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# COMPUTATIONAL STUDIES FOR ARTIFICIALLY SIMULATING HUMAN COLLABORATION IN DESIGN TEAMS

Doctoral Dissertation of

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# DECLARATION

I hereby declare that this written submission is my own work. To the best of my knowledge and belief, it contains no material previously published and written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or another institute of higher learning, except where due acknowledgement has been made in the text.

Place and date

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# Abstract

Collaborative teams are getting more and more popular. There is a current need to understand how the complex and dynamic system formed by collaborative teams behave when system parameters are changed to see their impact on project outcomes. Research in the past has focused on studying the single elements of the collaborative design like design task, design team structure, design tools and design process (idea generation and idea selection). Understanding the complete system of the design team collaboration is challenging to the researchers as it increases complexity. Therefore, the purpose of this research is to increase the understanding of a collaborative system composed of teams, tasks and its collaboration environment through an agent-based model called *MILANO* (Model of Influence, Learning, and Norms in Organizations).

This computational model is implemented using the Python programming language. MILANO is developed to mimic design team collaboration of the real world, hence it serves as a platform to study and simulate different scenarios of team dynamics that are challenging to control in a laboratory setting. The model is composed of agents that are analogous to humans in design teams who work on a design task by collaboratively generating and selecting solutions. Similar to the real world, the selected solutions are proposed to the controller agent (equivalent to a leader or manager to a problem-solving team), who provides feedback to the team. The research is broadly composed of three parts that fulfil the main purpose of the study. The first one is related to the common scenario where certain individuals who have high social influence (referred to as influencers) than others in the team, affect individual thinking during idea generation and selection. This is further investigated by varying the nature of the design task and the size of the team. The second part is related to the team compositions of experience and novices and their impact on the design outcome when changing the nature of the task. The last bit of the work is related to studying the impact of the collaboration environment (i.e., virtual vs face-to-face team collaboration) on the design outcome for various test cases (like teams with an experienced agent, half of the team with high self-efficacy, all agents with same self-efficacy and all agents with same self-efficacy working on a complex design task).

Though most of the model formation is based on the past literature and theories, it also has some assumptions and has parts that needed logical validation. These assumptions were validated through empirical studies conducted in the real world. The empirical results also provide insights into the relationship between model parameters and verified the logic behind its foundation. Although agent-based modelling is an effective approach for simulating collaborative design teams, the validation of the entire model is difficult, especially if there are plenty of parameters to control in a real-world setting. Therefore, continuously validating and verifying the model rationale by means of empirical studies, adds to the strength of the model and its results.

The extracted simulation results of the design task outcome were measured in terms of quality, exploration and other team performance parameters like the contribution of team agents. Broadly speaking, the model simulation results showed how varying the parameters of the collaboration design affects the outcomes of a design project. For example, different influencer- team composition has a significant difference in the generated solution quality of their team members. Moreover, having an experienced agent in a team of all novices can increase the quality of the solutions while reducing the variety. Likewise, having half of the team members as more influential, could results in a better outcome when the team collaboration is virtual. From the results, it is clear that a type of team that is effective in one situation might not perform well in other situations.

Besides, studying the social, cognitive and environmental factors that were unaccounted for in the past literature, this research introduces a novel way to stimulate learning in agents and metrics for measuring design outcomes related to artificial design agents' performance. Some of the research findings conform to the literature, hence suggesting that MILANO could be used to study collaboration in design teams and could provide meaningful insights into team formation and management. These findings could be useful in determining appropriate team and task management strategies to obtain near-optimal project outcomes in organizations during the early design phase. In academia, the model that artificially simulates human collaboration could be used as a faster approach to gain insights into different design team collaboration scenarios.

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I am so fortunate to be at this place in my life where I had the privilege to meet amazing people and be a part of this incredible institution.

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| | |
|---|---|
| $f(x)$ | A multi-dimension function to computationally represented the design problem, where each dimension denotes a design variable '$x$' is an $n$-dimensional array ($x_1, x_2, x_3....x_n$). |
| $M$ | The number (size) given to represent the solution space in 2D matrix. |
| $D$ | It represents the distance between the random point $(x_1,x_2)$ and the nearest best solutions. |
| $O(z')$ | Agent's energy to explore solution space, where $z'$ is the normalised length of the session. |
| $\sigma$ | Represents the shape parameter that affects the overall shape of the curve. |
| $c$ | Agent's energy value when the session starts |
| $S(d')$ | Magnitude of the learning vector from a positive event, where $d'$ is the normalised value of the similarity between the recalled and current agent state. |
| $\alpha$ | Position of the peak when learning from the positive experience |
| $E$ | Agent domain-expertise level |
| $\tau$ | Height of the peak when learning from the positive experience |
| $\Delta t$ | Difference between the sessions when the recalled event occurred and the current session |
| $n$ | The current session number of an agent |
| $S_n$ | The session when the recalled success occurred |
| $N$ | The given number of sessions |
| $\vec{v}_s$ | The learning from positive experience vector |
| $\vec{v}_k$ | The initial knowledge state vector of an agent |
| $\vec{v}_n$ | the resultant learning vector from the $\vec{v}_s$ and $\vec{v}_k$ |
| $F_{learning}$ | Failure learning capacity of an agent |
| $f_{feedback}$ | recalled failure feedback value |
| $p$ and $r$ | Variables to be adjusted to get the desired size of the maximum failure radius when the feedback is worst |
| $I$ | Influence value |
| $SE$ | The self-efficacy of an agent |
| $\Delta SE$ | Difference in the self-efficacies of the two agents |
| $T$ | Trust between the two agents |
| $w_1, w_2, w_3, w_4$ and $w_5$ | The weights that were decided in after the empirical studies |
| $R$ | The reputation of an agent |
| $N_a$ | The number of solutions that are accepted by the controller agent |
| $N_p$ | The total number of the solutions proposed by an agent. |
| $f$ | The familiarity between the two agents |
| $\vec{v}_I$ | The total amount of learning by an agent from its peers |
| $\vec{v}_{\grave{n}}$ | The amount of learning an agent does while generating solutions |
| $EI$ | Exploration index |
| $solns_{lowr}$ | The unique number of solutions explored on a reduced resolution of the solution space |
| $Area_{lowr}$ | The reduced resolution solution space area |
| $EQI$ | Quality exploration index |
| $t$ | Threshold taken to determine $EQI$ and $LEQI$ |

| | |
|---|---|
| $qSolns_{lowr}$ | The number of solutions that are greater than $t$ on a reduced resolution design space |
| $qTotSoln_{lowr}$ | The total number of solutions that are present in the solution space that are greater than $t$ |
| $LEQI$ | Local Exploration Quality Index |
| $solns$ | The number of solutions proposed that are above a certain threshold ($t$) |
| $totSoln$ | Total number of solutions proposed |
| $N_{Min}$ | The minimum number of agents that should propose solutions |
| $SA$ | Selected agents |
| $N_{SA}$ | The number of selected agents to propose solutions |
| $N_{tot}$ | Total number of agents in a team |
| $P_{SA}$ | The probability of an agent to be selected to propose its solution |
| $SE$ | Self-efficacy of an agent |
| $Team_{SE}$ | Team self-efficacy |
| $Var\ (Team_{SE})$ | The self-efficacy variance of a team |
| $Num_{totSoln}$ | The total number of solutions |
| $J(V)$ | The objective function that k- means aims at minimising |
| $S$ | The set of positions of the solutions points |
| $v$ | The positions of the centroids |
| $c$ | The number of clusters |
| $c_i$ | The number of solutions in a cluster $i$ |
| $P_A$ | The past amount agreement an agent had while deciding on the other agent's proposed solution |
| $A$ | The amount of agreement an agent has with the other agent on its proposed solution |
| $A_{total}$ | Total agreement on a proposed solution |
| $ps$ | Proposed solution |
| $Q$ | The number of proposed solutions. |
| $N_A$ | The number of agents who agreed with the proposed solution |
| $P_{feedback}$ | The probability of the feedback |
| $distribution(A_{total})$ | The distribution of the total agreement for all proposed solutions |
| $\eta$ | Communication effectiveness |
| $\tau$ | Technology mediation |
| $\varepsilon$ | Shape parameter for $\eta$ |
| $V_d$ | The degree of team virtuality |
| $\kappa$ | Conflict factor |
| $\theta$ | A parameter regulating $\kappa$ based on $\Delta SE$ |
| $\omega$ | Slope parameter for $\theta$ |
| $\zeta$ | Normalising parameter for $\theta$ |
| $\Delta I$ | The reduction in the influence value ($I$) |
| $a,b$ | slope parameter and power coefficient for calculating $\Delta I$ |
| $I_v$ | Influence during virtual team collaboration |
| $T_v$ | Trust during virtual team collaboration |
| $\lambda$ | Controlling parameter of gradual trust-building in virtual collaboration |

# Chapter 1

# Introduction

Though collaborative design is increasingly becoming popular; it has its barriers. Simply having a diverse team does not ensure successful projects. There are several factors such as individuals' characteristics, teams and organization structure, social, and environmental attributes that impact the collaborative design process and its outcomes. Since collaboration is an activity that involves interaction among individuals, a collaborative design could be considered as a social process that affects the products of a design process. Given the complexities associated with the dynamics of collaborative design teams from idea generation to the final proposal of the selected concept, understanding the obstacles and challenges at the micro and macro level may contribute to successful projects. Therefore, this research explores some aspects of the collaborative design involving an idea generation and selection process, and the effect of some of the social-cognitive factors on design project outcome. The work uses an agent-based modelling approach to simulate collaboration scenarios because this approach could capture details at the individual level besides being efficient in representing complex phenomenon.

This chapter describes the motivation behind the work and the research objectives that helped in fulfilling the purpose of the work. The chapter also presents the potential contribution of the research and its outcome, besides, providing an overview of the thesis structure.

## 1.1 Motivation

Organizations are increasingly using these collaborative teams (Mesner-Magnus & DeChurch, 2009) as they are considered essential for innovation that provides a competitive advantage (Mathieu et al., 2008). They rely on creative outcomes from their employees that facilitate performance and growth (Amabile, 1996). Since most of the employees are working in teams, understanding the team collaboration and how the design outcomes are impacted, could enhance project effectiveness (Drazin et al., 1999).

Though collaborative design teams have a lot of innovative potentials, they are difficult to manage. The teams may have difficulty in selecting ideas when team members have very diverse ideas or in producing variety when their thinking is affected by other team members' ideas (Nemeth, 1986). There may be problems related to information sharing (Paulus & Yang, 2000), conflicts from lack of efficient communication (Bettenhausen, 1991), the emergence of some influential individuals team (Brown & Pehrson, 2019) or may lack confidence and motivation in groups (Monge et al., 1992). Social cognitive features of the team like trust and familiarity or similarity among the team members may change their preference towards their peers in a team (Perry-Smith & Shalley, 2003). Understanding these aspects of collaboration would not only improve team experiences but also aid in managing design teams.

Social influence emerges in teams as there is an interaction among the team members (Myers, 1982). The magnitude of social influence is not evenly distributed across members of a team (Brown & Pehrson, 2019). The individuals who are perceived to have high influence are referred to as influencers and many impact idea generation and selection, hence the design outcome. These influencers in flat teams (where there are no appointed leaders) may govern the team processes and may impact the project outcome. Unlike the current trend towards studying the influencers in social media, the aspect of influence that occurs during collaborative design is not studied. Although researchers have tried to study the characteristics of these social media influencers, little is known about the characteristics of influencers in design teams. This further need investigation to reveal the characteristics and qualities, which give rise to the influencer effect in design teams.

The individuals in the team might agree with the most confident individual (influencer(s)) in the team or choose to go with others having similar opinions (Martínez, 2020). For example, individuals having similar thinking may strengthen their opinion and confidence. On the other hand, if they are not confident about their option, they may be easily influenced by the opinion of the influencer(s) in the team. Hence, factors affecting individuals' agreement in design teams need to be explored. This gives an opportunity to study a more complex situation during decision-making that may emerge because of influencer or the majority when selecting solutions.

The other aspect behind the research motivation is the design teams that are composed of individuals with varying levels of expertise which is challenging to study than 'individual design' as the interaction between the team members affects individuals' cognitive and social abilities. Though having a diversity of experiences within a team does add to the innovation potential of the team, the varying level of experience among the team members can influence design team dynamics and may give rise to power hierarchies. Experienced individuals are often more influential as they are confident and may affect learning and decision-making in novices in the team (Chamorro-Koc et al., 2009; Klucharev, et al., 2008). The design project results depend on the combination and interaction among the team members. Although research in the past has been done to compare the skills and approaches of novices and experienced practitioners, more attention is required to see the effect of social interactions on the design outcomes when addressing a routine and routine design task.

The last motivational aspect of the study has been the recent Covid-19 pandemic situation when most of the world has switched to virtual team collaboration (Waizenegger et al., 2020). During and possibly also when the pandemic is over, organizations may continue having virtual teams to work on routine tasks. This may result in a mix of teams in an organization where some may be completely distributed while others may be co-located, hence a situation with a different degree of team virtualness (Griffith et al., 2003). Virtual team collaborations are subjected to their limitations, for instance, trust-building and knowledge sharing is slower than face-to-face and virtuality affects communication and may give rise to more conflicts. The social influence is affected due to virtuality, hence the expert members may not be equally effective as in face-to-face team collaborations. Virtual collaboration in organisations have been accelerated due to the recent pandemic, hence it is important to understand and address the challenges associated with the performance of these teams.

Certainly, it is difficult to study collaborative activities in a real-world setting, as they are very resourced intensive (Becattini et al., 2019). Moreover, it is difficult to track and measure the factors that affect the decision-making during idea selection under experimental conditions as they change depending on individual characteristics such as personality, confidence level or persuasive power (Latane, 1981). To overcome these challenges, this work uses a computational model to explore and extend the understanding of the idea selection while considering social factors such as the influencer effect and majority effect during decision making. The paper deals with the agent-based modelling (ABM) approach for simulating the early design phase in non-hierarchical collaborative design teams. Several studies used ABM as a tool for computational modelling and representing real-world scenarios of team collaboration, but have lacked to focus on the human behavioural aspect in their model (Jamshidnezhad & Carley, 2015; Carley & Gasser, 1999). Thus, besides, taking into consideration the social factors during idea generation and selection in design teams that have not been studied in past, the work presents how different scenarios like teams with a different number of influencers, experience-novice agent teams and virtual collaboration environment affects design outcome.

## 1.2 Aim and objectives

The aim of the research is to explore and improve the understanding of the design team collaboration under the influence of various individual, team, task and environmental factors. Overall, the work provides a computational framework for simulating collaborative human behaviour in teams by employing an agent-based approach that is supported by the evidence from empirical studies. In order to fulfil the aim of the research, the following objectives could be identified:

1. To identify the main components of the collaboration in design teams that affect design outcomes.
   Based on the literature and the gaps in the past, the components important to the goal of the work will be identified.
2. To develop a computational framework that captures the cognitive and social phenomena in the design teams.
   The past theories, findings and assumptions will be used to frame a computational framework of collaborative design teams.
3. To develop a comprehensive model of idea generation and selection in the design process by identifying the parameters that affect them.
   The computational structure of design team collaboration that consists of idea generation and selection will be developed in Python during the research.
4. To design experiments with these parameters identified to validate the model assumptions.
   The empirical studies will be conducted to find support to the model assumptions and to provide logical verification.
5. To investigate the effect of unequal distribution of social influence in teams on design outcomes by means of model simulations.
   The results from the model that simulate the different influencer-team compositions will be analyzed.
6. To deploy the model for simulating other collaboration scenarios by varying model parameters.

The model will be used to simulate other team collaboration scenarios related to the research questions identified.

7. To validate these results by means of literature
   The literature will be used to validate some of the results of the simulation. However, the past studies that have exactly studied the same phenomena do not exist. Hence, reflection on some particular team behaviours with respect to a few studies from the state of the art (that are remotely related) will be done.
8. To expand the model to accommodate the effect of environment on the mode of collaboration (virtual and face-to-face) by identifying roles and relationships among the main parameters affecting it through empirical experiments.
9. To analyse the data extracted from the model.
   This will provide some insights into the behaviour of the collaborative system by providing inductive and deductive insights.
10. To discuss model results and their implications to propose further development.
   In the end, the implications of the results and areas of potential research related to this work will be identified.

## 1.3 Research contribution and significance

Increasingly, emphasis is being given to study the collaborative design process at the individual level and how social and cognitive factors could contribute to the final design output. Cross and Cross (1995), stated that team activity should be considered as a '*social process therefore, social interactions, roles and relationships cannot be ignored in the analysis of design activity teamwork*'. Anyone who is observing design activities like idea generation and idea selection should consider the social factors as they could aid design methodologies and improve understanding of team dynamics. Thus, the work explores the impact of some of these factors on design project outcomes.

Collaborative design teams can be viewed as social networks, but the role of influencers in small teams is still underexplored. This uneven distribution of social influence that gives rise to influencers in the design team has been studied neither empirically nor computationally before. Therefore the current research investigates these influencers in design teams by studying the characteristics that could lead to influencing and being influence behaviour, and the effect on team performance. The work provides a computational framework that could simulate influencer and majority effect in collaborative design activates. The research also contributes to the design engineering research as it explores how different experience-novice team composition affects design outcomes when placed together in a team. Lastly, the study contributes to the understanding of virtual team collaborations that are becoming increasingly popular these days.

This is done through an agent-based modelling approach, whose wider contribution is to provide a platform that could mimic collaboration in teams. The simulations were done from scratch using Phyton programming language, without relying on any existing agent-based frameworks (such as MESA, JADE, NETLOGO or MASON). This also provides future researchers to use the proposed model base in Phyton for their agent-based work. Additionally, the work provides a novel approach in stimulating learning in design teams (by considering appropriate model features such as design task, learning from past experience and influencer) is described in Chapter 3. Measuring design outcomes of the agents could be analogous to measuring artificial design agents' performance and the study also offers new metrics for assessing it.

The features and the logic behind the model formation such as the characteristics of an influencer, the presence of influencer and majority effect, and the assumption behind the agreement during idea selection was tested through empirical studies. These empirical studies were conducted as no support could be found in the literature, thus contributing to the design research in understanding human cognition and behaviour.

Overall, the work aids the design research by building a computational framework that could simulate different collaborative design scenarios. Besides, providing insights to the research questions explored in the work, it would also assist researchers and practitioners with a faster method to study collaborative processes. The results of the research offer insights into design team behaviour. It shows how different influencers in a team, experience-novice team composition and virtual vs face-to-face collaboration affect design outcome with respect to the nature of the design task. This provides a possibility to exploit the results to implement proper team management strategies to extract the full creative potential of the design teams.

## 1.4 Thesis overview

The research follows design research methodology (DRM) proposed by Blessing & Chakrabarti, (2009) (seen in Figure 1- 1), where DRM consists of four stages: Research clarification (RC), Descriptive study I (DS-I), Prescriptive Study (PS) and Descriptive Study II (DS-II).

The Research clarification stage consists of literature analysis to formulate the research focus area and the scope of the work. A review-based Descriptive study I was implemented in the current research that consisted of further review of the literature to identify research questions and model support. This stage was followed by a comprehensive Prescriptive Study where the development of support of answer the research questions identified in DS-I in the form of a computational model took place. The PS stage was followed by comprehensive Descriptive Study II where the evaluation of the model logic in the form of empirical studies was done to improve the model. DS-II was also used to verify the assumptions behind the model formation in DS-I. DRM is not a linear process but iterations within stages and between stages are present. Based on DRM framework, the research and this thesis structure could be organized as shown in Figure 1-1, closing associating with the Type 6 research projects.

