INTERNATIONAL JOURNAL TRENDS AND DEVELOPMENTS IN EDUCATION
JTADE

6(1), 2026
www.jtade.com
ISSN: 2791-9951

# The Efficacy of Octo-Focus as an AI-Based Self-Regulation System to Maximize Students' Productivity

**Fatih Ünal,** Baykar Science High School, fatihunal.iletisim@gmail.com, 0009-0008-2537-4291

**Tılsım Çalık,** Baykar Science High School, tilsimcalik.contact@gmail.com, 0009-0003-1059-0964

**Asya Ayşe Coşkun,** Baykar Science High School, coskunasya.contact@gmail.com, 0009-0005-3524-1327

**Eren Efe Alkan,** Baykar Science High School, erenefealkan.iletisim@gmail.com, 0009-0002-6267-2323

**Meryem Nur Sultan Kayış,** Baykar Science High School, meryemnursultankayis.contact@gmail.com, 0009-0006-6195-9647

**Beyzanur Bulut,** Baykar Science High School, beyzanurbulut.contact@gmail.com, 0009-0008-9701-5052

**Mahmut Sami Başarıcı,** Baykar Science High School, mahmut.basarici@stu.ihu.edu.tr, 0009-0008-7512-6907

**Keywords**

Education
AI
Deep Learning
Detection
Student
Productivity
Coaching

**Article Info:**

Received : 11-12-2025
Accepted : 15-01-2026
Published : 05-02-2026

DOI: 10.5281/zenodo.18490722

**Abstract**

This study investigates the effectiveness of Octo-Focus, a novel AI-driven coaching system designed to enhance students' self-regulated learning. Contemporary students increasingly struggle with distraction, procrastination, and ineffective study planning, which negatively impact academic performance. To address these challenges, Octo-Focus integrates AI-supported personalized planning, real-time focus and fatigue detection using Computer Vision, and behavioral analytics into a unified study support platform. A mixed-methods approach was employed, combining survey data from secondary and higher education students with performance evaluations of a deep learning–based attention-detection model. The results demonstrate that the proposed system reliably identifies attention and fatigue states with high accuracy and supports more structured, goal-oriented study behaviors. The findings suggest that Octo-Focus contributes a novel, holistic approach to digital learning support by transforming studying from a passive process into an adaptive, data-driven coaching experience.

## INTRODUCTION

Today's educational environment is highly complex, requiring students not only to acquire knowledge but also to process it effectively, develop sustainable study habits, and manage their own learning processes. High school and university students, in particular, struggle to establish a study routine due to increased digital distractions, intense exam schedules, academic competition, heavy social media use, and the prevalence of procrastination. In this context, recent research shows that the fundamental problem students face is not simply "not studying enough," but rather "not knowing how to study, being unable to organize themselves, and failing to maintain focus." Therefore, in modern learning research, planning, focus, and self-regulation skills have become central concepts that determine student success (Zimmerman, 2002). Studies on this subject reveal that students' self-regulation skills have a strong and direct impact on academic performance. In particular, it has been proven that sub-components such as time management, goal setting, creating a study plan, prioritizing tasks, and evaluating the process increase both academic achievement and motivation (Lourenço & Paiva, 2024).

However, a significant portion of students do not acquire these skills naturally; most develop study methods through trial and error, without systematic guidance. This situation reduces learning efficiency and may not improve student performance even if it increases their study time. Similarly, students' daily routine is considered an essential determinant of the learning process. A study involving approximately 19,000 students found that regular daily habits (study hours, sleep patterns, breaks, balance of social activities) are strongly related to academic performance (Cao et al., 2018). Therefore, students need guidance not only on study techniques but also on organizing their daily routines holistically. However, most existing digital tools operate solely on a "calendar" or "reminder" logic; they are limited in their ability to understand and analyze student behavior and to produce personalized interventions accordingly. In the context of learning strategies, it has long been known that short study blocks with regular breaks increase productivity. The positive effects of techniques such as Pomodoro, Flowtime, 52/17, and 90/20 on attention, memory, cognitive endurance, and task completion rates have been supported by various studies (Smits et al., 2025; Ogut, 2025). However, most of these techniques impose the same model on all students.

