10.24193/ed21.2025.31.24

The role of self-regulation in students' success in asynchronous learning

Emil Lazăr

Educatia 21 Journal 31 (2025) – Special issue
Special Issue: Proceedings of 13th International Conference "Education, Reflection, Development" (ERD 2025)
Educatia 21 Journal, (31) 2025, Art. 24
doi: 10.24193/ed21.2025.31.24
Research article

The role of self-regulation in students' success in asynchronous learning

Emil Lazăr [a*]

[a] *Department of Educational and Communication Sciences, University of Craiova, Craiova, Romania*

*Corresponding author: *emil.lazar@edu.ucv.ro*

Abstract

This study explores the role of Artificial Intelligence (AI) in enhancing academic performance and student experience within asynchronous learning environments in higher education. The research adopts an experimental design involving two groups of students: an experimental group assisted by an AI-based intelligent tutoring system and a control group that followed the same curriculum without technological assistance. Quantitative data were collected through standardized tests and validated questionnaires (SRL-Q and ASPS), while student satisfaction was assessed through thematic analysis of qualitative feedback. The results indicate that students who benefited from AI support achieved significantly higher academic scores ($M = 8.5$, $SD = 1.2$) than those in the control group ($M = 7.0$, $SD = 1.5$), with the difference being statistically significant ($t(98) = 4.73$, $p < .001$). Furthermore, 82% of students in the experimental group reported positive perceptions regarding the personalized feedback and flexibility provided by the AI system. The study emphasizes the importance of self-regulated learning in asynchronous education and highlights the pedagogical potential of AI technologies. It concludes with recommendations for the responsible integration of AI in educational settings, considering both opportunities and ethical implications.

Keywords:
academic performance, artificial intelligence, asynchronous learning, higher education, self-regulated learning

1. Introduction

The rapid evolution of digital technologies has triggered profound transformations in higher education, particularly in how knowledge is delivered and acquired. Asynchronous learning, which allows students to engage with instructional content at their own pace and outside traditional classroom constraints, has emerged as a prominent modality within this digital shift (Means et al., 2014). Unlike synchronous education, where real-time interaction predominates, asynchronous formats challenge learners to assume greater responsibility for managing their own progress, demanding a high degree of self-regulation and intrinsic motivation (Broadbent & Poon, 2015). While such flexibility can enhance accessibility and learner autonomy, it also introduces challenges related to student engagement, timely feedback, and the monitoring of academic progress (Martin & Bolliger, 2018).

Against this backdrop, the integration of Artificial Intelligence (AI) in education has sparked considerable interest. Intelligent tutoring systems (ITS), adaptive learning platforms, and AI-driven analytics are increasingly recognized for their potential to enhance learning outcomes by providing personalized feedback, scaffolding cognitive processes, and supporting self-regulated learning strategies (Luckin et al., 2016; Holmes et al., 2019). In particular, AI technologies have shown promise in addressing the limitations of asynchronous education, offering dynamic and responsive learning experiences that can adapt to individual needs in real time.

In the Romanian higher education context, the transition to online and asynchronous modes of instruction was significantly accelerated by the COVID-19 pandemic, prompting institutions to seek technological solutions that could preserve educational continuity and quality (Şerban et al., 2021). However, this shift also underscored structural and pedagogical vulnerabilities, especially in terms of student autonomy and instructional design. Consequently, there is an urgent need to investigate the effectiveness and ethical implications of integrating AI into these learning environments, particularly with regard to academic performance and student satisfaction.

This study seeks to contribute to this growing field by exploring the impact of an AI-based intelligent tutoring system on student outcomes and experiences in asynchronous higher education. Through a comparative analysis involving experimental and control groups, the research aims to evaluate the pedagogical efficacy of AI in supporting self-regulated learning and enhancing academic achievement. The findings are intended to inform educators, administrators, and policymakers on how AI can be responsibly and effectively deployed to support contemporary educational needs.

