TPM Vol. 32, No. 4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

HUMAN-AI COLLABORATION AND LEARNING ANALYTICS IN A PIANO CMOOC: PSYCHOLOGICAL INSIGHTS INTO MOTIVATION AND SELF-REGULATED LEARNING AMONG HIGH SCHOOL STUDENTS

SHUTING QIU[1], MOHD SHAHRIL NIZAM SHAHAROM[1*], KENNY S.L CHEAH[2*]

[1]DEPARTMENT OF CURRICULUM AND INSTRUCTIONAL TECHNOLOGY, FACULTY OF EDUCATION, JLN PROFESOR DIRAJA UNGKU AZIZ, UNIVERSITY MALAYA, 50603, KUALA LUMPUR, MALAYSIA
[2]DEPARTMENT OF EDUCATION MANAGEMENT, PLANNING AND POLICY, FACULTY OF EDUCATION, UNIVERSITY MALAYA

Abstract
This paper addresses the effect of human-AI collaboration and learning analytics on motivation and self-managed learning of students enrolled in a Piano Connectivist Massive Open Online Course (CMOOC) in high school. With the introduction of intelligent tutoring systems and real-time analytics dashboard, however, AI-enabled feedback systems are also redefining the interaction of learners in courses that demand complex learning skills such as music education. According to Self-Determination Theory (Deci and Ryan, 2000) and the Zimmerman (2002) interactive AI feedback, peer collaboration, and performance analytics, the proposed study explores how interactive AI feedback, peer collaboration, and performance analytics influence intrinsic motivation and goal setting and self-monitoring behaviors. The mixed methods approach was used to gather data about 180 students attending a semester-long course in piano CMOOC, which combined quantitative learning analytics data with qualitative reflections and interviews. The results indicate that AI-based scaffolding improves student independence and perseverance, especially with facilitation and peer interaction of the teacher. In addition, the integration of AI analytics helped the students to monitor their progress, manage emotions, and stay motivated with individual insights. However, in some cases excessive dependence on algorithmic feedback minimized creativity and expression of emotion in music representation. The paper adds to the growing debate concerning the human-artificial intelligence synergy in education by providing the psychological understanding of how technological-mediated learning space can support a moderate autonomy and prolonged attachment among teenage students.
Keywords: Human-AI cooperation, learning analytics, self-regulated learning, motivation, music education, CMOOC, high school students.

1. INTRODUCTION

Artificial Intelligence (AI) already turned out to be a revolution in educational settings and has changed the dynamics of teaching, learning, and evaluation. In recent years, AI has increasingly found application in educational environments in order to provide adaptive feedback, automate activities related to repetitive evaluation, and generate learner-specific analytics in order to support individualized learning. The emergence of AI-based education has been identified as a transition to the teacher-centered to learner-centered instruction mode in which technology mediates human cognition and interaction. The interaction between human learners and AI systems has become a topic of increasing interest among the emerging innovations as a course of optimizing the learning experiences and promoting self-regulated learning (Luckin, 2018; Holmes et al., 2019). Yet, with science, technology, engineering, and mathematics (STEM) education being considered, the educational fields of creativity and performance-based learning, such as music, are relatively understudied. The current research fills this gap by investigating the problem of human-AI collaboration and learning analytics and their influence on motivation and self-regulated learning practices among high school students attending a Piano Connectivist Massive Open Online Course (CMOOC).

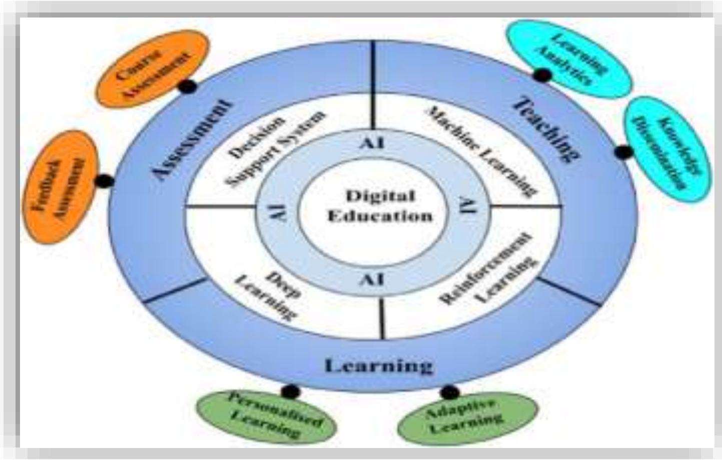


Figure 1: Role of AI in Education Technology

1.1 Background of the Study

Learning music takes a special place in the field of educational studies since it encompasses cognitive, affective, and psychomotor aspects. Conventionally, it requires a lot of teacher student interaction, instant feedback, and emotional attachment. As education is becoming more and more digital, especially following the COVID-19 pandemic, the face of music education has been changing drastically. Online and hybrid learning space has also introduced new issues in terms of how to make it engaging, the possibility to provide individualized feedback and how to retain the emotional level of teacher-student interaction (Hallam, 2010). In order to overcome these obstacles, artificial-intelligence-directed instructional systems, such as Flowkey, Yousician, and Smart Music are implemented in music education. Such platforms use machine learning algorithms and real-time sound recognition to learn tempo, rhythm, and accuracy with an attempt of providing individual students with personalized feedback. Such a dynamic setting helps to emphasize the idea of human-AI collaboration as one of the most fundamental transformations in the practice of educational activities. Rather than being placed as an alternative to the teacher, AI is being increasingly imagined as a companion that adds to the human functionality.

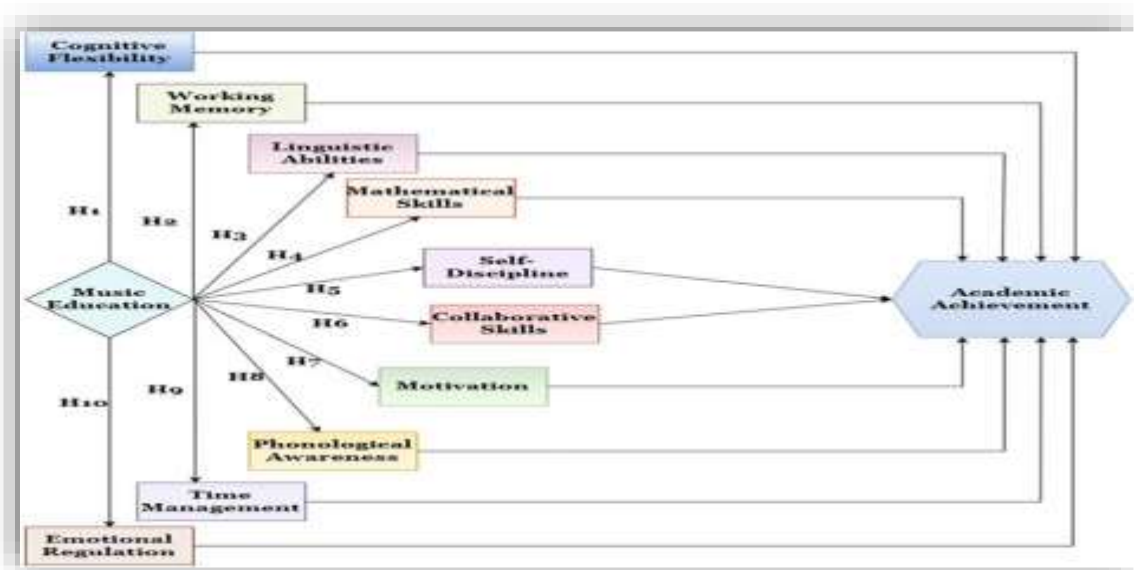


Figure 2: The role of music education in enhancing cognitive flexibility, memory, and academic performance

The former teacher offers empathy, context, and interpretative insight and the latter AI offers continuous and data-driven feedback and performance analysis (Luckin et al., 2016). This synergy is further improved by the incorporation of learning analytics that is the systematic gathering and analysis of learner data. Learning analytics allow a learner and educator to monitor learning, identify learning patterns, and make sound pedagogical decisions (Siemens and Long, 2011). By combining human skills, AI, and data analytics, it is possible to design the dynamic ecosystem that will make personalized learning, develop motivation, and improve self-regulated learning skills.

