EVALUATING CO-CREATION IN COLLABORATIVE DRAWING USING CREATIVE THINKING MODES

by

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ABSTRACT

ALI ALGARNI. Evaluating Co-Creation in Collaborative Drawing Using Creative Thinking Modes. (Under the direction of DR.MOHAMED SHEHAB)

Co-creation is a form of collaboration in which partners share, improve and blend ideas together to develop a creative product. It helps to share ideas and solve problems in a creative manner. Several co-creativity research works have focused on generating creative artifacts, but there is a limited amount of research in analyzing creative collaborations. Creative collaboration can be evaluated through examining interaction dynamics such as cognitive states, behavior, and the number of ideas generated. This dissertation conducted two different collaborative experiments to add a new contribution to human-human co-creation by modeling and quantifying co-creativity using divergent and convergent thinking modes. The first study conducted 15 collaborative users studies of a turn-based collaborative drawing task using a shared canvas to extract different patterns of creative collaboration. In the second study, we conducted 21 dyadic user studies of a turn-based collaborative drawing task to quantify and extract several co-creation patterns and compare co-creativity of users. The results of both studies showed significant differences of creative thinking between high and low creative performance. High co-creativity groups show balanced divergent and convergent thinking comparing to other works. The interaction dynamics of different creativity levels were also different in term of the number of ideas and objects created and modified. The work can be applied to different co-creation applications, and can be the starting point toward designing a computational creative thinking model in the future.

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CHAPTER 1: INTRODUCTION

Human collaboration involves two or more people working together in a joint activity to accomplish a goal [16]. People in the team work in a shared space (e.g. canvas or computer interface) and collaborate to achieve goals. The collaboration facilitates problem solving by integrating team skills and increasing the solution space [32]. Human collaboration can take different forms like face-to face or virtual environment [2]. People skills and contributions take different levels including leader-follower to balanced interaction style. The collaboration requires effective communication among team members, which they exchange information in a timely manner [16]. There are other forms of communication methods such as the shared artifact, body motion and gesture [6], emotions or social signals [42]. Investigating human collaboration is important to different research fields such as human-computer interaction and creativity support tools (CST).

Co-creation is a form of collaboration in which creativity is shared by two or more people [38]. It includes any act of collective creativity, in which a creative artifact is generated by sharing and blending ideas together [11]. Creative ideas grow through different stages of collaboration such as stretching, breaking problem boundaries, and building new associations between prevailing paradigms [35]. For example, group members may come up with new ideas as a combination from old ideas, or transform old ideas based on other experiences. Creative collaboration can take different dynamics like open-ended or turn-based collaboration. There are many cognitive mechanisms that underlie creative collaboration, such as shared mental models [17] or distributed cognition [31]. These mechanisms help to share ideas to others and build up new ideas based on other experiences. For example, distributed creativity is derived from distributed cognition and it means the creative product is generated by sharing different ideas from different people using techniques such as group brainstorming. Distributed creativity has been used to evaluate creative collaboration [39] and design a co-creative agent [14].

Divergent and convergent thinking have been used in creativity research. Divergent thinking is defined as an open-ended and ill-defined problem that motivates people to generate many solutions [36], while convergent thinking combines different ideas together to come up with a final and creative solution. Divergent thinking can bring a number of possible solutions, while convergent thinking can complete the creative process by blending different perspectives together to make a new and novel idea. While combinations of divergent and convergent thinking modes have been supported by creative cognition theories and mechanisms, these modes can evaluate collaborative tasks of creative domains. Collaboration that has more connected divergent and convergent from both partners will be more creative. Coupling is an interaction moment that occurs when two partners are engaged closely in specific ideas and contribute together to that idea. Computational creativity researchers can also design systems that use both divergence and convergence to make humans and machines brainstorm or perform critical thinking together to achieve novelty and co-creation.

1.1 Thesis Statement

There is a gap in the research about the interaction dynamics of co-creation. The majority of co-creation evaluation has focused on the final creative product, and there are few works that have examined creative processes during creative tasks. This dissertation uses creative thinking (divergent and convergent thinking) to evaluate the co-creation process in collaborative drawing. It also extracts different collaboration patterns of several drawing sessions to examine the differences of patterns between high and low creative sessions.

The dissertation seeks to answer the following research questions:

- How can co-creation be achieved via creative thinking modes?
- How do divergent and convergent thinking modes work as a creative cycle in co-creation?
- What are the interaction patterns and trends that could be considered creative?
- What are the factors that affect the quality of co-creation in collaborative drawing?

To answer these questions, the study analyzed collaborative drawing sessions, and coded interaction actions of both partners. Divergent and convergent actions were classified by observing turns in recorded videos and using a coding scheme. Divergent thinking includes actions that are different and not related, while convergent contains behaviors that improve partner's ideas. Coupling periods were also identified to measure the quality of co-creation. Creative thinking occurs when there are more coupling cycles, so we will have connected divergent and convergent thinking actions to generate and evaluate ideas. Interaction trends will be grouped based on participants' ranking of creativity in a post-task survey, and then compare between these groups and examine high creativity trends. Different analysis techniques were used to examine the differences between creativity levels.

This dissertation aims to add a new contribution to co-creativity works by using cognitive science theories to design a creative thinking model of co-creation. Divergent and convergent thinking modes are cognitive mechanisms that have been connected to creativity and creative products. A 15-users retrospective study was conducted to code partners' behaviors either divergence or convergence in the collaboration, and create creative trends to examine patterns of different creativity levels. The proposed model and analysis technique evaluate creative collaboration by visualizing and exploring correlation between trends and creativity level. We coded user behaviors into convergent and divergent interaction, and we analyzed the creative thinking trends through a creative session. The creative thinking model does not evaluate the co-creativity of the partners, i.e. the degree of creativity achieved in the session as measured by metrics such as originality, fluency, flexibility and elaboration. Instead, interaction dynamics and creative thinking modes are used to understand the overall flow of the co-creation. The second study ran 21 dyadic user studies of a turn-based collaborative drawing task using *Quantcollab* to quantify and extract several co-creation patterns and compare co-creativity of users. The results of both studies showed significant differences of creative thinking between high and low creative performance.

1.2 Dissertation Structure

This dissertation contains five chapters. Chapter 2 summarizes related works. Chapter 3 describes the creative thinking model of co-creation. It includes the model description, 15 user studies description, methodology procedures and results. Chapter 4 introduces quantifying and evaluating co-creativity in collaborative drawing using*QuantCollab*. It describes 21 dyadic studies smaple, procesdures and results. Chapter 5 includes discussion and describes the future works. Chapter 6 is the conclusion.

CHAPTER 2: RELATED WORKS

This chapter has five sections: teamwork in human collaboration, human-human co-creation, co-creation interaction dynamics, divergent and convergent in co-creation and co-creativity evaluation.

2.1 Teamwork Science in Human Collaboration

It is important to understand factors that facilitate human collaboration. There are some works that investigate the configurations of human collaboration that influence team performance and achieve the outcome such as team composition [5]. Team composition refers to the combination of individuals' characteristics that impact the team productivity and outcomes. Bell et al. introduced the four foundations of team composition, which are team member attributes, team operationalizations, the context, and time [5]. The attributes include different human characteristics that include physical attributes like gender or race, and psychological characteristics that appear through collaboration and time such as personality traits and attitudes. Operationalizations means merging and coordinating people's attributes together to achieve the outcome. Context shapes the relationship between team members in different situations such as the harmony of team members with diverse backgrounds and team performance using collaborative interdependence. These concepts are important to achieve better performance and team goals by influencing ABCs (affective states, behavioral processes, and cognitive states) of the team.

Salas et al. reviewed several teamwork science works and identified the key reflections of the team and future research concerns [37]. The paper lists 10 reflections of teamwork that presents the research progress in the teamwork science field. These reflections include: several theories underlie teamwork, the strength of collective work versus individual work, factors that affects the teamwork (e.g. individual psychology and task types), team of experts does not necessarily make an expert team, the importance of psychological safety for team to succeed, evaluating team outcomes using robust diagnostic measurement and others. The paper explains some future research concerns such as understanding more about multi-team systems, using new technologies for measurement and understanding teamwork, and closing the gap between theory and practice.

Driskell et al. explained the foundation of teamwork and collaboration [16]. In general, building relationships and forming teams is often an essential to achieve goals by merging skills of individuals together. Teamwork has different models that have been developed through the time. Several modern models identified eight central or core dimensions of teamwork, which include adaptability, shared understanding of the situation, performance monitoring and feedback, leadership, interpersonal relations, coordination, communication, and decision making [16]. These dimensions will be different from team to team based on the team goal, task, individual attributes and other factors. In addition, teamwork has different types of processes, and each process has a number of teamwork dimensions. The paper presented three types: transition processes (change of performances between different stages), action processes (activities of the teams toward aching the goals) and interpersonal processes (managing relationships between team members such as motivation) [15]. Teamwork science is relevant to this dissertation in terms of understanding the harmony of teamwork to increase the engagement and improve performance in the co-creation process. It is important to understand teamwork concepts and foundations as well individuals personalities and attitudes prior to running human collaborative study.

2.2 Human-human Co-creation

This section focused on human-human co-creation. Human-human co-creativity can be in two or more participants collaborating in a creative way to generate creative results [38]. Human-human co-creativity can be applied to different domains like design or writing , and can use different environments such as paper-based collaboration or computer-based systems to coordinate group co-creativity.

Kantosalo and Riihiaho evaluated the co-creativity of students in the writing domain [27]. They ran three co-creation experiments: human-computer, a human-human, and a human-human-computer process. In the human-human condition, students worked together as a pair to complete poetry writing. There were some alternatives to do the human-human condition by using Poetry Machine tool without AI support, Word Processing and paper. Post task questionnaires were used after each writing process to evaluate students' experience and a comparative questionnaire after finishing all processes. The paper used evaluation metrics for both the final product and co-creation process. These metric metrics were immediate fun, long-term enjoyment, creativity, self-expression, outcome satisfaction, ease of starting and finishing writing, quality of ideas and support from others, and ownership. Human-human co-creativity was significantly better in some metrics than human-computer co-creativity. These metrics include collaboration (quality of ideas and support from others)

Human centered computing has been utilized to support human-human co-design (co-creation in design field). He and Han presented a human-centered collaborative design model to support human-human interaction in collaborative computer-aided design (CAD) [21]. The model describes the structure of using collaborative CAD applications to help designers to do some design functions and collaborate with each other using a shared space. The paper also presented a computer based collaborative tool that is based on the human-centered collaborative design mode to support human-human collaborative design processes. The tool coordinates the co-design process between users via a group of functions called aware service. The aware service includes task management, communication channels, data portal and other functions that are available to a number of users during the design task. The tool includes several collaborative issues that coordinate human-human collaboration. Some modules are important to accomplish the co-creativity process such as group awareness and communication methods. The paper introduced an exploratory study using 3D collaborative tools between many geographically distributed participants. However, there are no results or evaluation metrics about the experiments. This work can help in designing systems that facilitate human-human co-creation such as group creativity support tools [40].

Human human co-creativity can be evaluated using computer-based systems. These systems coach users and organize their contributions during collaboration in order to achieve co-creation . Romero and Barbera have examined creative collaboration, and how it could be supported by the use of computer-based systems in online learning [35]. The study conducted experiments, and the participants worked in dyads. The task asked the student to design a creative advertising project during a period of four weeks.The evaluation has two parts: evaluating the individual creativity using McFadzean's creative continuum, and evaluating creative collaboration using Assessment Scale for Creative Collaboration (ASCC). ASCC investigates the students' perception of creative collaboration and the contextual variables of interest, such as the interest in the task, the degree of disagreement or tension between the team members. ASCC has 16 evaluation criteria that are related to creative collaboration. Some criteria can be used to evaluate the final creative goal, and other criteria can evaluate the co-creativity process such as engagement/interest in task. The results show that the social interrelations between the students highly impact the creative collaboration process of the team.

2.3 Interaction Dynamics of Co-Creation

Interaction dynamics describe the strategies of users' interaction in a scenario. For the domain of collaborative drawing, interaction dynamics can include elements such as turn-taking, turn length and contribution type. Interaction can be an individual endeavor, or it can be a collaboration between two or more partners. Understanding the interaction dynamics of collaboration is important to design and evaluate the co-creation process because it provides opportunities to analyze quantitative data and recognize patterns of creative collaboration. This section includes two types of interaction dynamics: timing contribution and user cognitive states.

The timing of collaboration actions or behaviors has been used in several co-creation works. Synchrony describes the time and structure of the partners' contributions when they work together. There are two types: open collaboration and turn-based collaboration. Open collaboration occurs when partners generate ideas at the same time and same turn. Turn taking interaction is a simple and effective way to design co-creative systems or creative collaboration between users. The structure of turn taking helps to evaluate the collaboration by recognizing each partner's actions and contributions per turn. It allows one person to perform, play, or otherwise make a contribution, while the partner observes and starts preparing ideas for the next turn. The dynamic of turn-taking facilitates coding and evaluating co-creation compared to open collaboration because open collaboration is more complex and has more challenges to quantify the collaboration. Turn-taking has been reported in several co-creative works such as drawing apprentice [12] and creative writing [28].

Cognitive theories have been used to describe interaction states present in collaboration. Davis et al. proposed the creative sense-making framework to evaluate interaction dynamics in creative collaboration [13]. The framework visualizes and quantifies video data of the interaction between the user and a co-creative system. The framework proposed two states of cognition: clamped and unclamped. Clamped cognition is when there is an adequate mental model predicting the environment. Unclamped cognition is when the individual is actively making sense of variables in the environment or mind. When they are inspecting the environment through interaction, it is a physical unclamped. If the individual is thinking, such as visualizing the problem, it is a perceptual unclamped. Accounting for partial unclamped in both directions makes up five cognitive states (physical unclamped, partial physical unclamped, clamped, partial perceptual unclamped and perceptual unclamped) that can each be coded through behavioral markers for each.

