Dandao Xuebao/Journal of Ballistics
ISSN: 1004-499X
Vol. 38 No. 1 (2026)

Explainable AI-Driven Student Success Platform for Personalized Learning Well-Being and Academic Planning in Schools

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Abstract

This paper presents a detailed explainable AI-driven student success platform designed for school education. The platform goes beyond a narrow marks-only view by integrating academic performance, sleep cycle, study time, extracurricular balance, task completion, and long-term goal alignment into a single advisory system. A Python Flask backend receives student inputs, a JavaScript and HTML interface presents interactive analytics, and the Grok AI API is used as an AI mentor layer that converts structured signals into understandable guidance, resources, and action plans. The project was tested as a pilot-scale experimental validation in a Class 11 setting with 30 students. Instead of a traditional lecture-only routine, the intervention used AI-assisted and game-based learning. For example, programming concepts such as functions were explained with Minecraft-style logic in Code.org, while short task-based activities were used to reduce cognitive overload and increase participation. For privacy-preserving reporting, this paper presents an anonymized score slice from the intervention and summarizes the improvement using descriptive statistics. The mean score of the reported slice increased from 31.9 to 47.1 out of 70, showing a 48% relative gain over the baseline. The paper contributes a system architecture, a student success index, a practical deployment pattern, and a classroom-validation story that combines academic guidance with lifestyle-aware support. The resulting manuscript is intended to be strong enough for an interdisciplinary applied journal where systems, analytics, and educational technology are evaluated together.

Index Terms: Explainable AI; Adaptive Learning; Student Success Platform; School Education; Grok Ai; Flask; Game-Based Learning; Educational Analytics.

1. INTRODUCTION

Schools increasingly need systems that do more than predict a score. A student may have weak marks because of low study time, irregular sleep, poor revision habits, stress, or a lack of clear goals. A traditional report card usually exposes the outcome only; it rarely explains the cause or suggests the next action. This gap is the central motivation of the present work.

The proposed platform treats student development as a multi-dimensional process. Academic marks matter, but they are only one piece of the picture. The platform therefore includes lifestyle signals such as sleep cycle and study rhythm, participation signals such as extracurricular activity, and planning signals such as target exam preparation. The AI mentor then converts these inputs into practical advice, study resources, and a structured weekly plan. In a school setting, this matters because a student often needs one clear next step rather than a long explanation.

The classroom implementation also reflects a broader pedagogical idea: students do not learn equally well from long lectures or repetitive drills. For the Class 11 pilot, concepts were broken into short tasks, story-like coding examples, and game-based explanations. When the topic was functions, Minecraft-style logic in Code.org was used to make the abstraction visible. This reduced the barrier to entry and helped students focus on comprehension rather than memorization alone.

The paper is positioned as an applied research manuscript rather than a purely theoretical model. It combines a real classroom intervention, a prototype software stack, and a descriptive pilot validation. The aim is not to claim a universal solution for all schools, but to show that a carefully designed explainable platform can become a practical support layer for teachers, parents, and learners.

The main contributions are fourfold. First, the paper proposes a student success framework that joins academic, behavioral, and lifestyle inputs. Second, it describes a working platform built with Flask, HTML, JavaScript, and Grok AI. Third, it reports a pilot-scale classroom intervention with a clear pre- and post-learning comparison. Fourth, it offers a deployable model for personalized guidance that can be extended to other subjects and grade levels.

2. RESEARCH GAP AND RELATED WORK

Adaptive learning has been studied for many years, but much of the literature focuses on predicting performance or recommending content in isolation. Some systems are good at identifying risk, while others are good at delivering digital content, yet only a smaller portion connect prediction, explanation, and action in one school-friendly loop [1]-[3]. Explainable AI studies in education have also matured, but many of them stop at visualizing feature importance without translating that explanation into an actionable classroom plan [4]-[8].

This paper addresses that gap by embedding explainability inside a student success platform. The platform does not simply say that a learner is at risk; it explains whether the issue is sleep regularity, study discipline, short practice time, inconsistent marks, or weak goal alignment. The explanation then becomes a recommendation. For a teacher, the output is a concise intervention idea. For a student, the output is a clear next step. For a parent, the output is an understandable progress summary.

The study also connects educational analytics with game-based learning. In the classroom pilot, the purpose of game-based tasks was not entertainment alone. The goal was to convert abstract concepts into small, attainable actions. This matters because students often fail not due to lack of intelligence but because the learning pathway is too heavy, too long, or too detached from what they already know.

