A COMPUTATIONAL MODEL OF TEAM-LEVEL NEGOTIATION: WITH AN APPLICATION IN CREATIVE PROBLEM SOLVING

by

Zahra Sajedinia

A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Department of Psychological Sciences

West Lafayette, Indiana

August 2021

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Sebastien Hélie, Chair

Department of Psychological Sciences, Purdue University

Dr. Gregory Francis

Department of Psychological Sciences, Purdue University

Dr. Franki Kung

Department of Psychological Sciences, Purdue University

Dr. Richard Schweickert

Department of Psychological Sciences, Purdue University

Approved by:

Dr. Kimberly Kinzig

ACKNOWLEDGMENTS

Throughout the writing of this dissertation, I have received a great deal of support and assistance. I would first like to thank my advisor, Dr. Sebastien Hélie, for his exceptional patience, encouragement, and support. Your knowledge and insightful feedback helped me a lot and brought my work to a higher level. Thank you for teaching me valuable ideas related to both academia and outside. I would also like to thank my committee member, Dr. Gregory Francis, for his constructive comments and for providing me with the tools I needed to complete this dissertation. I would also like to thank Dr. Franki Kung for his helpful suggestions and the necessary information I needed in this research. Furthermore, I would like to thank Dr. Richard Schweickert for his valuable suggestions. His welcoming attitude made the department a much more pleasant place to work. I also would like to thank Nancy O'Brien for all her help during this time.

My appreciation also goes out to my family and friends for their support all through my studies. First, I would like to thank my parents Mohammad Sajedinia and Nahid Pahlavan for their unwavering support; I could not follow my dream of studying Cognitive Science without you. Furthermore, I am incredibly grateful to my loving partner, Arman for his unparalleled support, and belief in me. You are always there for me and you cannot imagine how lucky I feel to have you in my life. In addition, I would also like to thank Reza and Mati for their help and kindness. I cannot say how grateful I am for all you have done for me. I also would like to thank Dr. Asghar, and Manijeh Sabbaghi; your heartwarming voices and encouragement helped me immensely. My friends Paria, Mabi, and Neda, I am so lucky to have found you all at Purdue. You made this town a much nicer place to live. Finally, I would like to thank my friends in the department: Pallavi, Maria, and Farzin, for all the stop-by-office moments and the cherished time we had at Purdue.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The ability to solve problems creatively has been crucial for the adaptation and survival of humans throughout history. In many real–life situations, cognitive processes are not isolated. Humans are social, they communicate and form groups to solve daily problems and make decisions. Therefore, the final output of cognitive processes can come from multi–brains in groups rather than an individual one. This multi–brain output can be largely different from the output that an individual person produces in isolation. As a result, it is essential to include team–level processes in cognitive models to make a more accurate description of real–world cognitive processes in general and problem solving in particular. This research aims to answer the general question of how working in a team affects creative problem solving. For doing that, first, we propose a computational model for multi-agent creative problem solving. Then, we show how the model can be used to study the factors that are involved in creativity in teams and potentially will suggest answers to questions such as, 'how team size is related to creativity'.

1. INTRODUCTION AND PREVIOUS RESEARCH

These days, many countries, governments, universities, scientific institutions, and organizations eagerly try to improve their innovation and creativity. Creativity has become an essential base for economic growth, development, and finding solutions for social and environmental issues. Moreover, for solving today's complex problems in society, science, and tech teams of diverse backgrounds are commonly used. Therefore, the importance of creativity has been shifted from individuals into teams [1].

Due to the growing interest in creativity, studies on individual and team creativity have become increasingly popular in different fields [2]. These studies used different approaches and consider a variety of aspects of creativity: some of these studies focus on how creativity can be measured [3], while others ask about the differences between artistic and scientific creativity [4]. There are studies on finding connections between personality characteristics and creativity [5], [6]. Other scientists are trying to understand the neural basis of creative processes in the brain [7], [8]. Furthermore, some studies focused on understanding the underlying mechanism and the important parameters in idea generation [9]–[12].

Given the variety of fields working on creativity, it is not surprising to encounter ambiguities in the definition of creativity. Table 1.1 provides an overview of previous attempts in defining creativity. Kampylis and Valtanen [13] found four components that are more common among these definitions:

1. Creativity can be considered as a key ability in an individual.
2. Creativity presumes to be an intentional activity.
3. Creative activities happen in a specific environment or context.
4. The result of creative activities is tangible or intangible products, which are novel (unconventional), and appropriate (useful or valuable) for at least the individual.

Other research alongside novelty and usefulness add the surprise factor to the definition of creativity [12], [14]–[18]. Based on this previous work, in this research we define creativity as producing tangible products, which are novel, surprising, and useful.

Table 1.1. Definition of creativity in different literature.
The Table is adapted from Kampylis and Valtanen [13].

Author(s)	Year	Page	Definition
Guilford	1950	444	"... refers to the abilities that are most characteristic of creative people. Creative abilities determine whether the individual has the power to exhibit creative behavior to a noteworthy degree."
Stein	1953	311	"... that process which results in a novel work that is accepted as tenable or useful or satisfying by a group at some point in time".
Rhodes	1961	305	"... is a noun naming the phenomenon in which a person communicates a new concept (which is the product). Mental activity (or mental process) is implicit in the definition, and of course no one could conceive of a person living or operating in a vacuum, so the term press is also implicit."
Mednick	1962	221	"... the forming of associative elements into new combinations which either meet specified requirements or are in some way useful. The more mutually remote the elements of the new combination, the more creative the process or solution."
Welsch	1980	97	"... the process of generating unique products by transformation of existing products. These products,tangible and intangible, must be unique only to the creator, and must meet the criteria of purpose and value established by the creator."
Boone and Hollingsworth	1990	3	"... any form of action that leads to results that are novel, useful, and predictable."

Csikszentmihalyi	1999	314	"... a phenomenon that is constructed through an interaction between producers and audience.Creativity is not the product of single individuals,but of social systems making judgments about individuals' products."
Carayiannis and Gonzalez	2003	588	"... the ability to perceive new connections among objects and concepts – in effect, reordering reality by using a novel framework for organizing perceptions."
Sawyer	2006	33	"... the emergence of something novel and appropriate, from a person, a group, or a society."
Ferrari, Cachia, and Punie	2009	14	"... is skill for everyone; ability to make new connections; capacity to generate new ideas; divergent thinking; ability to get out of the rails; capacity to produce original and valuable outcomes.
Saariluoma, Berki, and Saariluoma	2009	18	"... the activity (both mental and physical) that occurs in a specific time-space, social and cultural framework and leads to tangible or intangible outcomes that are original, useful, ethical and desirable, at least to the creator(s)."
Walia	2019	242	"Creativity is an act arising out of a perception of the environment that acknowledges a certain disequilibrium, resulting in productive activity that challenges patterned thought processes and norms, and gives rise to something new in the form of a physical object or even a mental or an emotional construct."

The word creative also has been used colloquially with meanings that are beyond the precise definition. For example, creativity likely means satisfaction when we say we did a creative work [19]. Therefore, the creativity concept involves more meanings in real life than the definitions described in previous paragraphs. As a result, the precise definitions that we will use in this research are based on simplifications in the meaning of creativity.

The thinking process in identifying creative solutions for ill-defined problems falls into two categories: convergence thinking and divergence thinking [20], [21]. Typically, in convergent thinking, there is one unique solution and thinking is directed toward reaching that solution. However, in divergent thinking, the problem solver searches various directions, and it usually happens when there is no unique solution for the problem [20].

Regarding the social aspects of creativity, there are debates based on a belief that creativity cannot be seen as an individual's attribute. It should be defined based on the judgments that social systems make about the individual [22]. Therefore, studying creativity may be more meaningful if it is done in a social environment.

One of the recent approaches for studying creativity is computational modeling. To date, different attempts have been made to make a computational model of the underlying processes of creativity in an individual human [10], [23], [24]. A unified theory and a widely accepted theory of creative problem solving is the Explicit-Implicit Interaction (EII) that is introduced by Hélie and Sun [10]. In this theory, the combination of simultaneous explicit rule-based and implicit associative processes describes the four stages of creative problem solving: preparation, incubation, insight, and verification [9].

The first stage, preparation, is a period of initial search by using logic and reasoning. If this search is successful and a solution is found, then the problem is solved and there is no need for other stages. However, in case of an ill defined or complex problem, it is unlikely for the preparation stage to find a solution by only using logic and reasoning. When an impasse is reached, the person stops attempting to find a solution for the problem. It is the beginning of the incubation stage in which the attention of the person is no longer devoted to the problem. There is no time limit for incubation, it can last from minutes to years. Insight happens when a solution spontaneously comes to consciousness. In the last stage, verification, the correctness of the insight solution is investigated. This stage, similar to the preparation stage uses deliberative thinking based on logic and reasoning. The insight problem might not be validated in the verification stage, in this case typically the person goes back to the preparation or incubation stages and tries to solve the problem again [10].

The models based on the EII theory are the only computational models of creativity that account for all of these four stages, and they were able to successfully reproduce different experimental studies [10]. However, a model of an individual human is not sufficient for capturing all aspects of creative problem solving. Nowadays, creativity and solving problems become more and more reliant on teams: scientific collaborations, organizational meetings, and online problem solving social networks are examples of the growing importance of teams in problem solving. Therefore, a computational model of the team–level processes of creative problem solving can lead to a more accurate understanding of these processes. Furthermore, this model can help to find the most efficient team characteristics that lead to a higher degree of creativity in a shorter time. To date, there are only a few computational models of multi-agent creativity [25], [26], and none of them are modeling the four stages of creative problem solving.

Based on the Wallas [9] widely accepted four stages of creativity, excluding any of these stages limits the model in presenting some important aspects of problem solving. This research uses the EII theory for modeling the underlying processes of an individual agent. Therefore, using EII provides the model with the possibility of including all four creative problem solving stages and results in a more comprehensive model of multi-agent creativity.

This document is organized as follows: the rest of this chapter provides information on previous models that are related to individual and team–level creativity. Then, in Chapter 2, a new model of team–level creativity is proposed and the relation between this model and the previous models is explained. Next, in Chapter 3, four experiments that are used towards model validation are presented. Finally, Chapter 4 provides a summary and discusses the limitations and real world applications of this work.

1.1 Individual Creativity

To date, different attempts have been made to introduce theories of creativity in an individual person. In this section, first in Subsection 1.1.1, we provide a summary of these attempts. Then, in Subsection 1.1.2 , we explain the details of the EII theory. The EII theory later will be of our interest in designing a multi-agent model of creativity.

1.1.1 Theories of Creativity

This subsection provides an overview of important theories on incubation, insight, and the EII theory.

Unconscious work theory of Incubation: First, the problem solver starts working consciously on the problem. Then, if she cannot find a solution, at some point, she stops the conscious work. In this theory, after stopping the conscious work, she continues to work unconsciously on the problem. The solutions that she has found during the unconscious work later may come to her consciousness [27], [28]. The theory of Unconscious work is compatible with the 'aha' moments that we experience and happened in the history of science. However, doing experiments on unconscious work is not an easy process [10], [28].

Conscious work theory of Incubation: In this theory, the problem solver continues to work on the problem in the incubation phase even if her attention is not fully dedicated to the problem. Unlike the Unconscious work theory, this continuing work on the problem is conscious. The problem solver intermittently works on the problem while her attention is on unrelated work such as driving. The problem solver's attention switches between the unrelated work and the incubated problem very fast. Therefore the problem solver forgets the short episodes of work on the incubated problem, and only the solution (the final step) is remembered. The Conscious work theory does not have the difficulties in experimental assessments that we had in Unconscious work theory [10], [28].

Remote association theory of Incubation: In this theory, the incubation phase is used for eliminating unrelated and stereotypical solutions. When the problem solver encounters a new problem, she first searches for similar problems and automatically retrieves their related stored solutions (starting from most likely solutions). These solutions may not be the best solution, or even they may not be correct. The incubation phase helps with retrieving more stored solutions (the unlikely ones) and finding more appropriate solutions [10].

Evolutionary theory of insight: This theory is based on the three principles of Darwin's evolution theory: 1- solutions are blindly generated 2- Solutions are evaluated and selected. 3- The retention of selected solutions is performed. In this theory, knowledge is represented by nodes of a graph. The evolutionary selection principles form the links or associations between nodes of this graph. Generating solutions is done by forming associations in unconscious processes. At any point, if one association or solution adequately solves the problem, then it comes to consciousness and is experienced as insight [10], [29]–[34].

Although the Darwinian idea generation approach was successful in many cases, there are arguments that evolutionary theories of creativity should not necessarily follow Darwinian principles. Gabora [35] explains that in the Darwinian approach, the ideas undergoing selective pressure should be generated at the same iteration. This may not be accurate because after an idea is generated, the context for generating other ideas is changed. Therefore, different ideas cannot be generated in the same context and undergo the same selective pressure. However, by considering sequential idea generation and change of context after each generated idea still, the evolutionary approach can be beneficial in explaining creativity processes [29], [35].

Constraint theory of insight: In this theory, the problem solver constructs a mental structure of initial states (problem) and the final state(s) (solution). Then, she tries to fill the gap between the initial and final states. It should be noted that the set of constraints on the problem can be very large [36], and the problem solver may not have enough cognitive resources to satisfy this large set simultaneously. Therefore, when the satisfaction of this large set occurs, the problem solver experiences an intense experience of insight [10].

Associationistic theory of insight: In this theory knowledge is represented in nodes of a graph [31], [32]. The problem solver's goal is to use a parallel search and find a path from one node to another (solution). If the association between the two nodes is strong, then insight is experienced. In other words, in this theory, insight only depends on the association of the two nodes and is not dependent on a separate system [10], [37], [38].

The EII Theory: The EII theory, which is introduced by Hélie and Sun [10] is a unified theory of all previously discussed theories. Unlike the previous theories, the EII theory considers all four stages of Wallas creative problem solving: preparation, incubation, insight, and verification [9], [10]. Moreover, the models based on the EII theory were able to successfully simulate the results of different creativity experiments [10], [39]. In Subsection

1.1.2, we explain the details of the EII theory and provide information on the simulations done by using this theory.

1.1.2 The EII Theory

The design of the EII theory is based on the non–action–centered subsystem of the CLARION cognitive architecture [40], [41]. As shown in Figure 1.1, the EII theory consists of two processing levels: explicit (top) and implicit (bottom). The EII theory accounts for Wallas's (1926) four stages of creative problem solving. First, Wallas explained the preparation stage as "the whole traditional art of logic". In the EII theory, the Explicit level, is also based on rule–based knowledge and can present logic–based reasoning [10]. Second, Wallas described incubation as the stage during which "we do not voluntarily or consciously think on a particular problem" and stated that incubation can continue for an extended period of time. In the EII theory, the Implicit level, in contrast to the Explicit level, is not consciously accessible. Furthermore, the implicit level does not require attentional resources to process information [10]. Third, Wallas viewed insight as "the appearance of the 'happy idea' together with the psychological events, which immediately preceded and accompanied that appearance." In the EII theory, insight is the integration of implicit and explicit knowledge that leads to a sudden change in the subject's confidence in a solution [10]. Fourth, the last stage is verification. Wallas stated that the verification stage "closely resembles the first stage of preparation." Based on the above explanations, the preparation and verification phases rely mostly on the Explicit level, while the incubation phase relies more on the Implicit level [10]. The EII theory is based on five main and two auxiliary principles:

1. There are two types of knowledge:
    - Explicit (easier to verbalize, needs more attention, symbolic, ...)
    - Implicit (harder to verbalize, noisier, inaccessible, ...)
2. The Explicit and Implicit subsystems can work simultaneously.

3. There is redundant information such as the representation of a problem in both Explicit and Implicit levels.

4. The results of the processes at the Implicit level are integrated into the results from the Explicit level.

5. It is possible to have iterative processes.

Auxiliary principles:

1. There is an internal confidence level (ICL) that refers to metacognition and shows how much a person is confident about her proposed solution.

2. If the ICL is above a threshold (ψ), then a stochastically selected solution is experienced as insight. Hélie and Sun [10] implemented this stochastic selection by representing each solution with one node and translating the activity of each node into a Boltzmann distribution. Equation 1.1 calculates the probability of selecting each solution as the output of EII and adds randomness to the results.

$$P\left(S_{\mathrm{i}}\right)=\frac{\mathrm{e}^{S_{\mathrm{j}}/\alpha}}{\sum_{\mathrm{j}}\mathrm{e}^{S_{\mathrm{j}}/\alpha}} \tag{1.1}$$

   Where S_{i} is the activity of solution i, and α is the temperature parameter. Higher α corresponds to higher noise and results in a complete search of the hypothesis space. On the other hand, lower α corresponds to lower noise and a narrow search of the hypothesis space, and it might lead to stereotyped responses.

The EII theory has been validated by accounting for different creativity–related experiments. Hélie and Sun [10] successfully reproduced multiple experiments. The first one is an experiment by Yaniv and Meyer [42] who showed that in a task with two subsequent problems of rare–association and lexical tasks, feeling–of–knowing the answer to the first problem primes the second problem on the same answer. The second experiment was done by Smith and Vela [43] who performed a two–phased free–recall task of memorizing line drawings in different incubation intervals. They showed that smaller incubation intervals

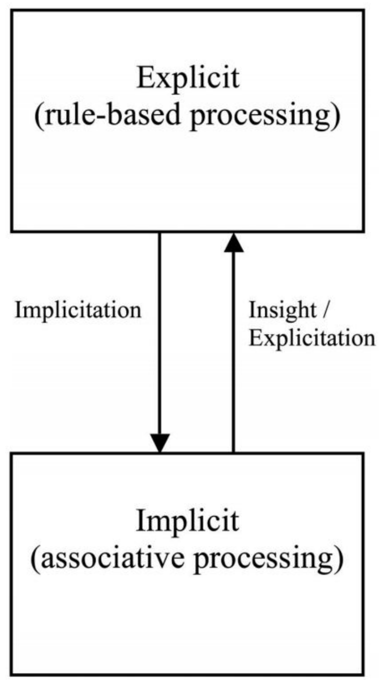

Figure 1.1. The EII theory is composed of top explicit and bottom implicit subsystems. The figure is from Hélie and Sun [10].

result in smaller reminiscence scores in comparison to longer incubation intervals. Reminiscence is defined as the recall of materials by an individual who was not successful in recalling them on a previous attempts [43].

The third experiment was done by Durso, Rea, and Dayton [44] in which participants were asked to read a story and answer insight questions about the story. They showed that participants' knowledge graphs before and after the occurrence of insight can be used for observing the insight. In addition to these experiments, Calic and Hélie [39] used the EII theory to simulate the effects of paradoxical creativity on creative outcomes. Paradoxical creativity is defined as an individual's attempt in achieving competing demands while simultaneously trying to creatively resolve a contradiction. The results from their EII simulation showed that creative outcomes are dependent on two factors: 1- the willingness of an agent to tolerate new ideas 2- The agent's capacity to search for new information [39].

1.2 Team–level Creativity

In this section, an overview of three different views on modeling team–level processes is provided: cognitive Science, communication studies, and information theory.

1.2.1 Cognitive Science Viewpoint

Bayesian Inference of Other Minds

Bayesian models are among the most popular models for describing human communication and group decision making [45]–[48].

In a multiple-round group decision making such as an organizational series of meetings, uncertainties about the intention and behavior of other team members are not fixed and can always be modified [48]. Therefore, a probabilistic reasoning model, which can update uncertainties of newly available information is useful for modeling team–level processes.

Park, Goïame, O'Connor, *et al.* [46] studied how social influence and interaction with a group pull one's decision towards the group decision. They proposed a Bayesian model of decision making. In this model, decisions are represented by normal distributions. The mean and the variance of each distribution show decision and confidence in decision respectively.

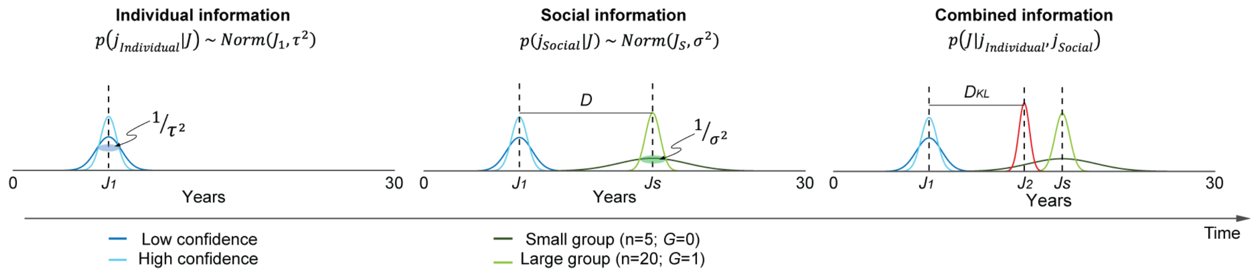

Figure 1.2. A Bayesian model of social influence on decision making. First, an agent makes a decision individually (left panel). Then, the agent observes the (average) decision of the group (Middle panel). Finally, the agent's decision (blue) and the group's decision (green) are integrated and form the agent's new decision (red). The change from the agent's first and second decision can be estimated by the Kullback–Leibler divergence (D_{KL}). The figure is from Park, Goïame, O'Connor, *et al.* [46]

The variance has an inverse relation with confidence. As the variance becomes smaller, the person is more confident in her decision.

