Observable Creative Sense-Making (OCSM): A Method For Quantifying Improvisational Co-Creative Interaction

Manoj Deshpande
Georgia Institute of Technology
Atlanta, Georgia, USA
manojdeshpande@gatech.edu

Milka Trajkova
Georgia Institute of Technology
Atlanta, Georgia, USA
mtrajkova3@gatech.edu

Andrea Knowlton
Kennesaw State University
Kennesaw, Georgia, USA
agisekno@kennesaw.edu

Brian Magerko
Georgia Institute of Technology
Atlanta, Georgia, USA
magerko@gatech.edu

ABSTRACT

This paper introduces a new method for quantifying open-ended collaborative embodied improvisation: Observable Creative Sense-Making (OCSM). This technique builds on previous work on Creative Sense-Making (CSM), examines its shortcomings, and addresses it by reformalizing and grounding CSM in current literature from embodied social cognition and an intersubjective perspective of creativity. We apply this method to empirical studies of human collaboration in dance improvisation with 16 advanced college dancers and establish the method's validity. The OCSM method described in this paper includes a qualitative coding technique, a web-based tool for coding the interaction, and the cognitive theory behind its application.

CCS CONCEPTS

• **Human-centered computing** → *User studies*; **HCI design and evaluation methods**.

KEYWORDS

co-creation, improvisation, embodiment, social cognition

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1 INTRODUCTION

Co-creativity (i.e., collaborative creativity) and improvisation with others are essential day-to-day human practices. They are crucial in helping us to make sense of our complex and dynamic environment [4, 20, 38, 49]. However, as standard as these practices are in our lives, it rarely characterizes our interactions with a computer. Furthermore, we have little understanding of how computers can co-creatively improvise with us in embodied domains like improvisational dance. Hence, the role of a computer is mainly limited to mediating instead of actively participating in such activities. To take a step towards designing such an improvisational system, we first need a method of analyzing and quantifying improvisational interaction.

Analyzing and understanding creative dynamics between collaborative individuals poses many challenges. Open-ended, improvisatory interactions are difficult to quantify as they include underlying factors that are not necessarily observable, especially in complex, non-verbal collaborations such as dance. In dyadic improvisational exercises, dancers have layers of knowledge, information, and stimuli that may impact their creative choice-making. This includes their training history, kinesthetic awareness of their body, their response to environmental stimuli, their relationship to their partner, their individual confidence and comfort, and their experience with improvisational explorations and partner work [5, 9, 37]. In all, improvisation in domains like dance is a highly embodied and phenomenological process that requires humans to think and express with their whole body [2, 34]. To design human-computer interactions as nuanced as those of dance partners, we must first better understand embodied co-creative practices and develop reliable methods to interpret and quantify interaction dynamics. To address this, we propose Observable Creative Sense-Making (OCSM), a new method for quantifying collaborative embodied improvisation.

Researchers have proposed several quantitative and qualitative methods to better understand human interaction during co-creative improvisation better. Researchers have applied the Creative Sense-Making (CSM) video-coding method to quantify and decode improvisational interactions in pretend play and collaborative drawing [15]. Thematic protocol analysis and interviews are also standard methods to uncover the dynamics during improvisation [24, 39, 47, 48]. Data logging is another method to quantify the emergence of new ideas and ideation strategies within improvisation [33]. Action research is yet another method for studying improvisational interaction, especially within dance [50]. Specifically for measuring the effectiveness of creativity support during user interaction, there are survey tools like the creativity support index (CSI) [11]. All methods (except CSM) we described require a time-consuming analysis process. However, for a computer to use this information during an embodied improvisation, it needs data mapped temporally and nearly in real-time. The method we

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describe in this paper - OCSM, is intended to be a step toward addressing this gap.

OCSM builds on previous work on CSM [15]. We utilize the socio-cognitive framework of participatory sense-making and embodied social view of creativity to formulate OCSM. The described method provides a means to rapidly, potentially automatically, and reliably quantify interaction dynamics continuously through time along three observable dimensions of participation, newness, and appropriateness. We applied OCSM to conduct empirical studies of human collaboration in dance improvisation to establish the method's validity. With the OCSM framework, we offer a set of techniques and instruments to investigate the overarching research question: RQ: how do we quantify the observable characteristics of embodied improvisational co-creativity between dyads?

In this paper, we make the following novel contributions:

- We introduce a new method for quantifying open-ended collaborative embodied improvisation through time - OCSM.
- We provide the OCSM theoretical framework based on literature from embodied social cognition, an intersubjective perspective of creativity, and previous work on CSM.
- We provide a coding scheme centered on the three observable behavior markers of OCSM: participation, newness, and appropriateness.

We organize the rest of the paper as follows: We begin with situating the original CSM with related cognitive science theories and briefly introduce how CSM works. Next, we report on the results of our application of CSM to study dyadic dance improvisation and highlight a few limitations of CSM. Following this, we review various social cognition and creativity theories we utilized to formulate OCSM. Next, we discuss the study design and results from the study we conducted applying OCSM. We conclude by discussing the implications of this work, the limitations of OCSM, and future work.

2 CSM AND RELATED THEORIES

Davis et al. developed creative sense-making (CSM) as a framework that casts the collaborative creative process as a dynamic social process in which individuals alternate between different cognitive states to make sense of the changing environment. In this section, we provide an overview of theories on which CSM is based or can help give context to CSM.

Social cognition or intersubjectivity is the ability to understand and interact with other cognitive agents [51]. It concerns the various psychological processes that enable individuals to take advantage of being part of a social group [22]. Traditional approaches to understanding social cognition include simulation theory (ST) and theory of mind theory (TMT). According to TMT, an individual, based on a general theory of how the mind works, can make inferences about others' mental states in a social situation and act accordingly [44]. According to ST, an individual doesn't require a theory; instead, they rely on their mind as a model to simulate others' mental states and base their action on this simulation [29].

Over the years, researchers have raised several critical issues [16, 23, 25] with TMT and ST; some of the key limitations are as follows. TMT and ST treat the mind as a separate entity in a different plane, which can simulate or theorize and infer others' mental states by observation. Fuchs and Jaegher refer to this limitation as the inner-world hypothesis [23]. Apart from this, ST and TMT are biased towards localizing social cognition in one participant's mind and assume that the participant is taking a third-person stance and just observing instead of interacting. The most significant limitation of ST and TMT is missing embodiment. It embraces Rene Descartes's notion of dualism, i.e., the cartesian split between mind and body. It reduces social cognition to two cartesian minds acting like a sender or receiver processing information and the body functioning just as a transmission device.

Unlike dualism, embodied cognition, especially enactivism, argues that cognition arises from or is constituted by sensorimotor activity and interaction with the environment. In other words, this stance contends that the individual does not receive information passively by observation; instead, the meaning emerges from active participation [51]. There are three varieties of enactivism: autopoietic enactivism, sensorimotor enactivism, and radical enactivism [58]. Autopoietic enactivism describes cognition in terms of the biodynamics of living systems. Di Paolo argues that cognition is the capacity of an organism to actively modify its relation to the environment to maintain its autopoietic identity [56]. In other words, for this version of enactivism, there is no distinction between mental and non-mental processes. For sensorimotor enactivism, cognition involves actively exploring the environment and establishing patterns of dependence between our actions, sensory states, and the world [51]. We can summarize this version of enactivism as thinking by doing. Here cognition results from the skillful exploitation of sensorimotor dependencies established during exploratory activities. Lastly, radical enactivism rejects the idea of mental states. It argues that cognition is dynamic patterns of adaptive environmental interactions without dependency on internal representations [58]. This version of enactivisim aims to analyze cognition in terms of an interplay between the biological, sensorimotor, and social dynamics without formulating internal mental representation [58].