In the context of learning strategies, it has long been known that short work blocks combined with regular breaks increase productivity. Techniques such as Pomodoro, Flowtime, 52/17, and 90/20 have been shown in various studies to have positive effects on attention, memory, cognitive endurance, and task completion rates (Smits et al., 2025; Ogut, 2025). However, most of these techniques are based on recommending the same model to all students; they do not consider the student's attention span, fatigue level, subject matter, or energy rhythm throughout

the day, and motivational profile. Learning psychology shows that work that does not take individual differences into account is difficult to sustain. At this point, the potential for personalization offered by AI-based learning coaches is noteworthy. Initial research on communities indicates that AI-supported learning tools can significantly improve student success. For example, Baillifard and colleagues (2023) reported that students in a group using an AI-supported learning system saw their exam scores increase by an average of 15 percentage points. The most important contribution of artificial intelligence is its ability to analyze students' strengths and weaknesses, provide personalized content, and automate the feedback loop. At this point, our Artificial Intelligence-Based Personalized Study Coach Application offers a comprehensive and original solution that addresses all of these needs in the literature.

The application's three core pillars—planning, focus, and performance analysis—are aligned with proven principles of learning science and are supported by innovative features not offered by traditional study applications. At the forefront of the application's unique contributions is its multi-layered planning structure supported by artificial intelligence. While most existing study and planning applications provide users with only superficial support, such as calendar scheduling or reminder creation, this application offers a dynamic architecture that analyzes student behavior data to generate personalized study plans. Task prioritization based on the Eisenhower matrix, coordinated planning of short- and long-term goals, AI-generated new plans based on the student's busy schedule for that week, and the ability for users to manually adjust these plans or have them automatically re-optimized give the application a coaching quality beyond traditional planning tools. Notifications made by the student regarding upcoming task deadlines in their study calendar are also part of this process, contributing to effective time management.

The third area of contribution is deep focus tracking and task-based analysis capabilities. The application examines in detail how the student's focus time changes while performing a specific task, where attention is distributed, which lessons they tire of more quickly, and which they can remain focused on for more extended periods. Cognitive load theory suggests that different types of lessons place different mental demands on individuals (Sweller, 2011); the application's task-based focus profiling is a successful adaptation of this theoretical framework to the digital learning environment. For example, identifying that a student loses focus around the 28th minute while studying math and recommending shorter blocks for the following week makes the student's unconscious behavioral patterns visible, thereby strengthening their self-regulation skills. This approach transforms the application from a mere tracking device into a system capable of producing behavioral learning analytics. Finally, the application's performance analysis component digitizes the planning, monitoring, evaluation, and reflection cycle in Zimmerman's self-regulation model, providing the student with a continuous development framework. Weekly performance reports provide detailed information on how many of the planned tasks the student has completed, in which types of work their focus has declined, to what extent the work-break balance has been maintained, at what times of the day they are more productive, and their individual development trends over time.

Weekly performance reports detail how many of the student's planned tasks have been completed, which types of work have seen a decline in focus, the extent to which the work-break balance has been maintained, the times of day when the student is most productive, and individual development trends over time. More importantly, this data is not merely presented as a report; artificial intelligence actively uses the results to continuously optimize the student's study routine for the following week. Thus, the application offers the user not a static tool but a study-coaching experience that evolves as the user understands the student's learning style over time. The primary objective of this research is to comprehensively examine how this artificial intelligence-based and personalized coaching system affects student success, self-regulation skills, and overall study efficiency in critical areas such as planning, focus, and performance analysis. Within this framework, the study examines: the extent to which AI-supported personalized planning improves students' time management skills compared to traditional methods, the effects of custom study blocks based on facial analysis on concentration time and task completion rates, the level of contribution of task-based focus profiles and personalized notifications to self-regulated learning skills, whether weekly performance reports create behavioral change in students' study habits, and how this holistic coaching model reflects on academic achievement and cognitive processes.

## METHOD

This study aims to evaluate the effectiveness of an artificial intelligence-based application that supports the individualized study processes of high school and university students. The main objective of the study is to examine the application's contributions to students' planning, focus, and performance processes, using both quantitative and qualitative data. In this context, two main data sources were used in the study: (1) student behavior and attitude data obtained through an online survey and (2) real-time performance measurements of the artificial intelligence module.