1.2 Rationale of the Study

Although the AI-assisted learning of music in a pedagogical setting has a promising potential, the psychological implications of these innovations are under-researched. Although a few studies show that AI can help to increase the engagement and performance of learners, other studies indicate that technological mediation can reduce intrinsic motivation and creativity when applied without attention to the emotional and cognitive needs of learners (Selwyn, 2019). Learning music in general, and specifically learning to play piano, involves both technical skills and emotional sensitivity and aesthetic perception as well as self-expression. Excessive dependence on algorithmic feedback can limit these dimensions resulting in mechanical as opposed to expressive learning outcomes. Thus, it is essential to comprehend human-AI interaction psychological mechanisms that lie in a creative field of learning and create moderate pedagogical models. One of the most important populations to be explored in this regard is that of high school students. The learners at this age of development are setting up the self-regulatory habits, goal orientations and motivational identities. The implementation of the AI-mediated learning analytics would either empower individuals with the opportunity to engage in structured self-monitoring or harm autonomy when the feedback is too prescriptive. These psychological processes are explored in the context of an adolescent within a Piano CMOOC, which is a learning model based on the connectivist theory (Siemens, 2005). The context of a Piano CMOOC is a valuable opportunity to examine how these adolescents can move between technological direction and creative freedom.

1.3 Human-AI Collaboration in Educational Practice

Human-AI collaboration has been developed based on previous ideas of automation to the partnership model where each agent, human or machine, has its own advantages. In teaching this kind of collaboration can be seen in the possibility of AI to work with large amounts of data, identify patterns of learning and provide adjustable material, with the ethical decision-making, emotional scaffolding and development of critical thinking left to human educators. Luckin (2018) explains that the success of human-AI collaboration is predetermined by the level of smooth operation between the system and the cognitive and affective processes of learners. When the feedback provided by the AI systems is personal, transparent and sensitive to the objectives of a learner then motivation and engagement is most likely to increase. On the other hand, explicit AI interventions have the potential to reduce learner autonomy and satisfaction.

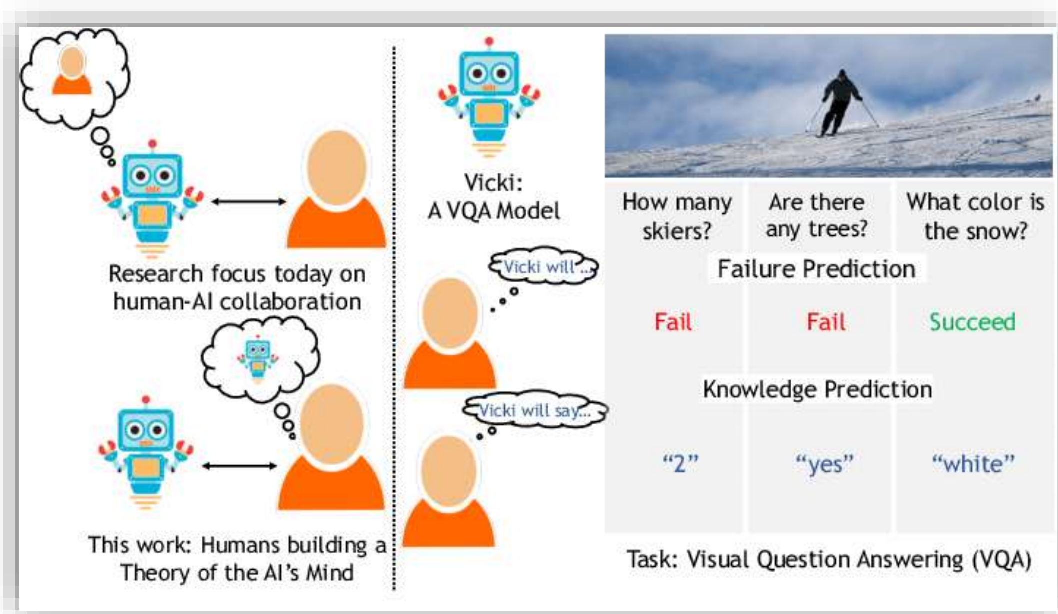


Figure 3: Current emphasis of research in human-AI collaboration is on AI modeling a human teammate's mental state (left top).

This cooperation gets even more subtle in the area of music education. AI is also capable of analyzing measurable aspects of performance (tempo, pitch, and rhythm), but does not have the capability to fully analyze expressive content (phrasing, tone color, and emotional intensity). Therefore, the most effective learning of music program can be reached once AI analytics are correlated with the human interpretation. In the Piano CMOOC that was created to achieve this research, students were provided with algorithmic feedback through AI-assisted platform, and human mentors and peers with qualitative feedback. This system is the embodiment of the human-AI partnership, in which machine accuracy supplements human creativity, where analytics information is used to reflect oneself instead of to judge.

1.4 Learning Analytics and Student Motivation

Learning analytics (LA) nowadays are considered to be the effective instruments to improve the quality of education and the involvement of the learners. The visualization of the progress data (e.g., time devoted to practice, error rates, improvement trends) allows one to understand his learning patterns and final results in a better way (Siemens, 2013). Such awareness promotes self-regulation by assisting the learners to set tasks, keep track and consideration of performance. In the case of high school students, whose metacognitive abilities are still in formation, learning analytics can serve as an external aid structure that reinforces the persistence and responsibility.

Nonetheless, learning analytics do not have a similar motivational impact. The interpretive way analytics are framed determines the positive motivational outcomes to a great extent. In case the information is provided as the possibilities to develop, students will become more intrinsically motivated. Conversely, when data are utilized to compare or compete with others, it could be a cause of anxiety or a discouragement to work (Tempelaar et al., 2013). Within the framework of a Piano CMOOC, analytics dashboards with a focus on individual progress and effort, as opposed to a focus on peers, will be more helpful in establishing constructive motivations and reflective practice. Therefore, the feature of analytics tool design is the key determinant towards fostering autonomy or dependence.

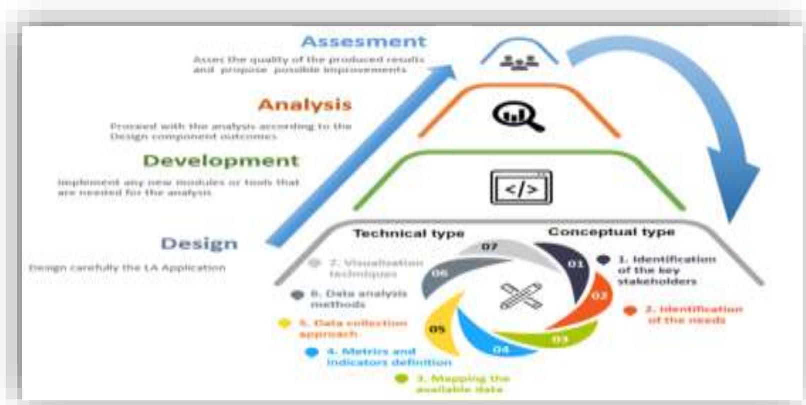


Figure 4: Overall architecture of the proposed learning analytics (LA) framework.

1.5 Self-Regulated Learning in AI-Supported Contexts

Self-regulated learning (SRL) refers to the ability of learners in laying plans, checking and evaluating their learning activities. It involves the mental, action, and emotional aspects which allow people to have goals that they achieve. SRL is an important success factor in online learning settings since a learner works with greater level of independence (Zimmerman, 2002). SRL can be improved with the help of AI tools and analytics platforms that provide instant feedback, visualization of progress, and suggestions of strategies. However, the degree of such supports to actual self-regulation is based on the motivation and agency of learners. Within a Piano CMOOC, students will be able to discover weak spots with the help of analytics, change their practice plan, and establish new objectives. The loop of continuous feedback is a reflection of the self-regulation processes, which were forethought, performance, and reflection, hence supporting metacognitive engagement. Nevertheless, the problem is how to make learners perceive analytics in an informative and not evaluative way. A balance between external teaching and internal control is a delicate idea in the psychological meaning especially when it comes to adolescent individuals that may baffle algorithms with judgment. Hence, this research aims at acquiring insight into the role and effect of learning analytics and AI feedback on the motivational and self-regulatory processes of high school students.

