Motivation- and Competency-Oriented AI-Based Adaptive Feedback Systems

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Abstract

The integration of Artificial Intelligence (AI) into educational environments has significantly increased, particularly within Learning Management Systems (LMS). However, many AI tools are not sufficiently aligned with the competency models of these environments, leading to cognitive overload and reduced learner motivation. This study examines the development and integration of an AI-based formative feedback system that is precisely aligned with the curriculum and learning objectives. The system, embedded within an LMS, uses a self-trained large language model to generate feedback based on predefined teaching materials. The aim is to minimize cognitive overload, enhance learning motivation—particularly performance motivation—and improve learning efficiency. Our empirical study with 250 students from the Universities of Leipzig and TU Dresden investigates how AI-generated feedback impacts learning performance, motivation, and the achievement of defined competencies. The findings demonstrate that a well-integrated AI feedback system can significantly enhance the effectiveness of adaptive learning environments by supporting learners in developing competencies and improving self-efficacy. The results highlight the importance of incorporating established pedagogical principles into the development of AI tools to achieve optimal learning outcomes.

Keywords: Artificial Intelligence, Motivation, Competency, Feedback, Adaptive, Performance

1. Introduction

The implementation of AI in learning environments, particularly in adaptive feedback systems, often faces the challenge that existing tools are not fully integrated with learner data, knowledge models, and the competency structures of the learning environment [24], [25]. This lack of integration limits the systems' ability to generate valid and targeted feedback aligned with instructional objectives [26]. AI should serve as a tool to address current challenges in education by providing a modern solution to reduce teachers' workload and improve the efficiency of teaching and learning processes.

Despite significant advances in AI research, many feedback systems remain theoretically underdeveloped, limiting their pedagogical and instructional-theoretical effectiveness [11]. Our research addresses this gap by developing an AI-based adaptive feedback system that adheres to didactic principles and is strictly aligned with defined instructional objectives and targeted competencies. Our system employs a large language model (LLM) with natural language processing (NLP), relational database systems, and a machine-based instructional model that utilizes methodically prepared teaching materials closely linked to learners' performance. The integration of this entire architecture into Learning Management Systems (LMS) plays a critical role in effectively applying the feedback system's output within existing teaching and learning environments. Unlike OpenAI or ChatGPT, we offer a closed infrastructure that exclusively encompasses domain-specific instructional content and predefined instructional goals. This approach, based on instructional theory, aims to optimize the teaching-learning process and achieve a significant, output-oriented improvement in learning efficiency.

The developed system not only avoids cognitive saturation but also promotes competency development in learners and enhances their performance motivation, as described in Heckhausen's Expectancy-Incentive Model [5]. It integrates seamlessly into the learning environment, improving both the effectiveness of feedback and the overall learning experience. Our research ensures that AI-based feedback systems are grounded in robust pedagogical and theoretical frameworks, while providing precise adaptation of feedback to individual learning objectives, existing competencies, and learners' prior knowledge.

Research Question

How can an effective AI-based adaptive feedback system be developed that aligns with instructional objectives and learning content, fosters performance motivation, enables cognitive relief, and supports significant competency development in learners?

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2. Theoretical Foundations

The development of an effective AI-based adaptive feedback system requires a thorough understanding of the concepts of feedback, formative assessment, and adaptive learning. Adaptive learning environments dynamically adjust to individual learner needs, as described by Brusilovsky, and employ advanced technologies to personalize the learning experience [7], [8]. Cognitive load reduction strategies also play a critical role in enhancing learning efficiency and maximizing learning outcomes. As emphasized by Bandura and Heckhausen, targeted reductions in cognitive load improve learners' self-efficacy expectations and motivate them to engage more deeply with the instructional content, thereby positively impacting learning performance [4], [12].

The lack of consistent definitions for formative feedback in the existing literature (literature review, June 2024) necessitates precise definitions based on established concepts. According to Dawson et al. (2019), feedback is essential for the learning process as it helps learners identify discrepancies in their performance and strive for improvement [9]. Faulconer et al. [10] add that feedback also serves instructors by enabling them to adapt their teaching strategies.

