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Enhancing self-directed learning and Python mastery through integration of a large language model and learning analytics dashboard

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Abstract: Self-directed learning (SDL) is a critical skill in the 21st century, particularly in online Python learning environments. Learning analytics (LA) can track and analyse learning processes, which can be leveraged to prompt students to reflect on their learning strategies and progress through learning analytics dashboards (LADs). However, LADs lack pedagogical domain knowledge and fail to provide effective personalised feedback and guidance. This study designs and presents a Generative AI-powered SDL tool, SDLChat. It integrates a large language model (ERNIE-3.5) with retrieval-augmented generation (RAG) technology to generate contextualised, actionable feedback for learners across the entire SDL cycle: planning, self-monitoring and self-reflection. To evaluate the impact of SDLChat on learners' SDL skills and Python knowledge, a randomised experimental study was conducted over a six-week Python online course. The study compared the changes in SDL skills and Python knowledge of students using both SDLChat and LAD group ($n=39$) and LAD-only group ($n=35$). The results indicate that: (1) students using SDLChat and LAD significantly outperformed those using LAD alone in Python knowledge mastery, self-monitoring and interpersonal skills and (2) the LAD-only group showed significant improvement only in Python knowledge mastery; however, (3) no

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significant differences were found in posttask motivation between these two groups. This study highlights the potential of integrating LLM with learning analytics to enhance SDL skills and learning performance in online learning contexts. It also establishes a theory-informed operational framework for understanding the LLM-empowered SDL process.

KEYWORDS

large language models, learning analytics dashboards, retrieval-augmented generation, self-directed learning

Practitioner notes

What is already known about this topic

- Self-directed learning (SDL) is essential for success in online learning environments, requiring learners to plan, manage, monitor and reflect on their learning processes.
- Learning analytics (LA), particularly in the form of learning analytics dashboards (LADs), is commonly used to track SDL processes and encourage learner reflection.
- Traditional LADs are incapable of providing personalised feedback, limiting their effectiveness in enhancing SDL skills and learning performance.

What this paper adds

- Introduces SDLChat, an LLM-powered SDL tool combining a large language model (ERNIE-3.5) and retrieval-augmented generation (RAG) technology to generate contextualised and actionable feedback across the full SDL cycle.
- Provides empirical evidence from a quasi-experimental study demonstrating that the integration of SDLChat and a LAD enhances self-monitoring and interpersonal skills.
- Highlights the superiority of the integration of SDLChat and LAD in improving learning performance.
- Proposes an AI4SDL operational framework by including a technological dimension to extend SDL theory in online learning environments.

Implications for practice and/or policy

- Educators and instructional designers can leverage AI-powered tools like SDLChat to provide personalised feedback, fostering key SDL skills and improving learning outcomes in online environments.
- Policymakers should establish SDL skills as curricular objectives and implement professional development programmes to enhance teachers' digital literacy and their capacity for human–AI collaborative instruction.
- Institutions offering online courses may benefit from adopting AI-driven solutions to enhance student engagement, self-monitoring and academic performance, potentially improving course completion rates and learner satisfaction.

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INTRODUCTION

Self-directed learning (SDL) is widely acknowledged as an essential 21st-century learning skill, especially in the context of online education. It is reported to empower students by enabling them to take charge of assessing their learning needs, setting goals, finding resources and tracking progress over time (Al Harrasi, 2023; Doo & Zhu, 2024; Morris, 2019). SDL is one of the crucial skills for lifelong learning, particularly in online learning environments where students need to manage their own learning paths. It is essential for sustaining student engagement and guaranteeing their success in online learning contexts, where students are physically distanced from instructors and peers and do not have constant guidance (Al Harrasi, 2023; Zhu, 2021). However, influenced by a traditionally exam-oriented education system, Chinese students are often accustomed to passive learning and tend to rely heavily on teacher-directed instruction, rather than actively engaging in SDL (Zhao et al., 2024). This is particularly evident among Chinese Master's students, whose SDL proficiency remains moderate to low, often not significantly surpassing that of undergraduates (Zeng, 2011). Therefore, exploring effective methods to bolster Master's students' SDL and enhance their learning performance is crucial.

Compared with traditional classrooms, where schedules and content are predetermined by the teacher, online learning provides greater flexibility in terms of learning content, time and location. Students can decide when and where to study, what materials to focus on and how to manage themselves (Al Harrasi, 2023; Zhu & Bonk, 2019, 2020). While this flexibility grants students more autonomy over their learning process, it requires a more self-directed approach. In online learning, students often struggle with a lack of motivation, self-control and the ability to track their progress. The absence of immediate feedback and regular guidance contributes to these challenges, leading to low engagement, motivation and difficulty in maintaining focus (Xu et al., 2022).

Learning analytics (LA) has been used to address these challenges in online learning environments, particularly in facilitating students' SDL. LA assists students in understanding their learning processes by evaluating students' learning activities, promoting transparency in the review of their learning process, allowing students to track their progress, identify their own strengths and shortcomings, and adapt their learning approaches. Learning analytics dashboards (LADs) are capable of helping students develop metacognitive abilities, such as goal setting and self-reflection, which are essential for navigating online learning independently (Jin et al., 2023). However, Cukurova (2025) pointed out that while LADs can present a wide range of data to users, they often emphasise data presentation rather than *providing contextualised recommendations for improvement*. As a result, in practice, even with this data presentation, students may struggle to interpret and apply it to their learning practices, which leads to confusion or insufficient use (Ramaswami et al., 2023).

Generative AI (GenAI), especially large language models (LLMs), shows great potential in supporting SDL by offering personalised feedback, inspiration and problem-solving solutions across domains like health and programming education (Karataş et al., 2024; Urban et al., 2024). However, general LLMs often fall short in SDL contexts due to their limited ability to personalise content, understand learning goals and support metacognitive development. Retrieval-augmented generation (RAG) enhances LLMs by combining real-time information retrieval with natural language generation; it has been reported to generate personalised feedback supporting teacher–student training, reading comprehension, classroom emotional detection and math education for kids (Fang, Huang, & Ogan, 2025; Fang, Tang, & Wang, 2025; Lewis et al., 2020; Venugopalan et al., 2025). Unlike standard LLMs, RAG-based LLMs can access external sources, such as course materials or learner profiles, to generate more context-aware and personalised feedback.

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This study introduces an operational framework for understanding AI-empowered SDL, AI4SDL and designs an intelligent SDL support system that integrates LADs with SDLChat, a RAG-based LLM (ERNIE-3.5-8K). SDLChat uses students' learning profiles (eg, Python mastery), behavioural data (eg, coding time and video usage) and study plans to provide personalised and situationally relevant feedback to scaffold self-planning, self-monitoring and self-reflection, which are key stages of the SDL process. Compared with standard LLMs, this approach offers more effective scaffolding tailored to learners' evolving goals and needs. To evaluate the effectiveness of this tool, an experimental study was conducted over 6 weeks in an online Python course. The findings of this empirical study provide insights into the potential of integrating LLM with LA to improve SDL skills and academic performance in online learning environments. In particular, this study addresses the following research questions:

RQ1: To what extent does the use of SDLChat and LADs have any impact on students' SDL skills and Python knowledge?
RQ2: Do students using both SDLChat and LADs demonstrate better SDL skills and Python knowledge compared with those using LADs alone?
RQ3: What are students' perceptions of their experiences with both SDLChat and LADs in developing SDL skills?

LITERATURE REVIEW

The following section first reviews the theoretical foundations and practical dimensions of SDL, which underpins this study's pedagogical design. It then explores how LLMs can enhance SDL in online Python education by offering personalised support.