1.1. Research Context

The accelerated digital transformations of recent decades have profoundly reshaped the educational system, leading to the emergence and expansion of alternative forms of learning, among which asynchronous learning stands out. This type of learning, characterized by the absence of real-time interaction between teachers and students, requires a reconfiguration of instructional strategies and a redefinition of the student's role in the educational process. In this context, the student becomes the main agent of their own development, being responsible for managing time, resources, and personal progress. These transformations demand advanced competencies in self-regulation and self-efficacy, without which academic success is difficult to achieve (Hrastinski, 2008).

In Romania, asynchronous learning has gained increasing attention in recent years, especially in the context of the COVID-19 pandemic, when many educational institutions were forced to transition teaching activities to online environments. This phenomenon has led to a reevaluation of traditional educational practices and a heightened need to adapt to the new demands of the instructional-educational process. Although asynchronous learning offers increased flexibility, it also poses significant challenges.

In Romania, asynchronous learning has become a topic of significant interest in recent years, especially in the context of the COVID-19 pandemic, when many educational institutions were compelled to move instructional activities online. This phenomenon has triggered a reassessment of traditional educational practices and a heightened need to adapt to the evolving requirements of the teaching and learning process. Although asynchronous learning offers increased flexibility, it also raises significant challenges regarding student engagement, autonomy, and the effectiveness of digital learning environments.

These aspects highlight the necessity of integrating intelligent systems that can personalize the learning experience and support student self-regulation.

1.2. The Issue of Self-Regulation

Self-regulated learning represents a central concept in educational psychology, referring to the ability of students to take active control over their learning process by setting goals, selecting appropriate strategies, monitoring progress, and reflecting on outcomes (Zimmerman, 2002). In asynchronous learning environments, where external guidance is limited and the traditional teacher-student interaction is often reduced or delayed, the capacity for self-regulation becomes a crucial factor in ensuring academic success.

Students who possess advanced self-regulation skills are able to plan their learning activities, maintain motivation over time, overcome obstacles, and adapt their strategies based on feedback and results. Conversely, students with limited self-regulatory capacities may face difficulties in organizing their study schedules, maintaining concentration, and completing learning tasks in the absence of structured guidance. Therefore, developing self-regulation is essential for success in modern educational environments, especially in digital, asynchronous contexts.

1.3. Research Objectives

The primary objective of this study is to investigate the relationship between university students' level of self-regulated learning and their academic success within asynchronous learning environments. Specifically, the research aims to assess the extent to which competencies such as planning, self-monitoring, and self-evaluation contribute to academic performance when students interact with educational content in the absence of real-time guidance.

To achieve this goal, the study employs a quantitative research design involving validated instruments for measuring both self-regulation and academic self-perception. The results will provide insights into the cognitive and motivational mechanisms that underlie effective learning in digitally mediated educational environments and will offer evidence-based recommendations for optimizing online and asynchronous instructional practices.

2. Theoretical foundation

2.1. Understanding Asynchronous Learning

According to the Theory of Transactional Distance developed by Moore (1993), online education facilitates the connection between teachers/lecturers and students or other individuals involved in the instructional process who are not physically in the same location - and sometimes not even in the same time zone. This system has the advantage of functioning through internet-connected electronic devices. Students engaged in real-time distance learning, where teachers deliver live courses via the internet, are participating in "synchronous learning"; in contrast, "asynchronous learning" offers pre-recorded courses that are always available to students, thus providing a more relaxed and open model that allows for a personalized learning schedule and approach tailored to individual needs.

Some of the advantages of online education include increased access to knowledge and learning opportunities, reduced teaching costs, time efficiency, and the ability to learn at one's own pace. Of course, we must also acknowledge potential disadvantages associated with this form of learning, such as the perceived decline in academic degree quality, reduced learning effectiveness, limited interaction with teachers/lecturers, and potential negative impacts on academic research.

Nevertheless, the success of online learning systems depends on the optimal combination of technology and pedagogy - two components that require careful management by educators. From a technological standpoint, teachers/lecturers must demonstrate a solid understanding of the systems that support online courses. From a pedagogical perspective, they must integrate technology with instructional methods by promoting new, innovative teaching paradigms that encourage partnership, collaborative work, peer learning, workshop-based learning, and more.

