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Fusing Self-Regulated Learning and Machine Learning to Enhance Open and Distance eLearning Systems. A systematic review

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Abstract – There are rapid advancements in the use of digital technologies in Open and Distance eLearning (ODeL) environments worldwide. Digital technologies have significantly enhanced Open and Distance eLearning by improving accessibility, flexibility, and the quality of education. Learners from remote and underserved areas can access educational resources anytime, thereby supporting inclusive education for everyone, regardless of their diverse needs. However, most ODeL systems face challenges such as high student dropouts, low retention rates, and lack of instant instructional and user support. These challenges have given birth to the need for innovative approaches that will enable learner autonomy, motivation, and personalized support. One strategy that ODeL institutions can employ involves combining Self-Regulated Learning (SRL) and Machine Learning (ML) techniques to create intelligent and adaptive learning environments. SRL is very important in ODeL because it allows learners to have control of their own learning by setting metacognitive strategies such as goal setting, strategic planning, self-monitoring, and self-evaluation. The purpose of this systematic review was to explore the extent to which SRL and ML have been fused to enhance teaching and learning in ODeL contexts. Using a systematic literature review methodology, the study utilized 39 peer-reviewed articles published between 2019 and 2025, drawing on major academic databases, including Google Scholar, SpringerLink, ScienceDirect, IEEE Xplore, and Scopus. This study focused on reviewing studies that implemented ML techniques to model, support, or enhance SRL strategies in ODeL digital learning platforms. Findings from the study indicated that a huge number of studies utilise ML algorithms such as reinforcement learning, natural language processing, supervised learning, and unsupervised clustering in analysing learners' data and provide adaptive feedback and recommendations that are related to SRL theory. While several studies highlight the effectiveness of ML in enhancing SRL, most are found within structured online courses or intelligent tutoring systems, rather than fully in open or distance learning environments. Furthermore, there is limited research that has focused on the development of ODeL systems that utilise both SRL and Machine Learning to enhance teaching and learning. This research study concluded by giving coding ideas on how ML and SRL can be combined to enable ODeL institutions to develop Learning Management Systems (LMS) that improve learner engagement, retention, and performance.

Keywords: Self-Regulated Learning, Machine Learning, Open and Distance, eLearning, Systems, Fusion

Introduction

The Open and Distance eLearning (ODeL) mode of education delivery has emerged as a very popular model worldwide. The ODeL learning model enables learners to access quality education electronically, irrespective of their geographical and social barriers. Furthermore, the ODeL model of learning is particularly critical in regions such as Southern Africa, as it addresses challenges such as limited infrastructure and strained resources in higher and tertiary institutions (Funda, Busiswa, and Mbangeleli, 2024). Although ODeL offers several advantages, such as accessibility and scalability, it also presents several pedagogical challenges. Several studies have highlighted that ODeL is associated with such difficulties as learner isolation, limited real-time instructional support, low motivation, and high student dropout rates (Bozkurt *et al.*, 2020). Challenges cited highlight the need for innovative tools and technologies to enhance student motivation, engagement, autonomy, and academic achievement on ODeL digital learning platforms.

Literature points out that Self-Regulated Learning (SRL) is a very critical determinant of academic achievement in ODeL learning environments (Azevedo and Gašević, 2019). SRL is defined as the process by which learners actively take control of their learning processes through the employment of cognitive, metacognitive strategies such as goal setting, planning, self-motivation, self-monitoring, and self-evaluation (Han, Zhao and Ng, 2021; Edisherashvili *et al.*, 2022) . SRL is particularly important for learners in ODeL environments, as they are expected to self-motivate and take control of their learning to achieve their goals. Several studies highlighted that although fostering SRL strategies in learners is very critical, it is very complex to do, especially in environments where instructional resources and personalised feedback are limited (Lim *et al.*, 2021; Taub *et al.*, 2022). Furthermore, several studies point out that Machine Learning (ML) can be utilised to address some of the challenges faced in ODeL.(Dever *et al.*, 2022; Yang, Wu and Ogata, 2024). Machine Learning is defined as a branch of artificial intelligence (AI) that is focused on the development of systems that discover patterns in data, formulate decisions, or predict outcomes based on what they've learned. (Dever *et al.*, 2023; Jin *et al.*, 2023).

When ML is fused with SRL, it can assist in the monitoring of learners' engagement with learning content, and identify SRL learning behaviours such as goal setting, planning, self-monitoring, and self-evaluation (Duffy and Azevedo, 2015; Dever *et al.*, 2022). Despite having several literatures on the utilisation of ML and SRL in educational contexts, the fusion of the two domains remains underexplored, especially within ODeL environments(Nuankaew, 2022; Jin *et al.*, 2023). Despite having several studies exploring how SRL can be utilised in traditional and blended learning environments, and others exploring how ML can apply to enhance personalised learning, very few studies have examined how ML can systematically be used to support SRL in ODeL learning environments (Bellhäuser, Liborius and Schmitz, 2022; Jin *et al.*, 2023). Additionally, many studies are focused on the general electronic learning and the application of ML to develop intelligent tutoring systems and have overlooked the unique pedagogical, contextual and infrastructural challenges linked to ODeL, particularly in regions with limited resources (Ifenthaler, Mah and Yau, 2019; Romero *et al.*, 2019).

This research study synthesizes recent research on the fusion of SRL and ML in ODeL environments, specifically investigating how SRL theory has been implemented in ODeL learning systems and how ML techniques have been applied to support SRL processes. Furthermore, the study identified the opportunities and challenges associated with integrating ML and SRL approaches, providing a comprehensive understanding of the current state in the field and informing directions for future research. The study informs the design and implementation of ODeL systems that are not only accessible and scalable, but also intelligent and learner-centered. By examining how ML and SRL can be fused through a systematic literature review, this study contributes to the ongoing research on how to utilise AI and SRL to develop ODeL systems that are effective, inclusive, and sustainable in this digital era.

