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RESEARCH ARTICLE

Potential for Game-based Assessment of Creativity using Biometric and Real-time Data

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ABSTRACT

This study explores the development of a game-based creativity assessment model using biometric and real-time data. By integrating game learning analytics (GLA) with neuroscience approaches such as functional near-infrared spectroscopy (fNIRS), the goal of this research is to provide a comprehensive, process-oriented approach to creativity. The study emphasizes the importance of social and affective dimensions of creativity, moving beyond traditional cognitive-focused models. By analyzing log data, social network interactions, and biometric feedback, the study highlights how these dimensions influence creative outcomes. The results demonstrate the effectiveness of using GLA to provide personalized and adaptive feedback, fostering a deeper understanding of creative processes and improving educational practices.

Key words: Game based assessment, log data analysis, neuroscientific approaches, fNIRS, social, affective, creativity

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Introduction

Fostering 21st century skills such as collaboration, communication, creativity, and critical thinking is becoming increasingly important (Takayama, 2013). In an era where artificial intelligence, such as ChatGPT, can instantly provide relevant solutions and information, the mere memorization of domain-specific knowledge has less value than ever before. Therefore, it is necessary to develop an appropriate competency assessment model. However, competency assessment is challenging due to its evolving and context-dependent nature (Koeppen et al., 2008). In addition, competency assessment requires the assessment of cognitive, social, and emotional dimensions (Koeppen et al., 2008). Traditional pencil-and-paper assessment models are limited in their ability to assess such multidimensional competencies.

Competency assessment involves evaluating the ability to apply skills in relevant contexts. However, traditional assessments tend to rely on generic questionnaires that do not capture the complexity of real-world situations. In addition, the development of competencies is not static, but evolves over time (Ryu, 2023). Therefore, to effectively measure 21st century competencies, assessment models must take into account their dynamic and multifaceted nature. Thus, this dynamic and emergent nature of competencies requires continuous assessment. The integration of game-based assessment (GBA) with game learning analytics (GLA) can address several limitations of traditional assessment methods by capitalizing on the dynamic capabilities of digital environments (Rafner et al., 2023). By analyzing log data, GLA captures a comprehensive record of in-game actions, decisions, and problem-solving strategies, providing a rich source of process-oriented assessment data (Ryu, 2023). Real-time screen recording allows for the observation of on-screen behaviors and interactions, providing context to log data and revealing patterns that may not be immediately apparent. In addition, the integration of biometric data such as heart rate, eye tracking, and brain imaging can provide insight into the emotional and cognitive states of learners, allowing for a more holistic view of their engagement and stress levels during creative tasks. These advanced GLA techniques facilitate continuous, in-depth analysis of learner performance and creativity, thereby contributing to the provision of personalized feedback and support for the development of domain-specific competencies (for a review, see; Ryu 2023).

In this paper, we explored the possibility of developing a game-based assessment model for creativity using the techniques of GLA. We begin with a brief review of relevant literacies. We briefly mention GBA and GLA, focusing on their potential for assessing competencies such as creativity (for a review, see Ryu 2023). We explored the potential of using game-log data analysis, along with videotaped conversation analysis, to develop a process-oriented assessment of the social dimension of creativity in which ongoing progress can be observed and taken into account. Next, we explored how learner style can be coordinated with the results of fNIRS brain image analysis to provide affective feedback. Finally, we discuss the potential of Game Based Assessment as a process-oriented assessment with social and affective feedback as an adaptive, individualized, and personalized assessment.

Theoretical Background

The Potential of GLA for Process-Oriented Assessment

To assess competencies such as creativity, the notion of performance assessment and, more recently, process-oriented assessment has been emphasized (Kim & Ryu, 2019; Ryu et al., 2018). A core approach of these assessments is that learning must be assessed in a relevant context through appropriately situated, ongoing performance. Log data analysis provides an ongoing record of players' interactions within a game performance, including decisions made for item choices, strategies, communication, game movement, and time spent on each activity (Li et al., 2022). Such analysis allows researchers to track a learner's progress over time by demonstrating improvements in decision making and strategy choices. Researchers can also identify striking patterns in which players' recurring behaviors are indicative of underlying competencies. Because decision choices are aligned with the level of play, decision choices allow researchers to assess embedded skills, knowledge, and abilities (Alonso-Fernández et al., 2019, 2020). In addition, such real-time log data analysis allows educators and researchers to provide immediate and tailored feedback both from outside the game play through human interaction or from within the game play through AI-enhanced feedback. The immediate and customized feedback encourages reflection and iterative learning (Alonso-Fernández et al., 2019, 2020).

Social network analysis (SNA) in an online gaming environment allows researchers to get a bird's eye view of student interactions (Ryu & Lombardi, 2015; Ryu, 2020); how students interact with each other provides insights into peer dynamics, collaboration, and leadership styles. To illustrate, SNA helps researchers uncover the structure and dynamics of social interactions by identifying leaders, followers, and isolated actors. SNA also allows educators and researchers to determine both the quality and quantity of collaboration within a game. For example, analysis of cliques, a small collection of nodes, or eigenvector analysis reveals who influences the network the most, how members of a group share information, and who plays the role of negotiator or gatekeeper in a network. In addition, SNA can be combined with discourse analysis to strengthen the results of observations and qualitative inferences.

Recent research has emphasized the significant influence of social and affective dimensions on creativity, moving beyond the traditional cognitive focus. Traditional models often rely on self-report measures such as questionnaires and surveys, which may not accurately reflect the active dynamics that influence creativity. To address this, real-time measures and techniques have been developed to capture these dynamics, incorporating social and affective dimensions.

Neuroimage Data Analysis for Game Based Assessment

In this section, we describe several types of neuroimaging techniques that could be applied to GBA with respect to the cognitive and affective dimensions of gameplay. Functional Magnetic Imaging (fMRI) uses blood oxygen level-dependent (BOLD) contrast to detect changes in blood flow associated with neural activity. fMRI provides high spatial resolution, allowing researchers to precisely identify brain areas with specific functions related to learning and development. However, it has limitations, such as the inability to move while measuring brain activity. This limitation makes it nearly impossible to measure brain activity during game play. (Duan et al., 2022; Kober et al., 2020) As a result, fMRI can only be used to measure complex cognitive tasks during game play for more detailed brain studies.

Compared to the use of fMRI, electroencephalography offers portability. A gamer can wear a cap with electrodes connected to a computer while playing. EEG measures changes in voltage - electrical activity in the brain via electrodes resulting from the summation of synchronous activity in the cortex. While EEG is an economically affordable portable device that allows players to move around and has higher temporal resolution, it has pitfalls such as lower spatial resolution, localization uncertainty with noise such as that generated by muscle/eye movements, and a relatively long electrode preparation time (Xu & Zhong, 2018).

Functional near-infrared spectroscopy (fNIRS) works by measuring changes in cerebral blood flow and oxygenation. It uses near-infrared light that penetrates the skull, with oxygenated and deoxygenated hemoglobin absorbing this light differently. The advantages of fNIRS include its portability and noninvasive nature, which allows for physical movement and makes it ideal for repeated and naturalistic applications (Nebel et al., 2016; Ninaus et al., 2014). However, drawbacks include its limitation to measurements of the cortical surface and its sensitivity to contamination from extracerebral sources. In the context of GBA, fNIRS is particularly effective for real-time monitoring of cognitive load and emotional states during gameplay, as well as for conducting longitudinal studies in naturalistic settings (Nebel et al., 2016; Ninaus et al., 2014).

Methods

Research Design for Assessing Social and Affective Dimensions: Collaborative Creativity and Learning Styles

The study was an exploratory research project in which the GLA was used to develop a game-based assessment of creativity. It should be noted, however, that the model was not validated due to the limited number of participants. The study was conducted in a class of 43 undergraduate students over the course of one semester. The 43 pre-service secondary teachers (24 males and 19 females) who took the course were students from a variety of majors and grade levels, most of whom had not interacted with each other prior to taking the course. A pre-survey was administered to determine the level of experience and manipulation with Minecraft that would be used in the class. Nine students indicated an advanced level, 18 students indicated a beginner level, and 16 students indicated that they had never played Minecraft before. After an initial review of the log data, we selected a group that demonstrated collaborative creativity for detailed analysis.