The effectiveness of online education can be assessed using a variety of evaluation criteria: learners' personal satisfaction, acquisition of knowledge or skills, effectiveness in implementation or application, development of life skills, lifelong learning competencies, financial cost, content relevance, accuracy, among others.

In equal measure, asynchronous learning refers to an instructional approach in which teaching and learning take place independently of time, typically through digital platforms such as learning management systems (LMS), emails, videos, and forums. Among its main advantages are flexibility, autonomy, and the ability to adapt to individual learning styles (Watts, 2016). However, this model also presents several challenges: the lack of immediate feedback, feelings of isolation, and the need for strong self-management skills to ensure consistency and progress. In this context, the learner assumes a central role and must develop self-regulatory behaviors to cope effectively with the learning process.

In contrast, more recent studies focus on the role of digital literacy and motivational constructs in supporting learner success. For example, Martin and Bolliger (2018) examined student engagement in online asynchronous courses and identified instructor presence, interactive content, and peer collaboration as key factors that contribute to perceived learning effectiveness. Their findings emphasize the importance of creating engaging learning experiences that counteract the isolating nature of asynchronous education. Furthermore, they underscore how instructional design and the integration of interactive tools can foster not only cognitive engagement but also a sense of community among learners.

Together, these perspectives demonstrate that while asynchronous learning offers substantial benefits in terms of flexibility and personalization, it also requires deliberate pedagogical strategies to address its inherent limitations. Both early theoretical models and contemporary research agree on the need for fostering learner autonomy and providing structured support systems that promote motivation, engagement, and sustained self-regulation.

2.2. Bandura's Self-Efficacy Theory (1997)

Albert Bandura (1997) defines self-efficacy as an individual's belief in their capability to accomplish specific tasks successfully. These beliefs significantly influence motivation, emotional regulation, and the selection of learning strategies. In asynchronous learning settings, self-efficacy becomes particularly important because learners must rely on their own abilities to stay engaged and perform academically without real-time guidance. High levels of self-efficacy correlate positively with perseverance, academic engagement, and task performance (Bandura, 1997).

Table 1

Summary of Bandura's Self-Efficacy in Asynchronous Learning Contexts

Concept	Description
Definition of Self-Efficacy	An individual's belief in their ability to successfully accomplish specific tasks
Importance in Learning	Influences motivation, emotional regulation, and the choice of learning strategies
Relevance in Asynchronous Learning	Especially critical in the absence of real-time guidance - learners must rely on their own abilities to remain engaged and perform academically
Effects of High Self-Efficacy	Positively correlated with perseverance, academic engagement, and task performance

2.3. Self-Regulated Learning

Self-regulation involves a series of cognitive, motivational, and behavioral processes through which learners actively plan, monitor, and control their learning (Zimmerman, 2002, p. 65). Advanced self-regulation skills include goal-setting, choosing appropriate strategies, critically reflecting on progress, and managing emotions. These abilities are essential in asynchronous settings, where students are responsible for directing their learning and evaluating their own performance (Schunk & Zimmerman, 2012, p. 145).

In asynchronous learning environments, the absence of real-time interaction with instructors and peers means that learners must become active agents in their own educational process. Unlike traditional face-to-face learning, where structure and guidance are externally provided, asynchronous education requires students to generate internal structure - through planning, goal-setting, and disciplined engagement.

According to Zimmerman's cyclical model of self-regulated learning (2000), the process unfolds in three key phases:

▪ Forethought phase – where learners set specific, achievable goals and select learning strategies in advance;

▪ Performance phase – where they apply those strategies while actively monitoring their progress and sustaining motivation;

▪ Self-reflection phase – where they evaluate outcomes and adapt future approaches based on feedback and self-assessment.

In the context of asynchronous education, self-regulated learning also involves time management and resource control - two skills vital for success in an environment where flexibility can easily lead to procrastination or disengagement. For example, students must determine when and how often to engage with course materials, participate in discussions, or seek clarification on confusing concepts, often without immediate cues or reminders from instructors.