Using retrospective analysis, the authors used the clamped and unclamped states coding to generate a creative curve for each user. This curve helps to determine features and patterns in the creative collaboration.

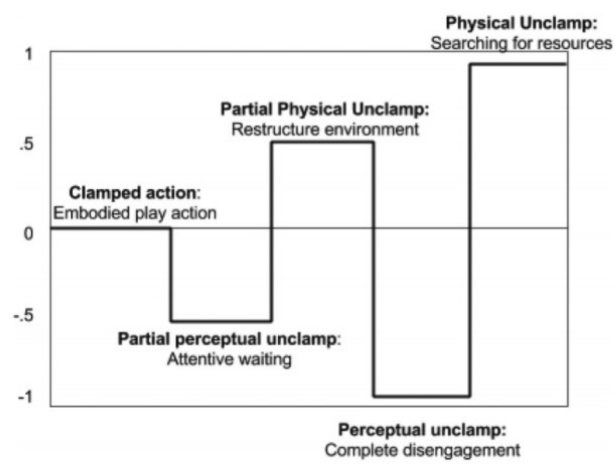

Figure 2.1: Clamped and unclamped states coding during time [9]

Another interesting interaction dynamic in computational creativity is improvisation. Improvisation is the act of doing something not planned before. Improvisation also includes making sense of the collaboration and the shared product. Users should be able to recognize and contribute to new and unexpected situations [10]. In successful improvisation, an individual is able to discern a pattern or theme and respond to that theme in a meaningful way. In collaboration, the user's contribution should be in real time and depends on the partner's actions. Computational creativity has utilized improvisation in several domains such as visual art or music. In artistic improvisation, users build creative trajectories through the collaboration with people or AI agents. The creative trajectory is the general flow and direction of the creative endeavor [10]. It describes collaboration behaviors and actions as interaction trajectories, such as establishing actions and deviation actions. The work uses the theory of enaction and creative sense making framework, in which both partners build creative ideas through the collaboration. In addition, improvisation has contributed to building numerous co-creativity tools of musical . For example, Shimon is an interactive improvisational co-creatiivty system developed for research in robotic musicianship [22]. Shimon listens to a human musician and continuously adapts its improvisation and choreography, while playing simultaneously with the human. The agent receives music rhythm or sound, analyzes it and then decides which actions (add rhythm) should be taken.

2.4 Divergent and Convergent Thinking

Divergent and convergent thinking are interconnected thinking modes that lead to creative thoughts. The literature of creativity and neurocognition has noted the role of both divergent and convergent thinking in creative endeavors. Divergent thinking is defined as an open-ended and ill-defined problem that motivates people to generate many solutions [41] [43]. Abraham and Windmann defined divergent thinking as the process of generating many ideas for situations that do not have right or wrong solutions [1]. Convergent thinking, also referred to as analytical thinking, is defined as bringing information that is related to the problem together to find a final and correct solution [19]. Both thinking modes can create cyclic phases to achieve creativity.

There are many creativity and neuro-cognitive theories that covered both divergent and convergent thinking modes. This section presents two theories: blind variation and selective retention (BVSR) and contextual focus and associative mode. BVSR describes the cognitive processes involved in creative work. The theory has two parts: blind variation and selective retention. Blind variation measures divergent thinking, and it describes the ability to generate a large number of possible ideas. Selective retention , on the other hand, measures convergent thinking by filtering ideas and selecting a solution for the problem [25]. The next theory is contextual focus and associative mode. Gabora focused her study on the contextual focus, which is the shift between the associative thoughts (divergent thinking) and convergent thoughts [18]. In her work, she claimed that creativity uses both associative/divergent and analytical/convergent thinking. The associative mode is more about ideation (generation of different ideas), while the analytic mode synthesizes thoughts created by the associative mode.

In the computational creativity discipline, there has been some research that investigates creative thinking contributions in the field. It was found that combining these creative thinking modes together improves creativity and generates unified novel and useful solutions [34]. Hoffmann proposed a human computer co-creativity model based on creative thinking [23]. He claimed that designing such systems needs explicit description of human and computer roles as the starting point, and each partner can do either divergent or convergent thinking during their turn. Examining Hoffmann's proposal demonstrates that it is an iterative process. Divergent thinking comes first and then followed by convergent roles as cyclic phases to generate creative products. The proposed work extends Hoffmann's work by using creative thinking modes to evaluate co-creation in collaborative drawing. It will change the collaboration into a series of divergence and convergence and focus on thinking patterns that are related to creativity mechanisms and theories. Number of diversion and coupling states will be used to evaluate each session.

2.5 Evaluating Co-creation

Co-creation has been evaluated through different methods. These methods vary with respect to different research goals and creative tasks (e.g., drawing vs writing). Some studies focused on evaluating co-creativity using the final artifacts, while others focused on communication and processes leading to the creative product. There are many research investigations into using creativity as a criterion of measurement or quantifying co-creativity, such as novelty [27] [20]. There is also research that focuses on defining creativity concepts in a specific context, and evaluating the work to see if the creativity concepts were achieved or not [28] [24]. Table below summarizes the evaluation of some current co-creative systems.

Karimi et al introduced an evaluation framework of co-creativity [30]. The framework was used to evaluate computational creativity systems , but it can also be used to evaluate human-human co-creation. The framework uses four questions that guide the evaluation process: Who is evaluating the creativity, what is being evaluated, when does evaluation occur and how the evaluation is performed. Figure 2.2 below shows a tree graph that explains these evaluation questions and the ways that each question measures the co-creativity. The proposed model in this thesis can be evaluated using the framework. Users and a research investigator (third party) can evaluate the co-creation. The user completed the post-task survey about co-creativity during the task. The research investigator observed and coded the interaction using cognitive theory of creative thinking. The model evaluates interaction more than the final product, it investigates the co-creation dynamics throughout the collaboration. The co-creation was evaluated after finishing the task (summative), because the investigator ran retrospective studies. The model evaluates co-creativity using an experiment, observation and survey methods. However, the model did not employ final product or creativity metrics in the evaluation because the model focuses more on collaborative and co-creation processes than creativity and the final product.

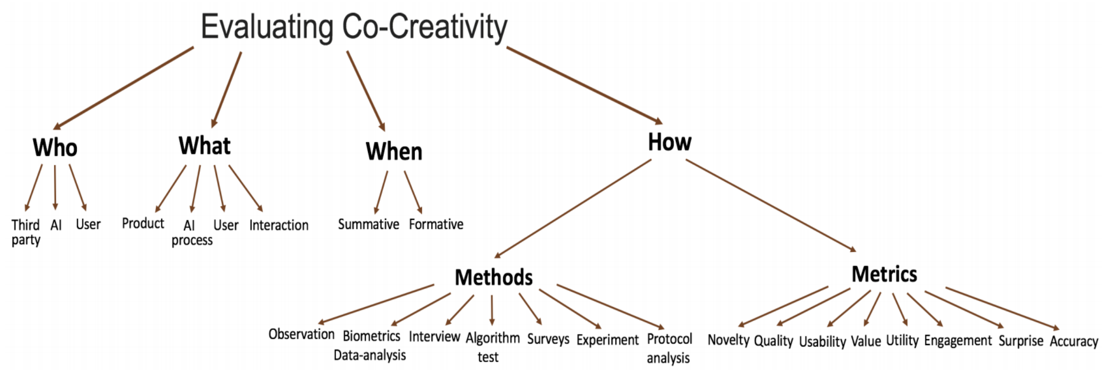

Figure 2.2: Co-Creativity Evaluating Framework [30]

Table 2.1 below lists co-creation evaluation of different works in different creative domains. The agent or framework explains the name of the system or framework that was evaluated. The second column explains the creative domains in which these works were applied to. The third column describes the methodology of evaluation such as running an experiment or user study. Metrics are the measurement or quantifying methods of the interaction. Metrics are quantitative methods that measure creativity and interaction dynamics such as coding actions, counting new ideas, measuring similarity of ideas and measuring time periods. For example, the creative sense making framework [13] coded the behavior states of participants using two states: clamped when the user engages in the task and has interaction fluency) and unclamped when the user is distracted or does not make sense of the task. The model uses some metrics and evaluation methods mentioned in Table 2.1 below. For example, similarity of the last turn is used to classify as either divergent or convergent. Other metrics such as fun or outcome satisfaction, are different from what are proposed in the work, because they only focus on the creativity of final products.

Table 2.1: Different computational creativity systems evaluation.

Agent or Framework	Evaluation method	Metrics
Drawing Apprentice [12]	User study	Voting feedback
LuminAI [33]	Public exhibit	NA
Creative Sketching Apprentice [29]	User study	Using similarity, Exploratory and transformational creativity
Poetry Machine [27]	User study	Immediate fun, long-term enjoyment, creativity and expressiveness, outcome satisfaction, ownership and others
Five C's framework [26]		Collective, collaboration, contributions, community and context
Game based Computational Co Creativity [7]		Value, learning-based, distance-based, empowerment and communication
Creative sense making framework [13]	User study	Cognitive clamping and unclamping

CHAPTER 3: CREATIVE THINKING MODEL OF CO-CREATION

3.1 Introduction Of Creative Thinking Model Of Co-Creation

The creative thinking model of co-creation is a model that measures and evaluates co-creativity of any turn-based collaboration task, and illustrates a trend of the collaboration. To build the trend, the model codes each collaboration turn using divergence (new ideas) and convergence (elaborate current ideas) modes. Classifying each turn only depends on the similarity and differences from last turn. It does not compare the turn to the old turns or to series of turns. It also describes idea generation and interaction coupling. Idea generation is the process of adding new and ill-defined ideas that needs to be refined, improved or transformed to different ideas. An interaction coupling occurs when the partner contributes to the most recent turn and both partners start building upon each other. Figure 3.1 below explains the core concept of the model.

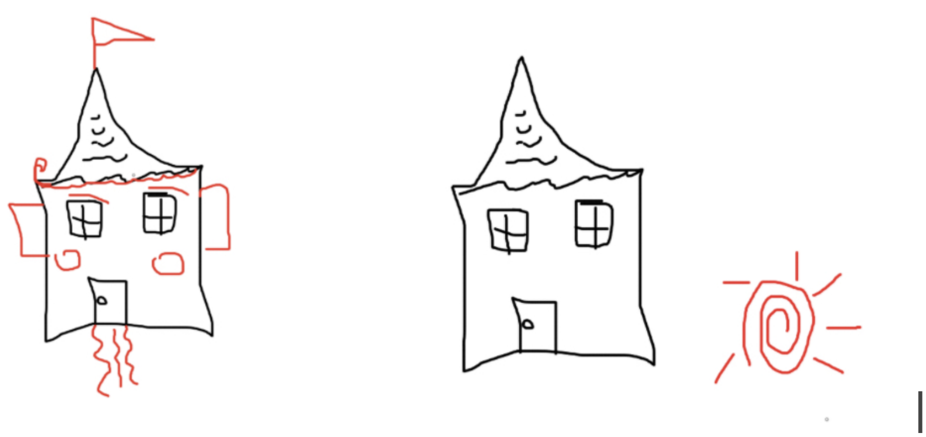

Figure 3.1: Users' contribution types that explain divergence and convergence of the model.

Figure 3.1 uses two different colors to distinguish between users' contributions. User 1, for example, uses black color and user 2 uses red color. The left drawing represents a coupling co-creation session when user 1 diverges (black object) and user 2 converges (red line). User one draws house, and user 2 adds to the house by extending ideas such as adding a flag at the top of the house. The right drawing shows an isolated interaction session. User 1 diverges (black) by drawing house, but user 2 adds a separated and different object (red circle and lines). In this scenario, there is no collaboration or co-creation because each user works on their own ideas separately. This work is inspired by the results from creativity and neuro-cognitive works that have claimed both divergent (generating mode-brain's default network) and convergent (analytical mode-brain's executive network) are key factors to generate novel ideas [4] [18]. In addition, creative thinking contribution has been reported in computational creativity research. Hoffmann presented some hypotheses about convergent or divergent thinking roles in designing human computer co-creative tools [23]. In his work, involving creative thinking should start by divergent, compare, consolidate, and then convergent, and the process could be iterative. The compare phase matches between divergent step results (possible solutions) and the requirement (depends on the problem). The consolidation step is similar to transformational creativity, in which inconsistent ideas are blended to consistent ones.

3.2 Coding Procedure

In the process of using the model, we coded the entire interaction to determine convergence, divergence, and the trends among them, such as interaction couplings. In our study, the collaboration occurred between two people in each session. The first person was a recruited participant and the second person was a facilitator (a member of the research team) who worked as a proxy for a co-creative AI. Coding turns include both participant and the facilitator contributions. Each collaboration session was observed by looking at the content of each turn and determining similarity to the previous turn. In this model, creative thinking is divided into two parts: divergence (new and independent idea compared to the previous turns) and convergence (extend and elaborate previous ideas).

The divergence takes different degrees based on the connection with the most recent turn. When creating the collaboration trend line, there are two dimensions: turns (x-axis) and divergence degree (y-axis). Divergence can be high or low using the dissimilarity of the contents of this turn compared to that of the previous turn. For example, if a user draws a straight line, and the partner adds a curve line in the next turn but is far and not elaborating the straight line, that is low divergence because of objects dissimilarity, but it is far away not connected to the previous turn. If the partner instead draws a house or star, that will be high divergence since the objects shape and uses are completely different. Divergence can be -2, -1, 1 or 2. Zero divergence occurs when there is convergent turn. Low divergence takes value 1 when participant 1 (P1) has the turn or -1 when participant 2 (P2) has the turn. High divergence takes value 2 when participant 1 (P1) has the turn or -2 when participant 2 (P2) has the turn.Converging ideas have different types based on targeted turns. Convergent is adding to the most recent turn, and that starts a coupling period. The model and coding scheme only counted the convergence to the most recent turn, and it takes 0 on the y-axis. Convergence to old actions are not included in the collaboration trend because they do not encourage engagement between participants.

