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Artificial Intelligence and Psychological Capital in STEM Education: A Systematic Review of High School Learning Contexts

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ABSTRACT

Aim: The aim of this study was to examine ways that artificial intelligence (AI) boosts psychological capital (PsyCap) comprising self-efficacy, resilience and optimism within students of high-school enrolled in science subjects. The study also addresses scarce synthesis of evidence connecting AI-enabled science learning alongside development of PsyCap at secondary education level. **Methodology:** The researcher used a secondary qualitative research design, adopting a systematic literature review (SLR). From 2015 to 2025, studies were extracted from ERIC, PubMed, Scopus, PsycINFO and Web of Science, including ten studies that were finally selected for the analysis. Braun and Clarke's thematic analysis guided the interpretation of the data. Theoretically, psychological capital theory and self-efficacy theory were adopted to provide insights into the potential impact of AI-enriched learning environments on students' cognitive and emotional growth. **Findings:** The review suggests that while results are mixed and depend on the specific context, AI interventions could have a positive effect on certain PsyCap dimensions, with only a limited number of contextually heterogeneous studies included. Some findings were context-specific, time-bound, or reliant on self-reported data, limiting validity. Jia and Tu (2024), for example, observed that AI's direct effect on critical thinking is minimal, suggesting it may not uniformly enhance PsyCap. AI tools—such as robotics, chatbots, and adaptive platforms—were found to strengthen self-efficacy through tailored feedback and interactive learning. Resilience improved as AI reduced student anxiety and aided emotional regulation, while optimism was boosted through renewed engagement in science learning. **Implications:** The study highlights the need for education policies that deliberately integrate AI into science and STEM curricula to foster PsyCap. Policymakers should prioritize access to AI-enabled tools and platforms while addressing the digital divide to ensure students from socioeconomic backgrounds benefit equally. With teacher support and digital access, the use of AI with equitable and ethically informed approaches could help foster resilience, optimism and self-efficacy in learning science.

Keywords: AI-assisted learning, STEM psychology, educational technology, adolescent learning, Phycological capital.

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1. Introduction

In the modern context of education, Artificial Intelligence (AI) has shown itself to be a transformative force, especially in the field of science, technology, engineering, and mathematics (STEM) education. In the field of secondary education, AI-powered technologies, such as intelligent tutors, adaptive learning platforms, learning analytics, virtual simulations, and chatbots, are becoming more common and are playing a growing role in delivering personalized and interactive educational experiences to students (Xu & Choi, 2023). These technologies not only enhance academic achievement, but they are also linked to socio-emotional learning outcomes, including motivation, engagement, confidence and persistence in learning science (Shin et al., 2024). AI-powered learning environments can offer real-time feedback, personalized guidance, and problem-solving assistance, particularly in science education, potentially enhancing students' psychological resources and promoting sustained engagement in STEM fields.

Psychological Capital (PsyCap) is a positive psychological state that boosts academic success, adaptive functioning, and well-being of students Luthans et al., (2007) often conceptualized as having four components such as hope, efficacy, resilience and optimism. In science education, PsyCap plays a significant role due to the persistence needed to be motivated, maintain motivation while dealing with difficult activities, and confidence in analytical reasoning as one of the subjects of science education. The literature on educational psychology suggests that students who have higher PsyCap have higher academic resilience, higher level of SLoL behaviours and higher level of persistence in STEM-related pathways. Therefore, using AI to support learning while developing PsyCap could be a crucial means to counter the observed problem of loss of student interest and retention in science subjects.

While there is a body of research that looks at the educational potential of AI, existing research is conceptually divergent in terms of the relationship between PsyCap and the use of AI in high school science education. The majority of the existing research centres on the cognitive dimensions, such as academic performance, knowledge retention, engagement and technological acceptance, with less research addressing broader socio-emotional and psychological aspects (Liang et al., 2023). Moreover, many studies for instance, Prayogo et al. (2025); Rajapakse et al. (2024) focus mainly on the constructs of PsyCap individually, such as self-efficacy or resilience, but do not assess the HERO construct as a multidimensional psychological resource. Consequently, the ways in which AI-infused learning environments can simultaneously instill hope, effectiveness, resilience and optimism are not fully understood.

Another one of its drawbacks is the incompleteness of the population within the literature that is available. Many of the studies such as Papaioannou et al. (2022); Patnaik et al. (2024) about AI and PsyCap have been carried out in a tertiary or higher education environment; there are significant differences between the developmental, motivational, and technological profile of learners in tertiary or higher education, versus learners in high schools. Although these higher education studies yield first glimpses of psychological outcomes enabled through the use of AI tools, results cannot be readily transferred to the learning environment of adolescent science learners. Recognising that high school students have unique socio-emotional developmental needs, academic pressures and identity formation processes, it is necessary that the impact of AI on Psychology of the Learner and PsyCap specifically in the context of secondary science education needs to be explored.

Furthermore, a comprehensive overall conceptual integration for the link between AI, SEL, PsyCap, and STEM persistence is lacking. AI-powered science classrooms can boost hope by designing learning pathways tailored to student goals, build efficacy through adaptive feedback, nurture resilience during challenging tasks, and cultivate positive emotions such as optimism through personalized encouragement and positive learning experiences. Taken together, these psychological resources could lead to greater involvement and retention in STEM education. There is limited empirical synthesis to consider these interrelated relationships, however, especially for high school students.

This study aims to fill an important gap in the literature and in practice by systematically examining the role of using AI to enhance the psychological capital of high school students in science. In particular, the study investigates the role of AI-powered educational tools in nurturing hope, efficacy, resilience and optimism in the context of science education. This review builds on existing research by compiling the latest findings, bringing together the theoretical frameworks for the potential of AI in supporting academic and socio-emotional learning in secondary STEM education and paving the way for future research.

Consequently, the study is directed by the subsequent objectives:

- To examine the role of artificial intelligence in nurturing psychological capital in science among high school students.
- To investigate the association amid artificial intelligence and effectiveness in science among high school students.

- To examine the role of artificial intelligence in fostering hope, resilience, and optimism in science subjects among high school students.

2. Research Methods

In addition, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework was also used to assure methodological transparency, reproducibility and rigor in the systematic review process as suggested by Hijriyah et al. (2024). The choice of PRISMA was made because it provides standardized procedures for identifying studies, screening, assessment of eligibility, data extraction and synthesis to minimize the selection bias and improve reliability, as stated by Nyoko and Hanafiah (2024) as well. The review protocol was created before the search process started to assist in the selection of databases, screening, inclusion criteria and thematic coding procedures. Whilst not formally registered, all methodological aspects were documented in a systematic manner in order to maximize the auditability and replicability.