A second experiment was conducted with nine of these students who volunteered to participate in an experiment using fNIRS. These students were all right-handed (Atsumori et al., 2010; McKendrick et al., 2016) and all had no history of heart or cardiovascular disease. The purpose and procedures of the study were fully explained to the participants in advance, and they gave their informed consent to participate in the study.

Students were invited to develop a prototype game scenario using Minecraft, a sandbox game. For example, one group of students developed a game scenario in which a main hero visited several villages with different types of problems caused by an environmental issue. The main hero asked questions of the villagers and used scientific knowledge and experiments to identify and solve the problems. In the first quest, the main hero visited a named green village, but now a desert, and talked to the village leader.

The study consists of two distinct parts. The first part investigates the phenomenon of collaborative creativity using an explanatory sequential mixed method. This involves the quantitative analysis of log data combined with the qualitative analysis of game play videos. Data sources include game log data, recordings of game play, and transcriptions of game play. The second part of the study deals with the relationship between learning styles and creativity. Data sources include the results of learning style and goal orientation surveys, fNIRS data, and game play creativity assessments. The learning styles and goal orientations of each player were interpreted in conjunction with the analysis of the fNIRS data, which was specifically designed to assess creativity. In the second part of the study, nine out of 43 students were invited to voluntarily participate in a learning style experiment that included a learning style and goal orientation survey and fNIRS data. For the second part of the study, students completed two different types of design tasks using Minecraft (simple vs. complex). The simple task asked players to use given resources to create a repetitively simple building. The complex task asked players to create a building that solved multiple problems (Table 1).

Table 1. Student activity, data source and analytic method

	Student activity/hour	Student activity description	Data source	Analysis method
Social dimension of creativity with coll aborative activity	Learning Scenario activity	Students come up with a learning topic. They plan for the implementation of a learning topic into a game	Video recordings, Transcription of selected episodes	Conversation analysis
	Implementation in Minecraft	Students develop detailed activities and implement them in Minecraft	Minecraft log data Video recordings Transcription of selected episodes	Log data analysis Social Network Analysis matching log data analysis and conversation analysis
Affective dimension of creativity with learning style	Answering learning style and achievement goal orientation survey	Students completed two surveys	Learning style and achievement orientation survey	Figuring out students' learning style and achievement goal orientation
	Minecraft simple -complex creativity activity	Students completed a simple-complex individual creativity task using Minecraft.	FNIRS data Video recordings	Statistical analysis of Brain area activation Conversation analysis
		Students completed a simple-complex creativity task using Minecraft in groups.	FNIRS data Video recordings	Statistical analysis of Brain area activation Conversation analysis

The student participants wore the NIRSIT device, thoroughly read the given problem, and diligently performed the tasks within Minecraft. The NIRSIT (NS1-H20A) developed by OBELAB Inc. was used to measure brain activity with fNIRS. This head-mounted device contains 24 laser sensors that emit near-infrared light at wavelengths of 780 nm and 850 nm into the cerebral cortex and 32 sensors that receive the returned light, forming a multichannel near-infrared device. The brain regions that can be measured with fNIRS include parts of the prefrontal cortex. This prefrontal cortex encompasses Brodmann Areas (BA) such as BA 8, BA 9, BA 10, BA 11, BA 12, BA 24, BA 25, BA 32, BA 44, BA 45, BA 46, and BA 47 (Murray, Wise, & Graham, 2017). The prefrontal cortex is broadly divided into four regions: the Dorsolateral Prefrontal Cortex (DLPFC), the Ventrolateral Prefrontal Cortex (VLPFC), the Frontopolar Prefrontal Cortex (FPC), and the Orbitofrontal Cortex (OFC). The DLPFC corresponds to BA 9 and BA 10, the VLPFC corresponds to BA 45 and BA 46, the FPC corresponds to BA 10, and the OFC consists of BA 11 and BA 47. The DLPFC is responsible for working memory, executive functions, and complex decision-making processes. The VLPFC is involved in language processing, inhibitory control, and social cognition functions. The FPC is responsible for goal setting, planning, and abstract thinking. The OFC plays a role in emotion processing, responses to rewards and punishments, and regulating decision-making processes.

During the experiment, participants were first instructed on precautions to ensure they remained comfortable, avoiding tension and unfamiliarity, including refraining from conversation or movement. The device was then carefully positioned, considering the curvature of the participant's forehead, to match the actual cortical areas with the channels of the device for the experiment.

The entire computer screen was recorded for use as supplementary analysis material, and the students' task-solving process was recorded from behind with a camcorder to observe their conversations and actions. In addition, the participants' task performance was videotaped to document any actions or decisions that might affect the research findings. After the experiment, the students explained their task results, and this explanation was also recorded for additional analysis.

A block design was used to efficiently measure brain activation (Table 2). The design improves signal-to-noise ratio and simplifies data analysis by contrasting resting and active durations. The task used Minecraft simple/complex tasks vs. rest for the active and control task, respectively. The simple task lasted for 2 minutes, and the complex task lasted 6 minutes, for a total of 3 sessions of 18 minutes. The breaks between tasks were set to 20 seconds.

Table 2. Block design

Start	Simple Task	Rest	Complex Task 1	Rest	Complex Task 2	Rest	Complex Task 3	Rest
Task	ST1	R1	CT1	R2	CT2	R3	CT3	R4
0 sec	2 min	20 sec	6 min	20 sec	6 min	20 sec	6 min	20 sec

Data Analysis

The assessment of creativity's social dimension focuses on group interactions, specifically how group dynamics and interaction patterns influence creative outcomes. The study examined group dynamics within a Minecraft game setting, identifying three significant patterns 1) Leadership style: we identified presence or absence of a leader and their interaction with group members. 2) Member participation: we identified the level of individual participation in activities; and 3) Task performance styles: we investigated the approaches to task completion.

These patterns were analyzed using log files, heat maps, and social network analysis. Visualization tools like Gephi were used to create visual representations of interactions, emphasizing item-mediated interactions. This analysis revealed how group dynamics affected creativity. To specify, total log data frequency per individual investigated the participation levels and distribution within subgroups. Frequency (Ratio) of Log data by behavior type analyzed command usage to measure understanding and operation skill in Minecraft.

Analyzing Social Dimension of Creativity: Log Data Analysis, SNA and Video Recording Analysis

The study utilized log data analysis, mapping, and Gephi to analyze creative interactions among participants. 1) Network visualization: Gephi created visual representations of interactions, mapping item flow and collaborative efforts 2) Item-based interactions: we analyzed the use of items like command blocks, revealing their role in collective problem-solving and creative expression 3) Mapping creative hotspots: we identified peak creative interactions, correlating with intense collaboration phases.

The log data was collected for the unit of a group play for one class during the semester. We used an opensource plug-in, *Playwatchdog* for the log data collection. The log data consists of four categories: Id, time, location, and action. The action type is categorized into five items: block place, block break, player commend, right click and player chat.