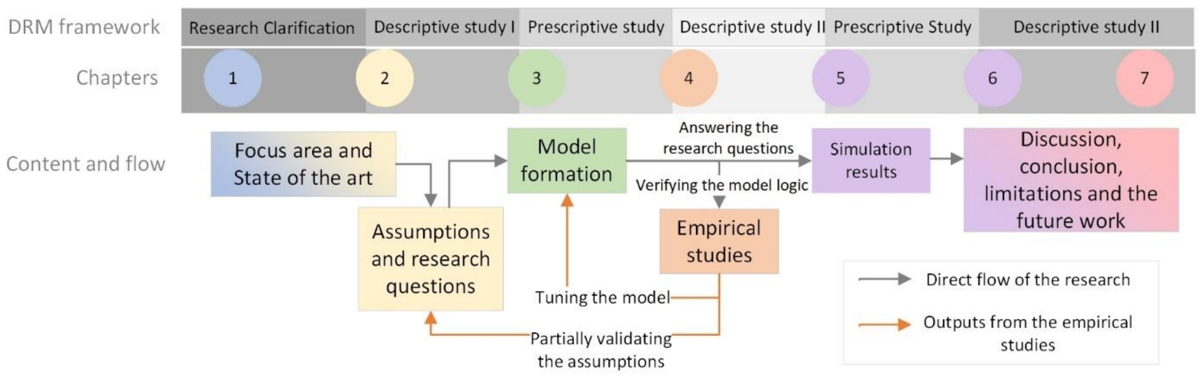



Figure1- 1 The layout of research and the thesis structure

The following Chapter 2 deals with the RC and DS-I by studying the state of the art. It contains a general overview of the focus area with an emphasis on collaboration from a social perspective.

Related work on collaboration team dynamics and computational modelling is followed by the identification of the gaps and formulation of the research questions.

Chapter 3 prescribes (PS) a computational model. The model formation is based on past literature and theories. It starts with a description of the design task and model agents. This is followed by the computational framework of idea generation and selection. It illustrates the aspects of agent learning and decision-making. The introductory description of the implementation of the computational framework in two scenarios; experience- novice team composition and virtual team collaboration, is presented at the end of this chapter.

The empirical studies were not used to validate the model findings but used to verify the model logic and validate the assumptions are presented in Chapter 4 (DS-II). The set- up and the details of each empirical study is presented in this chapter. The results from these empirical studies are also presented and discussed in the same chapter. The chapter ends with a summary of these results and how they were used in the context of the model formation.

Chapter 5 and Chapter 6 are related to the PS. Chapter 5 describes the results that demonstrate the functioning of the model like agent learning results. Chapter 5 also contains the description of the measures used to evaluate design performance. Chapter 6 on the other hand explains the simulation tools and setup used as well as the results that help in answering the research questions. The results related to the varying number of influencers, experienced-novice team compositions and the impact of collaboration environment are presented. In addition to these direct results related to the research questions, parts of this chapter also show how team and task characteristics influence design outcomes. Chapter 6 also has a discussion section that compares the published simulation results to some of the studies in the past. This chapter ends with reviewing the practical implications of the results and a discussion on the validation of the model.

Lastly, conclusions in Chapter 7 (DS-II) presents the review of the research by addressing the objectives that were identified at the beginning of the study. A summary of the findings that have addressed the research questions is also presented. The strengths and the limitations of the study are identified. Additionally, this chapter also discusses the areas that need further investigation along with future work objectives.

# Chapter 2

# Background

Social influence is present whenever there is interaction such as during team collaboration and changes over time as the collaborative session continues. The design project outcome depends on collaboration which in turn is affected by many parameters like individual, task, team or environmental attributes. This chapter presents the state of the art, it contains the general overview of the focus area with an emphasis on collaboration from a social perspective. This is followed by related work on collaboration team dynamics and computational modelling. A brief description of the literature that has used different ways to measure design performance and artificial design agents' performance is also given in this chapter. The review provides the base for the assumptions and the research questions discussed at the end of this chapter that form the foundation of the research (as in Figure 2- 1). A review of the literature is mainly related to the focus area but also sparsely contains work done in the different domains like group behaviour, social behaviour, social networks social cognition, organisational creativity, individual learning and other similar topics that complement the study.

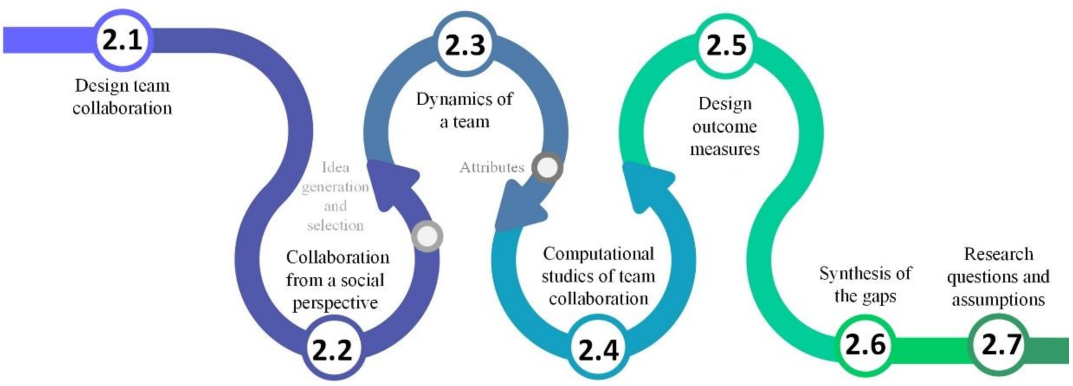



Figure 2- 1 Background presented in the thesis

To give a more relatable and clearer picture of the different aspects of model formation, the literature on which the model is grounded is presented in Chapter 3 along with its description. Similarly, the literature supporting the contents of the chapters is presented in the respective chapters.

## 2.1 Design team collaboration

In the world, today, where there's a continuous demand for innovative solutions, collaboration is one of the most effective strategies (Roberts, 2000). Collaboration not only gives access to individual's knowledge but also their unique way of thinking and mutual perspective on the issue at hand (Détienne et al., 2005). There are terms that are often used interchangeably such as co-creation, participatory design and co-design. Co-creation is a very broad phrase that means an "act of collective creativity by two or more people" and "co-design is a specific instance of co-creation" (Sanders & Stappers, 2008). The concept of co-designing has become very popular in organizations (Binder et al., 2008) as collaborative teams actively work towards a common goal, accomplishing more together than acting independently (Mitchell et al., 2016). A tremendous amount of work has been done to study co-design from different angles such as in various domains like health care (Fox et al., 2014) to the aerospace industry (Monell & Piland, 1999) or in different phases of design (Malins et al., 2014).

In the context of the research, the term collaboration design is used interchanging with design team collaboration. In order to make collaboration effective, there are various support tools and methods. For example, virtual and mixed reality environments (Ong & Shen, 2009), design platforms like Collaborative Creative Design Platform (COnCEPT) (Malins et al., 2014), Discourse Model (Case & Lu, 1996), Collective Design Method (Mclening & Warrington, 2016), Engineering workflow (EWF) approach (Rouibah & Caskey, 2003) and many more. However, conducting collaborative design sessions are often hard and tedious as there are many barriers that hinder these activities (Kleinsmann & Valkenburg, 2008). Communication plays the key role in successful results (Maier et al., 2009) but it might be affected as the collaborative design teams consist of diverse individuals in terms of their viewpoints (Détienne et al., 2005), diverse background ( Larsson, 2007), different level of experience (Ni & Broenink, 2014) and might lack empathy towards each other (Mattelmäki et al., 2011). On the other hand, different design tasks may result in different collaboration dynamics, such as routine tasks, creative design tasks or complex design problems (Haerem & Rau, 2007; Ball et al., 2004). Team size, diversity and different experience levels in the team members also affect team performance (Latané et al., 1979; Wang et al., 2017). Besides, organisation structure (Amabile, 1996), team collaboration environments such as face-to-face collaboration which is considered more powerful in developing social norms, authority, group culture and commitment might result in different team performance than virtual collaboration (Axtell et al., 2004).

## 2.2 Collaboration from a social perspective

Design teams collaboration has been relatively less studied as most of the past literature has focused on collaborative design outcomes or on individual designer's behaviour. Working in a team gives rise to different phenomenons as compared to working alone, such as; communicating with other team members, roles and relationships, information sharing, concept generation and adoption, and so on (Cross & Cross, 1995). In teams, various roles and relationships emerge over time that may affect the task outcome. For example, some individuals may be perceived as more influential as they have more capacity to influence others opinions, judgement and decisions. One major reason for this phenomenon is social influence. Interaction between individuals in a collaborative activity gives rise to social influence (Myers, 1982). Social influence is the process where individuals change their behaviour, attitudes, and opinions in the presence of social interaction. These individuals with high social influence and who have more capacity to influence their teammates are referred to as influencers in the context of this research (Aries et al., 1983).

The term "influencers" is borrowed from the social network research, where it is defined as "*key individuals who have many people following them, they promote companies' product and are motivated to adopt new information or product*" (More & Lingam, 2019). However, the role and effect of online influencers might be different from offline influencers (Solis, 2009), such as those studied here. However, a more powerful attraction may occur when these influencers have experience (i.e., they have knowledge of the task due to their past work experience) and may result in team polarisation. A study by Georgilas et al. (2019) showed that PP (professional practitioner) have an impact on the learning process and the delivery from the novices (students), hence negatively affects the creative potential of open-ended projects.

The individuals in the team might agree with the influencers or experienced members or they can choose to go with others having similar opinions (Moussaïd et al., 2013). For example, individuals having similar thinking may strengthen their opinion and confidence. On the other hand, if they are not confident about their option, they may be easily influenced by the opinion of the influencer(s) in the team. This majority effect is *'caused by the presence of a critical mass of laypeople sharing similar opinions'* (Moussaïd et al., 2013) Similar behaviour is also seen in animals where when making decisions to move collectively, combinations of different rules are applied (Petit & Bon, 2010). These rules could be individualized based (on inter-individual differences in physiology, energetic state, social status, etc.) and (or) self-organized (context and group size).

The focus on the social dimension of the collaborative design teams is being studied to gain more insights into team behaviour and its impact on design outcomes (Branki et al., 1993). It is clear that collaborative design teams should be viewed as a social process as there are many aspects of team activity that influence social processes (Cross & Cross, 1995). Therefore, as suggested by Cross & Cross, (1995) "*social interactions, roles and relationships cannot be ignored in the analysis of design activity performed by teams*". Little is known about the impact of the socio-cognitive aspects of the design process in collaborative teamwork (Woodman, et al., 1993; Stokols, et al., 2008) which can shed a light on team behaviour and provide additional explanations on expected outcomes.

### 2.2.1 Idea generation and selection

In the idea generation stage of problem-solving, potential solutions (interchangeably used terms like alternatives, ideas or concepts) are generated. Brainstorming is one of the approaches to generate potential solutions, it consists of individual idea generation and then communicating the ideas with the team to further build on them. Typically, idea selection follows idea generation where the design team decides what concept to pick. The selection of ideas is one of the key aspects of any collaborative design activity that shapes the success of a project. Besides serving as a foundation for any future decisions on time or people strategies, idea selection is crucial during the early design phase and decisions made when selecting final concepts are key to successful projects (Lindley et al., 2017). So, exploring the factors that influence idea generation and selection could provide an important component in understanding design team behaviour.

As already pointed by Perry-Smith & Coff, (2011) and Rietzschel et al., (2006) that creative solution (in terms of usefulness) requires both idea generation alternatives and selection of an alternative solution to pursue at the end of an early design phase. Relatively fewer studies are conducted that have simultaneously studied generation and selection. Broadly speaking idea generation is divergent while idea selection is a convergent process (where one or more ideas are selected and proposed). Factors that may favour idea generation might not be effective during selection (Toh & Miller, 2016). For example, having influencers in a team might result in a greater exploration of the design space when generating solutions but might have a fewer variety in the selected solutions as the other team members might be agreeing with the influencers when selecting solutions. Hence, as stated by Perry-Smith & Coff, (2011) that some teams may perform better at one stage of the design process and others at the other stage because the team outcome is affected by the factors present at that stage. Therefore, idea generation and selection are considered two distinct and sequential processes which start with generating different alternatives.

Cognitive processes occurring during brainstorming are known to be affected by social influence (Paulus & Dzindolet, 1993). Perry-Smith & Shalley,(2003) identified two important social dimensions that affect how individuals work in teams - interpersonal communication and interpersonal interaction, and exposure to team members' alternative solutions may result in more divergent behaviour. Generating diverse solutions are often related to higher creative performance e.g. (Pauhus & Camacho, 1993). Others have argued that idea generation in teams is inhibiting (Diehl et al., 2002) and results in 'productivity loss' which is relatively low in small teams (Diehl & Stroebe, 1987). Overall, it can be said that idea generation is a cognitive task that is influenced by various effects of team interaction which results in either cognitive stimulation or interference (Nijstad & Stroebe, 2006). Decision-making during idea selection could be affected by organizational culture (Amabile, 1996), individual's personality traits (Kichuk & Wiesner, 1997), and maybe exposed to the ownership bias (Onarheim & Christensen, 2012). Often individuals perform poorly in selecting ideas because of the biases toward self-generated concepts (Nikander et al., 2014) or bias towards familiar concepts (Rietzschel et al., 2010).

The social factors could cause inadequate team functioning resulting in power distribution (informal hierarchy) and could cause inefficiency in information flow, biases in making decisions and poor solution analysis (Badke-Schaub & Frankenberger, 1999). One such social factor like social influence not only affects people's willingness to adopt the opinions but also the norms of other more influential people (Zaki et al., 2011). Having an influencer(s) or an experienced individual(s) who exhibit more confidence (Chamorro-Koc et al., 2009) and has qualities of a leader (Germain, 2012), might have more influencing power over others. Hence, having them in a team might result in team members valuing their opinion more than other team members (Meshi et al., 2012). Conflicts or disagreements may also arise in teams when different team members (especially the more confident ones as they communicate more) favour different concepts (Cross & Cross, 1995).

## 2.3 Dynamics of a team

The team dynamic is created by underlying factors of a team (such as; individual personality, nature of the task, the relationship among team members or the collaboration environment) that simulates change within a system. Collaborative design activity could be affected by: team composition, communication, distribution, design approach, information, and nature of the problem (Ostergaard & Summers, 2009). Each individual in a team is not equally affected by the social and environmental factors, thus collaboration in teams is not an invariant process, but a dynamic one as repercussions are felt differently based on an individual's cognitive state. These individuals, team tasks and environmental factors influence how teams behave (Woodman, et al., 1993) which is related to the future performance of teams (Stevens & Campion, 1994). A right balance of these parameters may lead to product or process innovation (Pearce & Ensley, 2004). Thus, providing an opportunity to study what factors affect collaboration which ultimately impacts design outcome.

Most of the studies have focused on design solutions rather than the process which lead to that solution. Relatively fewer studies can be found that have focused on the dynamic nature of the collaborative session like the C3 framework which graphically captures creativity in context (Pedersen & Onarheim, 2015), a model for the cognitive processes of design teams (Stempfle & Petra, 2002) and a computational model for team interaction (Singh & Casakin, 2015). Authors like Case and Lu (1996) recognised three different forms of collaboration: loosely coupled, moderately coupled and closely coupled collaboration where a closely coupled approach is the one where communication is crucial for efficient collaboration. Bavendiek et al.(2016) described the factors affecting collaboration from 3 different views:

- The technical-methodical view*: focuses on the tools and methods used within the collaborative design process*. This view is to address the issues in the process and personal view.
- The process view: *describes organisational aspects of the collaboration*. The problems which could be found in this view are related to the shared understanding, information flow, organisation structure, distributed coordination, coordination during collaborative activities and collaborative design management.
- The personal view: *focuses on the competencies of the persons involved in a collaborative design task*. The issues in this view could be background/expertise, experience, language, different point of view and lack of empathy.

Some of these aspects from the views listed above that are important to the study are mentioned in the following sub-sections.

### 2.3.1 Individual attributes

Individual attributes are a critical component as they affect the interaction between team members hence, the team performance (Salas et al., 2005). An individual's attribute such as its expertise, experience, self-efficacy, motivation, domain knowledge and so on affect its behaviour (Salas et al., 2005). There are many characteristics that were considered in the agents-based models in the past, such as individual cognitive style based on Kirton Adaption-Innovation theory (Lapp et al., 2019), individual's busyness level (Singh et al., 2013) and emotional state like positive and negative emotions towards a given task (Martínez-Miranda et al., 2006). Researchers have also considered different behaviour styles in different work situations (Martínez-Miranda et al., 2006) and the individuals' personality traits in their work (Code & Langan-Fox, 2001). Consideration of these characteristics depends on the goal of the work. The individual attributes affect individuals' behaviour, roles and relationship in teams, which eventually impacts performance (Woodman et al., 1993).

One of the key individual features is self-efficacy, which is an individual's belief in their capacity to achieve goals (Bandura, 1977). Increased self-efficacy has been linked to many positive outcomes (Singh et al., 2020). Self-efficacy has been associated with enhanced engagement (Linnenbrink & Pintrich, 2003) and increased motivation (Ponton et al., 2001). Self-efficacy is a crucial feature to consider as it mediates individuals' personalities (Stajkovic et al., 2018) and is also responsible for an individuals' agreement with the other team members (Hegselmann & Krause, 2002). The other important individual or intra-individual aspect is trust. The importance of trust in team collaboration has been confirmed (Costa et al., 2018). Trust is an important attribute that influences individual and team performance is built among team members over time (Martínez-Miranda & Pavón, 2012). A cognitive approach used in the trust model proposed by Esfandiari & Chandrasekharan, (2001), where, mental states of agents lead them to trust another agent. In the models, the relationship between trust and model agents have been represented using features specific to each model (Sabater & Sierra, 2005). Given the evidence, trust is considered an important individual attribute that is further affected by an individual's reputation and familiarity with the team members (Costa, 2003; Tjøstheim et al., 2019).

Most of the computational models have used trust and reputation interchangeably (Sabater & Sierra, 2005) as a positive reputation of an agent builds trust. This was also found in an empirical study done in human-agent teamwork which showed that a positive reputation leads to greater trust as it reduces uncertainty on the agent teammate (Hafizoglu & Sen, 2018). Familiarity among the individuals depend on the interactions between them (Komiak & Benbasat, 2006) and enhances team performance (Hinds et al., 2000). It is an antecedent of trust that enables individuals to have confidence in each other (Luhmann, 2000).

An individual's past experience is another attribute that is related to performance (Chen, 2001). It is clear from the studies that novices and experienced individuals have different approaches towards the design task where experienced individuals use their strategies to solve the problem (Ahmed et al., 2003). Novices are unaware of these strategies employed by the experienced individuals hence use the trial and error approach (Ahmed, et al., 2003; Ahmed & Wallace, 2004). Singh and Casakin (2018) proposed an agent-based framework where experts and novices in a design team might use an analogy that influences team cohesion and team collaboration. While others like Perisic et al., (2019) have investigated their impact on the exploration of problem-solution space.

As mentioned above, due to the dynamic nature of a team, the values of these individual attributes differ for each individual, hence they are influenced by other socio cognitive variables. These attributes may diminish or exaggerate the agent behaviour, for instance; self-learning or influence of the influencers (social learning).

### 2.3.2 Team attributes

Team composition is another aspect of design team collaboration that affects performance. Teams could have different roles and responsibilities in their team members, team members could have a varying attitude towards common goals (Salas et al., 1999) or may have a different level of experience (Ball et al., 2004). The teams could be classified according to some typical dimensions like team structure, team composition and team size. A Team Coordination Model (TCM) developed by Rojas & Giachetti (2009) could simulate different composition and coordination methods in teams. They analysed the effect of some team attributes like team size, team member experience and skills, and team coordination on performance.

Team structure in organisations affects team behaviour as it impacts team members' learning and decision-making. There are several ways to classify teams based on their structure like flat, distributed flat and functional teams (Singh et al., 2013). The teams can be classified based on the level of analysis as individual-level (where individuals do not interact with one another), dyadic-based (where interaction is on a one-to-one basis) or at group-level (where interaction is with one another including the leader) (Dionne & Dionne, 2008) Teams are also classified based on team management like self-managing teams who regulate their own behaviour and may or may not have direct supervision (Morgeson, 2005). These teams were also found to be more effective than traditionally managed teams (Cohen & Ledford Jr, 1994).

The relationship between team size and performance is unclear as some previous studies have shown that large teams perform better than small teams when the problem-solving task requires fact-finding (Liker & Bókony, 2009) but are prone to social loafing (Latané et al., 1979; Dennis et al., 2019) and have poorer team processes, especially when operating under relatively high pressure (Curral et al., 2001). While small teams perform better when the task is well-defined and simple with clear goals (Seijts & Latham, 2000). Some studies on team sizes of 1, 3, and 5, found that teams of 3 produced the best designs as the team size increases the time spent on discussing previous ideas (Jacobs et al., 2019). Other studies have found that team size has no significant influence on individuals' workplace commitment (Ogungbamila et al., 2010). During decision-making, team members in large teams were efficient and more likely to reach group consensus (Oesch & Dunbar, 2018).