1. **Identification of relevant information sources** focusing on peer-reviewed primary studies from reputable academic databases.
2. **Systematic selection of eligible studies** based on predefined thematic and methodological relevance.
3. **Structured data extraction** to capture variables related to AI applications and psychological capital.
4. **Definition of inclusion and exclusion criteria,** ensuring alignment with the research objectives.
5. **Categorization of extracted data items** to facilitate thematic synthesis and critical analysis.

2.1 Research Question using PEO Framework

The Population, Exposure, Outcome (PEO) framework offered a structured approach through which the research question of this study is narrowed down suggested by Hosseini et al. (2024) as well. In the study, the Population was high school students who studied science at the critical stage of acquiring academic and psychological strengthening. The Exposure is the combination of the artificial intelligence tools in science learning, especially adaptive feedback, individualized goal-setting, and immersive simulation. The Outcome is the development of psychological capital, namely, efficacy, resilience, and optimism, which not only contribute to the learning process of science but also encourage long-term motivation in STEM disciplines. The presented framing allows focusing on the question of whether an AI-based approach to education can be used to impact the psychological well-being of students as well as their academic development. Therefore, based on the PEO framework, the following research question was developed:

> *How does the integration of AI-based tools in science education foster psychological capital among high school students?*

2.2 Research Strategy-Key Terms and Boolean Operators

Systematic research strategy was followed in this study as it guarantees that the studies included are detailed and cover all the possible aspects of the role of artificial intelligence in the development of psychological capital in science among high school students. The empirical and theoretical studies are identified through the use of academic databases like Scopus, Web of Science, ERIC, SpringerLink, and Google Scholar. Premier peer-reviewed articles published from 2015 to 2025 were sought to identify the most recent trends in the realm of AI-based education and psychological capital. Keywords were developed from three core concepts of the study: *artificial intelligence in education, psychological capital, and high school science learning*. The search criteria utilised in this database were Boolean statements including Boolean operator techniques, for example, artificial intelligence OR AI, AND (psychological capital OR PsyCap OR optimism OR resilience OR self-efficacy OR hope) AND (science education OR STEM OR high school students). The exclusion criteria excluded the studies that did not analyse the aspects of secondary or higher education, lacked an explicit connectivity between AI and psychological capital concepts, and did not consist of empirical data. Eligible studies were critically appraised by the use of the Critical Appraisal Skills Programme (CASP) checklist. The studies were assessed on the basis of the following criteria: clarity of the research purpose, methodological appropriateness, sampling adequacy, data collection procedures, analytical rigor, ethical issues, validity of findings. Research was assessed as having

Table 1 PEO Framework

Element	Definition	Application in Study
Population	Who is being studied?	High school students in science learning
Exposure	What intervention or factor is considered?	AI-based tools (adaptive feedback, simulations, prompts)
Outcome	What is being measured or improved?	Psychological capital (efficacy, resilience, optimism)

Source: Authors, 2026

a high, moderate and/or low methodological quality. Studies were synthesized only if they were deemed to be of high or moderate quality. To enhance interpretive reliability, a summary of the quality appraisal results was included in the data extraction and thematic analysis steps.

The search of the database was made in January and February 2026. In order to improve the results of the search and to be more reproducible, different search strings have been changed slightly as required by the indexing procedures of the various data-bases. The keywords used included Artificial Intelligence or the terms AI, Intelligent Tutoring Systems, or Adaptive Learning, and Psychological Capital or PsyCap, Hope, Self-efficacy, Resilience, or Optimism, and Science Education or STEM or Secondary Education or High School Students. Furthermore, some truncation symbols and phrase searching were used to facilitate the retrieval if they were supported by the database functions, to enhance the accuracy and comprehensiveness of the retrieval.

2.3 Resources and Study Selection

In this research, five specific databases were chosen strategically, which were comprised of ERIC, PsycINFO, Scopus, Web of Science, and PubMed. ERIC was chosen because of its focus on the education sector and practices that involve AI in the classrooms (Gusenbauer & Haddaway, 2020). The PsycINFO was used due to the fact that it covers studies that centre on psychological constructs like resilience, hope, and self-efficacy that are key in psychological capital (Heck et al., 2024). Both databases were used since they have a broad multi-disciplinary focus and index high-quality journals in which studies concerning AI application to science learning frequently appear (Schwager & Schalk, 2022). The PubMed was selected to incorporate cross-functional views on technological application and psychological well-being. The results of the search were manageable in each database Nowell et al., (2024). ERIC, PsycINFO, and Scopus yielded 383, 295, and 398 articles, respectively, whereas Web of Science and PubMed resulted in 790 and 850 articles, respectively. After excluding duplicates, assessing the relevance of articles, and performing a screening of the articles, ten quality articles remained to be synthesized, as shown in Figure 1.

2.4 Data Collection and Eligibility Criteria

The manual data collection was performed through systematic content analysis, with some of the essential items being the type of article, the source of the journal, the year of publication, the research objectives, methodological design, and the relationships between variables that these authors were trying to investigate. It was specifically of interest to identify the studies that have considered the effect of artificial intelligence intervention on the dimensions of psychological capital, which include efficacy, resilience, and optimism, in the study situation in a high school science subject. The inclusion criteria (IC) based on which this systematic review was carried out were formed to achieve both methodological soundness and theme-related relevance.

- First, IC was that the study included peer-reviewed original studies, which were only, published in English because English has been a dominant language in terms of the publication of scholarly work worldwide.
- Second IC was that the study's focus should be on the influences of AI-enabled tools on the

Table 2 CASP Appraisal

S. No.	Author(s) & Year	Clear Research Aim	Methodological Appropriateness	Data Collection & Analysis Rigor	Validity / Reliability	Ethical Considerations	Overall Quality Score (5)	Quality Level
1	Almetere (2024)	Yes	Yes	Yes	Moderate	Moderate	4	High
2	Nkedishu & Okonta (2024)	Yes	Yes	Yes	Yes	Moderate	4.5	High
3	Shin et al. (2024)	Yes	Yes	Yes	Yes	Yes	5	High
4	Zafeer et al. (2025)	Yes	Yes	Yes	Yes	Moderate	4.5	High
5	Kumar et al. (2023)	Yes	Yes	Moderate	Moderate	Moderate	3.5	Moderate
6	Jia & Tu (2024)	Yes	Yes	Yes	Yes	Yes	5	High
7	Ahmadzadeh & Dashti Moghadam (2024)	Yes	Yes	Yes	Yes	Yes	5	High
8	Razia et al. (2025)	Yes	Yes	Yes	Moderate	Moderate	4	High
9	Jajuri et al. (2019)	Yes	Moderate	Moderate	Moderate	Moderate	3	Moderate
10	Abdrakhmanov et al. (2024)	Yes	Yes	Yes	Yes	Moderate	4.5	High