Self-directed learning

SDL has been investigated from two perspectives: a process and a set of learner skills (Song & Hill, 2007). As a process, SDL involves learners taking active control of their learning by planning, implementing and evaluating their efforts (Merriam & Baumgartner, 2020; Song & Hill, 2007). Rather than passively receiving information, learners engage with and shape their learning environments, demonstrating autonomy, initiative and responsibility (Boyer et al., 2014; Morris, 2019). Knowles (1975) describes this process in five steps: (a) diagnosing learning needs, (b) formulating learning goals, (c) identifying human and material resources for learning, (d) choosing and implementing appropriate learning strategies, and (e) reflecting on learning outcomes. From the skills perspective, SDL necessitates the cultivation of four fundamental learner capabilities: motivation (Garrison, 1997), self-management (Künsting et al., 2013), self-monitoring (Doo & Zhu, 2024) and interpersonal skills (Brockett & Hiemstra, 2018; Merriam & Baumgartner, 2020). These inherent personal attributes critically influence the degree to which learners can effectively regulate and guide their own learning trajectories (Fisher et al., 2001; Guglielmino, 1977). Motivation, particularly intrinsic motivation, is foundational, driving learners to engage deeply with content and pursue mastery rather than relying solely on external incentives (Garrison, 1997; Ololube et al., 2015). In addition, self-management skills help learners organise their learning activities and stay focused, while self-monitoring skills enable them to reflect on their progress and adapt strategies when facing challenges (Doo & Zhu, 2024). Interpersonal skills also play a role, supporting collaboration and communication in increasingly social and networked learning environments (Brockett & Hiemstra, 2018; Merriam & Baumgartner, 2020).

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Building on the previous definitions of SDL process (Knowles, 1975; Merriam & Baumgartner, 2020; Song & Hill, 2007), the current study proposes a four-phase SDL process comprising goal setting, self-planning, self-monitoring and self-reflection, purposefully adapted to align with the pedagogical functions of the AI tools (ie, SDLChat and LADs) and support practical implementation in online learning environments. This adaptation aims to preserve the core logic of the established SDL process while offering a more streamlined and actionable structure. For example, our 'goal setting' and 'self-planning' phases consolidate elements from Knowles' (1975) initial stages of diagnosing learning needs, formulating learning goals and the identification of learning resources. Since the identification of learning resources is effectively handled by RAG-based LLMs through dynamic resource recommendations, it is not treated as a separate stage. The 'self-monitoring' phase corresponds to implementation and tracking; and 'self-reflection' aligns with evaluation. This adapted version better guides the integration of AI-driven feedback and support in promoting SDL.

Interpersonal skill is increasingly recognised as a critical component of effective SDL, particularly in online adult learning contexts (Brockett & Hiemstra, 2018). According to Brockett and Hiemstra (2018), SDL involves not only the ability to take responsibility for one's own learning but also the capacity to engage with others to enhance the learning process. Similarly, Merriam and Baumgartner (2020) argued that SDL occurs within social learning environments where interpersonal interaction facilitates cognitive growth and motivation. They stressed that collaborative learning, communication and support-seeking are vital, especially in online environments. In this study, interpersonal skills are crucial in an online Python learning environment, where students must collaborate with peers in discussion forums to utilise AI tools to solve programming problems. The LAD allows students to track the time they spend on peer discussions and AI-supported collaboration. SDLChat provides individualised prompts that encourage learners to reflect on their communication behaviours, seek help from others and participate in community dialogue.

LLM-enhanced self-directed learning in online Python education

Students undertaking self-directed Python programming courses in online environments frequently face several challenges, particularly in knowledge acquisition, problem solving and maintaining motivation. The complexity of programming demands learners to master a broad spectrum of topics, ranging from basic syntax to advanced algorithms, often without real-time access to instructors (McCartney et al., 2016). Furthermore, many students lack essential SDL skills, such as self-monitoring and self-management, which are crucial for tracking progress, organising study schedules and maintaining consistent effort in online learning environments (Fan et al., 2025). The absence of these skills can exacerbate difficulties in navigating the challenges of programming learning, especially in open and unstructured online courses (Zhu et al., 2024).

LA offers valuable information for improving self-directed programming education by collecting and analysing data on learners' behaviours and interactions with computers (Houlahan, 2024; Paulsen & Lindsay, 2024). In programming contexts, LA systems can track learners' progress, such as coding attempts, time spent on exercises and error frequencies, enabling the identification of specific learning obstacles (Kaur & Chahal, 2024). Descriptive feedback, such as progress bars or visualisations of time spent on learning activities, has shown promise in enhancing metacognitive skills by helping learners self-monitor their progress and adjust their strategies accordingly (Zheng et al., 2021). These tools provide learners with clear indicators of their performance, motivating them to set goals and take ownership of their learning process. However, descriptive feedback often lacks contextual depth, making it insufficient for addressing specific learning challenges (Susnjak et al., 2022). For example, while a progress bar shows overall progress, it does not offer actionable advice on strategies to overcome obstacles. These limitations suggest the need for LA systems to move beyond descriptive analytics towards more actionable, context-aware feedback mechanisms (Kim et al., 2023; Yilmaz & Yilmaz, 2021).

LLMs, such as GPT, offer significant potential in self-directed programming education (Sun et al., 2025). These models can assist learners in resolving specific coding issues, generating personalised explanations and offering targeted guidance that aligns with the learners' current progress, significantly enhancing SDL by enabling better self-monitoring and strategic planning (Barbosa et al., 2025). However, the effectiveness of LLMs in supporting SDL has yet to be well studied in literature (Ali et al., 2023). Exploring the interplay between the SDL process and LLM-generated feedback is essential to understanding how LLMs can be effectively leveraged to address the needs of self-directed learners in an online Python learning context.

AN OPERATIONAL FRAMEWORK FOR UNDERSTANDING AI-EMPOWERED SDL PROCESS

The AI4SDL framework is a theory-informed operational framework that conceptualises how AI technologies can enhance SDL in online environments. It draws on two widely accepted perspectives of SDL: as a process (Knowles, 1975; Song & Hill, 2007) and as a set of learner skills (Brockett & Hiemstra, 2018; Garrison, 1997; Künsting et al., 2013; Merriam & Baumgartner, 2020). AI4SDL offers a functional abstraction that maps these theoretical constructs onto the specific pedagogical roles played by the AI tools used in this study, namely SDLChat and the LAD.

The framework was developed following a theory-driven co-design method proposed by Järvelä et al. (2023), which emphasises the systematic integration of theories with empirical evidence and technological affordances. The development process unfolded in three key stages:

First, a rigorous theoretical synthesis of two dominant perspectives on SDL is conducted. The process perspective frames SDL as an iterative sequence involving goal setting, self-planning, self-monitoring and self-reflection (Knowles, 1975; Song & Hill, 2007), while the skills-based perspective conceptualises SDL as a set of learnable competencies, such as motivation and self-management (Brockett & Hiemstra, 2018; Garrison, 1997; Künsting et al., 2013; Merriam & Baumgartner, 2020). Rather than treating these two perspectives as separate, we emphasise their dynamic and interactive relationship. For example, effective goal setting requires sustained motivation, and self-reflection is enriched by interpersonal skills. Moreover, engagement in SDL processes can, in turn, strengthen the underlying skills (Song & Hill, 2007).

Second, building upon this theoretical synthesis, a co-design method was employed to develop practical use cases and corresponding system prototypes. This collaborative endeavour engaged two educational technology researchers, one AI developer and two experienced Python teachers. Through multiple iterative co-design sessions, these stakeholders collaboratively mapped SDL stages onto observable learner activities and identified how SDLChat could provide targeted and meaningful pedagogical support based on empirical evidence on these observable learner activities captured by AI and LA in SDL (eg, Aguilar et al., 2021; Hawkins, 2018; Sun et al., 2025; Yang et al., 2024; Zheng et al., 2021). Practical insights from the teachers, particularly regarding typical issues of learner engagement and challenges across each SDL phase, proved pivotal in iteratively refining AI prompts,

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dashboard and SDLChat interfaces. This co-design method was adopted to ensure that the integration of SDLChat into Python online learning remained developmentally appropriate and pedagogically effective.