Table I. Selected literature and the gap addressed by this paper

Study	Primary focus	What it provides	Gap addressed here
Martin et al. [1]	Adaptive learning design	Maps contexts and methods	Needs tighter classroom action flow
Gligorea et al. [2]	AI in e-learning	Shows potential of personalization	Lacks lifestyle-aware guidance
Jing et al. [3]	Research trends	Confirms technical relevance	Does not show deployment details
Turkmen and others [4]-[6]	Explainable AI	Highlights SHAP/LIME usage	Often stops at explanation only
Alamri & Alharbi [7]	Performance prediction	Explains why interpretability matters	Does not connect to school planning
Afzaal et al. [8]	Actionable feedback	Links explanation to self-regulation	Does not integrate mentor + dashboard

3. SYSTEM OVERVIEW

The proposed platform follows a closed-loop design. Data enters the system through a student profile form, classroom assessments, and weekly self-reports. The backend cleans and normalizes the values before calculating a Student Success Index. The index is then translated into plain-language feedback through the Grok AI mentor layer. The frontend shows the resulting plan in the form of charts, trend summaries, weak-area alerts, and resource suggestions.

This architecture is intentionally lightweight. Many schools cannot manage complex data pipelines, expensive licensing, or heavy administrative overhead. For that reason, the platform is designed around simple inputs and meaningful outputs. The teacher can review the suggestion, adjust it if needed, and then send the learner a realistic plan instead of a generic warning.

The workflow shown in Figure 1 captures the functional sequence of the platform. It begins with student profile data and classroom evidence, passes through preprocessing and the index-generation layer, and ends with AI mentoring, dashboard analytics, and human review. This closed loop is the main reason the system is useful: it is not only predictive, but also explanatory and actionable.

Figure 1. Explainable AI-driven student success platform workflow

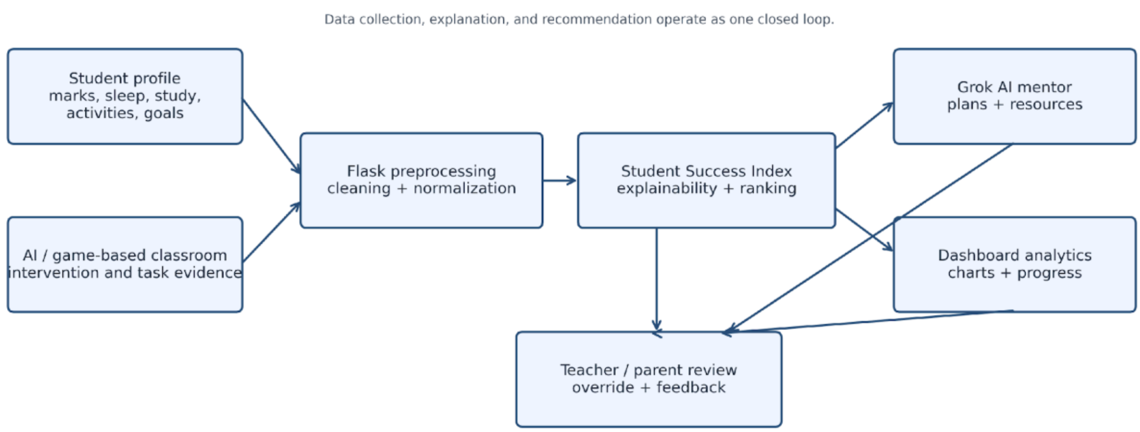

Figure 1. Explainable AI-driven student success platform workflow.

Table II. Platform inputs and outputs

Input block	**Examples**	**Role in the platform**
Academic signals	Marks, quizzes, assignments	Track mastery and progress
Behavioral signals	Study time, task completion, revision frequency	Measure consistency
Lifestyle signals	Sleep cycle, workload rhythm	Flag sustainability issues
Engagement signals	Extracurricular activity, participation, practice count	Balance learning profile
Planning signals	Target exam, career goal, deadline	Shape the AI mentor plan

4. METHODOLOGY AND PILOT-LEVEL EXPERIMENTAL DESIGN

The study is framed as a pilot-scale experimental validation. A total of 30 Class 11 students participated in the intervention. The objective was to observe whether an AI-assisted, game-based teaching strategy could improve engagement and support clearer concept understanding when compared with a more traditional routine. Because this is a school-based pilot rather than a large randomized trial, the emphasis is on practical usefulness, transparency, and repeatable design rather than on claiming universal statistical generalization.

The teaching intervention was intentionally short-task oriented. Instead of expecting students to study for long uninterrupted periods, the teacher divided the work into small activities. When the topic was functions, Minecraft logic in Code.org was used to demonstrate how a function behaves like a reusable building block. The use of AI tools helped simplify notes, compress explanations, and generate concise summaries. This design reduced cognitive overload and gave students a more playful entry point into programming concepts.