Formative assessment, as defined by Sadler, aims to provide learners with targeted feedback that facilitates improvement while minimizing inefficient learning strategies [19]. Formative feedback integrates these elements, focusing on the continuous support of learners by providing specific feedback on their performance that bridges the gap between their current and desired performance levels [17].

The significance of cognitive load reduction within adaptive systems is further highlighted. Reducing unnecessary mental effort enables learners to concentrate their cognitive resources on relevant tasks, directly correlating with improved learning outcomes, as deeper processing and more sustainable knowledge acquisition are achieved [14], [23]. Such approaches ensure that personalized learning environments not only cater to individual learner needs but also enhance the overall efficiency of the learning process. Furthermore, studies indicate that personalized feedback reflecting individual progress can strengthen intrinsic motivation by fostering a sense of progress and control over the learning process [22]. These theoretical foundations provide the basis for our research in developing an AI-based adaptive feedback system that delivers valid feedback while meeting pedagogical requirements. At the same time, our approach aims to enhance learners' motivation by providing them with targeted feedback that promotes greater self-efficacy and autonomy.

Paul Black and Dylan Wiliam are recognized scholars in educational research who have extensively studied the design of formative feedback in various didactic and pedagogical scenarios. Their five-step model serves as a key concept for promoting learning through effective assessment practices [6]:

i. Clarifying learning objectives and success criteria: It is crucial for both instructors and learners to have a clear understanding of the learning objectives and the criteria for success. Explicitly defining and understanding these objectives and criteria is fundamental to achieving learning success.

ii. Identifying learners' current learning status: Educators must evaluate students' current performance levels to determine where they stand in the learning process. This involves assessing their achievements and abilities in relation to the learning objectives.

iii. Providing feedback that fosters learning: Effective feedback should help learners understand what they are proficient in and where improvements are necessary. Constructive and specific feedback enhances understanding without causing demotivation.

iv. Activating learners: Learners should be actively involved in their learning process. This includes evaluating their work, setting personal goals, and monitoring their progress.

v. Activating learners as resources for each other: Learners can effectively support each other's learning through peer assessments, collaborative learning activities, and fostering cooperation.

These steps promote a deeper integration and application of formative feedback, which is essential for effectively supporting learners in achieving their goals. By integrating these principles into the design of our AI-based feedback system, we aim to create a learning environment that optimally supports both individual and collective competency development.

3. Research Design

Our research design utilizes Artificial Intelligence (AI) and computer-based methods to implement a theory-driven model of adaptive formative feedback in learning environments. Inspired by the five-step model of Paul Black and Dylan Wiliam, our approach aims to integrate this model seamlessly into adaptive learning environments, supported by advanced AI technologies. Feedback must be competency- and output-oriented, aligning with defined learning objectives and the corresponding instructional content. These requirements are grounded in instructional design theory, which provides a didactic foundation for generating effective recommendations. The approach also draws from cognitive learning theories, emphasizing the importance of structured and well-organized knowledge delivery for sustainable learning.

Additionally, the research design considers the critical role of motivation and self-efficacy in the learning process. Based on Deci and Ryan's Self-Determination Theory and Bandura's concept of self-efficacy, the study investigates how personalized feedback strengthens intrinsic motivation, goal orientation, and performance motivation in learners [18, 3]. Performance motivation is further supported by Heckhausen's Expectancy and Incentive Model , which posits that motivation increases when learners perceive a high probability of success (expectancy) and recognize significant value (incentive) in their learning objectives [12].

Step 1: Defining Learning Objectives and Competencies

Learning objectives and competencies are clearly defined to establish the foundation for an effective curriculum. This is achieved using Azizi Ghanbari's framework of parallel goal and content validity (2014), which highlights the importance of detailed descriptions of the competencies to be developed [1, 2].

