The Impact of Self-Paced Online Learning vs. Instructor-Led Online Learning:

Roles of Learner Engagement, Learning Outcomes, and AI-EnhancedTechnologies

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1. Introduction

Online learning has become a major part of education, professional training, and lifelong learning. With the rapid growth of technology and artificial intelligence (AI), online courses now allow learners to study more flexibly and in a personalized way. Two popular online learning approaches are widely used today: Self-Paced Online Learning (SPOL), where learners can progress at their own speed, and Instructor-Led Online Learning (ILOL), where learning is structured and guided by a teacher. Even though both methods are common, it is still unclear which one works better for different types of learners and in different learning situations (Means et al., 2013; Kundu & Das, 2024).

Many previous studies mainly focused on short-term test results and did not fully consider important learner characteristics such as motivation, self-regulation skills, digital literacy, and prior knowledge (The Mediating Role of Self-Regulated Online Learning Behaviors, 2024). Learners who are motivated and good at managing their own studies may perform better in SPOL, while those who need regular interaction and support may benefit more from ILOL.

Another gap in research is that long-term knowledge retention has not been studied well. Most research checks learning results only right after the course, but in real life, it is important to remember information even after months for jobs and future learning (Means et al., 2013).

In addition, AI-powered tools such as automated tutoring, adaptive feedback systems, and generative assistants like ChatGPT are becoming more common in online learning. These tools can provide personalized help and support, which may affect learner engagement and success differently in SPOL and ILOL (Zhang, 2025; Deng & Zhang, 2024). However, there is still limited research comparing how AI affects these two types of online learning.

Therefore, this study aims to explore how learner characteristics, engagement, and AI-enhanced tools influence learning outcomes and long-term retention in both SPOL and ILOL. This will help identify which approach is more effective for different types of learners in various online contexts.

1.1 Research Gap

While there are many studies on online learning, most of them focused only on one part of the problem. Earlier research has often examined either self-paced learning or instructor-led learning separately, and mostly measured results only in the short term (Means et al., 2013; Kundu & Das, 2024). At the same time, some recent studies explored the role of AI tools in improving engagement and performance, but they did not compare how AI influences both learning modes together (Zhang, 2025; Deng & Zhang, 2024).

So, there is still no clear understanding of:

- How SPOL and ILOL compare directly when AI tools are involved.
- How learner characteristics (such as motivation, self-regulation and digital literacy) affect outcomes differently in each format.
- How long-term knowledge retention differs between the two learning modes over several months.

Therefore, the main research gap lies in the absence of integrated studies that simultaneously examine SPOL and ILOL in the context of AI-enhanced learning and long-term knowledge retention. This research seeks to bridge that gap by providing a combined analysis of these factors.

2. Aim

The aim of this study is to evaluate and compare the effectiveness of Self-Paced Online Learning (SPOL) and Instructor-Led Online Learning (ILOL) by examining how learner characteristics, engagement behaviors, and AI-enhanced tools influence both learning outcomes and long-term knowledge retention. Furthermore, the study seeks to identify which learner profiles and instructional contexts derive the greatest benefit from each approach.

3. Research Questions

1. Learner characteristics: How do motivation, self-regulation, digital literacy, and prior knowledge moderate learning outcomes in SPOL vs. ILOL?
2. Retention over time: What are the differences in knowledge retention between SPOL and ILOL at post-test, 3-month, and 6-month follow-ups?
3. AI features: How do AI-based tools (adaptive feedback, automated tutoring, generative assistants) influence engagement and outcomes in each mode, and do their effects differ between SPOL and ILOL?

4. Literature Review

Online education has evolved into a central component of modern learning systems. Early evidence shows that learning formats with more structured interaction often achieve better outcomes than purely self-directed formats because they promote engagement, feedback, and learner accountability (Means et al., 2013). Building on this, Kundu and Das (2024) found that learning effectiveness depends largely on the degree of support and learner autonomy some learners perform better with flexible self-paced learning, while others benefit from instructor guidance and structured timelines.

A synthesis of recent studies highlights the importance of self-regulated learning (SRL) skills such as goal-setting, time management, and persistence as a key factor in online learning success. Learners with stronger SRL and digital literacy tend to engage more effectively and achieve better results, acting as mediators between individual traits and performance (The Mediating Role of Self-Regulated Online Learning Behaviors, 2024). Complementing this, a large meta-analysis covering studies from 2000 to 2024 found moderate to large effects for blended and structured online formats across both cognitive and emotional outcomes, emphasizing the value of interaction and scaffolding in digital environments (Unraveling the Impact of Blended Learning vs. Online Learning, 2025).