Third, following its synthesis from theoretical foundations and initial trials, the AI4SDL operational framework was subsequently evaluated by experts. The framework introduces AI as a dynamic third dimension that interacts with both SDL processes and learner skills. Technologies, such as LLMs and LADs serve a formative function, which provides personalised feedback, adaptive guidance and reflective prompts that directly support the SDL process and indirectly strengthen SDL-related skills (Hawkins, 2018). Five experts in educational technology and learning sciences evaluated the framework's coherence, practicality and theoretical alignment. Their feedback informed refinements, such as more precisely defining the role and positioning of adaptive guidance in the SDL process within the framework (See Figure 1 for the AI4SDL framework).

Guided by the AI4SDL framework, two tools were designed and implemented: a RAG-based LLM (SDLChat) and a LAD tailored for an online Python course supporting self-monitoring and fostering metacognitive awareness (Molenaar et al., 2023). The LADs provide visualised progress metrics, such as task completion rates and time distribution across activities (eg, watching videos, programming and participating in online peer discussions) which are perceived as useful by students in SDL environments (Xie et al., 2020), enabling students to assess their adherence to planned schedules.

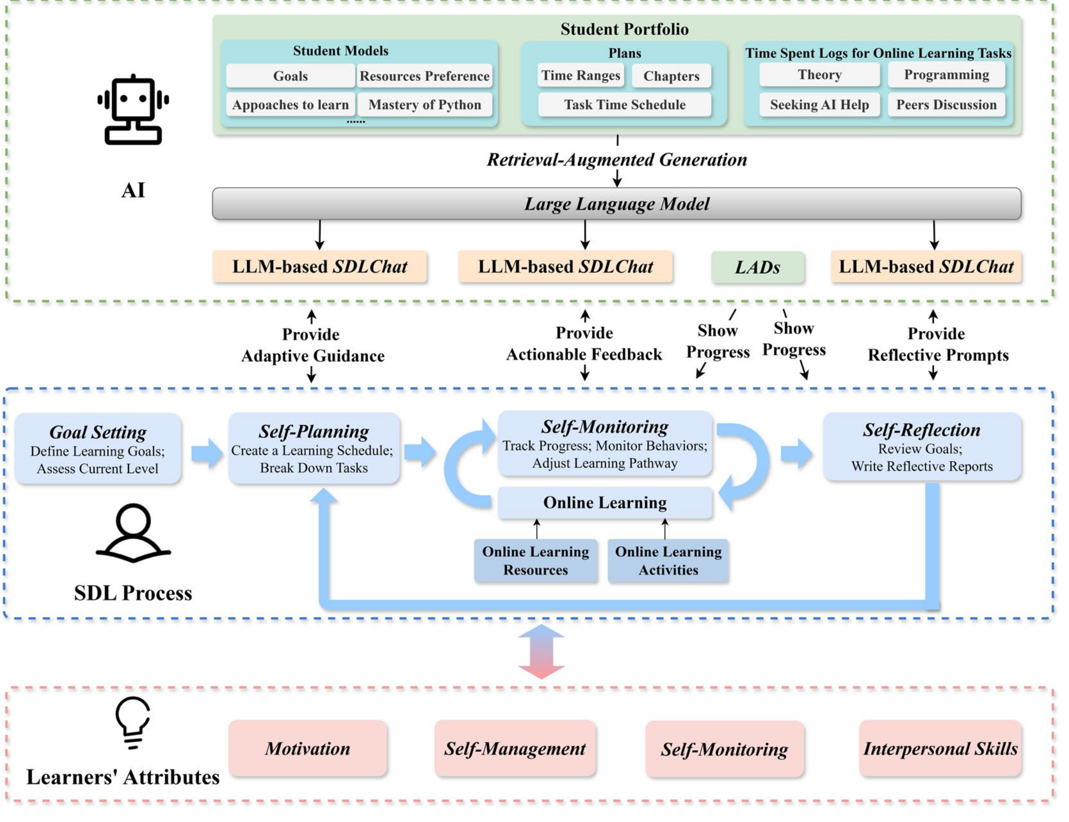

FIGURE 1 Operational framework for understanding artificial intelligence (AI)-empowered self-directed learning (SDL) process.

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WORKFLOW OF SDLCHAT

SDLChat features a context-aware LLM enhanced with RAG technology to provide personalised feedback that supports the SDL process. By integrating student profiles, learning plans and time spent on various learning activities from the student portfolio database (Figure 1), the RAG-based LLM develops a deeper understanding of individual learning goals, styles and progress. This enables it to generate more tailored recommendations for self-management and self-monitoring, surpassing the capabilities of standard LLMs. To ensure the accuracy and reliability of generated feedback, we conducted an initial evaluation in which two educators reviewed the system's feedback for five postgraduate students. Their assessment confirmed that the RAG-based LLMs effectively leveraged student data to generate context-aware and personalised feedback with high relevance and quality. Whenever students need to create a learning plan, monitor their progress or write reflective reports on their learning goals, they log into the system and initiate a conversation with SDLChat to receive personalised feedback. In our study, students typically make a weekly plan and monitor their learning progress two to three times per week.

The self-monitoring form, depicted in Figure 2, proceeds through three key stages. First, students complete a self-monitoring form consisting of four open-ended prompts aligned with the 'self-monitoring' phase of SDL (Knowles, 1975; Song & Hill, 2007). These prompts guide students to (1) assess their current progress ('How are you progressing with your plan?'), (2) analyse the factors contributing to success or difficulty, (3) reflect on their emotional state and (4) identify specific strategies for adjusting future learning activities. Second, by selecting the option 'How does Prof. L view your performance?', students activate SDLChat and receive a personalised diagnostic report. This report integrates data from the LAD and provides feedback on strengths, weaknesses and actionable suggestions. Building on this feedback, students could engage in multi-turn conversations with SDLChat to seek tailored advice prepared in advance for common challenges, such as slow progress, time management difficulties or decreased motivation. The main patterns of these interactions, along with an illustrative multi-round dialogue, are detailed in Appendix A. At the last stage, students revise and enrich their self-monitoring forms by incorporating the insights gained through this AI-supported reflection process.

SDLChat was designed not as a prescriptive tool but as a scaffolding mechanism to support students in developing SDL skills. In the early stages, when students may face challenges in time management and self-monitoring, the system offers structured support, providing both fine-grained recommendations, such as specific time allocations for different learning activities, and broader metacognitive feedback to guide reflection and strategy development. The present study aims to explore and validate this framework empirically through a quasi-experiment. By examining how the AI4SDL-informed tools influence students' SDL skills and learning outcomes in an online Python course, this study seeks to assess the framework's practical effectiveness and theoretical alignment.

METHODS

The study employed a two-phase randomised experimental research design, where the qualitative phase followed the quantitative phase to explain, interpret and elaborate on the initial quantitative findings. During the quantitative phase, data were collected from postgraduate students on an online learning platform through questionnaire surveys and Python knowledge tests (PKTs). To further investigate the relationships between feedback from SDLChat and the observed changes in SDL skills and Python proficiency revealed in the