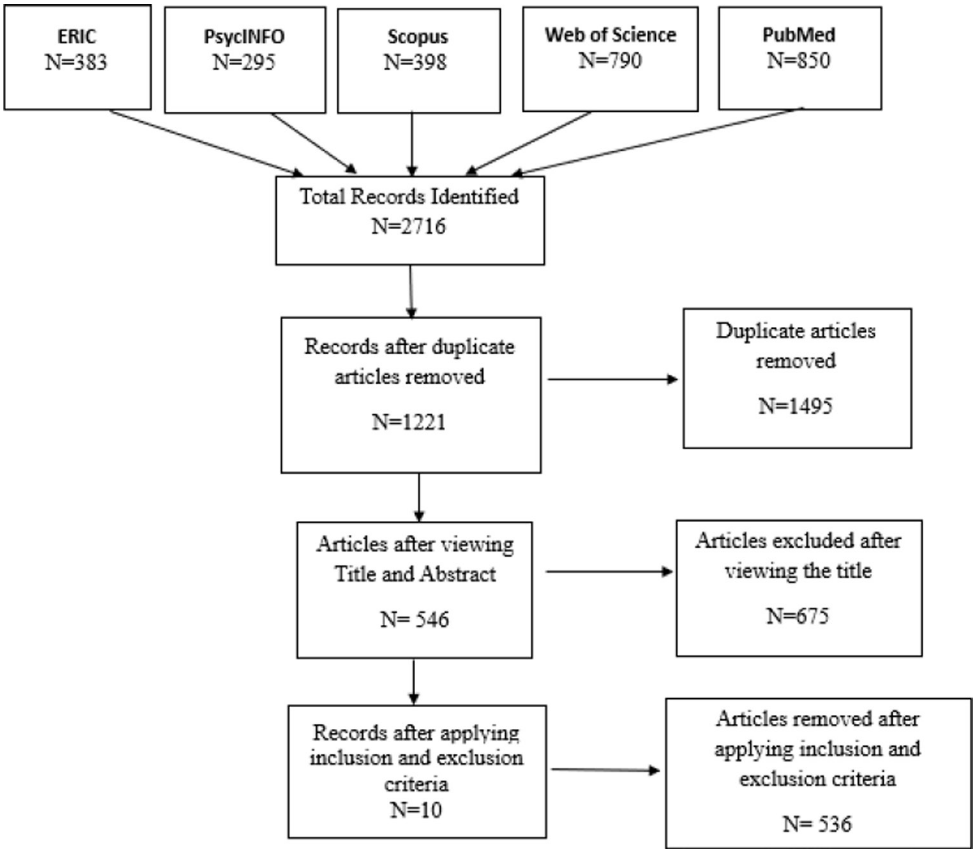

Figure 1. Prisma Flow Diagram
Source: Authors, 2026

outcomes of psychological capital in science among high school students.

- Third IC was based on selecting studies that used quantitative, qualitative, or mixed methods depending on a broad range of evidence.

The usage of these criteria made the review only synthesize high-quality studies and the one that were relevant in the context, therefore, providing high validity and applicability to the findings.

A two-independent-researcher approach (one group selecting the studies and another coding) was used to enhance the reliability of screening and minimize any subjectivity. A few initial challenges around article eligibility, theme classification and coding interpretation were discussed and agreed upon in the process of reviewing the articles. At the screening level, inter-reliability was examined; percentage agreement procedures were used and good consistency was found between the reviewers. Moreover, extracted items of data and thematic interpretations were compared with each other to confirm the accuracy of coding and consistency of the interpretations with the review goals. The process of validation has supported the methodological transparency and reduced the chances of researcher bias in the process of conducting the systematic review and thematic synthesis.

2.5 Data Items-Selection Process using Prisma

Based on the above-specified eligibility criteria for the inclusion of studies, 10 studies were selected from the total of 2716 records received after serving the predefined keywords on the pre-determined secondary databases. Out of the total 2716 records received, 1495 records were removed for being duplicates, leaving 1221 records for analysis of title and abstract for relevancy, as shown in Figure 1. This stage of records analysis led to the removal of 675 records, leaving 546 records tested through the eligibility criteria. Thus, 536 records were excluded due to not being peer-reviewed, different publication language, lack of focus on AI or psychological capital constructs, and being secondary studies. Therefore, the final 10 studies selected met the eligibility criteria (Figure 1). Only peer-reviewed and published studies were included, which allowed for the guarantee of the rigor, trustworthiness, credibility, and reliability of the findings. Unpublished, forthcoming, or preprint studies were excluded to avoid reservations associated with quality and reliability. This approach reinforces the cogency of findings, as all selected sources had endured formal peer review and encountered recognised scholarly standards.

Ten studies met the final inclusion criteria but this does not indicate methodological limitation, the inclusion criterion was often very specific based on the focus of the review. The review focused only on empirical research that investigated the impact of the psychological capital dimensions on science or STEM learning with the use of AI. Many studies which were excluded were at the higher education level, cognitive outcomes without psychological constructs, or conceptual discussions without empirical evidence. Due to the limited number of studies included, the relatively high quality of the studies was reinforced by the final sample, which achieved conceptual consistency, population relevance and methodological comparability, as shown in CASP quality appraisal table 2, to enhance the analytical depth and thematic precision of the review conducted.

2.6 Data Analysis Method

The thematic analysis approach of Braun and Clarke has been used in the current study to explain and analyse the findings and themes emerging from selected studies related to the influence of AI in developing psychological capital in science among high school adolescents (Byrne, 2022). One of the main reasons for choosing the thematic method was the flexibility, as it is used to identify, analyse, and report on patterns throughout qualitative data. In addition, the thematic method is also used for both deductive and inductive coding approaches (Braun & Clarke, 2021). Thematic analysis is especially appropriate in the synthesis of multi-disciplinary research in which there is an interaction of psychological constructs with technological interventions. Its thematic method's six-phase procedure consists of familiarization, coding, theme development, review, definition, and reporting, provides rigorous exploration of complicated associations between AI characteristics and mental phenomena such as hope, efficacy, resilience, and optimism. The procedure of coding had been done using two ways comprising inductive and deductive thematic coding. First, the extracted data from the included studies were reviewed repeatedly to gain familiarization with the data. Then open coding was used to identify the common concepts linked to the integration of AI in science learning that emerge. Next, an open coding approach was employed to discover common elements of the concepts linked with the AI supported psychological development in science learning. The following similar codes were then combined into higher-order thematic categories, corresponding to the HERO dimensions of psychological capital. Themes were developed by comparing studies in an iterative process to ensure them internal consistency and conceptual distinctiveness. The coding decisions and generation of themes was double checked by another researcher and problems were solved by discussion and rethematising.

2.7 Risk of Bias Assessment

The risk of bias was taken into account during the review process to guarantee that synthesized findings are credible. Publication bias, selective reporting, language bias because all the studies were in English and the limitation of the databases in indexing may have posed a threat to the results. To reduce these risks, the databases were searched in a systematic way, predefined eligibility criteria were consistently applied, and only empirical studies were included, of which only those that were peer-reviewed were used. Furthermore, methodological quality appraisal of the studies through CASP was helpful in recognizing the possible limitations in each study. However, the risk of not including relevant studies as well as publication-related bias cannot be ruled out.