For log analysis, the statistical visualization package R and the social network analysis visualization software Gephi were employed to characterize students' participation patterns and creative engagement. The collected log data is in the form of Figure 1, which consists of the time and coordinates of log data generation, behavior type, user ID, and specific action. Player actions include Block Place, Block Pause, Player Command, Player Click, and Player Chat. When a student performs an in-game action that falls under one of these five categories, the specific details are recorded as a line of log data. Among these actions, we are particularly interested in the use of Player Command because players can customize the environment and tools using Java-based coding when using Player Command. To specify, when a group employed the use of "player commands," it was evident that the group generated a greater number of ideas. This was because commands (i.e., a shorter code) were utilized to advance, converge, and upgrade existing items. Consequently, it can be concluded that the group was more creatively engaged in the game than the others. First, we identified specific variables from the log data that elucidate the group dynamics within our study. Utilizing R's 'subset' function, we quantified the frequency of each group's engagements with selected focus items, enabling a comparative analysis (Fig. 1). This analysis revealed distinct trends that outline the overarching characteristics of each group, potentially influencing their creative engagement during activities. Next, we identified the patterns within the log data that correlate with creative behaviors in the Minecraft environment. The variables "action type," "item used," and "log generation coordinates" were instrumental in delineating user behavior. By extracting relevant data points associated with creative activities, such as the construction of various objects in Minecraft, we utilized R's capabilities further. The subset function was employed to isolate pertinent data, which was then visualized over time and space using R's ggplot2 package. This facilitated an in-depth examination of significant patterns that manifest creative capabilities. Finally, to visualize the interactive dynamics within the Minecraft setting, we employed Gephi, an advanced tool for network analysis and visualization. Given the educational program's emphasis on reconstructing game content using diverse items, it is crucial to understand the interplay among students. Gephi enabled us to graphically represent and analyze the interactions based on behavioral types and the variety and frequency of items used. Through this visualization, we were able to interpret the emergent relationships and collaborative creativity fostered among group members.

Regarding the video records of gameplay, we captured the entirety of gameplay for each group, though not all footage was subject to analysis. We pinpointed scenes of interest by correlating them with insights from the log data analysis. Specifically, when log data highlighted instances of players' creative engagement, we determined the corresponding times and accessed those particular scenes. These selected scenes were closely reviewed, transcribed, and analyzed in conjunction with the log data. Our analysis focused on understanding the specific interactions occurring among group members and the contextual dynamics. We aimed to discern and delineate the aspects of creativity being manifested during these interactions.

time_video	action	player	name	gender	ability	item1	pos_x	pos_y	pos_z
0:00:02	Block Place	minechem6	KJI	M	C	JUNGLE_DOOR	-2152	69	5749
0:00:03	Block Break	minechem6	KJI	M	C	JUNGLE_DOOR	-2152	70	5749
0:00:04	Block Place	minechem6	KJI	M	C	JUNGLE_DOOR	-2151	69	5749
0:00:05	Block Break	minechem6	KJI	M	C	JUNGLE_DOOR	-2151	70	5749
0:00:08	Block Place	minechem6	KJI	M	C	SAND	-2151	69	5749
0:00:09	Right Click	minechem10	HJH	M	B	LEVER	194	64	65
0:00:11	Block Place	minechem6	KJI	M	C	SANDSTONE	-2151	70	5749
0:00:13	Block Break	minechem6	KJI	M	C	SANDSTONE	-2151	70	5749
0:00:14	Block Place	minechem6	KJI	M	C	SANDSTONE	-2151	70	5749
0:00:15	Block Break	minechem6	KJI	M	C	JUNGLE_DOOR	-2151	70	5748
0:00:15	Block Break	minechem6	KJI	M	C	JUNGLE_DOOR	-2151	70	5747
0:00:16	Player Command	minechem6	KJI	M	C		1133	65	2344
0:00:19	Right Click	minechem9	LDK	M	A	COMMAND	1126	67	2289
0:00:30	Block Place	minechem10	HJH	M	B	AIR	1075	73	2356
0:00:30	Right Click	minechem9	LDK	M	A	WOODEN_DOOR	1127	67	2290
0:00:31	Right Click	minechem9	LDK	M	A	COMMAND	1126	67	2289
0:00:32	Right Click	minechem9	LDK	M	A	COMMAND	1126	67	2289
0:00:34	Right Click	minechem9	LDK	M	A	COMMAND	1126	67	2289
0:00:35	Block Break	minechem7	KDS	F	A	CARPET	857	64	2892
0:00:37	Block Break	minechem6	KJI	M	C	STONE	853	91	2830

Fig. 1. Example of log data (csv format)

Analyzing Affective Dimension of Creativity: Learning Style and Goal Orientation Survey and fNIRS

The fNIRS measures of the students were analyzed in conjunction with the learning styles and goal orientations of the students. As described in detail later, fNIRS basically measures changes in the concentration of oxygenated hemoglobin in the frontal lobe. Based on the results of Kolb's Learning Style and Goal Orientation survey, three groups were formed. Fig. 2 shows the students' information processing style scores (horizontal axis) and information perception style scores (vertical axis) plotted on a graph of Kolb's learning styles. Three, A group students were Accommodator Kolb learning style, with Concrete Experience as their information perception style and Active Experiment as their information processing style. They had Mastery Approach Achievement Goal Orientation, which is intrinsically motivated by mastering the task itself (A group). Three of the students in the B group were Convergent Learning Style students. They showed Abstract Conceptualization for perception, Active Experimentation for processing. They are all Performance Approach Achievement Goal Oriented, which is extrinsically motivated to learn, with a focus on making performance meaningful and being judged competent by others. Three students in Group C were assimilator learners whose information perception style is abstract conceptualization, and their information processing style is reflective observation. They were all mastery approach goal oriented. The three students in the C group, i.e., the six students in the Adaptive A and Assimilator C groups, are all mastery goal oriented, and the three students in the Convergent B group are all performance goal oriented.

