DEVELOPING A COMPUTATIONAL FRAMEWORK TO STUDY THE EFFECTS OF USE OF ANALOGY IN DESIGN ON TEAM COHESION AND TEAM COLLABORATION

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Abstract

This paper presents a framework for a computational model about analogizing during team interactions when dealing with design problems. The framework is based on prior empirical research about the use of two types of analogies and their effect on team cohesion and team collaboration. The framework is a step towards developing an agent based simulation tool that will be used for studies on the use of analogy in design and their effects on team cohesion and team collaboration. This paper describes the key parameters, independent and dependent variables, and assumptions. At the agent level the independent variables pertain to parameters such as level of multidisciplinarity (range) and expertise. At the team level, aspects such as team size and team composition are considered. At the concept level, parameters such as analogical distance (within-domain and between-domain) and analogical purpose (problem identification, function finding, explanation, and solution generation) are considered. Team cohesion and team collaboration are the dependent variables. This research aims to lay the computational foundation for a means of studying design team behaviour when using analogies.

Keywords: Simulation, Research methodologies and methods, Collaborative design, Design management

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Please cite this paper as:
Surnames, Initials: *Title of paper*. In: Proceedings of the 20th International Conference on Engineering Design (ICED15), Vol. nn: Title of Volume, Milan, Italy, 27.-30.07.2015

1 INTRODUCTION

Analogizing is a commonly discussed topic in idea generation, typically viewed and explored in the context of the design outcomes, and as a source of design creativity (Casakin, 2012). More recently, researchers have begun to investigate the effects of analogizing in design on team dynamics (Ball and Christensen, 2009), especially on aspects such as team collaboration and team cohesion (Casakin et al., in press). The findings suggesting that the studied factors such as analogical distance and analogical purpose do have an effect on collaboration and cohesion aspects of team dynamics open a promising direction for research in this area.

However, several challenges exist in studying the effects of analogizing on team collaboration and cohesion. For instance, how controlled and reliable are the experimental setups, or to what extent the results obtained from a limited sample can be generalized to the whole population? Likewise, a number of additional parameters and open questions emerge from the findings so far. Repeatability is one of the ways to ascertain issues like these. Nevertheless, conducting a large number of similar experiments for the sake of dealing with all these issues requires vast efforts and investments in resources and time. From that viewpoint, agent based simulations, as complementary research methods with merits such as repeatability, control, and longitudinal studies allow conducting preliminary studies to test and generate hypotheses of interest, which can be used to internally validate hypotheses to conduct further empirical studies.

Therefore, this paper presents an ongoing research that aims to formulate a computational framework as a step towards developing an agent based simulation platform. Such a framework will enable the study of the effects of various key factors associated with the use of analogies in design teams on team cohesion and team collaboration. The proposed computational framework builds on theories, and findings based on empirical evidence reported in recent literature (Casakin et al., in press; Ball and Christensen, 2009; Christensen and Schunn, 2007).

The paper is organized in four sections. Section two briefly provides the theoretical background for the research, describing related previous research on the subject, as well as on the use of agent based models for social simulations. Section three presents the research framework detailing the variables of interest, and sample hypotheses and questions that can be investigated using that framework. This is followed in section four by a description of the computational framework, major assumptions, and implementation plans. Section five concludes the paper with a short discussion on the challenges, opportunities and limitations of the planned simulation model.

2 BACKGROUND

2.1 Analogical reasoning in design: analogical distance, and expertise

Analogizing is considered to be a powerful heuristic for idea generation in design problem solving (Goldschmidt, 1995), mainly at the early stages of the process. The employment of analogy is concerned with the access, retrieval, and transfer of prior knowledge from a familiar situation (the *source*) to a situation that needs to be elucidated (the *target*). By establishing correspondences between familiar relations in the source and potential relations in the target it is possible to see the new situation in terms of a known situation (Holyoak and Thagard, 1995). Depending on the distance existing between source and target, analogies can be categorized into those that are 'within-domain' (source and target domains are close) and 'between-domain' (source and target domains are distant). Moreover, the use of analogy was shown to be related to expertise. Casakin (2004), for example, demonstrated that whereas expert designers tend to retrieve analogies from between-domain visual sources, novices tend to use more within-domain sources.