In this model, instructors define learning objectives that are valid within a specific competency framework and aligned with expected outcomes. These objectives are subdivided into smaller, operationalized sub-objectives, each linked to specific instructional content, examples, and practice tasks, referred to as appropriation tasks. These sub-objectives are addressed in individual lectures or instructional units. A clear understanding of the instructional content and the resulting competencies by both instructors and learners is critical for ensuring the success of the learning process and aligns with the principles of Black and Wiliam's model.

Step 2: Competency Assessment and AI Integration

AI is employed to accurately assess and evaluate learners' current competency levels. This process is based on predefined learning objectives and validated tasks, including appropriation tasks and evaluation tasks in the form of assignments or tests. This allows for personalized and precise feedback tailored to learners' progress.

Step 3: Feedback and Instructional Design

Feedback is constructively designed to actively support the learning process. The approach follows a structured instructional design framework, focusing on systematically developing instructional materials and learning activities to effectively and efficiently achieve specific learning objectives.

Step 4: Continuous Performance Improvement and Feedback Evaluation

The system provides multiple opportunities for performance improvement and feedback evaluation. These are supported by AI and collaborative tools integrated into the adaptive learning environment, such as group chats and forums. These tools foster interaction and engagement among learners, enabling continuous self-regulation and critical reflection on their progress.

Step 5: Activating Learners as Learning Resources

Learners are activated as resources for one another by promoting self-regulated learning, following Zimmerman's model (2008). AI supports learners throughout all phases of the learning process—from preparation to execution to self-reflection—by providing personalized instructions and feedback tailored to their individual needs and prior learning behaviors [15, 28].

3.1. Design of Adaptive Feedback and Recommendations Based on Instructional Design Theory

Our AI-based adaptive feedback system is built on the model of parallel goal and content validity developed by Schott and Azizi Ghanbari (2012), which supports output-oriented validation of didactic applications and instructional materials. Learning objectives are divided into overarching general goals and specific sub-goals, with content and tasks closely aligned to these objectives [21].

The feedback process begins with assessing student performance against the learning objectives within our Learning Management System. This approach enables the generation of individualized feedback aligned with the learning objectives, incorporating the principles of effective feedback outlined by Paul Black and Dylan Wiliam (2009)—goal-oriented, actionable, and supportive. Initial feedback highlights positive aspects of the student's performance and provides constructive recommendations for improvement. This method fosters motivation and deeper understanding of the content [26].

Example of Adaptive Feedback

- Confirmation: "Thank you for your submission on structural functionalism. You clearly highlighted the core principles, including the role of Talcott Parsons."

- Recommendations: "Additionally, consider discussing the implications of meritocracy within the education system. Expand your analysis by examining the reproduction of power structures, supported by further literature, such as the works of Parsons and Fend, see lecture 1 – Slide 23”

The AI continuously analyzes student submissions to dynamically adapt feedback and learning strategies. This enables context-specific and individualized learning experiences that consider the students’ progress, needs, and prior knowledge.

Our approach follows the five-step model by Black and Wiliam, emphasizing that feedback should be continuous and supportive to effectively assist learners in achieving their goals. Every feedback element—from initial confirmation to adaptive adjustments—is designed to promote learning through targeted responses and proactive guidance. Importantly, the knowledge domain utilized by our system does not rely on general world knowledge, as seen in tools like ChatGPT. Instead, it is developed through meticulous analysis of instructional content and tasks and validated for accuracy. This ensures that the feedback generated is specific, relevant, and precisely aligned with the defined learning objectives.

3.2. Analysis of Learning Material

The analysis of learning materials aimed to ensure the content validity of the resources concerning the expected competency model. This involved a detailed review of instructional materials, such as lecture content, textbooks, and other resources, to confirm their alignment with the defined learning objectives.

The lecture materials were systematically analyzed to verify their correspondence with the intended competency traits. This included aligning theoretical content with the targeted learning objectives. Example tasks were examined to determine if they validly represented the competencies relevant to the lecture materials and whether they allowed students to practically apply those competencies. Based on the analyzed example tasks, specific assignments were developed in collaboration with instructors. These assignments were designed to ensure a direct application of the competencies learned in lectures while simultaneously assessing the validity of these competencies.