Participatory sense-making (PSM) is a cognitive framework proposed by Di Paolo and De Jaegher to understand social cognition. Enactive cognition forms the basis of PSM. Suppose we imagine autopoietic enactivism and sensorimotor enactivism on two ends of the spectrum. In that case, PSM is situated closer to autopoietic enactivism, but it draws some concepts from sensorimotor enactivism. Overall, PSM is a theory concerned with defining the social in terms of the embodiment of interaction, shifting and emerging levels of autonomous identity, joint sense-making, and experience [17]. PSM refers to the process of building an understanding of our environment through collaboration and often involves physical exploration (i.e., the intertwining of motor and cognitive functions to explore an environment) that inspires ideas and informs our decision-making processes.

Davis et al. designed the CSM tool as a video analysis tool to quantify and evaluate open-ended creative collaboration. CSM comes with a qualitative coding scheme focused on sense-making. The authors describe that CSM is based on the enactive cognitive framework of PSM and the free energy principle [15]. The free energy principle postulates that biological systems continually strive to reduce environmental surprises. When there is a new thing in the environment, the cognitive agent is surprised and goes to an unclamped mental state; hence has excess free energy and wants to

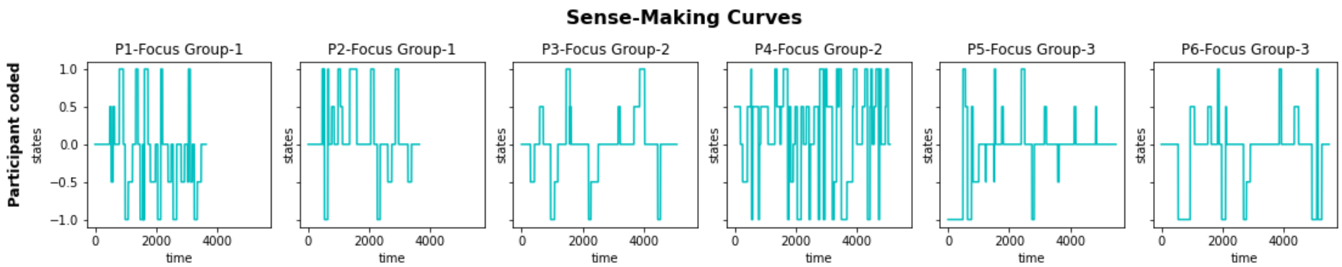

Figure 1: Sense-making curves of six participants from the study

reduce the free energy to reach equilibrium, which is the clamped mental state [21].

According to CSM, individuals alternate between mental exploration and planning (perceptually unclamped cognition state), executing plans (clamped cognition state), and interacting with the world (physically unclamped cognition state). Actions like disengaging from the interaction constitute a full perceptual unclamp, whereas pausing to observe the results of a particular action forms a partial perceptual unclamp. Similarly, disengaging from the interaction to gather resources is a full physical unclamp, whereas rearranging existing resources is a partial physical unclamp [15]. Further, we can use the CSM tool to code the behavioral markers to the corresponding cognitive states continuously. As a result of this continuous coding, we obtain the sense-making curve. We can uncover the interaction patterns by studying the individual's CSM curve and comparing it with their partner's.

3 APPLYING CSM TO STUDY DANCE IMPROVISATION

To aid in designing an embodied, co-creative, and improvisational dance AI agent, we conducted a series of focus group studies with dance students in a dance BA program in the southeastern United States. We wanted to understand what characterizes embodied dyadic interaction between expert dancers in co-creative domains like movement improvisation. Concerning CSM, we hoped to understand when dancers are switching between the clamped vs. unclamped creative sense-making states and to develop a codebook for identifying behavioral markers associated with the various cognitive states.

We conducted three 1.5hrs long CSM focus group studies with two dancers in each session. During the focus group, the dancers wore motion capture suits and participated in a 5-minute collaborative improvisation dance exercise. After the improvisation session, dancers participated in an open-ended group discussion in which they reflected on the improvisation session. Following this, the dancers participated in a retrospective video walk-through and self-coding of CSM curves. Improvisation, group discussion, and retrospective video walk-throughs were video and audio recorded.

Fig-1 shows the self-coded sense-making curves of the six dancers across three focus groups. As seen in the figure, we observed considerable variation in the data the dancers coded. There was a lot of variation in data coded by dancers within the same group. Dancers also expressed that the cognitive states and the terminologies like "clamping" and "unclamping" were unclear and confusing. Since these internal mental states are not observable, we could not ensure the data's correctness, nor were we sure of the replicability of the data. Overall the sense-making curves and subsequent analysis were ineffective in informing us about the interaction dynamics. We also were not able to identify behavior markers to develop the codebook.

These focus group studies prompted us to reflect on and reconsider the CSM theory. We found a few inconsistencies with CSM and its related theories, which we list below -

- According to CSM theory, we can observe behavioral markers corresponding to an individual's internal mental states and code the data. In other words, we are attributing mental states just by observation. This perspective is similar to the TMT or ST limitation of the inner-world hypothesis, which CSM claims to reject by embracing enactivism and PSM.
- CSM treats interaction as a result of individuals' mental states. While core tenet of PSM is that interaction is an emergent, autonomous, and irreducible unit and should be understood or analyzed as a whole [17].
- Lastly, PSM and CSM define sense-making differently. Sense-making, according to CSM, is "the process whereby a cognitive system gradually minimizes free energy by reflecting on and experimentally interacting with the environment to build and refine a more optimal generative mental model of that environment [15]." In contrast, PSM describes sense-making as the "regulation of interaction with the environment to maintain autonomous identity [17]."

From this reflection, we extrapolate that CSM is based on sensorimotor enactivism (as opposed to PSM) and the free energy principle. Even though CSM has been successfully applied to studying activities like pretend play and collaborative drawing, we can not effectively use CSM to explore a more embodied activity like movement improvisation owing to these conceptual discrepancies. This motivated us to reformalize creative sense-making for better studying embodied improvisation. This reformalization is not to negate CSM as a methodology. CSM is still a valuable tool for analyzing creative collaborations that have identifiable behavior markers for the corresponding cognitive states.

4 REFORMALIZING CSM

In this section, we review related theories and methods to reformalize creative sense-making (CSM) as a computational model for quantifying interaction dynamics within open-ended, improvisational, embodied, and creative collaboration.