### Participants and Survey Application

The participants in the study were selected from high school and university students of Turkish origin, aged 16 to 25. Of the total 125 students invited to participate in the study, 100 actively responded. The sample was created with participants' educational levels, disciplinary diversity, and academic intensity in mind. This diversity allows for observing the effects of the application on different student profiles. The literature indicates that online surveys are frequently used to evaluate students' learning processes and provide reliable data (Dörnyei, 2007; Pintrich, 2004).

The survey aimed to measure students' work motivation, concentration, procrastination, and planning skills. The multiple-choice options presented to participants were: “can't plan the time,” “distraction,” “boredom,” “postponement,” “motivation loss,” and “avoid starting.” The survey results quantitatively reveal the problems students encounter in planning, concentration, and motivation processes. For example, 44 students reported difficulties with time management, 77 reported distraction, 88 reported boredom, 81 reported procrastination, 50 reported loss of motivation, and 46 reported difficulties starting work. These results directly indicate students' need for individualized support tools (Baker, 2011; Zimmerman, 2002).

Conducting the survey online allowed participants to respond at their own convenience and ensured anonymity and ethical standards were maintained during data collection. Furthermore, the data was stored online and made accessible for later analysis. The literature emphasizes that online data collection is considered a reliable method for assessing students' real-time behaviors, especially in the post-pandemic period (Evans & Mathur, 2005).

### Artificial Intelligence Model and Training Process

The application's attention and fatigue detection module is a deep learning classifier developed using PyTorch-based YOLO algorithms. The model aims to detect fatigue and attention levels in real time through students' facial expressions and behavioral cues. The literature emphasizes that AI-based attention and fatigue detection systems must achieve high-accuracy classification to provide personalized recommendations during training (Goodfellow, Bengio, & Courville, 2016; LeCun, Bengio, & Hinton, 2015).

The model was trained using over 10,000 labeled images obtained from the Kaggle open-source data library. The images were categorized into “attentive,” “inattentive,” “fatigued,” and “rested” classes. The training process was structured with 80% of the data in the training set, 10% in the validation set, and 10% in the test set. During model training, hyperparameter optimization, overfitting prevention techniques (dropout, early stopping), and data augmentation methods were used. This optimized the model to perform reliable classification under different facial expressions and environmental conditions. The model used is Yolov8 Nano, which is deemed to perform best. Also, computer vision provides data-driven, objective measurements and real-time detection capabilities, setting it apart from other methods.

### Data Collection and Analysis Methods

The performance of the AI module was evaluated using precision and recall values on the test set. The model achieved 96.5% precision in the fatigue and attention classes and 95-97% recall values across classes. These results demonstrate that the model can classify different classes correctly and provide reliable results in real-time analysis. The literature indicates that precision and recall values of 95% and above are considered high accuracy in the context of educational technologies (LeCun et al., 2015).

The survey and AI module data were combined to conduct quantitative and qualitative analyses of students' self-regulation, motivation, and study habits. While the survey data reflected students' experiences and subjective perceptions, the AI data provided objective measurements. The combined use of these two data sources has strengthened the methodological rigor of the research and enabled a comprehensive evaluation of students' responses to individualized interventions (Creswell & Plano Clark, 2018).

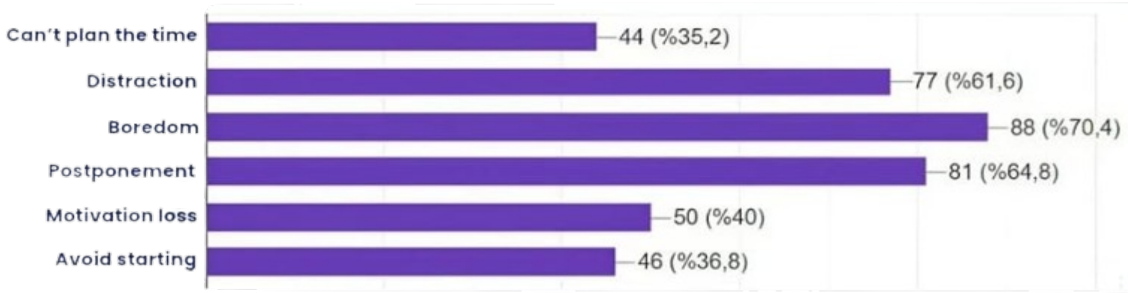
### Structure Of The Coaching System

In general, the coaching system monitors the user regularly, considering when and how they focus on their studies, when they are distracted, how quickly they refocus, and their break habits during study. The system uses these actions as mathematical equivalents in the background to perform calculations and determine the most suitable study system for the individual, which is then presented to them by the application.