Park, Goïame, O'Connor, *et al.* [46] showed that their Bayesian model provides a good account for observed behavior in a collective judgment decision making task. This task had two steps: first, subjects read a murder case and decided on the number of years that the criminal should be punished in prison (J_1) and rated their confidence in this decision. Second, subjects were informed about the average decision of other jurors. They were told that the other jurors were previous participants and they had a high confidence in their decision. After receiving this information, subjects were allowed to change their decision (J_2). The results of this experiment showed that people tend to pull their decision towards the decision of the group, and their confidence in their decision has an inverse relation with the magnitude of pulling. Figure 1.2 presents an overview of this model. In this figure, the horizontal axis represent the years of punishment and the y axis is the confidence of the subject about her decision.

The Bayesian model also accounts for neuro imaging data. Park, Goïame, O'Connor, *et al.* [46] performed a fMRI experiment of the collective judgment decision making task. The results from the experiment showed that the level of belief update is computed by the dorsal anterior cingulate cortex (dACC). However, they observed more activity in the bilateral frontopolar cortex (FPC) in individuals who credit more to the judgment of a larger group. Moreover, an increase in functional connectivity between the dACC and the FPC led to a higher influence of group size on credibility of social information. This increase in functional connectivity and having separate brain regions for the belief update and group credits are consistent with the Bayesian model [46].

A Neural Circuit Model of Decision Uncertainty and Change–of–mind

Decision confidence, persuasion, and change–of–mind are important aspects of decision making in a team. In this subsection, a recent neural circuit model of change–of–mind introduced by Atiya, Rañó, Prasad, *et al.* [49] (Figure 1.3) is presented. This model consists of three modules: 1- Sensorimotor, 2- Uncertainty monitoring and 3- Motor module. Each module contains two neural populations that mimic a canonical cortical microcircuit [49]. The model works as follows: first, the Sensorimotor module receives stimuli that activate its neural populations (in this module each neural population represents one possible choice option in a decision). Second, the Inhibitory neural population (green circle) inside the Uncertainty monitoring module receives activation from both neural populations in the Sensorimotor module. Third, the Inhibitory neural population inhibits the Uncertainty neural population (magenta circle). The Uncertainty neural population also receives a constant tonic excitatory input, which may differ in each trial. These two modules represent one cortical column [49], [50]. The tonic input is included to solve flooring effects. Due to the flooring effects (the non-negativity of neural firing) the Inhibitory neural population only can transmit signals if the destination neurons are not silent. Therefore, the tonic activity assures that the transmission between the Inhibitory and the Uncertainty neural populations can properly be done [49]. Fourth, the Uncertainty neural population feeds back excitatory signals to each neural population in the Sensorimotor module. This feedback loop allows the model to alter an initial choice into a new one. Finally, there is a Motor module, which is composed of neural populations of choice options (Each neural population in the Motor module corresponds to one neural population in the Sensorimotor module and vice versa). Each neural population in the Motor module receives temporally integrated input from the corresponding neural population in the Sensorimotor module. If the activity of one of the Motor neural populations exceeds a pre-defined threshold, then the corresponding choice is selected as an output decision [49].

The change–of–mind model is compatible with behavioral and neural recording data [49]. This model successfully reproduced the following results: 1 - The level of uncertainty that affects subsequent decisions in a multi–stage decision task paradigm [51]; 2 - Increasing the quality of evidence, under certain circumstances, monotonically decreases the probability of the change–of–mind [52]; 3 - Based on neural recording data, the neural activities that are related to a choice are reversely associated with the instantiation of the neural activity of change–of–mind [53].

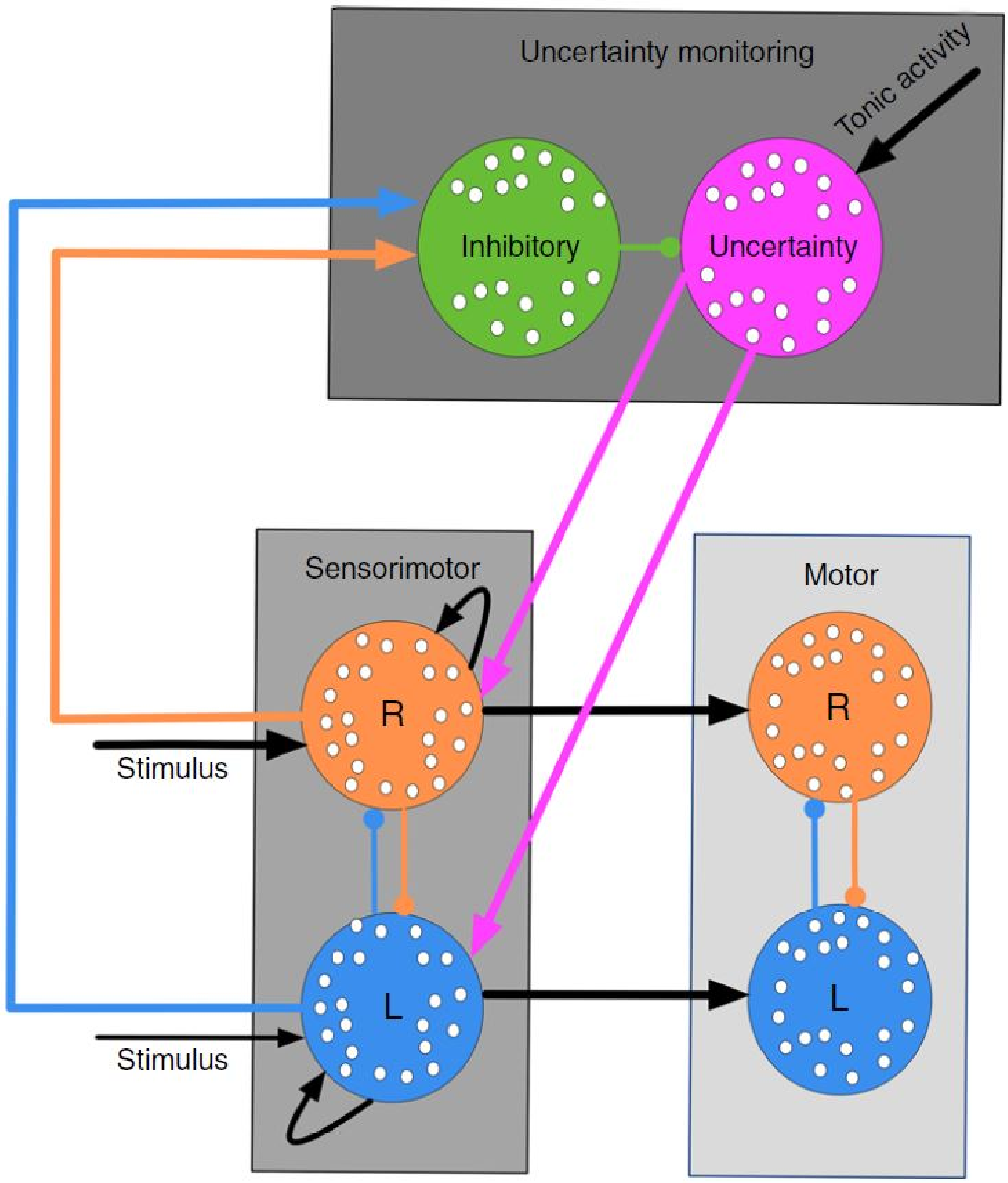

Figure 1.3. Schematic diagram of the change–of–mind model. Each circle represents a neural population and the connections between neural populations are shown by lines with arrows (excitatory) or filled circles (Inhibitory). In this example, there are only two choice options: R and L that represent right and left in a motion task [49].

1.2.2 Communication Studies Viewpoint

Communication Networks

Communication networks are regular patterns of information exchange among the members of a team. Sometimes, communication patterns in a team are deliberately set, for example, in a company with a hierarchical structure. However, even with the lack of a deliberate set of communication patterns, usually an informal network of communication forms between the team members. As the size of a team increases, patterns of communication become more complex. There are some common basic patterns in small teams as shown in Figure 1.4 [54].

One important aspect of communication networks is the degree of centralization. In a centralized network, there is one vertex, which is located at the crossroads of communications. In decentralized networks, the number of channels at each vertex is roughly equal. In Figure 1.4, 'Y' and 'Wheel' represent a centralized network. The 'Y' network, as the name suggests, has a Y–shaped structure and the 'Wheel' network has a central node, which is connected to isolated nodes. 'Circle' and 'All–Channel' are considered as decentralized networks [54]. The 'Circle' structure as the name suggests is a series of consecutively connected nodes that represent a circular shape, and 'All–channel' network is a fully connected network.

Studies done by Bavelas [55], [56] showed that teams with a centralized structure outperform decentralized teams in solving less complex problems. For example, it is shown that during solving a problem, teams with the 'Wheel' structure in comparison to decentralized teams send fewer messages, detect and correct more errors, and are quicker in finding a solution. Furthermore, in the 'Wheel' structure teams are more successful in improving their performance by practice [54], [57], [58]. However, in more complex tasks, decentralized teams outperform centralized ones [54].

1.2.3 Information Theory Viewpoint

The Information Transfer model by Shannon and Weaver [59] is one of the earliest models of communication. This model is linear and a source sends a message to a receiver through

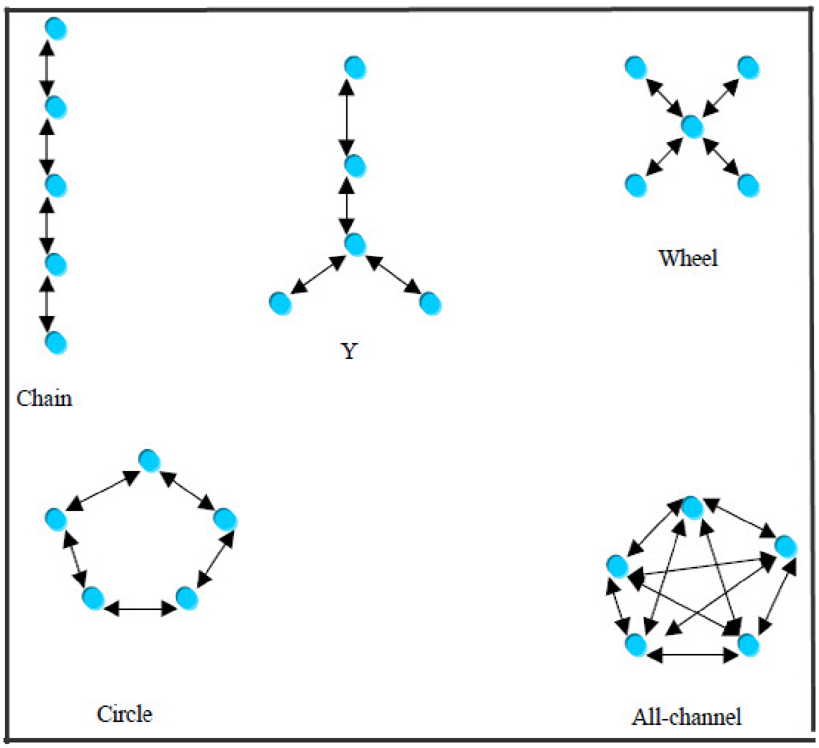

Figure 1.4. Five common types of architecture in a five-member team (The figure is from wisdomjobs.com).

a channel. In this model, the source puts thoughts into words or body language (encoding), then transmits them through a channel towards the receiver. The receiver assigns meaning to the message (decoding), but the message might not be fully transmitted. An interference that distracts the communicators can potentially intercept, interrupt or alter the message by adding noise [60]. There are four types of noise: physical, physiological, psychological, and semantic. Physical noise is a distraction caused by the external environment, such as sounds that interfere with hearing. Physiological noise is a biological influence, such as feeling sick, a pounding heart and butterflies in the stomach caused by speech anxiety. Psychological noise comes in the form of biases, preconceptions, and assumptions. Semantic noise appears in a choice of words that are not comprehensible, confusing or distracting, such as using an abbreviation that is not familiar to the listener and can draw attention to terminology and delude the content of the message [61].

One difficulty in using the Information Transfer model to describe team communications is its one-way transmission, which cannot capture human interactions. Therefore, a two–way Interactive model and a Transactional model are more appropriate for modeling team communications [60].

The Interactive model views communication as the sharing of meaning by allowing the receiver to act as a source. In this model, although communicators are both a source and a receiver, they take turns to act as a receiver or source. Since the Interactive model has loops between the communicators, it is no longer linear [60], [61]. Figure 1.5 illustrates the Interactive model.

The Transactional model of communication differs from the Interactive model in two ways. First, in the Transactional model, each communicator can simultaneously be a source or receiver. These characteristics make this model more compatible with the real–world human communication, because even when a person is listening, she sends verbal words such as “uh-huh”s or non-verbal messages through levels of eye contact, head nods, and hand gestures. Second, the Transactional model assigns a field of meaning to each communicator. A field of meaning consists of attitudes, beliefs, and ideas that a communicator has developed throughout her life. Figure 1.6 provides an overview of this model [60], [61].

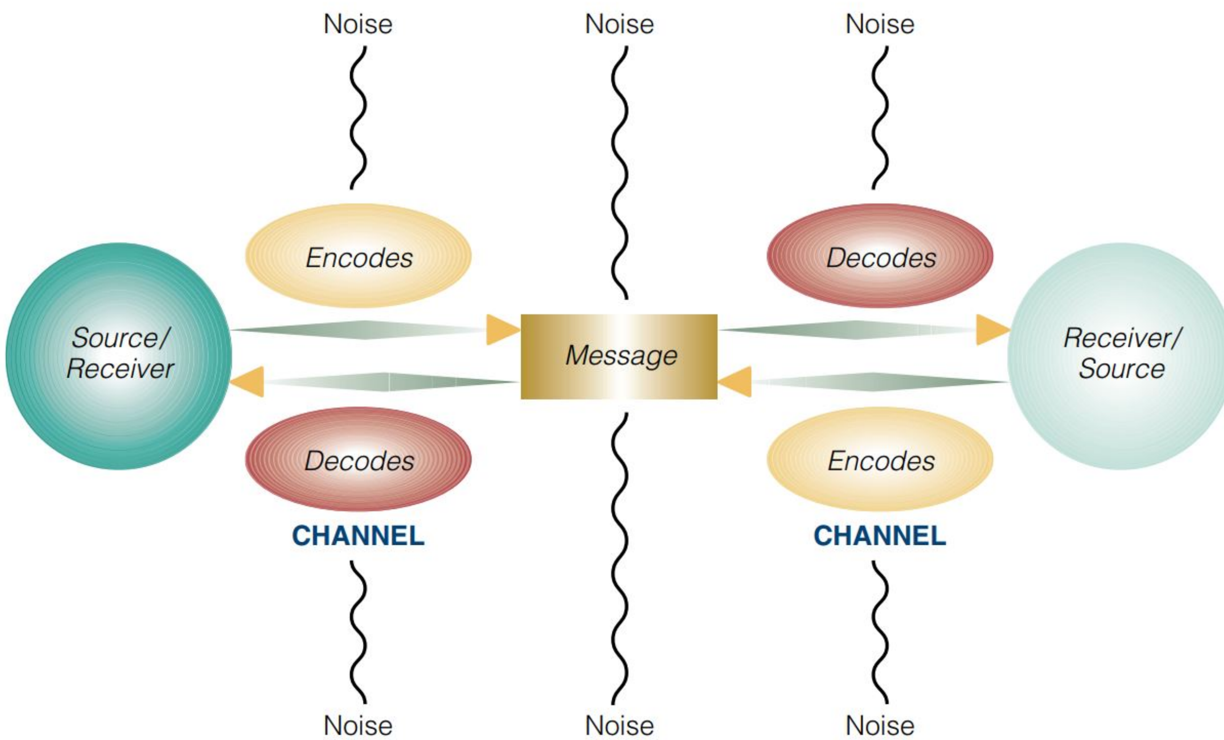

Figure 1.5. The Interactive model of communication. In this model, there is a two–way communication channel between communicators, however, communicators take turns to send or receive a message (Figure from Tran, Director, Hugel, *et al.* [60]).

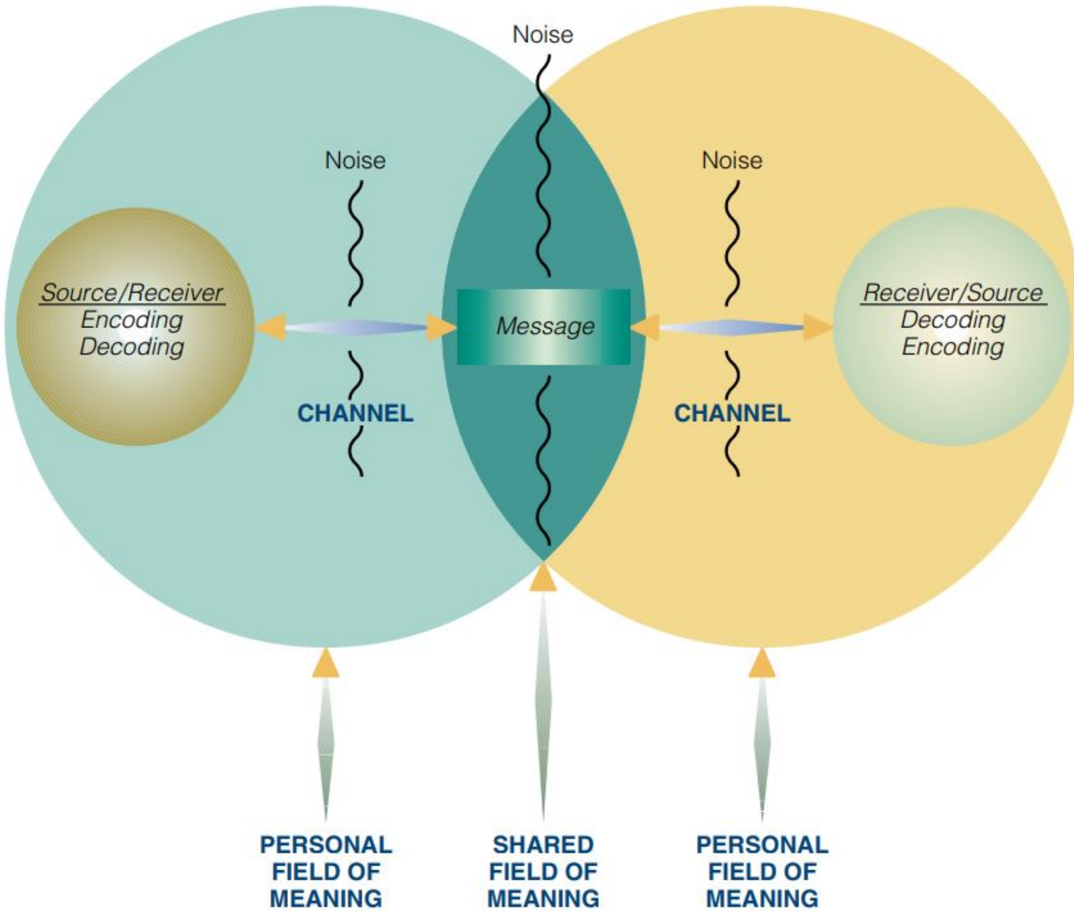

Figure 1.6. The Transactional model of communication. In this model, each communicator has a field of meaning and communicators simultaneously engage in encoding and decoding of messages [60].

The Transactional model identifies overlapped (shared) and non–overlapped areas in fields of meaning. This helps to model misunderstanding as a meaning that is outside of the shared field of meaning. A shared field of meaning is not fixed during a conversation. Persuasion (a form of influence) is a way to expand the shared field of meaning [60], [61].