When observing continuous contribution to a specific idea or object and noticing that both participant and facilitator were involved and had agreement and fluency in their contributions, these dynamics were defined as coupling. Each coupling should start by divergence, and then continue converging to that divergent thinking ideas. Coupling cycle must start first by divergence turn when creating a different and new idea, and then convergence turn should add and improve to the same idea. Coding values are explained in Table 3.1 below. When we coded each turn and gave it a value based on the coding scheme, we ended up with a divergent, convergent and coupling plot through the time. Creative trends were extracted from the regular plot by using a cumulative sum function.

Table 3.1: Divergent and Coding scheme

Thinking Mode	Thinking Degree	Description	Coding Value (P1)	Coding Value (P2)
Convergent	Coupling	Contribute to most recent idea and start coupling period	0	0
Divergent	Low	Similar object but different idea. Had a kind of inspiration	1	-1
Divergent	High	Different ideas and objects, there is no connection between ideas and create isolated brainstorming	2	-2

3.3 Visual Representation of the Model

The creative thinking model of co-creation uses a visual representation to illustrate the interaction dynamics of a co-creation. The representation uses a two-dimensional graph to show the change of interaction dynamics of each turn. Figure 3.2 depicts the visual representation of a collaboration trend. For example, the co-creation starts when P1 diverges and creates object A. The next turn is P2 converging by refining object A (as it is explained in Figure 3.1), and this creates a coupling period focusing on the same idea (object A). The process occurs again when P1 broke the coupling and drew a low divergent object B, but there is no coupling there because P2 did not contribute to P1's new idea. It is an iterative process by having different thinking modes and start/stop coupling cycles.

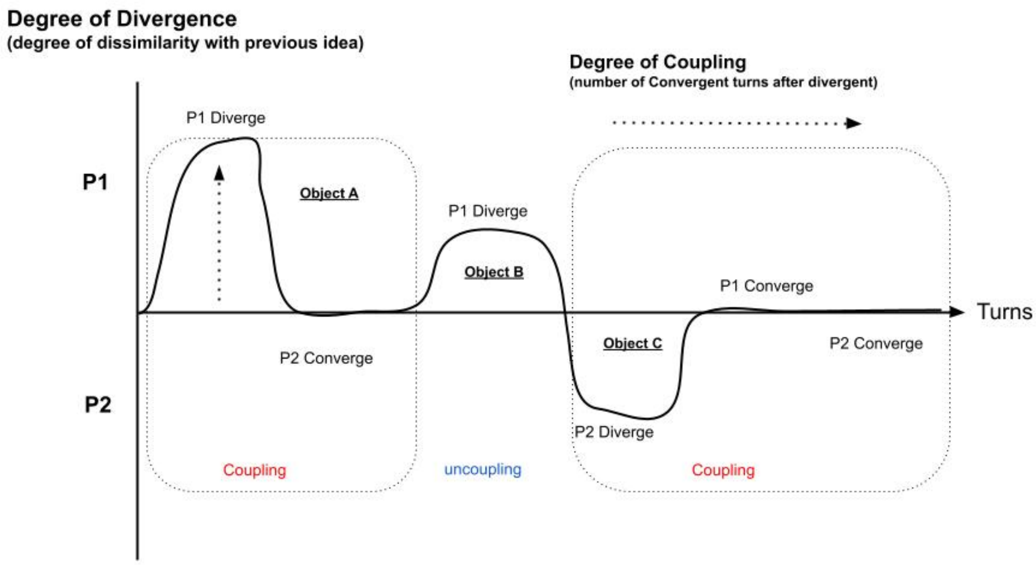

Figure 3.2: Creative thinking model of co-creation.

3.4 Coding Collaboration session and Building Creative Trends

The data was coded using a retrospective analysis by observing the action and drawing of one user in each turn and code that turn (either convergent or divergent action) in the collaborative task. Coding depends on contribution to the last turn.The participants and facilitator were observed during each turn to code that entire turn using one of the following codes: low divergent, high divergent and convergent to last turn. The values will be 2 for high divergent action, 1 for low divergent action and 0 for coupling action. When talking about the x-y axis diagram, these values are visualized in y-axis, while x-axis describes the turns. Figure below explains coding the entire session

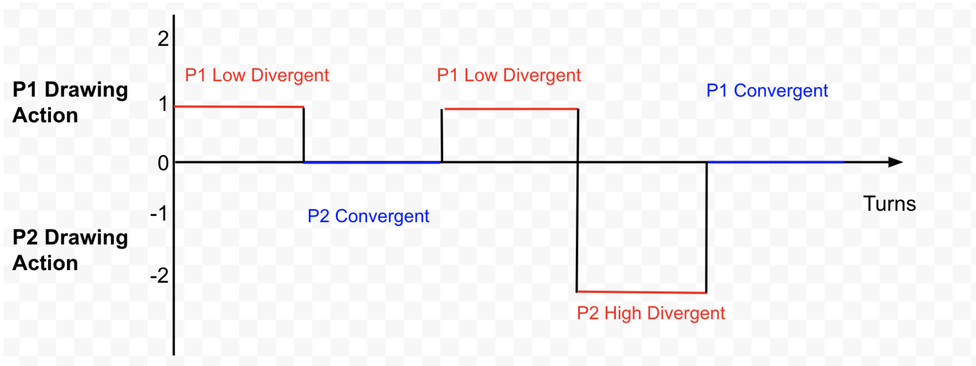

Figure 3.3: Creative thinking trend.

Participants codes will take positive values while facilitator codes are negative values. Negativity here does not have a particular meaning in analysis. It is only used to distinguish facilitator contributions from the participant and also to visualize the contribution of each partner in the same diagram. For example, P1 has ‘low divergent action’ in turn 1, P2 has ‘convergent action’ in turn 2, P1 has ‘low divergent action’ in turn 3, P2 has ‘high divergent action’ in turn 4 and so on.

After finishing the code, we used the cumulative sum function of both participant and facilitator in each session to build a trend called co-creation trend. Cumulative sum is an iterative sum of coding values, so each value will be added to the total of previous code values. We used the cumulative sum function to show the overall impact of both P1 and P2 contributions in collaboration and co-creation. The cumulative sum also shows different patterns of different collaboration sessions by aggregating divergent and convergent values from both partners (P1 and P2).

$$CumulativeSum = \sum_{i=1}^{n} x_i \tag{3.1}$$

Table 3.2 below explains generating a co-creation trend from coding scheme. Original code column explains the code of each turn explained in Figure 3.3 above. The cumulative sum column explains cumulative sum after each turn, and we used these values in the y-axis to build the co-creation trend.

Table 3.2: Divergent and Coding scheme

Turns	Partner	Original code	Cumulative sum
1	P1	1	1
2	P2	0	1
3	P1	1	2
4	P2	-2	0
5	P1	0	0

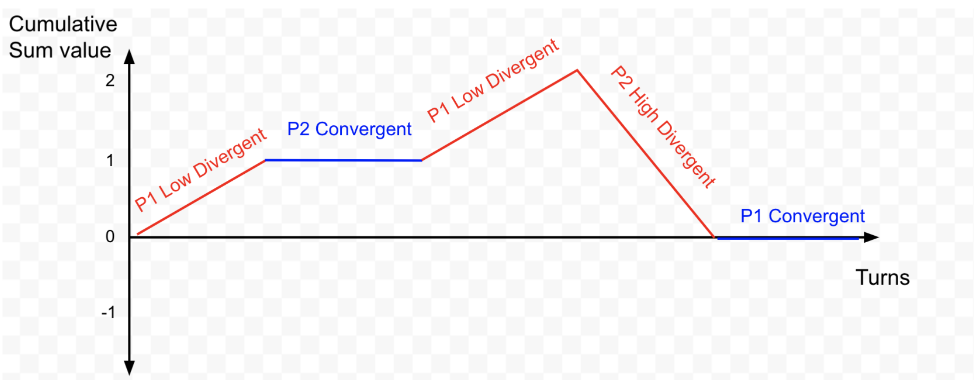

Figure 3.4: Co-creation trend.

Figure 3.4 above illustrates the co-creation trend using the cumulative sum values in Table 3.2. The trend of high quality co-creation shows balanced collaboration from both partners, more divergent actions from both sides and many deep coupling cycles during the session.

3.5 Evaluation and Results

3.5.1 Experiment Sample

Data was collected from a collaborative drawing study with N=15. The sample includes 7 females and 8 males. We required no preconditions for participating in the study. Participants were recruited via email that was sent to all people at UNC

Charlotte. The participants were distributed between all age categories with the youngest participant in the 18-25 age range and oldest in the over 45 years old age group. Two out of the 15 participants had art-related backgrounds, and the rest were from other disciplines including biology, chemistry, psychology and computer science.

3.5.2 Experiment Procedures

The experiment studied and evaluated structured human collaboration in a traditional drawing task using A4 paper. The main participants drew with the facilitator. The experiment included open-ended drawing collaboration and structured drawing collaboration. Structured collaboration is turn-based interaction that includes several stages. The time of each collaboration was 10 minutes. Figure 3.5 below shows the collaborative drawing product of some sessions

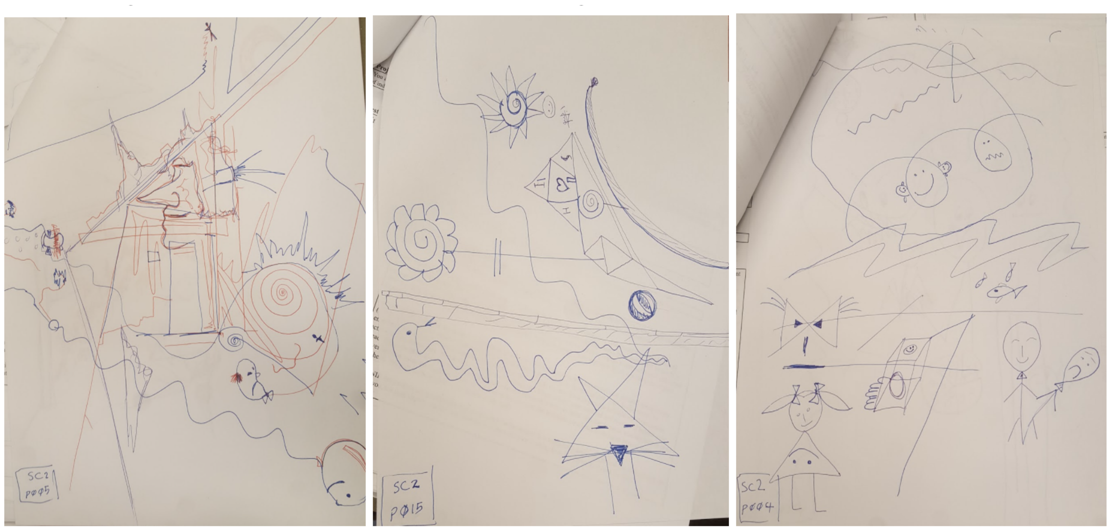

Figure 3.5: Different collaborative drawing products from sessions 5,15 and 4

The participants collaborate with a facilitator who facilitates the co-creation, and supports the creativity in the task. It was not expected that the facilitator would take the lead in the collaboration. Each session has multiple drawing tasks. Here, we analyze the data from the turn-taking based collaborative drawing. This task was ten minutes and it had five stages, which each determined what the participant contributed during their turn. The stages were: one line turn, 2 line turn, 3 line turn, find faces/objects and final editing phases. The coding focused only on the first three phases because they are turn-taking collaboration, while the last two stages are open collaboration. After finishing the session, the users answered a Likert scale post survey about their collaboration. The survey asked about their performances and identified the degree of task difficulty, enjoyment, collaboration (follower, leader or balanced) and creativity through task and creative products. The scale ranges between 1 (lowest) and 5(highest). Creativity during the task, for instance, can be 1 (low or no creativity at all), 3 (moderate), or 5 (high creativity).

We analyzed co-creation of participants using the coding scheme described above in Table 3.1. In the conventions introduced by our model, the degrees of divergence will be visualized as the variation from the baseline (sense making). The degree of the convergence is presented by the continuous stable line without going up or down, which means partners make sense of the previous turns and they refine and add to specific ideas or objects. Co-creation shows more balance in the contribution, more divergence and coupling sessions from both partners when divergence (create an incomplete and ill-defined idea) is directly followed by convergence (contributing to that idea once it is created).

3.5.3 Results and Analysis

3.5.3.1 Quantitative Analysis and Co-creation Trends

The results section examines the collected data from retrospective study to find patterns of different collaboration sessions. The section starts by showing descriptive statistics of each session, which includes trends cumulative sum, number of convergence (coupling moments) and creative scores. Table 3.3 illustrates descriptive statistics collected from observing creative trends.

The number of coupling (or convergence) means the number of ideas that were completed and refined by both participants. Creative score is the result of a 5 point likert scale in the post-task survey, when users ranked their collaboration. The trends cumulative sum is the cumulative sum of all divergent and convergent of both users. In the case that the user diverged, there is a fluctuation and deviation from baseline. The trend goes up if user 1 diverges (positive in y axis) and goes down if user 2 diverges (negative in y-axis). Convergence is represented as a stable straight line when users are making sense and focused on editing ideas. Total number of Convergence explains how many convergence and couplings periods during the task. Coupling cycles explains how many coupling moments (two participants work together in the same idea) occurred in the session. Creative scores are collected from the post-task survey.