Besides, the number of influential individuals in teams due to unequal distribution of influence (Brown & Pehrson, 2019) as an important team attribute, the experience-novice composition could be considered another crucial one. Novices gather knowledge from the experienced members in the team and use it to their existing knowledge to generate new solutions (Deken et al., 2012). Even a short exposure to an experienced individual can lead novices to follow them (Klucharev et al., 2008). The teams with novice-experienced in them consists of complicated interactions (Deken, et al., 2009). Some agent-based models have been built to study how novice-novice, expert-expert and novice-expert scrum team pairs affect productivity (Wang, 2018) or similar links affect collaboration network and team performance (Guimerà et al., 2005). Some studies have found that a moderate team size with a moderate level of experience has a higher chance of creating inventions (Wang et al., 2017).

### 2.3.3 Task attributes

The nature of the design problems is an important aspect of the design process (Cross & Cross, 1995). Design or problem-solving environment consists of features identified by Goel and Pirolli (1992). These features being the distribution of information, nature of constraints, size and complexity, component parts, the interconnectivity of parts, right and wrong answers, input-output and feedback loop. It is essential to consider be cautious when computationally representing a design task as unlike design thinking by human designers, computational thinking which imitates a computer's way of representing a process uses generalization and abstraction (Kelly & Gero, 2021). A computational design task could be a problem-solving task (Sayama et al., 2010), a decision-making task (Dionne & Dionne, 2008) or a design task (Lapp et al., 2019), depending on the nature of the study.

As it is also known that the nature of the task given to participants affects performance (Haerem & Rau, 2007; McComb et al., 2015). In other words, team processes and outcomes depend on the nature of the task given to the participants. Depending on the purpose of the study, the design task could be represented as Concurrent Sub-Space Optimization (CSSO) problem, Collaborative Optimization (CO) problem (Blouin et al., 2004) or search problems. Design teams are often not immediately aware of the quality of their solution and proceed by trial and error; this is especially true when the designers start working and they have no past experience. In this aspect, design tends to resemble a search task with a fixed design space and variables rather than a mathematical optimisation problem.

For task-related attributes, the complexity of a design task is a key component that affects team processes and performance (Weingart, 1992). Design task complexity could be described as the relationship between task input and information cues, where the highly complex task requires more knowledge, skills and resources than low complexity tasks (Wood, 1986). However, the definition of task complexity varies, for example, the task complexity used by Singh et al., (2013) defined simple tasks as tasks with unique solutions and agents performing such tasks will have the same solutions, while for complex task solutions varied from agent to agent. Usually, a design task has a large number of potential solutions to ensure that variety in the solutions, such as the design task used by McComb, et al., (2017b). Task complexity was also expressed as the number of objectives where difficult to achieve objectives were related to the complexity of the task (Song et al., 2021). Kennedy et al. (2011) defined project complexity in their work based on the dimensions identified by Campbell, (1988) as (1) approaches to perform a task, (2) end states that the task must satisfy, (3) conflicts and tradeoffs addressed and (4) decisions regarding approaches. Task complexity may impact team communication, coordination and decision-making. It was found that when the tasks become complex, individuals become less certain about their solutions and rely on others (Sosa et al., 2004; Yan & Dooley, 2013). Trust in teams plays important role in case of a highly complex task than lower (Choi & Cho, 2019). Task attributes are also based on the level of innovation that it requires such as highly innovative and low innovative tasks (Curral et al., 2001).

Routine and non-routine characteristics of a design task were studied by Gero, (1994). Computationally, he called routine tasks when all the necessary knowledge is available and the non-routine task where a design activity occurs in the presence of unexpected values (Gero, 1994). Similarly, Ball et al., (2001) also defined ‘routine’ when experienced designers were familiar with the problem at hand and ‘non-routine’ when they were less familiar with the design task. Thus, based on the task that could be similar or dissimilar to individuals experience, the novelty of ideas is affected (Meslec et al., 2020).

### 2.3.4 Collaboration environment

The collaboration environment generally refers to the organization in which the design team inhabits and the contextual factors that emerge from the environment could be related to team proximity, communication support, team incentives and organisation culture (Woodman et al., 1993). Some researchers have considered time pressure (Dionne & Dionne, 2008) or busyness level (Singh et al., 2013) as environmental factors in their model. However, the current research considers proximity of team members as the main attribute of collaboration environment, henceforth it will focus.

Due to the flexibility offered by virtual collaborations and fewer locational constraints, they are becoming more and more popular (Boland et al., 2020). Virtual team collaboration (a term contrary to face-to-face co-located collaboration) can be described as a degree of a team’s virtualness that is a function of the percentage of time spent working apart and level of technological enablement (Griffith & Neale, 2001). There are several terms like distributed, computer-mediated collaboration, di-located or online collaboration, the current study will use virtual team collaboration to describe the state when the team is not working face-to-face at the same location (Martins et al., 2004). It is known that the design team’s degree of virtuality moderates team composition and processes that ultimately affects virtual team performance (Hoch & Dulebohn, 2017).

On the prescriptive side different design tools have been proposed to assist collaboration like TeamWork- Station by ClearBoard and Distributed-sketching system (DSS) (Eris et al., 2014), synchronous and remote virtual environment called Wonderland by Sun Microsystems, 3D teleconferencing and CoReD (Collaborative platform for Remote Design) (Germani et al., 2012). The design processes in digital and traditional sketching environments for collaborative located and distributed teams were also studied in the past (Tang et al., 2011).

The descriptive research on team collaboration environment shows that virtual collaboration has its own drawback especially in terms of lower collaboration (Montoya et al., 2011) which leads to lower cohesion and weaker relationships in team members (Morrison-Smith & Ruiz, 2020) that negatively affects team performance (Malhotra & Majchrzak, 2014). Less collaboration in virtual teams is associated with weaker communication which is mainly attributed to the technology medium. As virtual teams solely rely on technology to conduct any form of communication, it is crucial to consider technology medium as an important attribute of virtual collaboration (Hinds & Bailey, 2003). Any technical problem in the technology medium (internet, servers, collaboration software and so on) would directly affect the communication among the team members as it reduces information sharing. Thus, increasing the probability of a conflict due to misunderstanding or miscommunication (Mortensen & Hinds, 2001).

Similar to face-to-face collaboration, developed relationships, shared understanding, and trust serves as important antecedents to virtual collaborations (Peters & Manz, 2007). These socio-emotional factors that affect the collaborative process should be considered when studying a collaborative learning environment (Isohätälä et al., 2017). Virtual team collaboration impacts group member attraction and task cohesion (i.e., *an individual's attraction to the team because of a liking for or a commitment to the group task)* (González et al., 2003) Virtual collaboration models like the ones proposed by Alsharo, et al., (2017) and Choi & Cho, (2019) suggests that knowledge sharing positively influences trust and collaboration among members, but trust does not have any significant impact on team effectiveness. While other studies showed that there is lower trust in virtual than face-to-face collaboration but increases towards the end of design activity (Baturay & Sacip, 2019). Unlike face-to-face collaboration, research has shown that virtual team collaboration reduces the effect of personality, power or group formations within teams (DeRosa et al., 2004) but could result in the polarisation of the decisions (Lea & Spears, 1991). Moreover, it was found that di-location in collaborative design teams might add to the number of iterations (Whitfield, et al., 2002). Di-location makes social connection challenging that causes challenges in decision making (Whitfield et al., 2002) and limits the modes of social learning (DeSanctis & Monge, 1999).

Despite the studies above that stated face-to-face team collaboration results in better performance, consideration of the different factors that might result in cases that perform better virtually than face-to-face. Knowledge, skills, abilities, and other characteristics (KSAOs) of individuals when working virtually differs from those working face-to-face (Schulze, et al., 2017). Schulze & Krumm (2017) found that distal characteristics like personality and experience were also important in virtual team collaboration. Chamakiotis et al. (2013) also identified individual, team and technology factors that influence creativity in virtual design teams (VDTs). Similar to face-to-face collaboration, virtual team interaction is also found to be affected by the available technology, task and group characteristics (Maznevski & Chudoba, 2000). A conceptual model for improving virtual team performance analysed the factors at an individual (like motivation, communication, comfort) and team (such as trust, social presence, leadership and so on) level to determine their impact on the overall performance (Dube & Marnewick, 2016). Communication, task complexity, degree of virtuality and interdependence were some of the factors considered when studying virtual teams (Marlow et al., 2017). Moreover, a review study that focused on team and design type in virtual teams, suggested that all virtual team configurations should not be considered equivalent (Gibbs et al., 2017).

## 2.4 Computational studies of team collaboration

Models could be of different kinds based on the phenomenon they are representing such as (1) scale models that are smaller versions of target and have reduced size and complexity, (2) ideal-type model where some characteristics are exaggerated or assumed to simplify the model, and (3) analogical models based on the analogy between a well-observed phenomenon and the target (Gilbert,2019). Modelling the design team members and their activities to compute their performance based on certain parameters, is comparatively a new approach. Before the modelling of teams became popular, quantitative models were being used (Zachary, et al., 2001). Computational models that had memory and 'intelligence' like SOAR and COGENT could perform problem-solving based on task complexities (Laird et al., 1987; Zachary et al., 1996). Though these models were widely used to simulate human behaviour in different fields, they focused on individual behaviour. Other models at the macro-level focused on organisation or system like the Virtual Design Team model (VDT) that was developed in the 1990s to simulate communication in engineering design teams based on the task types and design complexities (Jin & Levitt, 1996). These models focused on individual or organisational performance and lacked the team's social and behavioural aspects.

Other models like the one by Nowark et al. (1990) that considered team interaction and the social aspect, simulated a population of individuals having different opinions. These simulated individuals affect each other (based on social impact theory) and at the end of the simulation, a stable configuration of opinion was obtained. Another dynamic model of social factors in brainstorming was presented by Brown and Paulus (1996), where the model was based on idea generation, idea memory and idea output, taking into account the effects that group member exerts on each other's idea generation. In a model proposed by Paulus & Dzindolet, (2008), it was found that individuals tend to mimic the performance of their collaborative workers due to social comparison. While others showed in their work related to idea selection that assigned leaders or hierarchy in teams could be beneficial as it reduces the tendency in individuals to choose their own versus others' ideas (Keum & See, 2017).

One of the popular approaches as mentioned by Zachary et al.(2001) to simulate human behaviour by considering factors at the micro and macro level, is the agent-based modelling (ABM) approach. '*An agent-based modelling is a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment'* (Gilbert,2019). Agent-based models could model individual characteristics, provide analysis at micro and macro levels, and could simulate various scenarios of the real world (Gilbert,2019). The dynamic nature of a collaborative activity can be challenging to study using traditional human subject research. While it is important to study the interactions in such collaborative teams (Paulus, 2000), it requires a tremendous amount of time and effort (Becattini et al., 2019). Therefore, the current work uses the agent-based modelling approach. ABM has been used in many domains to infer and predict the behaviour of complex systems as in the domains of social sciences, biology, air traffic and many more (Abar et al., 2017). This approach consists of agents who are embedded in their environment/system and provides insights from agents' learning and the system's behaviour over time. Thus, can be used to study any dynamic phenomenons like decision-making in various fields; energy management (Zhao et al., 2013), stock trading (Luo et al.,2002) and spatial planning (Ligtenberg et al., 2004). ABM is useful in addressing autonomous and heterogeneous individual characteristics to represent and compute collaboration dynamics (Abar et al., 2017). Therefore, it is a useful tool that could describe the collaboration in a design team from the perspective of its agents', team, task or even collaboration environment (Bonabeau, 2001).

Many agent-based models focused on organisation performance like Construct which is a multi-agent model that considers the socio-cultural environments was proposed by Schreiber et al. (2004) to capture the dynamic behaviours in organizations was based on five moderators of the interaction (forgetting, proximity, transactive memory, referrals and access). Another model like the MAQM model focused on organisational productivity and quality management by considering individual's characteristics like problem-solving time and forgetfulness was proposed by Jamshidnezhad & Carley (2015). In the CORP model, one can choose the method of decision making, learning in agents, organizational structure and task type to predict organisational behaviour (Carley, 1996).

While some authors focused their computational models on the conceptual design phase (Ehrich & Haymaker, 2012; Cvetkovic´ & Parmee, 2002; Green, 1997), others created models to study distributed team coordination (Carley, 1996; Carley & Gasser, 1999; Lee & Lee, 2002) and multidisciplinary in teams (Maher et al., 2007; Hulse et al., 2018). Problem-solving behaviour of design teams simulated by some researchers like CISAT model where agents problem-solving was simulated as they learn, interact at irregular intervals and propose promising solutions (McComb et al., 2017; McComb et al., 2015). Models like KABBOM showed how agents learn and propose a solution based on Kirton's Adaptation–Innovation Theory (Lapp et al., 2019). Exploration of the solution space during problem-solving by a team of agents was simulated by Sosa & Gero (2013). Learning styles like collective learning where design team agents use input knowledge, environmental information, and design goals could be seen in Wu & Duffy (2004). Learning from experience in agents that while simulating curious behaviour was done by Saunders & Gero (2004). Social learning was simulated in agents and its effect on team performance was also studied (Singh, 2009). Creativity in agents was also simulated and was found to be affected by contextual factors like evaluation strategies (Kahl & Hansen, 2015).

There are other models that have focused on team performance by varying individual and team characteristics (Sosa, 2016). Studies on agent expertise and performance could be found where some have explored its relationship with an analogy (Singh & Casakin, 2018), nature of the task (Perišić et al., 2018) and interactions among agents (Gero & Kannengiesser, 2004). Leadership styles and team structure that affect decision-making and team performance were also modelled. Individual cognitive and experience-based components were varied among group members along with the leadership type by Dionne & Dionne (2008). Singh et al. (2011) modelled teams with varying team structures and suggested that flat teams facilitate the formation of team mental models, while functional teams are best for efficient task coordination. Some models explored how relational attributes affect team performance like Singh, (2009) who controlled team familiarity by replacing some or all of the team agents with new team agents to see its impact on team performance while others demonstrated that previous structural ties determine the choice of work partner (Hinds et al.,2000).

Computational studies found in the design research could be classified into three types based on the nature of their aim: exploration, modelling and support systems (Gero, 1994; Sosa, 2005). The one considered for the research presented in the thesis is of the computational exploration type, whose aim is not to study specific phenomena but to build a system that is capable of representing collaboration during team experimentations (Simon, 1995).

## 2.5 Design outcome measures

One of the ways to measure design team outcome is in terms of creativity. Creativity can be defined as novel and potentially useful ideas, products, or solutions (Amabile, 1983; Redmond & Mumford, 1993; Zhou, 1998). Shah et al., (2003) proposed four ways to measure the effectiveness of an idea: novelty, variety, quality and quantity. Novelty measures the unexpectedness of an idea as compared to other ideas. Exploration of the design space can be measured in terms of the number and variety of design alternatives discovered (Dorst & Cross, 2001). Thus, variety is the measure of how the explored solutions are different from each other. Quality, on the other hand, measures the usefulness (value) or the feasibility of an idea that satisfies the design specifications (Sarkar & Chakrabarti, 2011).

In order to measure the outcome generated by the artificial agents mimicking human idea generation, it is necessary to mirror the measuring approach used in the study of human design creativity. Therefore, creative outcome resulting from the individual/team agents in a computational model can be referred to as artificial creativity (Saunders & Gero, 2001). Kazjon & Maher, (2019) considered that creative processes can be modelled computationally therefore, the term computational creativity was proposed. To map human and computational creativity Kazjon & Maher, (2019) used the definition of a *creative system* (i.e., *A collection of processes, natural or automatic, which are* *capable of achieving or simulating behaviour which in humans would be deemed creative*) as proposed by (Wiggins, 2006).

Hence, the novelty of the outcomes by the artificial agents can be measured in terms of the Euclidean distance between the closest category prototype and a new input pattern (Saunders & Gero, 2001; Kazjon & Maher, 2019). The quality of the solutions generated by artificial agents was measured in terms of the value of a design problem function (Singh, 2009; McComb et al., 2017). Some studies have also measured variety in their work by comparing generated concepts to the base design (Song et al., 2021). Elements like surprise were measured using regression models that predicted expectations of how the attributes of a design relate (Kazjon & Maher, 2019). Clevenger & Haymaker(2011) identified metrics for 3 dimensions of a design process: challenge, strategy and exploration that Ehrich & Haymaker (2012) used in their model to measure quality (as OSQ), exploration (as DSS), interaction and time.

## 2.6 Synthesis of the gaps

- Most of the studies about collaborative design have focused on design activity outcome, only a fraction of them have studied the design process. Those who have studied the design process, have presented results from individual designers. The dynamic nature of collaborative design activities is less explored in the previous studies, hence the changes in the design outcomes with time need more exposure.
- Insufficient team-based studies are present that have studied collaborative design processes like idea generation and selection where the two processes have been considered simultaneously. Most of the work done in the past have considered the two processes interchangeable. The factors affecting idea generation (divergent) outcomes may not be the same as in idea selection (convergent), therefore, one should consider the two processes as separate where idea selection follows generation.
- A noteworthy, aspect of the prescriptive models that imitate human collaboration is that they propose ways or processes to obtain optimal solutions which designers in the real world rarely follow. Simon,(1981) acknowledges the idea generation process as not optimising, instead, designers search for any ‘acceptable’ solution to a design problem by applying satisfying principle. Therefore, a model that could imitate ‘close to the real-world’ human collaboration would be ideal. Macy & Willer, (2002) highlighted the shift in ABM from ‘factors’ to ‘actors’, and suggested that complex dynamics are better understood not at the global level but at the local. These local properties emerge due to local interaction among agents who influence one another. It can be seen from the past literature that the social or psychological factors of collaboration team dynamics have been ignored in many studies. Considering the collaboration in design teams as a social process (Cross & Cross, 1995) would aid in understanding the design team behaviour.
- Previous researches have shown that social aspects (such as roles and relationship) are crucial for creativity in groups (Paulus & Dzindolet, 1993; Monge et al., 1992). However, the assumption that all the team members are affected equally does not hold true as the social influence is not equally distributed in teams (Brown & Pehrson, 2019). Though it is clear that social influence affects creativity, the effect of the unequal distribution of social influence observed in practice is still unclear. Researchers know little about how the social context affects individual thinking when it comes to the generation of solutions or proposing of final concepts.
- Collaborative design teams are often composed of individuals with different levels of experience. Hence, having novices and experienced in the same design team affect learning

(especially during idea generation) and decision-making (especially when selecting ideas) in novices. An experienced individual can cause novices to follow them (Klucharev et al., 2008). The novice-experienced interactions in a team could be considered highly complex (Deken et al., 2009) and not much attention has been given when evaluating design team outcomes.

- In contrast to the rich literature found on the face-to-face collaboration environment, fewer studies are present that have studied how the mode of collaboration affects design team performance. Out of these many have focused on distributed teams have explored collaboration through software/tools like virtual worlds that assist designers (Rickel & Johnson, 2000). Others like (Anumba, et al., 2001; Wallis, et al., 1998) have studied collaboration in a distributed environment based on agent interaction, negotiation during collaborative design and conflict resolution. Though some have employed social elements like trust in their model to understand collaboration in virtual teams (Hossain & Wigand, 2004), the effect of the individual, team and task attributes during virtual collaboration is still not clear.
- Limited studies can be found on measuring the design outcome of computational studies. As simulating artificial human collaborations are becoming popular (Macy & Willer, 2002), defining metrics to measure these collaborations to mirror human collaboration outcome, need more attention.

## 2.7 Research questions and assumptions

Studying human behaviour under specific contexts and circumstances is not new and have been studied since the 1970s. Fan & Yen, (2004) highlighted the importance of human behaviour simulations for example they offer sufficient practice for human training, they provide a practical solution to improving readiness, they are useful in conducting 'what-if' scenarios and simulations of already occurred events could provide useful after analysis. Therefore, after identifying the gaps that exist in the past literature, the following research questions (RQ) have been identified based on the 'what-if' scenarios and common collaboration circumstances that are addressed in the study using the simulation.