Materials and Methods

This research employed a systematic literature review research methodology to examine the integration of Self-Regulated Learning (SRL) and Machine Learning (ML) in Open and Distance Electronic Learning (ODeL) environments. A systematic literature review was selected because it identifies, evaluates, and synthesizes existing research to answer defined questions. This study aimed to address four key questions. The first question focused on establishing how SRL has been conceptualized and supported in ODeL learning systems. Furthermore, a second question focused on how ML techniques have been utilised to enhance SRL strategies such as goal setting, planning, self-motivation, and self-evaluation in ODeL systems. Additionally, the study also focused on how SRL and ML have been integrated in ODeL systems and evaluated the results achieved. The study also examined the gaps in the literature to make recommendations for future research. Finally, the study generated coding ideas based on the literature reviewed to help guide the development of ODeL systems that utilise SRL and ML to enhance teaching and learning, specifically in ODeL learning environments. Several major academic databases were used in this study, including Google Scholar, Directory of Open Access Journals (DOAJ), ScienceDirect, Semantic Scholar, and ResearchGate. Keywords used to search for relevant literature included "Self-Regulated Learning" AND "Machine Learning,", "Machine Learning" AND "ODeL," "Machine Learning adoption" OR "AI implementation "AND "Self-Regulated Learning adoption" OR "SRL Fusion" AND "Open and Distance" OR "ODeL AND "eLearning" AND "Fusion "OR "Integration". Data obtained from the literature was analysed to identify trends and patterns where ML was applied to enhance and support SRL in ODeL systems.

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Data inclusion and exclusion strategy

Table 1 presents a summary of the inclusion and exclusion criteria used in this study. The criteria helped identify a sample of articles that were highly relevant to the study's objectives. This was done to select high-quality articles that give insight into the fusion of Self-Regulated Learning and Machine Learning to enhance Open and Distance eLearning (ODeL) systems

Table 1. Inclusion and Exclusion Criteria

Aspect	Inclusion Criteria	Exclusion Criteria
Subject	Articles that have the keywords of the research study	Articles that focused on other unrelated areas (Mining, Health, Agriculture, etc.)
Document Type	Peer-reviewed journal articles, Institutional repositories	Short Survey, Book Chapter, editorial
Selection Criteria	Articles that give access to the whole article	Articles that provide titles and abstracts
Year of publication	Articles from 2019-2025	Papers older than 2018
Language	English	Other Languages

Systematic Literature Review

The study selected relevant literature from Google Scholar, ResearchGate, the Directory of Open Access Journals (DOAJ), ScienceDirect, and Semantic Scholar, as outlined in Table 1 below. The first phase of the process retrieved a total of 378 papers. Furthermore, a total of 204 papers were selected in the second phase. The second phase involved selecting peer-reviewed articles relevant to the study to ensure the quality of the research. In the third phase, non-English and duplicate articles were removed, and a total of 43 articles were obtained. The final fourth phase resulted in the selection of 47 articles to support the study's objectives, as shown in Figure 1.

Table 2. Phase 1- Defining Results

Database	Search String	Hits
Google Scholar	“Self-Regulated Learning” AND “Machine Learning,” “Machine Learning” AND “ODeL,” “Machine Learning adoption” OR “AI implementation “AND “Self-Regulated Learning adoption” OR “SRL Fusion” AND “Open and Distance” OR “ODeL AND “eLearning” AND “Fusion” OR “Integration”	203
Directory of Open Access Journals (DOAJ)	“Self-Regulated Learning” AND “Machine Learning,” “Machine Learning” AND “ODeL,” “Machine Learning adoption” OR “AI implementation “AND “Self-Regulated Learning adoption” OR “SRL Fusion” AND “Open and Distance” OR “ODeL AND “eLearning” AND “Fusion” OR “Integration”	31
ResearchGate	“Self-Regulated Learning” AND “Machine Learning,” “Machine Learning” AND “ODeL,” “Machine Learning adoption” OR “AI implementation “AND “Self-Regulated Learning adoption” OR “SRL Fusion” AND “Open and Distance” OR “ODeL AND “eLearning” AND “Fusion” OR “Integration”	21
ScienceDirect	“Self-Regulated Learning” AND “Machine Learning,” “Machine Learning” AND “ODeL,” “Machine Learning adoption” OR “AI implementation “AND “Self-Regulated Learning adoption” OR “SRL Fusion” AND “Open and Distance” OR “ODeL AND “eLearning” AND “Fusion” OR “Integration”	71
Semantic Scholar	“Self-Regulated Learning” AND “Machine Learning,” “Machine Learning” AND “ODeL,” “Machine Learning adoption” OR “AI implementation “AND “Self-Regulated Learning adoption” OR “SRL Fusion” AND “Open and Distance” OR “ODeL AND “eLearning” AND “Fusion” OR “Integration”	52
Total Hits		378

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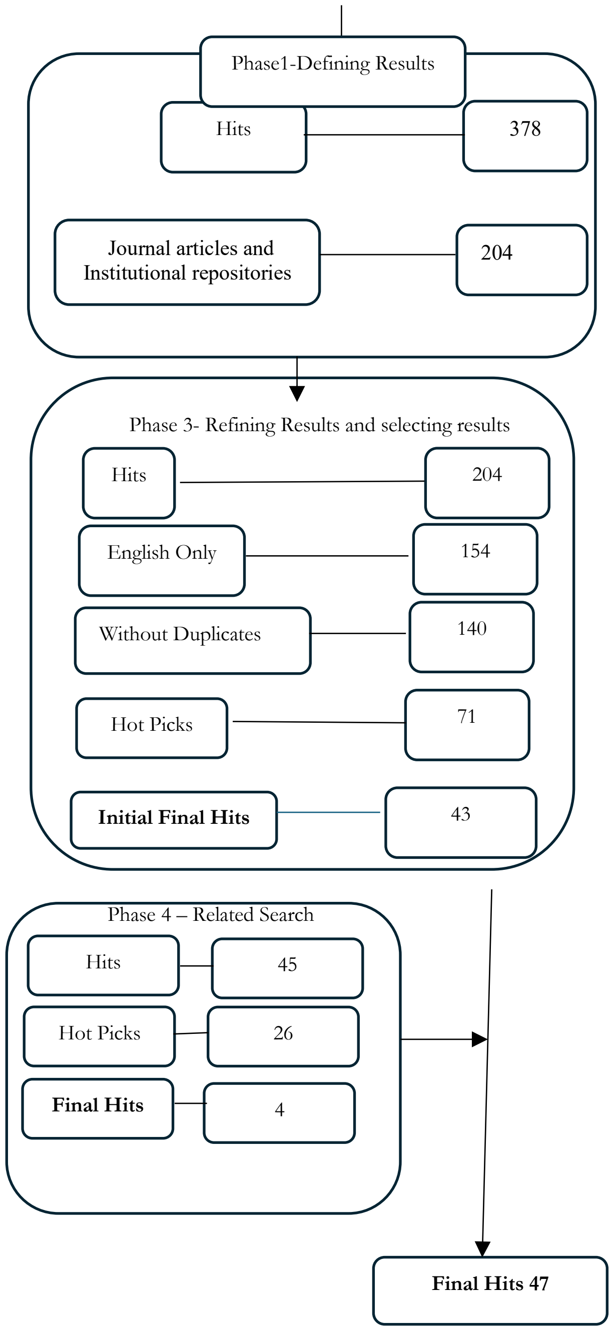

Figure 1. Definition of Final Results.