From an enactive perspective, researchers regard social cognition as a result of social interaction [17, 23, 56]. During social interactions, the participants unconsciously coordinate their movements and utterances [23]. This kind of coordination is similar to the ones exhibited by coupled physical and biological systems like pendulum clocks or fireflies. The coordination patterns include synchronization, phase-delayed behavior, rhythmic behavior, or relative coordination. Di Paolo and De Jaegher argue that within a social encounter, meaning emerges from a dynamical process of interaction and coordination of two embodied agents coupled to each other, and this is what they refer to as participatory sense-making and formally define it as "The coordination of intentional activity in interaction, whereby individual sense-making processes are affected, and new domains of social sense-making can be generated that were not available to each individual on their own [17]."

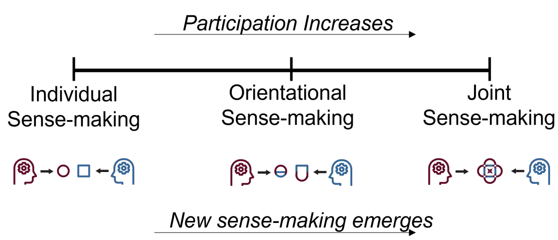

Figure 2: Degrees of participation and sense-making

We can study the effect of coordination and interaction on sense-making by mapping it to various degrees of participation that an individual has within social interaction. Fig-2 shows the degrees of participation and emergent levels of sense-making as described by Di Paolo and De Jaegher [17]. To understand the spectrum, let's consider a social encounter of two individuals trying to build a structure with lego blocks. Individual sense-making corresponds to the state where both individuals are not participating in creating a shared meaning and are mostly self-exploring lego blocks. Joint sense-making corresponds to the state where participation is highest. In this state, we find complex cases where individuals participate in a joint sense-making process, and shared meaning emerges. For the lego example, this would correspond to the dyad building on top of each other's lego blocks, and a new lego structure develops. Orientational sense-making is when one individual tries to influence or get influenced by another's sense-making activity. For the lego example, this state would correspond to individuals incorporating lego ideas from each other or trying to convince each other that their lego structure is better.

Sense-making and emergent meaning construction are processes that are related to creativity. But creativity historically has been studied from an individual perspective, like, Boden's P-creativity (psychological creativity) and H-creativity (historical creativity) [6] or Kaufman's four C's model: Big-C, Pro-c, little-c, and mini-c [32]. We must understand creativity from an embodied intersubjective perspective to better formulate creative sense-making. Csikszentmihalyi describes this as a "systems model of creativity" and elaborates that creativity is an interaction between the domain, the field, and the person [13]. Glaveanu builds on Csikszentmihalyi's model and recontextualizes Rhodes' 4P's (person, process, product, and press) framework of creativity [45] to the five A's framework of creativity. According to Glaveanu, creativity is the relationship between the actor, action, artifact, audience, and affordance [28]. The actor is an individual who has personal attributes concerning a societal context. The action involves coordination and behavioral manifestation from the individual. The artifact exists within its cultural context. Finally, audience and affordance capture the interdependence of individuals' social and material worlds.

Creativity, according to Glaveanu, is "a complex socio-cultural-psychological process that, through working with 'culturally - impregnated' materials within an intersubjective space, leads to the generation of artifacts that are evaluated as new and significant by one or more persons or communities at a given time [27]". From this definition "new" and "significant" which are more commonly referred as "novelty" and "appropriateness" by many creativity and computation creativity researchers [1, 6, 7, 14, 40] are essential to understand creativity.

Most creativity theories and frameworks study novelty and appropriateness over an extended period. However, we need a method to temporally measure novelty and appropriateness to quantify and map creativity within open-ended improvisational interaction. Carroll and Latulipe employ EEGs to measure in-the-moment creativity through physiological markers [8]. While EEG data might be helpful, getting EEG data while studying embodied improvisation may not always be feasible. Kupers et al. propose a coding framework for a micro-level measure of creativity. The coding frame allows for assessing the novelty and appropriateness on a 4-point scale at each moment during the creative process [35]. Based on Kupers et al. framework, we adopted a similar 4-point scale for measuring novelty and appropriateness for our methodology.

5 OBSERVABLE CREATIVE SENSE-MAKING (OCSM)

The primary aim of the reformulation of CSM was to make the constituent components observable and grounded in core arguments of embodied social cognition and creativity literature instead of mapping and measuring internal representations or mental states. From the above survey of the literature, described in section 4, three central elements stand out when dealing with open-ended embodied collaborative improvisation: the level of "participation" of each individual corresponds to emergent sense-making, the level of "newness" of the idea generated or explored within the improvisation, and the level of "appropriateness" associated with each action within the improvisation. Therefore Observable Creative Sense-Making (OCSM) has three dimensions of measurement- participation, newness, and appropriateness. OCSM differs from CSM in three key ways, as highlighted below:

- All the parameters and the associated coding states are observable behavior markers. OCSM doesn't attribute these behavior markers to any internal hidden cognitive state, unlike CSM.
- In CSM; one has to compute the creative trajectory curve, which quantifies the interaction dynamics, by calculating

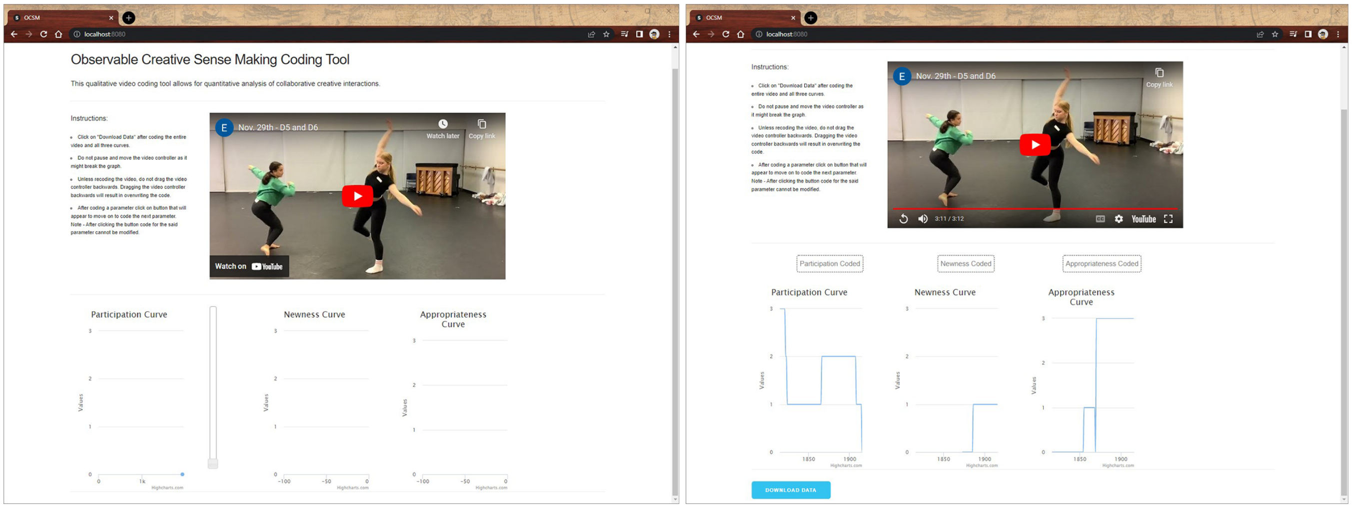

Figure 3: OCSM: Web-based video coding tool

cumulative integrals of individual sense-making curves and then adding them together [15]. In OCSM, the sense-making curves capture the interaction dynamics along the dimensions of participation, newness, and appropriateness.

