International Journal of Education, Psychology and Counseling
EISSN : 0128-164X
IJEPC
Volume 11 Issue 64 (September 2026) PP. 606-629

INTERNATIONAL JOURNAL OF EDUCATION, PSYCHOLOGY AND COUNSELLING (IJEPC)
https://gaexcellence.com/ijepc

GLOBAL ACADEMIC EXCELLENCE

THE INFLUENCE OF CHATGPT USE ON SELF-DIRECTED LEARNING AMONG UNIVERSITY STUDENTS: A SYSTEMATIC LITERATURE REVIEW

Sujiithra Selvendhiran[1]*, Hafiz Zaini[2]

[1] Faculty of Education, Universiti Kebangsaan Malaysia (UKM), 43600 Bangi, Selangor, Malaysia
[1]p165594@siswa.ukm.edu.my
[2]mhz@ukm.edu.my
[1] https://orcid.org/0009-0007-4843-793X
[2] https://orcid.org/0000-0001-5520-915X
*Corresponding Author

Article Info:

Article history:
Received date: 25.06.2026
Revised date: 12.07.2026
Accepted date: 30.07.2026
Published date: 08.09.2026

To cite this document:

Selvendhiran, S., & Zaini, H. (2026). The Influence of Chatgpt Use on Self-Directed Learning Among University Students: A Systematic Literature Review. *International Journal of Education, Psychology and Counselling, 11*(64), 606-629.

Abstract:

This systematic literature review examines how ChatGPT use is associated with self-directed learning among university students. It focuses on the purposes and patterns of use, the ways self-directed learning is defined and measured, and the positive outcomes, risks and limitations reported in previous studies. Searches were conducted in Scopus, Web of Science, ERIC and Google Scholar for publications dated from January 2020 to April 2025. The selection process followed PRISMA 2020 procedures. From 847 initially identified records, 15 studies met the eligibility and quality requirements. Data were extracted using a standardised form and analysed through thematic synthesis. Students used ChatGPT for learning-plan development, resource identification, explanation and feedback, language practice, academic writing, monitoring and reflection. Positive outcomes were more evident when tasks included prior reasoning, metacognitive prompts, collaborative activity or requirements to evaluate generated responses. Unguided use was associated with weak verification, cognitive offloading, over-reliance and reduced interaction with lecturers or peers. The review also found substantial variation in measurement. Few studies assessed self-directed learning directly, as most relied on self-regulated learning, metacognition, autonomy, motivation, engagement or academic performance. These outcomes are related to self-directed learning but do not provide equivalent evidence of its development. ChatGPT does not have a uniform effect on self-directed learning. Its contribution depends on task design, learner control, monitoring skills and the critical evaluation of generated information. Current evidence supports its use as a learning scaffold when students retain responsibility for planning, reasoning and evaluation. Evidence of sustained improvement in self-directed learning remains limited, indicating a need for longitudinal studies, direct measures and behavioural evidence of students' learning processes.

DOI: 10.35631/IJEPC.1164029

Keywords:

Artificial Intelligence, ChatGPT, Higher Education, Self-Directed Learning, Self-Regulated Learning, Systematic Literature Review

Introduction

ChatGPT is increasingly used by university students as part of their study practices. Students use it to clarify difficult concepts, generate draft text, summarise information, and obtain immediate responses to academic questions (Kasneci et al., 2023). However, the key issue is not only the frequency of use, but how such use may affect students' capacity for independent learning.

Self-directed learning refers to the learner's ability to set learning goals, select appropriate strategies, monitor progress, and evaluate learning outcomes. This capability is a central concern in higher education because university students are expected to develop increasing responsibility for their own academic growth (Knowles, 1975; Garrison, 1997). When students rely on ChatGPT for explanation, planning, drafting, and feedback, it becomes important to examine whether the tool supports independent learning or encourages dependence on automated assistance.

Although research on ChatGPT in education has expanded rapidly, much of the existing literature has focused on students' perceptions, academic performance, opportunities, and risks rather than on self-directed learning specifically (Lo, 2023). In the Malaysian higher education context, concerns have also been raised about the responsible integration of ChatGPT, particularly in relation to academic integrity, privacy, quality assurance, and institutional monitoring (Selvanathan & Narayanan, 2024). Therefore, the relationship between ChatGPT use and students' self-directed learning capability requires closer examination.

This review synthesises peer-reviewed evidence published between January 2020 and April 2025 to examine whether, and under what conditions, ChatGPT use supports or weakens self-directed learning among university students. The review is guided by the following research questions:

- **RQ1:** What purposes, learning activities and patterns of ChatGPT use are reported in relation to self-directed learning among university students?
- **RQ2:** How is self-directed learning conceptualised, operationalised and measured in studies examining ChatGPT use in higher education?
- **RQ3:** What positive outcomes, negative outcomes, risks and limitations of ChatGPT use across different dimensions of university students' self-directed learning are reported in the literature?

Literature Review

Self-Directed Learning in Higher Education

Self-directed learning (SDL) is the process through which learners identify their needs, set goals, locate resources, select strategies and evaluate outcomes (Knowles, 1975). Knowles treated SDL as both a learning process and a learner disposition, while Garrison (1997) organised it around self-management, self-monitoring and motivation. In higher education, SDL is important because students are expected to assume greater responsibility for their academic progress (Merriam & Baumgartner, 2020). This includes deciding what to learn, choosing suitable resources, monitoring progress and judging whether understanding is adequate. Because definitions and measurements vary, this review does not impose a single model. It considers direct measures of SDL and related processes that support students' ability to organise and evaluate learning.

Relationship Between SDL, SRL and Related Constructs

SDL is closely related to self-regulated learning (SRL), but they are not identical. SRL concerns how learners regulate cognition, behaviour and motivation during a task. Zimmerman's (2000) model describes forethought, performance and self-reflection, including planning, strategy use, monitoring and evaluation. SDL is broader because it also involves deciding what should be learned, why it matters and how learning should be organised. The concepts still overlap through goal setting, planning, monitoring, strategy selection and reflection (Garrison, 1997; Merriam & Baumgartner, 2020). ChatGPT studies also examine autonomy, metacognition, self-efficacy, motivation and engagement. These may contribute to SDL but are not equivalent to it. Their conceptual differences are therefore retained throughout the synthesis.

Conceptualisation, Operationalisation and Measurement

SDL and related constructs are measured in several ways. Established instruments include Guglielmino's (1977) Self-Directed Learning Readiness Scale and the Personal Responsibility Orientation to Self-Direction in Learning Scale developed by Stockdale and Brockett (2011). SRL studies often assess goal setting, strategy use, self-efficacy, metacognitive awareness and self-monitoring, while others use learning plans, observations, interviews, reflective records or interaction patterns. These differences affect interpretation. Satisfaction, perceived usefulness

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 606-629
and academic performance do not directly measure SDL, and higher achievement may reflect easier access to information rather than stronger self-direction. Direct measures assess SDL or SRL processes specifically, while indirect measures use related constructs such as autonomy, confidence and engagement. Academic outcomes should therefore be treated as a separate category.

