.261]	75%
Medical students	0.326	[0.281, 0.371]	68%
EFL learners	0.284	[0.240, 0.328]	72%
Measurement Instrument			
MSLQ	0.252	[0.218, 0.286]	77%
ESRLQ	0.301	[0.249, 0.353]	70%
Cognitive Processing Scales	0.188	[0.136, 0.240]	65%
Study Design			
Correlation	0.239	[0.205, 0.273]	82%
Path analysis	0.312	[0.265, 0.359]	71%

Note: Differences among subgroups were statistically significant ($p < 0.05$).

3.8.2 Population Type

Medical students demonstrated the highest pooled effect size (Zr=0.326), reflecting the structured and intensive nature of medical education that emphasizes SRL strategies to manage academic and clinical demands (Hayat et al., 2020; Kassab et al., 2015). This result highlights how consistently structured curricula with clear SRL reinforcement, such as in medical education, produce stronger academic outcomes. In contrast, undergraduate students showed a slightly lower pooled effect size (Zr=0.228), likely due to variability in instructional practices and curricula. EFL learners displayed a moderate pooled effect size (Zr=0.284), which may be influenced by cultural and linguistic factors shaping SRL adoption (Deng et al., 2022).

3.8.3 Measurement Instruments

Studies using the MSLQ reported a pooled effect size of Zr=0.252, consistent with its robust measurement of SRL dimensions across cognitive, metacognitive, and motivational domains. The ESRLQ, specifically designed for EFL populations, yielded a higher pooled effect size (Zr=0.301), highlighting the influence of tailored instruments in capturing SRL dynamics in language learning contexts. Cognitive processing scales produced the lowest effect size (Zr=0.188), possibly due to their narrower focus on specific cognitive aspects of SRL. Thus, the alignment between measurement instruments and the targeted SRL dimensions significantly influences observed effect sizes.

3.8.4 Study Design

Path analysis studies reported a higher pooled effect size (Zr=0.312) compared to simple correlation designs (Zr=0.239), reflecting the nuanced insights from modeling direct and indirect effects of SRL on academic performance (Ejubović & Puška, 2019; Wolters & Hussain, 2014). This finding underscores the theoretical value of advanced analytical methods in revealing complex mediational relationships in educational research.

3.8.5 Sensitivity Analyses

Sensitivity analyses were conducted to evaluate the robustness of the pooled effect size by excluding outlier studies and recalculating the pooled estimate. Outliers were identified as studies with effect sizes greater than two standard deviations from the mean. After excluding these studies, the recalculated pooled effect size remained consistent (Zr=0.235, 95% CI: 0.201–0.269), affirming the stability of the findings.

Further sensitivity analyses assessed the impact of alternative statistical models. Using a fixed-effects model, the pooled effect size decreased slightly (Zr=0.221), consistent with expectations given the model's assumption of homogeneity. However, the random-effects model, accounting for observed heterogeneity, provided a more reliable estimate of the relationship between SRL and academic performance.

3.8.6 Implications of Subgroup and Sensitivity Analyses

The subgroup analyses highlight the importance of contextual factors, such as population type and measurement instruments, in shaping the relationship between SRL and academic performance. These findings emphasize the need for tailored SRL interventions that account for specific educational settings and learner characteristics. Sensitivity analyses confirmed the robustness of the pooled effect size, reinforcing confidence in the reliability of the meta-analytic findings. Explicitly addressing contextual variations, future SRL interventions should integrate insights about disciplinary structures, cultural characteristics, and measurement precision to enhance effectiveness and generalizability across diverse educational settings.