Unlike the current trend towards studying the influencers in social media, the aspect of influence that occurs during collaborative design is not studied. Though the effect of social influence on brainstorming has been studied, its uneven distributed nature in the teams where some individuals tend to be more influenced or influential than others is still not explored. The study in this paper would investigate how the magnitude and distribution of influence affect individual thinking during idea generation and selection outcomes. Specifically, the answer to the research question (RQ1):

1. *How do the different number of influencers in teams affect design project outcomes?*
   1.1. *What is the impact of influencers on individual thinking outcomes during idea generation?*
   1.2. *What is the impact of influencers on idea selection outcomes?*

The assumptions (A1.1 and A1.2) behind the RQ1 are justified below:

However, before addressing the research question, it is first crucial to determine what makes an influencer. Although researchers have studied the characteristics of social media influencers, little is known about the characteristics of influencers in design teams. The work examined past studies on group behaviour, leadership studies and team dynamics, to hypothesize some underlying influencer characteristics. Baker, (2015) claimed that individuals' personalities, skills and communication could result in such phenomenon. Since communication is often influenced by one's confidence state, *self-efficacy* was one of the individual attributes that were considered. This assumption was made based on the common observation where the more confident individuals are the ones governing the team (Bandura, 1977). It is known that self-efficacy is one of the important factors that are responsible for transformational leadership improving team performance (Pillai & Williams, 2004), it is unclear how it might affect the degree of influence in teams. The other intrapersonal attribute that was chosen was *trust*, which arises from how well the two individuals have known each other previously that could also contribute to influencing power (Granovetter, 1973). Therefore, for this investigation, it was believed that self-efficacy (an individual's belief in his or her capacity to achieve goals) and trust could contribute to the influencer effect. Considering these two factors (self-efficacy and trust), an assumption (A1.1) was made to identify the influencers to address the above research question.

*A1.1 Self-efficacy and trust are some of the characteristics for influencing and being influenced behaviour*

According to Cialdini's Principles of Persuasion; consensus, liking and reciprocity lead to the conversion of one's opinion or agreement (Cialdini & Rhoads, 2001). Oyibo et al.(2017) in their study of linking 5 personality traits to Cialdini's Principles of Persuasion, found that people who are low in Openness are more susceptible to Authority, Consensus and Liking. Moreover, it is known that self-efficacy mediates Big 5 Personality traits (Stajkovic et al., 2018). Research on Citizen Influencers (CIs), identifies five characteristics like expertise, trustworthiness, likeability, similarity and familiarity as the main contributors that could contribute to persuasiveness (Martensen et al., 2018). As self-efficacy and trust are the characteristics considered for influencers in this model, influencers could be considered responsible for the persuasiveness of their solutions. It is already known the amount of influence affects the opinions of team members (Das et al., 2018), thus, it is possible that individuals in teams may agree more with the individuals having more degree of influence called influencers on their proposed solutions. Moreover, Cialdini & Rhoads (2001) proposed 'reciprocity' as one of their principles of persuasion where people tend to pay back favours done to them (as in people agree more with those who have agreed with them as a way of returning favours). These might affect decision-making in teams; therefore, the above research question cannot be addressed without first considering the parameters which impact an individual's agreement when evaluating other's proposed solution during idea selection. In order to support the model that addressed the above research question to evaluate the design outcomes based on different influencer compositions, the following assumption could be made that helps in the formation of the idea selection process:

*A1.2 The perceived degree of influence by an individual and the past agreement its peer had with him/her, are some of the factors affecting its agreement when evaluating the proposed solutions by its team members*.

The second assumption (A1.2) was made because the individuals having more degree of influence called influencers might affect decision-making in teams, therefore, the above research question cannot be addressed without considering the parameters which impact individual's agreement when evaluating other's proposed solution. Since not many articles could be found on factors affecting individuals' agreement in design teams, the paper also presents an empirical study for validating the assumption during idea selection.

As highlighted in the above literature, most prior work has studied individuals (i.e., either experienced or novices) and the effect of having novices and experienced individuals in the same flat team (a team where there is no organisational hierarchy and everyone could contribute) has not been explored. It is also known that the nature of the task given to novice and experienced participants affects the performance (Haerem & Rau, 2007; McComb et al., 2015). In other words, team processes and outcomes depend on the nature of the task given to the participants. In the context of this study, the complexity of a task is defined by the ease of finding an above-average solution. In order to understand the effect of these different team compositions of novice and experienced agents on design outcomes when working on a difficult task (that has fewer or one alternative solution thus hard to find solutions) or a simple easy task (multiple alternative solutions hence easy to find), the following research question (RQ2) is identified:

2. *How do different experience- novice agents in teams affect design project outcomes with respect to the design task?*

While most of the past literature has focused on directly comparing the virtual and traditional face-to-face team performance, the impact of collaboration elements such as project type or team compositions in the two collaboration modes has not been given much attention (Powell et al., 2004). For example, certain collaboration elements might result in better virtual team collaboration outcomes than in face-to-face. Hence a wider research question (RQ3) is identified that considers the effect of the individual, team and task attributes during virtual collaboration:

3. *How does virtual team collaboration affect design project outcomes with respect to face-to-face collaborations?*

Virtual teams face unique challenges (Powell et al., 2004), such as trust-building and knowledge sharing (Alsharo et al., 2017), communication affecting social influence or giving rise to more conflicts (Jarvenpaa & Leidner, 1999) and expert members may not guarantee good project outcome (Hemetsberger & Reinhardt, 2009). As more and more companies are switching to virtual team collaboration settings, these challenges, if not addressed and managed appropriately, can affect the performance of virtual teams (Piccoli et al., 2004). Therefore, to see the impact of communication in virtual team collaboration parameters, the following assumption (A3.1) was recognised to support RQ3.

*A3.1 Effective communication between individuals plays a significant role during virtual team collaboration as it impacts model parameters.*

Model lies towards the side of nomothetically-oriented simulations. The nomothetically-oriented simulations assume the presence of laws or theory such as interaction among agents depends on the attributes of an agent and the environment (Gilbert & Ahrweiler, 2006). The nomothetic simulations should be general in some respect, empirically satisfied in some domain and must belong to some scientific system (Gilbert & Ahrweiler, 2006). In simulations having social science elements, the results or the simulation data is obtained from the pre-defined rules and not directly from social phenomena (Sun, 2006). These results from the simulation may be used to derive inductive (to find patterns in data) and (or) deductive (to find consequences of assumptions or rules of the simulations) reasoning (Sun, 2006). Keeping these in mind, the flow of the research is provided in Figure 2- 2. The empirical studies were done after the initial model development was completed based on literature and assumptions. The computational model approximates the real-world system due to which needs verification and validation. The empirical study section provides an overview of how some of the logic used in the model were verified and at the same time validated the assumptions. From the results of the empirical studies, the general idea of the results clarifying the assumptions and variable relationships were implemented in the model and not the exact coefficients (since the experiments were done in different settings, implementing exact results would not be appropriate).

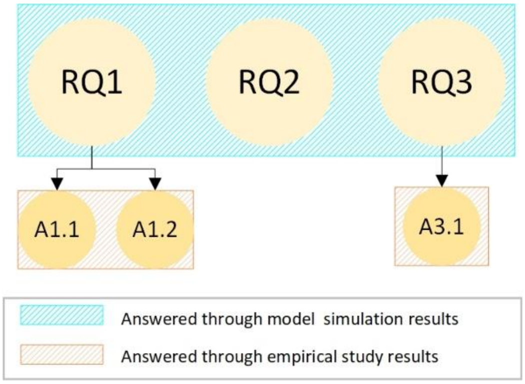



Figure 2- 2 Research flow that addresses the research questions and assumptions

# Chapter 3

# Model formation

Models could be of different kinds based on the phenomenon they are representing such as (1) scale models (2) ideal-type models and (3) analogical models (Gilbert,2019). The presented model fits in the ideal and analogical model types as it has some elements that are ideal-type that are exaggerated for the simplification of the model (for example, the design aspects of a design problem). It also has analogical elements as the movement of agents in the design space could resemble swarm intelligence found in nature such as bird flocking, bees finding hive locations or animal herding. Model is formed based on the past literature, common observations of the design teams and assumptions. Most of the collaborative studies using multi-agent models have focused on collaborative optimisation where an optimal strategy is used to achieve the best design solutions. However, many researchers have argued that collaborative design teams in the real world do not follow any optimal strategy but a more naturalistic approach. Simon (1981), stated that the idea generation process cannot be an optimising one because of limited information-processing capacity in human designers. On the contrary, the designers apply a 'satisficing' principle, where they search for any acceptable solution to a design problem and then get fixated around such a solution once it is identified (Simon, 1981). The model considers various attributes related to the individual designers (agents), design task, team as well as collaboration environment. This chapter describes the parameters considered in the model and the rationale behind the model formation. The chapter also includes a description of its elements like design tasks, agents and sessions containing idea generation and selection. A more detailed explanation of idea generation is given that further describes how an agent learns from its own past experience and is affected by influential team members. Idea selection formation considers some of the social factors in design teams that have received limited attention in past. The chapter also explains the formation of experienced novice agent team compositions and the elements incorporated to simulate virtual team collaboration.

## 3.1 Model parameters

There are several parameters that could be considered for an agent-based model when simulating design team collaborations (Salas et al., 2005). Considering all the parameters will make the model complex and will increase the use of computational resources. Therefore, the parameters useful in fulfilling the research objective should be considered (Langan-Fox et al., 2004). Hence the for the presented model some of these parameters shown in Figure 3- 1 are considered. Figure 3- 1 shows the design process activity with input, control and resource parameters that affect the design task output. This representation of Figure 3- 1 is inspired by IDEF0 graphical representation technique where the design process activity is affected by the transformations between input and output flow, by also taking into account the necessary resources present and the given rules that control them (IDEF, 2021).

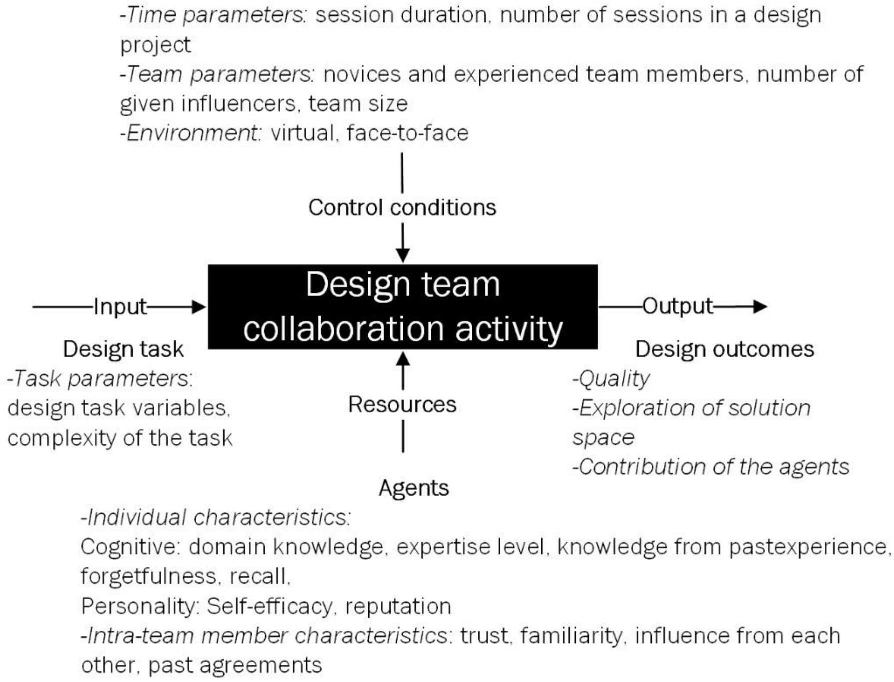



Figure 3- 1 Model input, output, control and resource parameters

These parameters can be classified as independent, intermediates and dependent (Figure 3- 2).

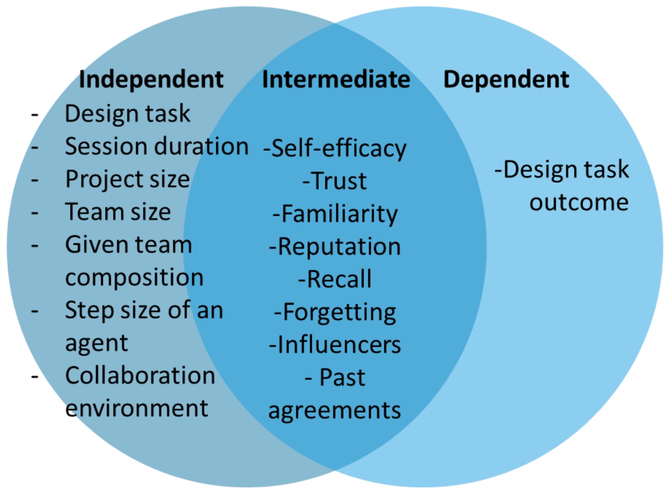



Figure 3- 2 Parameters classified as independent, intermediates and dependent

- Independent parameters remain unaffected by the process occurring in the model like duration of a session, the number of sessions in a project, design task and team size.
- Intermediate parameters are affected by the independent parameters, and in turn, affect the dependent parameters. Some of these include features like individuals' experience, learning abilities, influence value which change with the independent parameters. For example, the familiarity between the two individuals increases with the number of design sessions they have in common.
- Dependent parameters are susceptible to changes in independent and intermediate parameters. They include design output results in terms of quality, exploration of the solutions on the design space and contribution of agents. For example, if the size of the team is increased, the exploration of the design space is expected to be affected by it.

## 3.2 Model formation

The research is based on the theory of organisational creativity where the relationship between individuals, team, social and contextual influences, environment and project, that has been presented in Figure 3- 3 by Woodman et al., (1993). Similarly, the model formation takes into account the relationships among various individual, team, social, contextual and environmental characteristics that affect individual and team behaviour which eventually impacts the project outcomes and team performance. For example, individual characteristics such as one's self-efficacy affect one's perception of influence from others. Self-efficacy can also affect one's behaviour like communicating with the team members which in turn affects team behaviour. Team characteristics like team size can affect team behaviour and performance. Contextual factors such as the nature of a design task further influences individual and team behavioural performance. Lastly, collaboration environments like face-to-face or virtual impacts also design project performance in terms of quality or variety of the solutions.

Hence, the model proposed is called *MILANO (*Model of Influence, Learning, and Norms in Organizations) and the sections below will explore its formation.

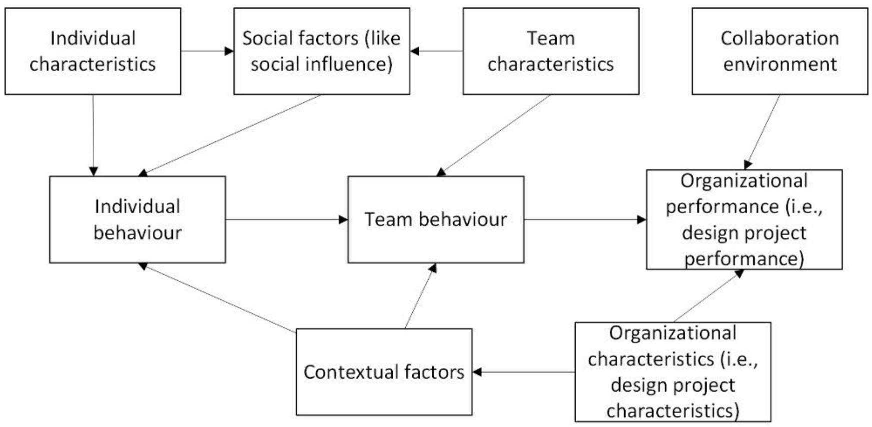



Figure 3- 3 The research is based on the model presented by Woodman et al., (1993)

The IMO (input-mediator-outcome) framework for team effectiveness (where mediating mechanisms are because of cognitive, motivational or affective states) suggests that feedback from one session (episode) influences the outcome and process on subsequent input, therefore team states are influenced by their progress over time (Ilgen et al., 2005). Similarly, in the presented model as shown in Figure 3- 4 collaborative design activity starts in the form of a project that has a set of design agents and a controller agent (agents explained in detail in section 3.3). The project consists of several sessions of idea generation and idea selection before receiving feedback on their proposed solution from the controller agent for that session. Olson et al.(1996), studied 10 design sessions of different projects and found that a large amount of time is spent on generating alternatives (i.e., exploring the design space). Thus, each idea generation in the model consists of several steps which are analogous to an agent thinking and exploring the solution space before proposing its solution to the team.

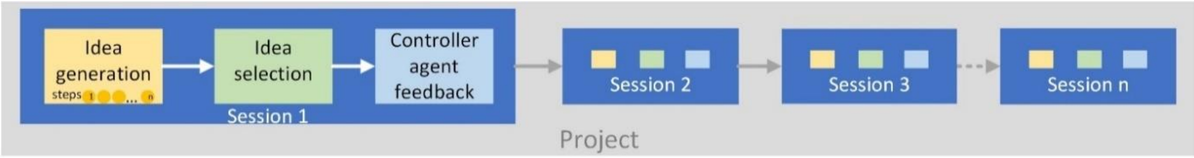



Figure 3- 4 The design schema for MILANO (Model of Influence, Learning, and Norms in Organizations)

The design problem-solving activity involves exploration of the problem, identification of the interconnections (in this case link between current task and the tasks done in the past), generating solutions in isolation and combining solutions (Goel & Pirolli, 1992). An example of a design session can be seen from Figure 3- 5 that starts with assigning a design task to a team of agents. It consists of idea generation and selection, followed by feedback from a controller agent at the end of a session. To see the effectiveness of the design session, the results are extracted and stored in a database which is evaluated in terms of quality, exploration and variety values.

MILANO takes into account some of the design problem-solving features as given by Goel & Pirolli (1992): (1) The initial start state of the agents in a design session is not defined and the goal (i.e., to produce high-value solutions) is specified. (2) Constraints on design task are known to the agents (i.e., the boundary conditions). (3) Size and complexity of the design task can be altered. (4) The design problem does not have any right or wrong answers but a range of answers with some being better than others. (5) Design problem-solving consists of input and output as indicated in Figure 3- 1. (6) The feedback is given to the designer agents at the end of the session after the final solution is proposed. This is feedback is considered in the following 'similar' session.

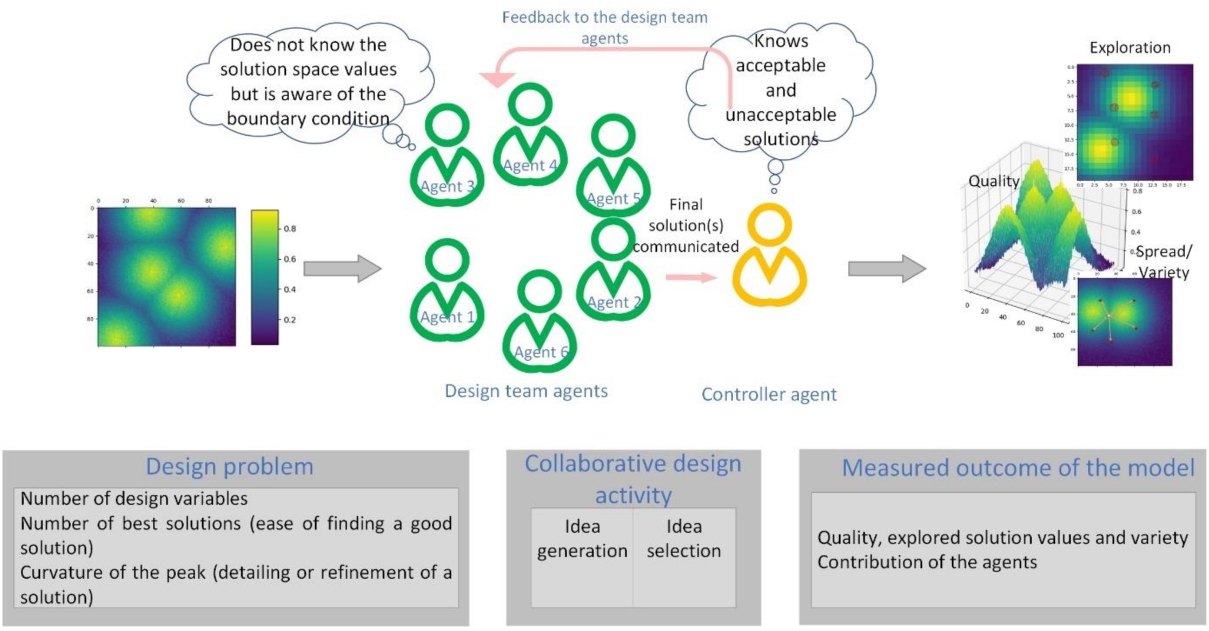



Figure 3- 5 An example of a collaborative design session

Most of the studies in the past have used multi-agent systems (MAS) to study collaborative optimisation (Ren et al., 2011). However, many researchers have argued that the real collaborative design session follows a naturalistic decision making (NDM) approach where “satisficing” is used rather than an optimising strategy (i.e., selection of a good enough solution, which might necessarily be the best one). In the ‘satisficing’ approach, the team aims to find an acceptable solution to a problem and then sticks with such a solution or similar solutions once the acceptable solution area is identified on the design space. (Ball et al., 2001) stated that perspective models of effective design practice hardly aim for optimal design solutions as (i) the design space of possible solution alternatives is extremely large and (ii) important design requirements are subjective and non-quantifiable. Hence, the MILANO aims to simulate a realistic idea generation and selection process rather than collaboration optimisation.