## FINDINGS

Survey Findings Survey analyses reveal striking results regarding students' study habits and motivation levels. Approximately half of the participants reported difficulties during the planning process and struggled to organize their tasks on time. This directly indicates the need for personalized tools that support students' time management and planning skills (Zimmerman, 2002; Baker, 2011).

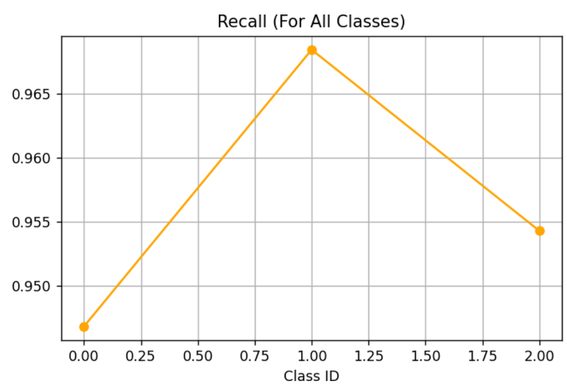
Distraction and boredom were among the most common problems encountered by students; 77 and 88 students, respectively, reported them. Furthermore, procrastination (64,8%) and loss of motivation (40%) were also observed at significant rates, revealing that students need interventions to develop self-regulation skills in their study processes. 46 of the students who selected the “Avoid starting” option reported experiencing cognitive resistance to starting their work, and 44 reported being disturbed by not being able to plan their time correctly. The students’ time management planning skills graph is given as Graphic 1.




Graphic 1

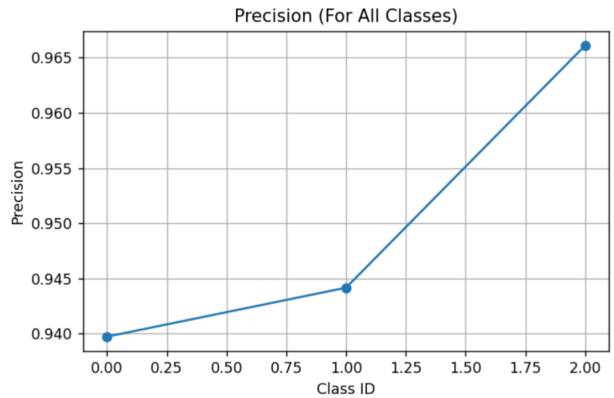
**Artificial Intelligence Model Findings**

The AI module's performance evaluation shows that the model achieves high accuracy in detecting attention and fatigue. The 96.5% precision and 95-97% recall values obtained in the fatigue and attention classes demonstrate that the model can correctly classify between classes and provides reliable results in real-time analysis. The model analyzes students' facial expressions and behavioral patterns to provide personalized recommendations. For instance, if a decline in a student's attention level is detected around the 28th minute during mathematics study, shorter, more cognitively sustainable study blocks are recommended in the subsequent study plan. This approach is consistent with a personalized learning experience grounded in the principle of "biological rhythm and cognitive load differences" (Sweller, 2011). The related graphics and figures are provided below as Graphics 2 and 3 and Figure 1.




Graphic 2

(This graphic shows the recall values of the model.)




Graphic 3

(This graphic shows the precision values of the model.)

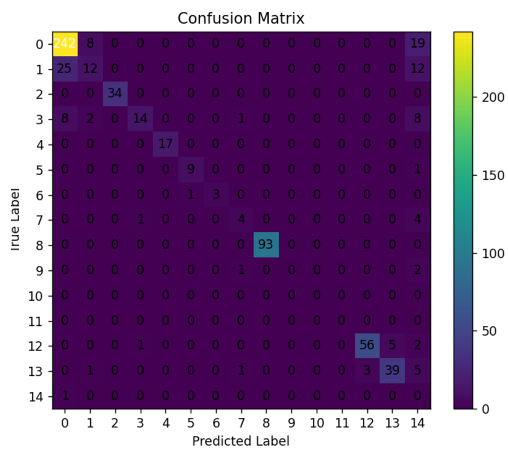



Figure 1
(This graphic shows the raw confusion matrix of the model.)