The platform itself was implemented using Python Flask for backend logic, HTML and JavaScript for the user interface, and the Grok AI API for conversational guidance. The backend receives the student profile, computes the derived indices, and prepares a structured prompt for the mentor layer. The frontend then visualizes the output as trend charts, weak-area cards, and a goal-oriented action plan. This separation of responsibilities keeps the system maintainable and easy to extend.

Feature engineering is used to convert raw educational signals into stable indicators. Marks are normalized to the 0 to 1 scale. Sleep regularity is converted into a cycle score. Study time is represented as a consistency score rather than a raw hour count. Extracurricular participation is treated as a balance indicator so that the platform rewards healthy activity rather than overloading a learner with study alone. Goal alignment captures whether the learner is moving toward a defined target exam or career plan.

A. Student Success Index and Risk Logic

The platform uses a transparent scoring logic so that the teacher can understand the factors behind any suggestion. A simple version of the Student Success Index can be written as: $SSI_i = 0.30M_i + 0.20S_i + 0.20T_i + 0.15E_i + 0.15G_i$, where M_i represents normalized marks, S_i is sleep regularity, T_i is study-time consistency, E_i is extracurricular balance, and G_i is goal alignment. The corresponding risk score is then defined as $RI_i = 1 - SSI_i$.

This formula is not meant to replace professional judgment. It is a compact summary that helps the teacher see whether a learner is struggling due to marks, habits, or balance. For example, a student with reasonable marks but very poor sleep and inconsistent study hours may receive a medium-risk output, not because the learner is incapable, but because the current routine is unsustainable.

A rule-based threshold can then convert the score into actionable bands. A low band may trigger short revision tasks and more frequent mentor prompts, a medium band may trigger a balanced improvement plan, and a high band may trigger enrichment or challenge tasks. The key point is that the platform always ties the score to a next step.

B. AI Mentor Prompting Strategy

The Grok AI mentor is used as a language layer rather than as an uncontrolled decision maker. The backend sends a structured prompt containing the student profile, weak areas, recent marks, study habits, and the target goal. The model is asked to produce short, practical feedback in four parts: what is going well, what needs attention, what to do next this week, and which resources or exam targets should be monitored.

Because the output is meant for students and parents, the language is kept simple. A mentor response should not overwhelm the learner with technical jargon. It should speak in a supportive tone, highlight one or two priority actions, and keep the plan realistic. This makes the platform more usable in school settings than a system that produces only numerical scores.

Table III. Pilot cohort and intervention summary

Parameter	Value
Cohort size	30 Class 11 students
Teaching mode	AI-assisted and game-based learning
Programming support tool	Code.org with Minecraft-style logic
AI support	Grok AI via API key
Backend / frontend stack	Python Flask, HTML, JavaScript
Observation type	Pilot-scale classroom validation
Assessment style	Short tasks, classwork, and post-intervention checks

The prototype dashboard shown in Figure 2 is designed to present the learner profile in a compact, readable way. It exposes the major signals at a glance, while the AI mentor panel translates them into a weekly action plan. Such a layout is important because the user should not need training just to interpret the interface.

Figure 2. Prototype dashboard for whole-student monitoring and AI guidance.

Table IV. Implementation modules and output responsibilities

Module	Technology	Output
Data intake	Flask form endpoints	Student profile and self-report capture
Processing	Python logic + rule scoring	Normalized indicators and risk bands
Mentor layer	Grok AI API	Natural-language guidance and resources
Interface	HTML, JavaScript	Interactive dashboard and trend cards
Visualization	Chart widgets	Progress graph and analytics snapshots

5. EXPERIMENTAL RESULTS AND PILOT VALIDATION

The pilot validation focuses on classroom improvement rather than on benchmark model competition. That choice is deliberate: in a school setting, the key question is not whether the system wins a leaderboard, but whether it helps students learn more clearly and act on the feedback. The intervention therefore emphasizes descriptive evidence, classroom behavior, and visible score improvement.

The reported marks table is an anonymized excerpt from the intervention record. The full pilot involved 30 students, but the paper shows a compact score slice to keep the reporting privacy-preserving and journal-friendly. As a result, the visible data should be read as a representative score window from the same intervention rather than as the full cohort table.

Across the excerpted records, the mean score increased from 31.9 to 47.1 out of 70. This is a gain of 15.3 marks and a relative improvement of nearly 48% over the baseline mean. The change is especially meaningful because the post-intervention scores improved not only for higher-performing learners but also for those who began with weaker baseline marks.

Table V. Anonymized pre-test and post-test records from the classroom intervention

Student	Before	After	Gain
S1	31	39	8
S2	15	41	26
S3	32	46	14
S4	36	55	19
S5	44	51	7
S6	32	36	4
S7	33	62	29

Figure 3visualizes the same records in chart form. The bars show that the post-test scores moved upward across the full reported subset, which supports the idea that short, playful, AI-assisted tasks can improve retention and confidence in a classroom.