2.8 Ethical Considerations

This is a systematic review using publicly available scholarly literature, so there was no interaction with humans or gathering of personal data, nor was intervention in an institution, which would normally require formal ethical approval. However, throughout the revision process, ethical practices of research were sustained by having proper citations, transparent reporting procedures and objective interpretation of findings. All the studies included were properly cited and methodological choices were systematically explained to maintain academic integrity, minimize interpretative bias, and ensure responsible integration and synthesis of the available scientific evidence on the topic of AI and psychological capital in science education.

3. Results

Following the comprehensive search and selection process, 10 relevant studies were found to have investigated the role of artificial intelligence (AI) in improving constituents of Psychological Capital (PsyCap), especially optimism, self-efficacy, and resilience in the context of high school students studying science-related or STEM subjects. The analysis showed that studies of optimism with regard to the adoption of AI in learning are still in an early stage and show positive student attitudes and motivations in terms of the adoption of AI technologies. The research on self-efficacy was mainly based on the influence of the AI capabilities, digital learning tools, and immersive technologies on motivation, critical thinking, and adaptive learning processes. Similarly, studies related to resilience also focused mainly on the possibilities of enhancing emotional regulation and academic adaptation and their persistence when based on the application of robotics, in STEM education facilitated with machine learning prediction models, and AI-enabled mindfulness interventions.

These studies were examined and analysed based on their general focus theme of the components of PsyCap. When categorised based on optimism, self-efficacy, and resilience, the results signal that there is indeed a preoccupation with self-efficacy (4 studies), followed by resilience (4 studies) and optimism (2 studies), see Table 2. Although several studies are said to have overlapped in more than one dimension, In the selected studies, the dimension of self-efficacy was the most commonly investigated PsyCap dimension in the studies involving AI-supported learning environments, with four of them examining this dimension.

While all of the reviewed studies revealed that AI-supported learning and PsyCap dimensions were generally positively related, there were variations in the magnitude and the intensity of this relation. The quantitative studies focused on improvements in engagement, confidence and academic adaptation, and mixed method studies focused on the students' subjective experiences of encouragement, personalisation and emotional support. Further, while Jia and Tu (2024) did find indirect impacts of AI on critical thinking in the area of self-efficacy and motivation, their direct cognitive impacts were statistically weak. Likewise, outcomes related to optimism were not as consistently operationalized as were self-efficacy and resilience across studies, and there was conceptual and methodological variation among the literature included.

3.1 Optimism and AI-Supported Science Learning

Other Hope-Related Outcomes were also noted, especially those in research on personalized AI support systems. Within the science learning context, Almetere (2024) revealed that the learning environment guided by a chatbot nurtured goal-oriented learning behaviour and maintained students' motivation to learn, which indicates that hope, as one of the important dimensions of PsyCap, may be developed by providing science learning guidance through an AI chatbot. Two studies specifically discussed the importance of optimism in influencing students in perceiving and deriving results through AI-based learning. Almetere (2024) emphasised that chatbots have a positive effect on student attitudes, and also stated that they feel hopeful and optimistic toward approaching science-related coursework with the assistance of the personalized help of artificial intelligence. The mixed-method surveys and structured interviews emphasized the idea that ease of seeking help was not the only factor that contributed to optimism, but the perception of encouragement by the respondents in real time. The findings of Nkedishu and Okonta (2024) supported the views of Lin and Yin (2024), specifically seeking to understand the multidimensional attitudes of high school students toward AI in enhancing science-related learning. The optimistic approach was seen in the attitude of students to consider that AI would enable a revolution in research, personalize learning in STEM subjects, and democratize education resources. Notably, AI literacy was revealed to affect the levels of optimism, thus showing that better-exposed and AI-competent students were more confident and optimistic about the enhanced conceptual understanding in science-related subjects.

3.2 Self-Efficacy and AI-Enhanced Learning Environments

Shin et al. (2024) also unveiled that STEM coursework with AI and data science did enhance the attitudes of students towards mathematics and science, and to a large extent, among low-scoring students. Students participated more and were more confident when using AI to undertake STEM tasks. AI-enabled. Zafeer et al. (2025) also reaffirmed these results and found that online learning tools had a positive effect on both student engagement and performance in science. The results demonstrated that teacher competency and access to technology are of key importance, indicating that students felt more assured and competent when these latter conditions were present.

Kumar et al. (2023) discussed the performances of Virtual Reality (VR), Augmented Reality (AR), and Artificial Intelligence (AI), which demonstrated that immersive

Table 3 Grouping of articles based on relationships between variables and authors

Relationship between variables (themes)	Authors	No. of articles (out of 10)
Optimism and AI in education	Almetere (2024); Nkedishu & Okonta (2024)	2
Self-efficacy and AI/technology use	Shin et al. (2024); Zafeer et al. (2025); Kumar et al. (2023); Jia & Tu (2024)	4
Resilience and AI/STEM interventions	Ahmadzadeh & Dashti Moghadam (2024); Razia et al. (2025); Jajuri et al. (2019); Abdrakhmanov et al. (2024)	4

Source: Authors, 2026

and adaptive systems facilitated inclusive environments in which students with various abilities could interact in more meaningful ways. In this case, the development of self-efficacy occurred through individualized learning with AI, as it shows the increase in self-efficacy in STEM domains. In the same way, Jia and Tu (2024) explored the ability of AI using the resource-based theory. The results implied that critical thinking awareness improved indirectly through increasing general self-efficacy and the enhancement of motivation because of the presence of AI. The direct influence of AI in the sphere of cognition was minor, but its implications in the area of self-belief and motivation showed considerable results.

3.3 Resilience and AI-Mediated STEM Interventions

According to Ahmadzadeh and Dashti Moghadam (2024), emotional intelligence among high school students and academic performance increased considerably through robotic-based learning. Sub-dimensions of emotional resilience, including self-control and social skills, were significantly enhanced. Razia et al. (2025) focused on the aspect of resilience through the perspective of mental health, highlighting that the AI-based interventions based on mindfulness and meditation decreased anxiety levels at the same time, increasing academic resilience among high school students while studying STEM subjects. AI-assisted mindfulness interventions resulted in increased academic resilience and emotional regulation among students and showed measurable progress in increases to mindfulness, resilience, and emotional well-being.

Jajuri et al. (2019) applied a socio-constructivist perspective to analyse STEM activities and concluded that their resilience was built through participation by developing social support, planning, and problem-solving ability. These dimensions are an expression of resilience not only as a trait of an individual but also of a social feature developed through cooperation suggested by Patnaik et al. (2024) as well. Lastly, Abdrakhmanov et al. (2024) used machine learning to determine future academic performance and resilience in science subjects and how the use of machine learning models was reported for identifying academically at-risk students early and possible interventions for resilience. However, the effectiveness of predictive AI-enabled science teaching applications is affected by concerns about privacy and security issues related to students' data while using AI-enabled technologies for science learning.