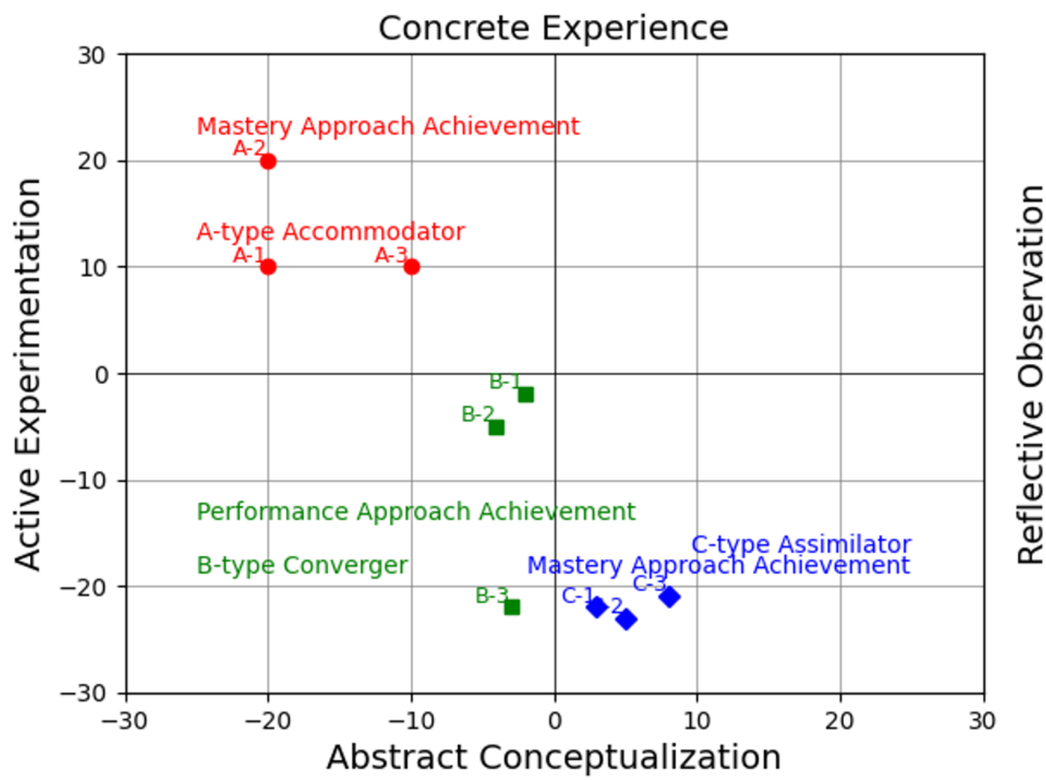

Fig. 2. Learning style and Achievement Goal Orientation

With regards to brain image analysis, the prefrontal activity results obtained from the NIRSIT fNIRS device were preprocessed using the NIRSIT Analysis Tool v2.2 to derive the change in concentration of oxygenated hemoglobin HbO_2 in the prefrontal lobe. The channels showing significant differences were analyzed by comparing the mean HbO_2 concentration change values between the same channels of the individual and group tasks using IBM SPSS Statistics 25.0, and the channels showing significant differences were also analyzed by comparing the mean HbO_2 concentration change values between the same channels of the simple and creative tasks. The preprocessing was performed by assigning task numbers to the raw data Excel files obtained during the fNIRS measurements using the markers in the Excel file and removing noise using a low-pass filter (DCT 0.1 Hz) and a high-pass filter (DCT 0.005 Hz) in the NIRSIT Analysis Tool v2.2-29 -Signal Processing step. The baseline was set to the first rest period (R1) because most participants did not properly rest during the second (R2) and third (R3) rest periods for various reasons, resulting in high signals. Data from poor channels with a signal-to-noise ratio (SNR) of less than 30 dB were excluded from the analysis (Delpy et al., In the final preprocessing step, Calculate Concentration, the Modified Beer-Lambert Law (MBLL) calculation method was used to calculate the blood oxyhemoglobin concentration data in millimoles. In addition, the Set Block Average function was used to extract the average value of the brain activation of the 48 channels and the Brodman area. The main objective of this study is to compare the average brain activity between Simple Task and Complex Task and between Single Task and Group Task in each group. Therefore, SPSS independent samples t-test was performed to identify channels with significant differences between Simple and Complex Task and between Single and Group Task.

Results

The results show how social and affective dimensions of creativity are assessed. Through log file analysis, social network analysis and video observation, the social dimension of creativity was assessed. Through the combination of learning style, goal orientation survey and fNIRS analysis, the affective dimension of creativity was assessed.

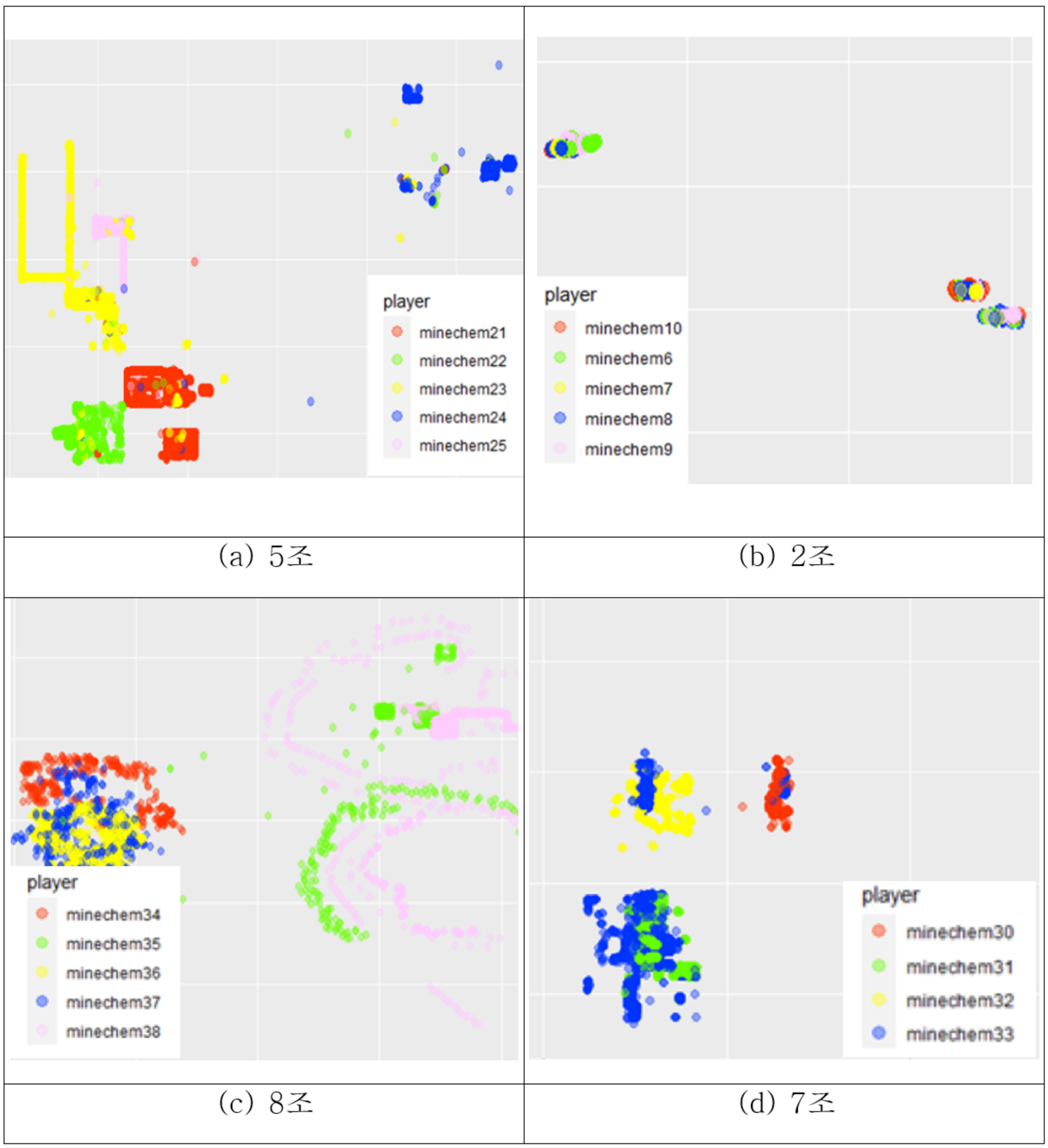

Fig. 3. Distribution of member activity based on log data

Social Dimension of Creativity

Fig. 3 shows the coordinate distributions of the log data for each member of the four subgroups identified as having distinct interaction characteristics for the activities in Sessions 9-13, which involved the actual creation of educational game content using Minecraft. (a) through (d) are two-dimensional visualizations of coordinates along the x- and y-axes, respectively, except for the z-axis coordinates, which correspond to height in the three-dimensional Minecraft world. Observations of students' movements within the Minecraft space during the lesson showed that most of them used the map extensively by moving along the x- and y-axes on the built-in flat ground, while movement along the z-axis was mainly limited to the process of building specific structures. Therefore, it is possible to identify the type of interaction between members with only two-dimensional information except for the z-axis coordinates.

As can be seen in (a), group 5 worked in their own independent areas and there was little interaction between members as they tended to focus on their own activities through the division of roles for the overall task. Group 2, on the other hand, as shown in (b), was characterized by cooperative interaction, with all members distributed in the same space and actively exchanging opinions on the same topic in the actual activity. Group 8 showed an intermediate form of division of labor and collaboration, as shown in (c), which is based on division of labor through role division, but also partially collaborative interactions, where individuals share problems with other members of the group when they encounter problems that are difficult to solve alone, and then gather in the space where the problem occurs to explore solutions. As shown in (d), group 7 also shows this intermediate form of log data distribution, where the log data of student 33 (minechem33) is evenly distributed among the main activity areas of the other students. In the course of the actual activity, Student 33 played a clear leadership role and participated in all activity areas of Group 7.

Creativity through Collaborative Interaction

The following example of Group 3 demonstrates how log analysis and item-based analysis with Gephi visualization inform creative interactions. Additionally, this analysis is strengthened when coordinated with video analysis.

Group 3 is characterized by a work style that combines division of labor with cooperative elements, clearly identifying a leader based on log data coordinates. Initially, all members developed the game content plan together. From Week 9, when they started using Minecraft, roles were allocated, and each member worked on their designated sections. Student 11, as the leader, circulated through all workspaces, checking progress and offering feedback, with a focus on enhancing the use of advanced Minecraft features (Fig. 4).