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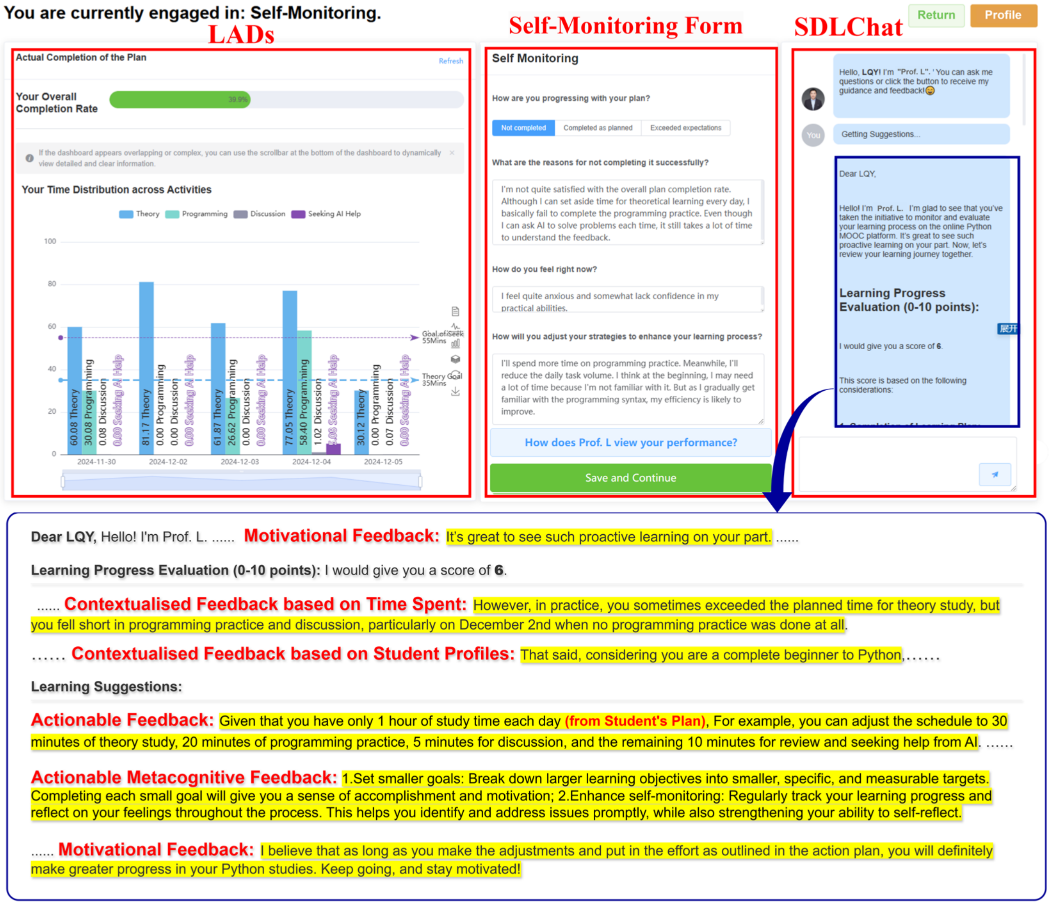

FIGURE 2 Interface of SDLChat and a learning analytics dashboard (LAD) supporting student self-monitoring.

quantitative data, semi-structured interviews were conducted with eight students to provide deeper and nuanced insights into the impact of the intervention.

Participants

Research participants were 74 university students from a prestigious university in southwest China in a seven-week online Python Basics learning programme starting from October to December 2024. The cohort predominantly consisted of postgraduate students, with 15% male and 85% female. All participants were majoring in educational technology and demonstrated sufficient information literacy to effectively utilise the online learning platform. However, most of them have not taken any Python courses before.

The participants were randomly divided into two groups. The treatment group (39 students) engaged with SDLChat integrated with LADs shown in Figure 3. The control group (35 students) only had access to the LADs, without the support of SDLChat. Ethical approval for this study was obtained from the Ethics Committee for affiliated institutions. All participants were informed about the purpose and procedures of the study, and written informed consent was obtained prior to data collection.

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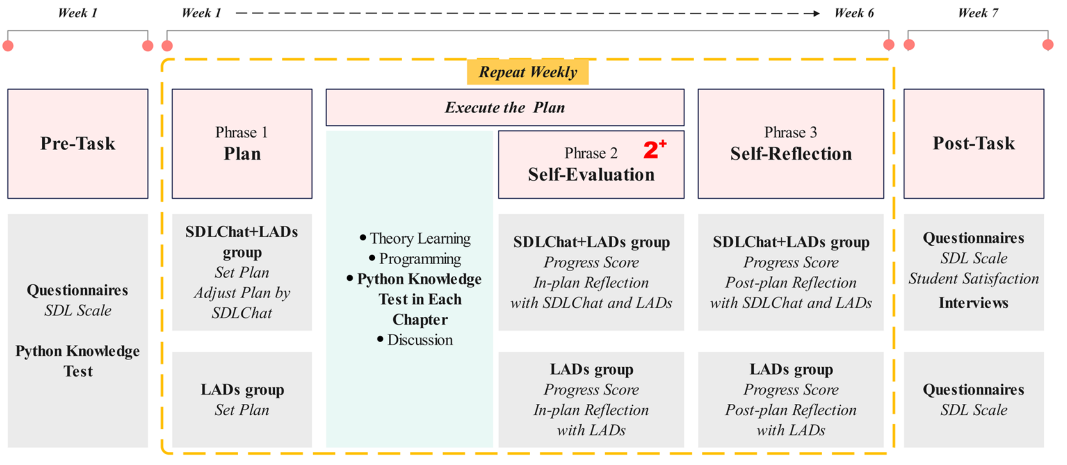

FIGURE 3 Research procedure.

Experimental setting and procedure

As illustrated in Figure 3, the experimental procedure followed three main phases. In the pre-experimental phase, all participants completed a pre-survey questionnaire to evaluate their SDL skills and a pretest to assess baseline knowledge of Python programming.

During the six-week intervention phase, both the treatment and control groups engaged with an online Python learning platform comprising 10 modules. At the beginning of each week, students set one or two learning goals. Based on their interests and prior experience, students could tailor the sequence and degree of module engagement, demonstrating autonomy in learning, which is a key aspect of SDL (Garrison, 1997; Song & Hill, 2007). Typically, students engaged with these tools two to three times per week to monitor their progress and adjust their plans accordingly. In addition, they submitted a weekly reflective report to document their learning process, challenges encountered and adjustments made.

Instructors adopted a deliberately non-directive yet facilitative role designed to foster authentic SDL. Rather than acting as content deliverers, they served as learning facilitators who encouraged student autonomy. At the outset of the course, instructors outlined the overall learning objectives for the course, which comprised 10 modules, but refrained from prescribing, pacing or scheduling tasks. Weekly class sessions functioned as collaborative forums for addressing common learning challenges, which were identified through students' analytics data and reflections. Instructors actively encouraged students to engage with the tools to support their weekly SDL activities, including self-planning, self-monitoring and self-reflection. They did not track individual task completion or provide direct instruction, thereby preserving learners' ownership of the process and reinforcing the principles of SDL.

In the post-experimental phase, both groups completed a post-survey questionnaire to assess changes in SDL skills. To further interpret and contextualise the quantitative findings, semi-structured interviews were conducted with participants in the treatment group, focusing on their experiences with SDLChat and LADs.

Instruments

To evaluate students' SDL skills, this study adapted established SDL scales from Zhu et al. (2024) and Cheng et al. (2010). The SDL Scale measured four dimensions: motivation

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(8 items), self-management (9 items), self-monitoring (6 items) and interpersonal skills (4 items), including examples like: 'I seek AI suggestions to complete learning tasks more effectively'. All question items were scored using a 5-point Likert scale. For the pretest of the SDL Scale, scores range from a minimum of 54 to a maximum of 128. Reliability coefficients for the scales range from 0.765 to 0.916 reported in previous studies (Cheng et al., 2010). In the present study, reliability analysis indicated strong internal consistency for the overall SDL scale (Cronbach's $\alpha=0.876$). The four subscales also demonstrated acceptable to good reliability: motivation ($\alpha=0.788$), self-management ($\alpha=0.752$), self-monitoring ($\alpha=0.780$) and interpersonal skills ($\alpha=0.815$).

The PKT was designed to align with the content of the course's 10 modules, covering topics, such as variables, conditionals, loops, functions, data structures, file and error handling, object-oriented programming and basic data analysis. Each posttest included 10 multiple-choice questions focusing on the core concepts of the respective module, while the pretest contained 20 questions sampling content from all modules to assess baseline knowledge. The PKTs were co-developed by two experienced computer science instructors based on the course objectives and reviewed by a third expert to ensure content validity. A pilot with 20 students was conducted to refine item clarity, difficulty and discrimination.

The interview protocol was designed to investigate the relationships between feedback from SDLChat and the observed changes in SDL skills in terms of four dimensions.

Data analysis

To address RQ1, paired-samples *t*-tests were conducted to examine within-group changes in Python knowledge and SDL skills before and after the intervention. Since the data met the normality assumption, this method was appropriate.