Most of the evidence reviewed consisted of quantitative and quasi-experimental studies that generally offered more empirical evidence on the relationships between PsyCap dimensions and AI-supported learning. Studies using a mixed-method approach provided further contextual knowledge of students' perceptions and emotional experiences, and qualitative data provided information on collaborative and socio-constructivist aspects of developing resilience. Nonetheless this was hampered by differences in study design, population characteristics, time of the intervention and measurement approaches. Thus, the conclusions drawn from the findings should be understood in the context of the evidence that is available at this particular time and should not be taken as definitive statements about the impact of AI on psychological capital.

4. Discussion

The aim of the review was to assess the role of artificial intelligence (AI) within the learning environment in building psychological capital (PsyCap) in science among high school students and specifically, optimism, self-efficacy, and resilience.

Two of the 10 (88%) empirical studies found that there was a strong relationship between the dimensions of psychological capital (PsyCap) and artificial intelligence (AI) in science education, with some, but not all, showing a stronger relationship. The synthesis of the 10 empirical studies found that psychological capital (PsyCap) dimensions were positively related to AI in science education and that some of these relationships were stronger, but not all. Instead of creating a one-size-fits-all impact, AI can be used to catalyse student motivation, emotional management, and confidence in learning, and has varying impacts based on the pedagogical design, access to technology, and learners' identities in science contexts within the high school. In the literature reviewed, AI-related tools (chatbots, adaptive learning systems, and mindfulness apps) were all linked to an increase in students' psychological capital, specifically optimism, self-efficacy, and resilience. The effects were not consistent, however, as cognitive outcomes were reported more often than affective outcomes. Some studies focused on the positive impact on performance and engagement, including those by Shin et al. (2024); Zafeer et al. (2025), while others pointed to the emotional and motivational benefits, as seen in the study by Almetere (2024); Razia et al. (2025). Thus, it can be implied that, when operating from an instructional design perspective, AI impacts PsyCap academically and through socio-emotional influences.

One very important factor that was found in every study reviewed is the lack of robust causal inference. The evidence is mostly from cross-sectional survey designs, short interventions or quasi-experimental designs, therefore, it is not possible to conclude if there is a direct impact of AI on psychological capital or if higher PsyCap students are simply more likely to use AI tools. Thus, the

Table 4 List and synthesis of articles

Author and Year	Research Focus	Research Approach	Findings and Significance
Almetere (2024)	Impact of chatbots on students' PsyCap (optimism, hope, self-efficacy, resilience).	Mixed-methods (survey & interviews)	Chatbots positively influenced PsyCap, particularly optimism and hope, improving academic support and psychological well-being.
Nkedishu & Okonta (2024)	Tertiary students' perceptions of AI (optimism vs concern).	Quantitative (survey, t-test, ANOVA)	Students viewed AI as advancing research and personalization; AI literacy strongly shaped optimism and proactive engagement.
Shin et al. (2024)	Effects of AI-based STEAM programs on attitudes to math/science.	Quantitative (latent transition analysis)	AI-enabled STEAM improved motivation and confidence, particularly in initially disengaged students, enhancing self-efficacy.
Zafeer et al. (2025)	Role of digital learning tools in engagement/achievement.	Quantitative (survey, SmartPLS)	Technology access and teacher competence significantly boosted student engagement, achievement, and classroom collaboration.
Kumar et al. (2023)	VR, AR, and AI in inclusive STEM education.	Mixed-methods (surveys & interviews)	Immersive and adaptive tools enhanced comprehension, motivation, and inclusivity, strengthening self-efficacy and critical skills.
Jia & Tu (2024)	AI capabilities, self-efficacy, motivation, and critical thinking.	Quantitative (survey, SEM)	AI indirectly fostered critical thinking via self-efficacy and motivation; mediation effects were significant though direct impact limited.
Ahmadzadeh & Dashti Moghadam (2024)	Robotics-based learning and its impact on EI and achievement.	Quasi-experimental (pre/post design)	Robotics significantly improved emotional intelligence and academic outcomes, bolstering resilience-related traits.
Razia et al. (2025)	AI-enabled mindfulness to reduce anxiety and build resilience.	Quasi-experimental (pre/post survey)	Mindfulness app reduced anxiety, improved resilience and mindfulness, showing strong psychological benefits for students.
Jajuri et al. (2019)	STEM activities' influence on academic resilience.	Qualitative (fuzzy Delphi technique)	STEM strengthened resilience via social support, planning, and problem-solving, producing globally competitive learners.
Abdrakhmanov et al. (2024)	Predicting STEM performance and resilience via ML models.	Quantitative (ML algorithms)	Ensemble ML improved resilience prediction, aiding early intervention; ethical concerns over data privacy no

Source: Authors, 2026

observed positive changes in self-efficacy and resilience should be interpreted as related to rather than directly causing the observed changes in emotional switching revealed in Kanwal and Dung (2025) also. To assess if there is a lasting effect of AI exposure on the psychology of science learning for adolescents, different experimental and longitudinal designs will be needed.

The results also reveal potential new issues of digital inequality. A few studies have shown that the impact of AI in learning varies across students based on their access to technology and digital literacy of teachers. In the context of limited resources, learners might have a lower realization of their psychological capital gains because of lack of infrastructure or not being sufficiently AI-literate. This means that there is a "psychological divide" in which the students with greater technological resources become more self-efficacious and optimistic in their attitudes to learning about science than their less well-resourced counterparts, thereby perpetuating inequalities in science education.

The findings emerge from the study indicates the fact that AI is an agent of both the cognitive and the affective capabilities that a student would require to thrive superficially in science subjects and enhance their psychological capital. There are some contradictory studies as well, for instance, Kundu and Bej (2025); Shiddiqi et al. (2025) warn that the use of AI in education cannot be assumed to be inherently positive, but rather, it requires careful pedagogical embodiment. On the same note, D'Silva et al. (2025) state that excessive focus on technological tools threatens to marginalise the socio-emotional dimensions of the learning process, despite them being the primary focus of PsyCap. The contrast brings to the fore a conflict between the empirical evidence of positive gains and the theoretical critique of structural constraints. Although Kundu and Bej (2025) and D'Silva (2025) were briefly mentioned, their findings are essential towards attaining a balanced understanding of the role that AI plays in nurturing psychological capital. The take-away from the results indicates that AI must be considered a pedagogically dependent teaching tool and not a standalone solution for building psychological capital. AI-based systems have the potential to improve engagement, resilience, and learning motivation in science learning, but they are dependent on the design of learning, mediation by teachers, and access to technology. Ethical issues also arise, such as over-dependence on automated feedback systems and the potential for learner autonomy reduction and profiling based on data in AI-supported prediction models in STEM learning environments. The use of AI in science education should, therefore, be balanced with pedagogic responsibility to ensure that the use of AI would enhance the psychological capital development sustainably, inclusively, and learner-centred.