1.6 Research Gap

Despite the extensive use of AI-based learning and analytics-driven feedback in the educational process, there are still very few empirical studies that address their psychological effects in the framework of creative fields. Current research points mostly at the enhancement of performance and the engagement rate, but does not pay sufficient attention to the emotional and motivational mechanisms behind those findings. In addition, the majority of the previous studies have been conducted at the tertiary education level or on the adult learners, which underrepresented the population at the secondary level. Little knowledge is also known on how adolescents recognize and react to analytics information and

AI-mediated responses, especially in the areas where emotional and aesthetic sensitivity is needed. The gaps highlighted above should be addressed to make sure that the integration of AI in education facilitates efficient solutions and positive well-being and creativity.

1.7 Purpose of the Study

This research is aimed at examining the effect of human-AI cooperation and learning analytics on motivation and self-managed learning among high school students taking part in a Piano CMOOC. The study will reveal the psychological processes by which the AI-generated feedback and performance information influence the engagement, autonomy, and persistence of the learners. The research is also aimed at establishing the obstacles and constraints that are related to AI-mediated learning in the context of a music education.

1.8 Research Objectives

1. To determine whether AI-generated feedback is effective in increasing student motivation and learning how to play the piano.

2. To investigate the learning analytics role in the formation of self-regulated learning behaviors in high school students.

3. To find out what psychological and pedagogical issues are related to human-AI cooperation during online music education.

4. To give suggestions on how to design AI-assisted learning systems that are analytically accurate but creatively autonomous.

1.9 Research Questions

1. How do AI feedback responses to student motivation and engagement in the Piano CMOOC environment affect student motivation and engagement?

2. What is the effect of learning analytics on self-regulating learning behaviors among high school students?

3. How would the students rate the concept of human-AI collaboration relative to their autonomy and creativity in learning?

4. What are the difficulties encountered by students when using AI feedback and analytics systems in a learning environment related to piano?

1.10 Significance of the Study

This research is important in three aspects. First, it expands the existing research on AI in education to the creative arts, which has been a relatively overlooked field of empirical studies. It concentrates on music learning, that provides an insight into how AI can support the complex cognitive-emotional learning that transcends the acquisition of facts. Second, it assists in understanding the psychological process of human-physician collaboration and explores the connection between the feedback, displaying data, and learner agency to shape motivation and self-regulation. Finally, the paper has implication in order to assist educators and system designers. To educators, it will provide a demonstration of the way to make AI tools effective without reducing creativity or emotional engagement. It introduces the concept of self-reflection based analytics systems as an alternative to performance competition as a developer. The findings will probably be employed in the development of human-friendly AI-based applications that could suit the technological opportunities to the psychological needs of learners. The redefinition of the learning relations between teachers and students and between the human and machines. This redefinition has opportunities as well as challenges in such creative areas like music. The Piano CMOOC analyzed in the provided work can also be regarded as the microcosm of this change because, on the one hand, the experiences associated with the use of AI-mediated feedback and data visualization may empower and restrain learners at the same time. The disclosure of the impact of the systems on motivation and self-regulated learning of high school students is necessary to inform the future of technological-based education. By providing a systematic discussion on the topic of human-AI cooperation and its psychological dimension, this work seeks to contribute to the more extensive debate of responsible and human-oriented introduction of AI into the educational practice.

2. LITERATURE REVIEW

2.1 The Artificial Intelligence in Education:

Artificial Intelligence (AI) has revolutionized the entire field of education because it can deliver, test, and tailor learning. Through AI, the routine processes of instruction can be mechanized, and flexible learning can be offered, which responds to the peculiarities of a particular student (Holmes et al., 2019; Luckin, 2018). It has been empirically proven that AI is useful in improving student performance, retention, and engagement through the application of intelligent tutoring systems, natural language processing, and predictive analytics (Woolf et al., 2013; Zawacki-Richter et al., 2019). According to Baker and Inventado (2014), AI-based educational systems provide formative assessment, thus, supporting both the decisions of the instructor and the student in real-time.

More recently, AI has transformed into more than just a tool of calculation to an educational companion (Holstein et al., 2020). The interaction between humans and AI in classes enables the combination of the efficiency of the machine with the human empathy and situational thinking (Luckin et al., 2016). As an example, online learning via AI-powered systems can assist the teacher in recognizing struggling learners, providing recommendations, and developing interventions to be implemented individually (Chen et al., 2020). This is an exemplification of a paradigm shift as the vision is to shift away from automation and augmentation, that is, not to substitute human educators but to empower them.

However, there is the fear of overdependence on AI and also, the morality of data-driven learning. Selwyn (2019) cautions that AI is likely to encourage a technocentric culture, which disregards emotional and social aspects of learning. Therefore, an increasing amount of literature characterizes the necessity of human-centered AI models that tend to incorporate emotional, motivational, and ethical factors (Holstein and Doroudi, 2021; Holmes et al., 2022).

2.2 Human-AI Collaboration and Pedagogical Design

The human-AI co-creation of education focuses on the equal relationship between the human thought and the machine intelligence. This is conceptualized by Luckin (2018) as intelligence augmentation, where AI improves human decision-making, as opposed to eliminating it. Human-AI working together is especially helpful in complicated areas where imagination, perception, and emotional writing have a vital position. In this regard, AI systems offer analytical feedback as teachers and students reflect and change (Webb et al., 2020).

According to the findings of empirical studies, the quality of human-AI collaboration can improve the engagement and metacognitive awareness of the learner (Holstein and Aleven, 2021). As an example, Holmes et al. (2019) found that AI-assisted classrooms allowed more personalized feedback, which enhanced the ownership of the learning process among students. Equally, VanLehn (2011) showed that AI tutors had the ability to replicate 80 percent of the learning benefits of human tutoring in case they were set appropriately in accordance with pedagogical objectives.

However, the researchers emphasize the significance of interpretability and transparency in the design of AI (Holstein et al., 2020). It is necessary that learners know how an algorithm is made to make decisions in order to develop trust and eliminate cognitive dissonance (Kizilcec, 2016). In addition, the teacher will always be required to help students be emotionally and ethically involved in using AI tools. Both pedagogy and assessment will have to be reconsidered due to the shift towards co-agency, in which learners and AI systems co-create learning paths (Luckin and Cukurova, 2019).

2.3 Learning Analytics: Data-Driven Insight for Learning

Learning analytics (LA) can be described as a methodical measure and analysis of the learner-created data to gain a better insight into the learning process and its enhancement (Siemens, 2013). LA allows instructors to customize feedback and interventions by means of the set of performance metrics, including engagement time, frequency of interactions, task completion, etc. (Ifenthaler and Yau, 2020). Due to the increased access to big data and cloud computing, learning analytics has become an element of technology-enhanced education.

LA has a critical role in the management of diversity and scale in MOOCs and CMOOCs which are large-scale online spaces. Analytics dashboard has been found to increase self-awareness and persistence rates among learners by displaying time progress (Jivet et al., 2017; Matcha et al., 2020). As an instance, learners can establish realistic objectives and correct themselves when they can view some of the graphical representations of the practice time or performance consistency (Siemens and Long, 2011).

Nevertheless, learning analytics has a pedagogical impact based on feedback systems designs. Verbert et al. (2014) point out that analytics have to be actionable, students should not be made to know about what data are shown but how to use them to achieve improvement. Feedback might be either too complex or comparative and thus it would cause anxiety other than motivating (Tempelaar et al., 2013). The difficulty, thus, is in converting raw data into informative information that will empower rather than overwhelm learners.