- Lastly, as detailed in section 2 CSM uses the free-energy principle to imply creativity implicitly. OCSM, on the other hand, doesn't use the free-energy principle and captures creativity explicitly along the dimensions of newness and appropriateness.

In this section, we describe the 4-point scale for the various components of OCSM and cover the web-based tool for coding the interaction.

5.1 Participation

As described in Table -1, the participation dimension assesses how an individual's engagement with the task varies temporally as they collaboratively improvise. We base the states on the degrees of participation described in section 4. In state 0, the individual is not doing any movement or visible action to that of the assigned task. State 1 corresponds to movements related to individual sense-making or self-exploration. State 2 categorizes all movements that belong to orientational sense-making; to add more clarity, we refer to this state as responding or reacting. Lastly, state 3 marks the highest participation by an individual; it corresponds to emergent movements or joint sense-making.

5.2 Newness

As described in Table - 2, the newness dimension assesses the variance of movements explored by the individual. It tracks the observed emergence of a new movement and changes in the movement temporally as they collaboratively improvise. We base the states on Kupers et al.'s creativity framework [35]. In state 0, the individual is repeating a previously explored movement. State 1 corresponds to movements that are slightly different from a previous movement. State 2 categorizes movements similar to the prior movement but with a significant difference. Lastly, state 3 marks the emergence of a new movement.

5.3 Appropriateness

As described in Table - 3, the appropriateness dimension assesses the temporal task pertinence of movements explored by the individual. For appropriateness, too, we base the states on Kupers et al.'s creativity framework [35]. In state 0, the individual is doing Off-task movements like walking away from the given task or doing something unrelated to the given prompt. State 1 corresponds to movements that are somewhat related to the given task. State 2 categorizes movements related to the given task but is not exactly what the prompt asks. Lastly, state 3 marks the movements that are explicitly what the task asked of the individual.

5.4 OCSM Tool – Interface and Video Coding

An analyst can apply the coding conventions described above to the video analysis to quantify the improvisational interaction. To accomplish this, the analyst reviews the video and assigns a numerical state to each moment based on the type of movement the participant is currently engaged in concerning the given task and the given dimension. This process is repeated for each participant in the improvisation three times to generate a dataset depicting a participant's movements through time along three dimensions.

Fig-3 shows the OCSM web-based video coding application. It's a simple Node.js application that uses the embedded HTML or YouTube video player to render the video on the screen. The charts are visualized using the HighChart.js library. To use the coding application, the user needs to enter the URL of the video. Then the screenshot similar to the left image in Fig-3 shows up. The coder will have to use the slider on the right side of the graph to apply the qualitative code to the video. The video coding is done sequentially in participation, newness, and appropriateness. The user can continue to code the next dimension only after confirming that the current dimension coding is complete. Users can download

Table 1: Participation coding states

<table>
<tr><th>State</th><th>State Description</th><th colspan="2">Example</th></tr>
<tr><td>0</td><td>No Participation: Doing completely unrelated movements to the task</td><td rowspan="4">Task: Dyadic collaborative dance improvisations using only a given action drive from a list of 8 terms defined by the Laban Movement Analysis framework [36].</td><td>Not dancing with the given Laban effort or standing still to observe</td></tr>
<tr><td>1</td><td>Individual Sense-Making: independent movement</td><td>Exploring the given Laban effort individually</td></tr>
<tr><td>2</td><td>Responding/Reacting: Reflecting or adapting the collaborator's movement elements.</td><td>Acknowledging a partner's prompt by incorporating its elements into your own exploration.</td></tr>
<tr><td>3</td><td>Joint Sense-Making: Consensual, co-creative exploration of movement elements.</td><td>Synergistically building a mutually understood creative exploration based on the inclusion of both partners' prompts.</td></tr>
</table>

Table 2: Newness coding states

<table>
<tr><th>State</th><th>State Description</th><th colspan="2">Example</th></tr>
<tr><td>0</td><td>Repetition: the movement replicates a previous movement during this task.</td><td rowspan="4">Task: Dyadic collaborative dance improvisations using only a given action drive from a list of 8 terms defined by the Laban Movement Analysis framework [36].</td><td>Mirroring or replicating a specific movement or gesture without intentional modification.

Right arm is extended high and draws a circle overhead; the task is repeated.</td></tr>
<tr><td>1</td><td>Minor Modification: the movement slightly differs from a previous movement during this task.</td><td>A specific movement is modified but still recognizable with the original movement. (Varying Size, Shape, Level, Speed, Adding or Subtracting elements)

First - The right arm is extended high and draws a circle overhead, then -Right arm is bent, and draws a circle overhead. Or the right arm is extended high and draws a circle overhead as the dancer jumps.</td></tr>
<tr><td>2</td><td>Major Modification: the movement significantly differs from a previous movement during this task.</td><td>A specific movement is modified and retains element/s from the original movement and new attributes.

First - The right arm is extended high and draws a circle overhead, then -The right arm is extended to the side and draws a circle as the dancer rotates in space. Or the head draws a circle overhead as the dancer shifts to balance on one leg.</td></tr>
<tr><td>3</td><td>New Movement: the movement includes elements that greatly differ from the prior movements explored during this task.</td><td>A new movement is introduced that has multiple elements previously unexplored.

First - The right arm is extended high and draws a circle overhead, then -The head tucks toward bent knees. Or the spine curves laterally as one leg extends to the side.</td></tr>
</table>

all their video codes and the corresponding timestamps (recorded in a CSV file) for further analysis after coding all three dimensions.

6 OCSM STUDY DESIGN

The study's primary purpose is to validate OCSM; in other words, verify if the parameters and the corresponding coding states are observable. We designed a video-recall study situated in and around a dance improvisation class with university dance major students. In this section, we will first explain why we selected these participants, namely the dancers, the dance training they underwent through a movement improvisation class, describe the details of class structure and content, then explain the study procedure.

6.1 Participant Dancers

We recruited 16 college-level students in a dance major program at a university in the southeastern United States. Our decision to

Table 3: Appropriateness coding states

<table>
<tr><th>State</th><th>State Description</th><th colspan="2">Example</th></tr>
<tr><td>0</td><td>Off-task movement: Walking away from the task, improvising on an unrelated subject, or doing something unrelated to the given prompt.</td><td rowspan="4">Task: Dyadic collaborative dance improvisations using only a given action drive from a list of 8 terms defined by the Laban Movement Analysis framework [36].</td><td>Not performing within the assigned task.

Standing still or walking away from the task.</td></tr>
<tr><td>1</td><td>Somewhat related to the task: Movements that are adjacently connected to the given prompt.</td><td>Movement choices are created with minimal consideration toward the prescribed task but may still share some adjacent qualities.

The dancer is asked to explore moving in a light, sudden, indirect way. However, the dancer explores light use of weight without consideration of the other two elements.</td></tr>
<tr><td>2</td><td>On-task movement: Movements connected to the task but not what the task asks for</td><td>Movement choices are created with consideration toward the prescribed task. Some elements may veer into adjacently similar qualities that were not directly prescribed.