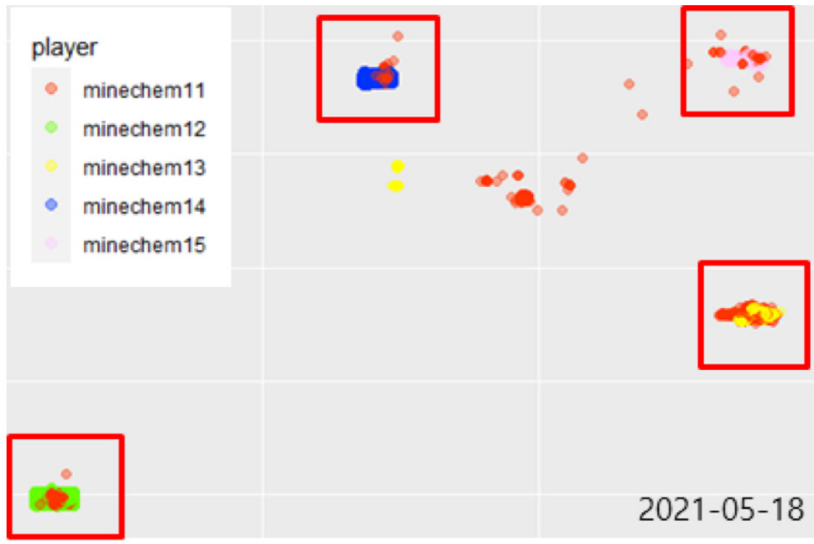

Fig. 4. Log data coordinates by Member

Fig. 5 illustrates the distribution of log data for each member during Session 12, showing that while Students 12 to 15 work in separate spaces, Student 11 is actively involved across all areas. The visualization highlights the team's division of labor with significant interactions led by Student 11, who showed a higher use of commands than other members, indicating superior Minecraft skills.

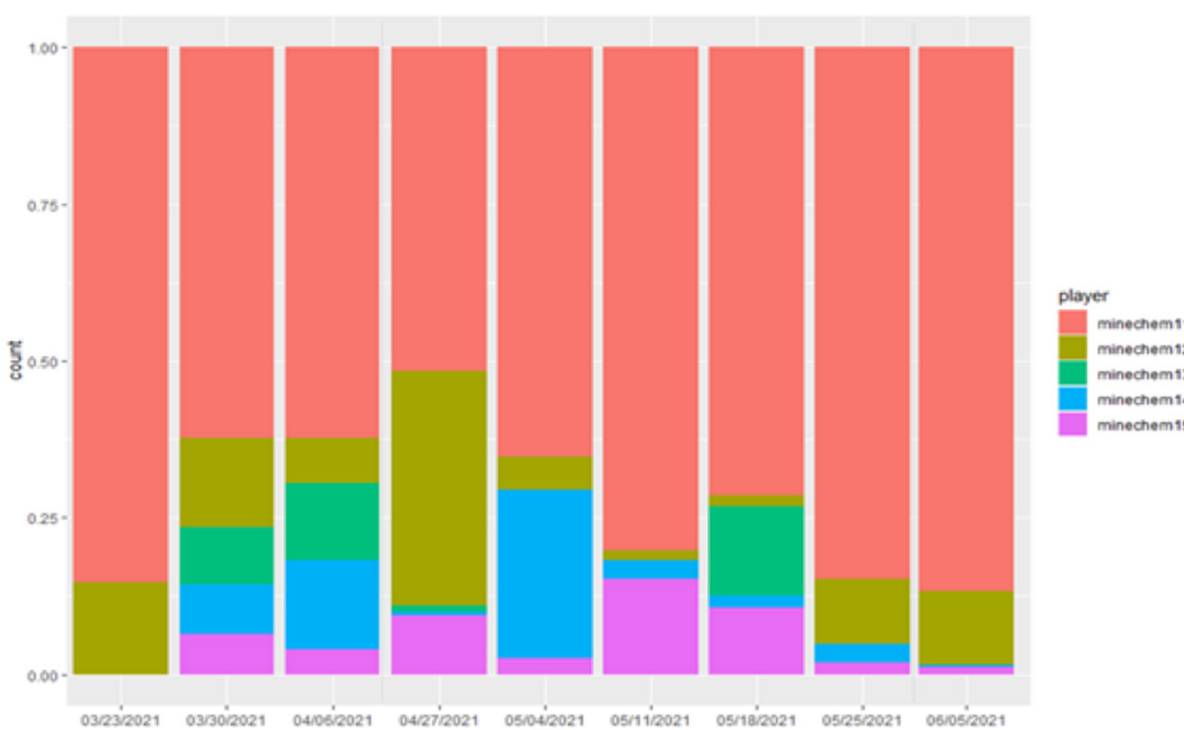

Fig. 5. Distribution of log data for each member (group3)

This pattern of leadership and expertise is further confirmed in Figure 5, where Student 11's command usage is notably higher than that of other team members. Student 11 shows the highest frequency of log data usage within the team, and Figure 13 confirms that on most activity dates, Student 11 has the highest usage rate, indicating active participation in all activities. Considering the even distribution of activity shown in Figure 11, it can be inferred that Student 11 is leading the overall activities of Group 3. The use of commands was identified as an indicator of creative activity in the game. That is, group members were somehow forced to use such commands when they needed to implement new strategies and items, which requires creativity. Based on the Java language, Minecraft allows users to code freely within the game to build logical systems, and the "command block" is an essential element that can be used in conjunction with several other elements to create a variety of applications. Therefore, the intensive use of these elements can be interpreted as an attempt by the user to build logical elements within the game, which is evidence of creative production to bring ideas from the planning stage into the game. The item-based interaction demonstrates such pattern.