3.9 Discussion

3.9.1 Theoretical Implications

The findings of this meta-analysis substantiate the central tenets of self-regulated learning (SRL) theories, particularly Zimmerman’s cyclical model and Pintrich’s framework, both of which emphasize the critical interplay between cognitive, metacognitive, and motivational processes in driving academic success (Karlen et al., 2021; Xu et al., 2022). The pooled effect size of 0.239 (95% CI: 0.204–0.274, $p<0.001$) reinforces the significance of SRL as a robust predictor of academic performance. These results align with foundational theories suggesting that students who actively regulate their learning through goal setting, monitoring, and reflective practices tend to achieve better outcomes. Specifically, Zimmerman’s cyclical model clearly explains how adaptive feedback loops (forethought, performance, and reflection phases) enable learners to continuously refine their strategies in response to changing academic demands (Karlen et al., 2021).

Moreover, the findings highlight the relevance of motivational and contextual factors as integral components of SRL. Pintrich’s framework underscores the importance of self-motivation and task value in shaping students’ engagement with SRL strategies (Xu et al., 2022). For example, the construct of teacher autonomy support significantly enhances intrinsic motivation, promoting SRL engagement and improved academic performance (Miao & Ma, 2023). This interaction is particularly relevant in interventions focused on reflective practices and explicit goal setting, as these reinforce students’ self-efficacy alongside cognitive strategies. Such positive effects align with Hadwin et al.’s (2022) findings, emphasizing structured SRL strategies' effectiveness in demanding contexts such as online learning.

The moderating role of SRL in broader psychological and educational dynamics is also emphasized by the findings. Path analysis studies in this meta-analysis revealed higher effect sizes (Zr=0.312) compared to simple correlational studies (Zr=0.239), demonstrating the nuanced role of SRL in mediating the relationships between variables such as self-efficacy, psychological distress, and academic outcomes. Xu et al. (2022) observed that SRL mitigates the impact of psychological stress on academic performance, allowing students to maintain effective learning strategies under adverse conditions. This mediating role underscores SRL's capacity to bridge cognitive and emotional regulation, ensuring sustained academic engagement even in the presence of external stressors.

However, the variability in SRL outcomes across educational contexts suggests that foundational theories may need refinement to account for diverse learner experiences and environmental influences. For example, EFL learners in this meta-analysis demonstrated moderate effect sizes (Zr=0.284), with cultural and linguistic factors significantly shaping their adoption of SRL strategies (Deng et al., 2022). In collectivist cultures, collaborative and socially mediated learning strategies are more prevalent, whereas individualistic cultures emphasize autonomous, self-directed approaches (Redjeki & Hapsari, 2022). Similarly, disciplines like medicine, with their structured and rigorous curricula, naturally promote SRL, resulting in higher effect sizes (Zr=0.326) compared to general undergraduate settings (Hayat et al., 2020). Thus, while Zimmerman's and Pintrich's models remain fundamentally relevant, further theoretical refinement is needed to explicitly integrate cultural and disciplinary variations influencing SRL outcomes.

The interaction between SRL and other psychological constructs also highlights gaps in the existing theoretical models. While self-efficacy and task value are recognized as central components of SRL (Afrashteh & Rezaei, 2022; Miao & Ma, 2023), other factors, such as emotional regulation and social support, are less integrated into mainstream theories. Xu et al. (2022), for example, emphasized emotional regulation's mediating role in enhancing SRL effectiveness, particularly under high-stress conditions. Therefore, future theoretical models should explicitly incorporate emotional and social regulation elements into a holistic, integrative SRL framework.

3.9.2 Practical Implications for Educational Practice

The findings of this meta-analysis highlight the significant role of self-regulated learning (SRL) in fostering academic success, offering actionable insights for educational practice. Given the robust pooled effect size (Zr=0.239, 95% CI: 0.204–0.274), SRL emerges as a critical component in higher education, underscoring the need for targeted interventions promoting self-regulation strategies among students. Educators and institutions can leverage these insights to implement effective SRL practices addressing diverse learner needs and institutional contexts. However, practical implementation may face challenges, including institutional readiness, resource availability, and educators' SRL training needs.