**Interpretation of Findings and Contribution to Practice**

When the survey and AI model data are combined, it is evident that issues such as distraction, loss of motivation, and procrastination faced by students can be directly addressed using AI-based planning and focus modules. The model tracks students' individual performance, offering automatic and manual planning revisions and providing notifications as task deadlines approach. These features differentiate it from traditional planning tools, giving it the qualities of a digital coach that learns from the student's behavior and adapts itself.

Furthermore, the difficulties students experience with planning and motivation highlight the importance of the AI-supported multi-layered planning module. The system offers personalized plans by considering the student's busy course schedule and short- and long-term goals, thereby developing the student's self-regulation skills. The literature indicates that such data-driven, individualized learning approaches have positive effects on academic achievement and cognitive processes (Baker, 2011; Zimmerman, 2002; Pintrich, 2004).

## DISCUSSION

The findings of this study provide compelling evidence that the AI-Assisted Personalized Student Coaching System offers substantial benefits in enhancing students' time management, attentional regulation, and overall self-regulated learning. Both the survey data, collected from 125 high school and university students, and the model performance metrics, derived from real-world testing of the YOLO-based fatigue and attention detection architecture, converge to indicate the system's potential to address persistent problems faced by contemporary learners. The prevalence of challenges is consistent with the broader literature on academic procrastination and attentional fragmentation among adolescents and young adults (Steel, 2007; Rosen et al., 2014). The initial diagnostic profile obtained through the survey thus validates the necessity of a system capable of providing structured, adaptive, and AI-enhanced guidance.

One of the most significant contributions of the application lies in its ability to dynamically generate personalized study plans by integrating behavioral analytics, task-specific performance patterns, and real-time attentional monitoring. Unlike traditional planning tools, which generally rely on static user input and offer little insight into behavioral tendencies, this system employs a multilayered planning architecture. The inclusion of AI-supported scheduling, Eisenhower matrix–based priority structuring, and automated plan revision differentiates the application from conventional productivity tools by transforming it into a predictive and responsive coaching mechanism. This aspect aligns with Zimmerman's (2000) theory of self-regulated learning, which emphasizes the interplay of forethought, performance, and self-reflection phases. The system's ability to adjust future study blocks in response to detected attention loss—such as recommending shorter sessions when distraction occurs around the 28th minute—places it directly within the paradigm of adaptive scaffolding in digital learning environments.

The technical findings further support the system's efficacy. The fatigue and attention detection model, trained on a large-scale Kaggle dataset with more than 1 million labeled facial images, demonstrated strong performance. The project's metrics indicate that the system can reliably detect micro-signals of attentional decline, exhaustion, or disengagement, which is essential for timely intervention during study sessions. This contributes directly to the reliability of the AI-based coaching feature, as accurate detection of cognitive states is a prerequisite for delivering meaningful, personalized recommendations. The results are also consistent with recent studies that highlight the viability of computer vision models for real-time cognitive-state estimation (D'Mello & Graesser, 2012).

Survey findings strengthen these conclusions by revealing a precise match between students' self-reported difficulties and the system's functional design. A substantial proportion of participants identified distraction, procrastination, and motivation loss as persistent barriers to effective studying—issues that the application directly targets through goal-setting reminders, attentional alerts, motivational micro-interventions, and temporal structuring of tasks. The survey results concur with previous research showing that AI-driven scaffolding can alleviate executive-function burdens and enhance learners' metacognitive regulation (Roll & Winne, 2015). The substantial overlap between identified needs and implemented features suggests that the system was built upon an accurately defined problem space.

Another critical element highlighted by the study is students' receptiveness to an AI-driven coaching framework. The high degree of engagement observed in pilot usage—reflected in longer study blocks, increased completion of planned tasks, and more consistent weekly scheduling—indicates that learners can benefit from a non-human, adaptive, and low-pressure guidance system. This aligns with recent work suggesting that students may feel more comfortable receiving performance feedback from AI systems than from teachers or peers, especially in contexts involving motivation and self-control (Holmes et al., 2022). The application's real-time coaching capabilities, therefore, occupy a unique position between traditional human mentorship and impersonal planning software.