The second was narrowed down to self-efficacy, which is the most prevalently examined dimension in the reviewed articles. In four papers, Shin et al. (2024), Zafeer et al. (2025), Kumar et al. (2023), and Jia and Tu (2024), displayed how efficacy can be bolstered considerably with the help of AI-enhanced environments while studying science-related subjects in the case of high school students. The studies reviewed (e.g., Zafeer et al., 2025) highlighted that self-efficacy was a key observed outcome, indicating that the use of AI in science education is primarily focused on enhancing performance or building confidence rather than on fostering deeper emotional growth. The use of AI-based STEM programs and digital learning systems often led to immediate feedback, learning opportunities for adaptive learning and personalized guidance, both of which have been linked to improved mastery experiences in Estrada-Araoz et al. (2025); Siddique et al. (2021) also. However, the evidence also suggests that there are varying degrees of effectiveness, depending on the sophistication of the digital literacy of learners the ability of teachers to facilitate their students' learning, and the continued engagement of learners with the digital content. This means access to technology is not enough on its own to make a difference in terms of psychological development in science learning contexts.

Simultaneously, critiques of these findings offer valuable arguments. Jia and Tu (2024) and Rajapakse et al. (2024) claim that AI could contribute to propagating inequalities, and the efficacy gains tend to be dependent on the availability of technology and the competence of a teacher, which Zafeer et al. (2025) also endorsed. Moreover, excess dependence on adaptive systems can yield a corresponding learned dependency, in which students refer to AI assistance to feel confident as opposed to self-belief. Although the phenomenon was not highlighted in any of the studies reviewed, it represents a potential risk. Hence, the findings imply that the use of tools that involve AI should be incorporated in the teaching process without passively depending on it. Second, the increased prominence of teacher digital literacy requires investment because the efficacy gains are moderated by the teacher's success in effectively leveraging AI.

The results also highlight issues of digital disparities and ethical implications in the adoption of AI in scientific education. As can be seen from several reviewed studies, students' access to digital infrastructure and teachers' technological competence has a strong impact on the psychological benefits of AI. Therefore, disparities in access to the learning environment they can create with AI can have a disproportionate impact on psychological capital development among students. Ethical issues also arise in relation to relying on an automated system by the learner and predictive analytics in educational decision making. The challenges indicate the need to ensure that AI is used within a transparent, equitable, and pedagogically informed framework, as opposed to technologically deterministic.

The third objective was to determine the impact on resilience and optimism, which are key components of the psychological capital of the high school science students. In this perspective, Ahmadzadeh and Dashti Moghadam (2024) showed that the robotics-based learning experience boosted emotional intelligence and achievement and reinforced positive adaptive characteristics, including self-control and social skills. Razia et al. (2025) concluded that AI-enhanced mindfulness was found to mitigate high anxiety levels, increase scholarly persistence, and directly combat stressors that exists in highly demanding science-related learning processes. In a similar vein, Jajuri et al. (2019) demonstrated resilience-enhancing capabilities of STEM activities by building resilience at the social support and setting of goals. Abdrakhmanov et al. (2024) used machine learning in predicting and pre-empting challenges relating to resilience in STEM students.

The impact on optimism was discussed by Almetere (2024) and Nkedishu and Okonta (2024). The result of both papers indicated that the AI tools encourage positive mindsets and students view technology as a complement of opportunity and customization towards enhanced learning in science-related subjects. Optimism, according to Chen et al. (2025) and Morales-Garcia et al. (2024), however, proved to be reliant on AI literacy, and this indicates that differences in access and awareness might contribute towards psychological capital differences. When compared to self-efficacy and resilience, optimism as an element of psychological capital has not been analysed in detail, like other psychological aspects such as resilience and self-efficacy have. Optimism can be seen as a comparatively understudied concept in AI science learning research, and it is connected to self-efficacy and resilience, but not as closely explored. Almetere (2024); Nkedishu and Okonta (2024) focuses on the notion of optimism as positive attitudes reported by students towards the use of AI for personalization, academic support and flexibility in learning. Optimism-related results, however, are generally based on attitudinal perceptions and less on solid psychological measures over the course of time. This restricted the causal interpretation of the data and indicates that a more theoretically supported investigation should be conducted to explore the impact of AI-enhanced learning environments on motivational beliefs for science learning and outlooks on science learning in secondary school.

In contrast, research on self-efficacy (Shin et al., 2024; Jia & Tu, 2024) or resilience (Razia et al., 2025; Ahmadzadeh & Moghadam, 2024) more commonly presented measurable outcomes, such as better test scores in science subjects, increased emotional intelligence, or decreased anxiety. The optimism-based results were, however, usually on the basis of attitudinal scales, which are weaker as a source of causal inferences. Still, optimism cannot be diminished, because it can provide a growth mindset and the willingness to continue working on complex tasks in science by high school students. In addition, the possibility of optimism supporting resilience and self-efficacy points to the supplementary role that the concepts might not capture well in the existing literature.

Although all of these are positive associations, the literature reviewed is limited when it comes to long-term causal relationship between the development of psychological capital and AI-supported learning. Unfortunately, the majority of studies utilized cross-sectional research design or survey-based research, or just a brief, one-off intervention, which hampered the ability to draw enclosures related to the direct effect of AI on psychological capital or to the indirect effect of psychological capital on positive engagement with AI technologies. Hence, caution must be taken when drawing conclusions from prior research findings, and more future longitudinal research is needed to determine if the psychological benefits seen can be maintained over time in the science classroom.

The implications of these findings are pretty sophisticated. Regarding resilience, the literature underlines AI as a potential solution, either as a direct intervention, such as mindfulness apps, or as a support indicator that robotics assists STEM activities, as also reflected in Shaddad (2023) and Chen et al. (2025). In the case of optimism, the question is how to design AI tools that contribute to positive attitudes in the short term and sustained hopes in confronting challenging science problems. A stronger theoretical representation is required when connecting the AI mechanisms in relation to each component of psychological capital. The self-efficacy theory proposed by Bandura explains the mechanism of building confidence through experience and feedback; it can be facilitated by AI tools that measure progress and give immediate feedback (Shin et al., 2024; Jia & Tu, 2024). The broaden-and-build theory by Fredrickson states that positive emotions help broaden the cognitive capacity of students, and the chatbots or virtual assistants can ease their minds through increasing optimism by lowering uncertainty and advising students promptly (Almetere, 2024). In this context, feedback reinforces self-efficacy, personalization maintains optimism, and simulation builds resilience.