Different collaboration trends were extracted from coding the collaboration sessions. This coding resulted in creative thinking trends that visualize the effect of thinking modes through the task. Trends were grouped in to high and low co-creativity based on the ranking of creativity during the task in the post-task survey. Figure 3.6 illustrates two high co-creation trends and Figure 3.7 illustrates two low co-creation trends. The main participant contribution is on the top of x-axis (positive y score), while the facilitator is on the bottom of the x-axis (negative y score).

Table 3.3: Descriptive statistics of drawing sessions

Session	Total number of Coupling	Trends cumulative sum	Creative score
1	5	2	2
2	6	1	5
3	4	0	5
4	6	7	3
5	6	3	4
6	2	2	4
7	2	0	4
8	10	15	4
9	6	6	4
10	4	4	4
11	4	-1	4
12	2	-2	4
13	6	9	4
14	6	-6	2
15	5	-4	1

The high creative trends illustrate symmetry when the trends go up (P1 diverge) and go down (P2 diverge). These trends shows ideas generation from both users. P1 and P2 diverged many times during the task. The trends also presents long stable periods of interaction coupling between the divergence moments, which explains the deepness of the interaction coupling. For example, both trends in Figure 3.6 show many long coupling sessions between divergent turns which describe the deep engagement in the collaboration. After initiating an idea or object, both users worked together to blend many ideas and improve the main ideas or object. In summary, both trends show P1 and P2 equally participated in both divergent and convergent thinking. The low creative collaboration trends illustrate significant drops in both low creativity trends. This means the interaction is controlled by one side, while the partner just mimicked and did not add new ideas. The majority of divergences were from the facilitator who broke the coupling several times and introduced new ideas. It was noted that one user (shown in the bottom trend of Figure 3.7) just spent a long time thinking and then mimicked what facilitator did.

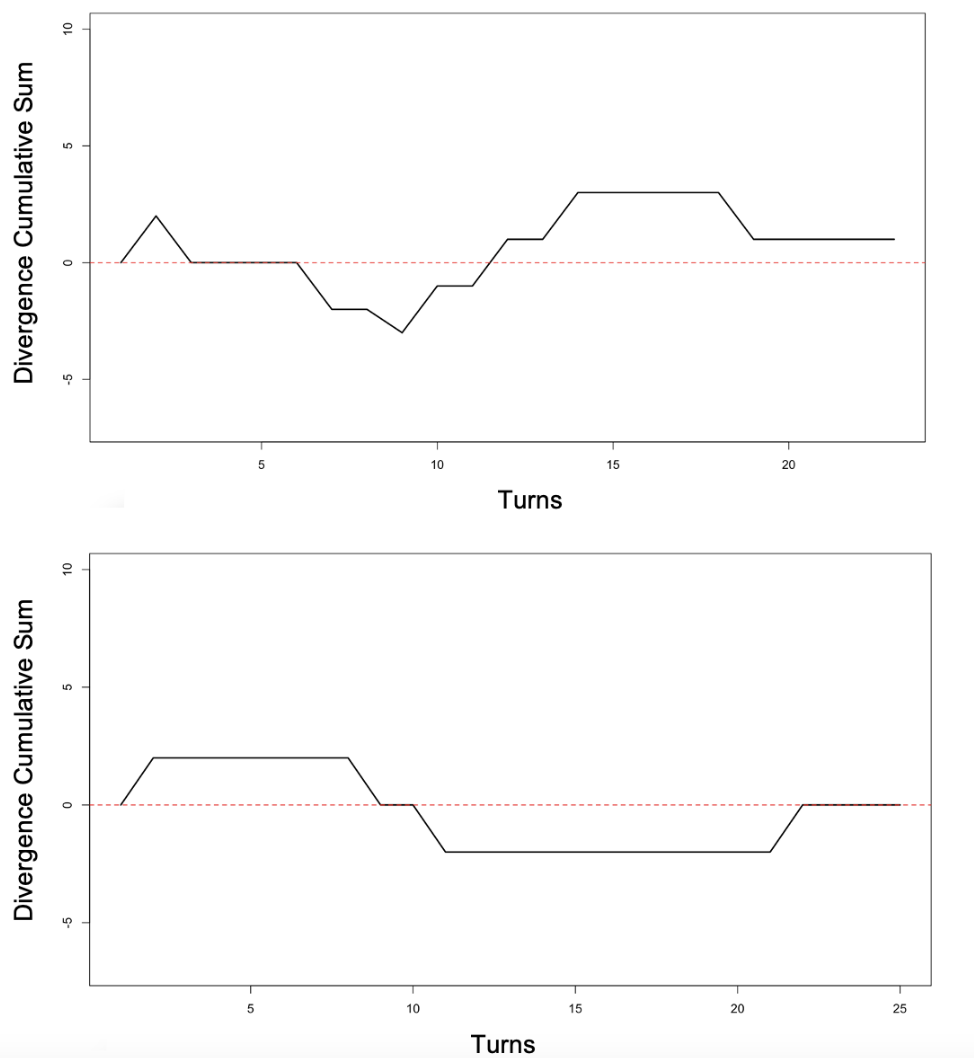

Figure 3.6: High co-creativity trends.

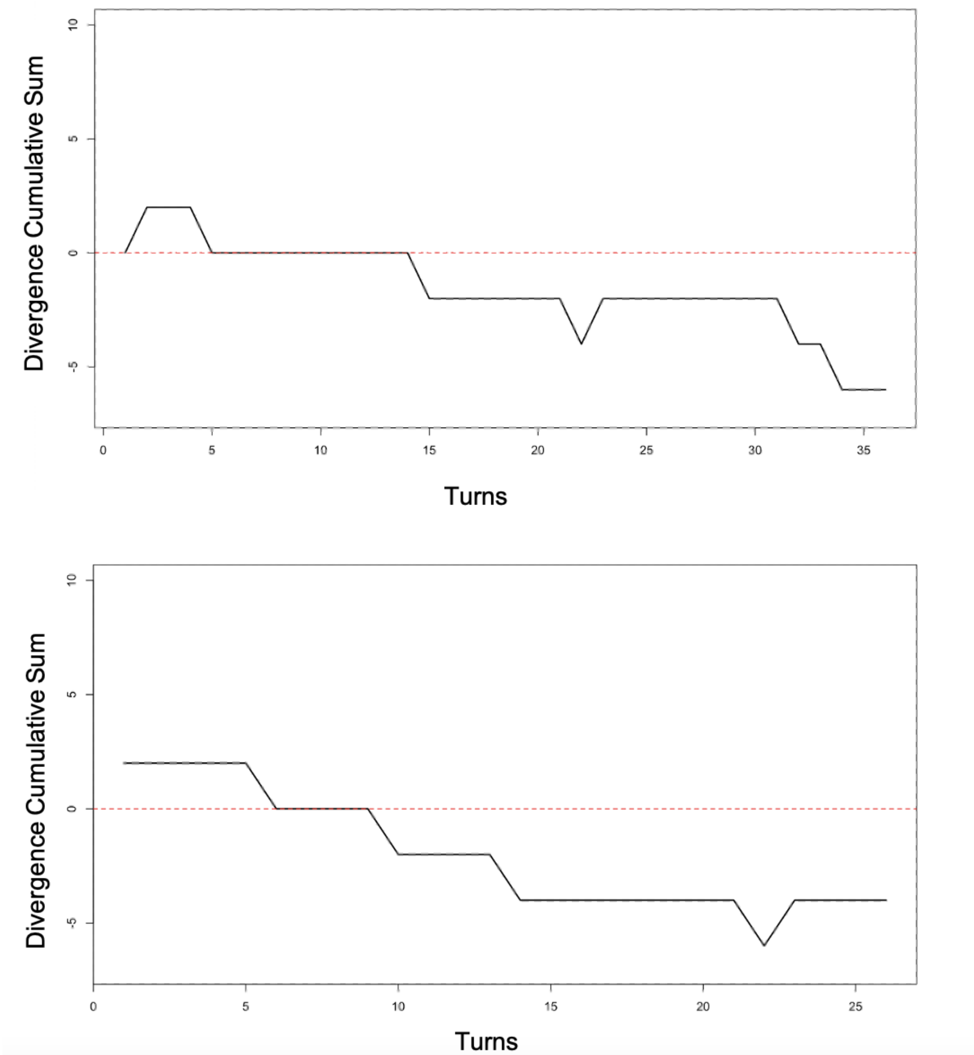

Figure 3.7: Low co-creativity trends.

3.5.3.2 Boxplot Analysis

Boxplot analysis was to compare between different creativity level groups of the experiment sessions: low, moderate and high creativity groups. We want to check if the creativity groups were different based on statistical distributions of coupling and accumulative sum values for each group. Figure 6 shows a box plot diagram of the creative trend sum of three different creativity levels: low, moderate, and high. The diagram describes the statistical distribution, average and outlier of each level. We can see high creativity is in the middle, low creativity in the bottom (negative trend slope) and moderate in the top (negative trend slope). The results show differences between the three groups. In this diagram, we can find that high creativity sessions are close to zero because both partners contribute equally. Moderate creativity sessions are higher because the trend moves in one direction when the main participant took the lead and controlled the collaboration. Low creativity sessions show that the trends go down (less than zero) because the facilitator led the collaboration, while the main participants just followed the facilitator.

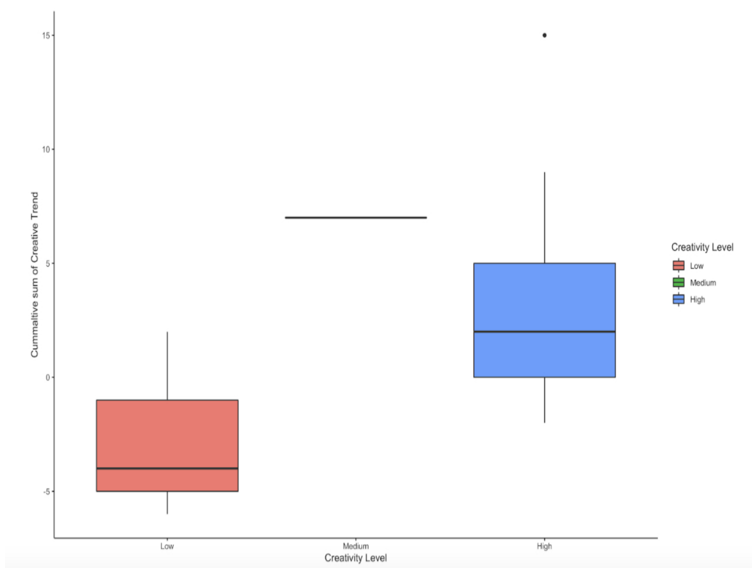

Figure 3.8: Box plot of the creativity levels.

3.5.3.3 K-Mean Clustering

Clustering technique is another analysis method that evaluates the similarity between trends in the same groups. K-Mean clustering was used to evaluate the creative thinking model of co-creativity by examining the similarity between trends in each creativity level. K-Mean algorithm uses numeric features to represent data points in multi-dimensional space. It measures the distances between these points and then groups points based on the calculated distances. We used creativity during the task score from the post-task survey, cumulative sum of the creative thinking trends and the number of coupling moments in the trends to perform the clustering.

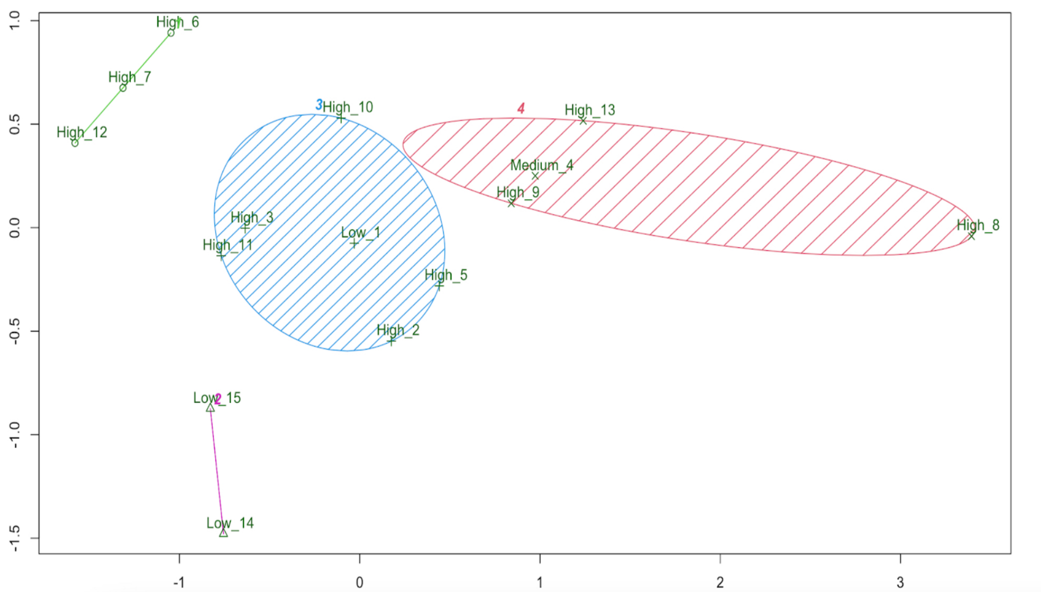

Figure 3.9: K-mean clustering algorithm to visualize similarity and dissimilarity between collaboration trends .