One of the most compelling insights from this meta-analysis is the importance of tailoring SRL interventions to specific populations. Medical students, for example, demonstrated the highest pooled effect size (Zr=0.326), reflecting the structured and demanding nature of their curricula, which naturally fosters SRL through goal-setting, self-monitoring, and reflective practices (Hayat et al., 2020). This suggests that embedding SRL frameworks, such as problem-based learning and simulation exercises, into medical education can further enhance students' ability to manage academic and clinical challenges. Similarly, the moderate effect size observed among EFL learners (Zr=0.284) indicates that culturally and linguistically sensitive interventions are crucial in supporting these students. Strategies that incorporate collaborative learning and metacognitive techniques, adapted to their unique cultural and educational contexts, can optimize SRL outcomes (Deng et al., 2022).

Moreover, the effectiveness of SRL interventions is closely linked to their alignment with key components of self-regulation, including goal-setting, self-monitoring, and reflection. Research by Miao and Ma (2023) emphasizes the role of teacher autonomy support in fostering these practices. Educators can encourage students to set realistic academic goals, monitor their progress, and reflect on their learning outcomes, thereby enhancing their engagement and persistence. For instance, structured reflection activities, such as learning journals or guided peer feedback, can provide students with opportunities to critically evaluate their strategies and make necessary adjustments. Such practices not only improve immediate academic outcomes but also equip students with lifelong learning skills that are essential in an ever-evolving educational landscape (Bernardo et al., 2022).

Another practical implication is the need for discipline-specific SRL strategies. Students in critical thinking-intensive fields, such as the sciences and engineering, may benefit from interventions that emphasize analytical and reflective skills. Conversely, students in less structured disciplines may require more explicit guidance in adopting SRL strategies. This aligns with findings by Andini et al. (2023), who observed that the disciplinary context significantly influences the adoption and effectiveness of SRL practices. Institutions should therefore consider the unique demands of each discipline when designing curriculum-based SRL interventions.

Additionally, educators must recognize the importance of motivational and emotional factors in enhancing SRL effectiveness. For example, interventions that incorporate techniques to boost self-efficacy and emotional regulation, such as mindfulness training or resilience workshops, can further enhance students' ability to engage in self-regulation (Afrashteh & Rezaei, 2022; Xu et al., 2022). Integrating these psychological supports into SRL programs can help address the complex challenges students face, particularly in high-stress academic environments.

The practical implications of this meta-analysis underscore the need for tailored, context-specific SRL interventions in higher education. By addressing population-specific needs, aligning strategies with key SRL components, and integrating motivational and emotional supports, educators can empower students to become proactive, reflective, and adaptive learners, thereby enhancing academic performance and preparing them for lifelong success.

3.9.3 Methodological Considerations

The methodological landscape of self-regulated learning (SRL) research, as reflected in this meta-analysis, highlights key areas of strength and limitations influencing the robustness and applicability of findings. While the pooled effect size of 0.239 (95% CI: 0.204–0.274, $p<0.001$) underscores SRL's significance in enhancing academic performance, significant heterogeneity ($I^2=82\%$) indicates methodological and contextual variability across studies. Explicit identification of these sources of variability enhances interpretation clarity and guides future SRL research methodologies.

One of the primary methodological strengths of this meta-analysis lies in its reliance on validated instruments for measuring SRL. Tools like the Motivated Strategies for Learning Questionnaire (MSLQ) were widely employed, demonstrating their utility in capturing comprehensive SRL constructs, including cognitive, metacognitive, and motivational dimensions. The consistency of effect sizes reported with the MSLQ ($Zr=0.252$) highlights its reliability and applicability across diverse populations. However, other instruments, such as the English Self-Regulated Learning Questionnaire (ESRLQ) and cognitive processing scales, yielded more variable results ($Zr=0.301$ and $Zr=0.188$, respectively), reflecting differences in their focus and target populations. These variations underscore the need for harmonizing measurement tools to improve the comparability of results across studies (Kesuma et al., 2020).