The dancer was asked to float, and they instead float and also glide.</td></tr>
<tr><td>3</td><td>Explicit reference to task elements: Movements that are explicitly associated with the task</td><td>Performing the assigned task (Laban effort) accurately and observably.</td></tr>
</table>

focus on studying college-level dance students was based on several key factors. Firstly, working with this demographic enabled us to gather a wealth of perspectives on the topics under examination by interviewing a substantial number of dancers, which stands in contrast to previous research in the field of HCI, which has often encountered difficulties in recruiting ample numbers of experts for in-depth interviews [53]. Secondly, we hypothesized that college-level students, being advanced in their training, would be able to provide insightful and detailed responses while still maintaining a learner's perspective on the topic and, thus, be better equipped to reflect on certain aspects of the research than a professional dancer, who may be subject to the phenomenon known as the 'expert's blind spot' [43].

We crafted the study around a semester-long class on dance improvisation, which served as the foundation for ensuring that all students had a common understanding of the fundamental principles involved in creative movement improvisation. An essential element of improvisation is the knowledge and skill of the domain [3, 12]. Therefore, we needed to ensure we established a common movement lexicon and grounded dancers with the same baseline of knowledge. Per Mentis and Johansson, it is essential to create a shared vocabulary and understanding of the effort category among dancers by "embody[ing] a movement quality before 'seeing' it" [41].

The class was offered over a 16-week meeting twice weekly for 75 minutes. All students came with previous dance training, an average of 14 years. The semester gave an overview of improvisational dance. While the content tends toward modern and contemporary dance forms, there was no explicit requirement for any particular style within the physical explorations. Students explored the Laban movement framework [36] within body, effort, space, and shape. During class, they performed improvisations based on Laban movement prompts to challenge and explore areas of their movement vocabulary that were previously unexplored. There was a particular focus on understanding the Laban effort actions as the source of guidance for the study improvisation sessions. Students throughout the semester were exposed to eight classes of Laban effort action drives: 1) Punch; 2) Dab; 3) Press; 4) Glide; 5) Slash; 6) Flick; 7) Wring; and 8) Float [36]. Each week, one effort category was taught by the instructor through embodying the movement quality.

6.2 Procedure

To understand the perspectives of college-level dance students, we devised the following approach.

Prior to the study, we gave an introduction to the class on the research background, purpose, principles of OCSM, an overview of the study design, and a demo of the tool. This introduction aimed to ensure dancers understood how to use the tool, code the data, and download their data.

Following the introduction, we began the study in the next class session. We structured the study over two class periods of 75 minutes in length. Each class period had all 16 dancers participating. Before the start of each study class period, the instructor led students through a warm-up that went over all the eight Laban efforts that served two purposes: 1) Warm up the body to dance; 2) Provide scaffolding and priming of all the action drives to refresh dancers' memory (see Fig-4 for reference)

As mentioned earlier, the purpose of the study was to verify if the OCSM parameters are observable. A clear indicator of observability is if the OCSM curves coded by the dancers are similar to the OCSM

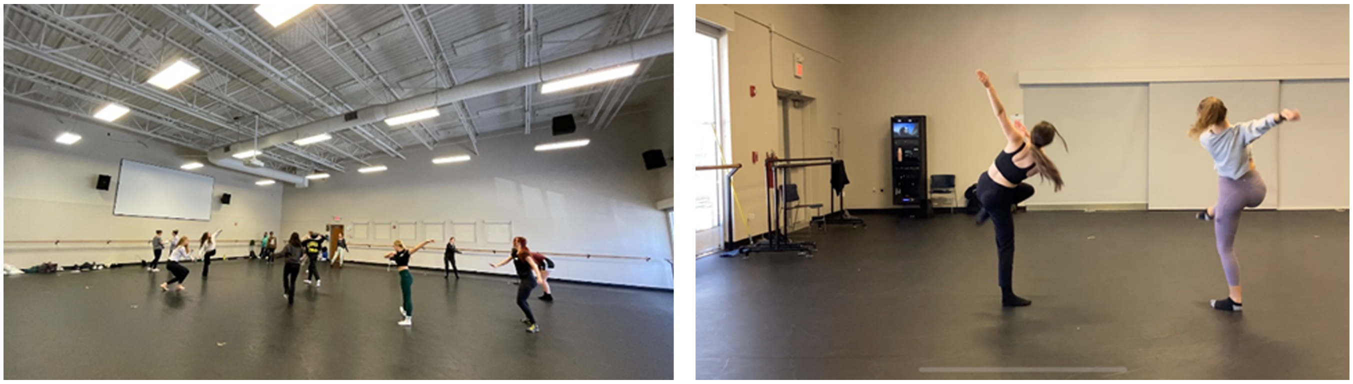

Figure 4: The warm-up and improvisation sessions during the study

curves coded by people just observing the dance. But observation can be in real-time, that is, seeing the dancers live or a recording of a previous dance session. Therefore, we divided 16 dancers (the total class strength) into three groups (see Fig-5): six participants (the dancers who will do movement improvisation), six observers (the dancers who will observe the movement improvisation live), and four blind observers (the dancers who will watch the recording of the movement improvisation). Ideally, all three groups would have had the same number of people, but since we wanted to include all 16 dancers for both class periods, we decided to have fewer blind observers than the other two groups.

Further, we divided the six participants into pairs, resulting in three dyads. Similarly, we divided the six observers into pairs and assigned them a participant dancer they were to observe. We had the same division for the subsequent study session (the second class period). The only difference was that the participant dancers for the second session were selected from those dancers who were grouped as observers or blind observers in the first study session. It is important to note that all 16 dancers had similar creative movement improvisation skills and understanding of laban action efforts due to their training in the class.

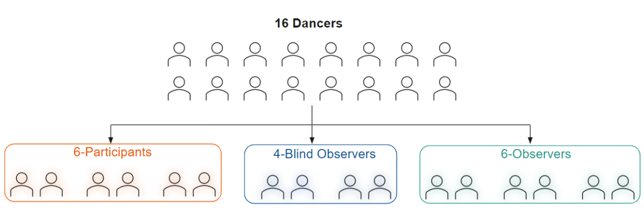

Figure 5: Division of participants into three study groups

6.2.1 Participant Role. We invited each pair of participants to engage in a movement improvisation session based on a prompt that a Laban movement expert and dance professor in the dance BA program carefully crafted. The prompt was designed to scaffold the improvisation session, and it is as follows: Each dancer was given one of the Laban effort action drive to communicate with their movement. Their partner was unaware of the given action drive. The two dancers should work together to communicate their given action drive and create a shared movement that explores both terms. Each pair had a different effort action drive they explored. We explored all eight Laban action drives over the two study class periods.

After the prompt was given to the dancers, we began the improvisation video recording. We placed three iPads across the studio to capture each dyad. The improvisational session was structured as follows: 1) Participant One physically embodied the Laban effort they were given to their partner for 30 seconds. Participant Two observed; 2) After, participant Two physically embodied their Laban effort to their partner for 30 secs while Participant One observed; 3) Then, they improvised together for 2 minutes.