The importance of analogical reasoning has been confirmed in a number of studies of design problem solving in fields such as engineering design (Ball et al. 2004; Ball and Christensen, 2009) and architecture (Casakin, 2004, 2010; Casakin and Goldschmidt, 1999).

2.2 Analogy and design teams

Analogical thinking is considered as a cognitive mechanism that can play a role in attaining common understanding among design team members with regard to a problem at hand. The use of analogy can broaden and enrich the idea generation process, which facilitates the communicative exchanges between team members in relation to each other's knowledge, skills and experiences (Stempfle and

Badke-Schaub, 2002). Effective design teams have high levels of communication and information sharing. Analogy in design was studied not only as an individual activity but also in the context of teamwork. However, less work has been carried out to explore how these cognitive strategies might support teamwork (Rousseau et al., 2006). Researchers such as Christensen and Schunn (2007), and Stacey et al. (2007) have explored how a team of designers made use of analogies when dealing with design problems in real life. A common finding was that analogizing is regularly used by design teams in a variety of design activities (Ball and Christensen, 2009). However, more research is needed in order to gain further insight into the ways that analogy can contribute to team dynamics dealing with creative design tasks.

2.3 Analogical purpose and design teams

Analogies can be studied in terms of the 'purpose' or activities that they can serve in when working in teams. Christensen and Schunn (2007) showed that analogising was largely used by teams for three major functions that included problem identification, problem solving, and explaining. These researchers also found that within-domain analogies were frequently employed for problem identification – which involved pointing out a potential problem in the design, where the problem was retrieved from an analogical source. On the other hand, between-domain analogies prevailed during explanation activities – that is, looking at a concept retrieved from a source domain to explain an aspect of the problem domain. In contrast, they observed an equal distribution of within-domain and between-domain analogies for solution generation – aimed at transferring prospective solution principles from an analogical source domain to the target domain. Ball and Christensen (2009) extended this study and showed that in addition to problem identification, explanation, and solution generation, analogical purpose also involved function finding – concerned with analogical mappings aimed to retrieve new functions to the design at hand.

2.4 Analogical purpose, team cohesion and team collaboration

Fluent communication exchange in design teams has previously been shown to play a significant role in team cohesion (Badke-Schaub et al., 2007; Owen, 1985) and team collaboration (Kleinsmann and Valkenburg, 2007). A design team is in a state of cohesion when its members have bonds linking them to one another and to the group as a whole, and in that way they prevent group fragmentation. A cohesive group has a propensity to be in unity whilst working toward a common goal, which may also embrace satisfying the emotional needs of its members (Forsyth, 2010). The creation and maintenance of a cohesive climate (Badke-Schaub et al., 2011) in the design team will imply that their members will desire to stay together in order to achieve a work.

While team cohesion embraces social, cultural, and emotional aspects and task-focused elements, team collaboration is aimed at information exchange to achieve effective design outcomes. Kleinsmann and Valkenburg (2007) refer to team collaboration as 'actors' communicating and integrating their knowledge about the design content and design process for the purpose of creating a 'shared understanding', in order to succeed in producing a new design outcome.

How analogizing can contribute to team cohesion and team collaboration is an important issue that was not investigated extensively. An exception is Casakin et al. (2014) who examined the relationship between analogical purpose, and team cohesion and team collaboration. These authors found that all four types of analogical purpose had a likely association with team cohesion, while solution generation and function finding had a stronger association with team collaboration (See Section 3.1).

2.5 Computational models for organizational and social studies

Several authors (e.g. Lant, 1994; Carley, 1994; Levitt et al, 2005) have suggested that computational models are suitable means for testing and generating hypotheses for organizational and social theory. Such studies can also be used to guide and design empirical studies and suggest what data to collect in the field. However, there should be an independent method to assess the reliability and effectiveness of a computational model used for studying social behaviour (Axelrod, 1997; Axtell et al., 1996; Levitt et al., 2005). Such computational models should facilitate an equivalency test, and a comparison with other models (Axtell et al., 1996). Recognizable social behaviour should emerge from the model, as compared to social scenarios being studied (Carley and Newell, 1994). Carley and Newell (1994) also suggest that those aspects of the computational model for which human data are not well

established, can be handled using Monte Carlo techniques. In addition, Carley suggests that as the complexity of the organizational structure increases, the ability to predict organizational behaviour with simpler computational agents, also increases.
Carley and Newell (1994) describe a social agent along two dimensions: (1) processing capabilities, and (2) differentiated knowledge of self, task, domain, and the environment. For studies in social sciences, such as a the present one, the model social agents tend to have lower information-processing capabilities, but higher knowledge (Carley and Newell, 1994; Wooldridge, 2002). The choice of an agent's information processing capabilities and knowledge levels should be based on the complexity of the environment and the focus of the study. A simple social agent may be adequate for this research, because the focus is on collective patterns instead of the aspects of individual cognition.