1.3 Summary and Discussion

As stated earlier, this research intends to build a computational model of team–level creativity. This model describes two distinct processes: individual and team–level processes. The EII theory will be used in modeling individual creativity. We believe that it is an appropriate choice because it unifies previous models of creative problem solving and it was compatible with multiple behavioral experiments. However, there is not a comprehensive model to describe team–level creativity processes. A model of team–level processes needs to include communications between agents, the influence of agents on each other, and change–of–mind. Modeling communications between humans was a popular topic in different fields such as Cognitive Neuroscience (Section 1.2.1), communication sciences (Section 1.2.2) and Information Theory (Section 1.2.3). Ideas from all of these fields will be used for modeling different aspects of communication. For modeling the influence of agents on each other, we will borrow ideas from the Social Bayesian model that is presented in Section 1.2.1. The reason for choosing this model is its success in explaining both behavioral and fMRI data. To model change–of–mind, ideas from the neural circuit model that is presented in Section 1.2.1 will be applied. The reason for choosing this model is because it accounts for both neural imaging and behavioral data. Finally, we will use the widely used communication network models in Section 1.2.2 to structure interactions and noise between agents. The next chapter explains the details of using these models in building a model of team–level creativity.

2. PROPOSED MODEL

This chapter proposes a model of team–level creativity. First, Section 2.1 presents the details of the model for an individual and a team. Then, Section 2.2 justifies the proposed model and explains how the proposed model is related to the previous models that are presented in Chapter 1.

2.1 A Model for Team–level Creative Problem Solving (TCP)

In this proposed model, the focus is on creative problem solving by two or more agents who are communicating with each other. This model works based on the following scenario: first, each agent receives a representation of a problem and tries to solve it in isolation. Then, all agents participate in a meeting and share their found *solutions* (if any) along with their confidence in those *solutions*. Agents, under the influence of other team members, might change their confidence, which ultimately can lead to an agents' change–of–mind. When all agents have one solution in their mind, then that solution will be considered as team output. In future meetings, other solutions will be discussed and new meetings are held until reaching the pre-defined maximum number of meetings. The final output of the team is all the *solutions* that the team members agree on during the meetings.

2.1.1 Modeling Processes in an Individual Agent

The first step is a model of an individual agent who sends and receives information. An individual agent needs to do creative problem solving, determine confidence in solutions, and have the ability of change–of–mind. For including these characteristics, the previous models that are presented in Chapter 1 are incorporated. Each individual agent in the TCP model consists of three modules: Explicit–Implicit Interaction (EII), Uncertainty monitoring, and Speech. A schematic view of this model is presented in Figure 2.1. For simplicity, at this point, we assume that there are only two possible solutions for each problem.

The individual part of the TCP model works based on Algorithm 1. First, each agent receives a representation of a problem and by applying the EII module tries to solve the

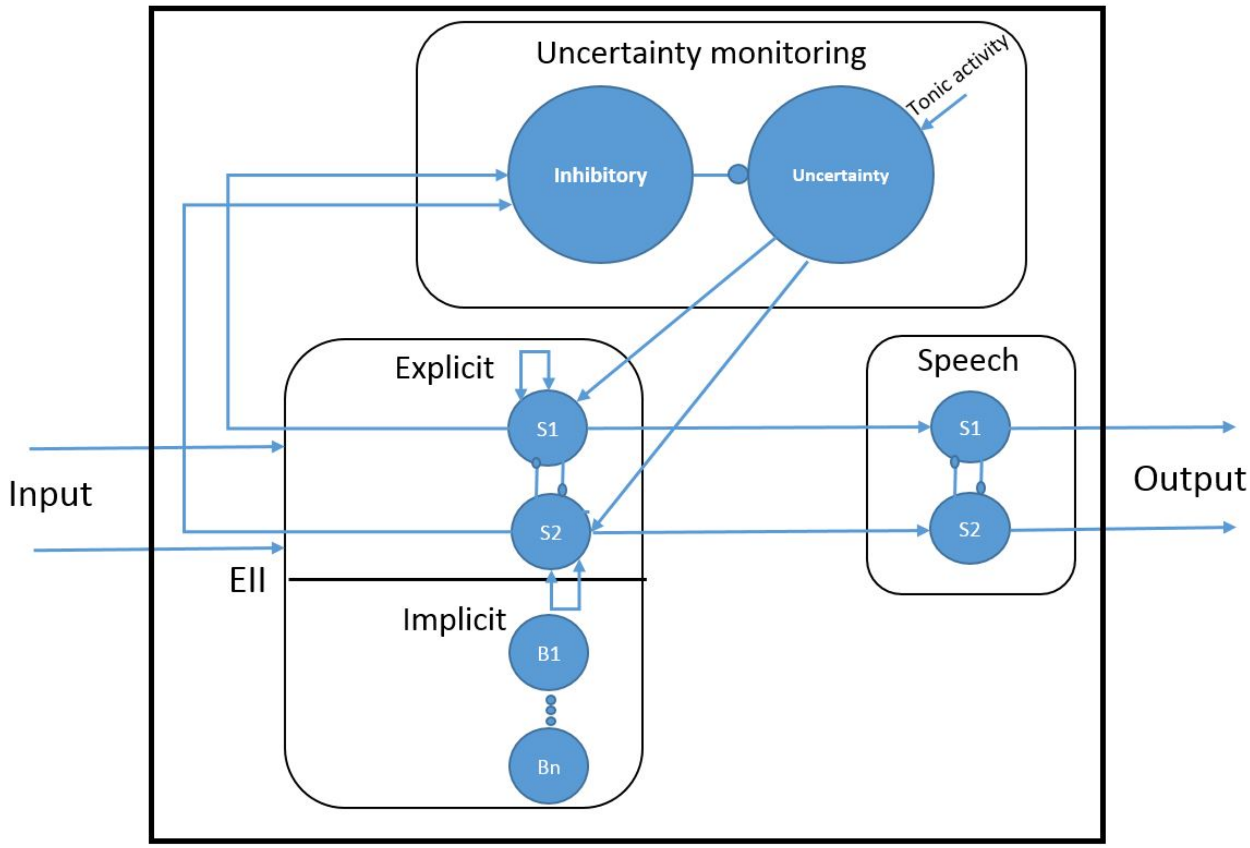

Figure 2.1. The individual agent
section of the TCP model. It includes three modules: EII, Uncertainty monitoring, and Speech modules in an individual agent who interacts with other team members. 'S1' and 'S2' represent *solution* 1 and *solution* 2 respectively. The input can be a problem (prior to meetings) or received information from other team members.

problem in isolation. If the activity of a *solution* in the Explicit EII[1] passes the EII threshold (ψ) then the agent is successful in finding a *solution* (Subsection 1). Then, the agent after receiving signals from the Uncertainty module may change her mind and find a new *solution* (Subsection 1). Finally, if the activity of one or more *solutions* in the Speech module exceeds the Speech threshold, then in a meeting, the agent talks about the *solution* that she has found (Subsection 1).

[1]↑the Explicit EII refers to the explicit level of the EII module.

input : 1- Representation of a problem:

a) Count of nodes in the EII Explicit left layer,

b) Count of nodes in the EII Explicit right layer,

c) Connections between EII Explicit nodes.

output: Normal(*solution number*, Inverse(confidence)) or Null

The agent attempts to solve the problem prior to the meetings:

while *activity (confidence) in each solution in the Explicit EII* $<$ *EII threshold* **do**

  if *time limit is not reached* **then**

    The EII module process the representation of the problem ;

    Run the uncertainty module ;

  else

    Output = Null (the agent is not successful in finding a *solution*) ;

    Break the While loop ;

  end

end

Speech module activity = ζ * Explicit EII activity

if *A solution's confidence in Speech module* $>$ *Speech threshold* **then**

  Output = Normal (The *solution's* number, 1/the *solution*'s activity);

else

  Output = Null (the agent was successful in finding a *solution*, but not willing to talk about the solution in the meeting) ;

end

return Output

Algorithm 1: Algorithm for modeling an individual agent who communicates with a team based on the model that is presented in Figure 2.1.

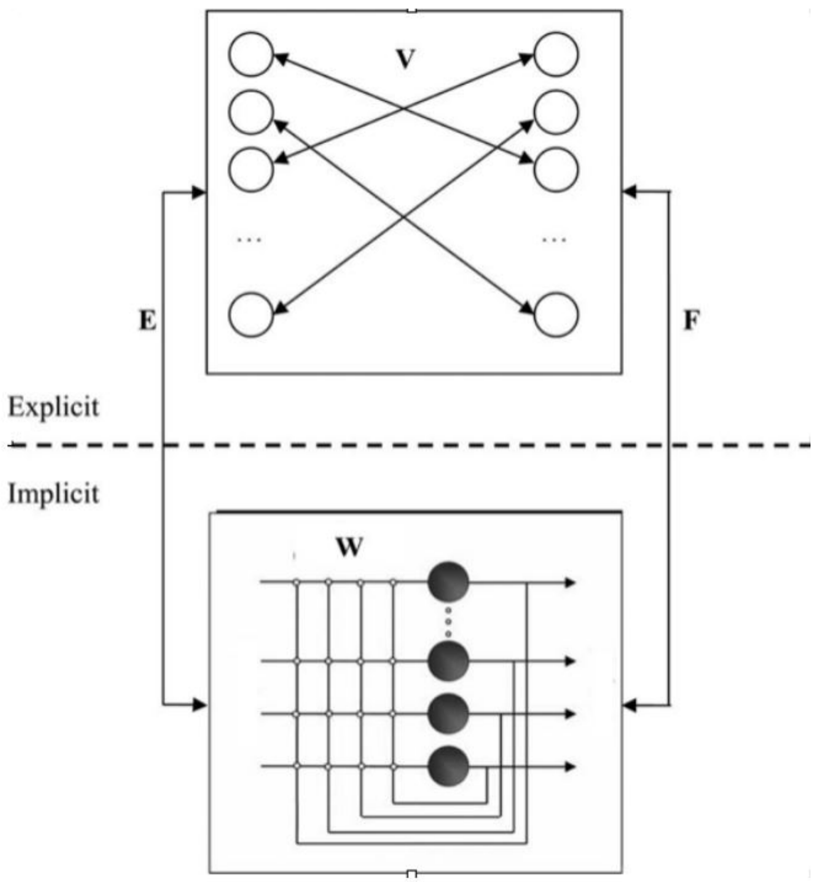

Figure 2.2. Implementation of the EII theory. The Explicit level is a two layer linear network and the Implicit level is a non-linear neural network (NDRAM). The figure is from Hélie and Sun [10].

Implementing the EII Module

The EII module is adapted from Hélie and Sun [10], and as explained in Section 1.1.2, it consists of two levels of processing: Explicit (top) and Implicit (bottom). Figure 2.2 presents this structure. The representation of a problem in the Explicit level can be implemented by a linear two–layer network: each node represents a concept or hypothesis, and a link between the left and right layer nodes is an explicit rule that relates these two concepts to each other. Each node in the left layer is one piece of knowledge that is required for solving the problem, and each node in the right layer represents one solution to the problem. In this modeling, it is assumed that the preparation stage is finished, and we are in the incubation stage. Therefore, the representation of the problem is modified from the preparation stage, and now all solutions in the right layer are relevant, and useful. The activity of each node in the right layer shows the confidence that the problem solver has in that node's corresponding solution. If this activity goes above the threshold ψ, then that solution comes into consciousness, and the problem is solved. These activities are changed in two ways: 1- propagation of activities from the Explicit left layer to the Explicit right layer using matrix V (change of confidence in the solution due to explicit processes). 2- propagation from the EII Implicit level to the Explicit right layer using matrix F (change of confidence in the solution due to implicit processes). In the following paragraphs, we explain this propagation and the corresponding matrices.

Matrix V in the Explicit level encodes the explicit rules. This matrix is pre-trained by using standard Hebbian learning [62] to to implement pre-existing (known) associations. This Hebbian learning rule ensures that the value of v_{ij} is one if there is an explicit rule that connects the i node in the Explicit left to the j node in the Explicit right, otherwise the value of v_{ij} is zero.

The activity of the left layer propagates to the right by using the following formula:

$$y_{\mathrm{i}} = \frac{1}{k_{\mathrm{i}}} \sum_{\mathrm{j}=1}^{n} \mathrm{v}_{\mathrm{ij}} \mathrm{x}_{\mathrm{j}} \tag{2.1}$$

where, $\mathbf{y} = \{y_1, y_2, \ldots, y_m\}$ and $\mathbf{x} = \{x_1, x_2, \ldots, x_n\}$ are activation of nodes in the right and left sides respectively. $\mathbf{V} = (v_{\mathrm{ij}})$ is a (simplified) explicit rule from node 'i' to node 'j'. k_{i} is the number of nodes in the left side that are connected to y_{i} in the right side.

In the Implicit level, implicit knowledge is encoded by the weight matrix 'W'. By using a contrastive Hebbian learning rule, the Implicit level is pretrained to learn implicit associations [10], [63]. The associations between the EII Explicit and Implicit levels are encoded using two weight matrices: E and F. These matrices are trained using a similar linear Hebbian rule used in training V. These matrices translate the activity in the Explicit nodes to the Implicit nodes and vice versa. The implicit processes are based on training the non-linear neural network (NDRAM) with random patterns for each explicit association (rule). The activity of Explicit left layer is translated into activation of nodes in the Implicit level through matrix E. Next, NDRAM produces a pattern and then this pattern is translated into activation of corresponding solutions in Explicit right layer through Matrix F.

For implementing the Implicit level, a non-linear neural network, NDRAM with 'r' nodes is used as shown in the following equation:

$$z_{\mathrm{i}[t+1]} = g\left(\sum_{\mathrm{j}=1}^{r} w_{\mathrm{ij}} z_{\mathrm{j}[t]}\right) \tag{2.2}$$

where $\mathbf{z}_{[t]} = \left\{z_{1[t]}, z_{2[t]}, \ldots, z_{r[t]}\right\}$ represents the activity of nodes in the Implicit network at time t. $\mathbf{W} = (w_{\mathrm{ij}})$ is the implicit associations between node i and j, and g is a non–linear function. The nodes in the Implicit level are linearly linked to the corresponding (concept-wise) nodes in the Explicit level. Once the Implicit network converges or a time–limit is reached, the information is sent to the Explicit level based on the following equation:

$$y_{[\text{bottom-up }]\mathrm{i}} = (k_{2\mathrm{i}})^{-1.1} \sum_{\mathrm{j}=1}^{r} f_{\mathrm{j:i}} z_{\mathrm{j}} \tag{2.3}$$

where, $\mathbf{y}_{[\text{bottom-up}]\ \mathrm{i}} = \left\{y_{[\text{bottom-up}]\ 1}, y_{[\text{bottom-up}]\ 2}, \ldots, , y_{[\text{bottom-up}]\ m}\right\}$ is the bottom–up activation of the Explicit right layer nodes. z_{j} represents the activation of node j in the Implicit–level. $k_{2\mathrm{i}}$ is the number of Implicit–level nodes (in z), which are connected to

$y_{[\text{bottom-up }]\text{i}}$ $(k_{2\text{i}} \leq r)$ and $F = (f_{\text{ij}})$ is a weight matrix that connects the distributed Implicit–level representations to their corresponding Explicit right layer representations.

In the next step, each $y_{[bottom-up]\text{i}}$ integrates with the corresponding nodes in the Explicit right layer based on the following equation:

$$y_{S\text{i}} = \text{Max}\left[y_{\text{i}}, \lambda \times y_{[\text{ bottom-up }]\text{i}}\right] \tag{2.4}$$

where, $y_{S\text{i}} = \{y_{[\text{ S }]1}, y_{[\text{ S }]2}, ..., y_{[\text{ S }]m}\}$ is the integrated activity in nodes on the right side of the explicit level, and λ is a scaling parameter for determining the degree of being implicit in the task processing.

If the activity of one node in the explicit level is more than the EII threshold (ψ), then the corresponding concept to that node suddenly comes into consciousness and is known as insight. If the activity of more than one node passes the threshold, the node with the highest activity is selected as the output solution. The activity of this node is considered as IAL (Internal Activity level). Otherwise, a new iteration starts and before starting the new iteration, the activity of the right layer of the Explicit is sent back to the left layer and the activity of the Implicit level is kept and added to the bottom–up integration during the next iteration. By having the Uncertainty module in the TCP model, there is no need for using the Boltzmann distribution as stated in Section 1.1.2. In other words, in the TCP model, the activity of nodes in the Explicit EII are directly compared with the EII threshold.

Implementing the Uncertainty Module

The Uncertainty monitoring module (adapted from Atiya, Rañó, Prasad, *et al.* [49]) has two functions: measuring the overall uncertainty of all possible solutions and change–of–mind. As shown in Figure 2.1, the Explicit EII sends excitatory signals to the Inhibitory neural population of the Uncertainty monitoring module. The activity of the Inhibitory neural population is coordinated with the overall activity (confidence) of solutions in the Explicit EII based on the following equation:

$$y_{[inhibition]} = \beta \sum_{\mathrm{j}=1}^{m} \mathrm{y}_{S\mathrm{j}}, \tag{2.5}$$

where $y_{[inhibition]}$ is the activation of the Inhibitory neural population. β is a constant parameter, which may be different in each individual and affects the involvement of internal confidence. m is the number of nodes in the right layer of the Explicit EII. Because of the inhibitory connection between the Inhibitory and Uncertainty neural populations, the higher (lower) overall confidence in the Explicit EII results in lower (higher) activity in the Uncertainty neural population. It should be mentioned that the Uncertainty neural population also receives a constant tonic excitatory signal to prevent the network from a floor effect. The activity of the Uncertainty neural population is calculated by using the following equation:

$$y_{[uncertainty]} = -\theta \times y_{[inhibition]} + y_{[tonic]}, \tag{2.6}$$

where $y_{[uncertainty]}$ is the activation of the Uncertainty neural population, θ is a constant parameter that shows the effect of the inhibitory population on uncertainty, and $y_{[tonic]}$ is a positive parameter to prevent a floor effect.

The overall uncertainty can lead to change–of–mind. Change–of–mind is implemented by feedback loops from the Uncertainty neural population into the *solutions* in the Explicit EII. The Uncertainty neural population sends equal but noisy excitatory signals to each *solution* in the Explicit EII. This feedback signal changes the activity of the solutions, which may result in having the highest activity in a solution that was not selected before (change–of–mind). The following equation shows how change–of–mind happens:

$$y_{S\mathrm{i}} = y_{S\mathrm{i}} + \gamma \times y_{[uncertainty]} + R_N(\mu, \sigma^2), \tag{2.7}$$

where $y_{S\mathrm{i}}$ is the current activation of the solution 'i' in the Explicit EII, γ is a constant parameter that determines the effects of the uncertainty population on the Explicit EII. The R_N function produces normal random noise with a mean μ and variance σ^2 (noise). By applying Equation 2.7, activity of all solutions ($y_{S\mathrm{i}}$) is updated (each *solution* is assigned to each node). This update may change the order of solutions based on their activity. Therefore, a different solution might now have the highest activation, passes the EII threshold, and be selected as the output of the EII. In this model, we should note that the required knowledge (Explicit left nodes) and solutions (Explicit right nodes) are finite. We assumed the EII model passed the preparation stage. As a result, unrelated knowledge, solutions that are not accessible during the limited time of meetings, and solutions that are not useful are removed from the representation of the problem.

Implementing the Speech Module

Finally, there is a Speech module. This module is inspired by the motor module that is described in Section 1.2.1. It determines if the subject talks about her solution in the meeting or prefers not to talk. When a *solution* in the Explicit EII is selected (pass the EII threshold), then the associated node in the Speech module receives activity of the selected *solution* (Internal Activity Level (IAL)) based on the following equation:

$$y_{[S\mathrm{i}_{Speech}]} = \zeta \times IAL_{\mathrm{i}}, \tag{2.8}$$

where $y_{[S\mathrm{i}_{Speech}]}$ is the activation of the node in the Speech module, which is associated with the EII's selected node, ζ is a constant parameter that determines the relation between internal confidence (Activity) and external confidence (the confidence that the agent shows in the meeting). $y_{[S_{selected}]}$ is the activation of the selected node in the Explicit EII.

If the activity of a solution in the Speech module passes the Speech threshold (α_m), then the agent becomes confident enough to talk in the meeting and shares her *solution* and IAL to other agents (more detail in Section 1). Otherwise, the agent is silent in the meeting although she has found a solution to the problem. In the case of having several solutions above the Speech threshold, the agent talks about all of these *solutions* consecutively.