ChatGPT-Supported Learning Activities

ChatGPT uses generative language-model technology to respond to natural-language prompts (Brown et al., 2020). Its conversational format supports follow-up questions, explanations, feedback and prompt revision, encouraging use in higher education (Baidoo-Anu & Owusu Ansah, 2023; Lo, 2023; Sok & Heng, 2024). Reported activities include concept clarification, idea generation, summarisation, writing, language practice and assignment planning (Baidoo-Anu & Owusu Ansah, 2023; Javaid et al., 2023; Sok & Heng, 2024). It may also support goals, resource identification, learning plans, monitoring and reflection (Li et al., 2024; Lin, 2024; Marquardson, 2024). Studies cover classroom and out-of-class language use (Dizon, 2024; Li et al., 2024; Van Horn, 2024), peer and group arrangements (Younis, 2024), and AI-assisted writing. Outcomes depend on the activity and learner control retained (Wang et al., 2024).

Potential Benefits, Risks and Limitations

ChatGPT may offer immediate explanations, personalised feedback and flexible support, allowing students to work at their own pace (Baidoo-Anu & Owusu Ansah, 2023; Lo, 2023). In language learning, it has supported autonomy, competence and personalised practice, although effectiveness varies with self-monitoring (Du & Alm, 2024; Li et al., 2024). It may also aid reflection when students explain, evaluate or revise their reasoning. However, positive attitudes do not establish lasting SDL development, especially when evidence comes from self-reports or short interventions (Albadarin et al., 2024). Risks include over-reliance, reduced cognitive effort and inaccurate information (Dergaa et al., 2023; Tlili et al., 2023). Cognitive offloading becomes problematic when the tool replaces reasoning (Hadi Mogavi et al., 2024). Reduced interaction may also weaken relatedness (Du & Alm, 2024).

Analytical Framework for the Review

The analytical framework follows the three research questions: patterns of ChatGPT use, the conceptualisation and measurement of SDL, and reported outcomes, risks and limitations. Drawing on Vygotsky's (1978) view that tools mediate cognitive activity, ChatGPT is placed on a continuum between cognitive scaffold and cognitive substitute. As a scaffold, it may extend thinking through prompts, explanations and feedback. As a substitute, it may perform planning, reasoning or evaluation that the learner would otherwise complete. This distinction is not fixed because the same learner may use ChatGPT differently across tasks. Its role may depend on the learning purpose, task structure, instructional guidance, AI literacy and the learner's ability to evaluate information. Responsible use therefore requires knowledge of AI capabilities and limitations (Ng et al., 2021).

Research Gap and Need for the Review

Research on ChatGPT and SDL remains limited. SDL is measured inconsistently, with some studies using direct measures and others relying on SRL, autonomy, motivation, engagement,

International Journal of Education, Psychology and Counseling IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 606-629
self-efficacy or metacognitive awareness. Findings are also mixed. ChatGPT has been linked to flexibility, personalised feedback, autonomy, planning and monitoring, but also to over-reliance, inaccurate information, reduced reasoning and weaker human interaction. Much of the evidence comes from perceptions, qualitative accounts and short interventions, so lasting changes in goal setting, resource selection, monitoring and self-evaluation remain uncertain. Studies also differ in design and evidential strength, yet experimental findings, associations and conceptual arguments are sometimes treated similarly. A systematic synthesis is therefore needed to clarify patterns of use, measurement differences, reported benefits, risks and limitations in university students' SDL.

Conceptual Framework

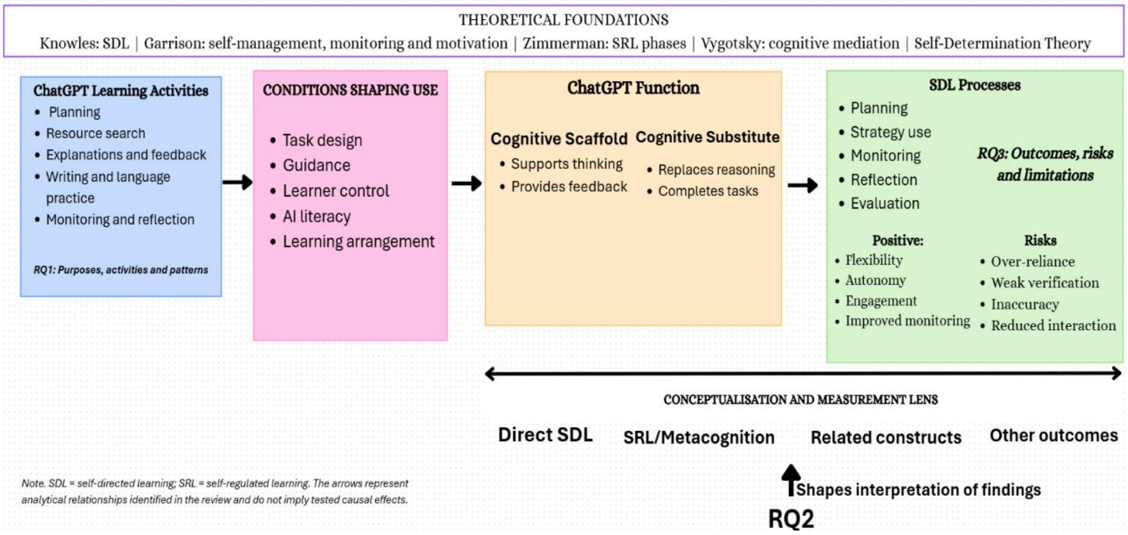

Figure 1: Conceptual Framework for Analysing ChatGPT Use and Self-Directed Learning

Source: Developed by the authors based on Knowles (1975), Garrison (1997), Vygotsky (1978), Zimmerman (2000)

Methodology

Study Design

This study employed a systematic literature review (SLR) methodology, which offers a structured, transparent, and reproducible approach to identifying, appraising, and synthesising existing research evidence (Petticrew & Roberts, 2006). Unlike a traditional narrative review, an SLR follows a clearly defined protocol at every stage, from the initial database search through to the final synthesis of findings. This reduces bias and ensures that conclusions are grounded in a comprehensive and consistently selected body of literature (Creswell & Creswell, 2018). The review protocol was designed in accordance with established standards for educational research (Cohen et al., 2018) and follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 guidelines (Page et al., 2021), which set out the reporting requirements for each stage of the review process. The thematic synthesis was structured around the three research questions and the analytical framework introduced in the Literature Review, namely the purposes and patterns of ChatGPT use, the conceptualisation and measurement of SDL, and the reported outcomes, risks, and limitations associated with

International Journal of Education, Psychology and Counseling
EISSN : 0128-164X
IJEPC
Volume 11 Issue 64 (September 2026) PP. 606-629

ChatGPT use. This ensured that the findings of the review remained directly connected to the theoretical foundation established earlier in the paper.

Search Strategy and Databases

A systematic search was conducted across three academic databases, namely Scopus, Web of Science and ERIC, together with the Google Scholar search engine. Google Scholar was included as a supplementary source to identify potentially relevant peer-reviewed publications that might not have been retrieved through Scopus, Web of Science or ERIC. The search was restricted to publications from January 2020 to April 2025, a period chosen to capture research that emerged alongside and after the widespread development and deployment of large language models including ChatGPT.

Boolean search strings were constructed using combinations of terms related to ChatGPT and generative artificial intelligence (AI), self-directed learning, and higher education contexts. The strings were applied to article titles, abstracts, and keywords across all four databases. Forward and backward citation searching was conducted on selected key studies to identify potentially relevant publications not retrieved through the database search. Forward and backward citation searching was conducted on selected key studies, and this process did not identify any additional unique records beyond those already retrieved through the database searches. Table 1 presents the specific search strings used for each database.