The papers selected contributed to the reporting of the study's findings. Figure 1 illustrates the steps taken to identify relevant and high-quality studies that help answer the research questions in this study.

Self-Regulated Learning (SRL)

The study selected relevant literature on Self-Regulated Learning (SRL), a critical component in Open and Distance Learning (ODeL) environments, as it enables students to engage with learning content with great autonomy and confidence (Klimova *et al.*, 2022; Lima *et al.*, 2023). SRL is defined as the process by which learners

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actively take control of their learning processes through the employment of cognitive, metacognitive strategies such as goal setting, planning, self-motivation, self-monitoring, and self-evaluation (Banihashem, Bergdahl, and Khosravi, no date; Klimova *et al.*, 2022). SRL consists of metacognitive strategies that include planning, goal setting, self-motivation, self-evaluation, and self-monitoring. SRL students can proactively set goals, plans, and self-monitor their progress and performance (Mafuhure, Kabanda, and Tsvere, 2023; Shafiee Rad, 2025).SRL consists of cyclical phases that include the forethought phase, performance phase, and the self-reflection phase (Duffy and Azevedo, 2015). The forethought phase involves analysing tasks given while applying self-motivation to accomplish them (Järvelä and Hadwin, 2024). The performance phase consists of developing self-control and self-observation strategies during the learning process. Finally, the self-reflection phase involves self-judging and self-reaction to results obtained after task completion (Duffy and Azevedo, 2015).

SRL is very critical in ODeL contexts because learners are expected to take responsibility and autonomy for their learning processes. Recent literature points out that SRL can enhance academic performance and engagement. In their study, (Mafuhure, Kabanda and Tsvere, 2023) It was found that learners who employ self-evaluation and self-motivation strategies can succeed in ODeL learning environments. According to (Borchers *et al.*, 2024)Effective SRL strategies can reduce the perception of learning incompetence if they are well implemented by learners in ODeL environments. In their research study, (Burro *et al.*, 2022) Highlighted that students' willingness to learn through ODeL is closely tied to SRL capabilities since this significantly affects their engagement and success. SRL can enhance cognitive, teaching, social, and collaborative presence, hence fostering an effective ODeL experience.

Recent advancements in ICT have accelerated the development of tools that support SRL. In their study, (Mafuhure, Kabanda and Tsvere, 2023) Developed an SRL tool (C-LEARN) to assist students in developing SRL strategies while learning computer programming in a large class setup. The results obtained highlighted that students who applied SRL strategies, such as planning, goal setting, and self-reflection, excelled in their exams compared to their counterparts in the control group. Additionally, (Li, XU and Chang, 2022) Developed a tool, FLoRA engine, which used learning analytics to measure and support learners' SRL activities. The tool would eventually provide personalised feedback and guidance to students. Furthermore, (Steinert *et al.*, 2023) Developed a learning platform (LEAP) which utilised large language models to give formative feedback to enhance students' SRL strategies. There is a greater need to develop technological tools that integrate SRL strategies into ODeL environments, promoting student engagement, autonomy, and accomplishment. (Samsonovich and Liu, 2024; Zhang, 2025).

Machine Learning (ML)

Machine Learning (ML) has emerged as a crucial component in enhancing Open and Distance education (ODeL). Machine Learning is defined as a branch of artificial intelligence (AI) that is focused on the development of systems that discover patterns in data, formulate decisions, or predict outcomes based on what they've learned (Gašević, no date; Ifenthaler, Mah and Yau, 2019). Machine learning offers transformative capabilities to address unique challenges, such as the lack of instant feedback and limited student-instructor involvement, among other challenges. Machine Learning makes use of large amounts of educational data and, through algorithms, assists in the prediction of student performance, personalisation of learning content, and identification of at-risk students (Fan *et al.*, 2021; Sun, Tsai and Cheng, 2023). According to (Molenaar, 2022) ML techniques can be implemented to analyse students' behavioural data, hence predict academic results and facilitate the identification of learners who need additional help (Sun, Tsai and Cheng, 2023; Järvelä and Hadwin, 2024). Additionally, ML-driven adaptive learning systems are capable of tailoring educational content based on a student's performance, needs, learning pace, and preferences, hence enhancing engagement in ODeL environments (Saqr *et al.*, 2024). The integration of ML into ODeL systems can assist with administrative tasks, such as grading and providing feedback, allowing instructors to shift their focus more towards research, instructional design, and student support. (Steinert *et al.*, 2023; Saqr *et al.*, 2024). Machine Learning is very important in ODeL systems because it can enhance educational outcomes, personalise learning experiences, and assist instructors, administrators and learners (Azevedo *et al.*, 2022a) .

Case studies on Integration of SRL and ML in ODeL

Several case studies have integrated Self-Regulated Learning (SRL) and Machine Learning (ML) to enhance learner autonomy and academic performance. In their study, Jin et al. (2023) developed an AI prototype that supported SRL Forethought, Performance, and Reflection phases. The prototype included AI analytics dashboards and AI Agents. The AI tool assisted students in developing cognitive, metacognitive, and behavioural regulation. However, the prototype was less effective in addressing self-motivation aspects of SRL, and participants' feedback highlighted that the tool needed to include factors related to learner identity and activeness. Additionally, a university in Ecuador developed an AI tool that integrated ML and data analytics into a Learning Management System (LMS) to enhance adaptive online education. The tool used a virtual assistant that monitored student activity and performance, sending reminders and adjusting learning material based on a learner's needs. This allowed the system to foster a supportive learning environment that promoted students to be self-regulated.