6.2.2 Observer Role. While the participants were improvising, the observer's role was to watch the session closely. Each participant had one observer tasked to them. The observer's task is to observe the assigned participant and the group closely as they try to communicate and create shared movements based on their effort. Before the improvisation session, the observers were informed about the prompt and the assigned action drive. Essentially, this role was to determine if the observers could produce OCSM curves similar to that of the participants. This role was essential to establish that the states in the OCSM framework are indeed observable.

6.2.3 Blind Observer Role. Dancers in this blind observer role stepped out of the studio during the 3-minute improvisation session. We designed this role to see how different or similar the OCSM curves of a person with equivalent dance knowledge and training would be if they coded the improvisation just by looking at the video recording. Like the observers, blind observers were also informed about the task and the assigned action drive of each participant they coded.

After the improvisational session ended, we uploaded the videos on YouTube with restricted view access and shared the link to the videos with each dancer for coding. We set up laptops around the studio that housed the participants and observers. We set an additional time for blind observers to come in and code the videos since they were not required to be physically present in the room. The participants and observers were spaced equally around the studio to give them the privacy they needed to annotate their videos using the OCSM tool. They worked through each dimension, and

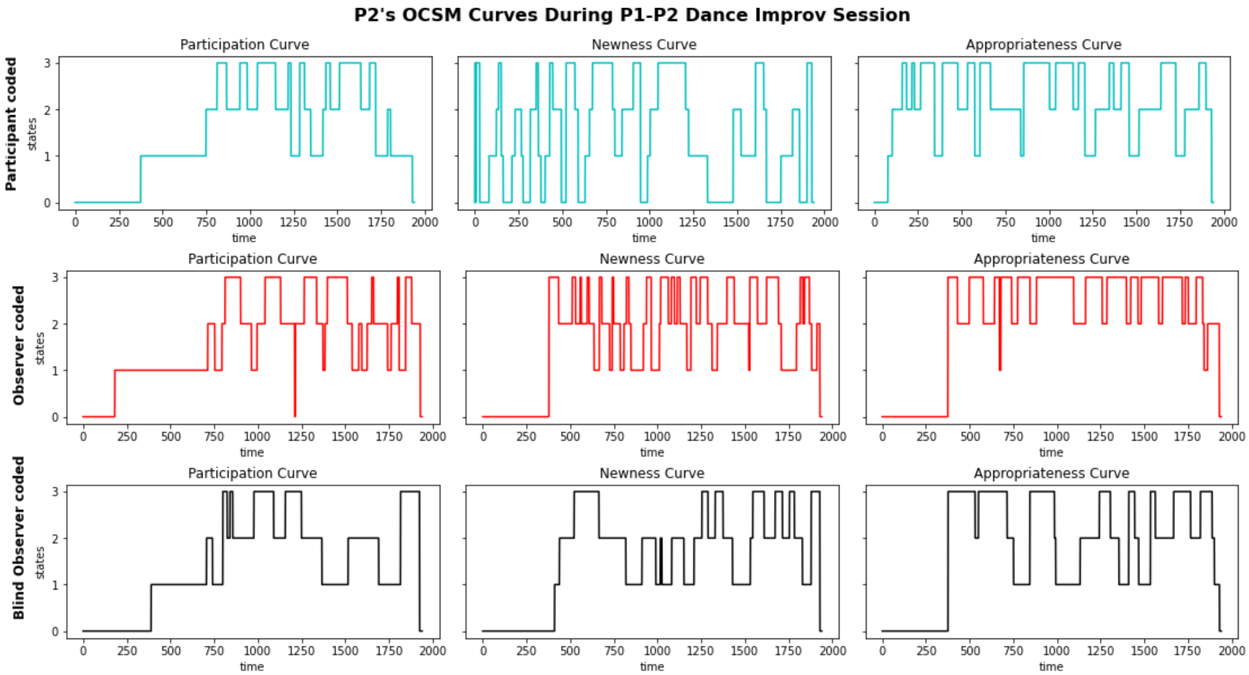

Figure 6: OCSM curves for P2

after completing the video coding, they downloaded their data and uploaded it to a shared Google Drive folder. This concluded their participation in the study.

6.2.4 Ethics. The university's institutional review board (IRB) reviewed and approved the study, and all participants provided informed consent before participating. We collected all data and stored it following the guidelines of the IRB.

7 OCSM STUDY RESULTS

In this section, we will present the results and subsequent analysis of the study we described in section 6. For interpreting the results, we consider the data self-reported by the participants, in our case dancers, to be the ground truth. Hence in what follows, we compare the data coded by participants to that coded by observers and blind observers. We used the matplotlib library to visualize the data.

7.1 OCSM Curves

Fig-6 shows the OCSM curves for a single participant -P2, from the dance Improvisation session between P1 and P2. The participants code the curves shown in blue (top row, Fig-6). The assigned observers coded the curves shown in red (middle row, Fig-6). Lastly, the blind observers coded the curves shown in black (bottom row, Fig-6). Each graph corresponds to one of the parameters in OCSM. The x-axis denotes the time elapsed during the interaction, and the y-axis corresponds to the states described in section 5. We can see from Fig-6 that while there is no exact overlap, the overall trend, as captured by the observer and the blind observer, is very similar to that reported by the participant. The similarity between the curves is more noticeable in the participation and appropriateness parameters, while the curves for the newness parameter have some variability.

To understand the overall effectiveness of this method in terms of states being observable. We took an average of all the participant-coded curves and compared it with the average curves coded by the observers and blind observers for all 12 dancers. Fig-7 shows the resultant graphs individually, and Fig-8 shows the coded curves overlayed on each other.

Visually we can see that the average participant-coded curve is very similar to the curves coded by observers and blind observers for all three parameters. Fig-8 shows a high degree of overlap between the participant-coded and observer-coded curve for all three parameters. The graphs in Fig-7 and Fig-8 evidently show that the states are indeed observable for all three parameters within OCSM.

Multiple factors might have led to the disparity between the curves coded by the blind observers compared to the other two groups. The primary factor for this might be mental fatigue. Blind observers were fewer in number (see section 6); as a result, each blind observer had to code multiple participants' OCSM curves, i.e., they had to watch and code the data three times for three different parameters and repeat it all over for the next participant. The different interpretations of codes might be another important reason for the disparity. The difference in interpretation is very noticeable in the graphs for the newness parameter. In Fig-8 in the newness graph, between the time marked from 250 to 750, we can observe that the blind observers coded this differently from the other two groups. Since we didn't give a particular criterion for newness, like focusing only on positions of various body parts, etc.,