The entire analysis of learning materials and the development of assessment tasks were grounded in the parallel goal and content validity model proposed by Schott and Azizi Ghanbari [21]. This model provided a scientific framework for validating the instructional materials and ensuring their coherence with the competency-based learning objectives.

3.3. Implementation of the AI Feedback System

The technical implementation of the feedback system was realized through an AI-based rule-driven system, supported by Amazon AWS’s Natural Language Algorithm [13] and complemented by OpenAI’s Large Language Model (GPT-4omni). This combination enabled precise analysis of student submissions, identification of relevant content, and generation of targeted, contextualized feedback [16].

The AI continuously tracks the achieved and unachieved competency traits of each student in a relational database. Students can revise and resubmit their work multiple times. The system dynamically evaluates their competency development based on new submissions and adjusts its feedback accordingly. The structure and phrasing of the feedback were developed based on the Five-Step Feedback Model by Black and Wiliam, ensuring clear, formative responses that promote learning. This rule-based approach prevents unreliable behavior from AI and allows tailored responses to edge cases, such as incorrect or irrelevant submissions.

The system also detects attempts at manipulation, such as students repeatedly submitting similar or identical texts without considering the feedback. In such cases, the system alerts the student to the issue and encourages more meaningful engagement with the received feedback. If students incorporate the feedback but fail to show visible competency improvement, the AI refines its guidance and shortens the feedback to provide clearer focus and more effective support in subsequent submission cycles, using the available learning materials. Our approach differs from existing systems by strictly adhering to validity and reliability standards, underpinned by theoretical frameworks and empirical research. This methodological rigor ensures that the AI feedback system is both valid and reliable, effectively contributing to students’ competency development.

4. Methodology

This study investigates the impact of an AI-supported formative feedback system on the learning performance and motivation of 250 students from the Universities of Leipzig and TU Dresden. These students are enrolled in courses such as “Education and Pedagogy” and “Media Education,” each consisting of 12 lectures and corresponding seminar assignments. Participation in the study, including the revision of submissions, was voluntary to ensure students’ intrinsic motivation and minimize potential biases.

Study Design

To gain a comprehensive understanding of the effectiveness of the AI feedback system, two separate studies were conducted with the same target group:

- Study on Learning Performance and Output: This study focused on students' learning performance in relation to the competency model and the defined learning objectives. The aim was to examine whether and to what extent the use of the AI feedback system led to a significant improvement in learning performance.

- Study on Student Motivation: The second study explored the influence of the AI feedback system on students' motivation. It examined learning and performance motivation, specifically intrinsic and extrinsic motivation, as well as amotivational tendencies and goal-setting strategies.

Data Recording and Interaction

Throughout the semester, the AI system generated individualized feedback for a total of 2000 student submissions. Students could revise their solutions as often as they wished based on the feedback and resubmit them. All interactions were continuously recorded in the Learning Management System, which documented both students' progress and the frequency and quality of feedback cycles.

The feedback system facilitated cyclical interactions, where students received specific feedback after each lecture and corresponding seminar assignment. This feedback highlighted unmet learning objectives and provided concrete suggestions for improvement. The AI algorithm dynamically adjusted the feedback based on the latest submissions and students' progress to promote continuous competency development.

Measurement of Learning Performance

Learning performance was measured by the number of achieved learning objectives before and after the feedback intervention.

The defined learning objectives included core areas such as equity, critical reflection, and the connection between the education system and social mobility. These objectives, derived from the "General Educational Pedagogy" seminar for teaching students, served as the basis for evaluating the effectiveness of the feedback system. The hypotheses on Learning Performance are as follows:

- Null Hypothesis (H_0): There is no significant improvement in the number of achieved learning objectives after the AI-based formative feedback.

- Alternative Hypothesis (H_1): There is a significant improvement in the number of achieved learning objectives after the AI-based formative feedback.

A one-tailed paired t-test was applied to assess differences before and after the intervention.