## 3.3 Design task

The design task stands for how a task is expected to be done in the best possible way which in this case is to obtain the best solution values. Design space can be defined as the count of all possible options for a given design task/problem and it is not fully known to the designers (Ullman, 1992). The definition of the design task is critical as it drives many aspects of the simulation. Some of the design tasks used in previous work are represented as binary functions (Schreiber et al., 2004; Dionne et al., 2010). Design tasks that are represented as binary functions often have extreme solution values (i.e., immediately next to the best solution, there is the worst solution). This is an inaccurate representation of the more stable design tasks seen in the real world. This was taken into account while mathematically representing the solution space for this work.

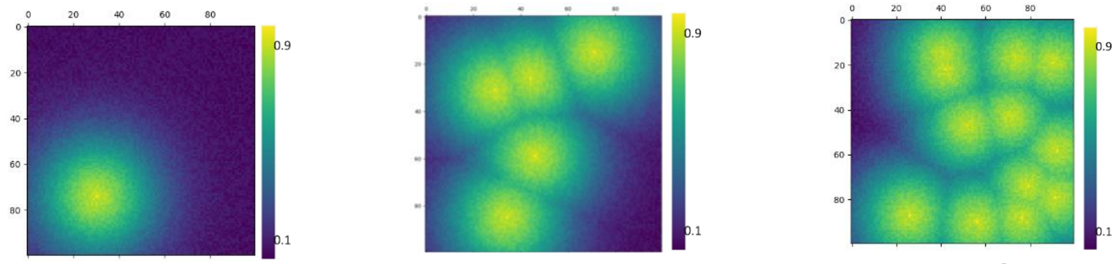
The design solution space in MILANO is modelled in such a way that there is a gradual slope between the best and worst solutions, hence the subtle decrease in the hues around the best solution values (examples can be seen from Figure 3- 6). Similar to the real-world design problems, some noise was added to the objective function so that the probability of having the best and the worst solution next to each other is not completely eliminated and the design problem could have multiple best solutions.

There is a strong thread of literature that uses a computational function to represent a design problem. Similarly, the design problem here can be computationally represented in multi-dimension that is composed of a landscape function $f(x)$ (see Equation 1) and the given number of best solutions (maximas or peaks). The landscape functions draw the desired shape around the given number of maximas. Here $x$ in $f(x)$ is an $n$-dimensional array ($x_1, x_2, x_3....x_n$) of design variables.The landscape function $f(x)$ constructs the slopes around the given number of peaks. The following general assumptions were made regarding the design solution space for this model.

- There is a limited number of $n$ design variables each ranging within a definite interval (unknown to the agents). The design space is represented by all the combinations of values of these $n$ variables. For initiation, simplification, and visualization purposes, two variables ($n=2$) are chosen to represent the design problem. However, for future work, it could be extended to multiple dimensions. A similar design problem representation was used by Lapp et al., (2019) when simulating teamwork based on a different cognitive style where the amplitude of their objective function (peaks) affected exploration. Other studies in problem-solving like Dionne et al., (2010) and Sayama et al., (2010) also used a similar 1-D and 2-D representation of the problem with peaks and valleys.
- Each point on the $n$-dimensional surface defines a potential solution to the design problem and can be evaluated to yield a quality value. The agents do not know the values of $f(x)$ for any solution of the design space before the start of the project, however, they are aware of the limits of the solution space.

**Equation 1** $$f(x) = \frac{1}{\left(1+e^{\left(\left(\frac{1}{\sqrt{M}}\right)D-2\right)}\right)}$$

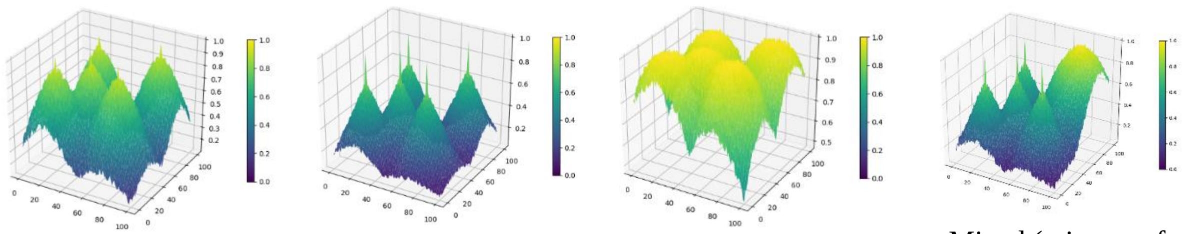
$M$ is the size given to represent the solution space in a 2D matrix. In this case, $M = 100$, such that the solution space was represented as a 100-by-100 matrix. $D$ represents the distance between the random point $(x_1,x_2)$ and the nearest best solutions. The number of best solutions or the peaks are specified at the beginning of the simulation. The design solution space has a maximum value of 1 (lightest hue) and a minimum of 0 (darkest hue), as shown in examples in Figure 3- 6.



1 Peak 5 Peaks 12 Peaks

Figure 3- 6 Examples of design space with 1, 5 and 12 peaks

The design space could be changed with relatively small effort based on the shape (gradient around the maxima), the number of peaks (number of maxima) and the distance between the peaks. The number peaks denote the best alternative options. The 1 best solution or peak could be considered equivalent to a conceptual design problem where it is difficult to find solutions while the 5 best solutions or peaks as a design problem where it is easy to find solutions (Figure 3- 6). In other words, the number of peaks could be analogous to the ease of finding a good solution for a conceptual design problem. The curvature of the peaks (steep or curved) could be analogous to the refinement or optimisation of detailed design activity. The examples of the design space with different peak curvatures (i.e., the gradient around the maxima) can be seen in Figure 3- 7.



Standard Steep Curved Mixed (mixture of steep and curved)

Figure 3- 7 Examples of design space of 5 peaks with different curvatures

Therefore, the number and the curvature of the peaks determines the nature of the design task. For example, there could be several ways to heat a cup of water for tea than heating water in a washing machine, hence multiple solutions or peaks in the solution space and the details of one of these solutions like the size of the cup, amount of water and so on define the curvature of the peaks. Likewise, a design task is more complex when its solution space has a single steep peak than a design task with multiple curved peaks. The results of the design outcome presented in the thesis are related to a various number of peaks and curvatures but more abundantly for 5 standard peaks.

## 3.4 Agents

The work deals with an agent-based approach for simulating team collaboration in self-managing collaborative design teams that are non-hierarchical. In self-managing teams (SMT), a group of individuals have collective autonomy and responsibility to perform tasks to achieve a common goal (Magpili & Pazos, 2018). The SMT members have a shared leadership model where all team members have a collective responsibility for the project outcome (Magpili & Pazos, 2018).

Many definitions of agents are present and various types of agents have been identified (Russell & Norvig, 2002; Wooldridge & Jennings, 1995). Wooldridge & Jennings, (1995) categorised agents into weak and strong agents, where most of the multi-agents systems have weak agents. Weak agents have autonomy, social ability, reactivity and pro-activeness. A strong agent, besides having the constituents of a weak agent, can also have knowledge, belief, intention and emotions. Broadly speaking, an agent could be anything that is autonomous, acts in its environment and does tasks for which it is designed. In the context of the thesis, agents represent individuals human who are a part of a design team (Figure 3- 8). Here an agent architecture and features define its type (Wooldridge & Jennings, 1995). Out of the three agents, architecture approaches were identified by Wooldridge & Jennings, (1995), the agents in MILANO could fit in the reactive architecture approach. This architecture approach as described by Brooks, (1991) where an intelligent creature's intelligence is incremental, it evolves with the dynamic environment and its behaviour emerges as it interacts with its environment.

The controller agent (analogous to a project leader, manager or others in a similar role) could be considered similar to an external leader in SMT who provide direction from outside of the team but are not involved in the team's routine activities (Morgeson, 2005). An influencer has a similar experience (i.e., no past experience) as the other team agents but has the highest self-efficacy. To gain clear and accurate insights on the effect of influencers on the design outcome, the dynamicity of the model processes was controlled. Thus, different self-efficacy combinations at the beginning of the simulation, various number of influencers were being formed and allocated to each influencer-team composition were formulated. Influence depends on both self-efficacy and trust that emerges (as it depends on other parameters like the agent's reputation and familiarity that are gradually formed in the model. Influencers, therefore, have more social influence in teams, similar to social media influencers (SMI), influencers in design teams can also affect some team members' thinking, attitudes, decision-making and behaviour more than the others. Therefore, an agent with high self-efficacy (that is defined at the beginning of the study) and trust (that emerges with the process), is referred to as an influencer.

An experienced agent is the one who has encountered similar tasks before, therefore has knowledge of failure or error points. The minds of individuals with prior knowledge work differently than those of the newcomers. For example, an experienced individual could see the design problem as well as the possible procedures for solving the problem. Similarly, in the model, an experienced agent has a tendency to work from its past known areas to solve the current unknowns as it has worked on similar problems and could recall those experiences when working on the current one. Novices (a term used contrary to experienced agents but are simply agents without experienced), on the other hand, work on the current unknown problem and use trial and error techniques to solve it. Since novices also lack the knowledge of failure points or zones when solving a problem, they take more time to reach a satisfactory solution.

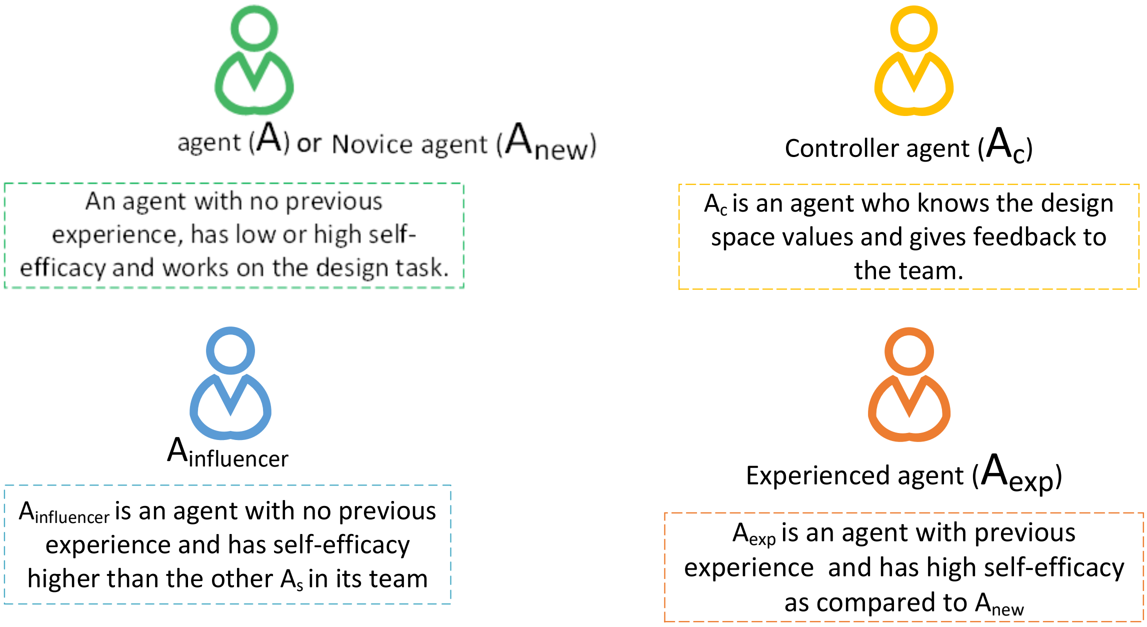



Figure 3- 8 Different types of agents that are referred to in the thesis

### 3.4.1 Agent features

The different kinds of agents are shown in Figure 3- 8. There agents (1) like $A/A_{new}$, $A_{influencer}$ and $A_{exp}$ who work on the design task and are equivalent to individual human designers, and (2) $A_c$ equivalent to a project leader, manager or others in a similar role who is responsible for assigning the task, evaluating the solution quality and providing feedback to the team. All agents ($A_s$) have some

initial features values (like self-efficacy value, initial energy to start exploring the design space, initial knowledge state and initial domain knowledge expertise level) that are allotted at the beginning of the simulation (Figure 3- 9). Based on these initial values given to an agent (A), other types of agents could emerge ($A_{influencer}$ and $A_{exp}$). For example, if A is given a higher self-efficacy value than others in the team, A is becomes $A_{influencer}$. Similarly, if A has high self-efficacy than others and also has past experience of working on the same task then A becomes $A_{exp}$. An agent (A) when used in comparison with an experienced agent ($A_{exp}$) are referred to as novice (new) agents ($A_{new}$).

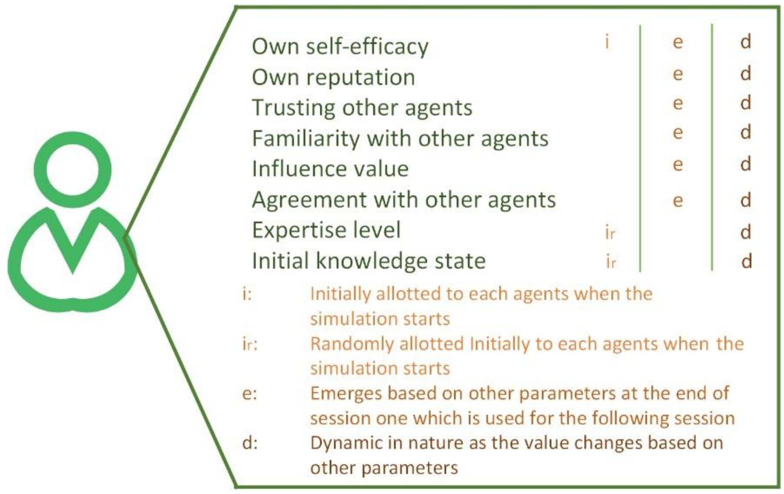



Figure 3- 9 Each agent has different features

As seen from Figure 3- 9 that some features of an agent emerge based on other features values and agent behaviour. The following part explains how some of these features and behaviour emerge and evolve throughout a design project, while the others are explained in sections 3.5 and 3.6 along with idea generation and selection.

***Self-efficacy of an agent***

Researchers in the other domains have tried to study the traits, attitudes and behaviours that lead to influence like behaviour in teams. Self-efficacy, an individual's belief in their capability to achieve goals, is taken as one of the characteristics that determine this behaviour (Bandura, 1977), as individuals who are confident in their abilities may drive the team process. The self-efficacy feature of each agent was allotted at the beginning of the simulation. Since trust between the two agents is a feature that emerges as an agent's reputation and familiarity that builds up, self-efficacy was used as a parameter that could control the number of influencers defined at the beginning of the simulation.

Besides, determining influence value, self-efficacy is an important feature that also governs communication in teams. In other words, agents who are more confident have more probability to propose their solution to their team. Studies also show that an individual proposes more ideas when the team accepts their ideas and high self-efficacy individuals get lesser change in their self-efficacies (increase and decrease) than the ones with lower self-efficacies (Pearson's ρ -0.7, p-value < 0.001) (Singh et al., 2020). Similarly, an agent's change in its self-efficacy is simulated in the model. Figure 3- 10 shows that self-efficacy depends on an individual's motivation, which is impacted by an appreciation by team members or rewards (in terms of positive feedback) given by the superiors. Computationally, appreciation based motivation happens for an agent when other agents select its solution and reward-based when the controller agent provides good feedback (Ryan & Deci, 2000). Both of these forms of motivation contribute to the individual's change in self-efficacy (also seen in Figure 3- 18). Despite the fact that these two phenomena have different mechanisms, they are modelled similarly.

The change in an agent's self-efficacy is given in Equation 2a and 2b, where $\Delta SE_I$ is the change due to motivation and $\Delta SE_D$ is the change due to demotivation for an agent $i$ with a given self-efficacy *(SE)*. φ is the factor that regulates $\Delta SE$ based on the design project length such that the simulation does not result in all agents having 0 or 1 self-efficacy as soon as the simulation starts. φ is taken as 0.1 for Equation 2a and 0.05 for Equation 2b, so that there is a maximum of 1/10$^{th}$ of a unit increase in self-efficacy in one session and a maximum of 1/20$^{th}$ of a unit decrease in self-efficacy in one session.

**Equation** 2a $$\Delta SE_I(SE) = \varphi SE/(SE + e^{1-7SE})$$
**Equation** 2b $$\Delta SE_D(SE) = \varphi(0.25^{SE})$$

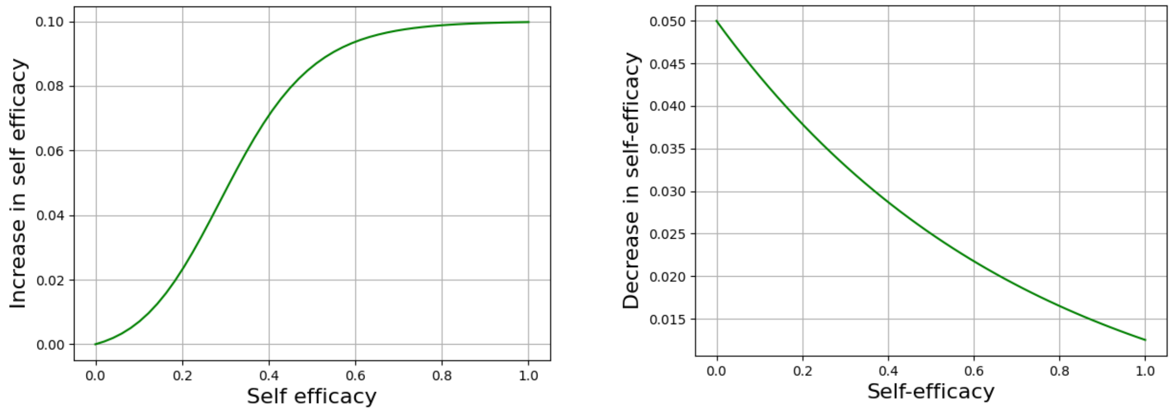



Figure 3- 10 Change in an agent's self-efficacy

***Trust between two agents***

Trust emerges between two individuals (Martínez-Miranda & Pavón, 2012) as it depends on other parameters like the agent's reputation and familiarity that are gradually formed in the model (Costa et al., 2018). The amount of trust an agent $i$ has on agent $j$ depends on $R$ and $f$ (Costa, 2003). $R$ is the reputation of an agent $j$ and $f$ is the familiarity (i.e. how well does an agent $i$ knows agent $j$ (Equation 3)

**Equation** 3 $$T(R,f)_i^j = w_1(R^j) + w_2(f_i^j)$$

***Reputation of an agent***

There are several definitions of reputation but the one closest to the context of MILANO is that reputation is a perception created by agents through other agent's past actions (Mui et al., 2002). The cognitive approach to model trust and reputation based on agent interaction was similar to the one shown in Equation 4 (Sabater & Sierra, 2005). Thus, the reputation of an agent $i$ is given as Equation 4, where $N_a$ is the number of solutions that are accepted by the controller agent and $N_p$ is the total number of the solutions proposed by an agent $i$.