At UniDistance Suisse, (Baillifard *et al.*, 2024) developed a personal AI tutor in a neuroscience course. The AI tutor utilized GPT to generate personalized microlearning questions and modeled each student's comprehension, thereby providing spaced retrieval practice based on the learner's knowledge level. Results obtained from the study indicate that students who actively used the AI-based tutor performed better in their academic work, and this indicates the importance of personalised AI support in the promotion of SRL strategies. Furthermore, (Azevedo *et al.*, 2022b) Used process mining techniques to track and analyse SRL behaviour of students in an e-learning module. They examined logs of 101 students and identified patterns of successful self-regulation. Students who consistently engaged with collaborative forums excelled in the module; hence, their analysis provided insight into the specific actions associated with SRL in ODeL environments.

Focusing on Southern Africa, the University of South Africa (UNISA) has been taking a leading role in the development and implementation of ML tools in ODeL systems. In their study, (Carow, Schmitz and Pretorius, 2023) used spatial data analytics to profile students to provide personalised support that promotes SRL. The tool developed analyzed geographical and socio-economic data to provide insight into students' learning patterns and then offer customized support strategies. In South Africa again, (Muazu *et al.*, 2024) Implemented a machine learning driven dynamic autoregressive distributed lag (dynARDL) model that simulated how mobile learning technologies impact school enrolment levels in South Africa. Findings obtained from the study highlighted ML has great potential in predicting and enhancing educational access. ML can help identify areas where students require additional support and resources.

In Zimbabwe, (Mafuhure, Kabanda and Tsvere, 2023) Developed a multimedia SRL teaching tool (C-Learn) that taught students to develop and utilise SRL strategies while learning computer programming in large classes. The tool utilised ML for grading tests and offering personalised feedback to students. Results obtained in their study highlighted that students who used the tool achieved better grades than their counterparts in the control group. Therefore, ML and SRL can be combined to help students achieve autonomy and academic success. In Zambia, (Zulu *et al.*, 2025) Did a study on the preparedness of students in using ICT-integrated ODeL systems. Their study highlighted that those learners who developed SRL strategies earlier adapted well to online learning platforms. They suggested that instructors should assist in fostering SRL skills for the successful use of ML-enhanced ODeL systems.

Coding Ideas on the Integration of SRL and Machine Learning

The research study reviewed several literatures and noted that integrating Self-Regulated Learning (SRL) and Machine Learning (ML) is very important in ODeL systems because it enhances learner autonomy, adaptability, and performance. (Villegas-Ch, Román-Cañizares and Palacios-Pacheco, 2020; Jin *et al.*, 2023). SRL assists students to set goals, plan, self-monitor, and self-evaluate, while ML assists students in personalised learning through analytics and prediction (Demertzi and Demertzis, 2020; Burro *et al.*, 2022). Based on the reviewed literature, this research study proposes a framework that demonstrates how SRL and ML can be integrated to enhance teaching and learning in ODeL environments, as illustrated in Figure 2. On the diagram below, seven critical educational components include goal setting and monitoring, engagement tracking, personalised learning, intelligent feedback, peer benchmarking, performance prediction, and reflective prompting. All the components represent the application of ML techniques to augment SRL strategies in ODeL systems. These critical components are linked to SRL cognitive and metacognitive strategies such as goal review, help-seeking, planning, self-evaluation, and reflective action. As shown on the diagram below, reflective prompting feeds into reflective action, intelligent feedback aids help-seeking behaviour, while goal setting leads to self-evaluation and recurrent goal review. The above SRL strategies enable learners to take control of their own learning, which is a critical concept in SRL theory (Zimmerman).

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As shown on the diagram, the SRL strategies are connected to several ML techniques. Planning is associated with clustering algorithms, which group learners based on their behavioral patterns. On the other hand, reflective action and help-seeking are supported by Natural Language Processing (NLP), which enables systems to interpret student input and provide appropriate responses. Furthermore, recommendation systems and predictive analytics enhance goal review and help-seeking strategies. This is achieved through the provision of timely suggestions and insights. (Viberg, Khalil and Baars, 2020; Saint *et al.*, 2022). The Self-evaluation SRL strategy can be enhanced by classification models, which can categorize learner performance. Lastly, the framework has a data update frequency that is crucial for the efficient provision of feedback and intervention. ML techniques such as clustering and NLP are very critical in supporting real-time feedback, while predictive analytics and recommendation systems help in the generation of daily reports and weekly reviews. The fusion of ML and SRL enables ODeL systems to be adaptive, responsive, and personalised. This conceptual model provides a comprehensive blueprint for developing AI-driven SRL environments in ODeL. Such systems can promote the convergence of personalization and automation, thereby assisting learners to become autonomous and successful in their academic journey.