Modeling Communication Networks, Weights, and Updates

The next step is modeling the processes that are related to a meeting. In a meeting, each team member takes a turn and based on Algorithm 2, sends her *solution* and confidence in the form of a normal distribution to other team members. In other words, each message between two agents contains two values: a mean and variance. These two numbers let the receiver generate a Normal distribution based on the sender's distribution. Each receiver agent updates her own confidence immediately after receiving the new information. In other words, the agent pulls her distribution towards the weighted *solution* of other agents.

input : $N(\mu_{agent}, \sigma^2_{agent})$

output: $N(\mu_{updated}, \sigma^2_{updated})$

if *The agent's turn to talk in the meeting == True* **then**

The agent sends $N(\mu, \sigma^2)$ to all other agents.

else

#The agent receives a distribution and updates hers in two steps:

1- Adjusting the received distribution based on the weight of the connection from the sender:

$\mu_{adj} = (\sigma^2_{sender} * \mu_{w_{sender->receiver}} + \sigma^2_{w_{sender->receiver}} * \mu_{sender})/(\sigma^2_{sender} + \sigma^2_{w_{sender->receiver}})$

$\sigma^2_{adj} = (\sigma^2_{sender} * \sigma^2_{w_{sender->receiver}})/(\sigma^2_{sender} + \sigma^2_{w_{sender->receiver}})$

2- Updating the Agent's mean and variance based on the adjusted distribution:

$\mu_{updated=(\sigma^2_{adj} * \mu_{agent} + \sigma^2_{agent} * \mu_{adj})/(\sigma^2_{adj} + \sigma^2_{agent})}$

$\sigma^2_{updated} = (\sigma^2_{adj} * \sigma^2_{agent}))/(\sigma^2_{adj} + \sigma^2_{agent})$

end

return $N(\mu_{updated}, \sigma^2_{updated})$

Algorithm 2: The algorithm of sending and receiving of information in a meeting by an individual agent

In more detail, normal distributions and Bayesian inference are used to encode and integrate trust, input, and output of an individual agent. *solution* and inverse of confidence (activity of the *solution* node in the Speech module (C_m)) [2]are the mean and the variance of the normal distribution[3]: $N\left(\mu = S_{selected}, \sigma^2 = f(C_m)\right)$. f is a function that translates confidence into variance. C_m is confidence of the agent. There is an inverse relation between confidence and variance or in other words, a large variance indicates a low degree of confidence and a small variance indicates a high degree of confidence. Weights on the communication network are considered as priors and they represent trust or the influence of the sender agent (i) on the receiver agent (j) before transferring the information: $N\left(\mu = S_{[guess]}, \sigma^2 = f(C_{[\mathrm{ij}]})\right)$. $C_{[}$ij] is related to the influence of agent i on agent j. Each weight shows that the receiver predicts the sender's *solution* $S_{[guess]}$. In most cases, this prediction ($S_{[guess]}$) or bias is equal to the sender's *solution*, however, in the case of miscommunication this prediction is different from the sender's *solution*. $C_{[\mathrm{ij}]}$ is the inverse of the variance of the weight between agent i and agent j, and it shows the influence of the agent i on agent j.

2.1.2 Architecture of Communication Networks

As presented in Section 1.2.2, there are different architectures for networks of communication. These architectures may have significant effects on the outcome of a team. In the TCP model, a fully connected network is considered (e.g. a meeting in which all members can communicate with all other members). Figure 2.3 presents a fully connected network between three agents. As can be seen, the EII module receives the input and the Speech module manages the output.

In this model of communication, weights are directional and they show social influence. In other words, they are the degree of change in the receiver's output after listening to the sender's opinion.

[2]↑C_m is $y_{s\mathrm{i}}$ when i is the selected *solution* in the speech module.
[3]↑For simplicity, this research only considers normal distributions.

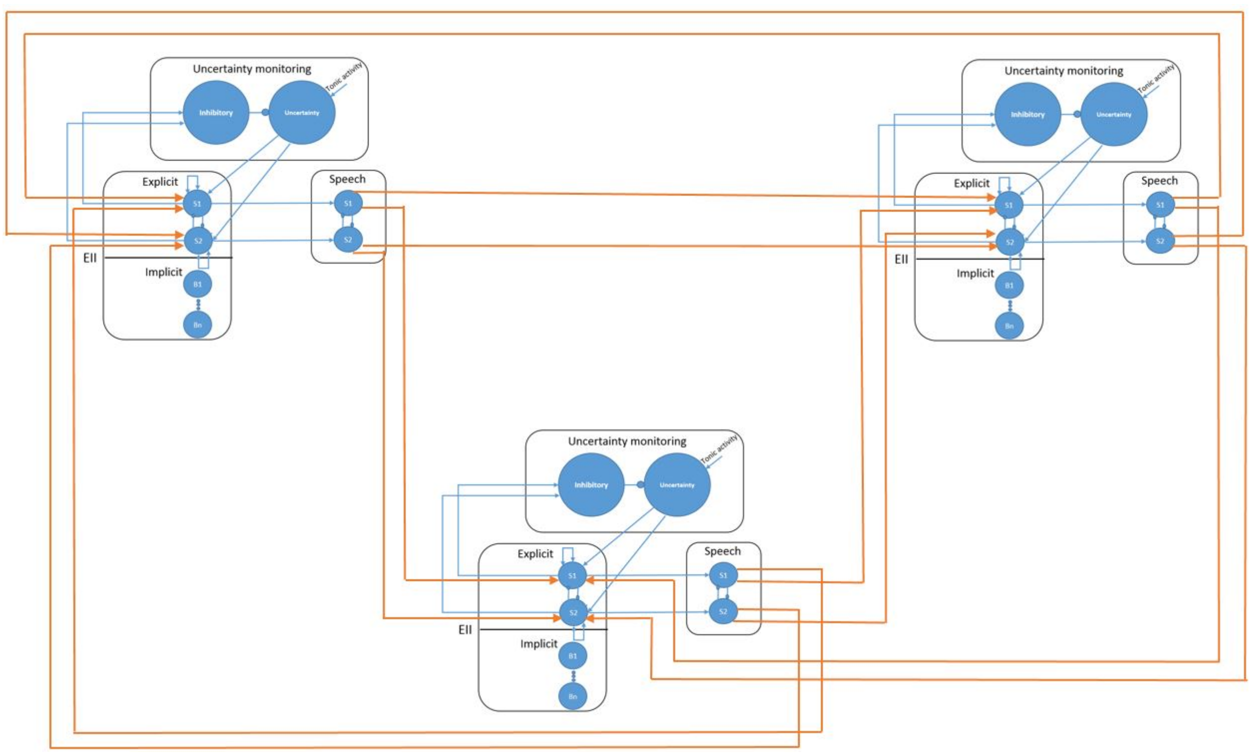

Figure 2.3. A fully connected communication network for a team of size three.

2.2 The Relation of the Proposed Model with Previous models

This section briefly explains how the proposed model is related to the previous models that are presented in Chapter 1.

Explicit–Implicit Interaction model (Section 1.1.2): the EII module is the core processing module of the TCP model. It simulates all processes that are involved in individual creative problem solving.

Bayesian Inference (Section 1.2.1): input, output, and weights (priors) are presented by normal distributions and integration of these distributions is based on Bayesian inference.

Neural circuit model (Section 1.2.1 of Chapter 1): the main architecture and algorithm of the proposed model are adapted from the neural circuit model. Similar to the circuit model, the TCP model consists of three modules with similar goals. Since the circuit model is compatible with cortical circuits (Section 1.2.1), the TCP model also partially represents biological circuits in the brain.

Communication networks (Section 1.2.2): a fully connected network is the most general architecture of networks. A fully connected network can easily be modified to other architectures by using ineffective weight values.

2.3 Discussion

This research aims to build the TCP model for human interactions and influence in the context of creative problem solving. The TCP model is formulated in terms of agent communication and influence. It is not meant to constitute a new individual creative problem solving model. We use the EII model in our work to obtain the output of an agent's problem solving process when it is performed in isolation. We then apply our proposed interaction and influence model to determine how team members agree on known solutions or identify new ones. the EII model underlies the individual processes in TCP, any features or limitations associated with the EII model are correspondingly transferred to the TCP model. As stated in [10], the simulations by EII focus on incubation and insight and are not on fine-grained modeling of the tasks. Similar to these simulations, the TCP model assumes the preparation stage is complete and simulates the processes of incubation and insight. The consequence of this assumption is that all solutions in EII are finite, relevant, and useful.

The TCP model assumes that a latent one-dimensional Normal distribution represents an agent's identified solutions. The solutions reside on a one-dimensional continuum, and can be ordered based on this dimension. If we have more than one group of independent solutions, a Multivariate Normal distribution is required in the modeling of solutions.

Although the output of the TCP model can differ from the outputs of the team members when they work in isolation, the underlying thinking process belongs more in the category of convergence rather than divergent processes. The solutions in EII are relevant, and the only possible outputs for the TCP model. Although some of these solutions may not be in the consciousness of any of the team members, the TCP model processes may lead to one of these solutions.

The parameters used in the TCP model were successfully used in previous research to model individual creative problem solving, uncertainty, change of mind, influence, and decision-making in a judgment task. Therefore, we assume that the parameters in the TCP model are relevant for capturing the essential characteristics of the type of cognition that we aim to simulate. We proceed to demonstrate in the next chapter that these parameters are adequate for replicating the results of three experiments and making additional predictions.

3. SIMULATION AND ANALYSES

This chapter presents four simulations that were implemented based on the TCP model. The first three simulations reproduce the results from human-subject experiments. The last simulation makes predictions on team performance. The general setup of these simulations is provided in Section 3.1. Our use of the simulation model to investigate the effects of emotions (Section 3.2), personality (Section 3.3), industrial organization factors (Section 3.4), and team size (Section 3.5) on team creativity are described in the remaining sections in this chapter. The first simulations (Sections 3.2, 3.3, and 3.4) involve the comparison of the outputs of the simulations to the corresponding human-subject experimental results. These experiments were selected because they capture team creativity in terms of both team-level and individual agent-level characteristics. The first experiment focuses on changeable characteristics of agents (e.g., happiness), and the second studies fixed characteristics (e.g., extroversion). The third experiment investigates team characteristics relating to communication (e.g., vision or discussions with individuals outside of a particular team). These three experiments ultimately enable us to test the TCP model with respect to different types of parameters at different levels.

3.1 Setup of Simulations

3.1.1 Description of Agents and Team Formation

All simulations in this chapter share the feature of individual agents who first solve a problem in isolation and then later form teams in which they can communicate with one another to identify solutions. This shared feature in the simulations motivated our decision to perform the simulations by generating a single pool of 6440 agents with random characteristics and then grouping them in teams across the different simulations.

To generate random agents, we focused on three main characteristics, which involve all three modules of an individual agent: the ability to find solutions, the ability to talk and share solutions in meetings, and the possibility of change of mind in isolation. The following parameters in an individual agent affect these characteristics and are selected in random:

the connections between the left and right layers of the EII (which determine the solution that an agent finds), the EII threshold ψ (which determines the minimum confidence the agent needs to bring a solution into consciousness), Speech threshold (which determines their ability to speak in a meeting), and Uncertainty feedback (which determines their frequency of changing their proposed solution). All these parameters are selected at random to produce agents with different random characteristics. The specified ranges used for choosing the parameters are described on Table 3.1 alongside all other parameters of an individual agent, which are fixed to facilitate the simulations. Only randomly selected parameters are used to define differences in agents. These parameters are selected to affect every module of an individual agent: 1- The parameters that are related to problem representation and the required confidence for having a solution in consciousness. 2- The parameter that affects the change of mind. 3- The parameter that influences the frequency of talking in meetings. To facilitate simulations, we selected fixed values for the rest of the parameters. Agents share similar characteristics in those parameters. For example, the degree of involvement of implicit processes in problem solving, which is controlled by the parameter β is fixed for all agents. The values of these parameters are either selected by using previous simulations of the EII model in Hélie and Sun [10] and Calic and Hélie [39] or by trial and error. The histograms of the Speech and EII thresholds are provided in Figures 3.1, 3.2.

3.1.2 Team Communication and Collaboration

Once teams are generated, the objective of our algorithm for team communication and collaboration is to simulate the dynamics of problem solving among the team members in a series of team meetings. The performances of the individual team members and the entire teams for solving randomly generated representation of problems will be obtained. The ultimate outcomes of interest are the performances of the teams. Finally, the results are categorized based on the requirements of each experiment and analyzed. Detailed information on these steps are provided in the remainder of this subsection.

This algorithm proceeds along three major steps. The first step occurs prior to any meeting, and just involves actions of the individual team members. The second major step

Table 3.1. Parameters used for generating an individual agent.

Parameter	Value
EII-Explicit Right nodes count	Uniform(2,20)
EII-Explicit Left nodes count	Uniform(2,10)
v_{ij}	Bernoulli(0.1)
EII threshold (ψ)	Uniform(0,1)
Speech Threshold	ψ + Uniform(0, 0.1)
EII-Implicit nodes count	500
EII-Implicit nodes associated to EII-ExplicitLeft	400
λ	0.4
λ_r	0.75
δ	0.4
xi	0.4
η	0.4
EIIImplicit-spines-learning	0.4
EIIImplicit-spines-recall	0.4
EIIImplicit-learn-iterations	0.4
EII-timeLimit	100
β	1
θ	1
ζ	1
μ_{R_N}	0
σ_{R_N}	Uniform(0, .1)
γ	1
$y_{[tonic]}$	EII-Explicit Right-nodes count

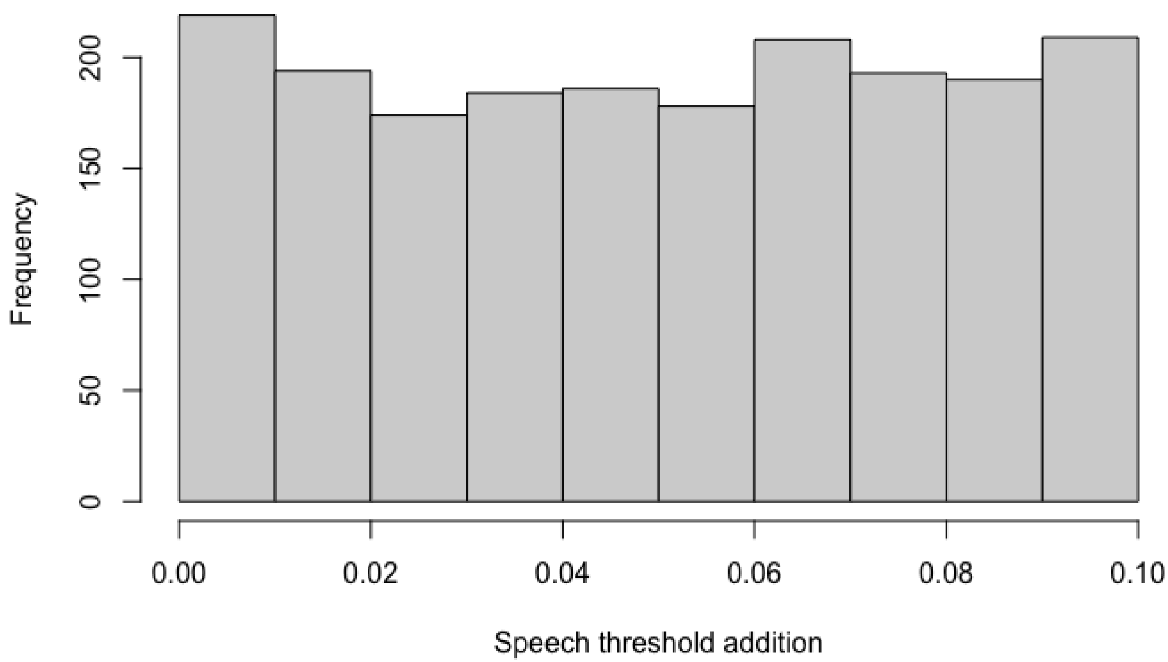

Figure 3.1. Histogram of the values that are added to the EII threshold to generate the Speech threshold for our simulations (The speech threshold is the summation of the EII threshold and a randomly generated value.)

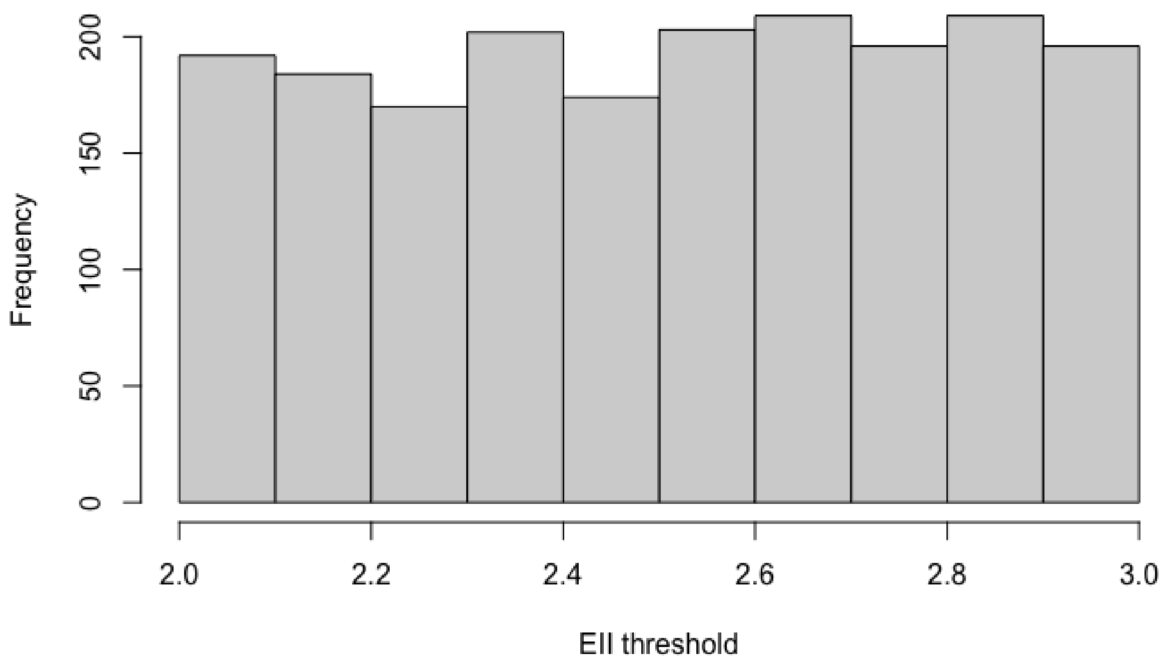

Figure 3.2. Histogram of EII threshold parameters.

captures the interactions of the team members in their meetings. The final outcome variable of interest is defined in the final step. Before the first team meeting, a problem is assigned to each team and the team members work on the problem individually. The problem is the same for all team members, however the agents use different representations of the problem Sternberg [64]. In other words, the number of nodes in the Explicit right and left layers are the same for all team members, but the connections between left and right layer (explicit rules) are different, which provide the agents with different representations of the problem. In more detail, the simulation of each problem is performed by means of the EII system (Section 2.1) and consists of two parts: knowledge and solutions. Each piece of knowledge in our problem simulation is represented by a node in the left layer of EII, and each solution is represented by a node in the right layer (Figure 3.3). The number of left and right nodes are randomly generated. Although agents may have different rules, knowledge, and solutions in general, to facilitate our simulations we assume all the knowledge that agents require for solving a problem are available in the problem itself. Thus, the left and right layers of the EII will be the same for all agents for a single problem given to them, all the nodes in the left layer will have the same numerical value of "1", and the connections between the left and right layers will differ across agents because the agents' rules may differ. Consequently, some solutions may not be accessible for some agents. The individual agents' solutions are obtained by executing the EII system. We represent the output of an agent as a Normal distribution with mean corresponding to the solution number and variance corresponding to the inverse of the activity or confidence in the solution. Two agents whose output means are the same are said to have identified identical solutions. Our selected representation of a problem in our algorithm is compatible with the definition of problems given by newell1959, namely, as initial state (knowledge), final states (solutions), and the rules used by the problem solver in identifying a path to a final state from the initial state. The network of Explicit EII is more similar to a semantic network than a neural network. Accordingly, we assume that each node represents a concept without focusing on having a precise concept definition.

It should be noted that the scope of the TCP model is limited by only allowing the simulation of solutions that can be ordered by a shared meaning. For example, in the problem of sharing a new space between an owner of an ice-cream shop and a bakery, the solutions can start from entirely favoring the ice-cream shop owner to entirely favoring the bakery shop owner:

1. All the new space is given to the ice-cream shop owner.
2. The new space is given to the ice-cream shop owner, but she put shelf and sells bakery products.
3. The shop is given to the ice-cream owner in six warm months and the bakery in 6 cold months.
4. The new place is given to the bakery, but they put a fridge and sell ice cream.
5. All the new space is given to the bakery.