**Equation** 4 $$R_i = \frac{N_a}{N_p}$$

***Familiarity between two agents***

It is known that an individuals' intrapersonal factors like an individual's familiarity with the other team members may affect team social psychology and could influence team effectiveness (Stokols et al., 2008). Thus, it is important to consider its impact when studying team collaboration. This research focuses on self-managing teams that work on design projects and undergo several interactions of idea generation and selection process. In many cases, the same team members need not be part of the same design session while, in other cases, they might have worked together in all the design sessions of a project. Thus, having a varying familiarity. Team familiarity in (Singh, 2009) was defined as the percentage of agents that were part of the same team earlier. Similarly in this model, familiarity, $f$ between two agents, is calculated as the number of sessions agent $i$ and $j$ have worked together, therefore familiar with each other (Equation 5).

**Equation** 5 $$f_i^j = Sessions_i \cap Sessions_j$$

Familiarity and reputation, in reality, may not be fully independent but here they are modelled as mutually independent parameters (Hinds et al., 2000). In the model, familiarity between the two agents increases with the number of idea generation sessions they have in common, as the agents at this point are not being shuffled (replaced, removed or added), the familiarity is the same for all of them. Thus, familiarity being constant, reputation is the only factor that is affecting trust.

***Energy to explore solution space***

The way agents explore the solution space in the model depends on their attention energy. The exploration of the design solution space is because individuals during the initial ideation phase are slower in exploring the solutions as they get warmed up in the beginning by triggering memory search. This is followed by more exploration by recalling past solutions from their memory. However, at some point, this recalling process becomes tiring, and the rate of exploration of the solution space drops towards the end of the session (Goucher-Lambert et al., 2019) (illustrated in Figure 3- 11). This behaviour is modelled mathematically as shown in Equation 6. Changing the shape parameter of the curve (σ) makes it possible to generate different exploration styles, assignable to different agents.

**Equation** 6 $$O(z') = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{ln(z')}{2\sigma^2}\right)} + c$$

The exploration of the solution space depends on the length of the idea generation session (i.e. the number of the steps), in the given Equation 5, *z'* is the normalised length of the session. The value of σ lies between $0 < \sigma \leq 1$, it represents the shape parameter that affects the overall shape of the curve. $c$ is the energy value when the session starts where $c < 0$ is randomly assigned to the agents as it was assumed that there is a certain amount of energy in individuals when the session starts.

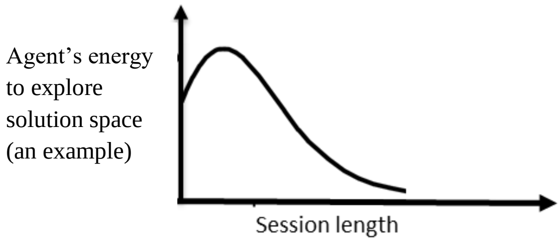



Figure 3- 11 An example plot of an agent's energy to explore solution space

***Memory***

Taking inspiration from the constructive memory concept (Liew & Gero, 2004), the model constructed here implements a simplified version of memories in agents where memory is created based on design agents' past experience. Different agents have different memory storage and store experience after working on the design task at the end of a session. These experiences are in the form of feedback from the controller agent. The experiences that are not utilised in the agent's current situation and are not recalled for a long time are forgotten from the memory. The forgetting in agents is based on the Decay Theory, which suggests that *"If there was no attempt to recall an event, the greater the time since the event the more likely it would be to forget the event"* (Oberauer & Lewandowsky, 2008). Accordingly, agents in the model exhibit the behaviour that suggests that memories are not permanent.

***Recall capability***

Recalling here refers to the act of bringing a past event back into one's mind. When an agent is unable to recall, it does not mean that the information is permanently removed from its memory but rather that it is unable to be retrieved from its memory for that situation. An individual in real situations might not be able to recall any similar experience from the past while approaching a problem in its current situation. Similarly, in the model, an agent has its feedback from the controller agent stored in its memory. This feedback is in the form of positive (successful experiences) or negative (failed experiences) events, but an agent might not be able to recall them while solving the problem.

An agent could recall the stored events in any order and the recalled events from the past alter the way it approaches the solution (Murdock, 1962). The recalling ability in agents depends on the intensity of the solution value and the time of recall as explained by (Banaji, 1986) and varies from agent to agent. Identical to the real-world situation where individuals recall their worst and best events results more clearly than their mediocre outcomes, this phenomenon of recency and primacy effect is simulated in the model as given by Murdock (1962). The effect means that the events that are either first or most recent are recalled more often than the events in between. Likewise, the events that are extreme (i.e., best and the worst) are more easily recalled. An example of the events being recalled is shown in Figure 3- 12. The red path is the trajectory that each agent takes before selecting the final solution. This red path is made of several steps that are analogous to a designer moving from one solution to another in a design space during an idea generation session. The set of recalled memories (shown as **R** in Figure 3- 12) could be of a positive (grey cross) or a negative event (orange cross).

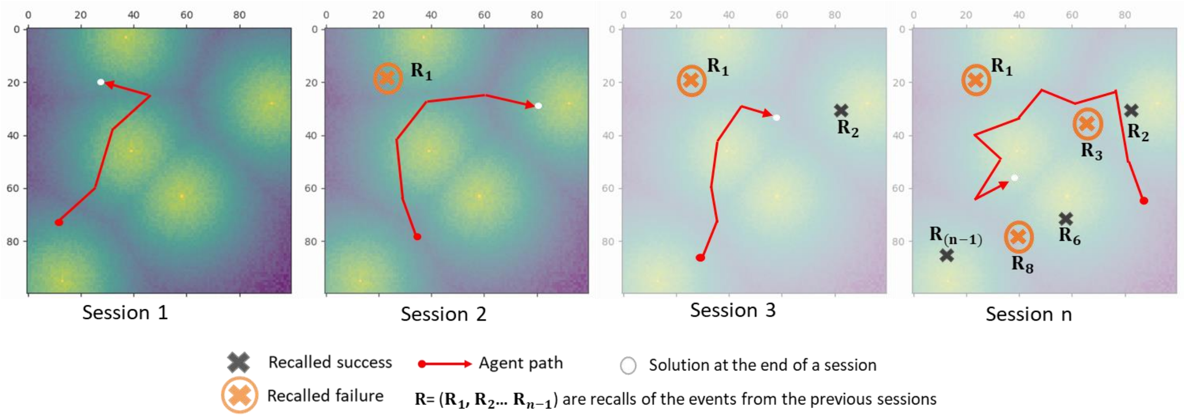



Figure 3- 12 An example showing an agent recalling events while exploring solutions

## 3.5 Idea generation

In order to simulate artificial humans, learning is an important feature to implement in the model. For example, studies have been done where agents learn collectively (Wu & Duffy, 2004), socially using mental models (Singh, 2009) or to simulate curiously in agents (Saunders & Gero, 2004). Most of the models described in the literature deal with some form of learning in their agents to accomplish the purpose of their work. The most common logic implemented in many models listed above is in the form of learning from experience (McComb, 2016; Lapp et al., 2019). However, while simulating learning it is often assumed that the agents are aware of the design solution space and they thrive for the optimal solution (McComb et al., 2017). This works perfectly when the goal of the model is to find the optimal solution depending on the configuration of its parameters. On the other hand, the model presented in this paper aims at mimicking a collaborative idea generation session where the design solution space is unknown to the agents in a way that is similar to a real brainstorming scenario, but at the same time, the individuals (agents in the model) are aware of the boundary conditions.

Collaborative behaviours involve giving and taking ideas, as the design teams have natural inclinations toward ‘giving’ and ‘taking’ ideas, both modes of synthesis were considered in the model (Elsbach & Flynn, 2013). The model represents design as a search process (i.e., when the design goals are defined at the beginning and focus of the design is not changed till the solution is found) as well as it has some of the elements of an exploration model (i.e., the parts of solution space are explored, however, the expansion in the solution space with changes in the design focus is not implemented) (Maher & Tang, 2003). Basic thinking in agents (generation, exploration, comparison and selection) was based on Stempfle & Badke-Schaub, (2002) model of thinking in design teams but implemented at an individual level where agents explore solution space; generate solutions by comparing them to their recalled events and finally selecting the one at the end of an idea generation session that they would propose to their team. The agents when thinking during idea generation move from one point to another on design space. This represents an agent systematically generating and evaluating a range of solution alternatives to any problem (Pahl & Beitz, 2013) before proposing it to its team.

### 3.5.1 Learning from experience

The most common form of simulating learning in agents is in the form of reinforcement learning, where the agents use feedback from the environment to determine their action for the current state (Hulse et al., 2019; Eliassi-Rad & Shavlik, 2003) as seen as arrow 2 in Figure 3- 13. Similarly, in the model, agents learn about the solutions space gradually as they receive feedback from the controller agent present in their environment. The behaviour resembles the one described by Cagan & Kotovsky (1997), where the agents move randomly when they start their search but become more regulated as they learn about their problem. According to the feedback (a numerical value) received by an agent at the end of a session, the event is broadly classified as positive (successful) and negative (failure) which are stored in its memory. The event is said to be in a positive category when the feedback values above a certain threshold and in a negative category when it is below, it could be seen from the example shown in Figure 3- 12 (as black and orange crosses). The learning from the past, which could be positive or negative experience is different and have a different impact on the current situation (Wimmer & Shohamy, 2017) are described below.

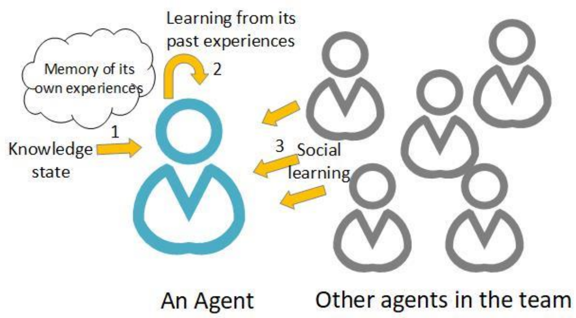



Figure 3- 13 An agent learning

Learning from a positive experience ($\vec{v}_s$) and how it affects an agent on its current solution depends on the following factors (Figure 3- 14):

- The magnitude of learning from the positive experience ($|v_s|$ = *S(d')*) depends on the similarity between an agent's current solution in 'mind' and the recalled positive event (Read & Grushka-Cockayne, 2010). If the recalled event is similar (closer on solution space) to the solution 'in mind', the agent is more influenced by its previous experience than those that are far in distance (not so similar) (Gentner, 1989). On the other hand, if the recalled positive event is too similar (i.e. too close) as the solution in mind, the agent's learning is less influenced by it. This assumed that an individual will not apply the exact same (or slightly different) knowledge from the past event to their current situation, hence compelling it to produce different solutions. Similarity is represented as the distance between the recalled and current agent position (*d*).
- The amount of learning from a positive experience also depends on the expertise level of an agent. It means that when an agent has a lower domain-expertise level, it will learn slower therefore a less steep slope than the agent who is more expertise (Ball et al., 2004). It is seen in Figure 3- 15 as the position of the peak of the learning curve. This is represented in Equation 7.1, as α which depends on an agent's expertise (*E*) level, where *E* was randomly assigned to the agents when the session starts.
- Lastly, learning from a positive experience depends on the time when the recalled event occurred (*Δt*). It is shown as the height of the learning curve in Figure 3- 15 where more is the height; greater is the learning when the positive experience is recent. Its height is represented in Equation 7.2 where $\tau$ is the adjusted value of *Δt* (Equation 7.3) so that value of the curve in Equation 7 is normalised.

The amount of learning from the positive experience recalled (magnitude of the learning vector as shown in Figure 3- 14) can be represented by *S(d')* and is given in Equation 6 below:

**Equation** 7 $$S(d') = \tau\left(\frac{\frac{1}{d'\alpha\sqrt{2\pi}}e^{\left(-\frac{(\ln(d'))}{2\alpha^2}\right)}}{0.7}\right)$$

$d' = 4.0 \cdot d + 0.1.$ Here *d'* is the adjusted value of *d* such that $0 \leq S(d') \leq 1$.

In computational terms, *d* is the distance between the current agent (solution) position in session *n* and recalled success (solution) position of session $S_n$. *d* is the similarity between the current design task and recalled positive experienced as explained above that similarity is one of the factors on which learning magnitude depends. In Equation 7, *S(d')* is divided by 0.7 to normalise it. The other variables in the above equation (on which learning magnitude depends) are explained as follows:

**Equation** 7.1 $$\alpha = 0.8 - (0.2 \cdot E)$$

**Equation** 7.2 $$\tau = 1 - (0.7 \cdot \Delta t))$$

**Equation** 7.3 $$\Delta t = n - \frac{S_n}{N},$$

where *n* is the current session number of an agent and $S_n$ is the session when the recalled success occurred. *N*=number of sessions.

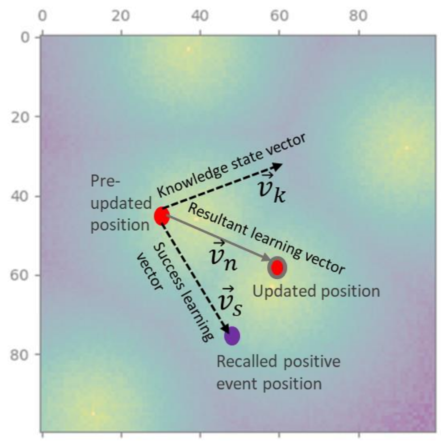



Figure 3- 14 The updated position on an agent after learning from a positive experience

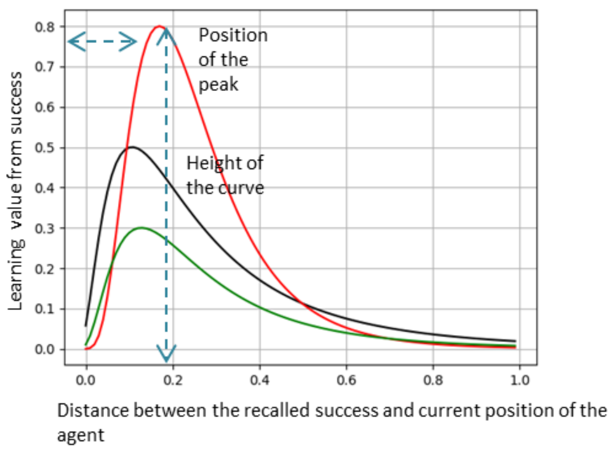



Figure 3- 15 Different amount of learning from one's own positive experience

The learning from positive experience vector, $\vec{v}_s$ is summed to the initial knowledge state vector of an agent $\vec{v}_k$ to get the resultant learning vector ($\vec{v}_n$ ) from the two learning states (arrows 1 and 2 shown in Figure 3- 13) for an idea generation session given as Equation 8.

**Equation** 8 $$\vec{v}_n = \sum_{i=1}^{N} \vec{v}_{s_i} + \vec{v}_k$$

Here, *N* is the number of positive experiences recalled in a session *n* and *i* is the initial starting index.

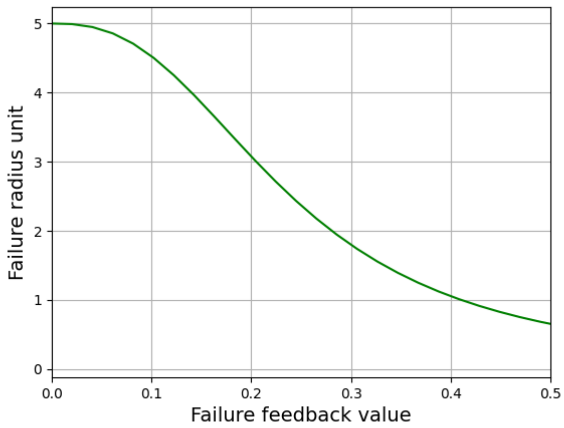



Figure 3- 16 Failure radius depends on the value of the recalled failure (where 5 units are the max radius for 100X100 units of solution space)

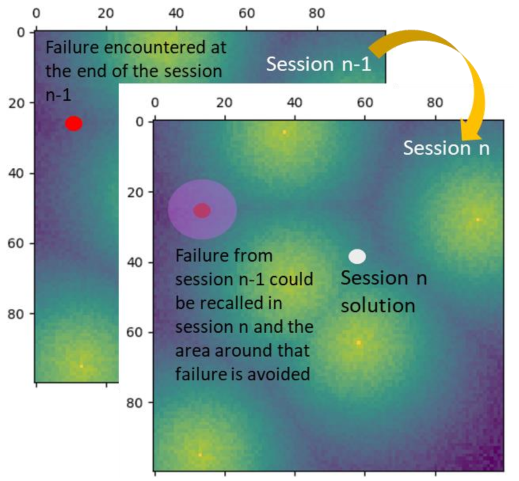



Figure 3- 17 An example where an agent (in red) encounters a failure at session n-1, which is being recalled in session n, an area around the failure is avoided

Learning for a negative experience is different from a positive experience as humans try to avoid the failures they have committed in the past and tend to follow the path that led to previous success (Wimmer & Shohamy, 2017). Similarly, learning from negative experiences is done in the form of avoiding the areas where previous failures have occurred. An agent avoids the negative experiences by forming a circle around the point where the recalled failure had occurred. Like the real scenario where an individual remembers the failure zones on the solution space while exploring new solutions. The radius of this circle differs from agent to agent and depends on the severity of the recalled negative event (Figure 3- 16) (Banaji, 1986). Similar to a positive event, an agent recalls a negative event that had very bad feedback (less than 0.4 in value). The agent will try to avoid a larger area around this recalled failure than the recalled failure with less severe feedback (Figure 3-16). The circular area around the failure solution is avoided by an agent. This behaviour could be represented by Equation 9. The failure radius or the size of the failure circle around the failure point depends on the learning capacity from a failure of an agent ($F_{learning}$), and an agent will avoid the circular area around the recalled failure ($f_{feedback}$). Seen in Figure 3- 17 as a purple circle for visualisation and it does not represent actual values.

**Equation** 9 $$F_{learning} = \text{ϝ} + (p - \text{ϝ})/(1 + (\frac{f_{feedback}}{(p/r^2)})^{p^2/r}), \text{ where } \text{ϝ} = p \cdot e^{-r}$$

Depending on the size of the design space, the value of $p$ and $r$ could be adjusted to get the desired size of the maximum failure radius when the feedback is worst. In this case, the maximum failure radius is chosen to be 5 units for a 100 X 100 design space therefore, $p$ and $r$ were taken as 5 and10 respectively.

## 3.5.2 Effect of the influencers

According to Bandura's Social Learning Theory people learn from their social environment through interactions while in Social Cognitive Theory, they learn passively through the social environment through observing others. In this model, the agents are familiar with each other and are 'interact' when proposing solutions. They are passively 'observing' whose solutions are being selected. Therefore, for this model social learning which is equivalent to social influence is represented as the imitation type. Therefore, agents imitate /learn most from those who influence them the most.

To investigate the factors that could give rise to the influencer effect in design teams, self-efficacy and trust (resulting from the mutual knowledge of each other) were chosen as initial parameters to begin the investigation. Self-efficacy is implemented in the model as a dynamic feature in agents that changes based on its intrinsic and extrinsic motivation (Ryan & Deci, 2000). Like self-efficacy, trust also changes throughout the simulation as in real situations where it depends on the interacting individual's familiarity and reputation (Costa, 2003; Mui et al., 2002). To model the 'influencing effect', each agent has an influencing value from other agents in the team and it depends on the factors shown in Figure 3- 18.