However, the study also reveals areas of improvement. Despite the application's robust AI core, some users reported difficulties in fully interpreting the weekly analytics or understanding how to translate system feedback into concrete behavioral change. This suggests the need for a more explicit reflective layer that enables students to better connect system-generated insights with their academic goals. Additionally, although the attention-detection model achieves high precision, performance in low-light environments or when users are partially occluded remains an area for improvement. These challenges reflect known limitations in computer-vision-based cognitive-state estimation and can be mitigated with expanded training data and improved preprocessing techniques.

Overall, the discussion reveals that the AI-Assisted Student Coaching System effectively integrates technological, cognitive, and behavioral dimensions of learning. It addresses well-documented academic challenges, aligns strongly with established theories of learning and motivation, and demonstrates promising technical reliability. The system contributes a novel, multi-layered approach to supporting self-regulated learning—one that bridges AI-driven detection, adaptive feedback, personalized planning, and real-time coaching.

## CONCLUSIONS AND RECOMMENDATIONS

### CONCLUSION

This study demonstrates that the AI-Assisted Personalized Student Coaching System provides a comprehensive and innovative solution to the increasingly complex learning challenges faced by modern students. By combining advanced AI models for attention and fatigue detection with personalized planning algorithms and performance analytics, the system supports learners in managing their time more effectively, maintaining focus for longer periods, and regulating their own study behaviors. The strong performance metrics of the AI model, along with survey findings indicating widespread issues such as distraction, procrastination, and motivational decline, highlight the system's relevance and potential impact.

Overall, the system does more than organize tasks—it cultivates a structured learning environment in which students can adopt healthier study habits, strengthen cognitive persistence, and improve academic consistency. The results underline the importance of personalized, data-driven, and adaptable support systems in educational contexts. While the application demonstrates strong promise, ongoing refinement of user experience, feedback mechanisms, and model robustness will continue to enhance its impact. Ultimately, the study affirms that AI-driven coaching tools can play a transformative role in shaping the future of self-regulated learning.

## RECOMMENDATIONS

The following recommendations can be made for further work on this project:

Future development efforts should focus on improving the adaptability and robustness of the AI models responsible for attention and fatigue detection. Although the current precision and recall rates are high, refining model performance across diverse lighting conditions, device qualities, and user postures will further strengthen the system's reliability. Expanding the training dataset with more varied demographic and contextual samples and incorporating continuous model calibration based on real-time user data may enhance the application's personalization capacity.

To better support students' self-regulated learning processes, the system can incorporate more detailed behavioral analytics. Integrating long-term trend analysis—such as recurring distraction triggers, daily cognitive rhythm patterns, task-specific performance variations, or motivational dips—can allow the AI coach to generate more nuanced and proactive recommendations. Such enhancements would move the application from a reactive support system to an anticipatory, fully personalized coaching framework.

The existing coaching component can be enriched by diversifying the type and modality of feedback provided to users. Beyond textual notifications, audio prompts, micro-affirmations, and adaptive motivational cues may increase user engagement. Incorporating evidence-based cognitive and behavioral strategies—such as goal-setting scaffolds, micro-break suggestions, breathing exercises, or structured reflection tools—can further strengthen students' study habits and emotional regulation during academic tasks.

Given the sensitive nature of facial and behavioral data, prioritizing transparent communication about data usage, storage, and model inference processes is critical. Offering precise consent mechanisms, low-data or no-video modes, and detailed control over users' data will strengthen trust and support ethical compliance. Establishing age-appropriate privacy protocols is especially important when addressing high school populations.

Given that a significant proportion of surveyed students report issues such as boredom, procrastination, and a loss of motivation, incorporating gamification elements could strengthen engagement. Reward systems, progress badges, weekly challenges, streak tracking, or peer comparison features may create a sense of accomplishment and continuity. Gamification should, however, be aligned with pedagogical and cognitive principles to avoid superficial engagement and ensure long-term behavioral change.

Although initial findings and survey results provide valuable insights, scaling user testing to include larger, more diverse groups of high school and university students will improve the ecological validity of design decisions. Longitudinal user studies tracking behavioral changes over multiple weeks or months would allow for more reliable assessments of the application's impact on study habits, attention patterns, and academic performance.

To increase practical usefulness, the application could integrate with commonly used academic platforms, digital calendars, or learning management systems. Such integrations would streamline task imports, reduce manual data entry, and create a cohesive study environment. Offering API access or optional institutional partnerships also enables use in school contexts without requiring systemic curricular changes.