The elbow method, which is a pre-step before clustering, was used to identify the number of clusters before running the algorithm, and the optimal number of clusters was 4. Figure 3.9 illustrates the result of k-mean clustering. K-Mean algorithm extracted different x-y axes from the original features, to visualize clusters in a 2-D graph and make it easier to show clusters' members. The new features (new x and y axis) distribute the data points (collaboration sessions) in the space in order to measure the similarity between data points using distance calculation (e.g. euclidean distance method)and create clusters. Each cluster contains similar trends, and these trends can be from different creativity groups. Cluster 1 (represented by green color) includes high creative collaboration sessions that have low divergent actions and deep coupling cycles. Cluster 2 (represented by pink color) includes two low creative trends that shows facilitator dominance. Cluster 3 (represented by blue color) includes high creative trends that have more divergent actions and more short-coupling cycles. Cluster 4 (represented by red color) also includes a majority of the high creative trends that show more contribution from the participants. These trends share some similarity in the trend slope and shape. In general, the results show that the model was able to generate different trends for each creativity level. We found all low creativity trends are similar to each other and they are different from high creativity trends. K-Mean also found different kinds of high creative trends by showing more than one cluster of high creativity groups. One cluster showed collaboration with more divergent actions and short coupling cycles, and the other illustrated few divergent actions and deep coupling periods.

There is only a high creativity trend (session 8) that was considered as an outlier, and it was identified by both box-plot and k-mean clustering analysis. In the box-plot graph, session 8 was far away from the normal distribution of the group. In K-Mean analysis, It is far away from the cluster center and other trends of the same cluster. This gives us an implication that the post-survey is biased sometimes. Participants might be confused between creativity and enjoyment. In many cases, people participating in creative work are expected to enjoy that work, but enjoyment does not guarantee creativity.

In summary, the model identifies creative trends that appear to be correlated with high and low creativity, and there are obvious dissimilarities between trends of each creativity group. Both collaboration trends and box plots show differences between the two groups such as balanced trends in high creative groups vs negatively dropping trends in low creative groups. Cluster analysis also supported the results of the model. By running k-means algorithm, we found low creative sessions were grouped together, while the high creative sessions were clustered well together.

CHAPTER 4: EVALUATING HUMAN CO-CREATIVITY USING QUANTCOLLAB TOOL

4.1 Introduction

Human co-creativity can take different forms like face-to face or virtual environment [2]. The online collaborative drawing is a common platform that allows users to collaborate and generate co-creativity [40]. Such systems have been utilized in research topics like Creativity support tools (CST) [8] and computational creativity [13]. It helps users to collaborate in a shared space and facilitates problem solving by integrating team skills and increasing the solution space [32].

Quantcollab is a web-based collaborative drawing tool that allows users to collaborate in turn-taking style. It provides a new contribution to quantifying collaboration and co-creation by generating different statistics about individuals and the collaboration session. The interface includes basic dynamic statistics that are displayed to the user during the task. The tool also uses a feedback prompt that describes users ideas and the relationship with partner's ideas. The basic statistics includes collaboration score (overall co-creation), New Idea generated (new ideas/divergent turns), New Idea Accepted (extending partner's ideas and it presents the convergent turn), Turns dedicated to own ideas (number of ideas or turns of completed one idea) and number of coupling initiated. In addition, there are other statistics that describe the interaction and coupling in advance. These statistics are not included in the interface, but they are available to download as a text file after completing the task.

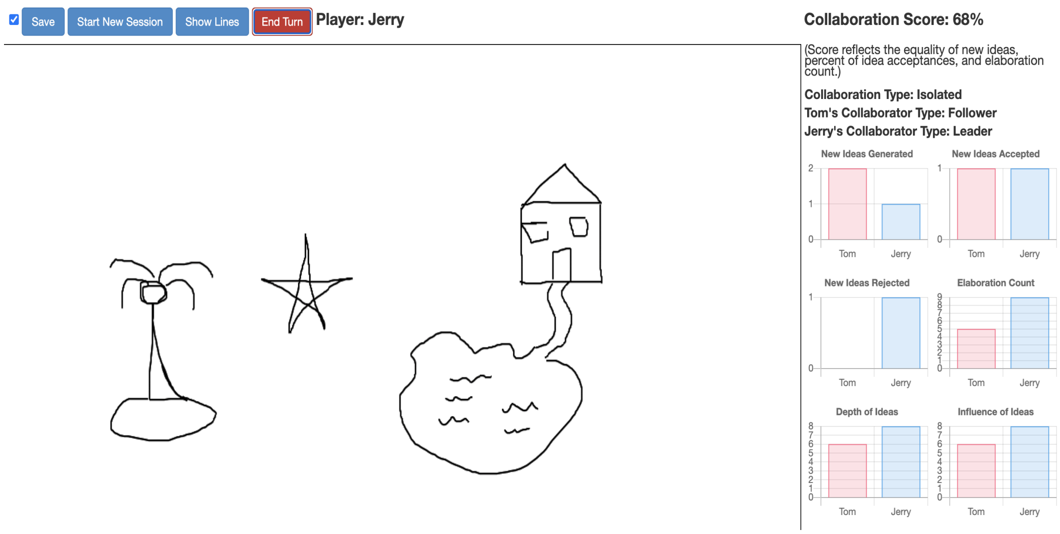

Figure 4.1: Quantcollab Interface.

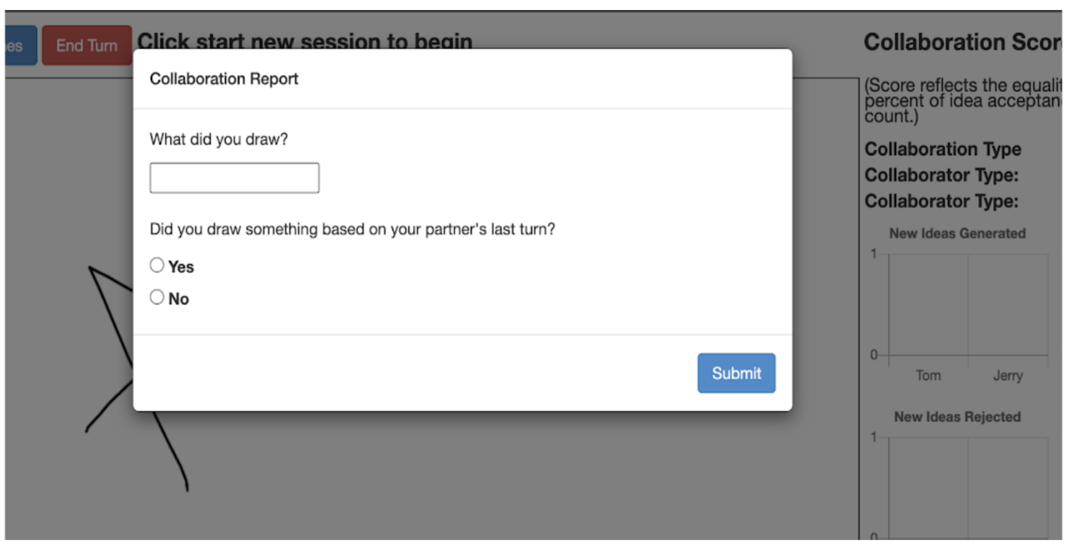

Figure 4.2: Quantcollab real time feedback.

The study has the following hypotheses:

- H1: There are differences in divergent, convergent and deep coupling between several creativity and collaboration groups.
- H2: Balanced collaboration achieve better co-creativity
- H3: More deep coupling cycles (long sequence of convergent actions to same

idea) correlates with higher quality collaboration (evaluated by user in post-task survey).

To validate the first and second hypotheses (H1 and H2), We are going to group sessions based on the post-task survey (ranking co-creation after finishing the task) and collaboration data generated by Quantcollab. Divergent turns, convergent turns and coupling will be counted for each session. After that, we will run significant differences between different groups using ANOVA test.

4.2 Study Description

This chapter introduces a user-study that investigates human-human creative collaboration in the domain of drawing using Quantcollab. The goal of the study is to investigate the co-creativity from different groups and also evaluate the tool for future improvements. Investigating co-creativity uses data generated by Quantcollab, and user self-reports. The study will use divergent (idea generation), convergent (idea acceptance) and coupling to evaluate the co-creativity of each study.

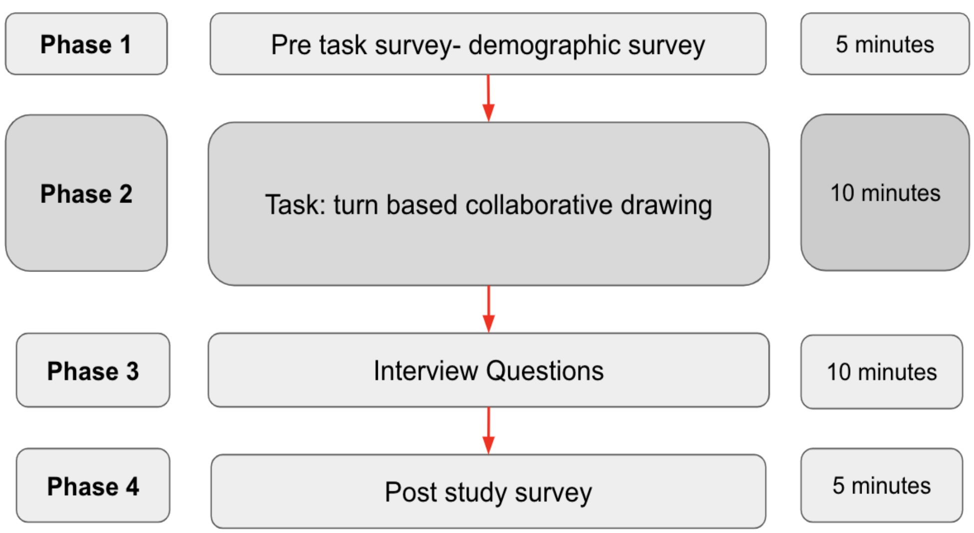

Figure 4.3: Experiment design.

Quantcollab generates different statistics based on collaborative interaction in order to quantify and evaluate creative works. Statistics describe individual performance, coupled interaction and the cumulative performance through the task. For instance, Quantcollab provides collaboration details such as collaboration style (i.e. follow the leader or isolated), a collaboration score, dynamic of the collaboration including the amount of times someone generated new ideas and whether that idea was accepted by the other participants as indicated by them adding to that idea.

4.3 Sample

Data was collected from a collaborative drawing study with N=42. Like the previous study, participants were recruited via email that was sent to all people at UNC Charlotte. The sample includes 23 females and 19 males. We required no preconditions for participating in the study. The participants were from different ages, and all participants were older than 17 years old. The sample includes students and employees who work at UNCC. There are two participants outside UNCC. Participants were from different disciplines including Accounting, Anthropology / FT employee, computer science and engineering. The study includes undergraduate, master and doctoral students. For collaborative drawing experience, most of the users were never engaged in collaborative drawing (55%), and only one user who collaborates frequently. In terms of drawing skills, the majority of the participants had moderate skills (41%).

4.4 Experiment

The user studies were 10-minutes turn-based and within-subjects experiments. They did not take place in a physical location, and they were online. At the beginning, participants completed a pre-study survey (demographic survey), and then Quantcollab was introduced to explain how to use the tool to collaborate in a turn-based drawing task. Since Quantcollab is a web-based application, participants had the tool's link before starting the task, they can draw in own turns and they are able to see partner drawing too. Each study had only one condition, in which participants interact with the tool by participating in a collaborative drawing. The condition is 10-minute turn-taking collaborative sessions, and all experiments used the same drawing theme (park theme). All sessions were recorded to capture collaborative interaction and audio during the session.

The collaboration started by one user who draws a new ideas on the empty drawing canvas. After finishing of the ideas, the user passed the turn to the partner by clicking "End Turn" button and completing feedback prompt. The process continued as shifting turns between both users until the experiment time is up. There were no restriction on user drawing or the turns, so turns were different in time windows. After each turn finished, QuantCollab's statistics were updated in a dynamic way. For example, the number of ideas accepted increased when the user completed partner's idea, and the number of the new ideas increased when the user generated different object(s). Also, the collaboration thinking sequence was updated after each turn, and Quantcollab fed the user's ideas and either divergent/convergent thinking mode to the sequence variable. after finishing each user study, the collaboration sequence had the same number of turns completed by both users. The results of user studies were different in term of users performances during the task, which led to different collaboration statistics and creative thinking sequence.

After finishing the drawing, the condition had downloadable files that included all measurements generated by the tool to be saved for the analysis purposes in the future. Users were asked interview questions about their performance, collaboration quality, and their expectations. Both participants were asked the questions, so the participants will be able to hear each other's responses. Before leaving each study, participants completed a questionnaire survey about their creativity and collaboration.

4.5 Results

The sample included 21 dyadic experiments, which included 42 participants. Quantcollab generates several measurements that describe the collaboration of each session and the contributions of each participant during the collaboration. These measurements include idea generation, idea evaluation, elaboration count, coupling initiated, and turns dedicated to user idea. There are other features that could be used for cognitive analysis such as average thinking time, average drawing time and average time per turn. We grouped users based on quality of collaboration, novelty of final drawing and collaboration role (e.g. leader) using self-report surveys after completing tasks.

4.5.1 Collaboration Quality

Users were distributed to three groups based on their collaboration quality in the post-survey. The groups are "Moderate" (9 users), "Good" (17 users) and "Collaborative" (16 users) groups. Figure 4.4 below shows the average values of measurements for each group. By looking at the diagram, we can see that "Good" and "Collaborative" groups show similar patterns. The number of idea generation and number of ideas acceptance are very close, which mean the these groups show form of co-creation. However, "Moderate" groups show highest number of idea generation among all groups, but they show small number of idea acceptance. It has the largest number of idea generation, but it has the lowest number of idea acceptance. This is a form of isolated interaction because there was not deep coupling between partners, so they generated new ideas without modifying partner ideas.

Coupling initiated and turns dedicated to ideas look similar in "Moderate" and "Collaborative" groups. In the "Good" group, coupling initiated and turns dedicated to ideas is more balanced than other groups.