Another example of an ordered solution is as follows. Many smartwatches face battery charging problems. They need to be charged a few hours every day that stops the owner from having a complete record of her activity or sleep. It can make the report ineffective or useless in some cases. The solutions to this problem range from entirely depending on the owner to entirely depending on the company:

1. The owner for charging the battery needs to find a time that is not affecting her performance (e.g., the owner charges the watch whenever she sits and uses her computer).
2. The company bans battery demanding software (e.g., the software that use vibration); now the battery will last for a few days, but the owner cannot use some software.
3. The company adds more powerful batteries to the watch that can work for a week; then, the owner does not need to charge the battery frequently.
4. The company needs to develop a new series of batteries that can be charged by hand movement. Therefore the owner does not need to charge the battery.

When agents in TCP talk to each other or pull each other's solutions toward their own solutions, they may stop on solutions that were not accessible to any of the team members at first. Furthermore, all solutions in the Explicit right layer of EII have some degree of creativity (we assume the preparation stage passed and relevant and useful solutions have remained in the incubation stage). Therefore, we argue that the TCP model is more than a consensus model. In addition to being a consensus model, it provides the team with the possibility of identifying creative solutions that were not available to any team members at first.

In the series of meetings that follow the first major step, all team members will join team meetings and share their individual solutions and confidence levels for their solutions. They will also further communicate about the problem with one another. During these meetings the team members can potentially change each other's proposed solutions and confidence levels for the newly selected solutions. Algorithm 3 formally describes the procedure taken by the team members when they join the meetings. In this procedure, each agent will send the mean and variance of her distribution to the other agents, which corresponds to communication about the solution. The other agents will receive the means and variances and update the mean and variances of their respective Normal distributions. The meeting is concluded once all agents have spoken. We assumed that agents do not work on the problem between two meetings. If no solution is identified by the team members in the first meeting, then they will not have any additional meetings, and it will be recorded that the team had only one meeting. Otherwise, the team will continue to have new meetings until all agents come to a consensus and select the same solution. The chosen solution is then removed from the right layer and the process is repeated for the same problem to identify new solutions. We place an upper limit of 20 on the total number of team meetings, irrespective of the number of solutions. It should be noted that the order of agents' talks remains the same in all meetings, i.e., the agent who talks first in the first meeting will also talk first in the rest of the meetings.

The weights of the connections between agents is a normal distribution with randomly generated variances. We assumed that agents do not have bias and difficulty in understanding each other, therefore the mean of the weight is the same as the mean of the sender. The variance or trust between the two agents is generated randomly from a Uniform distribution in the range of 0 and 1. The histogram of the weights that are used in one simulation is provided in Figure 3.4

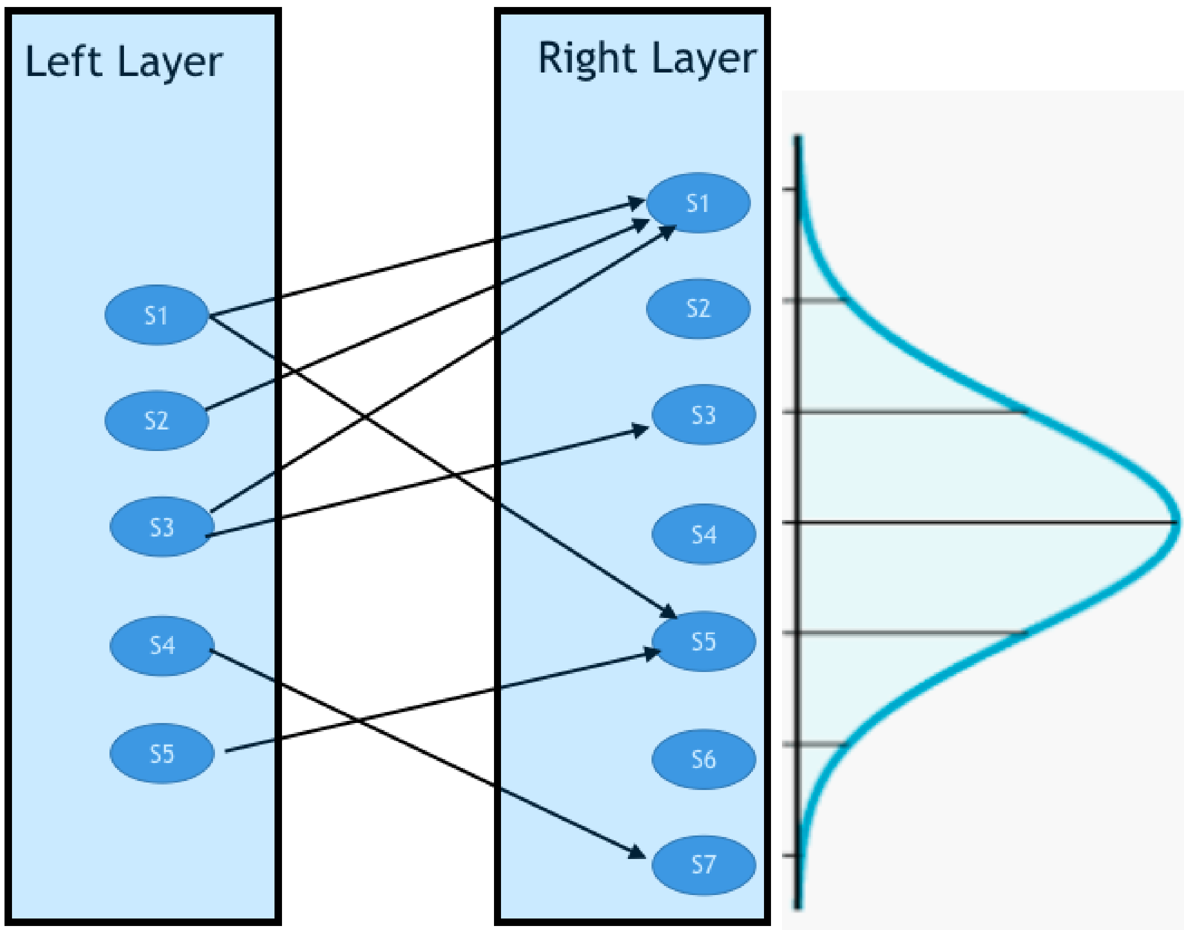

Figure 3.3. Illustration of the EII system used to simulate the problems that are assigned to the team members. Connections from the left to right layers represent rules that enable one to determine which piece of knowledge (left nodes) will lead to which solution (right nodes). Identifying each solution requires some specific knowledge. The right layer node's number with the highest activity becomes the mean, and the inverse of the node's activity is the variance of the normal distribution.

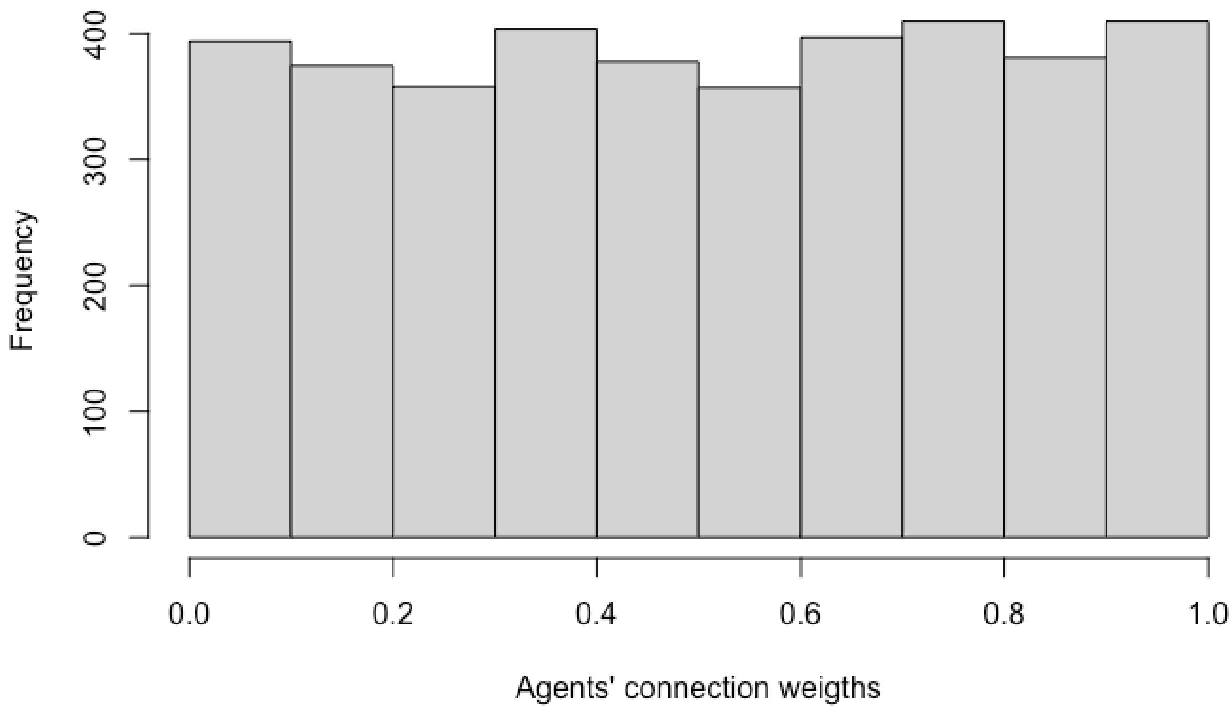

Figure 3.4. Histogram of the variance of the weights between the agents.

Each simulation used a different team with randomized agents and problem representations. The individual simulation results were averaged. Therefore, the model is not limited to specific team members' characteristics and representations of problems. This ensures the generalizability of the results.

The final outcome variable for a team is the summation of the non-negative creativity scores of the solutions that the team members identified. We assume all solutions in EII passed the preparation stage, and as result, only related and useful solutions have remained in the incubation stage. The solutions are assumed to be equally related and useful. Therefore, novelty is the determining factor for creativity. Novelty falls on a continuum and is determined by the rarity of the solution. We assign creativity scores to the different possible solutions based on the idea described in Calic, Hélie, Bontis, *et al.* [11] that less obvious or less accessible solutions often correspond to higher creativity. In our algorithm, solutions that have fewer connections will be less likely to be selected. We take the average of the number of connections to each solution for all agents in the team, and calculate the reverse ranking of the solutions based on the number of connections. Under this reverse ranking, the solution with the least connections will have the highest rank. The ranks serve as the creativity scores of the solutions. Our specified variable will ultimately capture the performance for the success of the team. Higher creativity scores indicate better performance. We first identify appropriate ranges for the parameters' possible values so as to select a simulation model that adequately reproduces the results of the kung2018impact experiment. To choose the ranges, we examined insight problems conducted by helie2010incubation and calic2018creative. Based on this examination, the upper bound for the number of nodes in the left and right layers were selected as $m = 20$ and $n = 10$, respectively. We then randomly connected left and right nodes based on the Bernouilli distribution with parameter 0.1, i.e., the probability that a left node is connected to a right node is 0.1 and the connections between left and right nodes are independently generated.

input : Agents and a problem

output: Total Creativity score

number-of-meetings = 0 ;

creativity–score = 0 ;

while *number-of-meetings < 20* **do**

  while *At least one agent has a different mean (solution)* **do**

    #Meeting starts:

    for *Agent* i $\in (1, n)$ **do**

      #Agent i talks and sends her mean(m_i) and variance(v_i) to all other agents ;

      for *Agent* j $\in (1, n)$ *and* j $\neq$ i **do**

        #before the agent receives, m_i and v_j are modified by trust between agents i and j ($w_{ij} : (m_{ij}, v_{ij})$)

        $m_{received} = (v_i * m_{ij} + v_{ij} * m_i)/(v_i + v_{ij})$

        $v_{received} = (v_i * v_{ij})/(v_i + v_{ij})$

        #Updating Agent j's mean(m_j) and variance (v_j):

        $m_j = (v_{received} * m_j + v_j * m_{received})/(v_{received} + v_j)$

        $v_j = (v_{received} * v_j)/(v_{received} + v_j)$

      end

    end

    Increase number-of-meetings by 1

  end

  creativity–score = creativity–score + score of the agreed solution

  #Preparing agents for next meetings:

  Remove the agreed solution from all agents

  Each agent selects her most active solution as her mean and inverse of the solution's activity as her variance.

end

return creativity–score

Algorithm 3: The general algorithm used in simulations for team communication and collaboration.

Table 3.2. Sample phrases that subjects in the experiment of Kung and Chao [65] were instructed to use to express anger and happiness.

Angry Condition	"this offer makes me really angry; I think I will offer. . ."	"this offer is really getting on my nerves! I'm not happy at all."
Happy Condition	"I am happy with this offer; I think I will offer. . ."	"this offer pleases me much! I'm very happy."

3.2 Analysis of Simulation 1: Effects of Emotions on Team Creativity

Our first analysis utilizes our simulation model to reproduce the results from a human experiment with respect to the effects of emotions on team creativity. This analysis serves to validate the simulation model in terms of the factor of emotion.

3.2.1 Description of the Experiment

kung2018impact performed an experiment to study how mixed emotions affect creativity in groups of two people (i.e., dyads). The experiment involved a face-to-face dyadic negotiation between two randomly assigned subjects. Prior to the negotiations, subjects were given negotiation packages that contained instructions for emotional manipulation. Some of the negotiation packages were randomly selected to instruct the subjects to express happiness during the negotiations, and the remaining packages instructed the subjects to express anger. This intervention was applied by means of instructions in the negotiation packages for the subjects to use phrases such as those in Table 3.2 to express either happiness or anger during the negotiations.

After practicing their role, the subjects completed a dyadic standardized negotiation task referred to as the "The Sweet Shop". In this task, one subject's role is as the owner of an ice cream shop, and the other's is as the owner of a bakery shop. The subjects are tasked to plan to share a space in a new location. However, there are four core issues involved in the task: temperature, staffing, maintenance, and design. Two optional issues also exist that must be resolved by negotiations: website design and delivery plans. Two to five solutions exist for each of the core issues, and subjects are not prevented from reaching any of the potential solutions. Points were assigned to each solution based on the creativity level involved in the solution, and the creativity performance of the dyad is measured by the sum of the individual gains for the two negotiators.

The experiment consisted of 105 total dyads: 37 happy-happy subject pairs, 35 angry-angry subject pairs, and 33 happy-angry pairs. The analysis of the experiment focused on the comparison of the emergence of creativity in the three different dyad groups against the zero-sum threshold. The summary of the results in Figure 3.5 indicate that the joint gains in mixed emotion dyads are statistically significantly higher than the zero-sum threshold. The other groups did not reach such statistical significance. Furthermore, based on exploratory pairwise comparisons involving Fisher's Least Significance Difference Kung and Chao [65, p. 7], the authors identified a statistically significant difference between mixed emotions and happy-happy emotion dyads.

3.2.2 Details of Simulation

The simulation algorithm for this case involves two agents per team who either demonstrate the characteristics of anger/unwillingness to cooperate, or happiness/easy-going in negotiation. The agents will try to agree on one solution in a fixed time period. The creativity score of the solution is be recorded, and the score is zero in the case that the agents do not agree on one solution. This process is repeated for 644 random dyads who work on distinct problems. The average score across the random dyads is reported. A problem is different from other problems in the knowledge it needs for solving the problem and the achievable solutions. Each agent has her representation of the problem by having different rules or connections between knowledge and solutions in her mind. Using the random representation of problems helps generalize the results and does not restrict us to one specific problem.

Model parameters that enable us to simulate anger and happiness in the agents are determined so as to respect the following two definitions of these emotions given by [p. 4]kung2018impact:

- "An angry negotiator tends to appear tough. Although the display of anger sometimes elicits more concession from the negotiation counterpart."

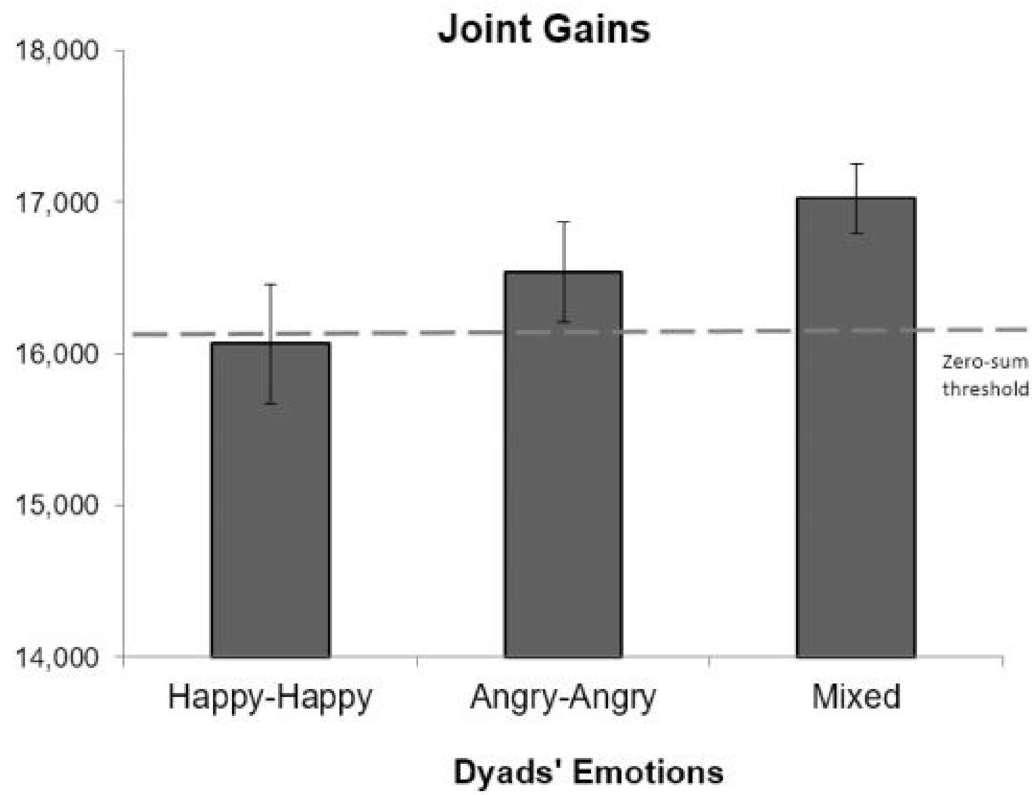

Figure 3.5. Average joint gains (i.e., average points earned by a dyad) for each of the dyad groups. The zero-sum threshold is defined so as to distinguish betwen creative and non-creative dyads. This figure is taken from Kung and Chao [65, p. 7].

- "A happy negotiator seems easygoing. The display of happiness can sometimes lead the counterpart to cooperate, implement the final agreement, and be willing to negotiate again in the future."

The two major characteristics of anger in the above definition are "appear tough" and "more concession from the negotiation counterpart". Appearing tough implies that an agent will have a smaller likelihood of changing her mind, or being under the influence of other team members. This characteristic can be achieved by selecting a large value for the variance of inward connections, as it makes the output from other team member less impactful on the angry agent. The second characteristic can be induced in the simulation model by selecting a small value for the variance of outward connections, as this results in the angry agent becoming more impactful and having a greater likelihood of changing the mind of the other team member. Similar to the case of anger, happiness involves two major characteristics of being "easy-going" and making the counterpart agent "more cooperative". These two characteristics can be induced in the simulation model by selecting a small value for the variance of both inward and outward connections. This is because both agents will have a higher degree of influence on each other under this situation. Specifically, a small variance on inward connections encourages the happy agent to quickly change her mind towards her counterpart's solution, and a small variance for outward connections similarly pulls the counterpart agent's mind more towards the happy agent's solution.