5. Conclusion

5.1 Summary of the Main Findings

The aim of the study was to examine the level of involvement of artificial intelligence (AI) in promoting psychological capital (PsyCap) in the science education of high school students in terms of self-efficacy, sense of resilience, and optimism. In the ten studies chosen, a number of findings were identified. The results suggest that high school students' psychological capital is positively related with key components of psychological capital, namely self-efficacy, resilience, and optimism when using AI-supported science learning environments. The following relationships were always observed with the tools that can be used with AI. These are comprised of higher learner confidence and emotional regulation, higher learner engagement and persistence, relationship between the tools and activities that require science learning, and increased learner persistence in science-related activities. Pedagogical quality, digital accessibility and pedagogical contextual implementation, however, had a strong influence on these psychological outcomes.

5.2 Limitations and Future Directions

Despite contributory findings in the existing body of knowledge related to induced psychological capital in science among high school students, the study also holds several limitations. At first, the study was limited to a small number of primary studies, which led to limited generalization of the findings over a larger sample of the high school student population. On the other hand, the findings imitate a particular context, such as science or STEM education, instead of diverse educational settings, which also limits the generalization of the findings. Additionally, there has been over-reliance on secondary data, and no empirical evidence has been generated. Besides, ethical and equity-related issues, for instance, AI literacy gaps, and the digital divide are negligibly discussed.

The main sources of the reviewed evidence were cross-sectional and short-term research, which made it difficult to draw causal and long-term relationships between learning psychological capital and the integration of AI. Moreover, the diversity of research presented, differences in educational context, and insufficient sampling of high school students diminish the generalizability of results. Interpretive power is limited, also by possible publication bias, and by secondary evidence. Longitudinal studies focused on the long-term psychological consequences of using AI to facilitate science teaching and learning should be conducted in the future. There is a need for more mixed methods studies to capture measurable outcomes and students lived experience when using AI in education. Comparative study across cultures of STEM would further enhance the knowledge of the differences among cultures regarding psychological capital development. Further research should also explore the ethical considerations of the implementation of AI, including the privacy of the data, dependence of learners on AI, and equitable technological access.

5.3 Policy Recommendations

The dynamic of combining access to AI tools with psychological support strategies should be incorporated into AI integration frameworks for secondary STEM education, in combination with structured guidelines. Professional development of teachers in AI assisted pedagogy and ethical practices of digital use should be given priority in schools. Furthermore, both governments and educational institutions need to adopt fair policies and laws on digital infrastructure to minimise inequalities between schools. National educational technology policies should also include clear guidelines on student data privacy, responsible uses of AI, and psychologically supporting AI design.

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Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this manuscript, the author(s) did not employ any of the Generative AI and/or AI-Assisted technologies for Language refinement, drafting background section and did not perform any Task of the technology.

References

Abdrakhmanov, R., Zhaxanova, A., Karatayeva, M., Niyazova, G. Z., Berkimbayev, K., & Tuimebayev, A. (2024). Development of a framework for predicting students' academic performance in STEM education using machine learning methods. *International Journal of Advanced Computer Science & Applications, 15*(1). https://doi.org/10.14569/IJACSA.2024.0150105

Ahmadzadeh, L., & Dashti Moghadam, K. (2024). Exploring the impact of robotics-based learning on students' emotional intelligence and academic achievement: A semi-experimental study. *Interdisciplinary Journal of Virtual Learning in Medical Sciences, 15*(4), 355–368. https://doi.org/10.30476/IJVLMS.2024.103359.1311

Almetere, E. (2024). *Transforming education: The impact of chatbots on students' psychological capital and academic success*. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1073&context=saudicis2024

Braun, V., & Clarke, V. (2021). *Thematic analysis: A practical guide*. SAGE.

Byrne, D. (2022). A worked example of Braun and Clarke's approach to reflexive thematic analysis. *Quality & Quantity, 56*(3), 1391–1412. https://doi.org/10.1007/s11135-021-01182-y

Chen, C., Hu, W., & Wei, X. (2025). From anxiety to action: Exploring the impact of artificial intelligence anxiety and artificial intelligence self-efficacy on motivated learning of undergraduate students. *Interactive Learning Environments, 33*(4), 3162–3177. https://doi.org/10.1080/10494820.2024.2440877

D'Silva, M. N. (2025). Building resilience and academic success: An integrated framework of multiple intelligences, mentoring, psychological well-being, and AI support in higher education. *Journal of Management and Social Research, 2*(2). https://jmsr-online.com/article/building-resilience-and-academic-success-an-integrated-framework-of-multiple-intelligences-mentoring-psychological-well-being-and-ai-support-in-higher-education-124/

Estrada-Araoz, E. G., Mamani-Roque, M., Quispe-Aquise, J., Manrique-Jaramillo, Y. V., & Cruz-Laricano, E. O. (2025). Academic self-efficacy and dependence on artificial intelligence in a sample of university students. *Sapienza: International Journal of Interdisciplinary Studies, 6*(1), e25008. https://doi.org/10.51798/sijis.v6i1.916

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

Heck, T., Keller, C., & Rittberger, M. (2024). Coverage and similarity of bibliographic databases to find most relevant literature for systematic reviews in education. *International Journal on Digital Libraries, 25*(2), 365–376. https://doi.org/10.1007/s00799-023-00364-3

Hijriyah, L., Alias, A., & Mohd Sahabuddin, M. F. (2024). Exploring walkability research trends based on systematic literature review (SLR) by applying PRISMA. *Open House International, 49*(1), 63–121. https://doi.org/10.1108/OHI-02-2023-0031

Hosseini, M. S., Jahanshahlou, F., Akbarzadeh, M. A., Zarei, M., & Vaez-Gharamaleki, Y. (2024). Formulating research questions for evidence-based studies. *Journal of Medicine, Surgery, and Public Health, 2*, 100046. https://doi.org/10.1016/j.glmedi.2023.100046

Jajuri, T., Hashim, S., Ali, M. N., & Abdullah, S. M. S. (2019). The implementation of science, technology, engineering and mathematics (STEM) activities and its effect on students' academic resilience. *Asia Pacific Journal of Educators and Education, 34*, 153–166. https://doi.org/10.21315/apjee2019.34.8

Jia, X. H., & Tu, J. C. (2024). Towards a new conceptual model of AI-enhanced learning for college students: The roles of artificial intelligence capabilities, general self-efficacy, learning motivation, and critical thinking awareness. *Systems, 12*(3), 74. https://doi.org/10.3390/systems12030074

Kanwal, N. D. S., & Dung, T. T. V. (2025). Charting the future: AI, ethics, and scholarly publishing in the humanities and social sciences. *Horizon Journal of Humanities & Social Sciences Research, 7*(S), 1–6. https://doi.org/10.37534/bp.jhssr.2025.v7.nS.id1300.p1-6

Kanwal, N. D. S., & Dung, T. T. V. (2025). *Charting the future: AI, ethics, and scholarly publishing in the humanities and social sciences.* Horizon Journal of Humanities & Social Sciences Research, 7(S), 1–6. DOI: https://doi.org/10.37534/bp.jhssr.2025.v7.nS.id1300.p1-6