To evaluate the effect of SDLChat while controlling for baseline differences, an ANCOVA was performed (Huck et al., 1974). Posttest scores on SDL (including total score, self-management, self-monitoring, interpersonal skills and motivation) served as dependent variables; group (SDLChat + LADs vs. LADs only) was the independent variable, and pretest scores were used as covariates. Assumptions of normality, equal variances and regression slope homogeneity were tested and satisfied. Adjusted posttest means were compared with assess SDLChat's effectiveness.

For the qualitative phase, 240 minutes of interviews were transcribed and analysed using thematic analysis (Braun & Clarke, 2006), combining both deductive and inductive approaches. Two researchers independently coded the data, achieving high inter-coder reliability (Cohen's Kappa = 0.786). Member checking with two participants was conducted to confirm accuracy and clarify interpretations. The coding procedure is detailed in Appendix B.

RESULTS

In this study, we adopted a mixed-methods approach to examine how integrating SDLChat with LADs influenced students' SDL skills and Python knowledge. First, we assessed within-group changes before and after the intervention (RQ1). Then, we compared posttest outcomes between groups using ANCOVA to determine the added value of SDLChat (RQ2). Finally, survey and interview data were analysed to explore students' experiences and uncover how the system supported different aspects of SDL (RQ3). The following sections detail the findings for each research question.

RQ1: To what extent does the use of SDLChat and LADs have an impact on students' SDL skills and Python knowledge?

Before the intervention, students' SDL scores (originally out of 135) were converted to a 100-point scale for easy comparison. Based on Zeng's (2011) classification of SDL performance levels, both groups showed moderate SDL proficiency (SDLChat + LADs: $M = 65.07$, $SD = 14.53$; LADs: $M = 65.74$, $SD = 9.98$). The higher standard deviation in the SDLChat group suggests varied SDL levels, highlighting the need for differentiated support. Kolmogorov–Smirnov tests confirmed normal distribution for all variables ($p > 0.05$), justifying the use of t-tests. As shown in Table 1, both groups made significant gains in Python knowledge after 6 weeks ($p < 0.05$), with large effect sizes (SDLChat + LADs: $d = -2.183$; LADs: $d = -2.238$), indicating a strong impact of both interventions (SDLChat + LADs and LADs) on knowledge acquisition.

Additionally, the SDLChat + LADs group exhibited significant increases in self-reported SDL total scores ($t(38) = 2.414$, $p = 0.021$, $d = 0.387$), self-management ($t(38) = 2.143$, $p = 0.039$, $d = 0.343$), self-monitoring ($t(38) = 3.031$, $p = 0.004$, $d = 0.485$), interpersonal skills ($t(38) = 2.610$, $p = 0.013$, $d = 0.418$). These results indicate small to moderate effects on SDL improvement. In contrast, the LAD-only group showed no significant gains in SDL scores, and even a decline in interpersonal skills ($t(34) = -2.423$, $p = 0.021$, $d = -0.410$). Motivation did not significantly change in either group, with negligible effect sizes (SDLChat + LADs: $t(38) = 1.490$, $p = 0.144$, $d = 0.239$; LADs: $t(34) = 0.564$, $p = 0.576$, $d = 0.095$).

RQ2: Do students using SDLChat and LADs demonstrate better SDL skills and Python knowledge compared with those using LADs alone?

Table 2 presents the posttest means, standard deviations, ANCOVA results and corresponding effect sizes for Python knowledge and SDL-related outcomes. After controlling for baseline differences, the SDLChat + LADs group demonstrated significantly better performance than the LADs group in several areas. Specifically, the SDLChat + LADs group achieved higher scores in Python knowledge, $F(1, 72) = 11.540$, $p = 0.001$, with a large effect size ($d = 0.830$), as well as in overall SDL, $F(1, 72) = 7.410$, $p = 0.008$, $d = 0.620$. Among the SDL subscales, significant improvements were observed in self-monitoring, $F(1, 72) = 8.970$, $p = 0.004$, $d = 0.680$ and interpersonal skills, $F(1, 72) = 10.880$, $p = 0.002$, $d = 0.720$. These findings indicate moderate to large effects in favour of the SDLChat-enhanced condition.

In contrast, no statistically significant differences were found between the two groups in SDL motivation ($F(1, 72) = 2.370$, $p = 0.128$, $d = 0.350$) or self-management ($F(1, 72) = 3.780$, $p = 0.056$, $d = 0.440$); though both showed small effect sizes, suggesting only limited practical advantages of the intervention in these domains.

Further comparisons of students' Python knowledge across individual modules are shown in Table 3. ANCOVA results revealed that the SDLChat + LADs group significantly outperformed the LADs group in 8 out of the 10 modules ($p < 0.05$), reflecting consistent learning gains across most content areas. However, no significant group differences were observed in Module 6 ($F(1, 72) = 3.935$, $p = 0.051$, $d = 0.283$) or Module 9 ($F(1, 72) = 2.014$, $p = 0.160$, $d = 0.146$), indicating comparable performance between the groups on these topics.

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TABLE 1 Paired *t*-test results for pretest and posttest in self-directed learning (SDL) and Python knowledge across groups.

			Pretest		Posttest		Paired sample test				
Category	**Group**	***N***	***M***	**SD**	***M***	**SD**	**Mean**	**SD**	***t***	***p***	**Cohen's *d***
PK	S+L	39	39.510	18.248	89.210	12.445	49.697	21.298	14.572	<0.001***	2.183
	L	35	35.090	16.232	73.840	26.624	38.756	26.523	8.645	<0.001***	2.238
SDL-T	S+L	39	97.280	14.528	104.15	14.559	6.872	17.774	2.414	0.021**	0.387
	L	35	98.090	10.634	94.740	16.229	−3.343	18.050	−1.096	0.281	−0.185
SDL-MT	S+L	39	30.590	4.794	32.080	4.585	1.487	6.232	1.490	0.144	0.239
	L	35	29.71	3.322	30.290	4.956	0.571	5.992	0.564	0.576	0.095
SDL-MA	S+L	39	30.460	5.251	32.820	5.839	2.359	6.877	2.142	0.039*	0.343
	L	35	31.110	4.227	30.290	6.345	−0.857	7.072	−0.717	0.478	−0.121
SDL-MO	S+L	39	21.920	3.413	23.690	3.001	1.769	3.645	3.031	0.004**	0.485
	L	35	22.230	2.881	20.740	5.431	−1.486	6.152	−1.429	0.162	−0.242
SDL-IS	S+L	39	14.310	2.473	15.560	2.722	1.256	3.006	2.610	0.013**	0.418
	L	35	15.030	2.331	13.460	3.329	−1.571	3.837	−2.423	0.021**	−0.410

Note: The term PK refers to Python knowledge, SDL-T refers to SDL Total, SDL-MT refers to SDL Motivation, SDL-MA refers to SDL Self-management, SDL-MO refers to SDL Self-Monitoring, SDL-IS refers to interpersonal skills, ‘S+L’ refers to ‘SDLChat+LADs’ and ‘L’ refers to ‘LADs’.

***$p<0.001$; **$p<0.01$; *$p<0.05$.

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TABLE 2 Self-directed learning (SDL) posttest results for SDLChat+LADs group and learning analytics dashboards (LADs) only group (controlling for pretest differences).

Category	SDLChat+LADs group $n=39$		LADs group $n=35$				
	M	SD	*M*	SD	*F*	*t*	Cohen's *d*
Python knowledge	89.210	12.445	73.840	23.624	11.536	0.001**	0.827
SDL total	104.15	14.559	94.650	16.463	7.407	0.008**	0.616
SDL motivation	30.590	4.794	29.710	3.371	2.371	0.128	0.349
SDL self-management	32.820	5.839	30.320	6.428	3.779	0.056	0.437
SDL self-monitoring	23.690	3.001	20.710	5.508	8.968	0.004**	0.682
SDL interpersonal skills	15.560	2.722	13.380	3.349	10.882	0.002**	0.719

**$p < 0.01$.

TABLE 3 Python knowledge test (PKT) module test results for SDLChat+LADs group and learning analytics dashboards (LADs) only group (controlling for pretest differences).