Measurement of Motivation

Student motivation was measured using a validated questionnaire based on the Academic Motivation Scale (AMS). This measurement was conducted once at the end of the semester and included only students who actively used the AI feedback system during the semester. This approach ensured that the collected data specifically reflected the experiences and perceptions of this target group regarding the support provided by the system. The questionnaire assessed the following dimensions:

- Intrinsic Motivation: Enjoyment and interest in learning for its own sake.

- Extrinsic Motivation: Learning as a means to achieve external goals, such as grades or recognition.

- Amotivation: A state of lack of motivation, where the purpose of learning appears unclear.

- Self-Efficacy and Goal setting: Based on Bandura's theories, this dimension assessed students' beliefs in their ability to achieve learning goals and their strategies for goal setting [3].

To optimize the measurement instruments, an Item-Response-Theory-based item selection was employed to specifically focus the items on the impact of AI usage. The results were analyzed using inferential statistical methods to evaluate the relationship between the use of the AI feedback system, learning output, and student motivation. Hypotheses on Motivation:

- Null Hypothesis (H_0): The use of the AI feedback system has no significant effect on students' motivation.

- Alternative Hypothesis (H_1): The use of the AI feedback system significantly increases students' motivation.

5. Analysis of Pre-Test Data

Descriptive Analysis

The participation of 250 students in the study resulted in 2000 submissions, of which 45 students incorporated the feedback into their final submissions. The initial analysis revealed an improvement in unachieved learning objectives from an average of 5.22 (SD = 1.74) in the first attempt to 3.22 (SD = 1.68) in the second attempt. The average competency growth was 2.00 (SD = 1.41). Additionally, an average of 250 words (SD = 176) was added to the revised texts, indicating an active engagement with the feedback.

Results of the t-Test

A one-tailed paired t-test confirmed a significant reduction in unachieved learning objectives ($p < 0.001$) with a large effect size (Cohen's $d = 1.41$). These results support the alternative hypothesis (H_1) and demonstrate the substantial impact of adaptive feedback on learning outcomes.

Pearson Correlation Test

The analysis of the relationship between competency growth and the number of additional words added revealed a correlation coefficient of $r = 0.217$. However, with a p-value of 0.151, this moderate positive relationship was not statistically significant, indicating no conclusive correlation between the two variables.

Analysis of Learning Motivation

The analysis of learning motivation was based on a Likert scale (1 = strongly agree; 7 = strongly disagree) and focused on the use of the AI feedback system. Of the 45 students who used the feedback system, only 8 participated in the motivation questionnaire. The mean scores are as follows:

- Intrinsic Motivation: M = 2.48 (SD = 0.509)
- Extrinsic Motivation: M = 3.69 (SD = 0.426)
- Amotivation: M = 5.69 (SD = 0.432)
- Goal Setting (Bandura): M = 3.37 (SD = 0.505)
- Overcoming Difficulties (Bandura): M = 5.41 (SD = 1.13)

Interpretation of Results

The results indicate that using the AI feedback system positively influenced students' intrinsic motivation. The low mean score for intrinsic motivation (M = 2.48) suggests that students found the system engaging and enjoyed interacting with the content.

The moderate score for extrinsic motivation (M = 3.69) indicates that the system did not overly emphasize external rewards such as grades or recognition but rather focused on fostering motivation centered on the learning process itself.

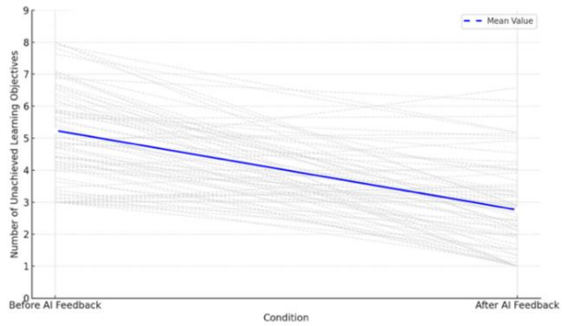
The high score for amotivation (M = 5.69) suggests that students rarely experienced demotivation while using the system. Similarly, high scores for overcoming difficulties (M = 5.41) and goal setting (M = 3.37) indicate that students perceived minimal barriers to setting and achieving their learning goals. These findings confirm that the AI feedback system played a supportive role in minimizing potential motivational and learning challenges.