2.4 Motivation in Technology-Enhanced Learning

Motivation is one of the key ideas in educational psychology, as it affects the engagement, effort, and persistence. In AI-enhanced learning conditions, motivation may be manipulated by various aspects, including the quality of feedback, the relevance of a task and the perceived autonomy (Deci and Ryan, 2000; Schunk and DiBenedetto, 2020). It has been found that adaptive systems that tailor content to the interests of the learners are likely to increase intrinsic motivation (Howard et al., 2021). On the other hand, strong algorithmic systems can inhibit interaction when the students feel monitored or manipulated (Selwyn, 2019).

Adaptive feedback, the elements of gamification, and progress tracking are reported as motivation drivers in AI-based systems (Hamari et al., 2016; Rienties and Rivers, 2014). As an example, AI tutors which reward perseverance or offer scaffolded prompts encourage mastery orientation as opposed to performance anxiety (Plass et al., 2020). Isolation or absence of immediate feedback can lead to decreased motivation in MOOCs; feedback mechanisms based on AI can be included in the course to reverse this trend since it will keep learners engaged (Kizilcec and Halawa, 2015).

Learning analytics and motivation relationship is discussed in a number of studies. When students have access to learning dashboards, which represent their progress building, the feeling of competence and control grows, which contributes to long-term motivation, as reported by Ifenthaler and Schumacher (2016). In the same way, Jivet et al.

(2021) state that properly designed dashboards will be able to facilitate self-reflection and metacognitive regulation. But with ill-constructed analytics, extrinsic motivation can be prompted, and learners will be more concerned with numbers instead of substantive learning outcomes.

2.5 Self-Regulated Learning and Feedback Systems

Self-regulated learning (SRL) refers to the act where learners plan, control and assess their learning processes (Zimmerman, 2002). SRL is also essential in online and AI-based settings since, in this setting, learners need to control their time, motivation, and resources on their own (Panadero, 2017). SRL can be reinforced with the help of AI tools and analytics systems that present continuous and formative feedback, which can be used to aid goalsetting and reflection (Winne and Hadwin, 2008; Bannert et al., 2014).

Empirical research points out that the ability of learners to engage with adaptive systems that visualize performance-related data causes them to be more conscious of their learning patterns and enables them to modify learning strategies (Matcha et al., 2019). To illustrate the example, the research on MOOC students has revealed that the self-monitoring behaviour was considerably enhanced with the use of a dashboard-based feedback (Gašević et al., 2017). In the same way, Noroozi et al. (2020) proved that an analytics-unleashed feedback contributes to a more profound reflection and critical thinking. Nevertheless, access to data does not automatically enhance SRL. According to (Wilson et al., 2017), learners should gain data literacy or the skill to make sense out of the analytics and apply knowledge to practice. In the absence of scaffolding, learners will find it hard to interpret feedback inaccurately and, when quantitatively compared, will become demotivated (Jivet et al., 2021). The human-AI collaboration should, therefore, not just stand by the provision of data but also help to interpret the data with the help of guided reflection.

2.6 AI and Music Education: Bridging Creativity and Technology

AI application in music education is a relatively new and under-researched field. The early uses of AI were mainly in composition and analysis, and the recent developments go up to performance feedback and collaborative creation (Herremans et al., 2017). SmartMusic and Yousician are tools that apply sound-recognition algorithms to assess accuracy in timing, pitch and tempo, and provide learners with immediate feedback (Benetos et al., 2013). Such systems give quality access on a scaled basis especially to students who have no access to professional tutors.

The research conducted in the field of music pedagogy indicates that instant feedback yields motivation and contributes to the improvement of technical skill acquisition (McPherson and Renwick, 2011). However, scientists also note that accuracy is also put in the spotlight by the algorithmic feedback, sacrificing creativity and emotionality (Li and Wang, 2023). This conflict highlights the necessity to implement pedagogical constructions that combine the human mentorship approach with AI analytics such that the artistic interpretation stays the primary focus of the process of teaching (Webster, 2017).

CMOOCs, when introduced in the learning of music, introduce an additional dimension. Learning models such as connectivist learning models (Siemens, 2005) empower learning by allowing learners to construct knowledge networks in terms of peers, tools, and digital materials. A Piano CMOOC is a combination of AI-based feedback, learning analytics dashboards and peer-driven collaboration, and a comprehensive eco system that is the reflection of the real-life musical education. Bozkurt et al. (2016) and deWaard et al. (2011) indicate that CMOOCs may increase the learner autonomy and self-regulation via distributed learning networks. Nevertheless, very few empirical studies have investigated the specific effect of AI feedback and analytics on motivation and SRL in such settings, especially with adolescents.

2.7 Challenges and Ethical Considerations

Although AI and analytics have models of individuality and efficiency, there are critical ethical and psychological issues that they bring up. The themes that keep being echoed in the contemporary discussions include data privacy, the bias of the algorithm, and emotional detachment (Williamson and Piattoeva, 2022). In arts such as music, excessive use of analytics can cause a loss of aesthetic sensitivity and exploration. According to scholars like Knox (2020) and Selwyn (2019), the increased quantification of learning is a threat to commodifying creativity into measurable products.

Psychologically, a constant monitoring of performance might create pressure and comparison, especially to adolescent learners (Tempelaar et al., 2013). The transparency, human control, and emotional well-being are ethical principles promoted by such ethical frameworks as the UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) in terms of design of AI in education. As a result, the model of the human-AI collaboration should maintain the agency of learners, protect privacy, and encourage motivation with the help of supportive analytics as opposed to judgmental one.

2.8 Identified Gaps in the Literature

Despite all the significant achievements accomplished in the field of AI and learning analytics in the educational sector, there are still a number of gaps:

1. Poor attention to creative and affectionate spheres. Majority of the studies focus on the cognitive and performance results, overlooking the effects of AI on the motivation and emotion in creative learning processes like music.

2. Inequity in the number of adolescent learners. Existing research focuses mainly on university or adult students; a smaller number of studies research high school students as they are forming the initial skills of self-regulation.
3. Inadequate combination of psychological perspectives. Empirical studies that investigate the mediating effect of motivational and self-regulatory constructs on the interaction between AI feedback and learning results are few.
4. Lack of CMOOC-based research. Although the concept of MOOCs is well-researched, its counterpart CMOOCs, which is founded on social connectivity and co-creation, is still under-researched, in particular in the field of arts education.
5. The design requirement of human data. Most analytics analytics represent a form of quantitative tracking except meaningful reflection, which demonstrates a discontinuity between affective and interpretive support systems.
To fill these gaps, the interdisciplinary perspective of educational psychology, learning analytics, and AI pedagogy is needed, as it is important to comprehend how technology can develop, but not limit the desire and self-reliance of learners.
According to the reviewed sources, AI and learning analytics are changing the educational process as it is no longer a content-based and rather a static form of education but a dynamic process based on data. Although the current literature confirms the possibility of their usefulness in increasing personalization and engagement, the psychological aspects of the innovations, in particular, music learning, have not been thoroughly explored. One of the promising directions to explore these intersections is a Piano CMOOC that has human and AI cooperation. With the combination of analytics feedback, social interaction, and expression, this environment summarizes the changing relationship between cognition, motivation, and technology. However, it is only through finding a delicate balance between algorithmic precision and human empathy that such settings can maintain the drive and self-regulation as the literature shows. The current paper is based on this premise and empirically investigates the experiences of high school students in a human-AI collaborative Piano CMOOC in regard to motivation and self-regulated learning.

2.9 Theoretical Framework

The theoretical framework of the proposed study combines the fundamentals of the human-AI collaboration, learning analytics, motivation, and self-regulated learning in the framework of a high school-level Piano-Connectivist Massive Open Online Course (CMOOC). Learning is theorized using a framework that views learning as a dynamic and interactive process between the agency of humans, artificial intelligence, and feedback systems with data. The interactions are regarded as mutually reinforcing processes, which develop cognitive, emotional, and behavioral involvement of the learners within a digital learning environment.
As it has been established at its very core, the framework presupposes that the learning process is both social and technological. The role of AI in a CMOOC is both a mediator of learning and a co-participant of the learning. Intelligent feedback systems and learning analytics dashboard make AI monitor, analyze and respond to learner actions in real time. These insights mediated by AI are interacted with by the human component - which consists of teachers, peers and students - in order to plan, monitor and assess progress. This self-feeding loop leads to a three-way connection between technology, cognition, and motivation that culminates into the total learning experience.