3 RESEARCH FRAMEWORK

The research framework, as shown in Figure 1, schematically represents the different parameters and variables considered in this research. This includes:
a) ***Independent variables:*** Analogical type/distance: i) within-domain analogy ii) between-domain analogy; Team composition/ Expertise of team members: i) Level of multi-disciplinarity ii) Level of expertise (expert/ novice); Team size.
b) ***Mediating variable:*** Analogical purpose: i) problem identification ii) function finding iii) solution generation iv) explanation.
c) ***Dependent variables:*** Team Collaboration; Team Cohesion.
The research framework is largely based on the findings obtained from the study carried out by Casakin et al. (2014). These researchers explored how the use of analogical reasoning influenced team interactions, in particular with regard to team cohesion and team collaboration. Analogies were further classified according to 'analogical distance' (i.e., within-domain or between-domain) and 'analogical purpose' (i.e., problem identification, function finding, solution generation and explanation). At the core of the framework is analogizing, which was found to increase team cohesion and team collaboration. Within-domain analogies played a higher role on team collaboration than between-domain ones. However, no differences were found in both types of analogies for team cohesion. On the other hand, all types of analogical purpose indicated a likely association with team cohesion, while solution generation and function finding had a stronger association with team collaboration compared to the other activities. A first expectation of the present study is that it will be possible to repeat the results obtained in Casakin et al. (In press) study when testing them in a computerized model.
Prior studies showed that whereas expert designers tend to use between-domain analogies more intensively than within-domain, novices demonstrated an opposite behaviour (Casakin, 2004). Provided that team composition is characterized by a higher number of experts than novices, a more frequent use of between-domain than within-domain analogies is expected, with consequently less team cohesion. Under a similar team composition, whether more team collaboration would exist is an open question that needs to be investigated. Moreover, what influence the type of analogy will have on team collaboration and team cohesion if the size and number of teams increase is another issue that was not explored yet.
As was shown before, Christensen and Schunn (2007) demonstrated that within-domain analogies prevailed during problem identification, whilst between-domain analogies were dominant during explanation. On the other hand, both within-domain and between-domain analogies were found to have a likely dominance during solution generation. Provided that team composition is characterized by a higher number of experts, then it is expected that the team analogizing behaviour will be higher in explanation and solution generation, than in problem identifications. Likewise, a higher number of experts is expected to augment solution generation, with a consequent enhancement in team collaboration. An open question is whether or not an augment in the number of experts will make a difference in team cohesion. Another question to be investigated is what influence will analogical purpose have on team collaboration and team cohesion if the size and number of teams increases.