Module	SDLChat+LADs group $n=39$		LADs group $n=35$				
	M	SD	*M*	SD	*F*	*p*	Cohen's *d*
1	93.74	7.896	77.86	9.493	58.553	<0.001***	0.478
2	90.90	8.950	73.29	15.901	34.536	<0.001***	0.484
3	90.13	9.562	76.57	7.551	39.438	<0.001***	1.052
4	81.79	16.242	71.43	16.160	6.655	0.012*	1.057
5	88.21	11.725	70.43	18.205	23.802	<0.001***	0.399
6	83.97	16.270	73.00	28.881	3.935	0.051	0.283
7	81.49	15.721	69.46	14.288	8.702	0.004**	0.886
8	85.59	13.018	67.31	17.521	22.473	<0.001***	0.554
9	74.87	21.135	63.86	32.269	2.014	0.160	0.146
10	78.21	21.960	57.14	29.884	9.987	0.002**	0.137

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

RQ3: What are students' perceptions of their experiences with the system in developing SDL skills?

To further explore students' perceptions of SDLChat in supporting their SDL, we collected both quantitative and qualitative data from the experimental group. A total of 33 students completed a self-report questionnaire designed to assess their perceived usefulness of the chatbot in enhancing SDL skills. In addition, semi-structured interviews were conducted with 8 students selected through purposeful sampling to reflect variation in learning outcomes—four students with high SDL skills and four with low skills. These classifications were determined using a quartile-based split method based on participants' posttest SDL scores (Srinivasan et al., 2007). Participants whose scores exceeded the 75th percentile (Q_3) were classified as high SDL, while those scoring at or below the 25th percentile (Q_1) were classified as low SDL. Among the interviewees, two were male and six were female, all aged between 23 and 25. To maintain confidentiality, interviewees are referred to using anonymous identifiers (eg, P01 and P02). Each participant reported using SDLChat at least twice per week to manage their learning progress. The data shown in Figure 4 are based on the responses from the 33 self-reports.

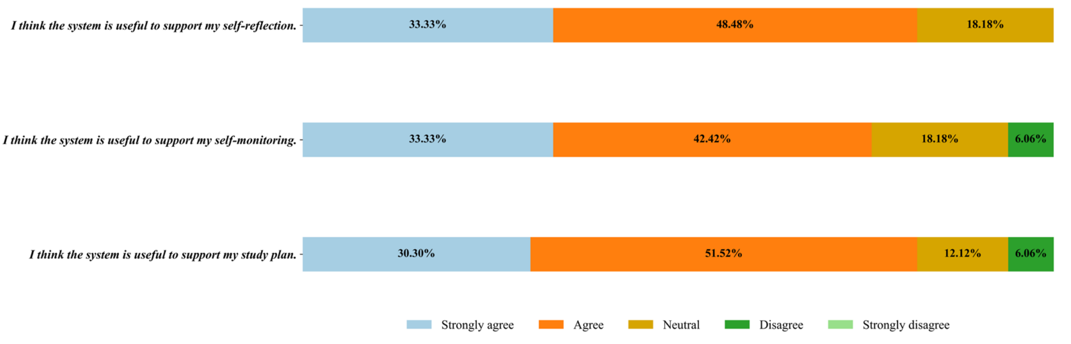

FIGURE 4 Student perceptions of system usefulness in supporting self-directed learning (SDL).

As shown in Figure 4, the results indicate that above 75.76% of students agreed or strongly agreed that the system is particularly helpful for creating learning plans, monitoring progress and performing reflection.

Based on the qualitative data analysis, four major themes emerged regarding the impact of the system on students' SDL skills.

Theme 1: SDLChat enhances self-monitoring and engagement

A significant majority of interviewees (seven out of eight) reported LADs significantly enhanced their self-monitoring by acting as an external cognitive scaffold. By visually displaying time allocation and progress, the LADs reduced cognitive load and fostered data-driven metacognitive awareness of learning behaviours. As one student stated, 'The learning dashboard helped me stay organised and relieved my pressure. I could see exactly how much time I was spending on different tasks, which helped me manage my time better'. (P01).

Furthermore, SDLChat's AI-driven personalised reminders and real-time feedback were crucial for sustaining engagement, as noted by six out of eight interviewees. These functioned as just-in-time behavioural scaffolding. When focus wavered, SDLChat delivered targeted prompts that enabled students to detect and correct lapses in attention as they occurred—thereby supporting behavioural self-regulation. One student emphasised, 'The chatbot's feedback kept me on track. Whenever I was lagging behind on my learning schedule, it reminded me to refocus'. (P05) This demonstrates how the system provided adaptive motivational nudges, helping learners regain focus and commitment. These observations suggest that combining data visualisation with AI-driven feedback fosters stronger self-management by improving both task organisation and sustained focus.

Theme 2: SDLChat improves self-reflection

All interviewees reported that visual log data significantly enhanced their attention to reflect their performances. The dashboard acted as a powerful reflective prompt, enabling metacognitive monitoring by externalising learning behaviour patterns. This facilitated identifying inefficiencies and adaptively adjusting strategies. One student recalled, 'The dashboard showed that I was spending too much time on coding exercises and neglecting theoretical concepts. Seeing this helped me balance my learning', (P02) illustrating how visual data provided feedback on action.

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In addition, the SDLChat's personalised feedback acted as intelligent cognitive prompts that triggered deeper reflection, as reported by seven out of eight interviewees. Rather than offering generic reminders, the chatbot delivered tailored insights into students' learning habits, nudging them towards more effective behaviours. As one participant explained, 'The chatbot pointed out that I spent long hours on practice tasks but wasn't engaging in discussions. That made me rethink my approach and start using AI interactions to deepen my understanding'. (P06) These AI-driven prompts thus served as catalysts for metacognitive regulation, encouraging learners to critically reassess and restructure their approaches.

Theme 3: SDLChat shapes a culture of collaborative learning

A notable portion of interviewees (four out of eight) noted that the SDLChat increased their awareness of communication styles by offering suggestions to optimise group interaction. This feedback provided an additional way to view and monitor their learning behaviour, helping them become aware of recurring behaviours, such as seldom initiating discussions. As one participant remarked, 'I didn't think much about my interaction style before, but when the chatbot pointed out that I rarely initiated conversations, I started paying attention'. (P01).

Half of the interviewees (four out of eight) also discussed sharing LLM-generated feedback with peers, collectively evaluating its accuracy and relevance to their interpersonal interactions. These discussions not only bolstered individual self-awareness but also fostered a culture of peer support and collaborative learning. One student recalled, "Sometimes, my friends and I compare our chatbot feedback and discuss whether we agree with it. This helped us understand each other's communication styles better and adjust accordingly." (P04).

Additionally, most interviewees (six out of eight) emphasised that SDLChat's conversational and motivational tone contributed to a feeling of being supported. Its human-like, encouraging language created a sense of social presence, making students more open to interacting with others. One student shared, 'Even though it was AI, the way it "talked" made it feel like someone cared about my progress'. (P06) This affective dimension helped lower interpersonal barriers and foster a more collaborative learning atmosphere. Thus, AI-driven social reflection served as both a catalyst for personal insight and a scaffold for group-level learning.

Theme 4: Motivation deficit despite technological support

The quantitative analysis revealed that SDLChat and LADs did not significantly enhance students' motivation. Interview data further suggested that when students perceived a disconnect between the course content and their professional goals, along with a lack of external incentives, the supportive tools provided by the learning environment could not meaningfully influence students' learning motivation. A significant majority (six out of eight) of interviewees expressed that the Python course content misaligned with their primary field of educational technology, which diminished their intrinsic motivation, as they struggled to see its relevance to their future careers. As one student noted, 'The course lacked integration with real-world educational technology scenarios, making it challenging to relate Python to my field'. (P07)

Additionally, the self-paced nature of the course, combined with minimal external regulation (eg, grades or firm deadlines), made it easier for students to relegate Python learning to a lower priority, as noted by five out of eight interviewees. One participant remarked, 'Without deadlines or assessments, I often found myself focusing on other courses that had more immediate requirements'. (P08) These results underscore the importance of aligning course content with learners' professional interests and offering structured external structure and rules to bolster motivation and foster SDL skills.