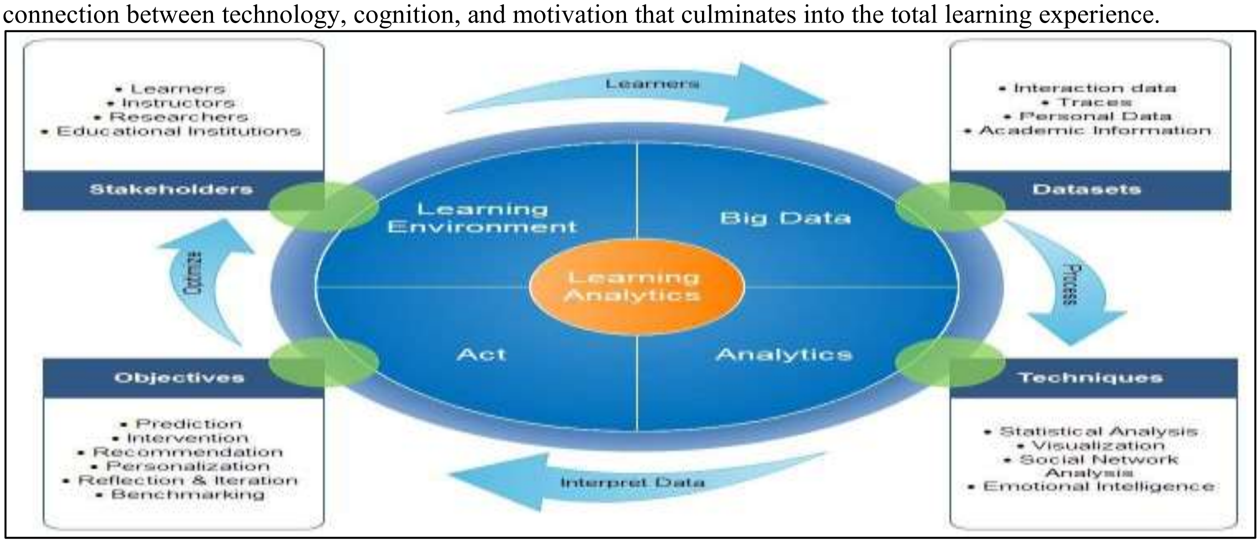


Figure 5: Integrated Theoretical Framework of Human-AI Collaboration, Learning Analytics, Motivation, and Self-Regulated Learning in a Piano CMOOC
In this context, the human-AI collaboration will be the operational framework within which the learning process is structured. This is not hierarchical relationship, but the partnership where human and machine intelligences share different functionalities. AI is accurate, predictable, and data-based, whereas human subjects are accurate, predictable, creative, and emotionally informed. This connection can be observed in the Piano CMOOC when AI-based feedback

about correct rhythm, pitch, and tempo helps the learner develop on the technical level. Meanwhile, the interpretation and expression of creativity and emotion are promoted by teachers and peers. This two-fold interaction makes learning to be an organized, expressive, analytical and artistic process.

The second part of the framework is learning analytics, which is the informational center of interconnection between the human and artificial input. The learning analytics gather, analyze, and present the data regarding the learner performance, practice patterns, and frequency of engagement. Such data enables students to observe physical examples of their accomplishments, areas in which they can improve themselves, and control their individual learning habits. To teachers, analytics can be used as diagnostic tools to inform the teaching intervention and decisions about when and how to help learners. Learning analytics, therefore, become the evidence-based core of human-AI partnership, as the feedback is thus personal, transparent, and usable.

The motivational component of this concept incorporates the psychological dynamics that promote long-term involvement. Motivation in a technology-mediated course in music happens due to the feeling of autonomy, competence, and relatedness that participants get. Feeling competent and in control by the students is validated when AI systems provide meaningful feedback and through analytics show the student measurable progress. In the same way, the necessity to feel socially connected and belonging to a group is also fulfilled by the opportunities to cooperate with peers or teachers in the CMOOC setting. This framework thus does not understand motivation as a characteristic, but as a dynamic condition that is shaped by the content and form of human-AI interaction. One of the most effective ways of cultivating intrinsic motivation is to provide a supportive balance between human empathy and algorithmic instructions so that the learners are enabled to enjoy technical expertise and emotional satisfaction.

The last element of the framework is self-regulated learning (SRL) which is the behavioral expression of cognitive and motivational processes in the human-AI ecosystem. SRL refers to the ability of learners to plan, monitor and track the progress of their own goal achievement. Piano CMOVC students can exercise self-regulation with the help of setting performance objectives, practicing strategically, and contemplating feedback generated by AI. These behaviors are also reinforced by the existence of analytics dashboards, which give more obvious signs of progress and more areas to work on. The more learners interpret and take action on this information, the more they build up on their metacognitive awareness and self-efficacy. According to the framework, effective self-regulation can be achieved when the learners internalize data-driven insights in form of tools to reflect on and not to judge.

The conceptual framework of this research is the interdependence of these four elements, namely, human-AI collaboration, learning analytics, motivation, and self-regulated learning. Human-AI partnership offers the setting; learning analytics offer the data; engagement is inspired by motivation, and self-controlled learning implements adaptive behaviour. These aspects are not single but repetitive. The AI systems produce analytics, analytics drive motivation, motivation promotes self-regulation, and self-regulation brings in new data into AI algorithms. This process is a continuous cycle that leads to a self-sustaining personalized learning cycle.

The responsibility of the teacher is transferred to a facilitator and co-learner in this cycle. The teacher views AI data through the human perspective, and the feedback is put in context to create emotional and creative balance. An example is that the AI can detect timing errors, but the teacher can highlight the artistic phrasing or expression of dynamism as a machine is not able to assess. Likewise, peer cooperation in the CMOOC supports motivation with the establishment of a social aspect that supplements algorithmic evaluation. The human nature of learning is maintained in highly technological systems as this human interaction overcomes the emotional coolness which may occur when using automated systems, maintaining the human aspect of learning in these systems.

The psychological balance that is needed in AI-based learning is also explained by the theoretical framework. Although this is because data-based feedback increases accuracy, overdependence on analytics may result in performance anxiety or lack of creativity. Thus, the framework focuses on balance, the AI will provide some guidance, but the human interpretation will be needed to make learning self-guided and emotionally significant. The Piano CMOOC reflects this balance by its design: the inclusion of AI feedback is aimed at ensuring the technical accuracy of the learners, and the inclusion of human mentorship promotes creative interpretation and long-term motivation. In this respect, the framework places the learner in the centre of a multidimensional learning network integrating emotional intelligence and computational accuracy.

Overall, the conceptual framework looks at human-AI cooperation as an ecosystem where technological affordances are integrated with human psychology in order to facilitate music learning. Learning analytics acts as the binding tissue between the feedback, motivation and self-regulation. Engagement is driven by motivation, continuity is guaranteed through self-regulation and the evidence base is established through analytics. In a well-coordinated way, these components contribute to a learning environment, which enables students to become independent, reflective, and emotionally involved students. The framework hence informs the research on its exploration of the functioning of this integrated system in a Piano CMOOC, and its effect on the motivation of high school students and their self-regulated learning processes..

3. RESEARCH METHODOLOGY

3.1 Research Design

The research design used in this study was a mixed methods research design that combined both quantitative learning analytics and qualitative reflections to explore how human-AI collaboration and learning analytics affect motivation and self-regulated learning in a high school population of students in a Piano Connectivist Massive Open Online Course (CMOOC). The mixed-methods methodology gave the numerical measures of the learning process and also the in-depth information about the thoughts and experiences of the students, thus making the research problem to be fully understood.