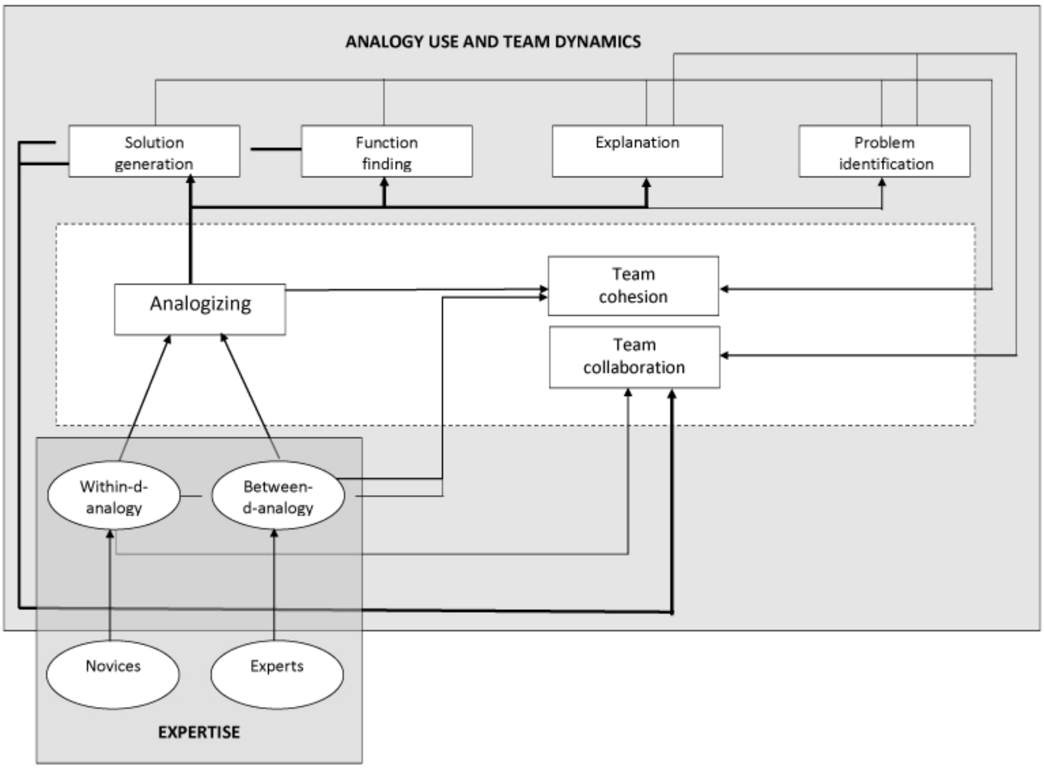

Figure 1: Research framework to study the effects of analogizing on team cohesion and collaboration

Based on the research framework, a number of hypotheses and open questions will be explored using a computational model to be developed in a future study. For example, as a first step, the findings obtained in Casakin et al. (2014) will be replicated in the computerized model and tested for their internal (logical) validity and consistency through repetitions. This first step will also allow the validity of the developed computational model. Thereafter, additional hypotheses and what-if scenarios will be investigated. For example, what role does analogy play in team cohesion if the team has a higher percentage of experts, that is, members who are as likely to use between-domain analogies as within-domain analogies. Similarly, how will team collaboration be affected by an increase in the number of novices, who typically use within-domain analogies?

4 COMPUTATIONAL FRAMEWORK

This section elaborates on the planned computational framework, including aspects such as task and knowledge representation, analogy, team interaction and the key parameters and measures. The design team is viewed as a collection of social agents who interact through message passing to collaborate and solve a given task.

4.1 Task and knowledge representation

A predefined knowledge base will be used to represent the design space and the tasks in order to be able to simulate scenarios pertaining to the use of within-domain, and between-domain analogies in design. Following are the key abstractions planned for this computational framework:
Multidisciplinarity: This can be represented as a finite set of knowledge domains available to the design society, discretely classified as m disciplines.
Discipline space: size of design/knowledge space in a given discipline can once again be represented as a discrete set of n concepts.
Figure 2 shows how each design solution can be seen as a set of compatible concepts, which can be pulled together from one or more disciplines. The design space, can be therefore represented as an $m \times n$ matrix. The same problem can have different solutions, some of which can be achieved by

replacing one or more concepts from a known solution, with equivalent concepts from the same or other disciplines retrieved by analogical reasoning.

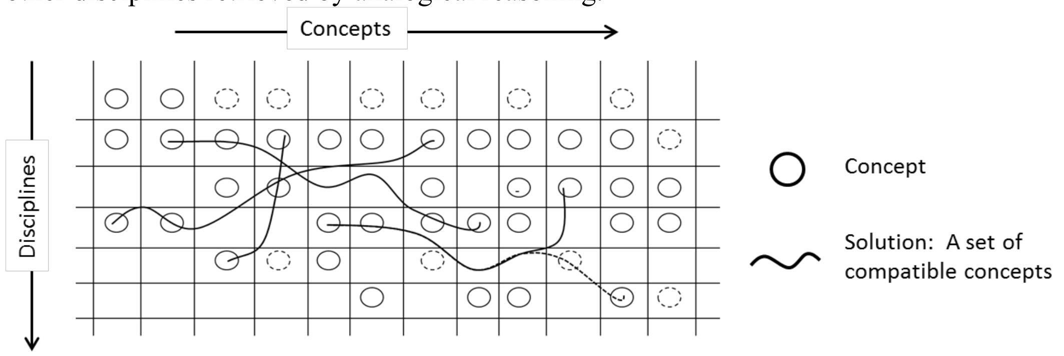

Figure 2: Design solutions as a set of compatible concepts from one or more disciplines