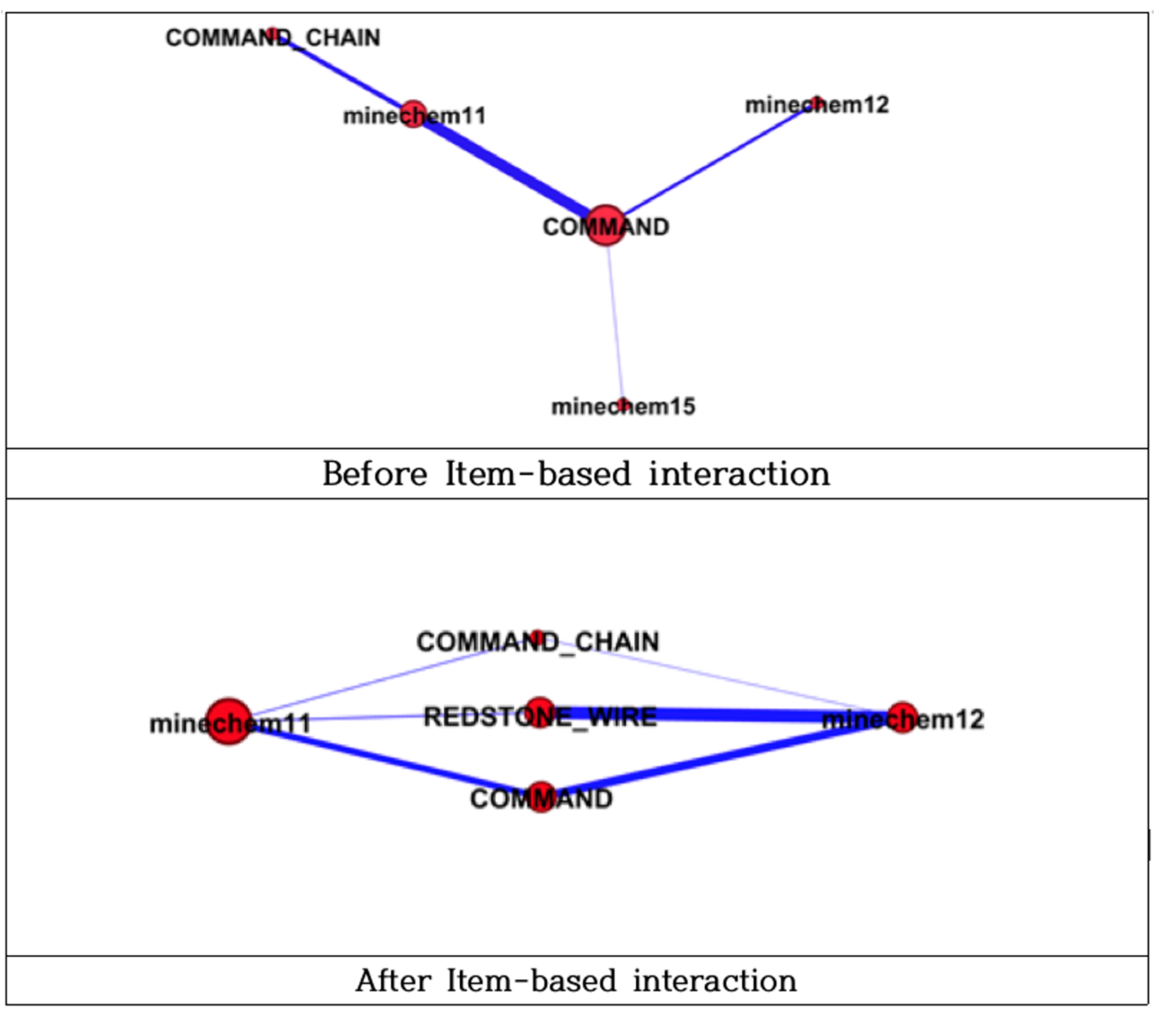

Fig. 6. Changes in item-based interaction

As shown fig 6, before the pattern emerged, Students 11 and 12 shared the "COMMAND" block, but the frequency of use by Student 12 was significantly lower, as indicated by the thinner edges in the visualization. Student 11 was the sole user of the "COMMAND_CHAIN" block. However, once Pattern 1 was triggered, not only the "COMMAND" block but also the "COMMAND_CHAIN" and "REDSTONE_WIRE" items were jointly used by Students 11 and 12. The range of command block-related items expanded, and the increased thickness of the edges suggests meaningful use of these items. As previously mentioned, the use of command blocks and related items is closely linked to the manifestation of creative capabilities. The sudden increase in the frequency of shared use of these items suggests that the two students were using them collaboratively with a common purpose. It is likely that they were engaging in creative production activities, utilizing coding through command blocks to construct logical and innovative systems. The interaction between student 11 and 12 was traced in video records and then, was fully transcribed.

Table 3. Item based conversation

students	Dialogue	Game action
Student 11	And this is a speech mark... if you say it all at once, it disappears quickly, right?	Student 12 repeatedly executed the game progress guide system created using multiple pressure plates and command blocks, identifying issues.
Student 11	Display commands one by one sequentially, or use Redstone to delay...	
Student 12	Hmm... specifically, which part?	Moved to Student 11's location.
Student 11	It is set up like this. You made it so that you step on them one by one...	Shared identified issues while re-executing the system.
	< Omitted >	
Student 11	This is a repeater, right? Originally, the signal goes one block at a time, but with a repeater, you can either speed up or delay the signal.	Student 11 installed and demonstrated the Redstone Repeater item, explaining its functions and characteristics to Student 12.
Student 11	Like this...	
Student 12	Ah, so I originally placed a lot of pressure plates to make it trigger when a person passes by, but I didn't need to do that.	
Student 11	Yes, if you input just one signal, it will proceed sequentially...	
Student 12	Then I'll try to make modifications to that part as well.	Improved the pre-made system focusing on the Redstone Repeater item.

The conversation analysis improved contextual understanding and strengthened the visualization results (Table 2). In table 3, Student 11 tested the game progression system implemented by Student 12 and identified deviations from the intended design. To address these issues, Student 11 explained the features of the "Redstone Repeater," a tool well suited for solving such problems. Student 11 then suggested that the system be redesigned using this tool. This interaction was critical in helping Student 12 identify the problems in his system and learn about the capabilities of the Redstone Repeater. Motivated by this newfound knowledge, Student 12 began to think about possible improvements. The conversation consisted primarily of Student 11 sharing existing knowledge and Student 12 actively accepting and applying this information. This collaborative process resulted in the creation of an innovative system. The overall process demonstrated originality in creativity and precision as Student 12 applied the new knowledge to improve the system and make it more in line with the original design plans.

Affective Dimension of Creativity

As described above, the participants' learning styles and goal orientation were assessed via surveys, and these affective features were interpreted in relation to creativity. The summary of the results is as follows (Table 4)

Table 4. Group learning style, brain activity and creativity features

Group	Learning Style	Goal Orientation	Creativity Features	Performance	Affective Dimension
A	Accommodator	Mastery-approach	Excel in group settings, leveraging social interactions	High creativity scores in group tasks	Positive response to collaborative environments, driven by social interaction and experimentation
B	Converger	Performance-approach	Excel in individual tasks, technical problem-solving	High creativity scores in individual tasks (especially flexibility)	Preference for solitary, goal-oriented tasks, motivated by the need for favorable evaluation and competition
C	Assimilator	Mastery-approach	Excel in individual tasks, deep cognitive engagement	Superior performance in individual creativity tasks	Preference for reflective, independent learning, driven by intrinsic motivation for understanding and integration

Group A (accommodators) prefer concrete experiences and active experimentation. Their goal orientation is mastery-approach, in which they focus on developing competencies and mastering tasks. Group A achieved higher scores in group tasks compared to individual tasks. This performance improvement in a collaborative setting implies that they are more engaged and effective when working with others, which often correlates with higher emotional engagement.

These results were warranted by their brain activation results. Due to the large number of channels, the statistical results of the t-test were tabulated by selecting only those channels with a p-value less than 0.05, which is traditionally considered statistically significant. The reason for the negative t-value is that we set the channel for individual assignments to Group 1 and the channel for group assignments to Group 2, and the larger value for Group 2 results in a negative value. When looking at their brain activation, group A exhibited higher brain activation in the ventrolateral prefrontal cortex (VLPFC) and dorsolateral prefrontal cortex (DLPFC) during group tasks (Table 5).

In Table 5(a), The VLPFC is associated with emotional regulation and social interactions, while the DLPFC is involved in planning, cognitive flexibility, and working memory. High activation in these areas during group tasks suggests increased engagement with social and emotional aspects of the task. Channel 4 is in the right ventrolateral prefrontal cortex (VLPFC), and channels 39 and 43 are in the left dorsolateral prefrontal cortex (DLPFC). The VLPFC is involved in decision making and conflict resolution by reasoning about which method is most effective (Levy & Wagner, 2011; Volz et al., 2005). Furthermore, the right VLPFC is responsible for emotional regulation for goal orientation, whereas the left VLPFC is in Broca's area and is involved in language production and comprehension(He et al., 2018). Therefore, it can be interpreted that the reasoning and emotional regulation of Group A students occurred through verbal interaction while performing the group task. Verbal interaction is closely related to an individual's reasoning ability, and private speech and social speech, especially social speech, play a pivotal role in improving reasoning ability (White, 1998). In addition, many recent studies have shown that verbal interaction is related to students' academic achievement and reasoning ability(Mercer et al., 1999). In conclusion, it can be inferred that Group A students' reasoning and emotional regulation occurred through verbal interaction, and creativity was expressed.

Table 5. Group A HbO_2 concentration change

(a) Group A Comparison of HbO_2 concentration change between individual and group tasks by channel

Region	BA	Hemisphere	Channel	t	p
DLPFC	46	L	39	-3.928	.033
	10	L	43	-3.436	.024
VLPFC	45	R	4	-4.057	.019

(b) Group A Comparison of HbO_2 concentration change between simple and complicated creative tasks

Region	BA	Hemisphere	Channel	t	p
DLPFC	10	R	17	-4.007	.030
	46	L	39	-4.634	.013
			43	-4.631	.032
VLPFC	45	L	40	-4.200	.019
			45	-3.332	.048
OFC	11	L	46	-3.633	.022

For the comparison between simple and complicated tasks, Channels 17, 39, and 43 correspond to the dorsolateral prefrontal cortex (DLPFC), which corresponds to BA10, BA46, and BA46 Brodmann areas, respectively (Table 5(b)). The DLPFC activation suggests that cognitive processes such as planning, cognitive flexibility, and working memory occurred while Group A students performed the Complex Task. Cognitive processes can be attributed to any of the creativity subcomponents. Channels 40 and 45 correspond to the ventrolateral prefrontal cortex (VLPFC), which corresponds to the BA45 Brodmann area. VLPFC activation suggests that Group A students are engaged in reasoning and emotional regulation through verbal interaction and creativity. Channel 46 corresponds to the orbitofrontal cortex (OFC) and is in the BA11 Brodmann area. The OFC is involved in rewarding choices (Ballesta et al., 2020). It is also directly connected to the limbic system, including the amygdala, which is involved in processing information related to desire or motivation (Ballesta et al., 2020; Stalnaker et al., 2015).Therefore, it can be interpreted that students in Group A, who had a mastery approach goal orientation through OFC activation, had greater intrinsic motivation when performing the creativity task than when performing the simple task.