Detailed Analysis of Learning Objectives

The learning objectives of the 12 seminars covered a wide range of aspects, such as critical reflection, applying theoretical concepts, and connecting theory with practice. Each seminar defined at least six specific learning objectives that students were expected to achieve.

The analysis of unachieved learning objectives showed that students achieved significant improvements after the first round of feedback. Figure 1 illustrates the reduction in average unachieved learning objectives, complemented by individual progress trajectories. These trajectories demonstrate that most students substantially reduced their competency deficits, highlighting the effectiveness of the AI feedback system.

Figure 1. Individual and Average Change in Unachieved Learning Objectives



The figure underscores that the feedback was not only effective in identifying deficits in learning objectives but also directly supported students in reducing these deficits. This effect is reflected in the significant improvement in learning performance, as confirmed by the t-test results.

6. Discussion

The results from the descriptive analysis and t-test demonstrate a significant improvement in the attainment of learning objectives following the implementation of the AI-based feedback system. The substantial reduction in unmet learning objectives and the increased word count in revised submissions confirm that students actively used the feedback to improve their work. These improvements underscore the effectiveness of adaptive feedback and its potential to support the learning process through targeted guidance and recommendations.

The significant improvement in learning performance reinforces the relevance of theories proposed by Paul Black and Dylan Wiliam, as well as the parallel goal and content validity model by Schott and Azizi Ghanbari [21]. The empirical findings align with theoretical expectations that formative feedback is essential for supporting learners in achieving their goals. The integration of AI-based feedback systems grounded in solid pedagogical theories demonstrates that the validity of learning objectives and embedding them in a well-structured competency model are critical for learning success.

A key finding of this study is the relationship between motivation and improved learning outcomes. The motivational analysis shows that the use of the AI-based feedback system enhanced learners' intrinsic motivation while reducing amotivation and perceived difficulties in goal setting. This increased motivation directly correlates with the active engagement of learners in revising their tasks, as evidenced by the increased word count in submissions and the reduction in unmet learning objectives. This supports Heckhausen's Expectancy and Incentive Model, which suggests that high motivation encourages learners to invest more effort and time in their tasks, resulting in higher learning outcomes [3].

The analysis also highlights that the AI feedback system contributes to cognitive relief by presenting instructional content and feedback in a clear, structured, and competency-oriented format. Cognitive Load Theory supports the notion that reducing unnecessary mental effort helps learners focus their cognitive resources on relevant tasks [23]. This reduction in cognitive load may play a pivotal role in sustaining motivation, as learners are more likely to engage with feedback and consistently pursue their goals when provided with clear guidance and reduced cognitive strain.

Another critical aspect is the scaffolding of prior knowledge: the AI system utilizes individual learning progress to provide personalized feedback tailored to the learners' existing knowledge base. This approach aligns with the principles of scaffolding [27] and enhances self-efficacy. Bandura (2001) emphasizes that the perception of one's own competence—the belief in one's ability to achieve a goal—is crucial for motivation and learner success [3]. Increased self-efficacy among students may also act as a mediating factor between motivation and learning outcomes, as learners with higher confidence in their abilities are more likely to exert additional effort.

The fact that only 45 of the 250 students voluntarily revised their submissions raises questions about the role of intrinsic motivation in the use of the feedback system. This observation aligns with findings from Sakai et al. (2017), which highlight the importance of intrinsic motivation for active participation in learning activities [20]. It becomes evident that additional strategies are required to engage and support less motivated learners, as emphasized by theories such as Self-Determination Theory (Deci and Ryan) and the need for supportive learning environments [18].