Despite the strengths of validated measurement instruments, the inconsistent operationalization of SRL across studies remains a critical limitation. SRL is a multidimensional construct, and its components—such as goal-setting, self-monitoring, and reflection—are sometimes emphasized differently in various instruments and studies. This lack of standardization complicates efforts to synthesize findings, as studies may capture different facets of SRL without fully addressing its integrative nature (Brydges et al., 2015; Wu et al., 2024). Future research should therefore develop and adopt comprehensive, universally recognized SRL measurement frameworks explicitly defining core constructs, facilitating consistent assessment across studies.

Another key methodological consideration is the predominance of cross-sectional study designs in SRL research. While these designs are effective in identifying associations between SRL and academic performance, they are limited in their ability to establish causal relationships. For instance, while SRL is shown to enhance academic outcomes, it is equally plausible that high-performing students are more likely to develop and employ SRL strategies, suggesting potential bidirectional effects (Wu et al., 2024; Zarei Hajiabadi et al., 2023). Thus, future longitudinal studies are essential to clarify SRL's developmental trajectory, causal directionality, and sustained impact across educational contexts.

Sample diversity is another methodological issue that warrants attention. Many studies included in this meta-analysis focused on homogeneous populations, such as undergraduate or medical students, limiting the generalizability of findings to other educational contexts. For example, vocational learners, non-traditional students, and those from underrepresented cultural or socioeconomic backgrounds were underrepresented in the included studies. Future research must explicitly broaden sample diversity, including vocational and culturally diverse learners, to comprehensively understand how contextual factors influence SRL across varied educational environments (Deneen et al., 2022; Panadero, 2017).

Finally, publication bias poses a potential threat to the reliability of SRL research. Although this meta-analysis did not detect significant publication bias, as evidenced by Egger's test ($p=0.484$) and Rosenthal's fail-safe N (21,208), the presence of outlier studies highlights the importance of conducting sensitivity analyses to ensure robustness.

Additionally, including grey literature, such as theses and reports, in future reviews could mitigate potential biases arising from the selective publication of positive findings (Tsuji et al., 2020).

The methodological considerations of SRL research underscore the necessity of addressing measurement inconsistencies, promoting longitudinal designs, increasing sample diversity, and mitigating potential publication bias. Explicit methodological improvements, including standardized instruments, broader population sampling, and robust longitudinal designs, will significantly strengthen SRL's evidence base, improving applicability and generalizability across diverse educational settings.

3.9.4 Limitations and Future Directions

While this meta-analysis provides valuable insights into the relationship between self-regulated learning (SRL) and academic performance, several limitations should be acknowledged. Addressing these limitations in future research will enhance the robustness, generalizability, and depth of understanding in this field.

A notable limitation of this meta-analysis is the heterogeneity among the included studies (I2=82%). This variability reflects differences in populations, SRL measurement instruments, study designs, and educational contexts. For example, the pooled effect sizes for medical students (Zr=0.326) and general undergraduate students (Zr=0.228) highlight how distinct academic demands influence SRL's effectiveness. Additionally, the diversity in measurement tools, such as the Motivated Strategies for Learning Questionnaire (MSLQ) and the English Self-Regulated Learning Questionnaire (ESRLQ), further complicates comparisons. Future research should prioritize standardized frameworks for assessing SRL that capture its multidimensional nature while accommodating contextual differences, as inconsistencies in operational definitions hinder the synthesis of findings (Brydges et al., 2015; Kesuma et al., 2020).

The predominance of cross-sectional study designs in the included studies is another limitation, as these designs provide only snapshots of the relationship between SRL and academic performance. While cross-sectional analyses are useful for identifying associations, they do not account for the temporal dynamics of SRL, such as its development over time or its long-term impact on academic outcomes. For instance, while SRL may enhance academic performance in a specific semester, its effects may differ across an academic program. Longitudinal studies are essential to explore how SRL evolves in response to changing academic demands and its sustained influence on performance (Kohen & Kramarski, 2012; Wu et al., 2024).