Analogical distance between concepts: The similarity and differences between concepts in the design space can be represented using multiple measures of (1) within and between domain distance, and (2) analogical distance. For example, in this model we can assume that the proximity between any two disciplines, m_i and m_j, for the purpose of representing analogical distance can be calculated as |j-i|. Similarly, the analogical distance between any two concepts n_{ka} and n_{kb}, in the k^{th} discipline can be calculated as |b-a|. By combining these two ways of representing the distance between disciplines and the distance between concepts, the analogical distance between any two concepts n_{ka} and n_{lb} across two disciplines k and l, can be calculated as $\left| \sqrt{[(l-k)^2+(b-a)^2]} \right|$. The schematic representation in Figure 2, can be implemented as shown in Figure 3a. This representation allows implementing within domain and between domain analogical distances, as shown in Figure 3b.

Knowledge space →

Disciplines

	C_1	C_2	C_3	.	C_l	.	C_n
D_1	C_{11}	C_{12}	C_{13}	-	-	-	-
D_2	C_{21}	C_{22}	C_{23}	-	-	-	-
D_3	C_{31}	C_{32}	C_{33}	-	-	-	-
-	-	-	-	-	-	-	-
D_k	-	-	-	-	C_{kl}	-	-
-	-	-	-	-	-	-	-
D_m	-	-	-	-	-	-	-

A: Disciplines and concepts in knowledge space

Analogical distance between concepts →

Analogical distance between disciplines ↓

	C_1	C_2	C_3	.	C_l	.	C_n
D_1	C_{11}	C_{12}	C_{13}	-	-	-	-
D_2	C_{21}	C_{22}	C_{23}	-	-	-	-
D_3	C_{31}	C_{32}	C_{33}	-	-	-	-
-	-	-	-	-	-	-	-
D_k	-	-	-	-	C_{kl}	-	-
-	-	-	-	-	-	-	-
D_m	-	-	-	-	-	-	-

B: Within and between domain analogical distance

Figure 3: Representing disciplines, concepts and analogical distances

Analogical purpose: The four types of analogical purposes shown in Figure 1, namely solution generation, function finding, explanation, and problem identification, will be pre-coded objectives such that the agents' action at any given instance is a reaction to the objectives at that instance. The objectives at any given instance will be a probabilistic function, also contingent on the actions and objectives in the preceding instances. Therefore, even if all the task knowledge and task related actions will be pre-coded in the model, the solutions and task related interactions in any given simulation will be non-deterministic, based on Monte Carlo results.

4.2 Agents and parameters

Level of multi-disciplinarity: The number of disciplines that an agent has knowledge of.
Expertise in a given discipline: The number of concepts in a discipline that are known to an agent.
The combination of the level of multidisciplinarity and level of expertise allows for multiple expertise profiles to be represented. As exemplified in Figure 4, an agent can have moderate level of expertise in any given discipline, but expertise across many disciplines. Similarly, another agent can have high expertise in one or two disciplines, but little or no expertise in any other discipline.