Group B (Convergers) prefer abstract conceptualization and active experimentation. Their goal orientation is performance-approach, in which they aim to demonstrate competence and achieve high scores. Group B achieved higher scores in individual tasks compared to group tasks. This performance trend indicates that they are more engaged and effective when working independently, which often correlates with a strong focus on personal achievement and technical problem-solving (Table 6).

These results were warranted by their brain activation patterns. When examining their brain activation, Group B exhibited higher activation in the dorsolateral prefrontal cortex (DLPFC) during individual tasks. The DLPFC is associated with focused cognitive processes such as problem-solving, attention, and working memory. High activation in this area during individual tasks suggests increased engagement with technical and cognitive aspects of the task, reflecting their preference for solitary and goal-oriented activities (Table 6).

Table 6. Group B HbO_2 concentration change

(a) Group B Comparison of HbO_2 concentration change between individual and group tasks by channel

Region	BA	Hemisphere	Channel	t	p
DLPFC	46	L	33	7.440	.013
		L	38	3.037	.045

(b) Group B Comparison of HbO_2 concentration change (mM) between simple and creative tasks

Region	BA	Hemisphere	Channel	t	p
DLPFC	9	R	3	-3.651	.047
	10	L	19	-3.031	.040
	46		35	-4.134	.034
FPC	10	L	36	-4.583	.017

In Table 6(a), Channels 33 and 38 correspond to the dorsolateral prefrontal cortex (DLPFC) and the BA46 Brodmann area (Table 4 (a)). Kolb's learning style is converger, which means that Group B students perceive information through Abstract Conceptualization and process information through Active Experiment. Convergers and Assimilators whose information perception style is Abstract Conceptualization are less interested in interpersonal aspects than other types and tend to prefer individual learning over group learning (Çelenk & Lehimler, 2019). Furthermore, when analyzing the camcorder recordings, we found that Group B students talked significantly less than Group A students during the Minecraft group task, and the flow of conversation was frequently interrupted. Therefore, we can conclude that Group B students were able to maintain a higher level of concentration in the individual task, regardless of their Minecraft score.

In Table 6(b), channels 3, 19, and 35 correspond to the dorsolateral prefrontal cortex (DLPFC), which corresponds to Brodmann areas BA9, BA10, and BA46, respectively. The DLPFC activation suggests that cognitive processes such as planning, cognitive flexibility, and working memory were engaged when Group B students performed the creativity task. The cognitive processes could be for any of the creativity subcomponents. Channel 36 corresponds to the frontopolar prefrontal cortex (FPC) and is in the BA10 Brodmann area. The FPC area is involved in metacognition (Bae, 2020) and is responsible for reasoning and judgment in decision making, including anticipating future actions and exploring new alternatives (Koechlin & Hyafil, 2007). Exploring new alternatives is particularly relevant to the flexibility subcomponent of creativity, as it involves coming up with different ideas to satisfy a condition. Since Group B students were the most flexible in the Minecraft task with the highest total flexibility score, it can be interpreted that Group B students showed greater flexibility in the creativity task and the resulting brain activation in the FPC region.

Group C (Assimilators) prefer abstract conceptualization and reflective observation. Their goal orientation is mastery-approach, focusing on understanding and integrating new knowledge. Group C achieved higher scores in individual tasks compared to group tasks. This performance pattern implies that they are more engaged and effective when working alone, which often correlates with deep cognitive engagement and reflective thinking.

These results were supported by their brain activation findings. When analyzing their brain activation, Group C exhibited higher activation in the dorsolateral prefrontal cortex (DLPFC) during individual tasks. The DLPFC is linked to reflective observation, abstract conceptualization, planning, and memory retention. High activation in this area during individual tasks suggests increased engagement with introspective and cognitive aspects of the task, highlighting their preference for solitary learning environments where they can focus on reflective and abstract thinking (Table 7).

Table 7. Group C HbO_2 concentration change

(a) Group C Comparison of HbO_2 concentration change (mM) between individual and group tasks by channel

Region	BA	Hemisphere	Channel	t	p
DLPFC	10	R	17	3.924	.003
		L	19	3.559	.028
		L	20	3.406	.029

(b) Group C Comparison of HbO_2 concentration change (mM) between simple and creative tasks

Region	BA	Hemisphere	Channel	t	p
DLPFC	9	R	3	-3.620	.022
	46		6	-4.028	.034
	10		11	-4.296	.015
FPC	10	R	7	-3.730	.021
			12	-7.771	.003
			13	-4.414	.016
			21	-7.768	.005
			26	-4.953	.008
		L	28	-4.467	.025
			37	-2.986	.044
			41	-2.865	.049
OFC	11	R	14	-3.441	.027
			16	-5.919	.007
			30	-3.645	.033
		L	31	-3.148	.046
			32	-4.942	.009
			46	-3.099	.049
			48	-3.620	.025

In Table 7 (a), channels 17, 19, and 20 all correspond to the dorsolateral prefrontal cortex (DLPFC) (Table 6(a)). And they're all in the BA10 Brodmann area. The DLPFC is responsible for problem solving and focusing and maintaining attention on a task (Hertrich et al., 2021),so it can be interpreted that Group C students were able to focus their attention and retain memory better when performing the Single Task.

In Table 7 (b), channels 3, 6, and 11 correspond to the dorsolateral prefrontal cortex (DLPFC), which corresponds to Brodmann areas BA9, BA46, and BA10, respectively. The DLPFC activation suggests that cognitive processes such as planning, cognitive flexibility, and working memory were engaged when the Group C students performed the creativity task (Table 7(b)). The cognitive processes could be for any of the creativity subcomponents. Channels 7, 12, 13, 21, 26, 28, 37, and 41 correspond to the frontopolar prefrontal cortex (FPC), all located in the BA10 Brodmann area. Activation of the FPC area is involved in metacognition and exploration of new alternatives, so we can see that the creativity subcomponent was flexible. Channels 14, 16, 30, 31, 32, 46, and 48 correspond to the orbitofrontal cortex (OFC), which corresponds to areas BA47 and BA11 Brodmann. The OFC is involved in judging rewards for choices and processing information related to desire or motivation, so we can see that Group C students were intrinsically motivated to perform the task. Since Group C students are mastery goal oriented, it can be interpreted that they were more motivated to perform the complex task than the simple task. Group C showed the greatest brain activation with significantly more significant channels than the other groups. Group C students were more creative than the other groups, suggesting that their creativity was achieved through extensive use and activation of the brain.

This study demonstrates the importance of social and affective dimensions in assessing creativity. Real-time measures and advanced visualization tools provided deep insights into how group dynamics and individual characteristics influence creative outcomes. By integrating social network analysis with brain imaging and learning style assessments, the research highlights the complex interplay of factors driving creativity in collaborative settings. The use of commands and item-based interactions in Minecraft served as effective indicators of creative activity, underscoring the value of innovative assessment models in educational research.

Discussion

In this study, we highlight the potential of game-based assessments (GBA) integrated with game learning analytics (GLA) and neuroscience approaches to provide a comprehensive and dynamic assessment of creativity. We explored how the integration of biometric data and real-time analytics within a game-based environment can enhance the assessment of creativity, focusing on both social and affective dimensions. The use of GLA in this study allowed for tracking the process of engaging in creative activity by analyzing in-game actions, decisions, and social interactions. Analysis of the log data provided insights into participants' problem-solving strategies, decision-making processes, and collaborative efforts. For example, the high frequency of command usage in Minecraft served as an indicator of creative engagement, reflecting the participants' ability to effectively generate and implement new ideas. The use of visual tools such as Gephi for social network analysis (SNA) further highlighted the dynamics of peer interactions, identifying leaders and patterns of collaboration that significantly influenced creative outcomes.