Table 1: Search Strings by Database

Database	**Search String**
Scopus / WoS	("ChatGPT" OR "generative AI" OR "large language model") AND ("self-directed learning" OR "autonomous learning" OR "self-regulated learning") AND ("higher education" OR "university students")
ERIC	("ChatGPT" OR "AI chatbot") AND ("student learning" OR "learning autonomy" OR "academic performance") AND ("university" OR "tertiary education" OR "college")
Google Scholar	("ChatGPT" OR "generative AI") AND ("self-directed learning" OR "SDL") AND ("higher education" OR "university") AND ("motivation" OR "autonomy" OR "self-regulation")
All Databases	("ChatGPT" AND "self-directed learning") AND ("university students") AND (2020:2025)

Inclusion And Exclusion Criteria

All records retrieved through the database search were systematically screened against a defined set of inclusion and exclusion criteria. These criteria were established prior to the search process to ensure consistency in decision-making and to reduce the risk of selection bias. Table 2 presents a summary of the criteria applied at each stage of the screening process.

Table 2: Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Year of Publication	January 2020–April 2025	Published before 2020
Study Type	Peer-reviewed journal articles, empirical studies, SLRs, meta-analyses	Books, theses, editorials, opinion pieces, conference abstracts
Language	Published in English	Non-English publications without an English abstract
Population	University or tertiary-level students	Studies focused solely on K-12 or pre-university students
Topic Focus	Studies examining ChatGPT or equivalent LLMs in relation to student learning, SDL, autonomous learning, or self-regulation	Studies focused solely on instructor use, institutional policy, or academic integrity without learning outcome measures
Learning Context	Higher education or tertiary academic settings	Studies conducted exclusively in corporate, vocational, or school settings
Access	Full text accessible	Abstract only; full text inaccessible

PRISMA 2020 Selection Process

The initial database search across all four platforms yielded a combined total of 847 records. Following a thorough deduplication process, 214 duplicate records were removed, leaving 633 unique records to be carried forward for screening. These records were then screened based on their titles and abstracts against the inclusion and exclusion criteria, resulting in the exclusion of 512 records that did not address SDL or an equivalent construct, or were not related to ChatGPT or generative AI in a learning context. Forward and backward citation searching was conducted as an additional search method. However, it did not produce any additional unique studies for inclusion; therefore, no records from citation searching were added to the PRISMA numerical pathway.

The remaining 121 records were retrieved in full text and assessed for eligibility. Of these, 105 were excluded for the following reasons: no direct empirical or theoretical link between ChatGPT and SDL-related learning processes (n=38); conceptual distinctions between SDL and SRL discussed without examining ChatGPT-supported learning outcomes (n=25); learner autonomy addressed conceptually without examining ChatGPT use (n=15); and learning intentions or progress evaluation addressed without examining ChatGPT (n=10), with the remaining records excluded for not meeting the publication date range, population, or full-text accessibility criteria (n=17). Following full-text eligibility assessment, 16 studies were retained for quality appraisal. One study did not meet the minimum quality threshold and was excluded, leaving 15 studies for the final thematic synthesis, where the priority is analytical depth rather than statistical generalisability (Hair et al., 2019). All inclusion and exclusion decisions were

International Journal of
Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 606-629
documented systematically to maintain methodological transparency and to minimise selection bias. The full four-stage selection process is presented in Figure 2.

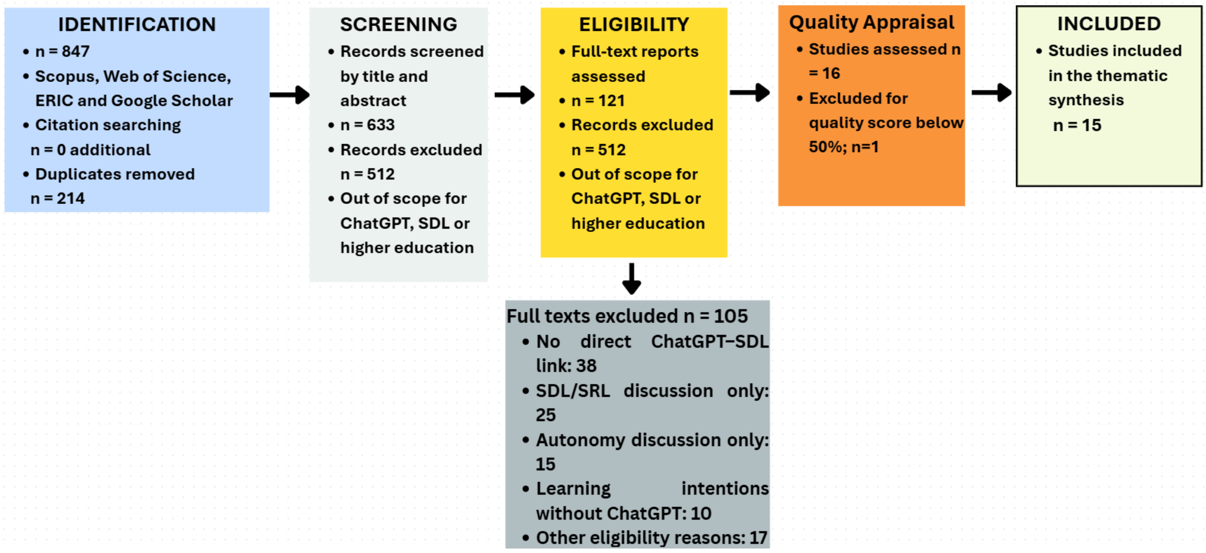

Figure 2: PRISMA 2020 Article Selection Process

Source: Adapted from Page et al. (2021).

Data Extraction and Quality Assessment

A standardised data extraction form was used to systematically record the following information from each of the 15 included studies: author or authors and year of publication, country and institutional context, research design, sample size and participant characteristics, the ChatGPT or AI tool examined, the SDL construct and measurement instrument used, key findings, and reported limitations. This structured approach ensured consistency across the extraction process and made it easier to compare findings across studies during the synthesis stage.

Quality assessment was carried out using two established appraisal tools selected according to study design. The Mixed Methods Appraisal Tool (MMAT) (Hong et al., 2018) was applied to qualitative, quantitative, and mixed-methods empirical studies, while conceptual or framework-based papers without an empirical study design were appraised separately based on the clarity of their theoretical contribution and relevance to the review's research questions. Studies that scored below 50 percent on their respective quality appraisal tool were considered insufficient in methodological rigour and were excluded from the final synthesis. This process resulted in the removal of one additional study, leaving the final corpus at 15 studies for analysis.

Thematic Synthesis

Thematic synthesis was selected as the analytical method for this review because of its capacity to move beyond simple description and to generate interpretive themes that span across diverse empirical contexts, research designs, and geographical settings (Thomas & Harden, 2008). The synthesis proceeded through three structured phases. In the first phase, the key findings and conclusions from each included study were carefully read and documented. In the second phase, related findings were grouped together to form descriptive themes that captured recurring patterns across the studies. In the third phase, analytical themes were developed by interpreting and connecting the descriptive themes in ways that directly addressed the three research questions guiding this review.

To ensure consistency throughout the process and to reduce the risk of interpretive bias, each study was reviewed against the standardised extraction table described above, and themes were developed through continuous comparison across studies. Researcher reflexivity was maintained by periodically revisiting interpretive assumptions and taking care to avoid blending SDL and self-regulated learning constructs where studies operationalised them differently. Inter-rater reliability was strengthened through independent review of a selected portion of the included studies by a second reviewer, after which findings were discussed and reconciled to reach a shared interpretation. This process ensured that the themes reported in this review reflected the collective evidence across the literature rather than the interpretive perspective of a single reviewer.