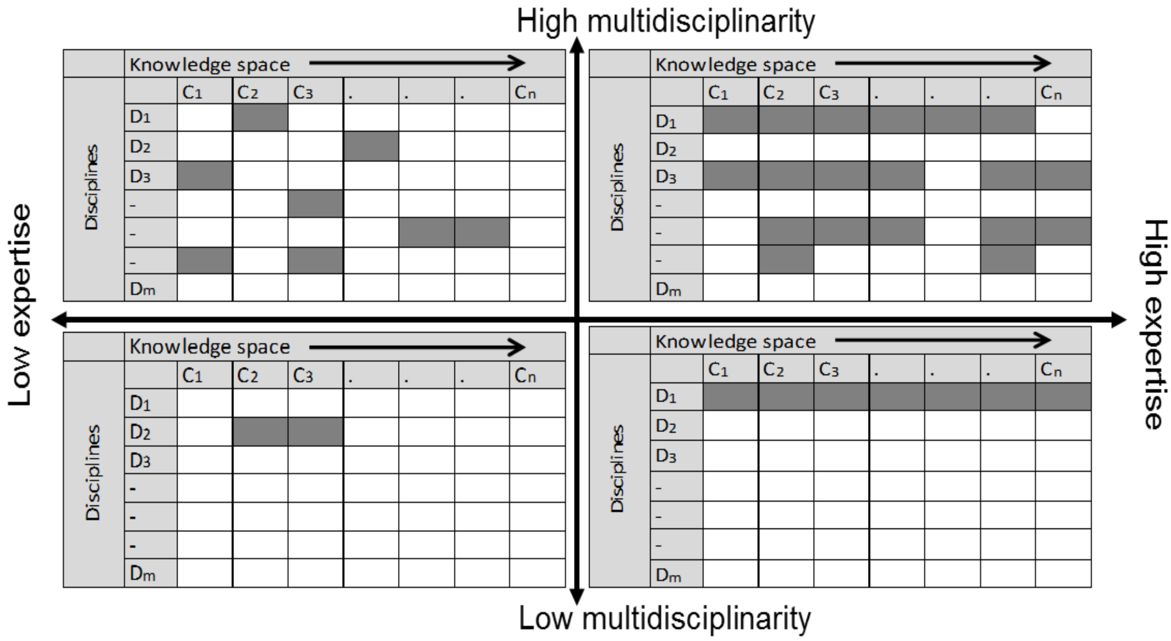

Figure 4: Example of different expertise and multidisciplinary profiles of agents

4.3 Team representation and parameters

Team composition: As parameters, the levels of multidisciplinarity and expertise allow various agent profiles that can be used to vary the team composition. For example, teams can be composed of agents that belong to one or two of the quadrant types in Figure 4, or can have a balance of agents representing each of the quadrant types.

Team size: Team size is another default parameter available in the framework. However, team size may not necessarily be independent of team composition. For example, small teams can be composed entirely of experts or novices; it is rarely the case that a large team is composed only by experts. Often large teams have a mixture of experts and novices. Therefore, assumptions about team size and team composition will be based on typical scenarios observed in practice. Consequently, team structure is another parameter that will be introduced in the computational framework.

4.4 Modelling collaboration and teamwork

For the agents to collectively solve a problem, other aspects of team interaction need to be modelled such as the mechanisms for knowledge sharing and information exchange. These mechanisms are by themselves not to be used as variables in this research, but these assumptions are necessary to model and simulate conditions under which the desired studies can be conducted. By keeping these modelling assumptions constant, their effects are nullified across the simulation cases.

Transactive memory: In order for agents in a team to be able to interact with other agents in the team, and collectively solve the given task, they need to know 'who knows what'. That is, agents need to have a transactive memory of the team (Wegner, 1995). This is represented as $m \times p$ matrix, where m is the number of disciplines, and q is the number of agents in the team.

Interaction between agents: Agents in the team interact through direct message passing. Messages can be one-to-one, or one-to-many. One-to-many messages can be used to simulate a group discussion, which is typical of small teams that will be simulated in the initial cases.

A comprehensive list of the different types of messages and message vocabulary that will suffice to simulate the desired cases will be pre-coded in the model. Once again, the sequence of messages and contents at any given instance will be a probabilistic function of the objectives at that instance, and how the problem and discussion emerges in the specific simulation case. Consequently, the message patterns will remain non-deterministic. Given this non-deterministic and emergent nature of the team discussion, data collected from the simulations can be subjected to a protocol analysis based on similar coding schemes used for empirical studies with human designers. Applying the coding schemes on the messages employed in simulation studies will be an objective task, because a limited and predefined vocabulary will be chosen to correspond to that coding scheme. The development of the message vocabulary is currently in progress.

***Protocol for message passing*:** The message passing across the agents will be based on FIPA-ACL (Foundation for Intelligent Physical Agents-Agent Communication Language) protocols, such that a typical message envelope holds details like message identification number (ID), sender's name, receiver(s)' name, message type (e.g. purpose, clarify, reject, accept, etc.), and the message body.