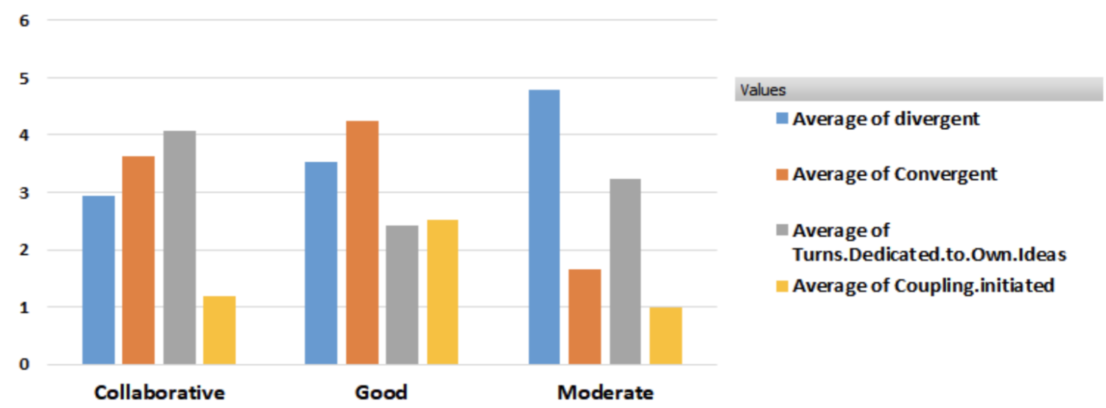

Figure 4.4: Interaction Dynamics of Collaboration groups.

By investigating the drawing and thinking time, the three groups show similar patterns. It was found that "Moderate" and "Collaborative" groups share similarities in terms of time spent on both drawing and thinking. We can see that in Figure 4.5 below

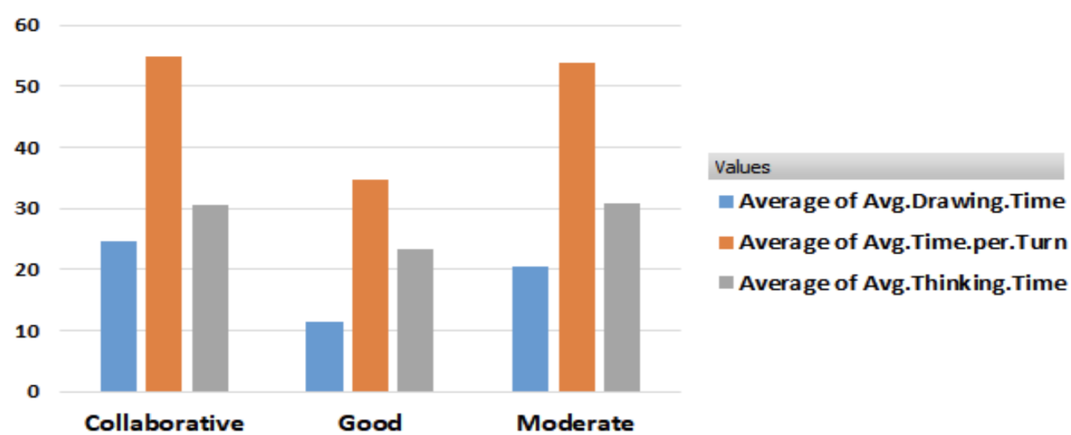

Figure 4.5: Averaged thinking time of Collaboration groups.

4.5.2 Novelty of the final Product

Creativity levels of users were grouped into different groups: low (4 participants), moderate (13 participants), good (16) and creative(9 users). The diagram below shows similar patterns in "Good" and "Creative" groups. Low and Moderate groups look opposite to each other. In the "low" creativity group, we can see there were a large number of coupling cycles created. However, these coupling periods were not deep, because the number of turns dedicated to these coupling were very low. This means one participant might accept the partner's ideas, but the team were moved to different ideas/concepts and not involved more in modifying and improving the idea. On the other hand, "Moderate" group showed the lowest number of coupling sessions, but these sessions were deep because the number of turns were very high. "Good" and "Creative" groups showed a kind of balance between divergent and convergent and between number of coupling and deepness of these coupling.

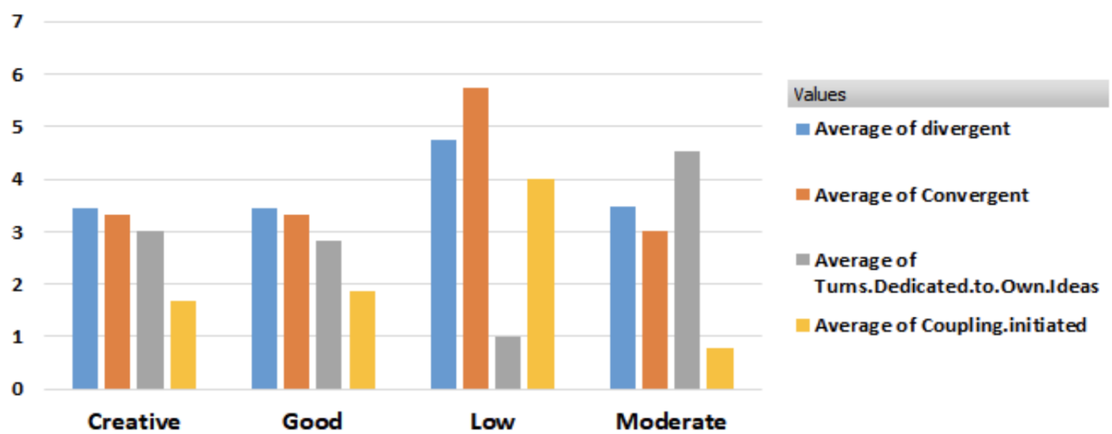

Figure 4.6: Interaction dynamics of Creativity groups groups.

By investigating drawing and thinking time spent during the task. All groups show similar patterns. However, "Low Creative" group did not spend much time in both thinking and drawing when compared to other groups. The creative group has the highest number of both drawing and thinking time. When talking about time per turn, The moderate group has the highest value. Figure 4.7 below illustrate the average thinking and turns time for each group.

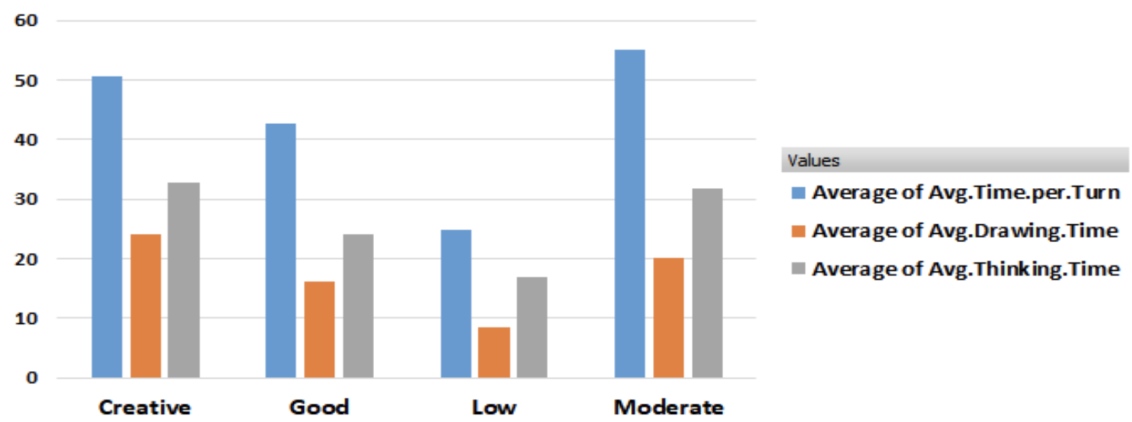

Figure 4.7: Averaged thinking time of Creativity groups.

4.5.3 Participants' Roles in Collaboration

We also grouped users based on their role during the task. The groups are Follower (14 users), Leaders (17 users) and Same Level of Contribution (11 users). By looking at the graph, the same contribution group had different patterns than follower and leader groups. Follower group showed more idea acceptance (number of convergent) and more short-term coupling cycles. Leader group, on the other hand, had more idea generation (divergent thinking) with few deep coupling cycles. In the group that has the same level of contribution, divergent and convergent look more balanced, and there are more deep coupling cycles.

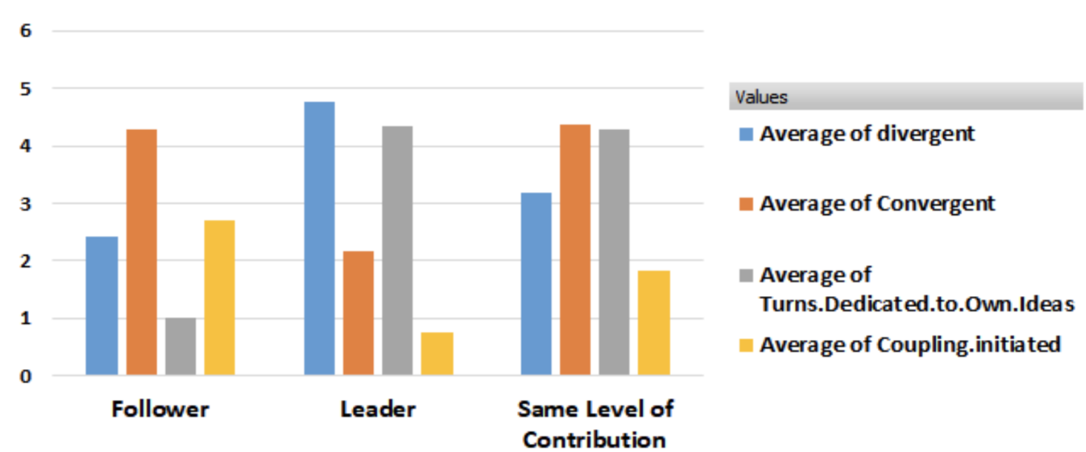

Figure 4.8: Interaction dynamics of Creativity groups groups.

By investigating the drawing and thinking time, it was found that Follower and leader groups show more time in thinking than drawing. However, there is a kind of balance between drawing and thinking times in the same contribution group. This could explain that the same contribution group may have more co-creativity because they balance between idea generation and evaluation and between divergent (drawing) and convergent thinking (thinking).

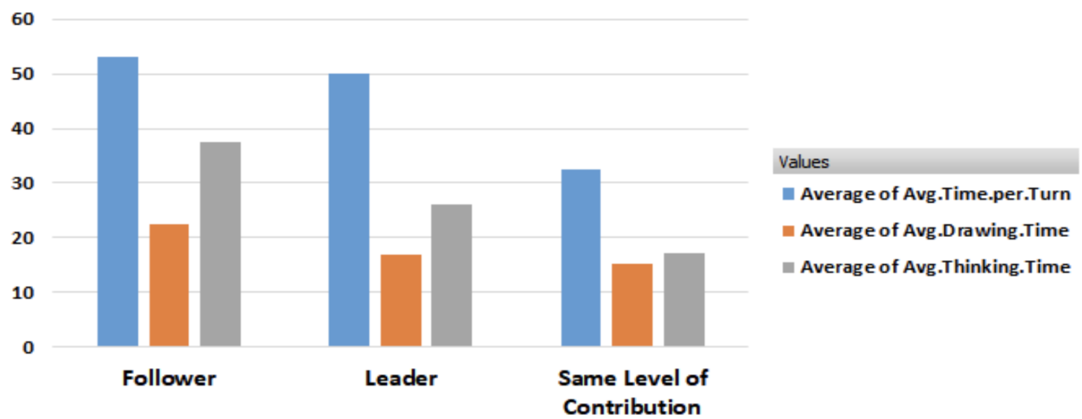

Figure 4.9: Averaged thinking time of collaboration role groups.

4.5.4 Significant Analysis

Analysis of variance (ANOVA) test helps to find out whether the differences between groups of data are statistically significant. The goal of using ANOVA is to compare between different collaboration and creativity groups to validate the first hypothesis. We will compare idea generation (Divergent), idea accepted (convergent) and deep couplings (Turns Dedicated to Own Ideas). I used both one-way ANOVA (aov) and Tukey Honest Significant Differences (Tukey HSD) functions in R: TukeyHSD is used to perform multiple pairwise-comparison between the means of groups, because ANOVA only shows the overall statistical significance test result.

4.5.4.1 Collaboration groups

Idea generation (divergent) did show significant differences between differentiation collaboration groups. All p-values were more than 0.05. However, the p-value of comparing Good and Collaborative with Moderate groups is still small. The difference between Collaborative and Moderate is 0.08, and 0.19 between Good and Moderate. When comparing Good and Collaborative, the p-value is high (0.84). This means the three groups did not have significant differences between divergent thinking efforts in different co-creation sessions. Generating new ideas is essential to any initiative and collaborative work, but it might not guarantee better co-creation. Generating new ideas sometimes leads to isolated interaction when users do not accept or refine the partner ideas.

Table 4.1: One-way ANOVA test for idea generation (Divergent Thinking). Mean value of each group is shown in the column's headers between parentheses

Groups	Moderate Group **(4.80)**	Good Group **(3.52)**	Collaborative Group **(2.94)**
Moderate Group	—	0.19	0.08
Good Group	—	—	0.84

On the other hand, we found idea acceptance (convergent thinking) is significantly different among some of the collaboration groups. Good and moderate groups were significantly different (p-value = 0.010). Collaborative and Moderate groups were not significantly different, but the p-value was small (0.06). The Collaborative and Good groups accepted the null hypotheses and there were no differences between the groups. It can be argued that good and collaborative groups spend more efforts on modifying ideas and engaged in coupling cycles, which might keep users involved in the collaboration and they might be inspired during the task. However, moderate group spent more efforts in idea generation than idea acceptance, and that might reduce co-creativity in this group.