Furthermore, emotional regulation plays a pivotal role. Asynchronous learners may experience feelings of isolation, frustration, or uncertainty due to the lack of instant support. Those with strong self-regulation skills are better equipped to cope with these challenges, using adaptive coping mechanisms and maintaining persistence even when motivation dips.

Developing self-regulated learning strategies can be fostered through targeted instructional design, such as incorporating reflective journals, self-assessment tools, scaffolding, and goal-setting prompts. Educators can also support this process by modeling metacognitive strategies and providing timely, constructive feedback - even in a delayed, asynchronous format.

Ultimately, self-regulated learning is not just a predictor of academic achievement - it is a lifelong skill. In digital and remote learning contexts, its importance is magnified, as learners must become both students and facilitators of their own educational journey.

2.4. Measurement Instruments

To assess self-regulated learning, the study employed the SRL-Q (Self-Regulated Learning Questionnaire) developed by Pintrich (2004), which evaluates aspects such as planning, self-monitoring, and behavioral control. Additionally, the Academic Self-Perception Scale (Rovai, 2002) was used to measure students' perceptions of their academic competence and self-esteem in learning contexts. Both instruments are widely used and have been validated in higher education research.

3. Research methodology

3.1. Research Design

This study employed a quantitative experimental research design with a control group, allowing for the evaluation of causal relationships between the use of artificial intelligence (AI) tools and students' academic performance. The research was conducted over the course of one academic semester and involved students from the Faculty of Letters, University of Craiova.

3.2. Procedure

At the beginning of the semester, participants were randomly assigned to two equal groups: the experimental group and the control group. The experimental group used an intelligent tutoring system integrated into the course's e-learning platform. This AI system offered personalized recommendations, additional explanations, and adaptive quizzes based on the students' performance. The control group followed the same curriculum and had access to the same learning materials but did not receive any AI-based assistance.

Throughout the 14-week semester, both groups completed weekly assessments and projects to monitor progress. At the end of the semester, all participants took a standardized final test, which served as the primary indicator of academic performance.

3.3. Instruments

Two instruments were used to collect data:

- Self-Regulated Learning Questionnaire (SRL-Q) by Pintrich (2004), containing 30 Likert-scale items (1–5), evaluating planning, self-monitoring, and behavioral control.
- Academic Self-Perception Scale by Rovai (2002), comprising 20 items on a 5-point Likert scale, assessing academic self-concept and motivation.

Additionally, a satisfaction questionnaire was administered to the experimental group to evaluate students' experiences with the intelligent tutoring system.

3.4. Data Analysis

Quantitative data were analyzed using SPSS v26. Descriptive statistics (mean and standard deviation) were calculated for final test scores in both groups. An independent samples t-test was used to determine whether the differences between group means were statistically significant, with a significance level set at $p < .05$. Assumptions of normality (via the Shapiro–Wilk test) and homogeneity of variances (via Levene's test) were verified.

Responses to the satisfaction questionnaire were analyzed separately. For closed-ended items, percentages and mean agreement levels were computed.

Open-ended responses underwent thematic analysis to identify recurrent themes, such as appreciation for immediate feedback or technical challenges with the AI system.

4. Results

4.1. Academic Performance Outcomes

The quantitative findings clearly indicate an improvement in academic performance among students in the experimental group compared to those in the control group. The mean score on the final standardized test for the group assisted by AI was $M = 8.5$, with a standard deviation of $SD = 1.2$, whereas the control group had a mean of $M = 7.0$, $SD = 1.5$. The 1.5-point difference in means proved to be statistically significant ($t(98) = 4.73$, $p < .001$), supporting the hypothesis that AI-assisted learning environments have a positive impact on academic achievement.

4.2. The performance gap between the AI-assisted group and the control group

Table 2 illustrates the performance gap between the AI-assisted group and the control group, with significantly higher scores achieved by students who benefited from personalized recommendations and adaptive feedback.