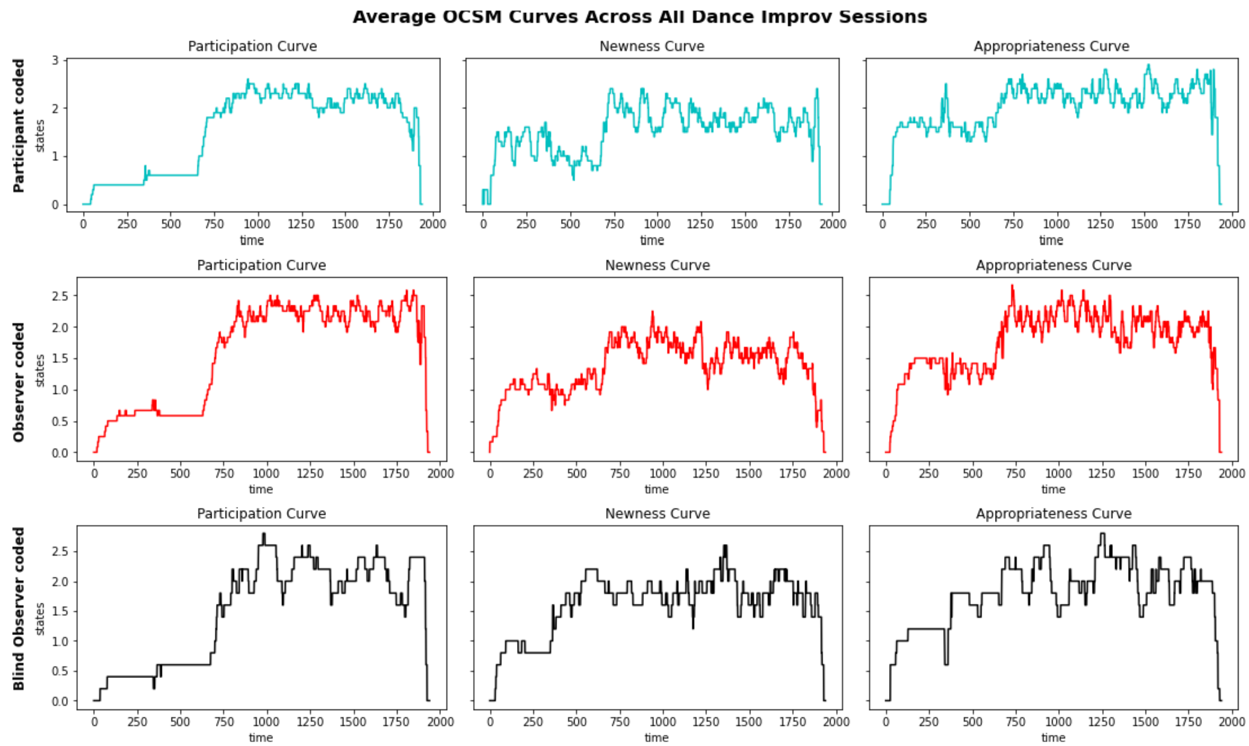

Figure 7: Average OCSM curves

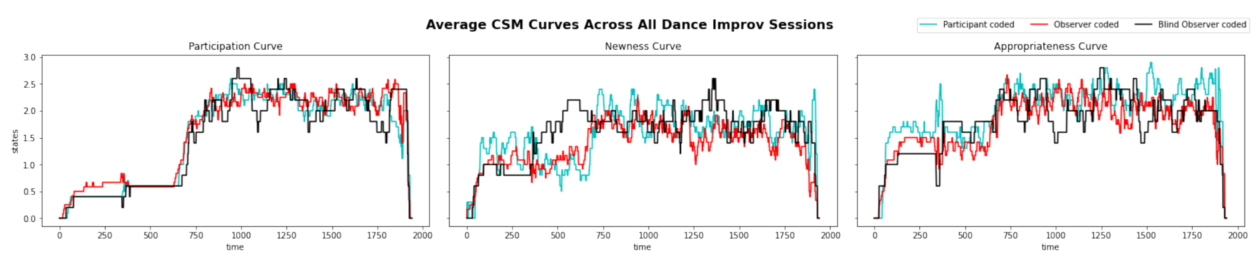

Figure 8: Average OCSM curves overlayed

it seems that blind observers had different interpretive criteria to code newness, like concentrating on speed changes or focusing on body form changes, etc. However, despite the drawbacks, the blind observers' average curve follows the general trend seen in the other two curves.

7.2 OCSM parameter correlations

Fig-9 compares the three parameters of the average OCSM curves as coded by the participants. The green line represents a simple linear regression line that indicates a positive correlation among the parameters. The graph on the left in Fig-9 shows that as participation increases, newness also increases. Similarly, the mid-graph indicates that appropriateness tends to increase as participation increases. Finally, the graph on the right shows that as appropriateness increases, newness also increases.

Further, we computed Pearson's correlation coefficient (R); the resultant correlation matrix is shown in Fig-10. All the R-values are greater than 0.7, which indicates a strong positive correlation. Since we formulated the OCSM parameters only using various theoretical frameworks, the strong R-values provide empirical evidence that these parameters work well.

7.3 OCSM curves similarity

To quantify the similarity of the curves, we used two metrics: the Discrete Frechet Distance (DFD) and the area between the curves. DFD is a measure of similarity between curves that considers the location and ordering of the points along the curves. It is often referred to as the dog-walking problem- A person is walking a dog on a leash: the person can move on one path, the dog on the other; they are free to vary their speed but are not allowed to backtrack. Given this scenario, DFD is the shortest leash length sufficient for