In this simulation, all the parameter values are similar to the ones explained in Section 3.1, the only additional parameters that we need are thresholds on weights' variances to determine the following connections (sender-to-receiver): happy-to-happy, happy-to-angry, angry-to-happy and angry-to-angry agents. These variances are dependent on both the outward connection from the sender and the inward connection to the receiver. Therefore, the happy-to-happy connection has a low variance (a happy sender highly affects the receiver and a happy receiver is highly affected by the sender). Similarly, we have a low variance for angry-to-happy agents. However, the angry-to-angry and happy-to-angry connections have a medium variance. By trial and error, we chose the threshold of 0.5 to determine a low variance and 0.76 to determine a large variance. Variances between 0.5 and 0.76 are

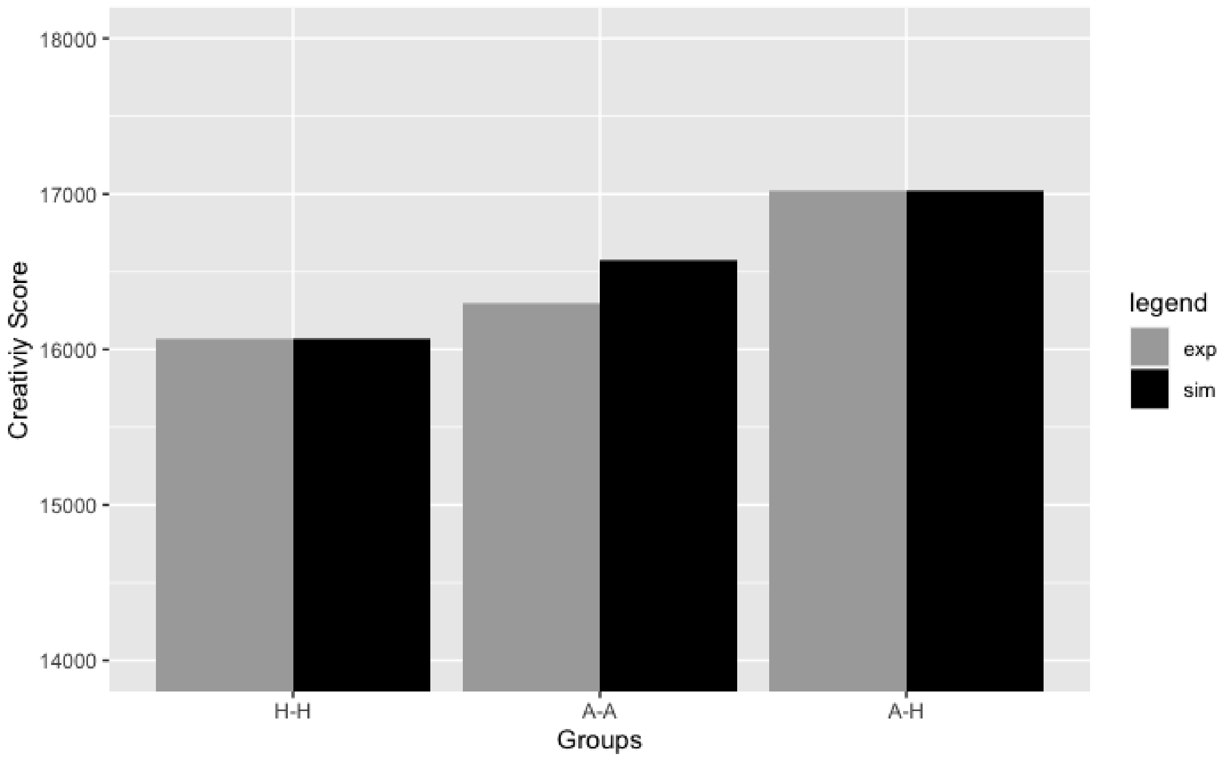

Figure 3.6. Simulated the results of the experiment by Kung and Chao [65].

considered as medium. Figures 3.6 summarizes the results of this simulation. The creativity score is linearly mapped to the range of the creativity score that is used in the experiment (Figure 3.5). As demonstrated in Figure 3.6, Happy-Happy teams receive lower creativity scores compared to Angry-Angry teams, which corresponds to the results from Kung and Chao [65]. The RMSD value is calculated. It is 91.58, which is small in comparison to the (14000,18000) range of creativity score. Furthermore, we investigate the relation between agent's connections to each other and creativity score. The results are provided in Figure 3.7. This figure demonstrates that when connections have similar values (i.e., similar variances), creativity scores are at their lowest values. Furthermore, as the difference between the values of the variances of the two connections between the agents becomes large, the creativity scores increase.

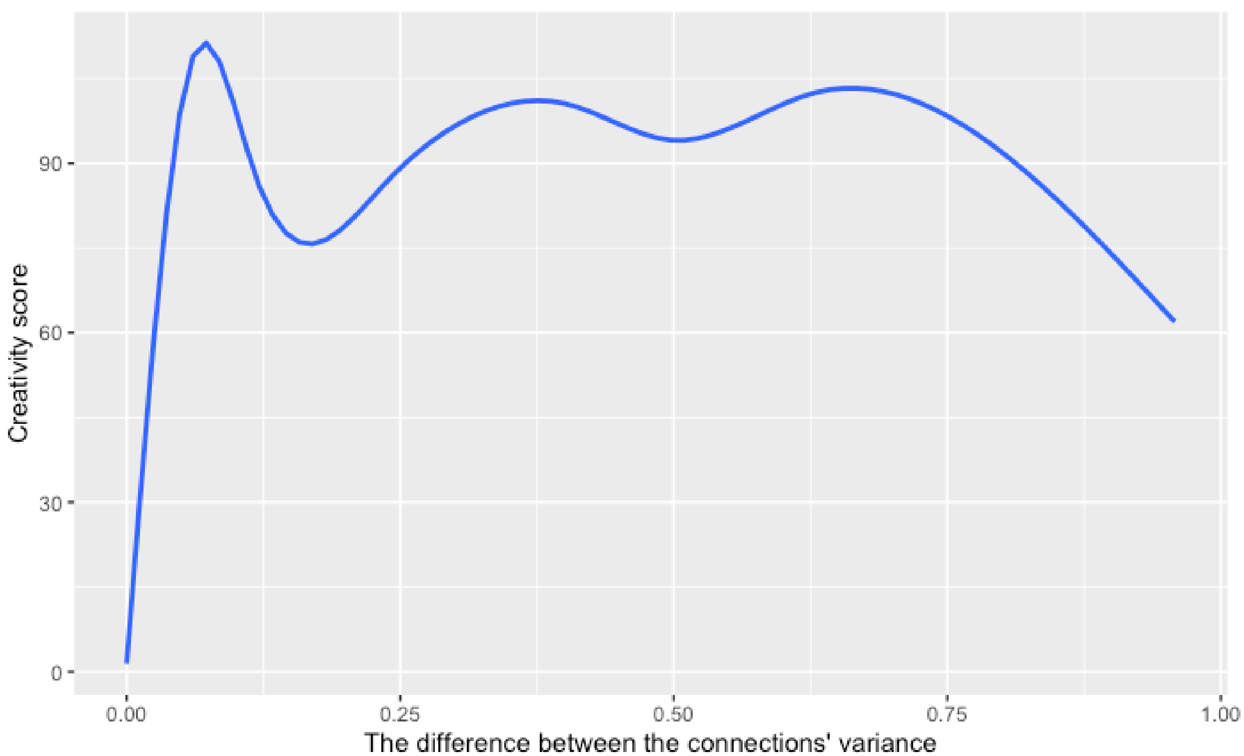

Figure 3.7. Illustration of the relation between differences in connections and team creativity.

3.2.3 Discussion

The results of the Kung and Chao [65] experiment shows that there is a difference between happy-happy and mixed emotions groups. We suggest that this result is due to the difference between inward and outward weights. If the weights are more similar, which would lead to lower creativity scores in Angry-Angry and Happy-Happy teams. Specifically, similar weights would lead to teams that lack agents who could convince others easily, and hence a great deal of back-and-forth on ideas that will take time for the teams to conduct. At the end of such processes, the teams would have agreed on fewer solutions. In other words, both the Happy-Happy and Angry-Angry teams have similar variances on the connections between the two agents, which lead to them earning lower creativity scores compared to mixed emotion teams who have different variances on the connections between the two agents.

3.3 Analysis of Simulation 2: Effects of Personality on Team Creativity

3.3.1 Description of the Experiment

Personality factors are essential for modeling human-like social agents and creating diversity in multi-agent systems. It is believed that personality is stable over decades in life in nearly every setting McCrae and John [66]. One of the most popular theories of personality is the Five-Factor Model Prada, Ma, and Nunes [67]. In this model, people's specific behaviors are captured by means of the five dimensions of extroversion, agreeableness, conscientiousness, neuroticism, and openness to experience. These dimensions are described as follows:

- Extroversion can be described as self assured, sociable, and talkative Baer, Oldham, Jacobsohn, *et al.* [6] and McCrae and Costa Jr [68]. extroverts are comfortable with expressing their ideas and they do not fear of being criticized by other team members Thoms, Moore, and Scott [69].
- Agreeableness relates to the degree to which agents agree, encourage, and assist others on their term. For example, an agent possessing high agreeableness will agree more often with other team members, will encourage them, and will perform more actions

for the benefit of the entire team rather than for herself Baer, Oldham, Jacobsohn, *et al.* [6].

- Conscientiousness refers to both the degree to which an agent is under the influence of the successful members of her team, and the amount of effort she puts into a task. For example, an agent with a high degree of conscientiousness is more influenced by her successful team members and not particularly influenced by the less successful team members, and she puts more effort into performing a task. High conscientiousness is associated with a higher likelihood of success Prada, Ma, and Nunes [67].

- Neuroticism is defined as the extent to which an agent attaches value to negative events compared to positive events. An agent with a high degree of neuroticism gives more value to negative events Baer, Oldham, Jacobsohn, *et al.* [6].

- Openness to experience can be described as broad minded, original, imaginative and curious Baer, Oldham, Jacobsohn, *et al.* [6] and Costa and McCrae [70]. People with higher degrees of openness are insightful and they experience unusual thought processes McCrae and John [66].

baer2008personality conducted an experiment to study the effects of the five personality factors on team creativity. The participants in this experiment first completed a survey to assess their personalities. They were then randomly grouped into teams of size three. Each team worked on an idea generation task across two sessions in which they were asked to generate as many creative solutions as they possibly could to different problems in the sessions. Each subject reported their confidence in their team's performance after the first session. The "team creative confidence" score was calculated based on the reports given by all members of a team. At the end of the experiment, an expert rated the solutions of each team across both sessions based on the level creativity involved in the solutions. The results of this experiment in high confidence cases are summarized in Figures 3.8, 3.9 and 3.10. These graphs demonstrate that generally the teams with high confidence perform better in the second session if they have more members with high openness, high extroversion, and low conscientiousness Baer, Oldham, Jacobsohn, *et al.* [6]. In addition, these results did

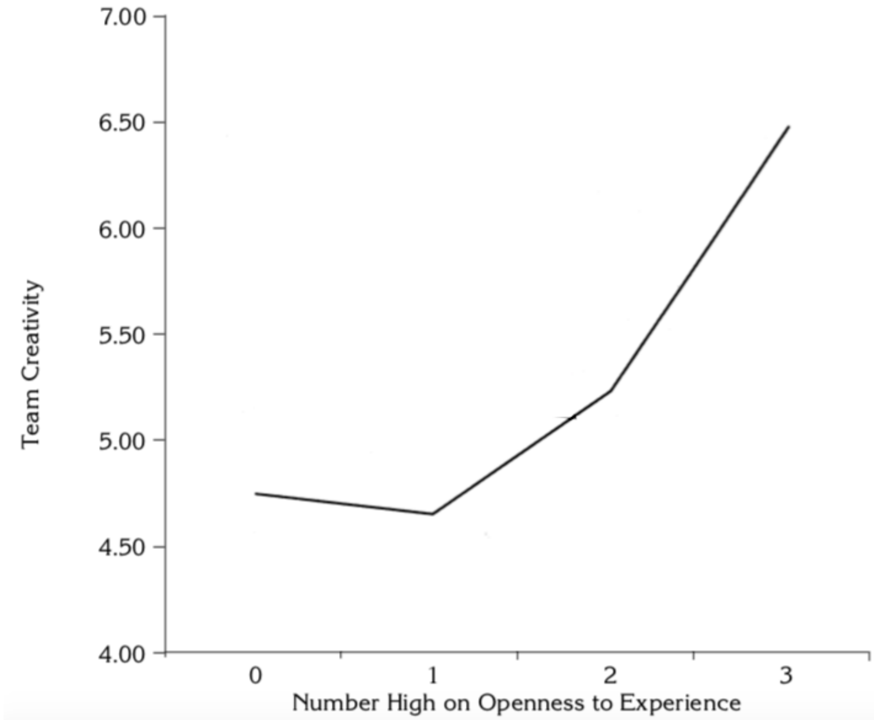

Figure 3.8. The effect of high openness on creativity of high confidence teams; adapted from Baer, Oldham, Jacobsohn, *et al.* [6, p. 270].

not provide any significant evidence for the effects of neuroticism and agreeableness on team performance in the second session.

3.3.2 Details of Simulation

Some aspects of personality have previously been simulated using the EII model. calic2018creative conducted a simulation study on the effects of paradox[1] on creativity of individuals with different thinking styles. Each thinking style included some of the personality factors, and was determined by the degree of integration (i.e., "the search for new and novel information") and differentiation (i.e., "the tolerance of novel ideas"). An individual with greater integration and/or differentiation is described as being more complex Calic and Hélie [39,

[1]↑Examples of paradox in management are being efficient and effective Van Thiel and Leeuw [71]; being competitive and also showing cooperation Brandenburger and Nalebuff [72]; making the company profitable and charitable Hahn, Preuss, Pinkse, *et al.* [73], and explore and exploit Andriopoulos and Lewis [74] and March [75]. It is believed that adapting adopting paradoxical frames can increase creative output Calic, Hélie, Bontis, *et al.* [11].

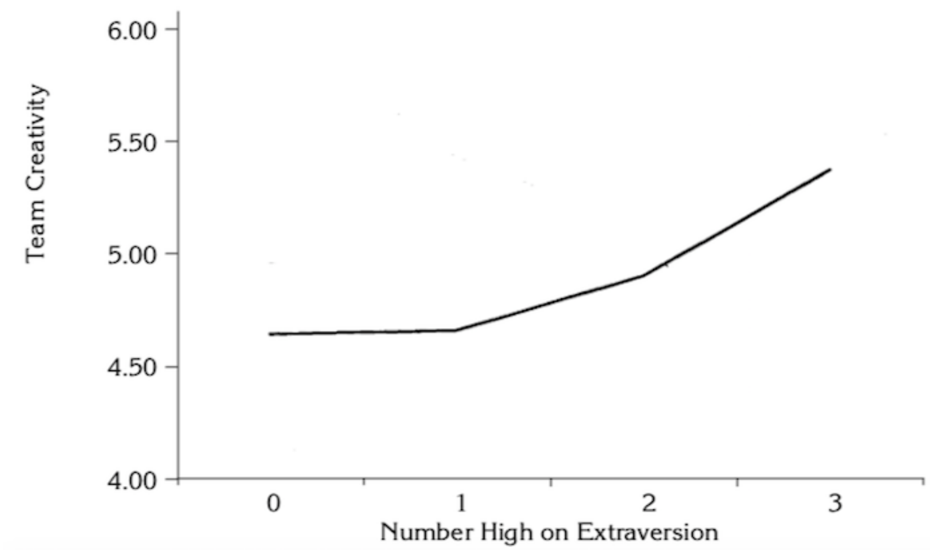

Figure 3.9. The effect of high extroversion on creativity of high confidence teams; adapted from Baer, Oldham, Jacobsohn, *et al.* [6, p. 271].

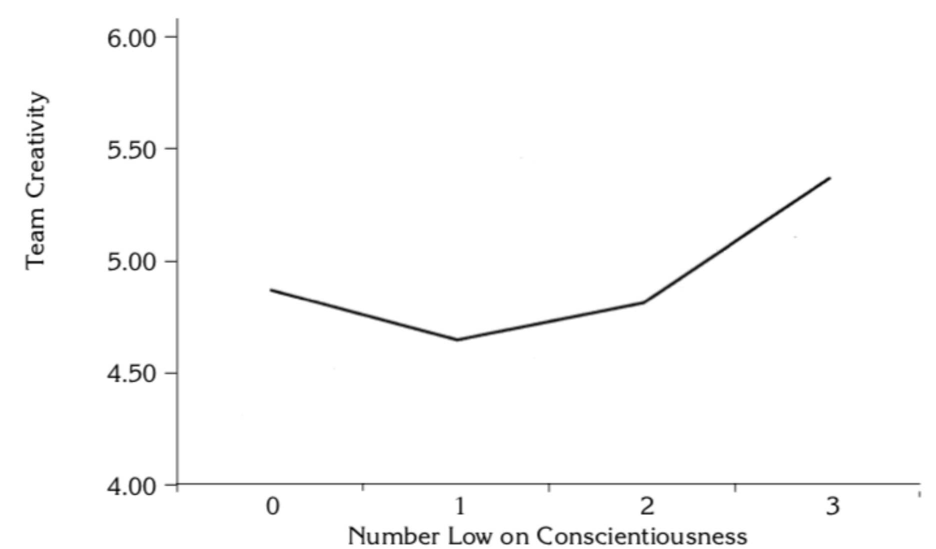

Figure 3.10. The effect of low conscientiousness on creativity of high confidence teams; adapted from Baer, Oldham, Jacobsohn, *et al.* [6, p. 272].

Table 3.3. Three personality factors and their corresponding parameters in the TCP model. The defined values for small, and large are presented in Table 3.4

Personality factor (high degree)	Implementing in TCP
Extroversion	Speech threshold is small. As a result, it is more likely for the agent to talk and express their ideas in meetings.
Conscientiousness	1- Variance of inward weights from agents who identified high creative solutions (successful agents) is small. As a result, the agent is more under the influence of successful agents. 2- The agent has identified solutions with high creativity score. As a result, the agent is considered as successful.
Openness	Adding noise to solutions' activities of an agent (As the result, the agent will explore unusual thought processes and it is more likely for her to identify more creative solutions).

p.]. The noise level α and the threshold ψ in the EII model were used to control the degree of integration and differentiation respectively. The results from the simulation study of calic2018creative suggest that paradox is beneficial for integrative simple thinkers, but that it has negative effects on the creative output of individuals who are intermediate in integration and low in differentiation.

In this setting, our simulations consist of teams of size three, and the parameters of our algorithm are specified so as to simulate agents with different personalities. The significant results of the experiment as shown in Figures 3.8–3.10 indicate that we need only to consider extroversion, conscientiousness, and openness. Due to the complications of showing null results, we do not consider neuroticism and agreeableness in our simulations. Furthermore, since the agents in our simulation are always influencing each other, there is always a chance of change of mind and agreeing on one or more solutions. For this reason, we assumed our agents are optimistic about team success and therefore they are categorized as high confidence teams. Now, we proceed to identify the relationships between the TCP parameters and the personality factors. A summary of our simulation parameters is in Table 3.3.

Extroversion, or the frequency of interaction, can be controlled by the Speech threshold parameter. A small Speech threshold corresponds to high extroversion. Specifically, a small Speech threshold enables an agent to talk with less activity in her Speech neurons, or equivalently, to talk with less activity in her right Explicit EII. A small threshold also implies that the agent interacts with other agents even when she is less confident in her solution. To simulate extroversion, we define high and low degrees of speech threshold. If the Speech threshold is low (high), then the agent is more (less) likely to talk in meetings and, she will be considered as a high (low) extrovert agent. The value of high Speech threshold along with other personality parameters are determined by a grid search and are provided in Table 3.4.

Conscientiousness is governed by the variance of inward weights from the agents who are successful in finding creative solutions. Decreasing this variance leads to agents with a higher degree of conscientiousness because they are more under the influence of successful agents. In addition, agents with high conscientiousness put more effort into solving a problem, and they have a higher likelihood of being successful in finding more solutions with high creativity scores. To simulate these two, we need to define small and large values for variance and high values for creativity scores. When the selected solution of an agent has a high creative score, we consider the agent as being successful. To summarize, agents with a high degree of conscientiousness have these two characteristics: the first solution that the agent has identified has a high creativity score. Second, the variance of inward weights from successful agents is small. The values that define small and large variances and high creativity scores are determined by grid search and are provided in Table 3.4.

As stated earlier, people with higher degrees of openness explore unconventional solutions. To achieve this, we add noise to the activity of an individual's solutions. As a result, the solutions that are unconventional now have the chance to gain the highest activity and be selected. To simulate this noise we added a randomly generated value from a normal distribution with mean 0 and standard deviation of 'Openness noise' to each solution's activity. This noise increases the likelihood of getting more activity in solutions that are naturally less accessible (more creative). Each agent has a 50% chance to be selected for representing high openness. The value of 'Openness noise' is determined by trial and error and is provided in Table 3.4.