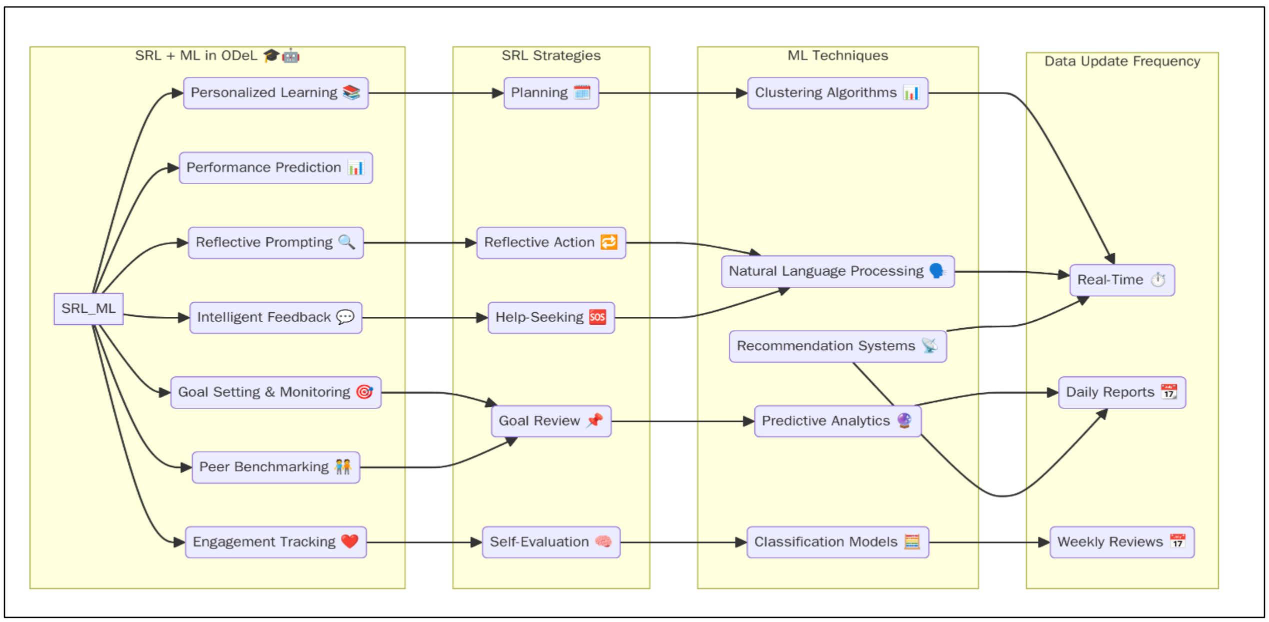

Figure 2. SRL and ML framework

Technologies to Be Used

By incorporating ML into an SRL framework, the system can analyze behavioural data (e.g., time spent on tasks, code submissions, engagement patterns) to adapt content, suggest resources, and guide learners based on their individual progress. Machine learning techniques, including supervised learning, unsupervised learning, reinforcement learning, and Natural Language Processing (NLP), are instrumental in powering this integration.(Cerezo *et al.*, 2020; Taub *et al.*, 2022). A conceptual model can be illustrated where SRL phases (goal setting, monitoring, and reflection) are supported by ML-driven modules for prediction, clustering, feedback generation, and personalization.

Programming Languages

This research study recommends a diverse set of programming languages that can be utilized to support the development of intelligent backend functionalities and a user-friendly, engaging frontend interface. Firstly, the study recommends using the Python programming language as the primary language because it is crucial in the development of machine learning models and handling backend logic (Banihashem, Bergdahl, and Khosravi, no date). The Python programming language utilises powerful libraries such as PyTorch, TensorFlow, and Scikit-learn, which are critical for tasks like predictive analytics, adaptive learning, and learner profiling, all of which are essential for enhancing SRL strategies (Samsonovich and Liu, 2024; Shafiee Rad, 2025). Additionally, the study also recommends the use of JavaScript because it provides dynamic interactivity and enables a responsive user

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experience. Furthermore, HTML and CSS are also recommended for frontend development. HTML and CSS help in structuring and styling the user interface to ensure that the system developed is accessible and usable across different devices (Mafuhure, Kabanda, and Tsvere, 2023). Lastly, PHP is also recommended, specifically the Laravel framework, because it is capable of handling data management, routing, and communication between the frontend and AI-driven backend services. The recommended programming languages, if utilised, can ensure the development of a robust and intelligent ODeL learning platform that effectively combines SRL and ML.

Machine Learning Algorithms

To develop a Learning Management System (LMS) that fuses ML and SRL in ODeL, several ML algorithms can be utilised. The ML algorithms assist in aspects such as learner interaction, personalisation, and provision of intelligent feedback. (Hanji, 2023). Supervised Machine learning algorithms, such as Support Vector Machines (SVM), XGBoost, Random Forest, and Logistic Regression, can be used to predict student behaviours, assess performance, and classify engagement levels based on historical data (Dever *et al.*, 2022; Jin *et al.*, 2023). These models can be used to identify students who may need additional support to minimise student dropout, especially in ODeL environments. (Dever *et al.*, 2022). Additionally, Unsupervised learning techniques such as K-Means Clustering, Principal Component Analysis (PCA), and DBSCAN can be used to track and uncover hidden patterns in learner data. (Poličar *et al.*, 2025). The techniques can also be used to put students into groups and help them produce better visualisation and analysis. .Natural Language Processing (NLP) models, such as GPT, BERT, and T5, are recommended to assist in the generation of automated feedback, goal prompting, and reflective analysis. The NLP tools are essential in the development of systems that support SRL because they enable intelligent dialogue and prompt SRL metacognitive awareness (Demertzi and Demertzis, 2020).

Frameworks and Libraries

To effectively implement an ODeL system with SRL and ML, the study recommends several frameworks and libraries that can be utilized for system development, deployment, and analytics. (Ifenthaler, Mah and Yau, 2019). Powerful machine learning libraries, such as TensorFlow, PyTorch, scikit-learn, XGBoost, and Keras, can be used to design, train, and evaluate predictive models and intelligent learning agents. (Rezapour and Elmshaeuser, 2022; Poličar *et al.*, 2025). The libraries contain essential tools that handle various ML tasks, ranging from deep learning to ensemble methods and statistical modeling. Django (Python) and Laravel (PHP) are important web frameworks that can also be used to provide scalable and secure architectures for the integration of ML and SRL. (Ifenthaler, Mah and Yau, 2019). The React.js frontend framework is recommended to build an interactive and responsive user interface. Furthermore, Experience API (xAPI) and Firebase Analytics can be integrated to capture user behavior and make data-driven decisions. These tools allow the system to monitor each learner's activities, track SRL behaviour, and generate personalised feedback (Hanji, 2023).

Databases and Storage

To develop an intelligent ODeL system that integrates SRL and ML, the study recommends utilizing several databases, including MongoDB, NoSQL, and MySQL. These databases can be used to store and manage both structured and unstructured data. Unstructured data, such as student activity logs, interactions, and behavioral traces, aid in the analysis of SRL behaviors and the training of ML models. (Rezapour and Elmshaeuser, 2022). The MySQL relational database is recommended for handling structured data, such as learning goals, user profiles, academic records, and progress reports. A MySQL database can also help ensure data integrity and facilitate effective data querying. Finally, Firebase can be utilised to provide real-time database functionalities and support flawless authentication of users into the system. The use of a hybrid database approach supports the development of flexible and robust ML-enhanced ODeL learning platforms.

Security and Authentication

The study recommends a robust security and authentication framework for the development of an ML and SRL-based ODeL system. The OAuth2 framework is one security framework that can be utilised because it uses trusted providers such as Google to ensure secure user authentication, hence minimising security breaches. Additionally, the study recommends using JSON Web Tokens (JWT) for managing and validating user sessions within the system. Furthermore, SSL/TLS encryption protocols can be utilized to ensure that data is transmitted securely between the client and server, protected from eavesdropping or man-in-the-middle attacks. This will ensure that sensitive data such as login details, progress reports, and feedback remains secure. The layered security approach will ensure user confidence and meet the data protection standards expected in educational technological systems.

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Functionality

This research study came up with code snippets on how ML and SRL may be fused to develop ODeL systems that can enhance teaching and learning. The study highlights the core functionalities of the SRL-ML tool, including the types and algorithms of ML to be used, as well as pseudocode implementations.