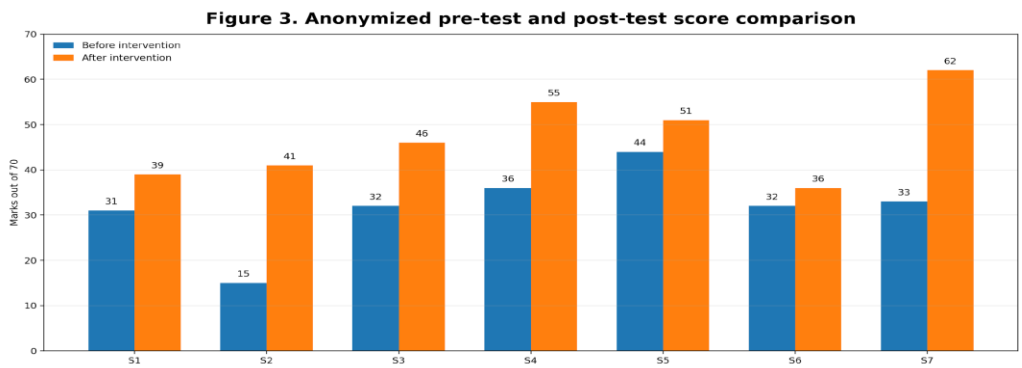

Figure 3. Anonymized pre-test and post-test score comparison.

Figure 4 summarizes the same improvement at the group level. The error bars indicate the spread of the reported subset and emphasize that the rise was not limited to a single student. Even when the starting point was weak, the intervention created a clearer learning path.

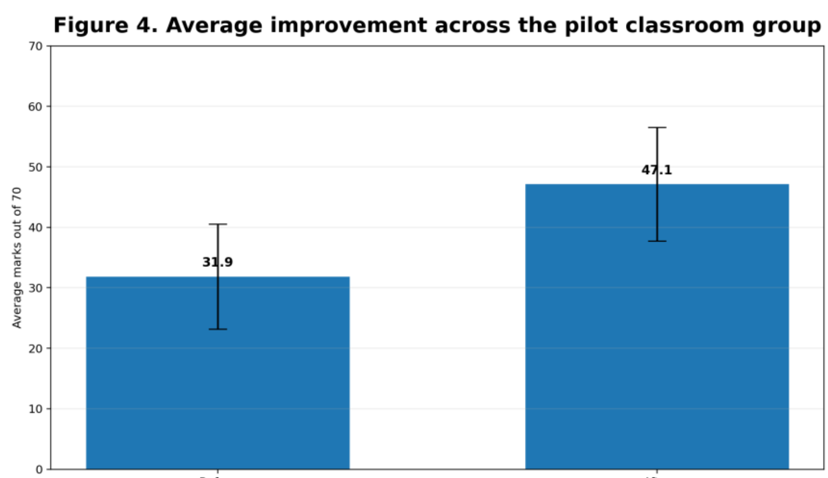

Figure 4. Average improvement across the pilot classroom group.

Table VI. Pilot-level validation summary

Metric	**Value**	**Interpretation**
Cohort size	30 Class 11 students	Pilot-scale classroom sample
Mean pre-intervention score	31.9 / 70	Baseline performance
Mean post-intervention score	47.1 / 70	Observed classroom improvement
Absolute gain	15.2 points	Change after intervention
Relative gain	48%	Improvement over baseline
Intervention mode	AI-assisted, game-based learning	Classroom strategy used
Validation type	Pilot-scale experimental validation	Feasibility-focused study

This pilot-level summary shows that the intervention produced a meaningful gain in a real classroom setting and provides a concise outcome view before the discussion section.

A. Classroom Interpretation

The improvement pattern suggests that the intervention was effective in two ways. First, it increased confidence because students could see abstract programming ideas through familiar game logic. Second, it encouraged shorter and more deliberate practice, which is often more sustainable than a long and exhausting study session. This is particularly important in schools where attention span, motivation, and workload vary widely across students.

The platform also helps teachers by compressing scattered classroom evidence into a single progress view. Instead of checking marks, sleep, study, and extracurricular activity separately, the teacher can inspect one dashboard and then decide whether a student needs reinforcement, pacing changes, or enrichment.

Table VII. Traditional classroom handling versus the proposed platform

Dimension	Traditional handling	Proposed platform
Feedback style	Delayed and generic	Immediate and personalized
Learning support	Mostly lecture based	AI + game-based tasks
Teacher view	Fragmented across notes	Single dashboard and summary
Student view	Marks only	Marks, habits, goals, and plan
Actionability	Low	High, because the next step is explicit

6. DISCUSSION

The pilot shows that an education system becomes more useful when it can interpret the student as a whole learner rather than as a single mark value. In the current design, sleep cycle matters because poor sleep often reduces attention and memory. Study time matters because consistent practice strengthens retrieval. Extracurricular activity matters because a healthy balance prevents burnout and improves long-term engagement. Goal alignment matters because students work better when they know why they are learning.