Bandura's research underscores that self-efficacy and goal setting are essential for fostering students' motivation and engagement. Implementing systems that provide regular feedback and clearly defined, attainable goals could further enhance intrinsic motivation. Additionally, the analysis suggests that extrinsic motivation (M = 3.69) plays a moderate role. This indicates that learning outcomes are primarily influenced by intrinsic factors, such as the enjoyment of the learning process and confidence in one's abilities. Strengthening extrinsic incentives could, however, help engage less motivated target groups

Limitations and Future Research

A significant limitation of this study is the small number of participants in the motivational analysis. Of the 45 students who actively used the AI feedback system, only 8 completed the questionnaire. This severely limits the interpretability of the results and prevents reliable conclusions about the entire target group. Future research should aim to increase participation in surveys, potentially through incentives or by integrating the surveys into the learning platform.

Another limitation is the relatively low percentage of students who voluntarily revised their submissions, which restricts the generalizability of the findings. Furthermore, the absence of a control group makes it challenging to isolate the effects of the AI feedback system from other influencing factors. Future studies should include a control group to better assess the causality of the observed effects. Additionally, larger and more diverse samples should be employed to enhance the robustness and generalizability of the results.

A further limitation lies in the measurement of motivation: the study only captured the end state of motivation, leaving the development of motivation throughout the semester unexplored. Longitudinal studies could provide valuable insights into how the use of AI feedback systems influences motivation and self-efficacy over time.

Finally, it would be important to investigate the long-term effects of feedback and evaluate how the system fosters the development of critical thinking and problem-solving skills. The integration of cognitive relief and scaffolding approaches should also be further explored to assess the effectiveness of such systems in more complex learning scenarios.

7. Conclusion

This study examined the effects of adaptive, AI-based feedback on students' learning performance and motivation, identifying significant improvements in the attainment of learning objectives. The reduction in unmet learning objectives and the increased word count in revised submissions illustrate that the AI-based feedback system promotes active engagement with learning content, thereby making a substantial contribution to learning outcomes.

Another key finding of this study is the positive impact of the AI feedback system on students' motivation. The results demonstrate that the system not only enhances intrinsic motivation but also reduces barriers such as amotivation and difficulties in goal setting. This highlights the importance of self-efficacy, as described by Bandura, which is supported through personalized, goal-oriented feedback. Particularly noteworthy is the role of cognitive relief achieved through well-structured, competency-oriented feedback. This relief enables learners to focus on relevant tasks and utilize their cognitive resources efficiently, resulting in a sustainable improvement in learning outcomes.

The connection between learning performance and motivation is another significant contribution of this research. The analysis suggests that increased motivation—particularly intrinsic motivation—is closely linked to more intensive engagement with learning content and greater competency development. This relationship is supported by Heckhausen's Expectancy and Incentive Model, which demonstrates that learners who perceive high success expectations and clear incentives in their goals invest more effort in their tasks.

The findings of this study encourage educational institutions and instructors to fully leverage the potential of AI-based feedback to optimize learning processes and improve educational outcomes. In addition to fostering learning performance and motivation, the system demonstrates its capability to support diverse learner groups by providing personalized feedback. Future research should focus on the long-term effects of AI-based feedback, particularly in fostering critical thinking, problem-solving skills, and the sustainable development of competencies.

Another area of focus for future research should be the investigation of motivation, especially performance motivation, which Bandura identified as closely correlated with learning outcomes. Using the Academic Motivation Scale questionnaire could provide deeper insights into the motivational aspects of learning and help develop strategies to better engage less motivated learners.

This study confirms that the use of advanced AI technology in education is not only feasible but also highly beneficial. It facilitates personalized learning and supports students in achieving their learning objectives more effectively and efficiently. Moreover, the research emphasizes that cognitive relief, the integration of prior knowledge, and the enhancement of self-efficacy are critical factors in optimizing the learning experience and improving overall educational quality.

The findings contribute valuable insights to the ongoing debate on integrating AI into education and set new benchmarks for leveraging technology to enhance educational outcomes. Continuing this research can provide a deeper understanding of how technology-supported feedback sustainably influences and improves the learning process, ultimately transforming teaching and learning practices and enabling a more personalized and effective educational experience.

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