Personalized Learning Paths

The pseudo code in Figure 3 employs a hybrid machine learning approach, combining Supervised Learning (Random Forest) and Unsupervised Learning (K-Means Clustering) to develop a system that personalizes content for students. As shown in the code snippet, the main function *generateLearningPath(studentProfile)* retrieves student performance data using the *getPerformanceData ()* function. The *getPerformanceData ()* function obtains performance data from a supervised learning model, such as Random Forest, which can analyse labelled data and classify performance outcomes. The *detectLearningStyle() function determines the student's learning style by utilizing unsupervised learning models, such as K-Means Clustering, to group students into learning style categories based on their* SRL behavior and interaction patterns. This function again calls the *identifySkillGaps(performanceData)* function to identify areas where the student is underperforming, applying data-driven thresholds and interaction patterns. When the system identifies gaps, it retrieves learning material modules that relate to the gaps and the student's learning style using the fetchModule*()* function. If the student is performing well, the system retrieves more advanced modules using the *fetchNextLevelModules* function. The approach recommended in this code snippet facilitates the development of intelligent tutoring systems that utilize historical performances and behavioral clustering to enhance learning. This empowers learners to take complete control of their learning process (SRL) by engaging with content that is relevant to their goals and plans, as well as key strategies for SRL.

ML Type: Supervised + Unsupervised Learning
Algorithms: Random Forest, K-Means Clustering
Pseudo code for creating personalised content

```
generateLearningPath(studentProfile):
    performanceData = getPerformanceData(studentProfile)
    learningStyle = detectLearningStyle(studentProfile)
    skillGaps = identifySkillGaps(performanceData)
    IF skillGaps.exists():
        recommendedModules = fetchModules (skillGaps, learningStyle)
    ELSE:
        recommendedModules = fetchNextLevelModules(studentProfile)
    RETURN recommendedModules
```

Figure 3. Personalized Learning Paths pseudo code

Performance Prediction

Performance prediction is significant in ODeL learning environments because it assists learners in identifying their strengths and weaknesses at an early stage, thereby adjusting SRL strategies accordingly. If students are flagged as "At-Risk", necessary interventions can be implemented early, and strategies can also be adjusted accordingly.

The pseudocode in Figure 4 illustrates how a supervised ML approach can be utilized to predict student performance using algorithms such as Logistic Regression, Support Vector Machines (SVM), and XGBoost. The models stated can be trained on labeled data where outcomes, such as successful versus at-risk students, are known. This allows the algorithms to learn patterns associated with different performance levels. As shown in the code snippet, the *predictPerformance(studentProfile)* function extracts student activity data using a method called *extractFeatures (studentProfile.activityLog)*. Activities that can be extracted include quiz scores, login frequency, time spent on tasks, and submission patterns. These extracted features are then passed into *the ML model. Predict (features),* an ML model that is trained to generate performance predictions.

If the model forecasts a student to be at "high-risk," for example, the system, through the triggerAlert() function, notifies the relevant stakeholders for action via the scheduleIntervention*()* function. This will enable early identification and intervention for students who need support from stakeholders such as administrators,

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instructors, and counsellors. This will enhance academic achievement, particularly in ODeL environments that are often associated with high student dropouts.

ML Type: Supervised Learning

```
Algorithms: Logistic Regression, SVM, XGBoost
Pseudocode for making predictions
predictPerformance(studentProfile):
   features = extractFeatures (studentProfile.activityLog)
   prediction = MLModel.predict(features)
   IF prediction == "high_risk":
      triggerAlert (studentProfile, "At-risk student detected")
      scheduleIntervention (studentProfile)
   RETURN prediction
```

Figure 4. Performance Prediction pseudo code

Intelligent Feedback and Tutoring

Self-reflection is one of the key SRL strategies, and with ML techniques, ODeL systems can help provide instant intelligent feedback so that students can reflect on their mistakes and take the necessary steps to rectify them (Rezapour and Elmshaeuser, 2022). The proposed pseudo-code combines supervised learning and NLP techniques to provide automated feedback to students who submit computer programming code for evaluation. LSTM (Long Short-Term Memory), BERT (Bidirectional Encoder Representations from Transformers), and GPT (Generative Pre-trained Transformer) are NLP models that can generate text that resembles human language.

In the code snippet in Figure 5, the models can be utilized to analyze and respond to programming code submitted by students. The function *provideCodeFeedback(codeSubmission)* checks the code submitted for syntax errors using the *checkSyntax(codeSubmission)* function to ensure that the submitted code does not violate programming language rules, such as missing semicolons or unmatched braces. The *analyzeLogicFlow(codeSubmission)* function can analyze the logical flow of the code to detect issues related to infinite loops and incorrect conditional statements. The AI models are invoked through *AIModel.generateTips(codeSubmission)* to provide suggestions, such as refining the code structure and performance optimization. The *mergeFeedback (syntaxErrors, logicErrors, modelSuggestions)* function then compiles all information and generates a very comprehensive feedback message addressing the code submitted by the student. The instant feedback generated by the system mimics that of a human instructor, thereby enhancing student-instructor interaction —an aspect that often lacks in ODeL environments.

```
ML Type: Supervised Learning + NLP
Algorithms: LSTM, BERT, GPT
Pseudocode for generating feedback
provideCodeFeedback(codeSubmission):
   syntaxErrors = checkSyntax(codeSubmission)
   logicErrors = analyzeLogicFlow(codeSubmission)
   modelSuggestions = AIModel.generateTips(codeSubmission)
   feedback = mergeFeedback (syntaxErrors, logicErrors, modelSuggestions)
   RETURN feedback
```

Figure 5. Intelligent Feedback and Tutoring pseudo code

Goal Setting and Self-Monitoring

In Self-Regulated Learning (SRL) theory, learners are encouraged to develop metacognitive strategies such as goal setting, planning, and self-monitoring. The code snippet below suggests how ML can assist students in developing SRL strategies in their academic journey. The pseudo code in Figure 6 utilizes Reinforcement Learning (RL) techniques, such as Q-Learning and Deep Q-Network (DQN), to assist students in setting and monitoring their academic goals. In the code snippet, *the assistGoalSetting(studentProfile) function evaluates each student's past performance using the analyzePerformance(studentProfile)* function. Based on an analysis of students' past performance, the system assists students in generating goals through the *generateSmartGoals(pastPerformance)*