Kumar, K., Selvan, T., Mahendraprabu, M., Ganesan, K., Ramnath, R., & Kumar, N. (2023). Examining the role of virtual reality, augmented reality, and artificial intelligence in adapting STEM education for next-generation inclusion. https://doi.org/10.70333/ijeks-02-12-025

Kundu, A., & Bej, T. (2025). Psychological impacts of AI use on school students: A systematic scoping review of the empirical literature. https://doi.org/10.58459/rptel.2025.20030

Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in Psychology, 14*, 1285392. https://doi.org/10.3389/fpsyg.2023.1285392

Maziriri, E. T., Mabuyana, B., & Nyagadza, B. (2025). Navigating the technopreneurial odyssey: Determining how technopreneurial self-efficacy, technopreneurial education and technological optimism cultivate tech-driven entrepreneurial intentions. *Management & Sustainability: An Arab Review*. https://doi.org/10.1108/MSAR-08-2024-0086

Morales-García, W. C., Sairitupa-Sanchez, L. Z., Morales-García, S. B., & Morales-García, M. (2024). Adaptation and psychometric properties of a brief version of the general self-efficacy scale for use with artificial intelligence (GSE-6AI) among university students. *Frontiers in Education, 9*, 1293437. https://doi.org/10.3389/feduc.2024.1293437

Nkedishu, V. C., & Okonta, V. (2024). Unpacking optimism versus concern: Tertiary students' multidimensional views on the rise of artificial intelligence (AI). *International Research Journal of Multidisciplinary Scope, 5*, 362–377. https://doi.org/10.47857/irjms.2024.v05i04.01261

Nowell, L., Keogh, B., Laios, E., Mckendrick-Calder, L., Lucas Molitor, W., & Wilbur, K. (2024). Public participation in healthcare students' education: An umbrella review. *Health Expectations, 27*(1), e13974. https://doi.org/10.1111/hex.13974

Nyoko, A. E., & Hanafiah, M. H. (2024). A systematic literature review on entrepreneurial intention: PRISMA method. *Advances in Economics, Business and Management Research*, 254–273. https://doi.org/10.2991/978-94-6463-411-2_21

Papaioannou, A., Papavassiliou-Alexiou, I., & Moutiaga, S. (2022). Career resilience and self-efficacy of Greek primary school leaders in times of socioeconomic crisis. *International Journal of Educational Management, 36*(2), 164–178. https://doi.org/10.1108/IJEM-01-2021-0024

Patnaik, S. R., Dicko, M., Subudhi, R. N., & Parhi, A. (2024). Socio-cultural and academic adaptation by international students: An impact study in the Indian context. *Horizon Journal of Humanities & Social Sciences Research, 6*(S), 65–75. https://doi.org/10.37534/bp.jhssr.2024.v6.nS.id1254.p65

Patnaik, S. R., Dicko, M., Subudhi, R. N., & Parhi, A. (2024). *Socio-cultural and academic adaptation by international students: An impact study in the Indian context.* Horizon Journal of Humanities & Social Sciences Research, 6(S), 65–75. DOI: https://doi.org/10.37534/bp.jhssr.2024.v6.nS.id1254.p65

Prayogo, P., Hartanti, J., Winarno, A., & Listyowati, A. (2025). Resilience and self-efficacy: Keys to students' change readiness in higher education. *Journal of Information and Organizational Sciences, 49*(1), 15–37. https://doi.org/10.31341/jios.49.1.2

Rajapakse, C., Ariyarathna, W., & Selvakan, S. (2024). A self-efficacy theory-based study on the teachers' readiness to teach artificial intelligence in public schools in Sri Lanka. *ACM Transactions on Computing Education, 24*(4), 1–25. https://doi.org/10.1145/3691354

Razia, E. T., Anwar, H., & Mustafa, S. (2025). Working on reducing the symptoms of anxiety and enhancing academic resilience through the use of AI-enabled mindfulness and meditation among college students. *Research Journal of*

Social Sciences and Economics Review, 6(1), 67–78. https://doi.org/10.36902/rjsser-vol6-iss1-2025(67-78)

Schwager, R., & Schalk, L. (2022). How systematic are systematic literature searches? *Atti del 5° Convegno sulle Didattiche Disciplinari*, 510–516. https://doi.org/10.33683/dida.22.05.83

Shaddad, A. (2023). Self-assessment and immunity in online language learning: Probing into the impacts of critical thinking, self-efficacy, and academic resilience. *Computer-Assisted Language Learning Electronic Journal, 24*(2). https://callej.org/index.php/journal/article/view/8/2

Shiddiqi, M. H. A., Pujiana, E., & Purwaningsih, D. (2025). The profile of students' self-efficacy in chemistry learning during the transformation of generative AI usage. *Proceedings of the International Conference on Islamic Education and Science Development, 3*(1), 519–529.

Shin, S. H., Sim, J., Moon, C., Kim, N., & Hwang, J. (2024). Effects of STEAM programs emphasizing data science and AI on students' attitudes toward mathematics and science. *KEDI Journal of Educational Policy, 21*(2). https://doi.org/10.22804/kjep.2024.21.2.005

Siddique, M., Ali, M. S., Nasir, N., Awan, T. H., & Siddique, A. (2021). Resilience and self-efficacy: A correlational study of 10th grade chemistry students in Pakistan. *Multicultural Education, 7*(9), 210–222. https://doi.org/10.5281/zenodo.5498287

Sie, Y. J., & Lin, K. Y. (2025). Effects of psychological capital and cognition on STEM learning in IoT smart energy-saving projects. *Journal of Baltic Science Education, 24*(2), 340–359. https://doi.org/10.33225/jbse/25.24.340

Wu, T. T., Lee, H. Y., Wang, W. S., Lin, C. J., & Huang, Y. M. (2023). Leveraging computer vision for adaptive learning in STEM education: Effect of engagement and self-efficacy. *International Journal of Educational Technology in Higher Education, 20*(1), 53. https://doi.org/10.1186/s41239-023-00422-5

Xu, J., & Choi, M. C. (2023). Can emotional intelligence increase the positive psychological capital and life satisfaction of Chinese university students? *Behavioral Sciences, 13*(7), 614. https://doi.org/10.3390/bs13070614

Zafeer, H. M. I., Maqbool, S., Rong, Y., & Maqbool, S. (2025). Impact of digital learning tools on students' engagement and achievement in middle school science classes. *International Journal of Technology in Education and Science, 9*(2), 177–196. https://doi.org/10.46328/ijtes.622

Zhao, J. (2025). The role of learners' AI literacy and resilience in boosting their engagement and motivation in AI-based settings: From an achievement goal theory perspective. *Learning and Motivation, 91*, 102152. https://doi.org/10.1016/j.lmot.2025.102152

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