Results and Findings

Characteristics of the Included Studies

The final synthesis comprised 15 studies published online between 2023 and 2025. One study was published in 2023, 12 in 2024, and two in 2025. The studies covered ten national or territorial contexts: the United States, Taiwan, Japan, New Zealand, South Korea, Hong Kong, Malaysia, Sri Lanka, Palestine, and China. The United States contributed four studies and Taiwan three; the remaining locations were represented by one study each.

The evidence base included five experimental or quasi-experimental studies, four mixed-methods studies, two qualitative studies, one quantitative survey, one descriptive case study and two conceptual papers. Most empirical studies involved university students or adult postsecondary learners. One included study, however, examined secondary-school students rather than university students (Ng, 2024), and this is treated as a scope limitation when the findings are interpreted. Sample sizes ranged from 24 postgraduate EAP students (Du & Alm, 2024) to 627 undergraduates (Biyiri et al., 2025).

The studies addressed blended learning, language learning, academic writing, science education, teacher education, cybersecurity, and general online learning. ChatGPT was used either as a general-purpose tool or through structured systems such as the ChatGPT-Based Intelligent Learning Aid, the Guidance-Based ChatGPT Learning Aid, and SRLbot. Measurement approaches included the Self-Directed Learning with Technology Scale, self-regulation questionnaires, metacognitive-awareness measures, pre- and post-tests, surveys, interviews, observations, and reflective records. Table 3 provides the study-level details.

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 606-629

Table 3: Summary of Studies Included in the Systematic Literature Review (N = 15)

Author and Year	Country	Study Design and Sample	ChatGPT Use / Learning Activity	SDL/SRL Conceptualisation and Measurement	Main Study Outcome
Lin (2024)	USA	Conceptual paper; no participant sample	Virtual tutor for goal-setting, resource identification, learning-plan development, performance monitoring and reflection	Knowles' SDL stages: self-initiation, goal-setting, resource identification, monitoring and reflective evaluation; conceptual mapping only	ChatGPT was proposed to support all five SDL stages, particularly goal-setting and personalised planning; over-reliance and limited institutional guidance were identified as risks.
Biyiri et al. (2025)	Sri Lanka	Quantitative online survey; 627 undergraduates from state universities	Self-directed academic study, information retrieval and personalised content access	Self-Directed Learning with Technology Scale (SDLTS) with UTAUT variables	Behavioural intention and facilitating conditions significantly predicted ChatGPT use for self-directed learning.
Wu et al. (2024)	Taiwan	Quasi-experimental study; undergraduate students in blended-learning courses	ChatGPT-Based Intelligent Learning Aid (CILA) for real-time question answering during blended-learning tasks	SRL assessed through motivation, engagement and self-efficacy measures; knowledge construction assessed through pre- and post-tests	CILA produced stronger SRL progress and knowledge construction than Google-based inquiry, with gains in self-efficacy and engagement.
Lee et al. (2024)	Taiwan	Quasi-experimental study; university undergraduates in blended learning	Guidance-Based ChatGPT Learning Aid (GCLA) requiring students to	Validated SRL scale; higher-order thinking measured through Bloom-aligned assessment; knowledge	The guided condition improved SRL, higher-order thinking and knowledge construction

Author and Year	Country	Study Design and Sample	ChatGPT Use / Learning Activity	SDL/SRL Conceptualisation and Measurement	Main Study Outcome
			state prior reasoning before consulting ChatGPT	construction assessed pre/post	compared with standard blended learning.
Ng (2024)	Hong Kong	Quasi-experimental pilot study; 74 secondary-school students	SRLbot for adaptive and personalised science-learning interactions	Zimmerman's SRL model; behavioural engagement, intrinsic motivation and science knowledge measured with validated instruments	SRLbot outperformed a rule-based chatbot in science knowledge, behavioural engagement and intrinsic motivation.
Dahri et al. (2024)	Malaysia	Mixed methods; SEM with post-reflection interviews and session records; 300 preservice teachers	Scenario-based ChatGPT activities supporting metacognitive self-regulated learning	Metacognitive SRL assessed through an extended TAM model, supported by qualitative reflection data	Personal competency, social influence, perceived usefulness, trust and perceived AI intelligence significantly predicted acceptance for metacognitive SRL.
Du and Alm (2024)	New Zealand	Qualitative study; semi-structured interviews with 24 postgraduate EAP students	Language practice and personalised feedback for academic writing and language development	Self-Determination Theory: autonomy, competence and relatedness	Students reported greater autonomy and competence through flexible, personalised practice; effects on relatedness were mixed.
Li et al. (2024)	USA	Mixed methods; 276 survey respondents and 11 interview participants	Conversation practice, vocabulary learning, grammar correction and self-directed	Knowles and Garrison frameworks: goal-setting, resource selection, self-monitoring and self-evaluation	Flexibility and personalisation encouraged use, while stronger self-monitoring was associated with more effective learning.

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 606-629

Author and Year	Country	Study Design and Sample	ChatGPT Use / Learning Activity	SDL/SRL Conceptualisation and Measurement	Main Study Outcome
			online language learning		
Van Horn (2024)	South Korea	Qualitative study; pre/post surveys, observations and interviews with 120 EFL university students over 15 weeks	In-class English practice and autonomous out-of-class language learning	Learner autonomy represented through metacognitive awareness, confidence and reduced instructor dependence; no formal SDL scale	Students reported increased confidence, metacognitive awareness and autonomous out-of-class learning behaviours.
Marquardson (2024)	USA	Descriptive case study; undergraduates in a cybersecurity capstone course	Topic selection, resource identification and execution of a self-directed learning plan	Self-reported goal-setting, topic selection, resource identification and learning-plan completion, aligned with Knowles' SDL principles	Students regarded ChatGPT as helpful for the self-directed assignment and expressed intention to use it for future learning.
Wang et al. (2024)	USA	Sequential mixed methods; 384 survey respondents and 10 interview participants	Idea generation, drafting, feedback and iterative revision in AI-assisted writing	Entering motivation, task motivation, self-monitoring and self-evaluation assessed through survey and thematic interview analysis	Survey results showed comparatively low self-monitoring, while interviews revealed variation in critical reflection and output verification.
Chang et al. (2023)	Taiwan	Conceptual framework paper; no participant sample	AI chatbot support for goal-setting, formative feedback and personalised learning-path design	Zimmerman's SRL phases: forethought, performance and self-reflection; Judgement of Learning used as a design mechanism	The paper proposed goal-setting, self-assessment/feedback and personalisation as core design principles for AI-supported SRL.

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 606-629

Author and Year	Country	Study Design and Sample	ChatGPT Use / Learning Activity	SDL/SRL Conceptualisation and Measurement	Main Study Outcome
Younis (2024)	Palestine	Quasi-experimental study; 100 undergraduates randomly assigned to independent, peer-assisted and group-based conditions	ChatGPT integrated into three online-learning configurations	Standardised self-regulation questionnaire, online-learning confidence and satisfaction/usefulness scales	Peer-assisted and group-based conditions produced stronger SRL, confidence and satisfaction than independent learning.
Dizon (2024)	Japan	Mixed methods; structured survey and open-ended responses from 101 adult foreign-language learners	Out-of-class conversation practice, vocabulary acquisition and grammar review	Self-reported out-of-class learning activities, goal intentions and evaluation of language progress	Learners valued accessibility and flexibility but expressed concern about reliability; use patterns varied by age and target language.
Xu et al. (2025)	China	Experimental study with control condition; university students in online higher education	Generative-AI learning with and without metacognitive scaffolding	Validated metacognitive-awareness inventory and learning-experience scale; pre/post comparison	Metacognitive support improved SRL outcomes, self-monitoring, strategy use and overall learning experience.