At the same time, AI-enhanced tools such as adaptive feedback systems, automated tutoring, and generative assistants are rapidly reshaping online education. Evidence suggests that AI tools can improve efficiency, engagement, and learner performance; however, their influence on deeper conceptual understanding appears mixed and often depends on instructional design and individual learner characteristics (Zhang, 2025). Similarly, Deng and Zhang (2024) note that while AI offers strong potential for personalization and real-time support, its impact is inconsistent across different learning contexts and learner groups.

Taken together, these studies offer valuable insights but also reveal clear limitations. Despite progress in online education, few studies directly compare Self-Paced Online Learning (SPOL) and Instructor-Led Online Learning (ILOL) while also examining the role of AI tools. Moreover, most research evaluates outcomes immediately after course completion, giving little attention to long-term knowledge retention. These gaps highlight the need for integrated research that connects learning mode, learner characteristics, and AI-enhanced support over extended periods (Means et al., 2013; Deng & Zhang, 2024; Zhang, 2025). Addressing these issues, the present study aims to understand how these elements interact to shape learner engagement, performance, and sustained knowledge retention.

5. Methodology

This study adopts a mixed-methods design combining both quantitative and qualitative approaches to comprehensively examine how learner characteristics, engagement, and AI-enhanced tools influence learning outcomes in Self-Paced Online Learning (SPOL) and Instructor-Led Online Learning (ILOL).

The quantitative part focuses on measurable outcomes such as performance, engagement, and retention over time, while the qualitative part explores learners' personal experiences to understand why certain results occur.

Together, these methods ensure both breadth and depth in understanding how different learning modes and technologies shape learner success.

5.1 Quantitative Methodology

The quantitative part of this study will examine differences in learning outcomes and long-term retention between Self-Paced Online Learning (SPOL) and Instructor-Led Online Learning (ILOL). A quasi-experimental design will be used since learners naturally enroll in either SPOL or ILOL courses (Means et al., 2013). This approach allows for real-world comparison while maintaining research validity.

Approximately 300–400 adult learners will be selected using purposive sampling from courses offered in both formats. Only participants aged 18 or above who provide informed consent will be included (Deng & Zhang, 2024).

Quantitative data will be collected in three main forms:

- **Knowledge Tests:** Conducted at four points: pre-test (before the course), post-test (after completion), and retention tests at 3 and 6 months to measure both short-term learning and long-term memory (Means et al., 2013).
- **Learner Surveys:** These will measure key learner characteristics such as motivation, self-regulation, and digital literacy, which earlier studies have shown to influence online performance (Kundu & Das, 2024; The Mediating Role of Self-Regulated Online Learning Behaviors, 2024).
- **LMS Engagement Logs:** Automatically collected throughout the course to track study behaviors, including:
  - Time spent on course content
  - Number of logins
  - Completion of activities
  - Use of AI-based tools such as automated tutoring and adaptive feedback systems (Zhang, 2025).

For analysis, descriptive statistics and reliability checks (e.g., Cronbach's alpha) will first be conducted to ensure data quality.

- To address RQ1, multilevel modeling will be used to test whether learner characteristics moderate the effects of learning mode on performance (Deng & Zhang, 2024).
- To address RQ2, growth-curve modeling and repeated-measures analysis will be used to examine how knowledge changes across time, from pre-test to 6-month retention (Means et al., 2013).

This analytical approach will reveal both short-term and long-term learning trends, helping identify which learning mode supports deeper and more sustained learning. Missing data will be treated using multiple imputation, and effect sizes will be reported to interpret the practical significance of findings (Zhang, 2025).

Participation will be voluntary, and learners may withdraw from the study at any time. All survey, test, and LMS data will remain confidential and linked only through coded IDs to protect participant identity under GDPR guidelines.

5.2 Qualitative Methodology

The qualitative part of this study will help explain why certain quantitative patterns occur by exploring learners' personal experiences in both SPOL and ILOL environments. A semi-structured interview design will be used, as it enables both consistent questioning and open discussion (Deng & Zhang, 2024). This approach is valuable for understanding how learners perceive structure, support, and the use of AI tools in different learning contexts.