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DISCUSSION

RQ1: To what extent does the use of SDLChat and LADs have an impact on students' SDL skills and Python knowledge?

Overall, this study shows that integrating SDLChat with a LAD supports students' SDL skill development and Python learning. Compared with the LAD-only group, SDLChat users showed greater improvements in self-management, self-monitoring, interpersonal skills and programming outcomes. However, these gains should be viewed in the context of the system's active support. Specifically, students responded to AI-generated prompts and feedback from SDLChat, such as reminders to refocus or notifications about time use, which acted as external scaffolds. While this reflects improved SDL performance during the intervention, it does not guarantee that students can apply these skills independently in unsupported settings.

The effectiveness of SDLChat may lie in its ability to transform learning data into context-aware and actionable guidance. By offering personalised feedback based on individual progress and learning behaviours, the system proved to help students navigate their learning more effectively. This aligns with prior research highlighting how tailored support and visualised progress tracking can scaffold self-regulated learning strategies (Chang et al., 2023; Lin & Chang, 2023; Schwendimann et al., 2017).

Additionally, SDLChat's conversational and motivational language seemed to foster interpersonal engagement. Students in the experimental group showed improved interpersonal skills, which may be attributed to the chatbot's encouragement of help-seeking and self-reflection—behaviours associated with more collaborative and communicative learning practices (Behforouz & Al Ghaithi, 2024; Huang et al., 2024). In contrast, students in the control group, who used LADs without LLM support, improved in Python knowledge but showed a decline in interpersonal skills, though not significantly. This suggests that LADs alone may promote cognitive learning but offer limited social or interactive scaffolding (Ramaswami et al., 2023). Unlike more advanced collaborative learning tools, the LAD employed here did not include features specifically designed to promote social engagement or facilitate communication among peers that are important for developing interpersonal skills.

Notably, neither group showed significant gains in motivation. Interview data indicated that students found limited relevance between Python and their major in educational technology, and that the lack of external regulations, such as grades or deadlines reduced engagement. These findings reflect Garrison's (1997) definition of SDL motivation, which emphasises both personal relevance and goal commitment. When learners cannot connect study tasks to their interests or receive minimal external reinforcement, motivation is less likely to improve, even with AI support (Dumas et al., 2024; Schulze & Janssen, 2024; Schweder & Raufelder, 2024).

RQ2: Do students using both SDLChat and LADs demonstrate better SDL skills and Python knowledge compared with those using LADs alone?

The posttest results indicate that students who used both SDLChat and LADs significantly outperformed those who used LADs alone in Python knowledge, overall SDL skills, self-monitoring and interpersonal skills. No significant differences were found in learning motivation or self-management. These findings suggest that integrating a LAD with an LLM-based chatbot can enhance specific dimensions of SDL, particularly those related to metacognitive awareness and social engagement.

The observed gains in self-monitoring highlight the effectiveness of SDLChat's personalised and contextualised feedback, which likely helped students recognise learning gaps and adjust their strategies accordingly. This aligns with previous research showing that adaptive educational chatbots can enhance SDL by offering tailored guidance and promoting active engagement (Chen, 2024; Tsai, 2023). While SDLChat was not designed to provide direct instruction, students in the experimental group also demonstrated significantly better Python knowledge. This suggests that the metacognitive support offered by SDLChat—through prompting goal setting, monitoring and help-seeking—may have indirectly improved content learning. This aligns with the findings of Broadbent and Poon (2015), Dent and Koenka (2016) and Panadero (2017), who emphasise the positive impact of well-supported SDL on academic achievement.

Further supporting this interpretation, the analysis of module-level test scores revealed that students in the experimental group outperformed the control group in 8 out of 10 modules. For Modules 6 (input/output and file handling) and 9 (object-oriented and modular programming), no significant differences were observed, which may be due to the limited instructional content provided by the platform. In response, many students resorted to external resources recommended by SDLChat (eg, Bilibili and CSDN). While this demonstrates learners' initiative in seeking supplementary materials, it also raises concerns about alignment: the recommended resources may not fully align with the intended curriculum outcomes. As Guo (2022) noted, effective metacognitive scaffolding should be tightly integrated with instructional goals. These results suggest a need to refine the RAG-based recommendation mechanism to ensure that feedback remains both contextually relevant and pedagogically aligned.

While SDLChat supported self-monitoring and self-management, it is necessary to critically reflect on whether such system-mediated behaviours can be classified as truly self-directed. Some scholars argue that when learners depend on AI-generated prompts, the process may shift from autonomous to externally guided regulation, which could undermine the core principle of SDL (Schunk & Zimmerman, 2012). In this study, SDLChat functioned as a *co-regulatory agent* that scaffolded students' metacognitive processes by making their learning behaviours visible and prompting reflection. This aligns with the concept of co-regulated learning, where external support helps learners manage tasks until they gain more independence (Hadwin et al., 2011; Järvelä et al., 2023). However, to support the long-term development of SDL, such scaffolds must be carefully designed to promote learner agency and reflection, rather than replacing them with automated decisions. Excessively directive or frequent feedback may risk reducing learners' engagement in self-monitoring.

Overall, these findings underscore the unique potential of integrating LADs with LLM-based chatbots: while LADs offer structured overviews and trend-based insights into their learning behaviours over time, the addition of a chatbot enables real-time, personalised guidance. This hybrid approach appears more effective in supporting SDL development and academic achievement than LADs alone, especially in areas requiring metacognitive support and interpersonal engagement (Cukurova, 2025; Ramaswami et al., 2023). Nonetheless, the design of such systems should strike a careful balance between guidance and autonomy to maintain the core spirit of SDL.

RQ3: What are students' perceptions of their experiences with the system in developing SDL skills?

The findings from RQ3 provide nuanced insights into how and why the SDLChat + LADs supported the development of students' SDL skills and Python learning, as reported in RQ1 and RQ2. Over 75% of students in the experimental group perceived the system as beneficial for

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their learning, particularly in planning, monitoring progress and engaging in reflection. These subjective perceptions help explain the measurable improvements in self-monitoring and content knowledge. As prior studies suggest (Broadbent & Poon, 2015; Panadero, 2017), students' metacognitive awareness and belief in their ability to regulate their own learning are strongly linked to actual performance outcomes. The sense of control and clarity provided by SDLChat's personalised feedback appears to have reinforced students' confidence in managing their learning process.

In addition to individual benefits, the qualitative data revealed a surprising but important mechanism: group learning through socially shared reflections. Students frequently discussed the feedback they received from SDLChat with their peers, compared their interaction approaches with SDLChat, and collaboratively adjusted their communication behaviours. This collective engagement explains the significant improvement in interpersonal skills observed in RQ1. Rather than conflicting with the idea of SDL, such group interaction complements it by adding a co-regulatory dimension. These findings are consistent with the theory of socially shared regulation of learning, which emphasises that learners can co-construct knowledge and regulatory strategies through dialogue and shared reflection (Järvelä et al., 2023). In this context, SDLChat acted as a shared reflective tool, supporting both self-regulated and socially co-regulated learning. Importantly, learner autonomy was preserved, as students voluntarily chose whether and how to engage with peer input and AI feedback. This highlights a social dimension of SDL, where personalised AI guidance becomes a catalyst for peer-supported self-regulation.

However, the qualitative findings also help interpret the lack of significant improvement in learning motivation reported in RQ1 and RQ2. Despite the system's personalised and interactive features, most students did not report feeling more motivated. Two main reasons emerged: First, students found it difficult to connect Python programming with their professional identity as educational technology majors, reducing the perceived value and relevance of the course. This aligns with Garrison's (1997) model of SDL, which underscores that meaningful engagement depends not only on cognitive and metacognitive regulation but also on motivational control rooted in personal relevance. Second, the lack of external incentives—such as grades, deadlines or teacher feedback—appears to have limited students' sustained effort and persistence. As prior research has shown (Schweder & Raufelder, 2024), self-paced environments that rely heavily on internal motivation can face challenges when learners do not perceive immediate accountability or extrinsic rewards.