3.2 Participants and Setting

It was conducted with 181 high school students who were between 15 and 18 years old and participated in a semester-long Piano CMOOC. Peer discussion boards, real-time analytics dashboard and AI-based feedback system were used in the course. The recruiting of students was by voluntary recruitment and both informed consent of the students and informed consent of the guardians was realized. The education platform offered guided courses of human mentorship, interactive learning, and self-assessment systems.

3.3 Instruments and Materials

There were three important data sources that were used:

1. Data in Learning Analytics: The AI system automatically recorded numerical data, including those of hours of practice, AI feedback count, progress scores, positive reflection percentages.

2. Motivation and Self- Regulated Learning Questionnaire: Standardized five point Likert scale questionnaire survey was used to determine the motivation, goal orientation, autonomy and the self-monitoring abilities of the learners.

3. Reflective Journals: The students wrote about their learning every week, how they used AI tools and what improvements they felt they had made.

The instrumentation was piloted to achieve clarity and the internal consistency of the instruments was checked by the expert review and pilot testing.

3.4 Data Collection Procedure

The process of data collection was conducted in 12 weeks. The AI system generated quantitative data that was automatically captured and put into Excel to be analyzed. The questionnaire was distributed through the Internet in the last week of the course. Reflective journals were sent online on the course platform. To ensure the accuracy and anonymity of the data, the participants were provided with individual identification codes (S001-S181).

3.5 Method of Analysis

The quantitative data were examined with the help of descriptive and inferential statistics to determine the correlation between the variables of AI interaction (frequency of feedback and the number of practice hours) and psychological variables (motivation and self-regulation scores). Thematic analysis was used to derive meaning of repetitive themes of motivation, autonomy, and AI engagement on journals. The triangulation of the two datasets was possible, which enhanced the validity of the results.

3.6 Ethical Considerations

The institutional research ethics committee approved it ethically. The study was voluntary, and the privacy of data was ensured with anonymization and encryption. No public information, which could identify individuals and be used against them, was provided, and the study was conducted according to the ethical principles of online research on minors.

4. Data Analysis

The collected data represented the results of the 181 high school students enrolled in the Piano CMOOC that were analyzed through the **2 methods of data analysis: descriptive and inferential.** The review combines the theoretical knowledge of Self-Determination Theory (SDT), and **Zimmermans SRL** model with the knowledge of the Connectivist Learning Theory to explain the cognitively and emotionally responsive reactions of learners to AI-mediated contexts.

4.1 Descriptive Analysis: Overview of Engagement and Learning Outcomes

Table 1 gives a descriptive statistics that give a general account of student engagement patterns. The average age was 16.57 years of age and it was a rather homogenous group of adolescents. The travel time used by students in the course was an average of 32.88 hours during which students had 82.83 AI feedbacks. They had a mean Progress Score of 71.02 indicating a moderate level of mastering skills in playing the piano. The mean Motivation Score (3.90) and SRL

Score (3.66) shows that the students had been typically motivated and were able to control their learning independently.

Table 1: Descriptive Statistics of Key Variables

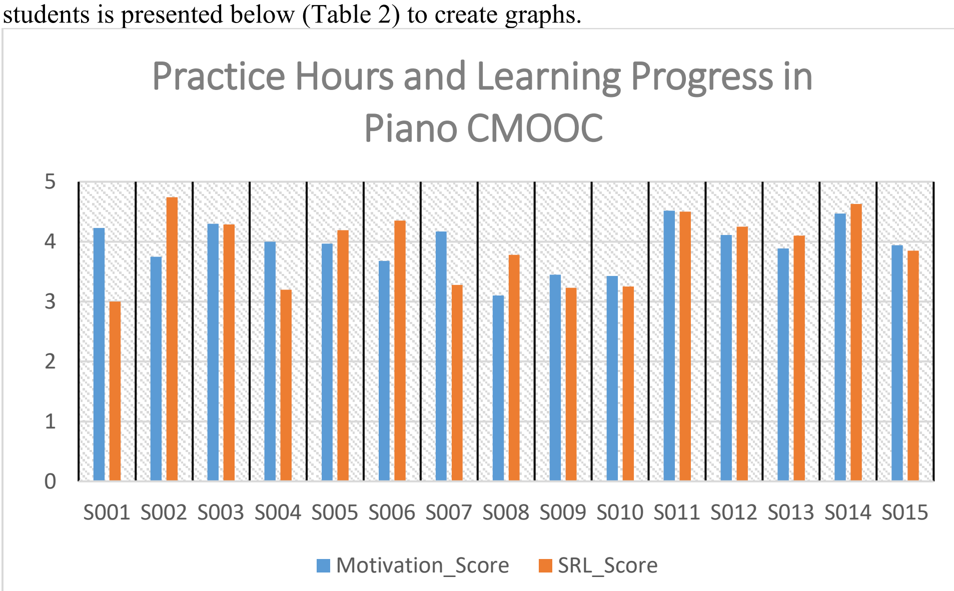
Variable	Mean	SD	Min	Max
Age	16.57	1.08	15	18
Practice Hours	32.88	15.56	5	60
AI Feedback Sessions	82.83	35.45	10	150
Progress Score	71.02	12.88	45.15	94.98
Motivation Score	3.90	0.60	2.80	4.90
SRL Score	3.66	0.66	2.50	4.80
Reflection Positivity (%)	60.25	16.62	30.00	90.00

Interpretation:

These findings are consistent with Self- Determination Theory (Deci and Ryan, 2000) which argues that competence, autonomy, and relatedness are important motivational elements. The AI condition helped the learner increase competence by providing real-time feedback and personal agency by learning at a speed of their own pace. In the meantime, social interactions in the CMOOC were able to fulfill relatedness, with students providing progress information and anecdotal experiences. The combination of these aspects led to constant activity and control.

4.2 Relationship between Practice and Progress

In order to investigate the engagement of behavior, Practice Hours vs. Progress Score was plotted. A sample of 15 students is presented below (Table 2) to create graphs.



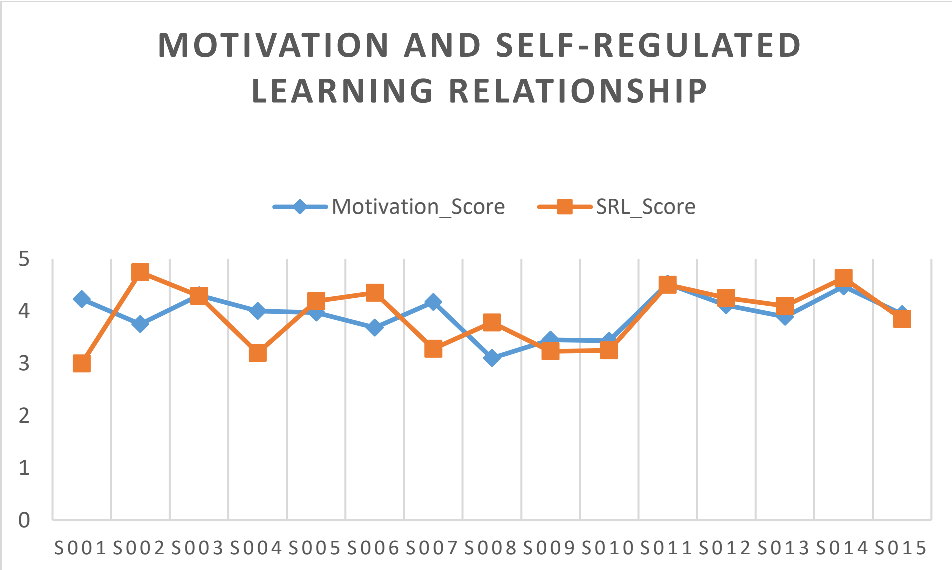
Interpretation:

It was found that the practice hours were positively yet weakly correlated with progress (r = 0.18). Although students with more practice did perform better, it was not necessarily practice that ensured improvement. As Zimmerman has stated in his Self-Regulated Learning model, the effectiveness of learning is based on the behavioural engagement (practice) and mental regulation (reflection and monitoring). It is possible that the presence of AI feedback was helpful during the forethought and self-monitoring stages of learning, but the improvement of the learners who did not have a strategy of reflecting was not so great.