The use of Grok AI as a mentor layer is significant because it turns a numerical score into a human-readable suggestion. Instead of saying that a learner is weak, the platform can say that the learner should revise functions for 20 minutes, complete one short task, and review one resource before the next class. That kind of message is easier to act on and less discouraging than a generic warning.

From a software perspective, the platform also has a practical benefit: it keeps the decision loop short. Data is entered, processed, explained, and returned as guidance without forcing the teacher to use several disconnected tools. This reduces the friction that often kills adoption in schools. A good education system must be useful, but it must also be simple enough to be used regularly.

A. Why the Game-Based Method Helped

Game-based explanation worked because it translated an abstract programming concept into a familiar interaction pattern. When a learner sees a function as a reusable action in a Minecraft-style environment, the concept becomes more concrete. This reduces the mental distance between the code and the visual outcome, which is often the biggest obstacle in beginner programming.

Short tasks also helped. Instead of asking students to absorb everything at once, the class received small, meaningful targets. That strategy matters in a school environment because attention is limited and motivation is uneven. Small wins build momentum, and momentum improves persistence.

B. Why the Platform Design Is Useful

The platform can be extended beyond computer science. The same logic can support mathematics, science, language learning, or exam preparation because the core principle is not subject-specific. The core principle is to observe how the learner works, identify where the learner is stuck, and recommend a next step that is small, clear, and achievable.

The design also encourages explainability at the center of the system. This is important because schools do not trust opaque tools that only output a score. Teachers want to know why a recommendation was made, parents want to know what the plan means, and students want feedback that sounds supportive rather than punitive.

7. LIMITATIONS AND FUTURE WORK

The first limitation is cohort size. Although the pilot involved 30 students, the study is still small in comparison with full-scale longitudinal educational research. For that reason, the findings should be interpreted as pilot-scale experimental validation rather than as a universal claim.

The second limitation is that some lifestyle variables are self-reported. Sleep cycle, study time, and extracurricular balance are valuable signals, but they can still contain noise if students record them inconsistently. A future version of the platform may combine self-reports with automated logging, calendar integration, or deeper learning analytics.

The third limitation is that the current mentor layer is still a prototype. The Grok AI integration is useful, but it will need stricter guardrails, school-specific prompts, and teacher moderation before large-scale deployment. Future work should therefore focus on improved prompt design, stronger analytics, more subjects, and longer-term classroom trials across several sections.

A promising future extension is a multi-school study that compares AI-assisted, game-based learning against a conventional teaching routine for the same topic. Another extension is a parent-facing view that transforms the same signals into simpler weekly suggestions and reminders. A final extension is a subject-agnostic analytics engine that can support the same architecture in mathematics, science, and language learning.

8. ETHICAL AND PRACTICAL CONSIDERATIONS

The pilot was reported in anonymized form. No student names, roll numbers, or sensitive identifiers are exposed in the manuscript. This is important because school-level research must preserve privacy while still communicating educational value.

The system is also designed to support teachers rather than replace them. The teacher remains the final decision-maker, and the dashboard output should always be interpreted as guidance. This human-in-the-loop posture is essential for responsible deployment in schools where educational judgment should stay with trained professionals.

The platform should also avoid using the dashboard as a punishment tool. If students think the system exists only to monitor and criticize them, adoption will fail. The platform should be introduced as a support mechanism that helps students improve without embarrassment.

9. CONCLUSION

This paper presented a detailed explainable AI-driven student success platform that combines academic analytics, lifestyle awareness, and personalized mentoring in one school-friendly design. The platform is implemented with Flask, HTML, JavaScript, and the Grok AI API, and it is aligned with real classroom usage rather than abstract laboratory conditions.

The pilot-scale classroom validation shows that AI-assisted, game-based learning can improve engagement and marks when the content is broken into short, understandable tasks. The reported score slice rose from 31.9 to 47.1 out of 70, supporting the claim that a well-designed intervention can help students move from confusion to action.

Overall, the study demonstrates that student success can be treated as a broader learning problem rather than a marks-only problem. By connecting data, explanation, and action, the proposed platform provides a practical model for schools that want to support academic growth, healthy habits, and goal-oriented learning at the same time.

The final implementation step is continuous refinement. Once the school begins to use the platform, the teacher should regularly review whether the suggestions are practical, whether the language is clear, and whether the dashboard remains easy to read. In a real classroom, success comes from small adjustments. A good system is not one that is frozen at the first release; it is one that improves with observed classroom behavior.