Note. SDL = self-directed learning; SRL = self-regulated learning; SDLTS = Self-Directed Learning with Technology Scale; UTAUT = Unified Theory of Acceptance and Use of Technology; TAM = Technology Acceptance Model; EAP = English for Academic Purposes; CILA = ChatGPT-Based Intelligent Learning Aid; GCLA = Guidance-Based ChatGPT Learning Aid. Ng et al. (2024) involved secondary-school students and should be identified in the methodology as a population exception or adjacent-evidence study.

RQ1: Purposes, Learning Activities and Patterns of ChatGPT Use

Learning Planning and Resource Identification

ChatGPT was used to support goal setting, topic selection, resource identification, and the preparation of learning plans. Lin (2024) mapped these functions onto the stages of self-directed learning and described ChatGPT as a virtual tutor for adult learners. Chang et al. (2023) similarly positioned goal setting and planning within the forethought phase of self-regulated learning. In a cybersecurity capstone course, students used ChatGPT to select topics, locate resources, and complete self-directed learning plans (Marquardson, 2024). Biyiri et al. (2025) found that behavioural intention and facilitating conditions predicted undergraduates' use of ChatGPT for self-directed study.

Personalised Explanations, Feedback and Academic Support

Several studies examined ChatGPT as a source of immediate explanation and feedback. Wu et al. (2024) used a ChatGPT-based learning aid to answer student questions during blended learning, whereas Lee et al. (2024) required learners to state their own reasoning before consulting ChatGPT. Both studies reported higher self-regulation and knowledge outcomes than their comparison conditions. Ng (2024) reported higher science knowledge, engagement, and motivation among secondary-school students using a generative chatbot than among those using a rule-based chatbot. Xu et al. (2025) found that metacognitive prompts improved self-monitoring and strategy use compared with unscaffolded generative AI use.

Language Learning And Academic Writing

Five studies focused on language or writing activities. Students used ChatGPT for conversation practice, vocabulary learning, grammar review, idea generation, drafting, feedback, and revision (Dizon, 2024; Du & Alm, 2024; Li et al., 2024; Van Horn, 2024; Wang et al., 2024). These activities occurred in both formal classes and self-directed out-of-class settings. Li et al. (2024) reported that flexibility and personalisation were prominent reasons for use, while Wang et al. (2024) found variation in the extent to which learners monitored and verified AI-generated writing.

Guided, Collaborative and Scaffolded Use

The studies also differed in how ChatGPT use was organised. Younis (2024) compared independent, peer, and group learning arrangements and found stronger self-regulation and confidence in the peer and group conditions than in the independent condition. Lee et al. (2024) and Xu et al. (2025) embedded explicit reasoning or metacognitive prompts in the learning task. Dahri et al. (2024) used scenario-based activities with preservice teachers, while Marquardson (2024) placed ChatGPT use within a structured assignment. Across RQ1, ChatGPT served as a planning tool, information source, feedback provider, language partner, writing assistant, and scaffold within individual and collaborative learning arrangements.

RQ2: Conceptualisation, Operationalisation and Measurement of SDL

Direct SDL Approaches

Direct treatment of self-directed learning was limited. Biyiri et al. (2025) used the Self-Directed Learning with Technology Scale together with UTAUT. Lin (2024) used a conceptual SDL framework based on self-initiation, goal setting, resource identification, monitoring, and reflection. Li et al. (2024) examined goal setting, resource selection, self-monitoring, and self-evaluation through survey and interview data. Marquardson (2024) used self-reported completion of goals, topic selection, resource identification, and learning plans rather than a validated SDL scale.

SRL and Metacognitive Approaches

A larger group of studies used self-regulated learning or metacognition as the principal construct. Wu et al. (2024), Lee et al. (2024), Ng (2024), Younis (2024), and Xu et al. (2025) assessed self-regulation, metacognitive awareness, engagement, motivation, self-efficacy, or strategy use through questionnaires and experimental comparisons. Dahri et al. (2024) examined metacognitive self-regulated learning through an extended technology-acceptance model. Chang et al. (2023) used Zimmerman's forethought, performance, and self-reflection phases to formulate design principles for AI-supported learning.

Autonomy and Related Constructs

Other studies used constructs related to, but not equivalent to, SDL. Du and Alm (2024) examined autonomy, competence, and relatedness through self-determination theory. Van Horn (2024) focused on metacognitive awareness, confidence, and reduced dependence on the instructor. Dizon (2024) used self-reported out-of-class learning activities and evaluations of language progress, while Wang et al. (2024) examined entering motivation, task motivation, self-monitoring, and self-evaluation. The studies therefore varied substantially in whether SDL was measured directly, represented through SRL, or inferred from associated motivational, metacognitive, and behavioural indicators.

RQ3: Reported Outcomes, Risks and Limitations

Reported Positive Outcomes

The most frequently reported benefits were flexibility, personalised support, and access to immediate feedback. Language learners described greater control over practice time and content, together with personalised assistance for writing and language development (Dizon, 2024; Du & Alm, 2024; Li et al., 2024). Structured interventions also reported improvements in self-regulation, self-monitoring, engagement, self-efficacy, knowledge construction, and higher-order thinking (Lee et al., 2024; Ng, 2024; Wu et al., 2024; Xu et al., 2025). Younis (2024) reported stronger outcomes in peer and group conditions than in independent use, indicating that the social arrangement of the task was relevant.

Mixed Findings and Reported Risks

The evidence was not uniformly positive. Wang et al. (2024) found comparatively low self-monitoring in the survey data, although some interview participants described checking and revising generated content. Dizon (2024) reported concerns about the reliability of language information, and Du and Alm (2024) found mixed effects on relatedness because some students perceived less need for human interaction. Lin (2024) and Chang et al. (2023) identified over-reliance and cognitive offloading as conceptual risks. Xu et al. (2025) found weaker self-monitoring when metacognitive support was absent.

Evidence Limitations Reported Across the Corpus

The evidence base included short interventions, self-reported data, context-specific samples, and conceptual papers without participant data. Several outcomes concerned motivation, engagement, acceptance, or academic performance rather than direct changes in SDL. The

International Journal of
Education, Psychology and Counseling
EISSN : 0128-164X
IJEPC
Volume 11 Issue 64 (September 2026) PP. 606-629
inclusion of Ng (2024), which studied secondary students, also reduces the consistency of the university-student population. Accordingly, the 15 studies reported a combination of direct SDL evidence, SRL-related outcomes, associated learner perceptions, and conceptual propositions.

Discussion

This review examined how ChatGPT is used in activities associated with self-directed learning, how that construct has been conceptualised and measured, and what outcomes, risks and limitations have been reported. The synthesis of 15 studies does not converge on a single verdict. ChatGPT appears neither as a dependable driver of self-direction nor as a consistent threat to it. What surfaces instead is a set of conditions under which the same tool produces markedly different learning processes. Since the evidence comes from previously published studies rather than from data collected for this review, the interpretation below concerns what the current literature can sustain, organised around the continuum between cognitive scaffold and cognitive substitute set out in the analytical framework.