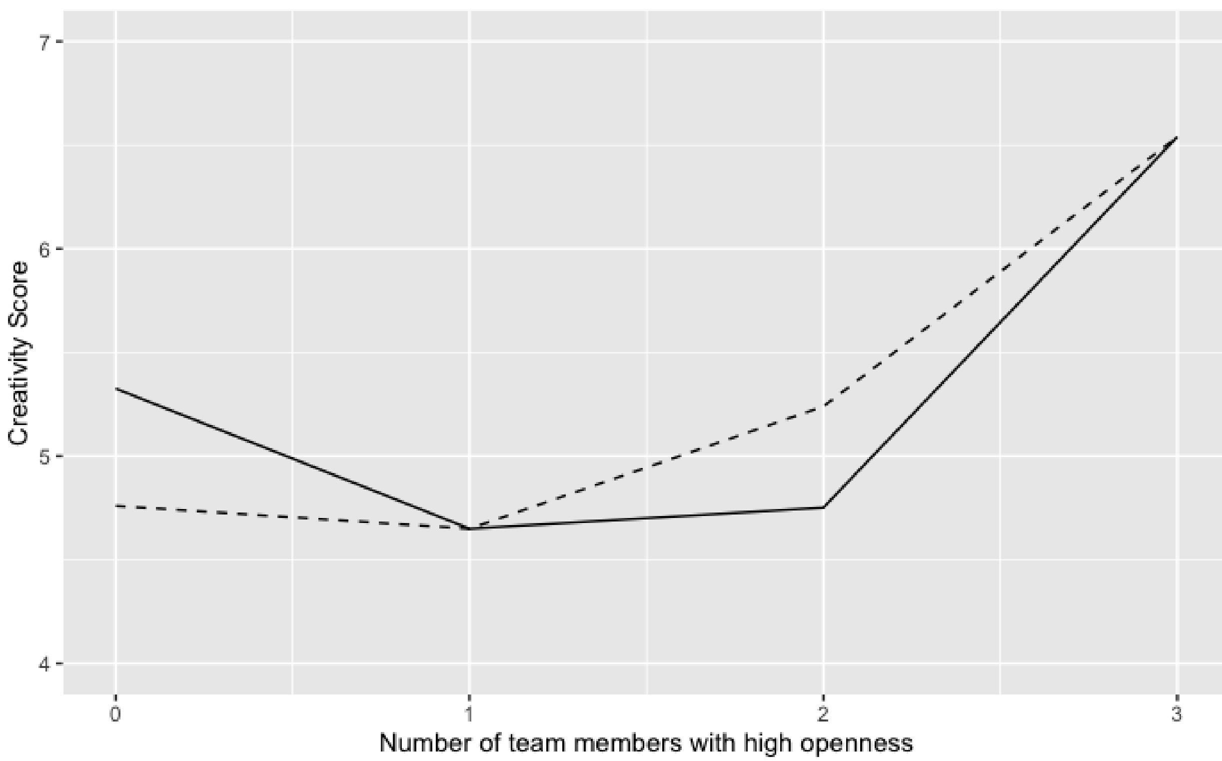

Figure 3.11. The results of the simulation (solid line) and the experiment (dashed line) on the effect of high openness on creativity of high confidence teams.

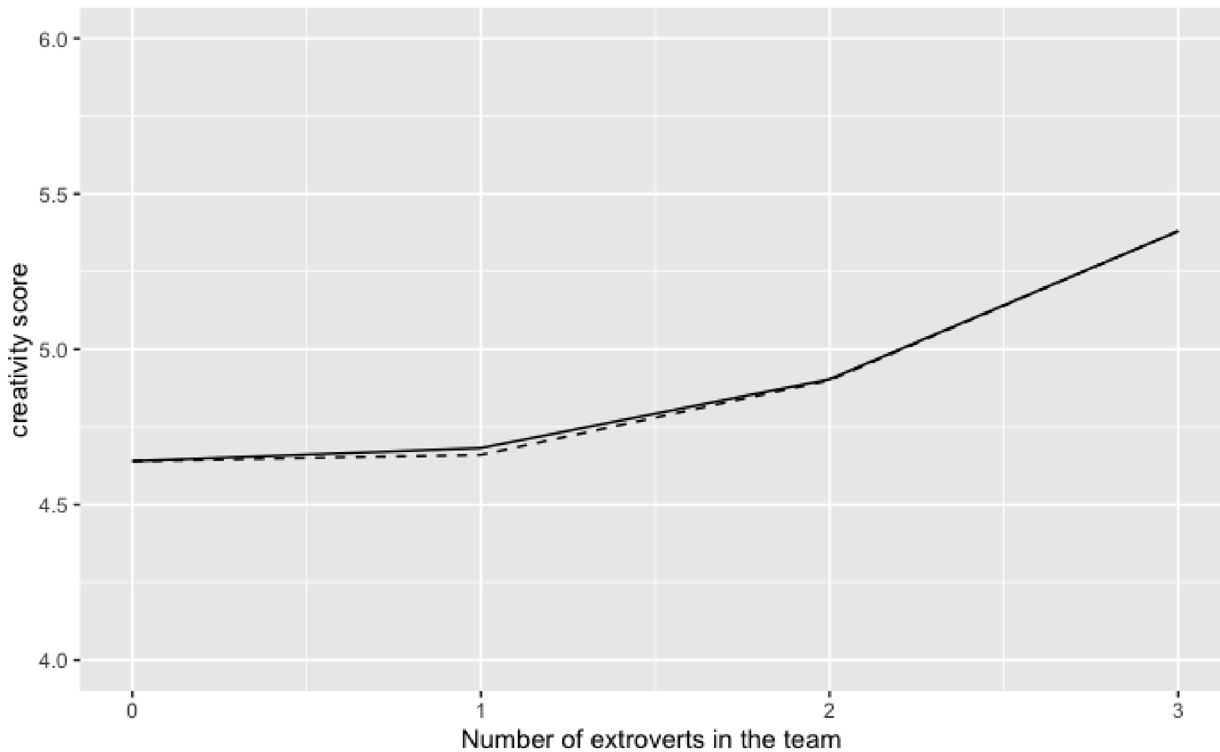

Figure 3.12. The results of the simulation (solid line) and the experiment (dashed line) on the effect of high extrov
ersion on creativity of high confidence teams.

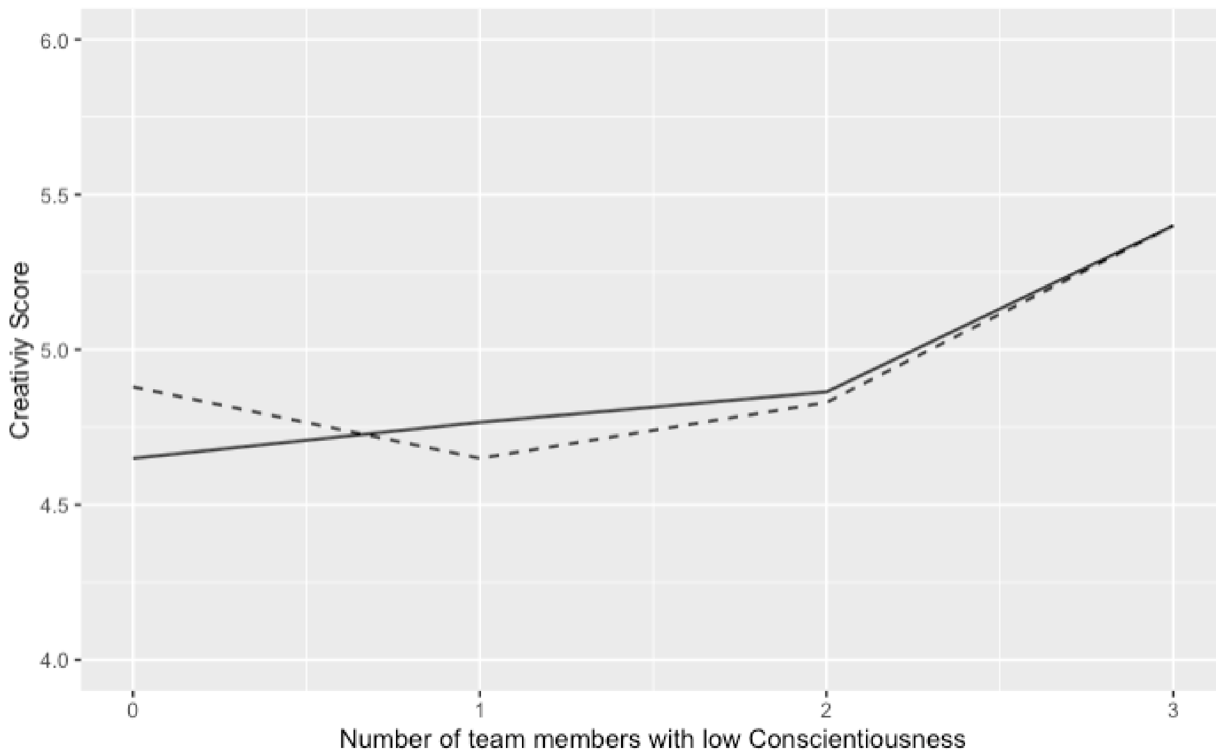

Figure 3.13. The results of the simulation (solid line) and the experiment (dashed line) on the effect of low conscientiousness on creativity of high confidence teams.

Table 3.4. Parameters used for simulating personality factors.

Parameter	Value
High Speech Threshold (Used in Extroversion Simulation)	> 2.5
High Creativity (Used in Conscientiousness simulation)	> 3
Low variance (Used in Conscientiousness simulation)	< 0.5
Noise (Used in Openness simulation)	$Normal(0, 1)$

The results of the simulation is provided in Figure 3.11, Figure 3.12, and Figure 3.13. The Root Mean Square Error for the simulation of openness, extroversion and conscientiousness are respectively as follows: 0.37, 0.01, 0.13. As can be seen, the results are generally consistent with the trend that is observed in the experiment. However, there are some incompatibilities that we will explain in the following Subsection.

3.3.3 Discussion

The results from openness and conscientiousness are not entirely matching the results from the experiment. The general trend of the results of the simulations and the experiments is the same. However, unlike the experimental results, in the conscientiousness simulation, the mean creativity score of the teams with one member with high conscientiousness is higher than the teams with no high conscientiousness members. In the openness case, the simulation shows that teams with two high openness members gain a lower creativity score than teams with no members with high openness. The experiment shows a reversed pattern in this comparison. One possibility of these differences is the experiment's specific condition: high confidence of team members. We assumed that team members always have high confidence in the team's success, because there is always a chance of change-of-mind and agreeing on solutions with high creativity score. However, in real-world situations, there might be conditions that people become pessimistic about the performance of teams even when there is a chance of success. We do not have all the real-world parameters that affect a team member's perception of success. The lack of these parameters might be one reason for the discrepancies in the results. Furthermore, the standard errors of the results of the experiment are not available. There is a possibility that the simulation results fall inside the acceptable range of the results. In future work, we will add new parameters such as an optimism parameter to the model to make it closer to real-world systems. The other direction of future work for solving this issue is replicating the experiment and finding the standard error bars for each data point. It can help us to check if the difference between the results of the simulation and the experiment is statistically significant or not.

3.4 Analysis of Simulation 3: Effects of Industrial Organization Factors on Team Creativity

3.4.1 Description of the Meta-Analysis

Interest in understanding the effects of different factors on creativity at work has grown over the past few decades. hulsheger2009team conducted a comprehensive meta-analysis of 104 studies on this topic. They identified 15 factors of interest. Among these 15 factors, vision, task orientation, and external communication exhibited a strong positive correlation with team creativity Hülsheger, Anderson, and Salgado [76]. Similar to the factors in Section 3.3.1, these factors are defined based on team behaviors.

- Vision corresponds to an idea of a valued outcome, and a force of motivation at work West [77]. In high vision teams, goals are clear to the members of the team. These goals are perceived as highly valued and attainable. Therefore, team members are motivated and feel committed to achieve these goals. Vision gives meaning to their work and motivates team members to increase innovative performance Hülsheger, Anderson, and Salgado [76].

- Task orientation or climate for excellence refers to a shared concern among team members with the excellence of quality of task performance towards shared outcomes West [77]. In the description of this factor, hulsheger2009team noted that teams that are highly task oriented strive to achieve the highest standards of performance. This may be the result of regular appraisals of ideas, feedback, and mutual monitoring of team members. The high task oriented teams reflect upon procedures, strategies and team objectives. Team members listen and evaluate each other's work in order to explore opposing ideas and improve the quality of their decisions.

- External communication relates to the sharing of information and ideas with people outside one's own team or organization. It enables team members to obtain new knowledge and new perspectives that may lead to the identification of new, creative solutions Hülsheger, Anderson, and Salgado [76].

3.4.2 Details of Simulation

Corresponding to the results of the meta-analysis, the objective of our simulation study in this setting is to demonstrate the existence of the effects of vision, task orientation, and external communication on creativity. Due to the complications of proving a Null effect, we do not simulate the parameters with Null effects. In these simulations, We consider teams of size three, and identify relations between the TCP parameters and the three industrial organization (IO) factors, to specify our simulation. These relations are described below and summarized in Table 3.5.

The following definition of vision: "If vision is high, team and organizational goals are highly valued, perceived as attainable, and team members feel committed to these goals." leads to the assumption in our simulation model that agents who do not share the same goal will either sit idle in a meeting, have less motivation at work, or produce unrelated solutions that do not affect those of the other members. In other words, "idle agents" are those team members who either do not produce solutions, talk in the meetings, listen to other team members, or who produce unrelated solutions (with corresponding scores of zero). We simulated lack of vision by turning some agents into idle agents. In more detail, each agent in each meeting, by 50% chance turns into an idle agent whose mean and variance are neither affected by the other team members, nor do they change the means and variances of others. Finally, the creativity score of a team that lacks vision is compared with a similar, paired team that has no idle agents or have a normal degree of vision.

"Task orientation" as defined in our simulation algorithm relates to the agents' attempts in increasing task performance quality. This is achieved by having more effective communication among agents. We directly incorporate this into our simulation via the amount of noise in the communication networks. Specifically, we added $Normal(0, 1)$ noise random variables

Table 3.5. Industrial Organization (IO) factors and their corresponding parameters in the TCP model.

IO factors	corresponding parameter in the TCP model
Vision	idle agents
Task Orientation	noise in communication networks
External Communication	one or more agents participate in the external team's meetings as a member and then participate in their original team's meetings

to both the means and variances of all agents participating in the meeting. If after adding noise, the mean becomes zero, then the mean is modified to the largest solution number and if the mean becomes greater than the largest solution number, then the mean is modified to zero. The addition of noise in our simulation leads to low task oriented teams, which we then compare to their respective similar, paired teams that have normal task orientation without any noise in their communication network.

The final factor of external communication is straightforward to incorporate into the simulation algorithm. First, we create a three member team to work on a problem. We call this team the original team. Then, before the start of the meetings, each team member joins another team with two new random members to work on a similar problem. These teams are considered as external teams. The external teams are similar to the original team in algorithm and parameters, only they differ in team members (one member is the same and two members are different). After the external teams finish working on the problem, the original team members come back and form a team. Due to participation in external meetings, the team member's mean and confidence may have been changed. Then, the original team works on the problem based on the algorithm and parameters that are explained in Section 3.1. Finally, we compare the results of these teams with their respective similar, paired teams that did not have external communication.

3.4.3 Results

The results of the simulation for vision, task orientation and external communication are analyzed by using nonparameteric bootstrap because the sample of paired differences are not

Table 3.6. 95% confidence intervals of the expected differences in the creativity scores between the teams who lack the IO factor and those who have normal IO factor levels.

IO factor	Confidence Interval
Normal Vision - Low Vision	(12.93, 16.41)
Normal Task Oriented - Low Task Oriented	(27.45, 32.52)
With External Communication - Without External Communication	(5.75, 13.83)

Normally distributed. As such, we utilize the nonparametric bootstrap Efron [78] and Efron and Tibshirani [79] to perform inferences on the mean of the paired differences. We sampled 10^5 elements from the data with replacement to build the distribution. Specifically, from the built distribution, we create the 95% nonparametric bootstrap confidence interval for the mean of the paired differences based on the 0.025 and 0.975 percentiles of the bootstrap distribution of the paired differences. Statistical significance is determined by checking to see whether 0 lies within the interval.

Table 3.6 summarizes the results of the simulations. None of the 95% confidence intervals in this table contain 0. This implies that we have statistically significant evidence at the $\alpha = 0.05$ level that vision, task orientation, and external communication have effects on team creativity.

3.4.4 Discussion

The results of the simulation show that the TCP model is capable of simulating experimental data on vision, task orientation and external communication. Furthermore, the simulation shows that the effects of low degrees of vision , low degrees of task orientation, and lack of external communication are negative on team creative performance.

To explain how these results are observed, we focus on the effects of each interference. In the low vision simulation, idle agents deprive the team by refusing to offer their solutions. Therefore, a high confidence agent pulls other agents' opinions toward her own opinion, but it may not result in consensus on the solution. In the next meeting, she may become idle, and another agent will start to convince people; therefore, the previous meeting is wasted and does not result in an agreed solution. Therefore, it is likely that it takes more time for the team to agree on one solution, and the total creativity score is negatively affected. In teams with low task orientation level, noise in the communication network affects both the variance and the mean. As the result, there will be changing solutions and confidence of team members. If an agent is confident about one solution and pulls other peoples' opinions toward that solution, in the next meeting, she may have another solution and will no longer convince other people on her original solution. This behavior increases the probability of pulling back and forth between solutions and having difficulty on agreeing on one solution. Therefore, the total creativity score is negatively affected in teams with low task orientation. In the external communication case, the agents who participated in external meetings may have an exceptionally high degree of confidence in their identified solutions because they would have already worked on the problem in the external team. This may result in very confident team members who are able to convince other team members easily, so the team is likely to produce more solutions at the conclusion of the simulation.

3.5 Analysis of Simulation 4: The Effects of Team Size on Team Performance

Our fourth analysis is used for predicting the effects of team size on creative problem solving. We perform this analysis based on a simulation of an organizational meeting. The set-up and parameter values are described in Subsection 3.1. The simulation commences with teams of size three and continually increases to teams of size 10. The result for each team size is calculated based on the average of the 644 simulations.

Figure 3.14 summarizes the results of the analyses for this simulation. As demonstrated in this figure, teams of size 5 have maximum creativity on average. Furthermore, creativity continually increases on average as a function of team size until size 5, after which the creativity decreases and essentially stabilizes in a small range of creativity values.

3.5.1 Discussion

The result shows that there is not a monotonic effect of team size on creativity. One possible real-world explanation for this result is that increasing the team size may be beneficial up to a certain point, as new ideas will be brought and discussed in an effective manner by a

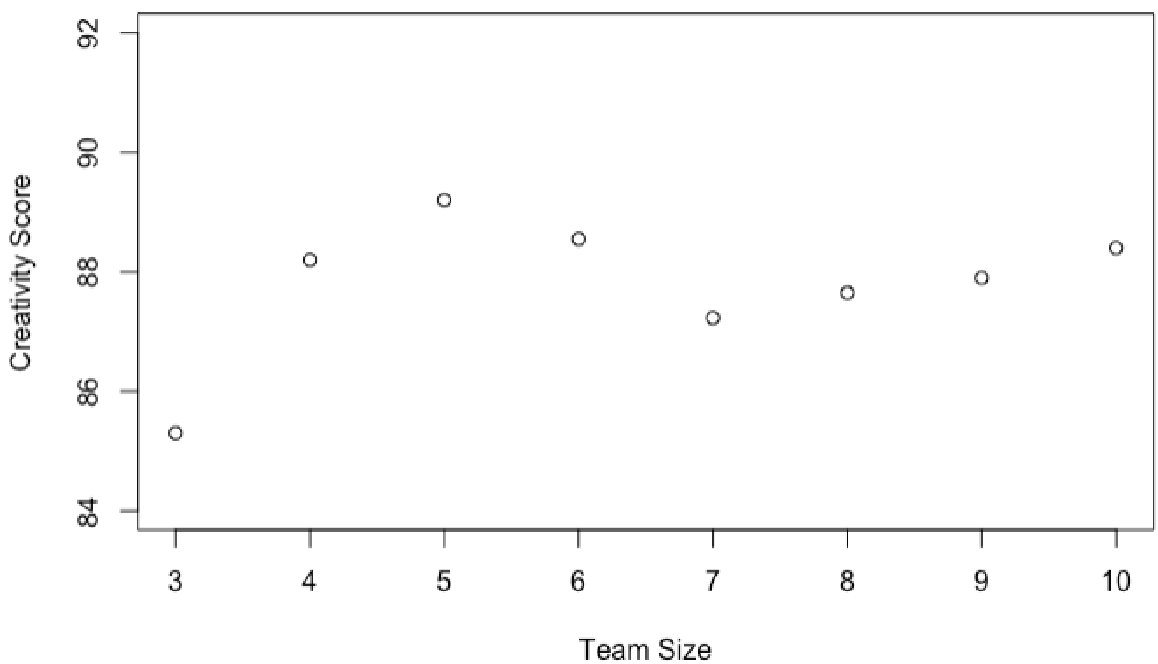

Figure 3.14. The relation between team size and creativity. The creativity score on the y-axis corresponds to the average creativity scores of the teams across the 644 simulations.

moderate number of team members during the meetings. However, after a critical threshold on the team size is reached, the many ideas that would be discussed in the meeting would entail the agents to go back and forth on different potential solutions, consequently makes it more difficult to reach a consensus.