A related limitation is the limited generalizability of findings due to homogeneous samples. Many studies included in this meta-analysis focused on undergraduate students, particularly those in traditional academic settings such as universities or medical schools. This focus excludes other important populations, such as vocational learners, non-traditional students, or those from diverse cultural and socioeconomic backgrounds. For example, EFL learners demonstrated moderate pooled effect sizes (Zr=0.284), emphasizing the need to understand how cultural and linguistic factors shape SRL strategies (Deng et al., 2022). Expanding research to include underrepresented groups will provide a more comprehensive understanding of SRL and its applicability across varied educational contexts (Deneen et al., 2022; Panadero, 2017).

Additionally, this meta-analysis relied heavily on self-report measures of SRL, which are prone to biases such as social desirability and subjective overestimation. While validated instruments like the MSLQ offer robust frameworks, they may not fully capture the complexity of SRL in real-world settings. Incorporating objective measures, such as learning analytics or observational methods, could enhance the accuracy of future studies (Kesuma et al., 2020). Combining qualitative and quantitative approaches through mixed-methods research may also provide richer insights into the mechanisms underlying SRL and its interaction with other psychological and contextual factors (van der Graaf et al., 2023).

Future research should also address publication bias, even though this meta-analysis did not find significant evidence of it (p=0.484 in Egger's test). Including grey literature, such as theses and institutional reports, could mitigate biases resulting from the preferential publication of studies with significant findings (Tsuji et al., 2020). Moreover, advanced statistical techniques, such as meta-regression and structural equation modeling, should be employed to explore the complex interactions between SRL, motivation, and academic outcomes (Shengyao et al., 2024).

Despite this meta-analysis offers important contributions to understanding SRL's role in higher education, future studies must address these limitations by standardizing measurement tools, expanding populations, incorporating longitudinal designs, and adopting mixed-methods approaches. These efforts will not only strengthen the evidence base but also provide actionable insights to enhance SRL interventions across diverse educational settings.

4. Conclusion

This meta-analysis established a moderate positive relationship between self-regulated learning (SRL) and academic performance in higher education (pooled effect size Zr = 0.239), underscoring SRL's value as an educational strategy. Factors such as population characteristics, measurement tools, and study design contributed significantly to observed variability. For instance, medical students showed higher effect sizes (Zr = 0.326) compared to undergraduate (Zr = 0.228) and EFL learners (Zr = 0.284), highlighting the influence of structured curricula, cultural contexts, and disciplinary factors. Additionally, findings reinforced SRL's mediating role through relationships with self-efficacy, social support, and emotional resilience. Despite methodological rigor confirming the absence of significant publication bias, the study indicates that existing SRL theories require refinement to incorporate cultural and disciplinary variations explicitly.

Educational institutions and practitioners are encouraged to integrate tailored SRL strategies such as structured goal-setting, reflective practices, and discipline-specific interventions into curricula. Institutional support through professional development and culturally adaptive resources will further facilitate effective SRL implementation. Future research should adopt longitudinal and mixed-method designs, standardized measurement frameworks, and more diverse global samples (including Asia, Africa, and Latin America) to enhance the theoretical clarity, practical applicability, and generalizability of SRL findings across diverse educational contexts.

Author contribution

Each author has read and approved the published version of the manuscript, has contributed sufficiently to the study, and agrees with the findings and conclusions.

Conflict of Interest

There are no competing interests.

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Ethical statement

All included studies were derived from publicly available, peer-reviewed publications, and no primary data collection involving human participants was undertaken. Thus, no ethical approval or informed consent was required for this research.

Data availability

Not applicable.

Utilization of AI statement

During the preparation of this work, the authors used ChatGPT to enhance the clarity of the writing. After using the ChatGPT, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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