Table 4.2: One-way ANOVA test for idea Acceptance (convergent thinking). Mean value of each group is shown in the column's headers between parentheses

Groups	Moderate Group **(1.6)**	Good Group **(4.24)**	Collaborative Group **(3.63)**
Moderate Group	—	0.010	0.06
Good Group	—	—	0.88

The depth of coupling did not find any significant results between the groups. All p-values between different groups are high.

4.5.4.2 Creativity Groups

By running ANOVA Test of idea acceptance, there were no statistically significant results between the groups. All values were more than 0.05. However, Creative, Good and Moderate groups showed some differences. When comparing these groups with the Low creativity group, we had small p-values (Moderate-Low was 0.06, Good-Low was 0.10, Creative-Low was 0.15). When comparing the three groups, we had very high values (around 0.97). Divergent thinking and coupling deepness did not show any statistical significance between creativity level groups.

4.5.4.3 User-Role Groups

By testing idea acceptance (convergent) between user-role groups (leader, follower and same level of contribution), there were significant results between leader and follower and between leader and same level of contribution. There were not differences between follower and same level of contribution groups.

Idea generation (divergent) did not show any significance. Coupling deep showed significant results between Follower and Leader groups and between Same Level of Contribution and Follower groups.

Table 4.3: One-way ANOVA Test for Idea Acceptance (convergent thinking). Mean value of each group is shown in the column's headers between parentheses

Groups	Leader Group **(2.17)**	Follower Group **(4.29)**	Same Level of Contribution Group **(4.36)**
Leader Group	—	0.014	0.018
Follower Group	—	—	0.99

Table 4.4: One-way ANOVA Test for Idea Generation (divergent thinking). Mean value of each group is shown in the column's headers between parentheses

Groups	Leader Group **(4.76)**	Follower Group **(2.43)**	Same Level of Contribution Group **(3.18)**
Leader Group	—	0.11	0.27
Follower Group	—	—	0.92

In summary, convergent thinking (idea generated) was statistical significance between different collaboration groups. It is partially support first hypothesis (H1). This means participants in good and collaborative groups showed better teamwork and they involved more in the collaboration. On the other hand, we did not find any significant differences in divergent thinking (idea generation) between different groups in both collaboration and creativity. There are similarities in generating new ideas among different groups. In general, most participants in different groups were able to generate new ideas or objects, but participants, who did not completely enjoy the task (moderate group), did not achieve co-creativity because they did not involved, modified and refined partner's ideas, and prefer to keep isolated by drawing new and different objects.

4.5.5 Markov Chain Model

Markov chain analysis is a stochastic model describing a sequence of states in which the probability of each state depends on the previous state. In this study, Markov chain analysis will investigate the shifting between idea generation (divergent) and idea acceptance (convergent) in different co-creation sessions. It also predicts the future states of co-creation for the next N number of steps, based on the current sequence.

The goal of using Markov here is to investigate the different sequences of different collaboration and creativity levels. We used Markov chain model to investigate the probabilities of shifting to idea generation or idea acceptance in low creativity groups, and then compare it with moderate or high groups.

QuantCollab used the user's feedback prompt after finishing each turn to collect some information. Information includes the idea(s) that were generated, and whether it is connected to the previous tun or not. When the idea is connected to the previous turns, it will be coded as "Convergent". Otherwise, it will be coded as "Divergent". After finishing each session, QuantCollab saved these codes as a sequence that follows the order of participants' turns during the task. The statistics on the right side of the interface count the users actions without recording the sequence of these actions.

Markov chain analyzes each session, so it is not focused on individuals. We used the user feedback in past study surveys to create intervals of collaboration quality. For example, collaboration quality was coded 80-100% for collaborative sessions , 60-80% for good collaboration, 40-60% for low-moderate, and isolated for less than or equal to 40%. The sessions were only distributed to the first three groups. There were no sessions classified as low group (less than or equal to 40%).

I picked two sessions from good collaboration groups and 2 collaborative groups. However, We had only one session that was classified as a low-moderate group.

When looking at the low-moderate group, it was found that collaboration is dominant by one action either convergent or divergent. We had only one session that was classified as low-Moderate (session 3).

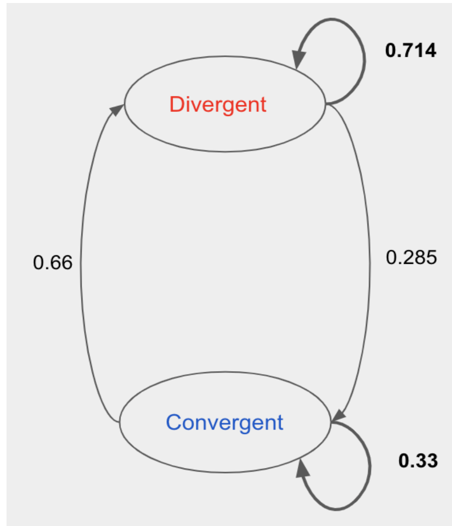

Figure 4.10: Transition between collaboration states in low creativity group.

Figure 4.10 shows the transitions probabilities from one state to another state based on divergent-convergent sequence of the collaboration. We can see that Divergent highly moves to Divergent (0.71), and there is small probability to move to Convergent (0.29). On the other hand, Convergent states most likely move to Divergent in the next step (0.67) other than continue to the same state (0.33). This shows a kind of isolated collaboration, because it was dominated by Divergent state and the partners did not accept other ideas.

When looking at the good creativity groups, we have the following graphs.

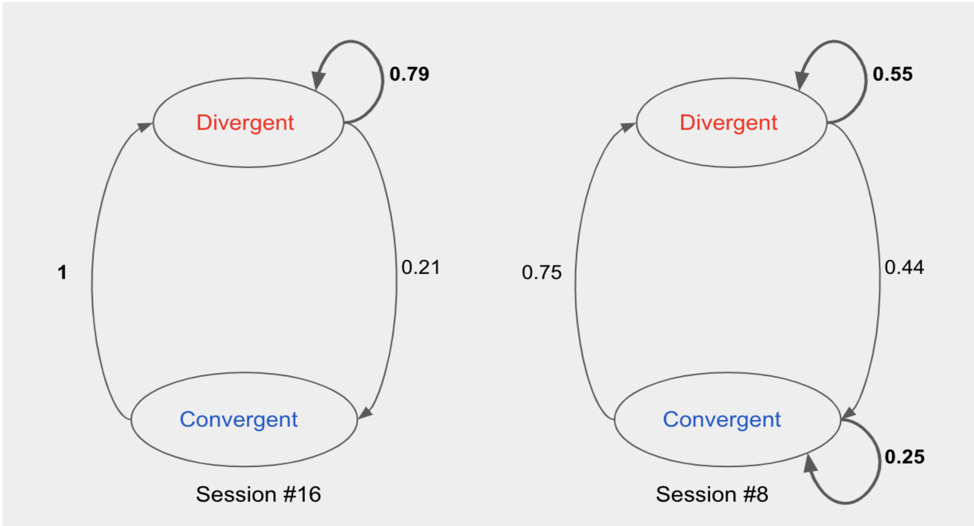

Figure 4.11: Transition between collaboration states in good creativity group.

We can see Markov model analysis for session 16, and the left side graph shows a significant transition to Divergent than Convergent. The probability of changing from Convergent state to Divergent in the next step is 100%. Moving from Divergent is highly going to Divergent (0.79) with weak probability of transition to Convergent (0.21). This good creativity session has similarity with low creativity group in term of dominance of idea generation over idea acceptance. We can see both Divergent and Convergent trends were stable of high probability of idea generation and kind of isolated collaboration. Session 8 illustrates similar results with small increase in transition to Convergent states.

By looking to the creative groups, we have the following Markov graphs:

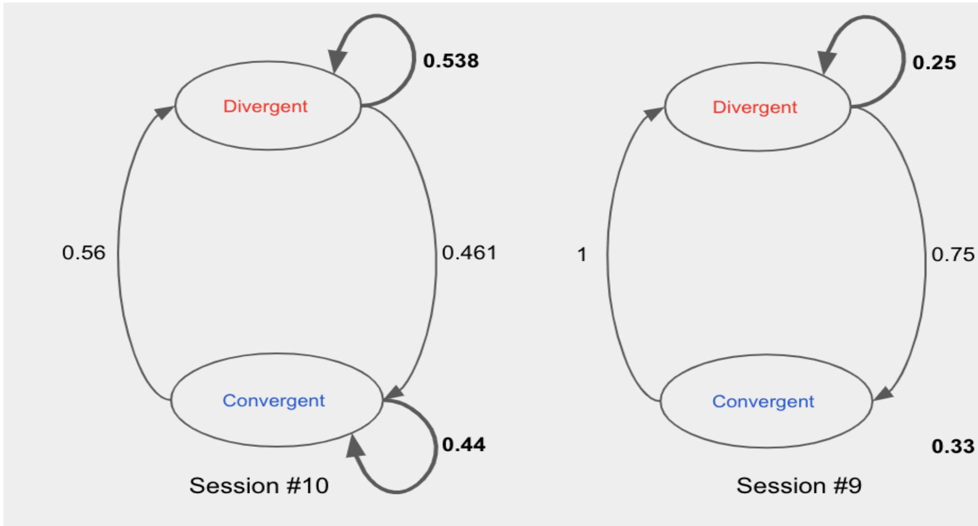

Figure 4.12: Transition between collaboration states in the creative groups.

In Figure 4.12 above, Session 9 (on the right) show kind of iterative process of shifting between divergent and convergent thinking. The probability of having different thinking mode is higher than have the same mode in the next step. for example, the probability of shifting from divergent to convergent is 75% versus 25% of moving from divergent to divergent in the next step. On the opposite side, moving from convergent to divergent is 100%. This show a pattern of balanced collaboration and it is supported by some cognitive science works that claimed creative work needs iterative divergent and convergent thinking process [18]. By looking to session 10 (left graph), we can see another pattern of balanced co-creation. The probabilities of divergent or convergent states were very close to each other (both are close to 50%) . Shifting from divergent to convergent was 46% versus 54% of moving fro divergent to divergent. Om the other node, having divergent after convergent is about 56% while moving to convergent state from convergent is 44%. The co-creation here showed higher percentage of idea acceptance than good and low co-creation sessions. These patterns actually support first and second hypotheses (H1 and H2)

In summary, we can conclude that co-creativity increased when there is a balance between divergent and convergent turns in the collaboration. The difference between probability percentage of both Divergent and Convergent states were reduced when collaboration quality increased. Markov chain analysis evaluated the whole session instead of grouping users. The sessions were classified based on team performance that was reported in the post study self-report. We had low, moderate and high co-creation groups. The analysis in this section did not present Markov chain analysis for each individual session, instead it presented examples of each co-creativity group. There are 6 sessions that were excluded from the results due to low sample sizes and transitions. For example, we excluded two collaboration sessions, because they had a small number of transitions between states (session 14 and 13 had only four turns during the 10-minutes drawing), these sequences were small and would not generate meaningful Markov chain models as reported by the Markov chain modeler used in the R language. The reason was the small number of turns in these sequences when comparing them with the remaining sequences. In addition, we had about 4 sequences that showed almost dominance of one state (e.g. convergent state was about 93% in session 2), and those sequences would show one state in the model. There was no reasons to investigate the probabilities of shifting between divergent and convergent, because the sequence is almost one thinking mode. We only picked the sequences that had a good amount of turns between partners during the task. We might expand the states to be more two states in the future such as change idea generation, idea modification and idea transformation codes. These issues impacted the results in term of missing different patterns of each group. We might have more explanation about collaboration mechanisms for each co-creativity level. It might presented better sequences if the time would be more than 10 minutes. The number of states might be better if we would have more than two states. However, we found some creative thinking patterns for different co-creation levels.

CHAPTER 5: DISCUSSION

5.1 QuantCollab Evaluation

One goal of running this experiment is to evaluate QuantCollab. QuantCollab is still in the early stages, and it needs more improvement. In this section, I will focus on three parts: the tool's statistics, interface and feedback prompt.

In statistics evaluation, the major improvement is related to the Collaboration Score. In the interview, Participants were asked a question about the final collaboration score. The tool did a good job in some situations, because some participants agreed with the percentages. I found similarity between their self reports and final score. I also checked the collaboration types generated by the tool and compared it with their roles in self report. There was some agreement between the results. For example, one study was classified as balanced collaboration by the tool, and it has the highest collaboration score (90%). When checking the video, we found partners had a similar amount of contribution in terms of divergent and convergent turns, and it was reported they were engaged in both idea generation and idea evaluation. They both rated the session as a collaborative task (5 out of 5).

On the other hand, it was also found some users did not agree with results and they expected higher percentages. For example, participants in one of the studies were surprised by the collaboration score (57%).They agreed the percentage should be around 80%. They suggested including communication in building the score. They reported that drawing using QuantCollab reduced their creativity due to many reasons like canvas space, limited utilities of the tool, and using mouse to draw, but communication and discussion could improve the quality of evaluating collaboration.

There are some measurements that did not contribute to the analysis and it is better to be removed from the tool. For example, Idea Rejected did not have independent data. Idea rejected is actually data generation, because when the user. There are many statistics that were not utilized in this study such as elaboration score and Influence of Idea, but they may help in the future.

Interface evaluation collected user perspectives about the current version and how QuantCollab can be developed. The major concern is missing digital drawing tool utilities . Like any other drawing tool, users suggested improvements such as adding colors, link width, eraser and undo buttons. That could help them to express their ideas and add better contribution to the shared space. Another issue is the fluency of drawing. Users used their mouses/track-points devices to draw and they reported some difficulties expressing their ideas, and they were confused by partners' ideas. At this time, we may not be able to fix that, since there is no perfect version of the tool for tablets and smartphones, and many laptop models do not support touchscreen to make it easy. Also, QuantCollab has not been tested in touchscreen laptops to see the usability of using pens or fingers in drawing. The last suggestion is to increase the size of the drawing canvas. A few users reported that they needed enough space to add their ideas, and they were not used to drawing in small areas. That could happen by reorganizing the interface, and minimizing and moving statistics to the bottom. However, screen size is still a challenge even if the canvas is maximized. Also, usability should be maintained when reorganizing the interface. For example, statistics need a good position for some users who may be interested in tracking the performance during the task.