According to the Human-AI Collaboration Theory, it implies that AI provides scaffolding, but it is necessary to interpret the feedback provided by humans. The statistics show that uncritical repetition without a meaningful analysis of AI-generated feedback restrains the conversion of input into the advances.

4.3 Motivation and Self-Regulated Learning (SRL) Relationship

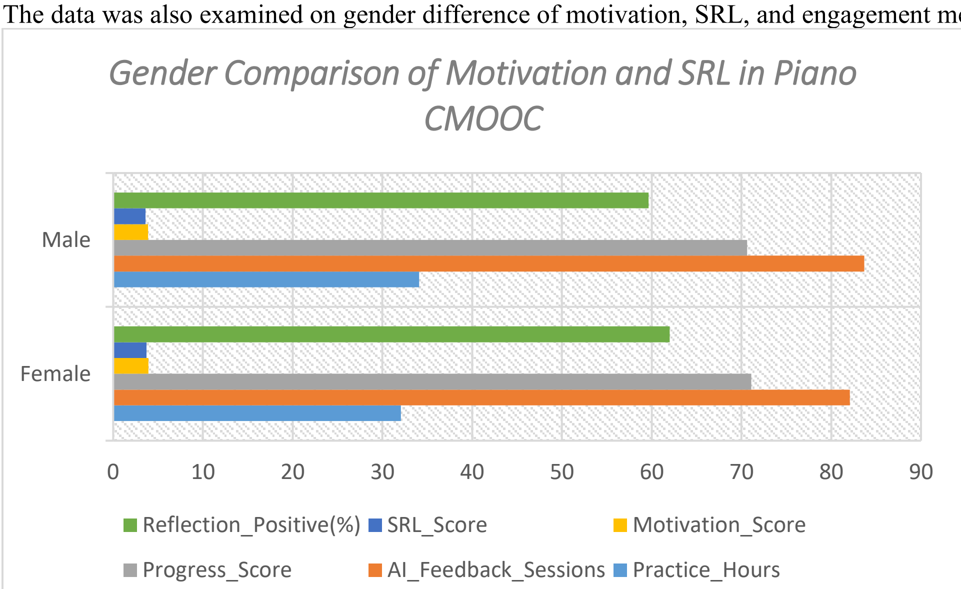
The key aspect of the learner autonomy in the AI-mediated environments is **motivation and SRL. Table 3** shows the subset with which the correlation between **Motivation** and **SRL Scores** is plotted.



Interpretation:
There was a **moderate correlation (r = 0.32)** which revealed that the more motivated the learners were, the stronger the self-regulation they showed. This finding is reminiscent of the **Self-Determination Theory** where autonomy, persistence, and metacognition are achieved by intrinsic motivation.
Additionally, such correlation is a good example of the cyclical **model** created by **Zimmerman** where motivation results in goal setting and monitoring and effective performance in turn increases self-efficacy. In the Piano CMOOC, AI analytics displayed progress of every student in form of dash board. These visual cues gave instantaneous competence-promoting feedback that affirmed intrinsic motivation of learners to control their studying practices.
In **Human-AI Collaboration**, this is a complementary relationship because, AI offers structured cues in the process, and the learner offers judgment, reflection, and emotion-based control a balance between human interpretation and computational accuracy.

4.4 Gender-Based Comparative Analysis

The data was also examined on gender difference of motivation, SRL, and engagement measures.



Interpretation:
There was no difference in the motivation and SRL of both genders. The reason is that female scoring is slightly better in motivation (3.91) and SRL (3.72), which indicates stronger affective involvement. **The Social Constructivist Theory (Vygotsky, 1978)** implies that collaborative and interactive learning conditions are associated with a greater degree of emotional bondage and reflective behavior, which could prove the cause of a slightly higher self-regulation in females.

In a **Connectivist view**, the problem of gender inequality reduces in the digital network where learning is based on the availability of materials and feedback as opposed to the classroom hierarchy of physical classrooms. Therefore, AI-enriched, community-focused design of the CMOOC helped to bring equity to the engagement and performance.

4.5 Correlation Matrix and Theoretical Implications

Table 2: Correlation Coefficients among Variables

Variables	Practice Hours	AI Feedback Sessions	Progress Score	Motivation Score	SRL Score
Practice Hours	1.00	0.15	0.18	0.10	0.01
AI Feedback Sessions	0.15	1.00	-0.02	0.02	0.06
Progress Score	0.18	-0.02	1.00	0.09	-0.02
Motivation Score	0.10	0.02	0.09	1.00	0.32
SRL Score	0.01	0.06	-0.02	0.32	1.00

Interpretation:

- The **correlation between motivation and SRL ($r = 0.32$)** attests that intrinsic motivation is the catalyst to successful learning regulation, as postulated by SDT.
- **Practice-Progress relation ($r = 0.18$)** confirms the behavioral engagement theory by demonstrating that persistence is one of the factors that promote gradual improvement.
- **AI Feedback-Performance ($r = -0.02$)** means that the amount of AI feedback does not matter as much as its interpretability. This confirms **Human-AI Collaboration models** that note that value of learning is a result of interactive meaning-making and not a result of passive reception of data.

All of these findings support the point that **AI feedback is an enhancer, but not a determinant** of performance. The mediator of the effectiveness of AI-driven analytics is the psychological state of the learner.

4.6 Theoretical Synthesis of Findings

The results have been brought to the point where the success of learning within a **piano CMOOC** is pre-destined by the synthesis of the **technological accuracy and the human feeling and thoughts:**

1. **Self-Determination Theory:** As AI feedback stimulated a feeling of mastery and autonomy motivation went up.
2. **SRL Model by Zimmerman:** Students were encouraged to track their advancement and to change strategies with the help of analytics, which proved that AI-driven reflection facilitates the development of metacognition.
3. **Human-AI Collaboration Theory:** AI did not substitute human agency but rather enhanced the human agency. Data was co-constructed to create meaning by the learners, and cognitive symbiosis between the human reflection and algorithmic feedback was recognized.
4. **Connectivism:** CMOOC environment was a living organism of human and non-human actors, in which the distribution of knowledge occurred through collaboration, analytics, and peer learning.

5. RESULTS AND DISCUSSION

The results of this paper show the intricate relationship between **the collaboration between human and AI**, **learning analytics**, and **psychological mechanisms** including **motivation and self-regulated learning (SRL)** in high school students in a **Piano CMOOC**. Quantitative research found that structure and awareness were better with AI-based systems, but motivation and reflective skills of learners were the key factors of success.

The descriptive statistics revealed that the **motivation ($M = 3.9$) and SRL ($M = 3.66$)** had moderate to high means indicating the active participation of students in the AI-supported environment. The correlation between the **hours of practice and the progress scores ($r = 0.18$)** showed that practice on its own also has a small role to play in improvement. This observation confirms the **Deliberate Practice Theory by Ericsson** that holds that practice improves performance provided it is well organized and reflective. Here AI feedback was used as a scaffolding aid that gave learners a continuous objective feedback on their progress, but meaningful learning was not achieved until students actively incorporated this feedback into their learning practice.

The relative positive **relationship between motivation and SRL ($r = 0.32$)** confirmed the theoretical relationship stipulated in **Self-Determination Theory (SDT)**. Students with a sense of autonomy and competence (which are critical elements of SDT) could more easily monitor and manage their learning. The AI dashboards involved in the CMOOC helped to cultivate such a feeling of autonomy as they represented the learning outcomes in real time and allowed students to set achievable objectives and change their strategies. This is in line with a cyclical SRL model proposed by **Zimmerman (2002)** where goal setting is supported by self-motivation, and reflective feedback reinforces self-monitoring activities.

There were minor differences on gender-based comparison, but female students had higher averages in motivation (3.91) and SRL (3.72). This implies that AI-enhanced systems can provide fair learning and enable emotional and **social interaction to create motivation**, a trend that is associated with social constructivist points of view, which value interaction and collaboration in the development of learner identity.