Privacy and data protection must be part of the rollout plan. The platform should collect only the information needed for educational guidance, store it securely, and keep the visibility controlled. Individual-level data should be visible only to the appropriate teacher, the student, and, when necessary, the parent. This approach keeps the project aligned with school ethics and reduces the risk of misuse.

Student orientation matters just as much. Learners should know that the platform is meant to support them, not to embarrass them. If students believe that the dashboard is only there to punish poor performance, they may stop engaging honestly with the questions or the weekly reports. A better message is that the platform is a personal improvement tool that helps them become more organized, more confident, and more aware of their own progress.

Teacher orientation is essential. Before the system is used at scale, the teacher should understand what the Student Success Index means, how the AI mentor chooses its language, and how the dashboard should be interpreted. Without this orientation, there is a risk that people will either trust the system blindly or ignore it completely. Neither extreme is helpful. The system becomes valuable only when the teacher uses it as a decision aid.

A school should not introduce the platform as a sudden replacement for existing teaching methods. The better approach is a phased rollout. In phase one, the teacher can use the platform only for reflection after class. In phase two, the system can guide revision sessions and short practice tasks. In phase three, it can support planning, enrichment, and parent communication. This gradual method reduces resistance and gives the school time to understand the output properly.

10. SCHOOL ROLLOUT STRATEGY AND IMPLEMENTATION PRACTICE

Because the mentor layer is connected to a school platform, it should also explain its reasoning in a friendly way. Students should be able to see why a particular task was suggested and why a particular resource was recommended. When the explanation is visible, the learner is more likely to trust the guidance and less likely to view it as arbitrary or punitive.

The mentor output can be organized into four lines of guidance: praise, diagnosis, action, and check-back. Praise builds confidence by acknowledging what is already working. Diagnosis explains the main weakness in simple language. Action suggests one or two concrete steps for the coming week. Check-back tells the learner what will be reviewed next, such as marks, task completion, or study consistency. This structure makes the response easier for students to follow and easier for teachers to monitor.

The AI mentor should behave like a disciplined guide, not like an unrestricted chatbot. In school use, the mentor must remain focused on the learner's current stage, recent behavior, and next academic target. If the system is asked about a student who is weak in functions, the response should not wander into unrelated topics. It should stay tightly connected to functions, practice time, revision habit, and one recommended resource.

A. Role of the AI Mentor in Daily Use

In the present pilot, the emphasis is on clarity rather than statistical complexity. The main question is whether the teacher can quickly see the risk pattern and whether the student can quickly understand the next step. The answer from the classroom pilot is positive. The platform may still evolve, but even in its current form it can convert scattered signals into a structured learning conversation.

A future full-scale deployment can use these metrics for cross-term and cross-section analysis. This would allow the school to see whether the platform benefits only a single group or whether it improves planning and learning across multiple classes. It would also make it possible to study how much of the improvement comes from the AI mentor itself and how much comes from the game-based classroom intervention.

The system can also report the degree to which students follow the recommended plan. A plan that looks impressive on paper is not useful if the learner never follows it. Therefore, the platform should measure the difference between recommendation and actual behavior. If the student sleeps earlier, practices regularly, and improves marks, the dashboard should show that positive trend. If the student ignores the plan, the teacher receives an early warning that the plan needs to be simplified.

Sleep regularity matters because students rarely perform at their best when they are tired, and study-time consistency matters because a repeated short practice routine is usually more effective than an irregular long session. Extracurricular balance matters because learning quality declines when the school day becomes too narrow and too stressful. Goal alignment matters because a student learns faster when the purpose of the work is clear. Together, these metrics form a broader view of student development.

The platform is designed to report more than a single score. A useful school dashboard should show what changed, why it changed, and what should happen next. For that reason, the reporting layer can track the mean marks score, task completion rate, sleep regularity, study time consistency, extracurricular balance, and mentor suggestion acceptance rate. Each metric has a different purpose. Marks show academic progress, while the behavioral indicators show whether the current routine is sustainable.

B. Reporting Metrics and Interpretation

This four-stage pattern is valuable because it reduces overload. A student is often willing to act when the task is specific and small. The platform therefore avoids large, vague instructions such as "study harder" or "work more". Instead, it suggests visible, manageable actions such as revising one concept, practicing for 20 minutes, sleeping earlier, or completing one goal-oriented resource before the next class.

The student journey therefore passes through four practical stages: discovery, diagnosis, action, and review. In the discovery stage the learner becomes aware of the current pattern. In the diagnosis stage the system identifies the strongest reason for the difficulty. In the action stage the learner receives a short plan. In the review stage the platform checks whether the next score, the next practice task, or the next weekly habit has improved.