These results agree with previous studies by Hülsheger, Anderson, and Salgado [76], Anderson and King [80], and Stewart [81] on the positive effect of team size on creative problem solving. Ultimately, the results of the last simulation study suggest that the positive effects identified in the literature may exist only to a certain team size, and that larger teams after the critical team size may not be as effective.

4. DISCUSSION

This chapter first, in Section 4.1, provides a summary of the TCP model and the four simulations that are performed in Chapter 3. Then, in Section 4.2, the advantages of the TCP model and the limitations associated with using this model are discussed. Afterward, the implications of the TCP model is provided. Finally, Section 4.4 states the future directions on developing and using the TCP model.

4.1 Summary

This research introduces a new model of multi-agent creative problem solving. This model is inspired by previous models of creativity, uncertainty, change-of-mind, influence, and communication. The difference between the TCP model and these previous models is discussed in the following Subsection.

For testing the TCP model, we considered three categories of parameters: 1- changeable characteristics of individuals such as emotions 2- fixed characteristics of individuals such as extroversion 3- characteristics related to team dynamics such as vision, and external communication. The results from the three first simulations in Chapter 3 show that the TCP model is capable of simulating all of these characteristics and produce results that are similar to human subjects'. The fourth experiment in Chapter 3 makes a prediction by using the TCP model. It predicts that on average, teams of size 5 achieve the highest creativity score compared to smaller or larger teams. It should be noted that the problems in TCP were presented in an abstract form, and this abstract form can represent problems with a continuous problem space.

4.2 Advantages and Limitations

The TCP model is different from previous models in both individual and team–level characteristics. Unlike the previous models, the underlying processes in the TCP model benefit from the EII theory. In our implementations, similar to simulations in Hélie and Sun [10], only incubation and insight stages are considered. Based on EII theory, other stages of creative problem solving can be added to the EII module in future work. Furthermore, the TCP model uses probability distributions for describing the weights of the connections between agents. It allows the model to effectively capture the uncertainty that naturally appears in human communications and use Bayesian inference concepts in modeling social influence, trust, and bias. Moreover, using biologically motivated models of Bayesian communication, uncertainty, and change–of–mind potentially makes the TCP model close to the processes in the brain and leads to a more accurate model of human problem solving. One other characteristic of the TCP model is separate subsystems. This allows the TCP model to go further than a model for problem solving by substituting the EII module with the desired model of a cognitive process such as decision making.

Along with the advantages of using the TCP model as explained in the previous paragraph, there are some limitations. First, this model uses only a few parameters to represent different real-world systems' characteristics and structures. The abundant number of parameters that can affect social communications can decrease the accuracy of the results that this model produces. Secondly, for modeling social interactions on a large scale such as a million-user social network, the TCP model becomes overly complex (It should be noted that reducing the complexity of the TCP model may decrease accuracy sharply and may not be appropriate). Furthermore, The solutions in the TCP model are described continuously: there is an assumption that solutions with close assigned numbers are more similar to each other. This type of modeling may not be appropriate for describing the independent solutions from each other. In those cases, multi-variate Normal distribution or putting an independent solution far from other solutions in tails of a Normal distribution can be used for describing different independent groups of solutions, which is not implemented in this version of the TCP model.

One other limitation in simulations of this research is using parameter values that may not fully capture the characteristics of humans. For example, we used fixed values for weighting the transferred activity from the EII module to the Uncertainty module. These values surely are not be fully capturing the characteristics of a human subject. Furthermore, uniform and normal distributions are used for producing random numbers. These distributions may not be the appropriate distribution for producing real-world phenomena. New human subjects experiments need to be done for understanding these phenomena and using more accurate values for the parameters of the TCP model.

4.3 Implications

One important application of the TCP model is in organizational management. The TCP model can suggest the most effective use of resources such as the number of people in a team or a communication structure to reach the desired level of creative output. Also, the TCP model can be used in human resource sections of organizations by specifying the personality and other characteristics of an applicant that matches most with other team members, structure, and organization's goals.

Another application of the TCP model that we briefly discussed is using the TCP model as a human communication model. It can be achieved by replacing the subsystems related to problem solving with a cognitive model of interest. Since human communication models are popular in many fields such as Information Theory, Social Psychology, and Robotics, the TCP model can be used in these fields too. For example, in building swarm robots, the TCP model can be used in robots' communication algorithms.

The TCP model also can be used in interactive computer programs. Many modern programs communicate with users and try to show human–like behavior. A TCP model in programs can simulate the coder's behavior based on her specific characteristics such as personality factors and adjusts the program interactions based on the user's needs. For example, the program first takes a personality test from the coder. Then, it simulates a series of meetings of problem solving with an agent with similar personality characteristics. By doing this simulation, the program can guess the timing (meeting number) for suggesting a solution that leads to the highest creativity.

4.4 Future work

The future work on the TCP model can be directed in two main ways. The first one is developing the model and performing more accurate simulations. The second direction is using the TCP model in predicting team performance in different scenarios. The following paragraphs provide information on these two directions, respectively.

In future work, we can add learning to the TCP model. One possible types of learning is over all the sessions of meetings. Currently, the bias and trust of team members in each other are constant in all meetings. Reinforcement learning can be used to modify these parameters when agents learn more about each other. For example, trust in team members who frequently generate highly creative solutions will increase over time.

The TCP model uses parameters for quantifying uncertainty, bias, change-of-mind, personality factors, etc. Some experiments are previously done that can help us in guessing the appropriate values of these parameters. However, the exact values of many of these parameters are still unknown. We used grid search for guessing these parameters. To use more accurate values, we need to design and perform human-subject experiments to make more appropriate choices for these parameter values.

The other direction of future work is using the TCP model in simulating and predicting the effects of different factors on team performance. For example, on the topology of teams, Bavelas [55], [56] proposed that teams with the centralized structure are more successful than decentralized teams in solving less complex problems. They showed that the 'Wheel' structure needs fewer messages and can solve problems faster than centralized teams. This characteristic first can be tested by simulating centralized and decentralized teams and furthermore, the TCP model can be used to evaluate all possible team structures that are not yet tested on human teams.

REFERENCES

[1] P. B. Paulus, M. Dzindolet, and N. W. Kohn, "Collaborative creativity—group creativity and team innovation," in *Handbook of organizational creativity*, Elsevier, 2012, pp. 327–357.

[2] M. A. Boden, "Creativity," in *Artificial intelligence*, Elsevier, 1996, pp. 267–291.

[3] A. J. Cropley, "Defining and measuring creativity: Are creativity tests worth using?" *Roeper review*, vol. 23, no. 2, pp. 72–79, 2000.

[4] B. Shi, X. Cao, Q. Chen, K. Zhuang, and J. Qiu, "Different brain structures associated with artistic and scientific creativity: A voxel-based morphometry study," *Scientific reports*, vol. 7, no. 1, pp. 1–8, 2017.

[5] G. J. Feist, "A meta-analysis of personality in scientific and artistic creativity," *Personality and social psychology review*, vol. 2, no. 4, pp. 290–309, 1998.

[6] M. Baer, G. R. Oldham, G. C. Jacobsohn, and A. B. Hollingshead, "The personality composition of teams and creativity: The moderating role of team creative confidence," *The Journal of Creative Behavior*, vol. 42, no. 4, pp. 255–282, 2008.

[7] S. Zeki, "Artistic creativity and the brain," *Science*, vol. 293, no. 5527, pp. 51–52, 2001.

[8] J. Luo, W. Li, J. Qiu, D. Wei, Y. Liu, and Q. Zhang, "Neural basis of scientific innovation induced by heuristic prototype," *PLoS One*, vol. 8, no. 1, e49231, 2013.

[9] G. Wallas, "The art of thought," 1926.

[10] S. Hélie and R. Sun, "Incubation, insight, and creative problem solving: A unified theory and a connectionist model.," *Psychological review*, vol. 117, no. 3, p. 994, 2010.

[11] G. Calic, S. Hélie, N. Bontis, and E. Mosakowski, "Creativity from paradoxical experience: A theory of how individuals achieve creativity while adopting paradoxical frames," *Journal of Knowledge Management*, 2019.

[12] M. A. Boden, *The creative mind: Myths and mechanisms*. Routledge, 2004.

[13] P. G. Kampylis and J. Valtanen, "Redefining creativity—analyzing definitions, collocations, and consequences," *The Journal of Creative Behavior*, vol. 44, no. 3, pp. 191–214, 2010.

[14] D. K. Simonton, "Creativity and discovery as blind variation and selective retention: Multiple-variant definition and blind-sighted integration.," *Psychology of Aesthetics, Creativity, and the Arts*, vol. 5, no. 3, p. 222, 2011.

[15] L. Macedo and A. Cardoso, "Creativity and surprise," in *IN PROCEEDINGS OF THE AISB'01 SYMPOSIUM ON CREATIVITY IN ARTS AND SCIENCE. SSAISB*, Citeseer, 2001.

[16] M. E. Q. Gonzalez *et al.*, "Creativity: Surprise and abductive reasoning," *Semiotica*, vol. 2005, no. 153, pp. 325–342, 2005.

[17] M. A. Runco and G. J. Jaeger, "The standard definition of creativity," *Creativity research journal*, vol. 24, no. 1, pp. 92–96, 2012.

[18] M. L. Maher, K. Brady, and D. H. Fisher, "Computational models of surprise in evaluating creative design," in *Proceedings of the fourth international conference on computational creativity*, Citeseer, vol. 147, 2013.

[19] T. R. Kurtzberg, "Feeling creative, being creative: An empirical study of diversity and creativity in teams," *Creativity Research Journal*, vol. 17, no. 1, pp. 51–65, 2005.

[20] J. P. Guilford, "The structure of intellect.," *Psychological bulletin*, vol. 53, no. 4, p. 267, 1956.

[21] S. Jaarsveld, T. Lachmann, and C. van Leeuwen, "Creative reasoning across developmental levels: Convergence and divergence in problem creation," *Intelligence*, vol. 40, no. 2, pp. 172–188, 2012.

[22] M. Csikszentmihalyi, "The domain of creativity.," 1990.

[23] J. Rowe and D. Partridge, "Creativity: A survey of ai approaches," *Artificial Intelligence Review*, vol. 7, no. 1, pp. 43–70, 1993.

[24] D. R. Hofstadter and M. Mitchell, "The copycat project: A model of mental fluidity and analogy-making.," 1994.

[25] G. Cattani and S. Ferriani, "A core/periphery perspective on individual creative performance: Social networks and cinematic achievements in the hollywood film industry," *Organization science*, vol. 19, no. 6, pp. 824–844, 2008.

[26] R. Sosa and J. S. Gero, "Social models of creativity," in *Proceedings of the International Conference of Computational and Cognitive Models of Creative Design VI*, 2005, pp. 19–44.

[27] J. Dorfman, V. A. Shames, and J. F. Kihlstrom, “Intuition, incubation, and insight: Implicit cognition in problem solving,” *Implicit cognition*, pp. 257–296, 1996.

[28] S. Smith, *Dodds (1999) incubation entry in the encyclopaedia of creativity, edited by runco ma. and pritzker sr*, 1999.

[29] S. Hélie and A.-M. Olteteanu, “Computational models of creativity. In R. Sun (Ed.),” in, Cambridge University press, In Press.

[30] D. T. Campbell, “Blind variation and selective retentions in creative thought as in other knowledge processes.,” *Psychological review*, vol. 67, no. 6, p. 380, 1960.

[31] A. J. Pols, “Insight problem solving,” *Unpublished doctoral dissertation). University of Utrecht, Utrecht, the Netherlands*, 2002.

[32] M. A. Schilling, “A” small-world” network model of cognitive insight,” *Creativity Research Journal*, vol. 17, no. 2-3, pp. 131–154, 2005.

[33] D. K. Simonton, “Foresight in insight? a darwinian answer.,” 1995.

[34] J. Hadamard, “The psychology of invention in the mathematical field princeton university press,” *HadamardThe Psychology of Invention in the Mathematical Field1945*, 1945.

[35] L. Gabora, “Creative thought as a non darwinian evolutionary process,” *The Journal of Creative Behavior*, vol. 39, no. 4, pp. 262–283, 2005.

[36] H. A. Simon, “Theories of bounded rationality,” *Decision and organization*, vol. 1, no. 1, pp. 161–176, 1972.

[37] R. E. Mayer, “The search for insight: Grappling with gestalt psychology’s unanswered questions.,” 1995.

[38] J. W. Schooler and J. Melcher, “The ineffability of insight.,” 1995.

[39] G. Calic and S. Hélie, “Creative sparks or paralysis traps? the effects of contradictions on creative processing and creative products,” *Frontiers in psychology*, vol. 9, p. 1489, 2018.

[40] R. Sun and X. Zhang, “Accounting for a variety of reasoning data within a cognitive architecture,” *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 18, no. 2, pp. 169–191, 2006.

[41] R. Sun, P. Slusarz, and C. Terry, “The interaction of the explicit and the implicit in skill learning: A dual-process approach.,” *Psychological review*, vol. 112, no. 1, p. 159, 2005.

[42] I. Yaniv and D. E. Meyer, “Activation and metacognition of inaccessible stored information: Potential bases for incubation effects in problem solving.,” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, vol. 13, no. 2, p. 187, 1987.

[43] S. M. Smith and E. Vela, “Incubated reminiscence effects,” *Memory & Cognition*, vol. 19, no. 2, pp. 168–176, 1991.

[44] F. T. Durso, C. B. Rea, and T. Dayton, “Graph-theoretic confirmation of restructuring during insight,” *Psychological Science*, vol. 5, no. 2, pp. 94–98, 1994.

[45] U. Toelch and R. J. Dolan, “Informational and normative influences in conformity from a neurocomputational perspective,” *Trends in cognitive sciences*, vol. 19, no. 10, pp. 579–589, 2015.

[46] S. A. Park, S. Goïame, D. A. O’Connor, and J.-C. Dreher, “Integration of individual and social information for decision-making in groups of different sizes,” *PLoS biology*, vol. 15, no. 6, e2001958, 2017.

[47] D. Acemoglu, M. A. Dahleh, I. Lobel, and A. Ozdaglar, “Bayesian learning in social networks,” *The Review of Economic Studies*, vol. 78, no. 4, pp. 1201–1236, 2011.

[48] K. Khalvati, S. A. Park, S. Mirbagheri, R. Philippe, M. Sestito, J.-C. Dreher, and R. P. Rao, “Bayesian inference of other minds explains human choices in group decision making,” *bioRxiv*, p. 419 515, 2018.

[49] N. A. Atiya, I. Rañó, G. Prasad, and K. Wong-Lin, “A neural circuit model of decision uncertainty and change-of-mind,” *Nature Communications*, vol. 10, no. 1, p. 2287, 2019.

[50] H. R. Wilson and J. D. Cowan, “Excitatory and inhibitory interactions in localized populations of model neurons,” *Biophysical journal*, vol. 12, no. 1, pp. 1–24, 1972.

[51] R. Van den Berg, A. Zylberberg, R. Kiani, M. N. Shadlen, and D. M. Wolpert, “Confidence is the bridge between multi-stage decisions,” *Current Biology*, vol. 26, no. 23, pp. 3157–3168, 2016.

[52] R. Kiani and M. N. Shadlen, “Representation of confidence associated with a decision by neurons in the parietal cortex,” *science*, vol. 324, no. 5928, pp. 759–764, 2009.

[53] R. Kiani, C. J. Cueva, J. B. Reppas, and W. T. Newsome, “Dynamics of neural population responses in prefrontal cortex indicate changes of mind on single trials,” *Current Biology*, vol. 24, no. 13, pp. 1542–1547, 2014.

[54] D. R. Forsyth, *Group dynamics*. Thomson Wadsworth, 2006.

[55] A. Bavelas, “A mathematical model for group structures,” *Human organization*, vol. 7, no. 3, p. 16, 1948.

[56] A. Bavelas, “Communication patterns in task-oriented groups,” *The Journal of the Acoustical Society of America*, vol. 22, no. 6, pp. 725–730, 1950.

[57] M. E. Shaw, “Communication networks,” in *Advances in experimental social psychology*, vol. 1, Elsevier, 1964, pp. 111–147.

[58] M. E. Shaw, “Communication networks fourteen years later,” *Group processes*, pp. 351–361, 1978.

[59] C. E. Shannon and W. Weaver, *The mathematical theory of communication (urbana, il*, 1949.

[60] A. Tran, C. Director, R. Hugel, E. A. Director, M. Epes, S. Forsling, and H. Chastain, “Human communication: Motivation, knowledge, and skills, sherwyn p. morreale, brian h. spitzberg, j. kevin barge,” 2007.

[61] J. D. Rothwell, *In the company of others: An introduction to communication*. Oxford University Press New York, 2010.

[62] T. Kohonen, “Correlation matrix memories,” *IEEE transactions on computers*, vol. 100, no. 4, pp. 353–359, 1972.

[63] S. Chartier and R. Proulx, “Ndram: Nonlinear dynamic recurrent associative memory for learning bipolar and nonbipolar correlated patterns,” *IEEE Transactions on Neural Networks*, vol. 16, no. 6, pp. 1393–1400, 2005.

[64] R. J. Sternberg, “The nature of creativity,” *Creativity research journal*, vol. 18, no. 1, p. 87, 2006.

[65] F. Y. Kung and M. M. Chao, “The impact of mixed emotions on creativity in negotiation: An interpersonal perspective,” *Frontiers in Psychology*, vol. 9, 2018.

[66] R. R. McCrae and O. P. John, “An introduction to the five-factor model and its applications,” *Journal of personality*, vol. 60, no. 2, pp. 175–215, 1992.

[67] R. Prada, S. Ma, and M. A. Nunes, "Personality in social group dynamics," in *2009 International Conference on Computational Science and Engineering*, IEEE, vol. 4, 2009, pp. 607–612.

[68] R. R. McCrae and P. T. Costa Jr, "A contemplated revision of the neo five-factor inventory," *Personality and individual differences*, vol. 36, no. 3, pp. 587–596, 2004.

[69] P. Thoms, K. S. Moore, and K. S. Scott, "The relationship between self-efficacy for participating in self-managed work groups and the big five personality dimensions," *Journal of Organizational Behavior*, vol. 17, no. 4, pp. 349–362, 1996.

[70] P. T. Costa and R. R. McCrae, *Revised NEO personality inventory (NEO-PI-R) and Neo five-factor inventory (NEO-FFI)*. Psychological Assessment Resources, 1992.

[71] S. Van Thiel and F. L. Leeuw, "The performance paradox in the public sector," *Public performance & management review*, vol. 25, no. 3, pp. 267–281, 2002.

[72] A. M. Brandenburger and B. J. Nalebuff, *Co-opetition*. Currency, 2011.

[73] T. Hahn, L. Preuss, J. Pinkse, and F. Figge, "Cognitive frames in corporate sustainability: Managerial sensemaking with paradoxical and business case frames," *Academy of management review*, vol. 39, no. 4, pp. 463–487, 2014.

[74] C. Andriopoulos and M. W. Lewis, "Exploitation-exploration tensions and organizational ambidexterity: Managing paradoxes of innovation," *Organization science*, vol. 20, no. 4, pp. 696–717, 2009.

[75] J. G. March, "Exploration and exploitation in organizational learning," *Organization science*, vol. 2, no. 1, pp. 71–87, 1991.

[76] U. R. Hülsheger, N. Anderson, and J. F. Salgado, "Team-level predictors of innovation at work: A comprehensive meta-analysis spanning three decades of research.," *Journal of Applied psychology*, vol. 94, no. 5, p. 1128, 2009.

[77] M. A. West, "The social psychology of innovation in groups.," 1990.

[78] B. Efron, "Bootstrap methods: Another look at the jackknife," *Annals of Statistics*, vol. 7, no. 1, pp. 1–26, 1979.

[79] B. Efron and R. J. Tibshirani, *An Introduction to the Bootstrap*. Chapman & Hall/CRC, 1993.

[80] N. Anderson and N. King, "Lnnovatlon in organizations," *lnternational Review of lndustrial and Organizational Psychology*, vol. 8, pp. 1–34, 1993.

[81] G. L. Stewart, “A meta-analytic review of relationships between team design features and team performance,” *Journal of management*, vol. 32, no. 1, pp. 29–55, 2006.