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function. The system may allow students to confirm or edit the recommended goals, ensuring they are always involved in the goal-setting process. The *monitorGoals(studentProfile)* function will continually evaluate a student's progress toward goals set earlier. The *trackGoalProgress(studentProfile)* function retrieves the current student goals from their profile and performs the monitoring process. Suppose a student's progress is below 50% and the goal's deadlines are near. In that case, the *deadlineApproaching(currentGoals)* function will detect and send a reminder to the student, informing them that they are behind. In RL, such system involvements represent actions taken by an agent to respond to state changes in an environment, and in this case, it's a decline in progress. This efficient feedback-driven approach assists students in developing SRL strategies to enhance their academic performance.

```
ML Type: Reinforcement Learning
Algorithms: Q-learning, Deep Q-Network
Pseudocode for goal setting and self-monitoring
FUNCTION assistGoalSetting(studentProfile):
  pastPerformance = analyzePerformance(studentProfile)
  recommendedGoals = generateSmartGoals(pastPerformance)
  PROMPT studentProfile TO confirmOrEdit(recommendedGoals)
FUNCTION monitorGoals(studentProfile):
  currentGoals = studentProfile.goals
  progress = trackGoalProgress(studentProfile)
        IF progress < 50% AND deadlineApproaching(currentGoals):
    SEND reminder ("You're falling behind on goal:", currentGoals.name)
```

Figure 6. Goal Setting and Self-Monitoring pseudo code

Reflective Prompting

Self-regulated students must continually reflect on their academic work and progress to succeed in their educational journey. NLP reflective prompts enable students to reflect deeply on their successes and failures, thereby cultivating a habit of self-evaluation. Ultimately, students will be able to adjust their learning strategies based on the results obtained. The pseudocode in Figure 7 shows how NLP can be utilised to facilitate reflective learning for students in an ODeL environment. Advanced models, such as GPT, T5, and Sentiment Analysis, can be used since they are capable of comprehending, generating, and evaluating human language input. The students' learning performance and behavior metrics are retrieved by the promptReflection (studentProfile) function through the getRecentActivity (studentProfile) and getLatestFeedback *(studentProfile)* functions. The *performanceTrend(recentActivity)* function will assess whether the student's performance is improving or decreasing. Additionally, students may be asked to identify the strategies they used to accomplish a task. This is very important because it may help students develop SRL strategies and eventually become self-regulated. Student reflections may be saved to the student profile by using the SAVE studentReflection TO studentProfile command for future interventions. This approach may help students develop self-awareness and promote engagement through AI.

```
ML Type: NLP
Algorithms: GPT, T5, Sentiment Analysis
Pseudocode for Reflective Prompting
FUNCTION promptReflection(studentProfile):
  recentActivity = getRecentActivity(studentProfile)
  feedback = getLatestFeedback(studentProfile)
  IF performanceTrend(recentActivity) == "declining":
    PROMPT "What obstacles did you face recently?"
  ELSE:
    PROMPT "What strategies helped you succeed this week?"
  SAVE studentReflection TO studentProfile
```

Figure 7. Reflective Prompting pseudo code

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Motivation and Engagement Tracking

In the Self-regulated learning theory, self-motivation is one of the critical strategies students need to develop for them to achieve academic success. Several studies state that instructors should assist students in developing SRL strategies for them to stay consistent in self-directed learning environments. The pseudocode in Figure 8 can be utilized, as it demonstrates how Supervised Learning and Time Series Analysis can be combined to monitor and enhance student engagement. Algorithms that can be used may include Recurrent Neural Networks (RNNs), ARIMA (Autoregressive Integrated Moving Average), and Random Forest. These algorithms can detect temporal patterns and classify engagement trends. In the code snippet, the function trackEngagement(studentProfile) computes two critical metrics: login frequency and task completion, using the countLogins(studentProfile) and getTaskCompletionRate(studentProfile) functions, respectively. *calculateEngagementScore(loginFrequency, taskCompletion) is a core function that synthesizes the behavioral* metric to form a single engagement score.

Time series models, such as ARIMA and RNNs, can help capture patterns and variations in student behavior over time. The Random Forest can be used to classify engagement levels based on historical labeled data. The system may check the score, and if it is below the set threshold, a motivational message can be generated to encourage the student to continue (SEND motivationalMessage*("Keep going! You can do it."))*. If the score exceeds the higher threshold, the system may reward the student by awarding a badge (awardBadge*(studentProfile, "Focused Learner")*). This intelligent feedback mechanism can help students develop positive behaviours towards learning, thereby fostering sustained engagement through personalised recognition and encouragement.

ML Type: Supervised Learning + Time Series Analysis
Algorithms: RNN, ARIMA, Random Forest
Pseudocode for Motivation and Engagement Tracking

```
FUNCTION trackEngagement(studentProfile):
   loginFrequency = countLogins(studentProfile)
   taskCompletion = getTaskCompletionRate(studentProfile)
   engagementScore = calculateEngagementScore (loginFrequency, taskCompletion)
   IF engagementScore < threshold:
      SEND motivationalMessage ("Keep going! You can do it.")
   ELSE IF engagementScore > highThreshold:
      awardBadge (studentProfile, "Focused Learner")
```

Figure 8. Motivation and Engagement Tracking pseudo code

Peer Benchmarking and Recommendations

Students' performance can be compared to that of their peers to reflect their approaches, thereby encouraging learning, collaboration, and the adoption of new strategies. This socially driven approach encourages adaptive learning behaviours. The pseudocode in Figure 9 shows how unsupervised learning can be utilised to support peer-based learning through intelligent comparisons. Algorithms such as K-Means Clustering and Principal Component Analysis (PCA) can identify hidden structures and patterns in the student data. Through the K-Means Clustering, the function *suggests peer comparisons (studentProfile) via MLModel—clusterSimilarLearners (studentProfile), grouping students with related learning profiles, behavior patterns,* and performance metrics.

The PCA algorithm can be used to reduce dimensionality, improving clustering efficiency and interpretability. After each student is allocated a cluster, the *getTopLearners(cluster)* function identifies top-performing students and iterates through all profiles of top performers, compiling a list of strategies they employed through *suggestions.ADD ("Peer " + peer. name + " used " + peer.studyStrategy) personalized,* such as "Peer Peter used mind mapping to comprehend concepts". The approach may help students improve their learning by employing strategies used by relatable peers. This supports SRL because students can be motivated to learn by connecting with effective strategies utilized by fellow students in their cluster, as far as performance is concerned.