The teacher view is equally important. A teacher can inspect the dashboard, review the AI suggestion, and then decide whether the recommendation should be accepted, refined, or expanded. This human review keeps the system aligned with classroom reality. A learner may need an easier task, a slower pace, or a different explanation style, and the teacher can make that adjustment before the suggestion is sent back to the student.

After onboarding, the platform moves into a weekly cycle. The student receives a short set of tasks, a quick reminder about the current weak area, and a summary of the next recommended action. The mentor layer does not try to solve everything at once. It focuses on the most important issue for the current week, such as irregular sleep, low revision time, or weak concept retention. This makes the guidance easier to follow and easier to remember.

The deployment workflow begins when a student creates a profile and enters the basic context needed by the platform: class, preferred goal, target exam, study routine, sleep pattern, recent marks, and extracurricular involvement. This intake step is intentionally short so that it does not feel like a burden. The goal is to collect enough information to build a useful starting profile without forcing the learner to complete a long and tiring questionnaire.

11. DEPLOYMENT WORKFLOW AND USER JOURNEY

In that sense, the platform is not simply a software project. It is a decision-support environment for schools. It aligns the teacher, the learner, and the administration around one shared objective: better learning with less confusion, more clarity, and more accountability. That practical orientation is part of what makes the manuscript strong enough to present as applied research.

If the platform is scaled carefully, it can also support a culture of early intervention. Instead of waiting for a student to fail a major assessment, the school can notice small warning signs earlier and respond in time. This is one of the most valuable features of analytics in education: the ability to react before the problem grows larger.

For administration, the platform also improves communication. A parent-facing summary can present progress in simple terms, while a teacher-facing view can remain slightly more detailed. This layered communication helps different users receive information at the right depth. A single platform can therefore serve several roles without forcing everyone to see the same message.

The value of the platform is not limited to students. School leaders can also benefit from a clear view of how students are progressing, where support is needed, and which intervention style appears to work best. This makes it easier to plan teacher support, design remedial classes, and identify topics that require a stronger explanation in the next teaching cycle.

12. PRACTICAL VALUE FOR SCHOOL ADMINISTRATION

Over time, the recommendation engine may also become a knowledge map. It can remember which resources worked best for which student type and which explanation style helped the most. That means the platform can become smarter without becoming more complicated for the user. The best educational technology often feels simple on the surface while remaining highly organized underneath.

The platform can also support important exam awareness. If a student is moving toward a competitive exam, the AI mentor can remind the student about deadlines, subject priorities, revision intervals, and practice windows. This reduces last-minute confusion and helps the learner build a more realistic plan. A good educational system should not only tell the student what is weak; it should also remind the student what matters next.

The resource logic can be aligned with the learner goal. A student preparing for a board exam needs revision notes, question practice, and time management advice. A student preparing for a coding competition may need problem-solving resources and task sequencing. A student who is behind on a chapter may need a simpler explanation and a smaller practice set. This personalization makes the mentor feel more relevant and more trustworthy.

One of the most useful promises of the platform is the ability to recommend the right resource at the right time. A student does not always need a long list of links. Sometimes one carefully chosen note, one short concept explanation, or one exam reminder is enough. The mentor layer can therefore prioritize curation over volume. In other words, the platform should recommend fewer but better resources.

A. Resource Curation and Exam Guidance

In practical terms, the ideal classroom workflow is simple. The teacher reviews the output, checks the explanation, makes any needed changes, and then shares the final plan with the student. The student receives one coherent action plan rather than a fragmented set of instructions from multiple tools. That simplicity is one of the reasons the platform can be adopted in real schools.

The dashboard should also include a visible explanation trail. If the system highlights weak sleep and low study time, the teacher should be able to see that the recommendation is based on those factors, not on hidden assumptions. This visible trace increases trust and makes it easier for the learner to accept the advice without feeling that the system is arbitrary.

Human oversight also helps in cases where the data is incomplete. A student may be stressed because of a personal matter, may have missed school for a genuine reason, or may have a one-time drop in performance that should not be treated as a long-term pattern. In such situations, a teacher can add context that a software model will never fully understand. The platform therefore acts as a support layer, not a replacement for judgment.

A major strength of the present design is that it keeps the human teacher at the center of decision-making. The system does not and should not make final academic decisions on its own. It generates a recommendation, explains why the recommendation was made, and then waits for a teacher to approve, modify, or reject it. This structure is important because schooling is not a fully automated environment.

B. Human-in-the-Loop Governance

The platform is ready for this kind of future study because the data model is already broad enough to support repeated observation. The system records learning signals, habit signals, and goal signals in a form that can be reviewed week after week. As the data grows, the mentor layer can also learn which type of advice leads to the strongest follow-through.