Last evaluation is about the feedback prompt. The current prompt worked well. It helps to classify users' actions as either idea generation or idea acceptance, and it tells the name of the object or idea. It also helps to build divergent and convergent turns' sequences in order to run Markov chain model and evaluate the mechanism of co-creativity in that collaboration. However, the prompt is only viewable to the user completing the feedback, but the partners couldn't see that. In some sessions, the partners did not talk much to each other, and sometimes they did not mention what they drew. This might cause a kind of isolation or confusion between the partners' ideas, and then reduce the co-creation quality. There were suggestions to make the feedback prompt viewable for all users at the same moment. Another suggestion to add more feedback ways like include communications during the task.

5.2 Evaluating Creative Thinking Model of Co-Creation

The creative thinking model of co-creation relies on cognitive theories and mechanisms that connect to creativity. Divergent-convergent thinking and generative-analytical thinking have been reported in several creativity and neuro-cognitive research works. Evaluating creativity in this work focuses on quantifying collaboration processes and interactions dynamics that leads to creative works rather than focusing on evaluating the final creative products. The creative thinking model of co-creation identifies trends and patterns in the co-creation process. However, more work needs to be done in order to determine how these patterns influence the effectiveness of collaboration and the quality of the final product. The creative thinking model does not evaluate the co-creativity of the partners, i.e. the degree of creativity achieved in the session as measured by metrics such as originality, fluency, flexibility and elaboration. Instead, interaction dynamics and creative thinking modes are used to understand the overall flow of the co-creation.

Using the proposed model to evaluate creative tasks requires a retrospective analysis that includes observing the collaboration and classifying user behaviors. Using recorded sessions helps to analyze the user performance and code the behaviors throughout the session as either divergent or convergent. The model suggested that co-creation needs more coupling (spending more time working on the same ideas) and iterative divergent and convergent modes. The creative paths, as shown in Figures 3.6 and 3.7, are the results of cumulative sum of the different codes through turns.

It is expected to see different collaboration trends based on different creativity levels, either high or low, in the post survey after finishing the session.

Measuring global creativity in co-creativity is still a big challenge. Global creativity means connecting all small and separated coupling cycles (local divergent and convergent) together to make a final whole and novel solution. The model codes only local couplings in co-creation processes that happen in specific moments, without investigating the connection between several different coupling periods. For example, converging to the most recent divergent action was counted as coupling and more creative work, but converging to old and isolated coupling sessions were not classified as coupling. Future work could expand this model to measure the global creativity and investigate how users go back to old ideas and merge it with new ideas ($\text{coupling}_1 + \text{coupling}_2 + ... + \text{coupling}_n$) to generate a final, whole, combinatorial or transformational creative idea.

Evaluating collaboration in co-creation systems still needs more research efforts. Much research focuses on offline evaluation, which occurs after finishing the collaboration, and evaluating the creativity of the final product. The proposed work presents an interaction dynamics model of co-creation using summative evaluation method (retrospective analysis). The model aims to measure and evaluate real time co-creation processes between humans. Real time feedback gives more details about interaction dynamics. It is possible to get user feedback about the collaboration and final product using different ways such as turn voting [12] and user text feedback used in Quantcollab (figure 4.2).

5.3 Limitations and Future Works

In the presented study, some patterns did support some of the hypotheses. QuantCollab generated some statistics that could be used for more analysis. However, there are some limitations that may impact the results. One challenge is collaborative drawing of some users. The collaborative drawing time was good for many users, and we found those users were able to collaborate and exchange the turns in a good way. However, in few students, the time was not enough to collaborate effectively and generate a good number of turns for analysis. For example, one study had only four turns in 10 minutes, which led to difficulties in the analysis (especially Markov chain model) for that session. Also, this type of collaboration did not help to run significant analysis because of the limited number of states (categorical variables). Also, Some users filled the screen and did not leave enough space in the canvas for partners to collaborate.

Another limitation is the users' biased feedback when evaluating co-creativity. Self-report is a common way to evaluate user or partner performance, and it has been used in many works. However, using a triangulation method to evaluate user creativity or collaboration will affect the reliability of the overall results, and alleviate the potential biases. Improving the reliability of collaboration score, generated by the tool, could be a suggestion for future work. Also, external judge or expert in co-creativity domain would be recommended to evaluate users and session performances in addition to using self-report survey. In this work we were not able to triangulate the evaluation and we will include this in our future studies to improve our analysis.

Another challenge is the online platform. Users were not asked to evaluate the online study. However, it was obvious that some participants were not fully engaged in the task. For example, one study had overlapping issues between the partners. One user continued to draw even after finishing her own turn (clicked the End Turn button), and she did not know it was the time for the partner to draw.

The current version of QuantCollab presented number of limitation in this study. The tool is still in the early stages, and it needs to improve some features or add new ones. As it was explained in the evaluation section, the tool did not have features to improve productivity of participants. Users reported using colors would improve their drawing and collaboration. In addition, several participants have suggested the addition of a redo and eraser features, which would be helpful to change or refine user drawing before moving the turn to the partner, and the partner can make sense about the drawing and co-creation process. In addition, using the mouse and track-point devices were not the efficient ways in visual art performance. Users had some difficulties to draw the accurate shapes of objects, and that affected the agreement between partners. The current tool version does not support different interaction modalities such as stylus pens or touchscreen. Using a mouse, for example, made some users suggest a redo or eraser feature. Also, drawing canvas was a limitation for some participants.

The last limitation was the number of users recruited in this study. Since there was a limited fund to run this study, our sample was small and we had a limited to a number of participants (N=42). Also, few number of participants could not show up in some experiments. Two user studies were canceled because one user, in each, did not present at the meeting time, and were not able to reschedule them due to the time availability. Another experiment was canceled because of a technical issue when launching the tool by the study investigator, and that study was not rescheduled for the same reason. The analysis data and quality could have benefited from a larger sample size which could have provided more insights into different patterns of collaboration and creativity.

Future Works can be applied to two related areas: creativity support tools (CST) and Computational creativity. In CST , the tool can be improved to achieve human co-creativity by adding more features that help users to be more creative. Feedback could be given by both participants at any turn. In the current version, the feedback prompt will be completed by the user who completed own turn. The other user can evaluate a partner's ideas by using thumb-up, evaluation scale, or add text describing thoughts about partners ideas. Communication and negotiation could be included in the interface to let the team express themselves. Another future work is changing drawing states to include more than two states. We may use idea generation, idea refining and idea transformation to investigate the patterns of different creative types such as exploratory and transformational creativity [30]. Designing a co-creative agent is an interesting topic that could be a new extension for this work. There are many co-creative agents (Drawing Apprentice [13] and Creative Sketching Apprentice [29] that could inspire this work. The prediction of drawing states that are generated via Markov model could be helpful for designing a collaborative agent based on the sequence of states.

Future work can also improve QuantCollab tool to be more interactive, and support co-creativity process in collaborative works. The limitation of the tool were mentioned before, so the future work could enhance the interface and add more features, such as eraser or undo button, to increase the QuantCollab efficiency. Collaboration score was not used in the evaluation of users co-creation, because it did not have a comprehensive method to calculate the score and was biased. There was no distribution of final score, so it can describe the collaboration in details to figure out the contribution of both users during the task. The score also required normalization of the values used in calculation, such as idea acceptance and elaboration count, in order to calculate more accurate final score.

Cognitive mechanisms, such as clamped /unclamped modes of cognition [9], can be used to improve QuantCollab performance. Convergent thinking can be connected more to clamped states, while divergent could be related to the unclamped state when the user is still confused and does not make sense of the collaboration. Associative thinking is another cognitive mechanism [18] that can be used too to identify user divergence. These examples of cognitive science theories can improve the tool to Identify what is convergent or divergent, and also help to measure the degree of each action. For example, if a participant is perceptually unclamped and tries to create new ideas, that could be a very high divergence. The participant could hesitate to contribute to the ideas (partially has perceptual unclamped), so that will be convergent without coupling. In addition, it becomes hard, in some situations, to code when a person either diverges or converges, but adding cognitive theories can make it more easier and efficient to quantify actions.

5.4 Extending Recent Work and Applying to Other Co-creation Domains

This research added a new contribution to co-creativity works by using cognitive science theories to design a creative thinking model of co-creation. The results showed significant differences of creative thinking between high and low co-creativity performance. High co-creativity groups show balanced divergent and convergent thinking comparing to other works. The interaction dynamics of different creativity levels were also different in term of the number of ideas and objects created and modified.

This study collected different data about users behavior and collaboration that was not used in the current thesis. We only focused new idea generation, ideas acceptance, coupling data and feedback sequences to compare between different co-creation patterns. There are many statistics that could be used for advanced analysis of co-creation from cognitive science perspectives. The study collected data of clamped and unclamped moments as well the elapsed time in both thinking and drawing during the task, which could be used for collaboration sense making research (e.g. enactive model [11]. The current results could be used to improve QuantCollab either by modifying the tool to be more interactive, or to improve collaboration and co-creativity evaluation. For example, collaboration score could be normalized and used different factors to be more accurate.

Quantifying co-creation using creative thinking modes can be applied to different domains that utilize teamwork and group problem solving. Domains that use turn taking and improvisational styles are the target of the model. This work applied the model to the domain of drawing. One partner can start the interaction by drawing an object as a divergent step. The other person can either diverge (if there is no sense making from the previous step) by adding new and unrelated objects or converge by extending and refining the previous object. The coupling degree will be counted by how many turns are dedicated for a specific object. Future work will expand the measurement of divergent, convergent and couplings using more data from retrospective analysis and Quantcollab tool. The potential turn-based creative domains of the model include creative writing, education and games. In creative writing, one partner can start writing some independent words or phrases as a divergent step. The partner can either add semantic words to the previous turns, or make new words that are related to a different topic, character or story. Coupling here can be classified as how long partners spend time working directly together and how many words or phrases that are added to build the final co-creation product like a full poetry or story.

In the education domain, There are many collaborative tools that have been used to encourage students working together to achieve co-creation. Examples of such tools include Google Doc and Google Colab. In computer science education, the model can be used to quantify how students are contributing during each turn in pair-programming tasks. Divergent actions include starting a new class or functions, and convergent actions include adding to what partners created. Classroom salon is a collaborative tool that allows students to work together and Benefit from group intelligence to achieve the co-creation process [3]. Students can share their work with classmates to find code's bugs and comment on others' suggestions. Classroom Salon can be evaluated by the model when the user creates new comments or writes part of the code (diverge), and then teammates can comment, start discussion or edit the code (converge). In the database course, students can work together to create disconnected tables (divergent) and then start refining the whole database scheme (entity relationship diagram) as a convergent action. There will be local divergent and convergent for each table like creating a view of the table and then adding attributes or constraints keys (PK and FK). In conclusion, the model can be applied to turn-based creative tasks that use co-creation mechanisms

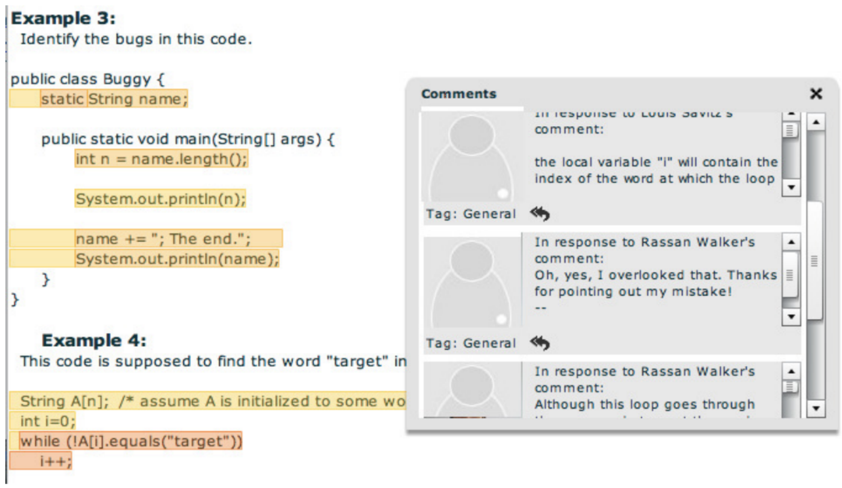

Figure 5.1: Classroom Salon Debugging Code [3]

CHAPTER 6: CONCLUSIONS

Co-creation is a form of collaboration in which partners share, improve and blend ideas together to develop a creative product. Divergent and Convergent thinking modes are cognitive mechanisms that have been connected to creativity in several works. This dissertation added several contribution to co-creation fields. First, it utilized cognitive mechanisms of creative thinking to measures the interaction dynamic of the co-creation process. Second, it introduced creative thinking model that evaluate human collaboration and generates co-creation trends for each interaction session. Third, it investigated difference sequences of thinking states among different users' groups.In addition,the dissertation did a preliminary contribution to the field of creative support tool (CST) by introducing *QuantColab* tool and evaluate it from users perspective for more improvements, and connect it to different research problems (computational creativity by designing AI version of the tool). The results of this dissertation supported first and second hypotheses (H1 and H2). There were differences between ideas generation and idea acceptance among different groups. It also found several interaction dynamics of different creativity and collaboration groups using Markov chain model. The dissertation evaluated the tool and listed number of recommendation to improve the tool for future researches studies.

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