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```
ML Type: Unsupervised Learning
Algorithms: K-Means Clustering, PCA
Pseudocode for Benchmarking and Recommendations
FUNCTION suggestPeerComparisons(studentProfile):
   cluster = MLModel.clusterSimilarLearners(studentProfile)
   topPerformers = getTopLearners(cluster)
   FOR each peer IN topPerformers:
      suggestions.ADD ("Peer " + peer.name + " used " + peer. studyStrategy)
   RETURN suggestions
```

Figure 9. Motivation and engagement tracking pseudo code

Results

The systematic literature review identified 47 studies that met the inclusion criteria. An initial pool of 378 was identified from various databases, including Google Scholar, ResearchGate, the Directory of Open Access Journals (DOAJ), Institutional repositories, ScienceDirect, and Semantic Scholar. The results obtained from the study were centered around three themes, namely conceptualisation and support of SRL in ODeL environments, the application of Machine Learning (ML) techniques to enhance SRL behaviours, and fusion of SRL and ML in digital ODeL systems. Findings from the study highlight that SRL in ODeL systems is primarily anchored in Zimmerman's cyclical model of SRL. The model consists of three phases: forethought, performance, and self-reflection. Several studies highlighted the importance of developing metacognitive strategies, time management, and reflective prompts as crucial for academic success in ODeL environments.

On the other hand, several studies highlighted how ML can be utilised to detect, classify, and predict student behaviour that is related to SRL processes. Machine Learning techniques frequently employed included Random Forest, Support Vector Machines (SVMs), K-Means Clustering, and Deep Neural Networks to analyze patterns such as engagement logs, assessments, forum activity, and clickstream data. The ML algorithms were utilized to perform real-time monitoring of learners' SRL behaviors and facilitate personalized learning and predictive analytics. Most systems used ML models to predict at-risk students, procrastination, and ultimately make recommendations based on student actions and preferences. (Saqr *et al.*, 2024).

There is a growing number of studies that highlight the importance of fusing SRL and ML to form a unified framework. The integration of SRL and ML may help visualize student progress and facilitate instant interventions if SRL deficiencies are detected. In some studies, ML and SRL were combined to allow students to set goals, plans, and self-monitor their progress. In contrast, others utilized reinforcement learning agents to adjust content delivery based on student profiles (Han, Zhao, and Ng, 2021). The implementation of ML and SRL systems varies across regions; consequently, more advanced integrations are found in Europe and the Americas compared to areas such as Sub-Saharan Africa. Generally, many studies reviewed in this study suggested that integrating ML and SRL in ODeL environments can bring improvements in learners' autonomy, student retention rates, and enhanced academic performance. However, despite promising innovations, few studies have highlighted how ML and SRL can be practically implemented to develop robust ODeL systems that enhance teaching and learning.

Discussion

The research study revealed a growing interest in integrating SRL and ML, especially in ODeL learning environments. This is because SRL emphasizes promoting learner autonomy and metacognition, which aligns well with ML's capabilities of providing real-time monitoring, predictive interventions, pattern recognition, and personalized learning. (Burro *et al.*, 2022; Rezapour and Elmshaeuser, 2022; Saqr *et al.*, 2024). ML can enhance SRL processes through the detection of hidden patterns in a learner's behaviour, hence dynamically adapt learning environments to satisfy everyone's learning needs (Ifenthaler, Mah and Yau, 2019; Poličar *et al.*, 2025). This is particularly important, especially in ODeL learning environments, which are characterized by limited student-instructor interaction, learner isolation, and a significant amount of responsibility for self-directing their own learning. (Lim *et al.*, 2021).

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Incorporating ML algorithms that are capable of monitoring login activity, performance indicators, and clickstream data, ODeL systems can provide timely, data-driven decisions that are in support of SRL strategies such as goal setting, planning, self-monitoring, and self-evaluation (Dever *et al.*, 2022; Jin *et al.*, 2023). However, while there is potential for SRL and ML integration, a lack of consensus exists on standardized models that can be used in implementing the process, resulting in fragmented approaches that cannot be generalized across contexts. (Banihashem, Bergdahl and Khosravi, no date).

The study also noted that several implementations of ML and SRL are still in the experimental and pilot phases due to limited resources, especially in regions in Sub-Saharan Africa, where infrastructural and financial challenges prevent large-scale adoption. Despite the challenges cited in integrating SRL and ML, this study recommends interdisciplinary collaborations among stakeholders, including cognitive psychologists, educational technologists, developers, and data scientists, to develop unified frameworks that support the development of ODeL systems integrating SRL and ML, thereby enhancing teaching and learning.

The study also recommends the development of culturally responsive ODeL systems so that they are contextually relevant and inclusive. There is still room to explore the potential of advanced ML methods in deep learning, NLP, and Reinforcement Learning to model complex SRL behaviours so that human-like feedback and support can be given to learners in ODeL environments. (Villegas-Ch, Román-Cañizares and Palacios-Pacheco, 2020; Borchers *et al.*, 2024). There is a need for investment in infrastructure and capacity building to support the scalable and sustainable deployment of SRL-ML systems in ODeL. Although the fusion of SRL and ML is still an emerging area, it holds transformative power to enhance personalised learning, student academic success, and redefine the future of ODeL in higher education. (Shafiee Rad, 2025).

Conclusion

This research study highlighted how SRL and ML can be fused to enhance teaching and learning in ODeL environments. With the growing demand for ODeL worldwide, learners should be assisted in developing SRL strategies that promote autonomy, motivation, and self-direction. SRL provides a framework for learners to set goals, plan, self-monitor, and self-evaluate their processes. On the other hand, ML provides powerful tools that enable automation and analysis of learner behaviors, hence providing adaptive, data-driven support. SRL and ML systems can significantly enhance learners' engagement, performance, and retention through personalised feedback, predicting learning outcomes, and dynamically adjusting content. Looking ahead, the development of SRL and ML-based ODeL systems has the promise to transform ODeL education; hence, there is a need to focus on the development of unified, theory-driven models that integrate the two concepts to promote transparency and data protection standards. The models developed need to be tested in different contexts, especially in underrepresented regions such as Sub-Saharan Africa, where cultural considerations are very crucial. The study highlighted the importance of integrating SRL and ML in ODeL to enhance teaching and learning in a practical manner, and as a transformative educational strategy with great potential for transforming ODeL in the 21st century.

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