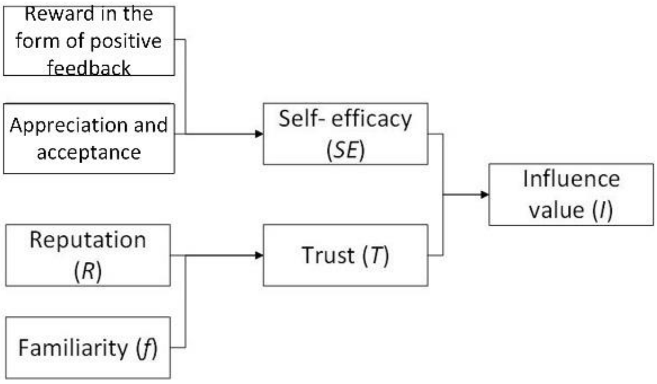



Figure 3- 18 Factors considered for determining the influence value

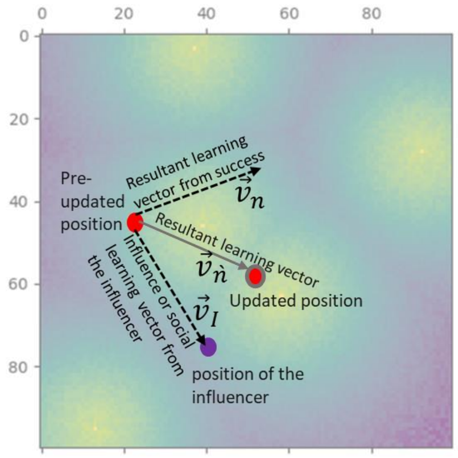



Figure 3- 19 The updated position on an agent is the sum of the vectors of its resultant learning vector from recalled success and the influence value vector

The influence value $I$ (same magnitude of the social learning vector $|\vec{v}_I|$), for an agent $i$ of agent $j$ is computed as Equation 10. Here, $j$ varies until the total number of agents present in a team and $j \neq i$.

**Equation** 10 $$I_i^j(\Delta SE, SE, T) = w_1(\Delta SE_{i-j})^{1.5} + w_2\left(SE^j\right) + w_3\left(T_i^j\right)$$

Where, $\Delta SE$ = difference in self-efficacy of agent $i$ and agent $j$, $T$ is the degree of trust of agent $i$ has on agent $j$. $SE$ is the self-efficacy of an agent $j$. The weights $w_1$, $w_2$ and $w_3$ were decided after the empirical studies, presented in the next section. As seen from section 3.4.1, the amount of trust ($T$) an agent $i$ has on agent $j$ depends on $R$ and $f$ (Costa, 2003). $R$ is the reputation of an agent $j$ and $f$ is the familiarity (i.e. how well does an agent $i$ knows agent $j$).

$\vec{v}_{I_i}$ is the total amount of learning by an agent $i$ from its peers (arrow 3 as shown in Figure 3- 13 and in Figure 3- 19) given in Equation 11. The resultant vector $\vec{v}_{\acute{n}}$ is the total amount of learning an agent does while generating solutions to the design problem (Equation 12) and $\vec{v}_n$ is as calculated in Equation 8 (above).

**Equation** 11 $$\vec{v}_{I_i} = \sum_{\substack{j=1 \\ j \neq i}}^{N} I_i^j$$

**Equation** 12 $$\vec{v}_{\acute{n}} = \sum_{i=1}^{N} \vec{v}_{I_i} + \vec{v}_n$$

Here, $N$ is the number of agents in a session $n$ with the agent $i$ and $j$ is the initial starting index.

## 3.6 Idea selection

Cross & Cross, (1995) studied how concepts are developed and how team members persuade others to adopt their concepts in a team. Some of their observations included, strong disagreement in teams on the design concepts to which different members of the team were committed, teams found ways to avoid conflicts and team members often do 'noncommittal agreements'. In the end, they suggested that social processes emerging from social interactions, roles and relationships in teams, cannot be avoided when studying a design activity. Therefore, MILANO considers some of these social processes like the influencer effect and majority effect in its idea selection formation. Often the models of opinion formation in a group that could lead to consensus, polarization or fragmentation are based on the confidence level of agents (Hegselmann & Krause, 2002), where confident individuals could influence other's opinion (i.e., influencer effect). While others like Martínez, (2020) have studied opinion formation in coalition groups formed based on majority rule (i.e., when the majority of neighbours share similar opinions, they will act as a coalition group and the influence as a group on an agent will be greater than their individual impact (Das et al., 2018)).

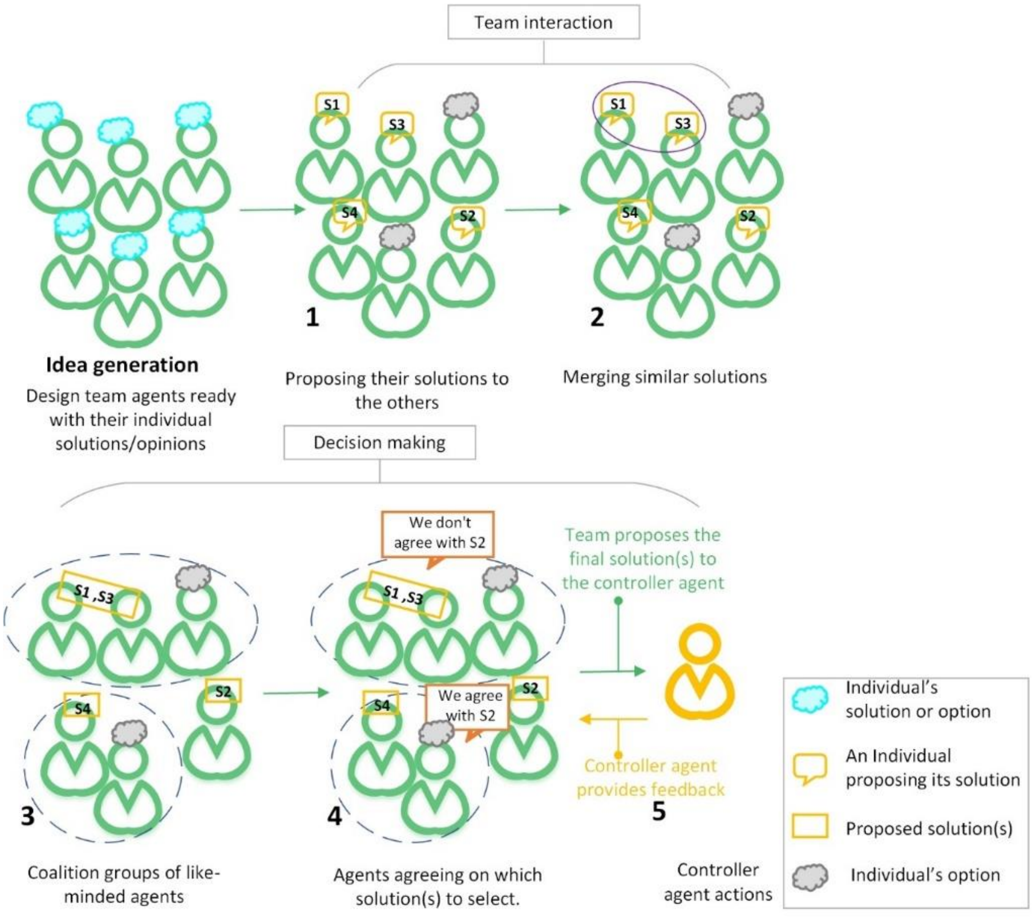



Figure 3- 20 Flow of processes during idea selection in a design session

The agents-based model used to study opinion dynamics in teams due to social influence could be classified into 3 types: Models of assimilative social influence, Models with similarity biased influence and Models with repulsive influence (Flache et al., 2017). The presented model in this paper closely fits in the category of models with assimilative social influence (*models in this class are based on the assumption that if two individuals are connected by an influence relationship, they will always exert influence on each other towards reducing their opinion differences (assimilation))* and models with similarity biased influence (*models in this class are under the assumption that a similarity bias can generate a self-reinforcing dynamic in which agreement strengthens influence and influence leads to greater agreement with those who already have a similar opinion*) (Flache et al., 2017). Models with assimilative social influence led to a reduction in opinion differences and all agents eventually align with the emergent consensus while models based on similarity, could result in opinion clusters based on similarity in agents' opinions (Flache et al., 2017). Overall, depending on the self-efficacy distribution in teams that affects influencer formation and the distributions of initial opinions of agents, the simulation may result in consensus formation based on coalition groups' opinion clusters or group polarisation. An example of idea selection in a session could be seen in Figure 3- 20, the steps in this figure will be explained in the following parts.

### 3.6.1 Proposing solutions

Idea selection comprises team interaction and decision-making (Figure 3- 20). The team interaction starts after the design team agents are ready with their solutions to communicate with the team. As it is known that communication is key in the design process and communication depends on the individual's self-efficacy level. Self-efficacy mediates the 5 big personality traits, including extrovertism (Stajkovic et al., 2018), therefore, even though all individuals generate ideas, some might not be enough confident to propose to their peers as seen in step 1 of Figure 3- 20. Similarly, in the model, there is a low probability that all the agents will propose solutions (Singh et al., 2020). Agents, who have higher self-efficacy than others do, communicate their ideas more often. However, the possibility of a low self-efficacy agent proposing its solution to the team is not completely eliminated. The number of agents who are selected to propose their solutions is given in Equation 13.

**Equation** 13 $$N_{Min} \leq (N_{SA}) \leq N_{tot}$$

$N_{Min}$ are the minimum number of agents that should at least propose solutions. Based on educational experiences as described by authors in their studies (Lahti et.al., 2004; Reid and Reed, 2000) as well as a common observation made during the experiment presented in this study that more than 30% of individuals in design teams propose solutions. Since the model simulates a team of 6 agents, $N_{Min}$ here was taken to be 3. $N_{SA}$ is the number of selected agents that propose solutions out of the total number of agents in a team $N_{tot}$.

The probability of an agent being selected to propose its solution *($P_{SA}$)* depends on how the self-efficacy is varied in the team *(Var (Team$_{SE}$)* (Equation 14 and 15).

**Equation** 14 $$P_{SA} \alpha \, Var(Team_{SE})$$

**Equation** 15 $$Var(Team_{SE}) = \frac{\sum_{i=1}^{N_{tot}} (SE_i - \mu)^2}{N_{tot}}$$

where $\mu$ is the mean of the self-efficacy of agents in a team and *SE* is the self-efficacy of an agent *i*. This means that there is a high probability of all the agents who are selected (or selected agents, *SA*) to propose their solution have high self-efficacy when the team self-efficacy variance is high. When the team self-efficacy variance is low, i.e. all the agents have either low self-efficacy or high, agents are randomly selected to propose their solutions. Cases when then $N_{SA}$ is higher than the number of agents with high self-efficacy, additional low self-efficacy agents are selected randomly selected to propose their solutions. Agents who did not propose their solution still have their solution in their minds that will be regarded as opinions for the further decision-making process.

### 3.6.2 Merging of solutions

After individually generating ideas, collective work is required. Likewise, at this stage at step 2 in Figure 3- 20, agents who have proposed their solutions merge similar ones. The similarity between the solutions is computationally defined as the distance between the solution points on s design space, i.e. the two solutions are similar if they are close to each other on a solution space. Merging similar solutions uses the k-means clustering method. k- means clustering is a popular and simplest cluster analysis method in data mining that uses Euclidean distances between points for a given number of k (clusters). However, in order to define the value of k, one approach is to try different values of k, for example, with k =1, k =2 and so on until k = total number of solutions (data points), by comparing the variation within the clusters (Steorts, 2017). In this work, k is chosen randomly and lies between 2 < k $< Num_{totSoln} - 2$ where $Num_{totSoln}$ is the total number of solutions. By choosing k within this range would give optimal and near-optimal values of k. The using near-optimal values of k in the model could be justified by the presence of environmental noise or other unaccounted factors, which affected the optimal way of merging similar solutions (data points). However, this approach will be altered if the team size becomes very large.

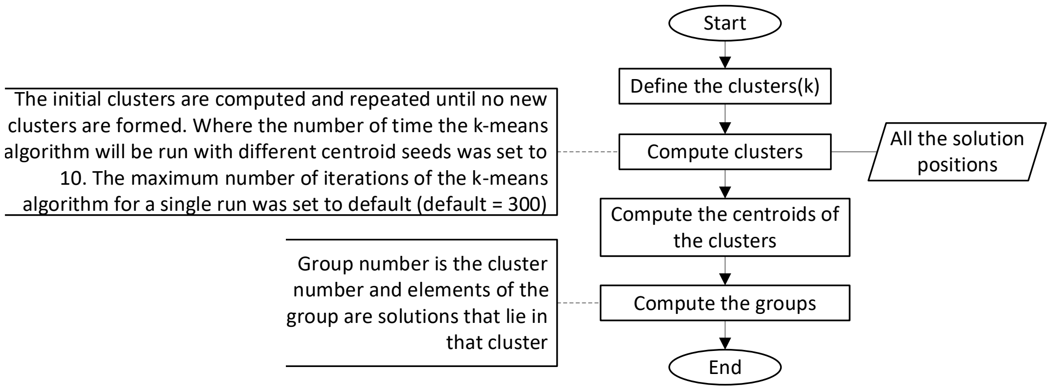



Figure 3- 21 Flowchart for merging similar solutions

For the clustering (i.e. merging) similar solutions proposed by the agents, python's Scikit-learn machine learning library was used. The flowchart for getting the solutions that should be merged is given in Figure 3- 21. The merged solution that becomes the new common proposed for the selected agents in the cluster is the centroid. k- means aims at minimising an objective function given in Equation 16.

**Equation** 16

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} \left( \left| \left| S_i - v_j \right| \right| \right)^2$$

Where, $||S_i\text{-}v_j||$ is the Euclidean distance between $S_i$ and $v_j$ ($S$ is the set of positions of the solutions points and $v_j$ is the positions of the centroids. $c$ is the number of clusters and $c_i$ is the number of solutions in cluster $i$.

### 3.6.3 Collation groups of like-minded agents

Most of the literature focuses on strategies for decision making that is used to assist decision-makers to solve problems in a systematic and consistent manner to reach optimal solutions. However, here the goal of this study is not to simulate agents to make an optimal decision but to understand how different team dynamics affect the design outcome. Taking this into consideration step 3 and 4 in Figure 3- 20 shows that during decision-making the individuals' opinion could be affected by the (i) the influencer's effect (stated as expert effect '*induced by the presence of a highly confident individual in the group*') or (ii) the majority effect '*caused by the presence of a critical mass of laypeople sharing similar opinions'* (Moussaïd et al., 2013).

The majority effect (in Step 3 and 4 of Figure 3- 20) is based on Cartwright, (1971) model of choice shift that explains why group decision making is more complicated than just taking an average of group members' decisions. Cartwright, (1971) stated two subtypes of majority influence processes: coalition process and pure majority process. Coalition (step 3) takes place when the judgements (opinions) of individuals are close to each other and it tends to dominate the group judgment process. Majority process (step 4), where the judgement of a larger (majority) group of individuals influences the judgement of other team members. Both coalition and majority process contribute to majority influence such that the influence of individual team members or influencer(s) is less effective during decision-making. However, in the case when all the individuals are closer (have a similar opinion) to that of an influencer, its effect would be exaggerated.

1. *Creation of coalition groups:*

Some studies of social network show that opinions in a social network suffer locality effect, i.e they get localized to given groups without infecting the whole society (Wu & Huberman, 2004). Similarly, agents could form coalition groups with (as shown in Figure 3- 22) (i) the agent(s) who have proposed the solution or (ii) the agent(s) who did not propose any solutions. (iii) Agents could also not be a part of these coalition groups. The (i) and (ii) occurs when their opinion on the problem is similar to that of the other (Read & Grushka-Cockayne, 2007; Cartwright, 1971). Computationally this means that the distance between their proposed solution/opinion (not a proposed solution) and other members' solution/opinion are close such that they form a coalition group. The groups formed based on similar opinions behave collectively when evaluating proposed solutions. Case (iii) occurs when an agent's opinion is not similar (close) to the others, hence it stays alone.

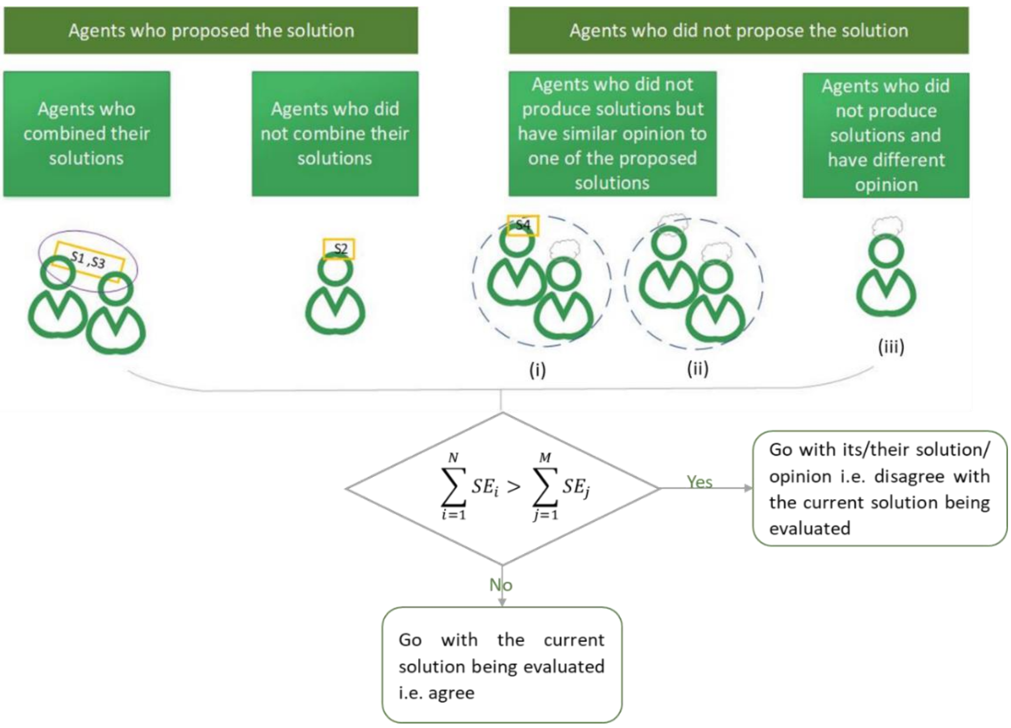



Figure 3- 22 An example of a decision-making scenario during Idea selection

2. *Deciding which solution to choose:*

In collaborative design sessions, the design team is not aware of the quality of their solutions, similarly, in the model, the design team agents are not informed of the design solution space, i.e. they do not know the quality values of the solutions. The majority of the models of opinion formation in a group that could lead to consensus, polarization or fragmentation are based on the confidence level of agents (Hegselmann & Krause, 2002). Therefore, the two behavioural factors that were considered when deciding on which solution(s) to select are the number of agents in the coalition group and their self-efficacies. The first factor was chosen as it is known that influence increases with the number of individuals in the group (to a certain point) (Bond, 2005), hence affecting other team members' actions during decision-making. The second factor was chosen as individuals with lower self-esteem, those who are dependent on and those who have a strong need for approval from others are also more conforming (Jhangiani & Tarry , 2014). Thus, similar to the real world, the model also behaves in a manner where more and more individuals have the same opinion, a less confident individual is likely to act like a 'sheep' and a more confident one is independent to think for itself when evaluating the proposed solutions.

This majority influence is explained by the coalition and majority process, where the behaviours and beliefs of a larger (majority) of individuals in a coalition group influence the behaviours and beliefs of a smaller group (Nemeth, 1986). This happens when the group of 'like-minded' agents have higher cumulative self-efficacy than those who proposed the solution. Hence, it is more likely that the latter group of agents (or an agent) will agree with the former group (DeRue et.al., 2010). On the contrary, when the cumulative self-efficacy of the coalition group is less than other groups/individual, minority influence occurs, and the group is likely to agree with the proposed solution of the influencer(s). Similarly, studies like Hegselmann & Krause, (2002) simulated symmetric or asymmetric confidence in team agents, where opinions of agents moved that plurality, to polarisation and then to consensus. They found that in symmetric (all agents having similar confidence) cases the opinions split into many profiles (clusters) (Hegselmann & Krause, 2002). While asymmetric cases resulted in convergence into the direction that was governed by asymmetric confidence.

As an example shown in Figure 3- 22, whether an agent is in a coalition group or alone, self-efficacy decides whether to agree with the proposed solution or not. When the self-efficacy is lower than the compared group/individual, how much an agent *(i)* agrees *(A)* with the other agent's *(j)* proposed solution depends on two factors is given in Equation 17. In some models agreement is represented as binary (i.e. 0 = disagree while 1= agree), however, based on the social opinion formation model, individuals are affected by their peers in a socially connected system (Nguyen et al., 2020). Thus, they could have a range of agreement, in other words, they could agree more with some and slightly less with the others. Based on this, the agreement in the model is not binary but a continuous value that depends on the following factors (as hypnotized at the beginning):

- The amount of influence *(I)* 'proposed solution agent' *j* has on the agent *i* who is evaluating its support to the proposed solution.
- The past amount agreement *($P_A$)* agent *j* had while deciding on agent *i's* proposed solution.