Taken together, the interview data underscore that students perceived the system as a supportive and empowering tool for developing SDL skills, especially in fostering metacognitive awareness and reflective behaviours. Moreover, the integration of individual and group-level regulation processes through AI feedback adds a novel, socially embedded layer to SDL. Nonetheless, the system's limited impact on motivation suggests that future designs should consider aligning learning content more closely with students' professional goals and incorporating structured incentives to sustain engagement.

CONCLUSION AND FUTURE WORK

This study demonstrates the potential of integrating a LAD with a RAG-based LLM chatbot to enhance students' SDL skills and Python knowledge. The treatment group, which used the integrated system, showed significant improvements across various SDL dimensions compared with the control group. These findings highlight the value of combining visualised progress tracking with personalised feedback in promoting SDL skill development and provide validation for the proposed AI4SDL theoretical model in online learning environments.

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These findings highlight the value of integrating LADs with LLM-based RAG chatbots to support SDL skill development, suggest practical strategies for educators and instructional designers to leverage personalised AI feedback, and underscore the need for policymakers and institutions to promote SDL-focused curricula and digital literacy training for effective human–AI collaboration in online learning environments.

Despite the promising results, several limitations offer opportunities for future improvement. First, there is a concern about over-reliance on AI-generated task-level feedback, which may hinder the development of critical thinking and long-term SDL skills. Currently, the system provides both specific task-level guidance and broader metacognitive feedback without tailoring the type of feedback to the learner's proficiency in SDL. Second, the exclusive focus on Master's students may limit the generalisability of the findings to broader learner populations. Graduate students are often assumed to possess more advanced SDL skills compared with undergraduates (Zeng, 2011), which may have influenced how they interacted with SDLChat and benefited from its features. Lastly, caution is needed when interpreting self-reported improvements in self-management and self-monitoring, as it remains unclear whether these improvements will be sustained once AI support is withdrawn.

In future work, we plan to implement a personalised fading scaffolding strategy that gradually reduces detailed guidance and emphasises metacognitive feedback as learners' SDL abilities improve. This approach aims to promote long-term SDL development while minimising reliance on AI-generated recommendations (Azevedo & Hadwin, 2005). Additionally, it will be important to evaluate the effectiveness of SDLChat with undergraduate students and novice self-directed learners to assess its adaptability and impact across diverse learner populations. Finally, exploring the long-term effects of SDLChat on students' self-management skills is crucial, particularly regarding whether improvements can be maintained without AI support.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to disclose. There are no real or potential conflicts of interest that could be seen as having an influence on the research.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available by contacting the corresponding author with a reasonable request.

ETHICS STATEMENT

Ethics approval for this study was granted by the Southwest University. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee. Informed consent was obtained from all individual participants included in the study.

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APPENDIX A

AN EXAMPLE OF CONVERSATIONS BETWEEN STUDENTS AND SDLCHAT

We analysed identified five recurring interaction types in the conversations between students and SDLChat. These reflect how SDLChat provided personalised support based on students' reflections, LAD data and learning context:

1. Focus and time management: When students expressed slow progress, the SDLChat suggested strategies like reducing distractions and applying the Pomodoro technique to improve learning efficiency.
2. Adaptive resource recommendation: When students found lecture slides difficult, SDLChat recommended videos or peer discussion posts aligned with their preferred learning style.
3. Data-driven reflection: SDLChat guided them to review low engagement periods and explore underlying causes.
4. Fragmented learning support: For students concerned about limited available time, the chatbot proposed micro-learning strategies and optimal study time windows based on past patterns.
5. Motivational scaffolding: When learners showed reduced motivation, SDLChat provided empathetic encouragement, reframed challenges and helped revise learning goals.

An example of conversations between SDLChat and students is as follows:

Student: I planned to complete 3 units of study this week, but I've only finished one so far. I'm a bit worried I won't meet my goal.

SDLChat: I noticed that you spent 30% more time on the first unit than expected. Based on your learning history, this could be because the unit contains more abstract concepts. Don't worry, we can adjust the learning strategy together.

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Student: Yes, those concepts are harder to understand, and I tend to get distracted during the lecture videos.

SDLChat: Based on your learning preferences, you tend to be more of a visual learner. You might want to try converting the course content into mind maps or diagrams. If it's helpful, you can also draw connections between key concepts to deepen your understanding.

Student: Great idea. I've also noticed that I get tired and my attention drops when I study for long periods.

SDLChat: You could try breaking your study time into shorter sessions, like 45 minutes of studying followed by a 10-minute break. According to your data, the hours between 3 PM and 5 PM are when you're most focused, so I recommend scheduling your more intense study sessions during that time.

Student: Got it. But recently, I've been feeling a bit discouraged, and my motivation isn't what it used to be.

SDLChat: I understand how you feel. It's completely normal to feel tired when facing challenges. In fact, you've already made it through the first unit, which is a significant achievement. You've faced similar situations before and managed to overcome them by adjusting your strategy. We can work together to create a more flexible study plan to keep you on track.

Student: Thank you. Can you help me figure out how I should adjust my plan for the rest of the week?

SDLChat: Of course. Based on your current progress and available time each day, I've reorganized your plan for the week. We'll break the second and third units into smaller modules, spread over the next 4 days and include a short review session at the end of each study day to reflect and fill in any gaps.

Student: That sounds good. I'll give it a try.

SDLChat: Great! I'll continue to track your progress and provide feedback and suggestions after you complete each module. Feel free to let me know your thoughts or any difficulties you encounter along the way, and we'll optimize the learning process together.

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APPENDIX B

THEMATIC CODING PROCESS

To provide a more comprehensive understanding of the qualitative findings, Table B1 outlines the thematic coding process, including initial codes, their grouping into initial themes and the final emergent themes. To address the prevalence of these themes, we have included a 'No. of Participants ($n=8$)' column, indicating the number of interviewed participants (out of a total of eight) whose responses contributed to each specific code or related set of codes. This provides an indication of how widely each concept was discussed or experienced within our interview sample, enhancing the trustworthiness of the findings.

TABLE B1 Thematic coding progress and prevalence.

Initial codes	Initial theme	Final theme	No. of participants ($n=8$)
Data visualisation helped students allocate time clearly, enhancing task planning efficiency	Structured learning activities	SDLChat enhances self-monitoring and engagement	7
The learning dashboard helped students organise their time and stay on track with their learning plan			7
The personalised reminders from the chatbot helped students stay focused, especially when tasks were falling behind	Personalised feedback supports focus		6
Students paid more attention to their learning behaviours through visual data, identifying inefficiencies and adjusting strategies accordingly	Data tracking promotes self-monitoring	SDLChat improves self-reflection	8
Data visualisation enabled students to reflect on their strengths and weaknesses, fostering self-awareness			8
SDLChat's feedback helped students identify ineffective learning habits and offered suggestions for improvement	AI feedback guides learning strategy adjustment		7
Students adjusted their learning strategies and engaged more in reflective activities, such as using AI interactions to deepen understanding			6
SDLChat feedback helped students become aware of their communication patterns, especially recognising when they rarely initiated discussions	Increased awareness of communication styles	SDLChat fosters social engagement and collaborative learning	4
Students began to focus on optimising their communication in group interactions			4
Students shared and discussed chatbot feedback with peers, collectively evaluating its accuracy and relevance, fostering peer support and collaborative learning	Peer social learning		4

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TABLE B1 (Continued)

Initial codes	Initial theme	Final theme	No. of participants ($n=8$)
Students perceived a disconnect between the Python course content and their primary field of educational technology, which reduced intrinsic motivation	Lack of professional relevance	Diminished motivation due to lack of professional relevance and insufficient external incentives	6
Students found it difficult to relate Python learning to their professional context, impacting their motivation to learn			6
The course lacked strict external incentives (eg, grades or deadlines), causing students to prioritise other courses with more immediate requirements	Insufficient external incentives		5
The self-paced nature of the course and the lack of external rewards led students to deprioritise Python learning, resulting in decreased motivation			5

Note: Some participants contributed to more than one theme. Prevalence was determined based on explicit reference to theme-related behaviours or perceptions during interviews.

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