4.5 Measuring outcomes: Team collaboration and team cohesion

This research adopts a similar approach to measuring team collaboration and team cohesion, as used in Casakin et al. (in press). Team collaboration and team cohesion are both measured using protocol analysis of the messages exchanged between the agents.

Measuring team collaboration: Following Casakin et al. (in press), team collaboration is categorized to be present or absent in any given episode of design activity, depending on whether more than one agent contributed to the objectives. This type of interaction is established when one or more agents either acknowledge it explicitly through message passing, or through the modified actions on the design task.

Measuring team cohesion: Based on Casakin et al. (in press), team cohesion is assumed to have occurred in any given episode of design activity when a shared understanding of an analogy or an analogical distance across the discussed concepts between two or more agents is observed. This development of shared understanding is explicitly observed in the exchanged messages, especially through message types such as clarification and acknowledgement.

5 DISCUSSION

This paper provides the preliminary details of a computational framework being developed as a step towards an agent based simulation tool that will enable to study the effects of analogizing in design teams, particularly with regard to team collaboration and team cohesion. Despite the preliminary stage of development of the framework, the paper raises a few notable points, which are:

Focus on social effects of analogy in design: Most studies on analogy focus on cognition and associated learning, as analogizing is considered to be primarily a cognitive process. Consequently, the social aspects tend to be overlooked, more so in computational discussions where authors have previously attempted to computationally simulate or mimic analogical processes (e.g. Gero et al, 2008; Gero and Kannengiesser, 2012), or understand analogical processes from cognition and intelligence viewpoints (e.g. Chan et al, 2011; Fu et al, 2013). This research attempts to make a novel contribution by accomplishing first steps towards the development of a computational framework that focuses on the social effects of analogy. A key challenge, however, is the tendency to consider a cognitively rich agent in the simulations. While it will be desirable to use cognitive agents in future simulations, as a bottom-up process, it may suffice at this stage to begin with simple reactive agents, and yet be able to study the social effects of analogy. This paper presents a first attempt to demonstrate how such bottom-up approach can be adopted by using simple social agents with limited cognitive capabilities.

***Focus on team dynamics rather than on design solutions*:** Consistent with the previous point, most studies on the use of analogy in design centered on aspects like creativity and the design outcome, while the effects of analogy on team dynamics have not been sufficiently explored. This is reflected in previous literature in design computing on analogy (e.g. Gero et al, 2008; Fu et al, 2013). Therefore, this research focusses on the effects of analogizing on team collaboration and team cohesion, based on recent empirical studies that can inform the development of the computational model., It is important to note that the proposed model is not intended for studying the effects of analogy on design outcomes. Hence, it is acceptable that the models have a pre-coded design and knowledge space, so that all the design solutions generated during the team activity are limited within this design space. This implies that it is sufficient to abstract design problems and solutions in symbolic terms, instead of a direct reference to disciplines and concepts from the real world.

***Objective description of aspects such as multidisciplinarity expertise*:** While developing the computational framework, it was difficult to find an objective description in design literature on what constitutes multidisciplinary expertise, and how it can be measured. An objective description for this concept is essential for a computational model, provided that most descriptions typically found in design teamwork and team collaboration literature are subjective and inadequate. For example, it is often stated that multidisciplinary teams are desirable, but it remains unclear what should be the desirable profile of the members of such a team. Should team members have moderate level expertise across many disciplines, or should they have a high level of expertise in fewer disciplines? From that perspective, one of the key contributions of this research so far is the identification of this gap in the design literature. It is therefore anticipated that as the computational framework will be developed further, more gaps in existing empirical studies will be identified.

6 LIMITATIONS

This paper presents a preliminary framework in progress intended for a computational model about analogizing during team interactions when dealing with design problems. Further theoretical and empirical studies in the areas of multidisciplinarity and analogy will be considered in a following stage while developing the computational framework.

From the experience gained while developing previous models of computational social simulations (e.g. Singh et al, 2009, 2013), we recognize the iterative nature of the process. Therefore, it is expected that as the research progresses from a conceptual framework stage to a more concrete computational implementation, further conceptual clarity and objectivity will be accomplished. Together with this, we acknowledge that at each stage, some level of abstraction and simplification is also necessary to implement the model. These assumptions should be taken into consideration when assessing the scope of the framework and interpreting the results.

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