Another meaningful extension is a longitudinal design. Instead of measuring only one immediate pre-test and post-test outcome, the school could monitor students over several weeks or even a full term. This would show whether the benefit remains stable after the novelty effect fades. In educational research, long-term consistency is often more valuable than short-term excitement.

A future study can also use cross-sectional views, meaning that the same framework is observed across more than one class or subject. This will make it possible to see whether the platform behaves similarly in computer science, mathematics, and science. It will also help determine whether the game-based strategy is most effective for beginners, for intermediate learners, or for students who are already confident but need structured direction.

The most useful metrics for the next stage are not limited to accuracy or marks. In an education platform, success also includes recommendation acceptance, task completion, reduction in repeated mistakes, stability of study routines, and consistency of weekly growth. A student may not always jump immediately to a much higher score, but a steady improvement in habits often predicts a stronger long-term result than a one-time spike.

A stronger future version of the study can be evaluated with a more formal benchmark plan. The platform is already suitable for a comparison framework in which the proposed system is measured against a marks-only baseline, a teacher-only baseline, and a non-explainable digital learning baseline. Such a comparison would help isolate the value of the AI mentor, the value of explainability, and the value of the lifestyle-aware input design.

13. FUTURE EVALUATION METRICS AND COMPARISON PLAN

From a publication standpoint, this interdisciplinary reach is useful because it shows that the contribution is not limited to one classroom subject. The platform demonstrates a general method for combining student state, behavioral evidence, explanation, and guided action. That broader framing gives the paper a stronger research identity and makes it more suitable for an applied journal that welcomes cross-domain innovation.

The same logic can be adapted to other domains that involve progress tracking and personalized advice. A similar structure could be applied to professional learning, workplace training, or skill-based certification programs. The core idea remains the same: capture meaningful signals, explain the strongest pattern, and convert that explanation into a clear next step. This makes the model attractive to researchers who work in AI systems, education, and human-computer interaction.

Although the implementation is rooted in educational technology, the manuscript is intentionally interdisciplinary. It combines artificial intelligence, software engineering, human-centered design, educational analytics, and classroom practice. That breadth is important because modern journals increasingly value applied systems that can travel across domains rather than stay inside one narrow technical box. The student success platform is therefore not only a school tool; it is also a general decision-support pattern.

14. INTERDISCIPLINARY RELEVANCE

A weekly template generated by the platform can also standardize improvement. One week may focus on sleep stability, the next on study time consistency, the next on concept practice, and the next on goal planning. This prevents the learner from being overloaded and gives the platform a clear rhythm. The result is a more humane form of analytics, where the system supports growth without making the student feel judged.

The same structure can be translated into a teacher summary. The teacher view can state the weak factor, the likely cause, the recommended intervention, and the follow-up date. This makes the dashboard useful for parent communication as well. A parent does not need every technical detail; a parent needs to know the learner's current priority and how the home routine can support it.

The next part of the output should be action oriented. The system can suggest one focused revision task, one short practice task, and one habit adjustment for the week. This format works because it gives the learner only a few clear priorities. A student is much more likely to act on three short steps than on a long list of instructions that feels impossible to complete.

To show how the platform behaves in practice, the mentor can generate a short student-facing summary after each assessment cycle. A typical response would begin with the strongest observation, then identify the main weakness, and finally provide a short plan for the next week. For example, if a student has acceptable marks but irregular sleep and weak revision habits, the mentor can say that the current performance is promising but not yet stable.

15. SAMPLE AI MENTOR OUTPUT AND WEEKLY PLAN TEMPLATE

A sample mentor output can be short and structured. For instance, the platform may tell the learner that the marks are improving, but the current routine is still unstable because sleep and revision are not yet consistent. This style is useful because it gives a balanced message: the student is encouraged, the problem is explained, and the next step is made visible immediately.

The platform can then convert that explanation into a weekly plan. The plan may include one concept to revise, one task to practice, one habit to stabilize, and one resource to review. The learner should not receive too many instructions at once. A short plan is more likely to be completed, and completion is what creates momentum in a school environment.

Teachers can also use the same output in a parent summary. A parent-facing message can be written in simpler language, with the emphasis placed on support at home, sleep discipline, and regular practice. This makes the platform useful beyond the classroom because it becomes a communication bridge between school and home.

The sample mentor template completes the loop that this paper proposes. Data enters the system, the system explains the data, the mentor converts the explanation into an action plan, and the teacher reviews the final decision. That closed loop is the practical strength of the platform and the reason it can be deployed as a real school support tool.

ACKNOWLEDGMENT

The authors acknowledge the support of the classroom environment, the students who participated in the pilot intervention, and the educational resources that informed the design of the platform. No external funding was received for this work.

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