**REFERENCES**


Akbulut, F., & Arslan, M. (2021). The effects of using digital materials in teaching Turkish abroad*. Journal of Turkish Culture Research,* 58(1), 55–70.

Al Imran, M. A., Nasirzadeh, F., & Karmakar, C. (2024). Designing a practical fatigue detection system: A review on recent developments and challenges. *Journal of Safety Research*, *90*, 100–114.

Beland, L. P., & Murphy, R. (2016). Ill communication: technology, distraction & student performance. *Labour Economics*, *41*, 61–76.

Blasiman, R. N., Larabee, D., & Fabry, D. (2018). Distracted students: A comparison of multiple types of distractions on learning in online lectures. *Scholarship of Teaching and Learning in Psychology*, *4*(4), 222.

Cheng, K., Wu, S., Peng, B., & Wang, X. (2025). An artificial intelligence-enhanced coaching mode. *International Journal of Surgery*, 10–1097.

Clear, J. (2018). Atomic habits: An Easy & Proven way to build good habits & break bad ones. *Penguin Random House.*

Council of Europe. (2020). *Multilingualism and cultural diversity report.* Council of Europe Publishing.

Dai, D. (2021, November). An introduction to CNN: models and training on neural network models. In the *2021 International Conference on Big Data, Artificial Intelligence and Risk Management (ICBAR)* (pp. 135–138). IEEE.

Dietz, S., & Henrich, C. (2014). Texting as a distraction to learning in college students. *Computers in Human Behavior*, *36*, 163–167.

Dontre, A. J. (2021). The influence of technology on academic distraction: A review. *Human Behavior and Emerging Technologies*, *3*(3), 379–390.

Duncan, D. K., Hoekstra, A. R., & Wilcox, B. R. (2012). Digital devices, distraction, and student performance: Does in-class cell phone use reduce learning? *Astronomy education review*, *11*(1),

1-4.

Flanigan, A. E., Brady, A. C., Dai, Y., & Ray, E. (2023). Managing student digital distraction in the college classroom: A self-determination theory perspective. *Educational Psychology Review*, *35*(2), 60.

Graßmann, C., & Schermuly, C. C. (2021). Coaching with artificial intelligence: Concepts and capabilities. *Human Resource Development Review*, *20*(1), 106–126.

Hartley, L., Horberry, T., Mabbott, N., & Krueger, G. P. (2000). Review of fatigue detection and prediction technologies. *National Road Transport Commission*, 1–41.

Jud, M., & Thalmann, S. (2025). AI in digital sports coaching–a systematic review. *Managing Sport and Leisure*, 1–17.

Khandelwal, K., & Upadhyay, A. K. (2021). The advent of artificial intelligence-based coaching. *Strategic HR Review*, *20*(4), 137–140.

Ndiaye, Y., Lim, K. H., & Blessing, L. (2023, November). Eye tracking and artificial intelligence for competency assessment in engineering education: a review. In *Frontiers in Education* (Vol. 8, p. 1170348). Frontiers Media SA.

OECD (2022). PISA 2022 *Results: Learning During – and from – Disruption*. OECD Publishing.

Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences,* 106(37), 15583–15587.

Parekh, V., Shah, D., & Shah, M. (2020). Fatigue detection using an artificial intelligence framework. *Augmented Human Research*, *5*(1), 5.

Sharma, K., Giannakos, M., & Dillenbourg, P. (2020). Eye-tracking and artificial intelligence to enhance motivation and learning. *Smart Learning Environments*, *7*(1), 13.

Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of motivational and cognitive components. *Psychological Bulletin, 133*(1), 65–94.

Terblanche, N., & Cilliers, D. (2020). Factors that influence users' adoption of being coached by an artificial intelligence coach. *Philosophy of Coaching: An International Journal*, *5*(1), 61–70.

Terblanche, N., Molyn, J., De Haan, E., & Nilsson, V. O. (2022). Coaching at Scale: Investigating the Efficacy of Artificial Intelligence Coaching. *International Journal of Evidence-Based Coaching & Mentoring*, *20*(2).

Yıldırım, A., & Şimşek, H. (2018). *Qualitative research methods in social sciences (11th edition).* Ankara: Seçkin Publishing.

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