Social Dimension of Creativity

The social dimension of creativity was a major focus of this study. Analysis of game logs and social network analysis (SNA) revealed how group dynamics, leadership roles, and peer interactions contributed to creative processes. As described, the interaction between a leader (Student 11) and a group member (Student 12) demonstrated the value of collaborative problem solving and knowledge sharing in bringing a creative idea to fruition. Student 11's guidance and explanation of the Redstone Repeater tool enabled Student 12 to identify problems and consider innovative solutions, demonstrating the impact of effective communication and teamwork in fostering creativity. This finding is consistent with the collaborative dimension of Lucas's five-dimensional model of creativity (Lucas, 2016), which highlights the importance of the social dimension. He suggested that sharing creative output, giving and receiving feedback, and collaborating effectively through active communication are the main aspects of the collaborative dimension that contribute to fostering creativity. Moreover, recent efforts to advance professional fields such as science, technology, and business have emphasized the importance of the social dimension (e.g., shared goals, active feedback, shared products) as a fuel for creativity (Amabile & Pillemer, 2012; Laudel, 2001).

Affective Dimensions and Learning Styles

The incorporation of functional near-infrared spectroscopy (fNIRS) provided a unique perspective on the affective dimension of creativity. By measuring brain activity, the study was able to correlate cognitive and emotional states with creative performance. The results showed that students with different learning styles and goal orientations exhibited different levels of brain activation during creative tasks. For example, Group A (Accommodators) showed higher brain activation in social and emotional areas during group tasks, suggesting that collaborative environments enhance their creative engagement. In contrast, Group B (convergers) and Group C (assimilators) showed higher activation in cognitive and reflective areas during individual tasks, highlighting their preference for solitary, goal-oriented activities.

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This is consistent with research on individual learning styles and creativity, which found that both independent and collaborative learning styles foster creativity through different mechanisms. Independent learners benefit from self-efficacy, while collaborative learners thrive on the enjoyment derived from social interactions (Sitar et al., 2016). The fNIRS data underscore the importance of tailoring educational approaches to these different learning preferences, ensuring that both cognitive and affective dimensions of creativity are nurtured.

Furthermore, these findings resonate with recent research on affective creativity (Vass et al., 2014). They highlight the central role of affect and emotional connectedness in collaborative creative processes. Vass et al. found that affectively constituted strategies, such as shared associations and collective pooling, were critical in fostering collaborative ideation and reflection among children. Integrating these findings underscores the importance of considering both cognitive and affective dimensions in educational practices to effectively support creativity. By tailoring educational approaches to different learning preferences and leveraging emotional connectedness, educators can create environments that foster both individual and collaborative creativity, thereby enhancing overall creative performance.

Social and Affective Feedback for Creativity

The development of an assessment model has been difficult due to the limited ability to validate the model. However, an implication that provides social and affective feedback in creative activity can be provided by assessing the social and affective dimensions of creativity. This assessment approach emphasizes the importance of understanding how social interactions and emotional states influence creative processes, providing a more holistic view of creativity that goes beyond traditional cognitive-focused models (Averill & Thomas-Knowles, 2005; Megalakaki et al, 2017).By integrating game learning analytics with neuroimaging techniques such as fNIRS, educators can provide personalized feedback that enhances both the social and affective dimensions of student learning, ultimately fostering a more supportive and effective educational environment(Davidesco et al., 2021; Kazlauskiene & Irina Barabanova, 2020; Mercier & Bédard, 2017). With regard to the social dimension, the analysis of how students interact within the game allows us to identify patterns of collaboration and social dynamics. The information about leaders, isolators, and negotiators, as well as interaction patterns, helps teachers and students to change and improve the participation structure. In particular, the example of peer influence can show how peer interactions contribute to creative outcomes. In this study, we used fNIRS results as biometric data to support students' learning styles and goal orientation. Regarding goal orientation, by analyzing how different goal orientations (e.g., mastery vs. performance) affect creativity, the assessment model can provide feedback that helps students understand their motivational drivers. Knowing these motivational drivers with the diagnosis of creativity traits via fNIRs can help learners develop individualized and personalized strategies. For example, a learner may find that individual performance on a complex task to master a related skill can increase her originality. A learner whose goal is performance-oriented and who prefers to work collaboratively may find that she would maximize her flexibility and fluency, stimulated by higher emotional involvement.

While the results of this study are certainly limited by the small number of participants, these types of feedback show potential to contribute to the development of creative competence. First, social and affective feedback can help students reflect on their learning not only along cognitive dimensions, but also along metacognitive dimensions. Such feedback can promote greater self-awareness and adaptive learning strategies. Second, the integration of social and affective feedback can encourage students to engage in voluntary iterative learning, where students continuously improve their creative processes.

Implications for Creativity Assessment

The results of this study have potential implications for educational practice. The combination of GLA and neuroscience data, such as fNIRS, offers a promising framework for assessing and promoting creativity in educational contexts. By providing real-time, personalized feedback based on social and affective dimensions, educators can tailor learning experiences to the needs and preferences of individual students. This approach not only improves creative outcomes, but also promotes a deeper understanding of the creative process. However, the implementation of GLA and biometric assessments has both strengths and weaknesses. The strengths include providing real-time feedback, offering a holistic view of creativity by incorporating cognitive and affective dimensions, and using objective data from biometric measures to reduce subjectivity. In addition, these interactive and technology-enabled assessments can increase student engagement and motivation (Rafner et al., 2022, 2023; Shute et al., 2019). On the downside, the technical complexity and cost associated with these methods can be prohibitive for some educational settings. In addition, there are significant privacy and ethical concerns associated with the collection of biometric data that require careful management. To effectively implement these advanced methods, schools should invest in technology and training, begin with pilot programs, gradually integrate these assessments into the curriculum, focus on ethical practices, and continually evaluate their effectiveness. By addressing these factors, educational institutions can leverage the strengths of GLA and biometric data to create more effective and personalized creativity assessments, ultimately fostering a richer and more supportive learning environment for students.

Conclusion

This study underscores the critical importance of considering social and affective dimensions in the assessment of creativity. These factors have a significant impact on creative performance and should be integrated into assessment models to capture the full complexity of creative processes.

The methods used in this research - game-based learning analytics and neuroscience approaches - provide a promising framework for the comprehensive assessment of creativity. Real-time data collection and analysis, combined with advanced visualization tools such as Gephi, effectively monitor and evaluate social interactions and collaborative efforts among participants. Social network analysis (SNA) maps these interactions and provides insights into group dynamics, leadership roles, and peer influence that are critical to understanding the social dimension of creativity.

The use of fNIRS provides valuable biometric data that reveal how cognitive and emotional states influence creativity. By analyzing brain activity, this method provides insights into the affective dimension of creativity, including emotional engagement and stress levels during creative tasks. This holistic approach enables the provision of tailored feedback that promotes continuous improvement and deeper engagement in creative activities.

The study also highlights the value of personalized and adaptive learning environments. By understanding individual differences in learning styles and goal orientations, educators can design more effective and engaging educational experiences. The integration of social network analysis further enhances this model by identifying key contributors to collaborative creativity and optimizing group interactions.

In summary, this innovative assessment model leverages the strengths of digital environments and neuroscience data to provide a comprehensive assessment of creativity. It addresses the limitations of traditional assessments and provides a more dynamic and personalized approach to fostering creativity.

Finally, the results of this study are limited by the small sample size. In addition, the complexity of data integration and ethical concerns regarding the use of biometric data may pose some challenges. Future research can be expanded with participants from a diverse participant base to increase generalizability.

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Conflicts of Interest

The author(s) declared no conflicts of interest.

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