ChatGPT as a Scaffold or Substitute for Learning

The included studies describe ChatGPT setting goals, locating resources, preparing learning plans, supplying explanations, supporting language practice, drafting and revising written work, and prompting reflection (Dizon, 2024; Li et al., 2024; Lin, 2024; Marquardson, 2024; Van Horn, 2024; Wang et al., 2024). Read at surface level, that coverage looks like strong support for the proposition that ChatGPT supports self-direction. Read against Knowles (1975), it supports a weaker one. Knowles located self-direction in the learner's assumption of responsibility for those processes, not in the processes being performed. A learning plan generated by the tool and accepted without scrutiny satisfies the activity description while removing the decision that gives the activity its developmental value. Breadth of use should therefore not be mistaken for depth of effect.

The scaffold and substitute distinction consequently functions as an interpretive lens rather than as a set of categories into which studies can be sorted. Vygotsky's (1978) account of tools as mediators of cognitive activity implies that a single instrument may extend or displace the activity it mediates, depending on how it enters the task. Lee et al. (2024) required students to articulate their own reasoning before consulting a guidance-based learning aid, whereas Wang et al. (2024) observed largely unconstrained use across the stages of academic writing. Both involve planning, drafting and revision. They differ in whether the learner's judgement survived the point at which the tool was introduced, and the reported outcomes differ accordingly.

What the Structured Interventions Can and Cannot Show

The most favourable results in the corpus come from studies that constrained how ChatGPT could be used. Lee et al. (2024) reported stronger self-regulation, higher-order thinking and knowledge construction under a guidance mechanism, Wu et al. (2024) comparable gains from a structured learning aid, Xu et al. (2025) improved self-monitoring and strategy use when metacognitive prompts were added, Ng (2024) higher science knowledge and engagement, and Younis (2024) stronger self-regulation in peer and group conditions. Placed side by side, these read as consistent evidence that ChatGPT improves learning.

The comparison conditions complicate that reading. Wu et al. (2024) contrasted their learning aid with Google-based inquiry, Lee et al. (2024) a guided condition with standard blended learning, and Ng (2024) a generative chatbot with a rule-based one, so each comparison moves more than one variable, and the gain cannot be traced to a single feature. Only two studies held the technology constant. Xu et al. (2025) varied metacognitive support with generative AI present in both conditions, and Younis (2024) varied the social arrangement while ChatGPT remained available throughout. In both, the improvement belongs to the condition surrounding the tool rather than to the tool itself. The experimental evidence in this field is therefore more convincing as evidence about instructional design than about ChatGPT. That result is not theoretically surprising, since scaffolding effects of this kind are anticipated by Vygotsky (1978) and by the design principles Chang et al. (2023) proposed for AI-supported learning, but it matters for how claims are stated, because enthusiasm surrounding generative AI in education often credits the technology with what belongs to the pedagogy built around it (Kasneci et al., 2023).

Interpretation of Self-Directed Learning and Related Measures

Direct treatment of self-directed learning was uncommon. Biyiri et al. (2025) applied the Self-Directed Learning with Technology Scale, but embedded it within a UTAUT model, so what the study predicted was intention to use ChatGPT rather than change in self-direction. Lin (2024) mapped functions onto Knowles' stages conceptually and involved no participants. Li et al. (2024) and Marquardson (2024) examined goal setting, resource selection, monitoring and evaluation through self-report rather than through established instruments such as Guglielmino's (1977) readiness scale or the measure developed by Stockdale and Brockett (2011). No study applied a validated self-directed learning instrument to a pre- and post-intervention comparison.

Most studies used self-regulated learning or metacognition instead (Chang et al., 2023; Dahri et al., 2024; Lee et al., 2024; Wu et al., 2024; Xu et al., 2025; Younis, 2024). This substitution is usually treated as a reporting inconvenience, yet it carries a heavier cost. Zimmerman's (2000) model concerns regulation within a task that has already been set, whereas Knowles (1975) and Garrison (1997) place part of self-direction in the decision about what should be learned and why. The structured interventions that produced the clearest gains necessarily fixed the learning task in advance, removing the element that separates self-directed from self-regulated learning. The designs best equipped to demonstrate measurable improvement are thus among the least equipped to test the construct examined here, which goes some way towards explaining why findings in this field remain difficult to reconcile. A related caution applies where acceptance models supply the outcome measure, as in Dahri et al. (2024), since predictors of adoption describe a precondition for a learning effect rather than evidence of one. Reported gains in confidence, satisfaction or knowledge scores warrant the same treatment (Albadarin et al., 2024).

Conditions Shaping Positive and Negative Outcomes

Four conditions recur across the reported outcomes. The first is task design. Requiring students to state prior reasoning, respond to metacognitive prompts or complete a defined learning plan kept them inside the cognitive process (Lee et al., 2024; Xu et al., 2025). Structure of this kind does not restrict access to the tool but sequences it, so that an initial judgement precedes consultation and evaluation follows it.

Volume 11 Issue 64 (September 2026) PP. 606-629

The second is the learner's existing evaluative capacity. Li et al. (2024) associated more effective self-directed language learning with stronger self-monitoring, while Wang et al. (2024) found substantial variation in whether students checked and revised generated writing. Identical access does not produce an identical learning process. The pattern is consistent with amplification of existing capability rather than compensation for its absence, which raises a question the corpus does not resolve. If benefit depends on evaluative habits students already hold, those who most need support with planning and monitoring may be least positioned to gain from the tool. That possibility complicates the accessibility argument advanced in the wider literature (Lo, 2023), and no included study tested it directly.

The third is social organisation. Younis (2024) reported stronger self-regulation and online-learning confidence in peer-assisted and group-based conditions than in independent use, while Du and Alm (2024) found that some learners felt less need to interact with teachers or peers once ChatGPT was available. The private, low-pressure character students value is also what removes the discussion and challenge that appear to strengthen outcomes. Self-directed learning should not be equated with solitary study, since Garrison (1997) treats self-management, self-monitoring and motivation as interacting dimensions that collaborative activity can support without displacing individual responsibility.

The fourth is the capacity to evaluate generated content. Dizon (2024) found learners questioning the reliability of some language information and Wang et al. (2024) found systematic checking uncommon, against a broader literature documenting inaccurate or misleading output (Tlili et al., 2023). What the corpus adds is a reason to treat verification as discipline-bound rather than generic. A student cannot recognise a fluent but incorrect subject claim without some command of the subject, so learners at the earliest stages of a discipline are exposed twice, first to the error and then to their inability to detect it. This is consistent with framing AI literacy around knowing what the technology can and cannot do reliably (Ng et al., 2021), and it explains why cognitive offloading becomes damaging precisely when reasoning is transferred rather than supported (Hadi Mogavi et al., 2024). Across all four conditions, the reported benefits and risks are not independent of one another. Immediacy, flexibility and personalisation are the properties learners valued most (Du & Alm, 2024), and they are the same properties that make planning, reasoning and verification easy to skip. The relationship between ChatGPT and self-directed learning is therefore better described as a design tension to be managed than as a trade-off to be optimised away.

Implications for Higher Education Practice

These implications are offered as design guidance rather than validated prescription, given an evidence base that is small, recent and heavily reliant on short-term self-reported outcomes. For students, the most defensible working principle is to form a position before consulting the tool and to record what changed afterwards, the sequence operationalised by Lee et al. (2024) and supported by the metacognitive prompts in Xu et al. (2025). Verification habits matter alongside it, including comparison against course readings and peer-reviewed sources, given the reliability concerns learners themselves raised in Dizon (2024). For lecturers, the useful lever is the point at which assistance enters the task rather than whether it is permitted at all. Activities can ask students to submit an initial answer, identify what they do not understand, consult ChatGPT, and then explain whether the response altered their reasoning. Peer and group

Volume 11 Issue 64 (September 2026) PP. 606-629
arrangements deserve deliberate retention rather than incidental survival, since these outperformed independent use in Younis (2024).