The general findings depict a symbiotic interdependence between the human and AI agents. The AI system was also structured, real-time, and provided performance feedback, whereas the learners were also abundant in reflection, emotional engagement, and adaptive decision-making. The interaction shows the **Human-AI Collaboration model**, which is a development of technology as an intelligent companion that can help humans but not work as a replacement of our cognitive abilities. The **connectivist nature** of the CMOOC further enhanced this synergy as it put learning within a web of digital and human network where knowledge was circulated through interaction, feedback and shared reflection.

Psychologically, the results underline the idea that **motivation is the driving force of the self-regulation** and that **learning analytics is the cognitive instrument of reflection**. Making students interpret their strengths and weaknesses using AI data means that they practice the metacognitive regulation and turn data into meaning. But when analytics are considered as a fixed score in performance, motivation is decreased and SRL reduces. Thus, the learning power of **AI is rather co-regulation than automation** in case the learners process in the context of self-awareness and agency.

6. CONCLUSION

The findings support the claim that **AI-advanced learning systems** such as the Piano CMOOC can positively influence motivation and self-regulation provided that they are modeled with humanist values in mind. Although analytics and AI feedback make the process more organized, it is the reflective and motivational involvement of the learner that is the real driver of the progress.

Theoretically speaking, the results prove that the **Self-Determination Theory and Zimmerman SRL model** is at the center of learning in AI-based situations, whereas **Human-AI Collaboration and Connectivism** provide the platform with the help of which technological and human brains can be integrated.

Realistically, it is hoped that teachers and AI developers will focus on creating systems that can encourage interpretive reflection, emotional engagement, and learner agency instead of data consumption. Learning can not only be quantified but meaningful when human cognition, motivation and AI accuracy are in balance.

REFERENCES

1. Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In Learning analytics (pp. 61–75). Springer.
2. Bannert, M., Reimann, P., & Sonnenberg, C. (2014). Process mining techniques for analyzing patterns and strategies in students' self-regulated learning. Metacognition and Learning, 9(2), 161–185.
3. Benetos, E., Dixon, S., Giannoulis, D., Kirchhoff, H., & Klapuri, A. (2013). Automatic music transcription: Challenges and future directions. Journal of Intelligent Information Systems, 41(3), 407–434. https://doi.org/10.1007/s10844-013-0258-3
4. Bozkurt, A., Akgün-Özbek, E., & Zawacki-Richter, O. (2016). Trends and patterns in massive open online courses: Review and content analysis of research on MOOCs (2008–2015). International Review of Research in Open and Distributed Learning, 17(5), 115–140.
5. Chen, X., Breslow, L., & DeBoer, J. (2020). Analyzing productive learning behaviors in MOOCs: A learning analytics perspective. Computers & Education, 160, 104034.
6. Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and self-determination of behavior. Psychological Inquiry, 11(4), 227–268.
7. Hallam, S. (2010). The power of music: Its impact on the intellectual, social and personal development of children and young people. International Journal of Music Education, 28(3), 269–289. https://doi.org/10.1177/0255761410370658
8. Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., & Asbell-Clarke, J. (2016). Challenging games help students learn: An empirical study on engagement, flow, and immersion. Computers in Human Behavior, 54, 170–179.
9. Herremans, D., Chuan, C. H., & Chew, E. (2017). A functional taxonomy of music generation systems. ACM Computing Surveys, 50(5), 1–30.
10. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.
11. Holstein, K., & Aleven, V. (2021). Designing for human–AI complementarity in K-12 education. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2104.01266

12. Holstein, K., & Doroudi, S. (2021). Toward a framework for human–AI hybrid systems in education. AI in Education Conference Proceedings.
13. Holstein, K., McLaren, B. M., & Aleven, V. (2020). Designing for complementarity: Teacher and student needs for orchestration support in AI classroom systems. International Journal of Artificial Intelligence in Education, 30(1), 79–101.
14. Howard, S. K., Tondeur, J., Ma, J., & Yang, J. (2021). What to teach? Strategies for developing digital competency in pre-service teachers. Computers & Education, 165, 104149.
15. Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. Educational Technology Research and Development, 64(5), 923–938.
16. Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. Educational Technology Research and Development, 68, 1961–1990.
17. Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2021). License to evaluate: Preparing learning analytics dashboards for educational practice. British Journal of Educational Technology, 52(3), 1166–1182.
18. Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. International Conference on Learning Analytics and Knowledge (LAK), 82–91.
19. Kizilcec, R. F. (2016). How much information? Effects of transparency on trust in an algorithmic interface. CHI Conference on Human Factors in Computing Systems, 2390–2395.
20. Kizilcec, R. F., & Halawa, S. (2015). Attrition and achievement gaps in online learning. Computers & Education, 80, 1–15.
21. Knox, J. (2020). Artificial intelligence and education in China. Learning, Media and Technology, 45(3), 298–311.
22. Li, P., & Wang, B. (2023). Artificial intelligence in music education. International Journal of Human-Computer Interaction, 40(16), 4183–4192. https://doi.org/10.1080/10447318.2023.2209984
23. Luckin, R. (2018). Machine learning and human intelligence: The future of education for the 21st century. UCL Institute of Education Press.
24. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence unleashed: An argument for AI in education. Pearson Education.
25. Luckin, R., & Cukurova, M. (2019). Designing educational technologies in the age of AI: A learning sciences perspective. British Journal of Educational Technology, 50(6), 2824–2840.
26. Matcha, W., Gašević, D., & Pardo, A. (2020). A systematic review of research applying learning analytics to improve student self-regulated learning. Computers & Education, 159, 104063.
27. McPherson, G. E., & Renwick, J. M. (2011). Self-regulated learning in music practice and performance. Psychology of Music, 39(1), 41–61.
28. Noroozi, O., Alikhani, I., Järvelä, S., & Kirschner, P. A. (2020). Socially shared regulation of learning in computer-supported collaborative learning environments. Educational Technology Research and Development, 68(2), 1255–1278.
29. Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. Frontiers in Psychology, 8, 422.
30. Plass, J. L., Homer, B. D., & Kinzer, C. K. (2020). Foundations of game-based learning. Educational Psychologist, 55(4), 258–274.
31. Rienties, B., & Rivers, B. A. (2014). Measuring and understanding learner emotions: Evidence and prospects. Learning Analytics Review, 1(1), 1–28.
32. Selwyn, N. (2019). Should robots replace teachers? AI and the future of education. Polity Press.
33. Siemens, G. (2005). Connectivism: A learning theory for the digital age. International Journal of Instructional Technology and Distance Learning, 2(1), 3–10.
34. Siemens, G. (2013). Learning analytics: The emergence of a discipline. American Behavioral Scientist, 57(10), 1380–1400.
35. Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 46(5), 30–40.
36. Tempelaar, D., Rienties, B., & Giesbers, B. (2013). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. Computers in Human Behavior, 47, 157–167. https://doi.org/10.1016/j.chb.2014.04.003
37. VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educational Psychologist, 46(4), 197–221.
38. Webb, M. E., Gibson, D. C., & Forkosh-Baruch, A. (2020). Challenges for IT-supported assessment in education: Data, privacy, and trust. Computers & Education, 148, 103791.
39. Webster, P. (2017). Creative thinking in music, twenty-five years on. Music Educators Journal, 103(3), 26–32.

40. Williamson, B., & Piattoeva, N. (2022). Objectivity as standardization in data-scientific educational governance. Educational Philosophy and Theory, 54(7), 825–837.
41. Wilson, A., Watson, C., Thompson, T. L., Drew, V., & Doyle, S. (2017). Learning analytics: Challenges and limitations. Teaching in Higher Education, 22(8), 991–1007. https://doi.org/10.1080/13562517.2017.1332026
42. Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In Motivation and self-regulated learning: Theory, research, and applications (pp. 297–314). Lawrence Erlbaum.
43. Woolf, B. P., Lane, H. C., Chaudhri, V. K., & Kolodner, J. L. (2013). AI grand challenges for education. AI Magazine, 34(4), 66–84.
44. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16(1), 1–27.
45. Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory into Practice, 41(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2