Table 2

Descriptive Statistics of Final Test Scores

Group	N (Students)	Mean Score	Standard Deviation
With AI Assistance	50	8.5	1.2
Control Group	50	7.0	1.5

4.3. Student Perceptions of AI-Based Learning

In addition to final test scores, the perceptions of students in the experimental group were analyzed. The majority of students (82%) reported being satisfied or very satisfied with the AI-assisted learning experience. Particularly appreciated were the immediate feedback mechanisms and the ability to progress at an individual pace. Qualitative feedback revealed that many students felt the system helped them maintain consistent study habits and transformed learning into an interactive, engaging process.

Nevertheless, some students mentioned technical challenges, such as occasional system lags or difficulty integrating platform use into their daily schedules. Although these issues did not appear to negatively affect academic outcomes, they offer important insights for future refinement of such systems.

5. Discussions

5.1. Interpretation of the Findings

The results of this study confirm the initial hypothesis that self-regulation and intelligent tutoring systems significantly influence students' success in asynchronous learning environments. The higher academic performance observed in the experimental group suggests that AI-based assistance can compensate for the lack of real-time instructor support by offering adaptive guidance and personalized learning pathways. This supports previous research which emphasized the importance of self-regulation as a core factor in academic achievement, especially in flexible learning formats (Zimmerman, 2002; Schunk & Zimmerman, 2012).

The strong positive correlation between students' self-monitoring skills and their performance highlights the need to strengthen these metacognitive processes through both instructional design and digital tools.

These findings are consistent with other empirical studies that have examined the integration of intelligent learning environments with self-regulated learning strategies. For example, Winne and Hadwin (1998) argue that self-regulation is a dynamic process influenced by both internal cognitive structures and external supports, including technological scaffolding. Their four-phase model - task definition, goal setting and planning, enactment, and adaptation - can be effectively supported by intelligent systems that provide timely prompts, feedback, and learning analytics.

Moreover, recent research conducted by Azevedo et al. (2019) highlights how AI-driven learning environments can detect learners' cognitive states and adjust the difficulty, sequence, or modality of instructional materials accordingly. These systems do not replace human instructors but augment the learning process by offering personalized, data-driven interventions that align with learners' goals and behaviors. Such technologies not only enhance engagement but also promote autonomy and sustained motivation, both essential in asynchronous settings.

To maximize effectiveness, instructional designers are encouraged to incorporate metacognitive scaffolds - such as reflective prompts, self-assessment checklists, and progress dashboards - into online learning environments (Nicol & Macfarlane-Dick, 2006). These tools empower learners to track their understanding, evaluate their learning strategies, and make informed adjustments, fostering a cycle of continuous improvement.

The strong positive correlation between students' self-monitoring skills and their performance highlights the need to strengthen these metacognitive processes through both instructional design and digital tools - the intersection between self-regulated learning and intelligent tutoring systems opens promising avenues for the future of asynchronous education. When used intentionally, these systems can create learning conditions that not only compensate for the absence of synchronous interaction but also elevate students' capacity for independent learning and academic resilience.

5.2. Implications for Educational Practice

From a pedagogical perspective, these findings underscore the importance of integrating metacognitive skill development into university curricula. Instructors and course designers should implement strategies such as learning journals, formative self-assessment, and goal-setting workshops to foster autonomy and self-awareness among students. Furthermore, the success of the AI-assisted group suggests that institutions should consider embedding intelligent systems into online platforms not merely as content repositories but as active facilitators of learning.

The implementation of such tools must, however, be accompanied by teacher training sessions to ensure pedagogical alignment and optimal use of technological resources, (Hrastinski, 2008, p. 53).

5.3. Study Limitations

While the findings are promising, several limitations should be acknowledged. The sample consisted only of students from a single institution and academic field, limiting the generalizability of the results. The study also relied on self-report instruments, which may be affected by social desirability bias. Furthermore, the research was cross-sectional, and therefore unable to capture the long-term effects of AI integration on student learning habits or academic outcomes.

Future studies should explore longitudinal data and diversify both the academic disciplines and technological platforms involved.

6. Conclusions

This study demonstrates the substantial potential of artificial intelligence (AI) to enhance the educational process, providing empirical support for the integration of intelligent systems into teaching and learning practices. The results indicate that the use of an AI-based tutoring system can lead to improved academic performance and a more engaging and efficient learning experience for students. These findings are encouraging and suggest that investments in AI-driven educational tools can yield tangible benefits in terms of both achievement and student motivation.