At programme level the evidence favours graduated scaffolding rather than a uniform rule. Where benefit depends on evaluative capability the learner already holds (Li et al., 2024), heavier structure is justified early in undergraduate study and can be relaxed as students demonstrate independent monitoring. Marquardson (2024) illustrates this at course level, where ChatGPT was built into a structured self-directed assignment without becoming the sole source of direction, and Chang et al. (2023) supply a design vocabulary for such tasks. Planning and goal setting warrant particular attention from academic advisors, since these are the stages where substitution is easiest to perform and hardest to detect, and where Lin (2024) identified over-reliance and limited institutional guidance as the principal risks. An AI-generated study plan is better treated as a draft to be interrogated, with students asked to justify its sequence, its criteria and its omissions.

Assessment carries the heaviest revision burden, because evaluation of a final product cannot distinguish a scaffold from a substitute. Where use is permitted, assessment should reach the process through initial plans, prompt records, source comparisons, revision histories and reflective explanation. Wang et al. (2024) provides the clearest warrant, having found differences in critical checking that survey scores did not capture. Artificial intelligence literacy is more likely to hold when embedded in disciplinary teaching than delivered separately, since the understanding of capabilities and limitations described by Ng et al. (2021) becomes operational only when students can judge whether a response is plausible within their field. Institutional guidance should move past the choice between unrestricted access and prohibition, specifying acceptable purposes, expected verification practices, declaration norms and the process evidence students are expected to retain. This speaks directly to the integrity, privacy and quality assurance concerns raised in Malaysian higher education by Selvanathan and Narayanan (2024). Staff development belongs within the same policy, since lecturers cannot design for verification and reflection without having tested the tool's limits themselves.

Limitations of the Present Interpretation

Several limitations bound these conclusions. The synthesis rests on 15 studies analysed thematically (Thomas & Harden, 2008), so it reports patterns across reported evidence rather than pooled effects, and no statement of effect size is possible. All included studies appeared between 2023 and 2025, with 12 published in 2024, which leaves little room for replication across disciplines, institutions or student populations. The experimental and quasi-experimental studies ran over short periods within defined courses, and none measured whether gains persisted once the intervention ended or transferred to tasks completed without AI support, which is precisely the evidence a claim about self-directed learning capability requires (Garrison, 1997; Knowles, 1975). Much of the remaining evidence relies on surveys, interviews and reflective accounts, and the divergence between the two in Wang et al. (2024) shows how far conclusions can depend on the instrument chosen.

Coverage is uneven in other respects. Five of the fifteen studies concern language learning or academic writing, so the synthesis carries some of the assumptions of that field, and Ng (2024) examined secondary-school students and reads as adjacent rather than direct evidence about university learners. Quality appraisal (Hong et al., 2018) removed one study below the fifty per cent threshold, which excludes weak work without equalising the evidential strength of what

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 606-629
remains, and reliance on published literature leaves under-reporting of null results possible. These constraints point towards a research agenda built on longitudinal designs, validated self-directed learning instruments applied before and after intervention, and behavioural evidence such as prompt records and source-checking logs. Most usefully, future studies should hold the technology constant while varying the surrounding conditions, since that design has already proved the most informative approach in this corpus (Xu et al., 2025; Younis, 2024).

Taken together, the evidence does not support a general claim that ChatGPT either builds or erodes self-directed learning. Its influence is contingent on how it is used, how much cognitive responsibility the learner retains, the structure of the task, and the learner's capacity to evaluate what the tool produces. Where those conditions hold, ChatGPT extends planning, practice, monitoring and reflection while leaving judgement with the student. Where they do not, it absorbs the processes that self-direction is meant to develop. The distinction is not a property of the technology and cannot be settled by policy alone, since it is produced by the design of learning tasks, the preparation of students to interrogate what they receive, and the willingness of institutions to treat those surrounding conditions as their own responsibility.

Conclusion

This review synthesised 15 peer-reviewed studies through thematic analysis to examine whether ChatGPT supports or weakens self-directed learning among university students. The overall finding is that ChatGPT had no uniform relationship with SDL. Its influence depended on how it was used, how much cognitive responsibility remained with the learner, the structure of the learning task, and the learner's capacity to evaluate generated information.

Students used ChatGPT for goal setting, resource identification, learning-plan preparation, explanation and feedback, language practice, writing, monitoring, and reflection, both individually and in peer or group arrangements. Direct measurement of SDL was limited; most studies assessed self-regulated learning, autonomy, motivation, or engagement rather than SDL itself. Several studies reported improvements in self-monitoring, strategy use, and task performance under structured conditions, while several others reported risks including over-reliance on generated content, weak output verification, reduced human interaction, and cognitive offloading. Gains in motivation, confidence, or knowledge scores were not treated as direct evidence of stronger SDL capability.

This review contributes by distinguishing the purpose of ChatGPT use from the learning process through which it is used, and by separating SDL evidence from SRL, motivational, and academic-performance outcomes. Positioning ChatGPT on a continuum between cognitive scaffold and cognitive substitute shows that guided tasks, learner control, metacognitive monitoring, and output verification appear to shape whether the tool extends or replaces learner reasoning. Practically, the findings support requiring students to articulate prior reasoning before consulting ChatGPT, verify responses against academic sources, and document their revision process. Assessing reasoning and reflection rather than final products alone, teaching AI literacy, and preserving lecturer and peer interaction are also indicated.

Future research should use longitudinal designs, validated SDL instruments, and behavioural evidence such as prompt records and source-checking logs. Comparative studies are also needed across varied disciplines and institutional contexts, contrasting guided with unguided use and individual with collaborative arrangements. Whether ChatGPT ultimately strengthens independent learning capacity or increases dependence on AI assistance remains the field's central unresolved question. ChatGPT supports SDL when it extends planning, practice, monitoring and reflection while leaving judgement with the learner; when it replaces those processes, it risks undermining the independence SDL is meant to develop.

Acknowledgements:	The author wish to express sincere gratitude to the Faculty of Education, Universiti Kebangsaan Malaysia, for providing the academic environment and institutional support that enabled this review. Appreciation is also extended to supervisors, colleagues, and reviewers for their valuable feedback and constructive input in strengthening this manuscript.
Funding Statement:	No Funding
Conflict of Interest Statement:	The author declares no conflict of interest. The author has contributed solely to this work and approves the final version for submission to IJEPC.
Ethics Statement:	This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
Author Contribution Statement:	Sujiithra Selvendhiran held primary responsibility for all aspects of this manuscript: conceptualisation, systematic search design and execution, screening, data extraction, thematic synthesis, drafting, critical revision, and final approval for submission. Hafiz Zaini contributed through academic supervision and advisory guidance throughout the research process.

References

Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. *Discover Education, 3*, Article 60. https://doi.org/10.1007/s44217-024-00138-2

Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI, 7*(1), 52–62. https://doi.org/10.61969/jai.1337500

Biyiri, E. W., Dahanayake, S. N. S., Dassanayake, D. M. C., Nayyar, A., Dayangana, K. T. L. U. S., & Jayasinghe, J. A. P. M. (2025). ChatGPT in self-directed learning: Exploring acceptance and utilization among undergraduates of state universities in Sri Lanka. *Education and Information Technologies, 30*, 10381–10409. https://doi.org/10.1007/s10639-024-13269-8

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., … Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems, 33*, 1877–1901.