A purposeful sample of approximately 30–40 participants will be chosen from the main dataset, ensuring variation across learning mode, engagement level, and performance. Each interview will last about 30–45 minutes and will be conducted online via secure video calls. Participants will receive complete study information and provide recorded consent prior to the interview.

Interviews will explore topics such as:

- How learners plan, manage, and regulate their study time
- How they experience support and structure in their learning mode
- How AI tools (e.g., automated tutoring, adaptive feedback) influence motivation, confidence, and engagement (Zhang, 2025)
- The challenges and barriers they face during online learning

All interviews will be audio-recorded, transcribed, and anonymized by replacing personal identifiers with coded IDs. The data will then be analyzed using thematic analysis, following Braun and Clarke's (2006) six-step process: familiarization, coding, theme generation, reviewing, defining, and reporting. Two researchers will code independently to ensure inter-coder reliability and trustworthiness.

The qualitative findings will primarily address RQ3, explaining how AI tools and instructional design influence learner engagement and performance. These insights will also help interpret quantitative results, strengthening the mixed-methods integration by uncovering the reasons behind observed patterns.

6. Research Questions and Method Alignment

This section outlines how each research question will be addressed through specific data sources and analysis techniques. It ensures a clear and logical connection between the study's objectives and the selected methodological approaches, maintaining coherence and testability throughout the research process.

Research Question	Data Source	Data Analysis Approach
RQ1: How do learner characteristics (motivation, self-regulation, and digital literacy) moderate learning outcomes in SPOL vs. ILOL?	Surveys + LMS engagement data	Correlation analysis + Multilevel modeling (Mode × Trait moderation)
RQ2: What are the differences in knowledge retention between SPOL and ILOL over time?	Pre-test, Post-test, 3- & 6-month retention tests	Growth-curve modeling + Repeated-measures analysis
RQ3: How do AI-based tools influence engagement and outcomes in each mode, and do their effects differ between SPOL and ILOL?	Interviews + LMS AI-usage logs	Thematic analysis + Integration with quantitative results

Notes for interpretation:

- RQ1 examines whether different learner profiles (based on motivation, self-regulation, and digital literacy) perform better in one learning mode than the other.
- RQ2 tracks knowledge growth and retention across several time points, allowing comparison of short-term and long-term learning patterns.
- RQ3 explores how AI tools shape engagement and outcomes in both SPOL and ILOL and explains differences observed in the quantitative phase.

This alignment ensures that each research question is supported by appropriate evidence, reliable data, and valid analytical techniques, strengthening the overall rigor and interpretability of the study.

7.1 Quantitative Data Collection

Quantitative data will be collected systematically throughout the study to measure learning progress, engagement behavior, and knowledge retention across Self-Paced Online Learning (SPOL) and Instructor-Led Online Learning (ILOL) formats.

Participant Recruitment and Data Gathering Process

The study aims to include 300–400 adult learners enrolled in courses that are offered in both SPOL and ILOL formats. Participants will be selected using purposive sampling in collaboration with course coordinators and instructors at participating institutions.

Invitation and Consent: An email invitation describing the study's purpose, duration, and voluntary nature will be sent to all eligible learners. Those interested will complete an online consent form before participation begins.

Data Collection Platform: All instruments (tests and surveys) will be administered digitally through the Learning Management System (LMS) and a secure survey tool such as Qualtrics or Google Forms, ensuring convenience and accessibility.

Timeline: Data collection will occur at multiple stages: before, during, and after course completion, with automated LMS tracking throughout.

Data Collected

- **LMS Metrics:** Time spent on course materials, number of logins, activity completion rate, and AI-tool interactions (e.g., adaptive feedback, tutoring sessions).
- **Knowledge Tests:** Conducted at four stages,pre-test (baseline), post-test (end of course), and retention tests at 3-month and 6-month intervals to capture long-term memory.
- **Learner Survey:** Measures of motivation, self-regulation, and digital literacy collected at the baseline stage.

Data Linking: All datasets (tests, surveys, LMS logs) will be connected through anonymous participant codes, ensuring privacy and GDPR compliance.

This structured approach allows for accurate comparison of learning outcomes and engagement across both modes, while maintaining participant confidentiality and ethical research standards.