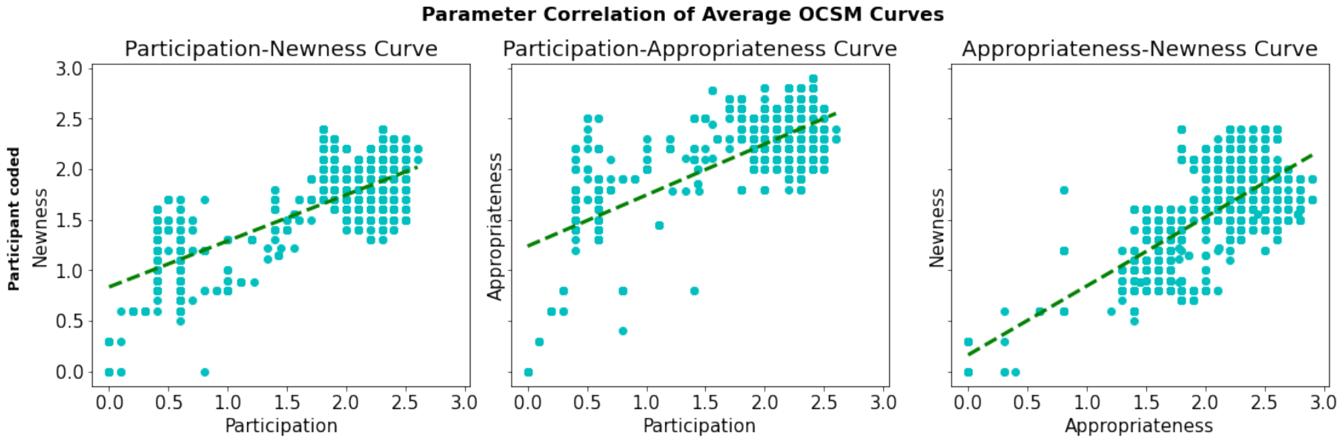

Figure 9: Parameter correlation of average OCSM curves

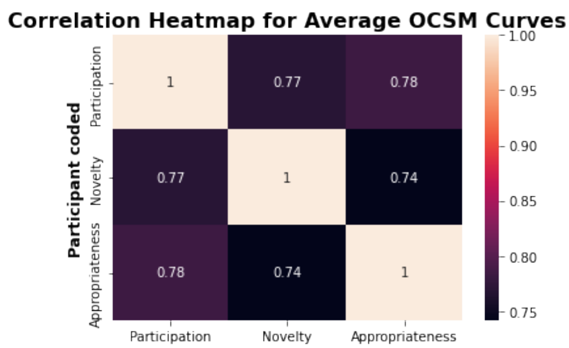

Figure 10: Correlation heatmap for average OCSM curves

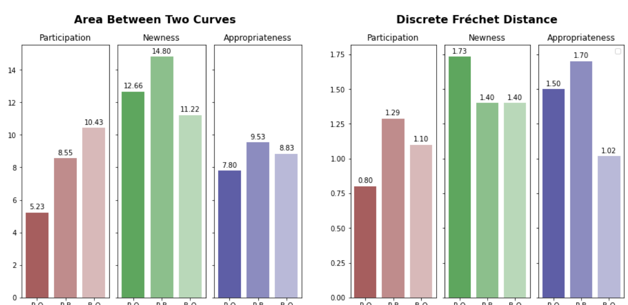

Figure 11: Curves similarity

traversing both paths [19]. The area between the curves is another method researchers have employed to quantify curve similarity [31]. In an ideal case, if the two curves are precisely the same, both area and DFD would be zero, indicating a complete overlap. For computing these similarity metrics, we utilized the Python library-similaritymeasures [30].

Fig-11 shows the bar charts of curve similarity for all three parameters (area on the left, DFD on the right). The area and DFD between the curves coded by participant and observer (P-O) is the least for participation (5.23 and 0.80, respectively); this signifies that the participation curves are very similar. Overall for the participation parameter, both area and DFD are lower than other parameters, indicating that the overall participation curves coded by different groups are similar. For the appropriateness parameter, lower area and higher DFD suggest that the curves overlap, i.e., they are similar, but there are a few dissimilar regions, consistent with the appropriateness graph in Fig-7 where we can see that at the beginning and towards the end of interaction the curves look different. For the newness parameter, both area and DFD are higher, indicating that these curves have the most dissimilarity compared to the other parameters. As mentioned earlier, the codes for newness had an element of interpretation; we believe that a more explicit coding scheme would resolve this issue.

To summarize, in this section, through various data visualization and analyses, we show that the parameters in OCSM have a strong correlation and are primarily observable. One of the factors in the dissimilarity in the newness curves may be due to the interpretive nature of the coding scheme we utilized. One of the factors in the difference in blind observers' coded curves to the curves coded by other groups is mental fatigue caused by coding multiple interactions of multiple participants within a short time.

8 DISCUSSION

While study results validate that the behavior markers for the three parameters are indeed mostly observable, we identified a few limitations with employing this approach. The intent behind a movement is not visible; in other words, the decision-making heuristics are not explicit. A set of decision-making heuristics mapped to the OCSM curves will significantly help design AI systems that can replicate the interaction using the heuristics in combination with the OCSM curves. We can potentially address this limitation by incorporating and prompting the participants to narrate their thoughts during the retrospective video walk-through (in other words, using retrospective think-aloud) and, later, doing a thematic analysis of the audio data. OCSM also suffers from procedural limitations associated with retrospective video coding. Due to the subjective nature of each analyst's coding method, there might be a slight delay between movement onset and the video coding with the slider. This limitation has a drastic effect when comparing individual OCSM curves, but the effect should reduce when we take the average of curves coded by different analysts similar to the analysis described in section 7.

The difference between the curves, coded by observers and blind observers, was noteworthy. Apart from the possible cognitive overload of blind observers, as we mentioned in section 7, another underlying neurological factor known as neural mirroring might have led to observers' curves being more similar to participants' curves. Researchers have demonstrated that observing a movement requires the exact motor representations utilized to produce the movement [10, 54]. Due to this neural mirroring, the observers may develop kinesthetic empathy with the performer [26]. During our study as well some of the dancers did mention kinesthetic empathy. We plan to explore this phenomenon by conducting more studies in the future.

Including other physiological markers of the participants mapped onto the OCSM curves might be beneficial, we believe there might be patterns between physiological markers and sense-making. To achieve this, we plan on including a variety of sensors like breath sensors, eye gaze, heart rate, a non-intrusive sensor for measuring EEG, or even mixed-reality headsets for bio-sensing such as OpenBCI's Galea [55] and studying how it corresponds to various states and parameters within the OCSM framework. Having data that maps physiological markers to OCSM curves might help improve interaction and increase the authenticity of digital avatars. We can see evidence for such a use case in the study by Saffaryazdi et al., who explored integrating EEG, GSR, and PPG data with facial "micro-expressions" to enhance emotional authenticity in digital avatar communication [46].

9 FUTURE WORK AND APPLICATIONS

The continuous nature of OCSM curves enables us to treat the data like a time series. Hence, we plan to use machine learning algorithms to analyze further, like classification or identifying trends within and amongst the curves. The observable nature of the curves will also help us use machine learning algorithms to code the ongoing interaction automatically or with human interventions, thus reducing the time required for coding.

Instead of using OCSM as an analytical method, as discussed in this paper, we also plan on using OCSM as a method for guiding generative AI. Most generative AI using deep learning techniques has an internal learned representation called the latent space. Researchers have utilized latent space exploration to produce creative outputs like music, stylized images, etc. [59]. We plan on using OCSM parameters of participation, newness, and appropriateness to navigate, explore and guide the AI model in this latent space, thus allowing it to quantify the ongoing interaction and respond based on this understanding of the current interaction.

OCSM analysis can have a variety of applications in different domains like human-robot interaction, sports, etc. For example, Sheridan highlights that one of the primary challenges in human-robot interaction is the need for a mutual mental model between the human and the robot [52].OCSM curves can provide a quantifiable metric for the robot and the human to build a shared mental model of the ongoing interaction; this can be a step towards facilitating human-robot social interaction. In sports training through similar retrospective video analysis described in this paper, OCSM curves can quantify individual players' improvisation or collaboration skills in group sports, such as football or baseball. Players can then develop or improve their collaborative or improvisational skills and better their game [18, 42].

In addition to the applications we highlighted above, OCSM can be used to understand the collaborative creativity of players while playing video games or quantify a game controller's effectiveness in fostering collaborative play, creating a social space or inter-reliance amongst players [57]. OCSM can also be applied to analyze non-creative activities like measuring the effectiveness of workers in routine office meetings. By focusing on observable behavior markers related to participation, newness, and appropriateness, OCSM can provide a means of quantifying and analyzing the dynamics of interactions amongst workers during the meeting. This can help improve or re-structure the way meeting is conducted or provide valuable metrics for workers to reflect upon and improve their collaborative and participatory skills.

10 CONCLUSION

In this paper, we presented a new method - Observable Creative Sense-Making (OCSM). We described how the prior framework of Creative Sense-Making (CSM) has conceptual limitations, making its applicability difficult in studying domains like dance improvisation. OCSM framework provides a new method to visualize and quantify embodied co-creative improvisational interaction. We described the theories based on which we identified OCSM parameters of participation, newness, and appropriateness and developed the coding scheme centered on observable behavior markers. We applied the OCSM method to empirical studies of human collaboration in dance improvisation, described the results, and subsequent analysis to establish the method's validity. We propose OCSM as a general technique researchers can use to study domains or design products involving open-ended creative collaboration and embodied co-creation.

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