Chang, D. H., Lin, M. P.-C., Hajian, S., & Wang, Q. Q. (2023). Educational design principles of using AI chatbot that supports self-regulated learning in education: Goal setting, feedback, and personalization. *Sustainability, 15*(17), Article 12921. https://doi.org/10.3390/su151712921

Cohen, L., Manion, L., & Morrison, K. (2018). *Research methods in education* (8th ed.). Routledge. https://doi.org/10.4324/9781315456539

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Aldraiweesh, A., Alturki, U., Almutairy, S., Shutaleva, A., & Soomro, R. B. (2024). Extended TAM based acceptance of AI-powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study. *Heliyon, 10*(8), Article e29317. https://doi.org/10.1016/j.heliyon.2024.e29317

Dergaa, I., Chamari, K., Zmijewski, P., & Ben Saad, H. (2023). From human writing to artificial intelligence generated text: Examining the prospects and potential threats of ChatGPT in academic writing. *Biology of Sport, 40*(2), 615–622. https://doi.org/10.5114/biolsport.2023.125623

Dizon, G. (2024). ChatGPT as a tool for self-directed foreign language learning. *Innovation in Language Learning and Teaching*. Advance online publication. https://doi.org/10.1080/17501229.2024.2413406

Du, J., & Alm, A. (2024). The impact of ChatGPT on English for Academic Purposes students' language learning experience: A self-determination theory perspective. *Education Sciences, 14*(7), Article 726. https://doi.org/10.3390/educsci14070726

Garrison, D. R. (1997). Self-directed learning: Toward a comprehensive model. *Adult Education Quarterly, 48*(1), 18–33. https://doi.org/10.1177/074171369704800103

Guglielmino, L. M. (1977). *Development of the Self-Directed Learning Readiness Scale* [Unpublished doctoral dissertation]. University of Georgia.

Hadi Mogavi, R., Deng, C., Kim, J. J., Zhou, P., Kwon, Y. D., Hosny Saleh Metwally, A., Tlili, A., Bassanelli, S., Bucchiarone, A., Gujar, S., Nacke, L. E., & Hui, P. (2024). ChatGPT in education: A blessing or a curse? A qualitative study exploring early adopters' utilization and perceptions. *Computers in Human Behavior: Artificial Humans, 2*(1), Article 100027. https://doi.org/10.1016/j.chbah.2023.100027

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. doi:10.1108/EBR-11-2018-0203. https://doi.org/10.1108/EBR-11-2018-0203

Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M.-P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M.-C., & Vedel, I. (2018). *Mixed Methods Appraisal Tool (MMAT), version 2018: User guide*. McGill University.

Javaid, M., Haleem, A., Singh, R. P., Khan, S., & Khan, I. H. (2023). Unlocking the opportunities through ChatGPT tool towards ameliorating the education system. *BenchCouncil Transactions on Benchmarks, Standards and Evaluations, 3*(2), Article 100115. https://doi.org/10.1016/j.tbench.2023.100115

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Knowles, M. S. (1975). *Self-directed learning: A guide for learners and teachers*. Association Press.

Lee, H.-Y., Chen, P.-H., Wang, W.-S., Huang, Y.-M., & Wu, T.-T. (2024). Empowering ChatGPT with guidance mechanism in blended learning: Effects of self-regulated learning, higher-order thinking skills, and knowledge construction. *International Journal of Educational Technology in Higher Education, 21*, Article 16. https://doi.org/10.1186/s41239-024-00447-4

Li, Z., Wang, C., & Bonk, C. J. (2024). Exploring the utility of ChatGPT for self-directed online language learning. *Online Learning, 28*(3), 157–180. https://doi.org/10.24059/olj.v28i3.4497

Lin, X. (2024). Exploring the role of ChatGPT as a facilitator for motivating self-directed learning among adult learners. *Adult Learning, 35*(3), 156–166. https://doi.org/10.1177/10451595231184928

Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. *Education Sciences, 13*(4), Article 410. https://doi.org/10.3390/educsci13040410

Marquardson, J. (2024). Embracing artificial intelligence to improve self-directed learning: A cybersecurity classroom study. *Information Systems Education Journal, 22*(1), 4–13. https://doi.org/10.62273/WZBY3952

Merriam, S. B., & Baumgartner, L. M. (2020). *Learning in adulthood: A comprehensive guide* (4th ed.). Jossey-Bass.

Ng, D. T. K. (2024). Empowering student self-regulated learning and science education through ChatGPT: A pioneering pilot study. *British Journal of Educational Technology, 55*(4), 1328–1353. https://doi.org/10.1111/bjet.13454

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, Article 100041. https://doi.org/10.1016/j.caeai.2021.100041

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article n71. https://doi.org/10.1136/bmj.n71

Petticrew, M., & Roberts, H. (2006). *Systematic reviews in the social sciences: A practical guide*. Blackwell Publishing. https://doi.org/10.1002/9780470754887

Selvanathan, B., & Narayanan, S. (2024). ChatGPT in higher education Malaysia: An opportunity or threat to the education system? *International Journal of Academic Research in Progressive Education and Development, 13*(3), 965–979. https://doi.org/10.6007/IJARPED/v13-i3/21455

Sok, S., & Heng, K. (2024). Opportunities, challenges, and strategies for using ChatGPT in higher education: A literature review. *Journal of Digital Educational Technology, 4*(1), Article ep2401. https://doi.org/10.30935/jdet/14027

Stockdale, S. L., & Brockett, R. G. (2011). Development of the PRO-SDLS: A measure of self-direction in learning based on the Personal Responsibility Orientation model. *Adult Education Quarterly, 61*(2), 161–180. https://doi.org/10.1177/0741713610380447

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology, 8*, Article 45. https://doi.org/10.1186/1471-2288-8-45

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments, 10*, Article 15. https://doi.org/10.1186/s40561-023-00237-x

Van Horn, K. R. (2024). ChatGPT in English language learning: Exploring perceptions and promoting autonomy in a university EFL context. *TESL-EJ, 28*(1), 1–26. https://doi.org/10.55593/ej.28109a8

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (M. Cole, V. John-Steiner, S. Scribner, & E. Souberman, Eds.). Harvard University Press.

Wang, C., Li, Z., & Bonk, C. J. (2024). Understanding self-directed learning in AI-assisted writing: A mixed methods study of postsecondary learners. *Computers and Education: Artificial Intelligence, 6*, Article 100247. https://doi.org/10.1016/j.caeai.2024.100247

Wu, T.-T., Lee, H.-Y., Li, P.-H., Huang, C.-N., & Huang, Y.-M. (2024). Promoting self-regulation progress and knowledge construction in blended learning via ChatGPT-based learning aid. *Journal of Educational Computing Research, 61(8), 3–31*. https://doi.org/10.1177/07356331231191125

Xu, X., Qiao, L., Cheng, N., Liu, H., & Zhao, W. (2025). Enhancing self-regulated learning and learning experience in generative AI environments: The critical role of metacognitive support. *British Journal of Educational Technology, 56*(5), 1842–1863. https://doi.org/10.1111/bjet.13599

Younis, B. K. (2024). Examining students' self-regulation skills, confidence to learn online, and perception of satisfaction and usefulness of online classes in three suggested online learning environments that integrate ChatGPT. *Online Learning, 28*(2). https://doi.org/10.24059/olj.v28i2.4397

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7