7.2 Qualitative Data Collection

The qualitative data collection aims to explore learners' real experiences, perceptions, and challenges within Self-Paced Online Learning (SPOL) and Instructor-Led Online Learning (ILOL) environments. This part focuses on understanding why certain learning patterns occur and how AI tools influence engagement and motivation across different modes of study.

Participant Selection

A total of 30–40 participants will be invited to take part in the interview process. Participants will be chosen to represent a variety of learning experiences, including:

- Different learning formats (SPOL and ILOL)
- Varying levels of engagement and motivation
- Both high and moderate-performing learners

The selection will ensure a balanced representation of perspectives from both learning modes to provide rich and diverse qualitative insights.

Interview Process

Each participant will be contacted individually through email or the learning platform's internal messaging system to schedule an interview time that best suits them. Once they agree to participate, a digital consent form will be shared, detailing the purpose of the study, interview procedure, and confidentiality assurances.

- **Format:** Semi-structured interviews will be used to allow flexibility while keeping the discussion aligned with the study's objectives.
- **Mode:** Interviews will be conducted online via Zoom or Microsoft Teams, ensuring accessibility and convenience for all participants.
- **Duration:** Each interview will last approximately 30–45 minutes.
- **Recording:** With participant consent, sessions will be audio-recorded to ensure accuracy. All recordings will later be transcribed verbatim and anonymized.

Interview Topics

Interviews will focus on learners' study behaviors, attitudes, and their experiences using AI tools in online education, covering themes such as:

- How learners plan and manage their study time
- The level of structure and support they experience in SPOL vs. ILOL
- The influence of AI-based tools like automated tutoring and adaptive feedback
- Motivation, confidence, and barriers faced while studying online

Data Handling and Confidentiality

All interview data will be securely stored on encrypted drives, accessible only to the research team. Identifying details will be replaced with coded identifiers to maintain anonymity. Data management will follow GDPR standards and Dalarna University's ethical guidelines.

This qualitative phase will provide valuable insights into learners' emotional, cognitive, and behavioral engagement, helping to explain why quantitative results differ between SPOL and ILOL environments.

8. Data Analysis

The analysis will be conducted in two main stages: quantitative and qualitative. Each dataset will first be analyzed separately to preserve methodological clarity, and the findings will later be combined to build a more complete understanding of learning effectiveness across Self-Paced Online Learning (SPOL) and Instructor-Led Online Learning (ILOL).

8.1 Quantitative Data Analysis

Quantitative data will be examined to identify patterns and differences in learning performance, engagement, and retention between SPOL and ILOL. The analysis will include:

- **Multilevel modeling (MLM):** To test whether learner characteristics such as motivation, self-regulation, and digital literacy moderate the relationship between learning mode and performance outcomes.

- **Growth-curve analysis:** To track learning progress from the pre-test to post-test, and again at 3- and 6-month intervals, helping measure long-term retention.

- **Descriptive and reliability statistics:** To assess internal consistency (e.g., Cronbach's alpha) and address missing data through imputation methods.

These analyses directly address Research Questions 1 and 2 (RQ1, RQ2) by identifying which learner characteristics and modes of learning most effectively support immediate and sustained learning outcomes.

8.2 Qualitative Data Analysis

All interview recordings will be transcribed verbatim and reviewed multiple times for accuracy and familiarity with the content. Analysis will follow Braun and Clarke's (2006) thematic analysis framework, involving:

- **Coding:** Systematically labeling important statements and phrases related to engagement, motivation, and experiences with AI tools.

- **Theme development:** Grouping codes into broader, recurring themes that explain behaviors and perceptions within SPOL and ILOL contexts.

- **Double coding:** Two independent researchers will code the data separately, followed by comparison and discussion to enhance trustworthiness and reliability.

This qualitative analysis will directly address Research Question 3 (RQ3) by revealing learners' perceptions and experiences that help explain why engagement and outcomes differ across learning modes.

8.3 Mixed-Methods Integration

Finally, findings from both analyses will be combined through triangulation, comparing quantitative patterns (e.g., performance trends, engagement scores) with qualitative insights (e.g., motivation, perceptions of AI). This integrated approach will help interpret how and why certain patterns occur, providing a holistic understanding of learner performance and engagement.

The integration process ensures that the results from one method support and validate those from the other, enhancing the overall validity and coherence of the study.

9. Ethical Considerations

Before joining the study, all students will receive clear information about what the research is about and how their data will be used. Participation will be completely voluntary, and learners can withdraw at any time without any problem.