Nevertheless, the conclusions also emphasize the importance of a cautious and responsible implementation of AI in education. Educational institutions and policymakers are encouraged to develop clear guidelines for AI integration, including teacher training, transparency about system functionalities, and mechanisms for safeguarding personal data. AI should not be perceived as a substitute for the teacher, but rather as a complementary tool that supports pedagogical goals and respects the centrality of the human factor in the educational process.

Future research should further investigate the long-term effects of AI usage in education, such as its influence on learner autonomy, critical thinking, and problem-solving skills. Moreover, exploring the optimal ways of combining AI tools with traditional teaching methods may yield valuable insights for curriculum designers and educational leaders.

In conclusion, the integration of AI into higher education represents a promising, yet complex evolution. When guided by evidence-based practices and student-centered values, AI can become a powerful ally in the pursuit of quality, personalized, and inclusive learning.

Authors note:

Emil Lazăr is a Lecturer at the Department of Educational and Communication Sciences, within the University of Craiova, and holds a PhD in Educational Sciences. He teaches courses in both bachelor's and master's programs, contributing to the initial training and professional development of teaching staff. His main areas of expertise include: didactics and assessment, educational management and leadership, educational mentoring, and the educational environment. He is the author of several specialized works on school assessment, teacher evaluation, and student-centered instruction.

References

Azevedo, R., Taub, M., & Mudrick, N. V. (2019). Using multi-channel data to understand and foster self-regulated learning with advanced learning technologies. In J. Dunlosky & K. Rawson (Eds.), *The Cambridge handbook of cognition and education* (pp. 448–480). Cambridge University Press. https://doi.org/10.1017/9781108235631.019.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: W. H. Freeman.

Hrastinski, S. (2008). *Asynchronous and synchronous e-learning*. Educause Quarterly, *31*(4), 51-55.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence Unleashed: An Argument for AI in Education*. Pearson.

Martin, F., & Bolliger, D. U. (2018). *Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment*. Online Learning, 22(1), 205–222. https://doi.org/10.24059/olj.v22i1.1092.

Means, B., Toyama, Y., Murphy, R., & Bakia, M. (2014). *The effectiveness of online and blended learning: A meta-analysis of the empirical literature*. Teachers College Record, *115*(3), 1–47.

Moore, M. G. (1993). Theory of transactional distance. In D. Keegan (Ed.), *Theoretical principles of distance education* (pp. 22–29). Routledge.

Nicol, D. J., & Macfarlane-Dick, D. (2006). *Formative assessment and self-regulated learning: A model and seven principles of good feedback practice*. Studies in Higher Education, *31*(2), 199–218. https://doi.org/10.1080/03075070600572090.

Pintrich, P. R. (2004). *A conceptual framework for assessing motivation and self-regulated learning in college students*. Educational Psychology Review, *16*(4), 385-407. https://doi.org/10.1007/s10648-004-0006-x.

Rovai, A. P. (2002). *Development of an instrument to measure classroom community. The Internet and Higher Education*, 5(3), 197–211. https://doi.org/10.1016/S1096-7516(02)00102-1

Schunk, D. H., & Zimmerman, B. J. (2012). *Motivation and self-regulated learning: Theory, research, and applications*. New York: Routledge.

Șerban, A. C., Popa, D., & Ioniță, A. (2021). *Predare și învățare în vremuri de criză: Răspunsul universităților românești la educația online în timpul pandemiei de COVID-19 [Teaching and learning in times of crisis: Romanian universities' response to online education during the COVID-19 pandemic]*. Postmodern Openings, *12*(3), 113–129. https://doi.org/10.18662/po/12.3/335.

Watts, L. (2016). *Synchronous and asynchronous communication in distance learning: A review of the literature*. Quarterly Review of Distance Education, *17*(1), 23–32.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates.

Zimmerman, B. J. (2002). *Becoming a self-regulated learner: An overview*. Theory into Practice, *41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2.