To protect privacy, all personal details will be removed and replaced with anonymous codes. Data such as surveys, LMS logs, and interview recordings will be stored securely and only used for research. Everything will follow Dalarna University's ethical guidelines and the GDPR for data protection.

Before starting, participants will give informed consent, and separate permission will be taken for recording interviews. This ensures the study is carried out responsibly and respectfully.

10. Limitations

This study focuses on a specific group of online learners, so the results may not represent all students or subjects. Some learners might not complete the 3- or 6-month follow-up tests, which could affect long-term results.

Other factors, such as internet access, experience with AI tools, or differences in teaching style, might also influence how students perform. Mixing survey data and interview findings can sometimes be difficult, but using a clear process and comparing results carefully will help reduce these issues.

Even with these limits, the study is designed to give a fair and useful comparison between Self-Paced and Instructor-Led online learning.

11. Expected Results

Based on earlier studies, it is expected that learners with higher motivation, self-regulation, and digital literacy will perform better in Self-Paced Online Learning (SPOL), since this mode requires independence, planning, and discipline. In contrast, students who prefer structure and frequent support are likely to perform better in Instructor-Led Online Learning (ILOL), where the instructor provides direction and interaction. This will help answer RQ1, showing how learner traits influence performance in both learning modes.

For RQ2, it is expected that knowledge retention will vary over time. SPOL learners may learn more slowly at first but remember the material longer because they study more deeply on their own. ILOL learners might score higher immediately after instruction but forget faster if they rely too much on teacher guidance. Comparing test results at post-test, 3 months, and 6 months will reveal these differences in long-term learning.

For RQ3, AI tools like automated feedback, intelligent tutoring, and generative assistants are expected to improve both engagement and confidence in learning. However, their role may differ between the two modes:

- In SPOL, AI may act as a personal guide, offering adaptive help and replacing some instructor functions.
- In ILOL, AI may serve as a support tool, enhancing feedback and practice alongside teacher input.

These patterns could lead to different engagement levels and performance outcomes depending on how actively learners use AI tools.

Overall, the study expects that:

- Learner traits matter SPOL suits self-regulated learners, while ILOL benefits those needing structure.
- AI can enhance learning in both modes, but its effect depends on how it is used.
- Long-term retention will differ, showing distinct strengths for SPOL and ILOL over time.

These findings will help educators and institutions choose the right learning mode for different types of students and use AI effectively to improve engagement and long-term learning success.

12. Practical Implications

The results of this study can help teachers, course designers, and universities choose the most effective online learning approach for different types of students. Learners with strong motivation and self-regulation skills may benefit more from Self-Paced Online Learning (SPOL), which encourages independence and flexibility. Meanwhile, students who need more structure, feedback, and regular interaction may perform better in Instructor-Led Online Learning (ILOL).

AI tools can also be used more strategically to enhance both learning modes. By identifying where students face difficulties, these tools can offer personalized feedback and support, helping learners stay engaged and improving overall success.

Practical benefits of this research include:

- Helping educators make better decisions about when to use SPOL or ILOL based on learner characteristics.
- Supporting improved teaching strategies by integrating AI tools that keep learners motivated and on track.
- Enhancing long-term learning outcomes by matching learning modes to the right type of learner.

These findings can guide the future design of online courses, making them more adaptive, inclusive, and effective for diverse learners. They can also encourage educational institutions to combine human instruction and AI support in ways that create balanced, engaging, and high-quality digital learning environments.

13. References

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3* (2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Deng, R., & Zhang, X. (2024). Does ChatGPT enhance student learning? A systematic review. *Computers & Education, 176*, 104347.

Kundu, R., & Das, S. (2024). A comparative study of learning outcomes of self-directed and instructor-led learning for postgraduate students in an Indian B-School. Alliance University.

Means, B., Toyama, Y., Murphy, R., Bakia, M., & Jones, K. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. U.S. Department of Education.

The Mediating Role of Self-Regulated Online Learning Behaviors. (2024). *Journal of Online Learning and Teaching, 20* (4), 55–72.

Unraveling the Impact of Blended Learning vs. Online Learning on Learners' Performance: Perspective of Self-Determination Theory. (2025). *Educational Research Review, 36*, 101485.

Zhang, J. (2025). Meta-analysis of artificial intelligence in education. *Higher Education Studies, 15* (2), 189–203.