**Equation** 17 $$A_i^j(I, P_A) = w_1(I_i^j) + w_2\,(P_{A\,j}^{\;i})$$

The weights ($w_1 \, and \, w_2$) used in Equation 16 were taken as 0.5. $I$ is the degree of influence from agent *j* perceived by agent *i*, is given below as a function of $\Delta SE, SE \; and \; T$. $\Delta SE$ = difference in self-efficacy of agent *i* and agent *j*, *T* is the degree of trust of agent *i* has on agent *j*. $SE$ is the self-efficacy of an agent *j* (Equation 9).

### 3.6.4 Controller agent actions

Before the solution(s) are communicated to the controller agent who is analogous to the project manager, project leader, professor or others in a similar position, the total agreement *($A_{total}$)* on a proposed solution *(ps)* is calculated (as the Equation 18) for all the proposed solution (step 5 in Figure 3- 20).

**Equation** 18
$$A_{total_q} = \sum_{i=1}^{N_A} A_i$$

$\forall q \in \{ps_1, ps_2 \ldots, ps_Q\}$ where $Q$ is the number of proposed solutions. $N_A$ is the total number of agents who agreed with the proposed solution *(ps)* and *i* as the initial starting index.

At times, it is seen that the design team selected one final or multiple concepts. Here the maximum number of multiple solutions was chosen to be 3 as based on common observation where small student design teams often (are told to or do it by themselves) select upto 3 concepts[1]. Therefore, for the results the two extremes i.e., 1 or 3 solutions were extracted and analysed to see more variation. To simulate similar behaviour in the model to decide whether one or multiple solutions are proposed to the controller agent, the distribution of the total agreement *($A_{total}$)* for all proposed solution is calculated as in Equation 19. In order words, the probability of the design team to propose one final solution to the controller agent is more when the distribution is high (i.e. high agreement on some proposed solutions). Conversely, there is a higher probability that the agents would propose three solutions to the controller agent when the distribution of the agreements on the proposed solution is low (i.e. similar agreement values on all the proposed solutions), thus, there is no dominant solution.

**Equation** 19
$$distribution(A_{total}) = \sqrt{\frac{\sum_{q=1}^{Q}(A_{total_q} - \mu)^2}{Q}}$$

$Q$ = number of proposed solutions, $q$ is the starting index and $\mu$ is the mean.

When the other team agents select one or more solutions to communicate to the controller agents, the self-efficacy of the agents whose solutions or merged solutions were selected increases. While the self-efficacy of those whose solutions were not selected decreases[2].

The controller agent can assess the solutions proposed by the team and give feedback (for example a senior designer, project manager, leader and others in similar roles who evaluate the outcome of a team of novice or less experience designers or students) as seen in Equation 20. The feedback is based on a probability ($P_{feedback}$) value that. Hence, there is a higher probability of getting a higher feedback value when the quality of the solution is high (Equation 20.1). However, the probability of getting lower feedback value on a high-quality solution is not completely eliminated as in real-world teams often fail despite having a good concept due to external factors (such as wrong market timing or

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[1] It is a model parameter that can be easily adjusted

[2] As the team moves from one session to another, increase and decrease in self-efficacies of agents might cause situations (especially in teams with well-defined influencers) where some agents will never again propose or will never agree with other's solutions.

change in the consumer behaviour). Alternatively, there is a very small chance of getting good feedback on a bad quality solution.

**Equation** 20 $$feedback\ = P_{feedback}$$

**Equation** 20.1 $$P_{feedback}\alpha\ solution\ quality\ ,$$

where, $P_{feedback}$ is the probability of the feedback obtained by generating a random number and checking if this random number is less than the solution quality value.

In this case, when multiple (3 concepts) are proposed to the controller agent, it picks the best concept based on their quality values and provides the team with feedback according to the selected concept quality. Good feedback results in an increase in self-efficacy of the design team agents and low feedback decrease self-efficacy. The amount of increase and decrease in the self-efficacy depends on the current self-efficacy level of an agent (Equations 2a and 2b). Besides affecting self-efficacy, the reputation of agents is also updating (Equation 4).

## 3.7 Experience-novice team compositions

A team of design agents with varying levels of past experience of working on a given design task are created in the model. The flowchart in Figure 3- 23 shows how experienced agents were created and a team of novice-experience agents were made. Computationally, experienced agents are the ones having the knowledge of failure or error points, as they have worked on similar tasks before. For novice agents, on the other hand, work on the current design problem that is unknown to them.

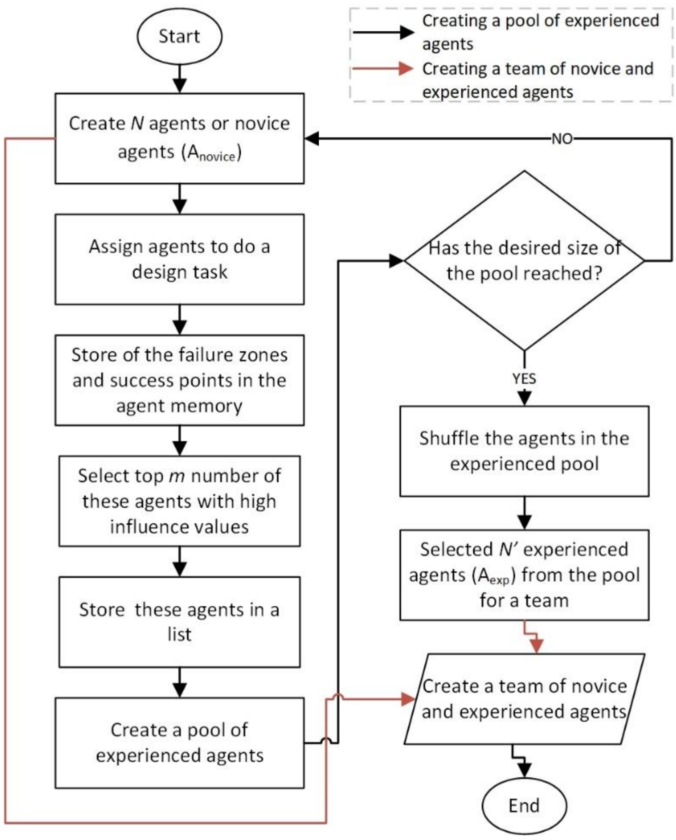



Figure 3- 23 A flowchart showing the creation of novice-experience agent teams

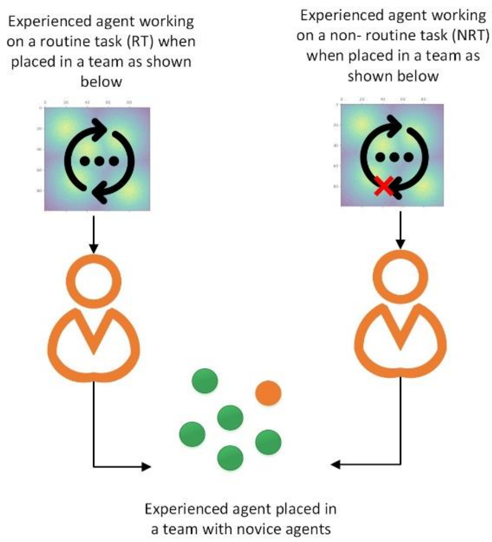



Figure 3- 24 Creating agents with experience who are placed in teams with novices that have routine and non-routine tasks

It is often seen that familiarity with the task affects the performance of experts and novices. Ball et al., (2004) found that experts and novices use different forms of analogical reasoning in highly familiar domain problems and less familiar domain problems. Therefore, it can be said that most of the expert designers' knowledge when solving a problem is 'routine' (i.e., *familiar kinds of problem will often have readily retrievable solutions*) in nature (Ball et al., 2001). Often, experts are deal with situations where the design task is less familiar to them or 'non- routine' where the knowledge gathered by them from their prior experience is not directly applicable (Ball et al., 2004). Thus, the non-routine nature of the task when given to an experienced agent in a team with novices is an interesting aspect to study. In the model, an experienced agent who has worked on a task similar to the current problem in hand is referred to as a routine task (RT). Or an experienced agent could be placed in a team of novices who working on a task that is not exactly similar to that of an experienced agent experienced, thus referred to as a non-routine task (NRT) as seen in Figure 3- 24.

## 3.8 Virtual team collaboration

Some studies in the past have identified direct and indirect antecedents that affect virtual team effectiveness mainly in terms of output quality and quantity (Caya et al., 2013). While others have investigated the impact of various factors (team, task, leadership and many more) on virtual team performance (Marlow et al., 2017; Liao, 2017). Similar to face-to-face collaboration, relationships, shared understanding, and trust serves as important antecedents to virtual collaborations (Peters & Manz, 2007). Virtual collaboration differs from face-to-face collaborations. Face-to-face collaborations are more powerful in developing social norms, authority, group culture and commitment (Axtell et al., 2004) while virtual collaboration results in lower collaboration (Montoya et al., 2011) which leads to lower cohesion and weaker relationships in team members(Warkentin et al., 1997). Thus, the socio-emotional factors that affect the collaborative process (Isohätälä et al., 2017) behave differently in the two collaboration modes. In order to simulate virtual team collaboration, some of the parameters of MILANO, need to be adjusted (Figure 3- 25). The next part of this section presents the description of the adjustments made in MILANO (face-to-face collaboration simulation) to simulate virtual team collaborations.

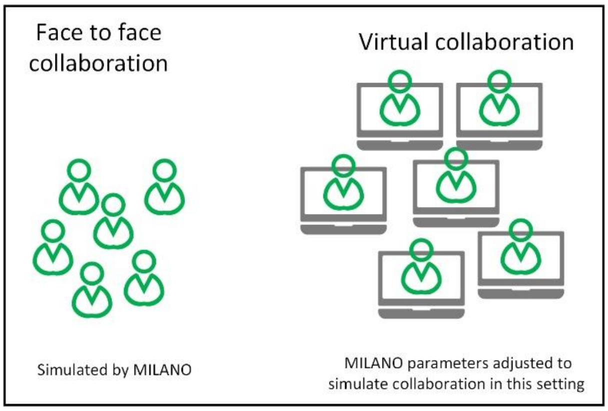



Figure 3- 25 Face-to-face and virtual team collaboration mode

### 3.8.1 Team virtuality and technology impacting communication

In contrast to the rich interaction and better communication during face-to-face work, there is evidence that communication frequency decreases with physical separation in teams (Allen, 1977). However, many of these observations were made decades ago, when virtual collaboration technology was in its infancy. With the development of more advanced technology in the past ten years, the relationship between communication and distance is now mediated by a variety of effective collaborative technologies (Hinds & Bailey, 2003). Krawczyk-Bryłka, (2017) built a hybrid team model based on team virtuality level (i.e., in-between face-to-face and fully virtual teams). Similarly, model parameters could be adjusted to simulate any virtuality level collaboration with varying technology efficiency. These factors are taken into consideration in Equation 21, where communication effectiveness ($\eta$) depends on technology mediation ($\tau$) and the degree of team virtuality ($V_d$), while $\varepsilon$ is the shape parameter.

**Equation** 21 $$\eta = \varepsilon/((\varepsilon - 1) + e^{(\tau * V_d)})$$

$\tau$ ranges from 0.3-0.7 and $V_d$ ranges from 0.0-4.0, (in order to constrain communication efficiency in the domain [0 1]). The value of $\varepsilon$ changes ranges between 1-2 times $s'$ (for example $s' = 10$, in this case). This gives the desired behaviour of least communication effectiveness when completely virtual team collaboration has the worst technology mediation. The value of communication effectiveness ($\eta$) is close to 1 (i.e., maximum effective communication) when the teams are face-to-face.

### 3.8.2 Communication affecting conflicts

The past literature showed that effective communication among the team members helps in resolving conflicts (Hinds & Mortensen, 2005). However, the empirical study (4.4) showed a weak relationship between communication and the number of conflicts emerging in the team. One possible reason revealed in the study was the difference in the self-efficacies of the two individuals ($\Delta SE$). This means that if the two individuals have similar self-efficacy ($\Delta SE \sim 0$ ), there is a higher probability of conflict or disagreement. Hence, Equation 22 can be formed to map this behaviour, where conflict factor ($\kappa$) depends on the effectiveness of the communication ($\eta$) and $\theta$ which in turn depends on the difference in the self-efficacies of the two agents (Equation 23).

**Equation** 22 $$\kappa = \theta/((\theta - 1) + e^{\frac{\theta}{2}\eta})$$

**Equation** 23 $$\theta = \omega + \zeta \Delta SE_{i-j}$$

$\omega$ in the above equation determines the slope of the curve and ranges from 0-2 (0 when the two agents ($i$ and $j$) have similar high self-efficacies and 2 when one of the agents has higher self-efficacy than the other). $\zeta = 2$ for the model to get the desired function value between 0-1. $\kappa$ is a probability where the chance of having a conflict is more when the two agents have similar high self-efficacies. In this way, the model does not eliminate the chance of having any conflicts between a high and a low self-efficacy agent.

### 3.8.3 Reduction in influence between team members

Thomas et al.,(1992) indicated that factors like trust, positive mutual regard, mutual attraction, cohesiveness, and social interaction are crucial for collaboration and some of these are affected by communication mediated by technology (Hinds & Bailey, 2003). Research in the past has shown that distance reduces the development of friendships or attraction (cohesiveness) to each other that give rise to conflicts (Hinds & Bailey, 2003; González et al., 2003). It was also seen from the empirical study (4.4) that good communication between the two individuals results in a higher influence value. Therefore, the model considers the conflict between the two agents ($\kappa$) reduces the influence value as perceived by one agent from the other (Equation 24).

**Equation** 24 $$\Delta I_i^j = a \cdot \kappa^b$$

Where $\Delta I$ is the reduction in the influence value ($I$) of an agent $j$ by agent $i$, and $a$ (slope parameter) and $b$ (power coefficient) were selected as 0.5 and 2 respectively. Influence value $I$ as given in Equation 10 for face-to-face collaboration is the influence value perceived by agent $i$ from $j$. Where $\Delta SE$ = difference in self-efficacy of agent $i$ and agent $j$), $T$ is the degree of trust of agent $i$ has on agent $j$. $SE$ is the self-efficacy of an agent $j$. Therefore, the influence $I_v$ during the virtual team, collaboration is reduced by $\Delta I$ depending on the conflict and could be given as Equation 25.

**Equation** 25 $${I_v}_i^j = I_i^j(\Delta SE, SE, T) - \Delta I_i^j(\kappa)$$

## 3.8.4 Gradual trust in virtual team members

Trust is one of the most important antecedents of virtual collaboration suggested by Peters and Manz, (2007). From the empirical study (4.4), little difference could be seen in the mean trust values ($T$) for virtual and face-to-face collaborations. As the empirical study was a cross-section study, it doesn't capture the building of trust among team members. Studies also suggest that the communication medium alters the rate at which trust develops in teams working electronically (Wilson et al., 2006). Specifically, they have found that trust ($T$) in electronic teams is lower than face-to-face collaborations at the beginning but gradually becomes comparable. Similarly, other studies like the one by DeRosa et al., (2004) mentioned that trust develops slowly than in face-to-face teams. Therefore, trust-building between the two agents for virtual collaboration ($T_v$) is lower and develops gradually than in face-to-face teams (Equation 26).

**Equation** 26 $${T_v}_i^j = \lambda \cdot T_i^j$$

Where $\lambda$ is a factor that results in gradual trust-building and lies between 0.7-1.0 (1 when $V_d$ is completely face-to-face).

# Chapter 4

# Empirical studies

In order to support the computational model formation, empirical studies are necessary. With the advancements in today's research, they provide support by bringing real-world insights. The computational model approximates the real-world system due to which needs verification and validation. The empirical studies provide an overview of how some of the logics used in the model were verified and at the same time validated the assumptions. The studies presented in this section were exploratory and observational in nature. This chapter presents 4 empirical studies with their setup and findings.

From the results of the empirical studies, the general idea of the results clarifying the assumptions and variable relationships was implemented in the model and not the exact coefficients (since the experiments were done in different settings, implementing exact results would not be appropriate).

## 4.1 Empirical study 1

Empirical study 1 was conducted at the beginning of the research and had the following purposes:

Purpose 1 (*P1.1*): Provide validity to the assumption (A1.1) behind the RQ1 (i.e., self-efficacy and trust are some of the individual characteristics responsible for the influencer effect)

Purpose 2 (*P1.2*): Provide logical verification to support the model formation like- (i) Change in self-efficacy is less for those having high self-efficacy than those with lower. (ii) Individuals' self-efficacy and influence affect their behaviour during engineering design activities. (iii) Degree of influence from influencers in teams affects team performance.

### 4.1.1 Set-up 1

The empirical experiment was based on the theory of organisational creativity, which defines the relationship between individuals, teams, social and contextual influences, environment and project (Woodman et al., 1993). The individual characteristics of interest in this context were individual's self-efficacy, influence related data and individual behaviour (Figure 4- 1). Team characteristics such as team composition and team behaviour are aggregated values representing the individuals who form a team.

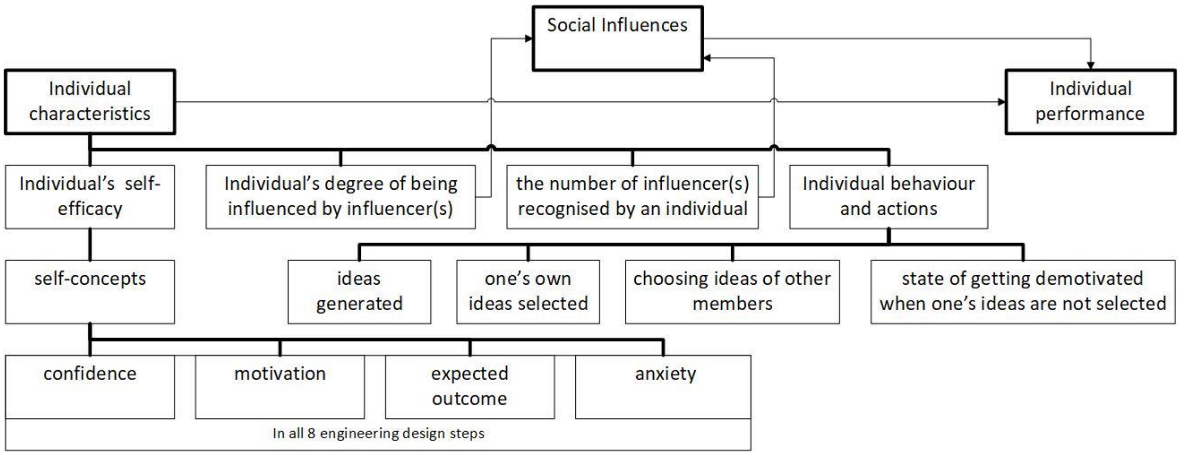



Figure 4-1 Composition of individual characteristics for the empirical study 1

The data was collcted during the ASP (Alta Scuola Politecnica)[3] spring workshop in May,2019. In contrast to a controlled experiment, the *in situ* observations of design teams employed here makes it possible to capture real behaviour. The ASP, founded by Politecnico di Milano and Politecnico di Torino in 2004, is restricted to 150 highly qualified students from engineering, design, and architecture) spring course in which observations were conducted was focused on Design Methods and Processes. The design task was given to the students aimed at enabling the students to work on a product-service system project, where eight teams were involved in a multi-disciplinary design contest. The design task was given by Red Cross to design a solution for a hospital in a developing country prone to attacks and calamities. The students had to provide a novel ER service concept with the particular objective to set up a service for normal situations and as well with mass casualties incidents. The teams were graded at the end of every day for four consecutive days. The last day comprised of the final pitching of the concepts by the teams, intra-team voting for the best concept, and final grading by the mentors.

The data was collected in two parts (pre- and post-course) as seen from Table 4- 1 from 116 participants. Basic demographic information like gender, nationality, educational background was collected in both parts. Students were identified by a code composed of the team name plus the last three digits of their university ID, which helped to maintain the anonymity of the participants while still making it possible to link pre-course responses to post-course responses. In the pre-course survey, participants completed the engineering design self-efficacy instrument by Carberry et al.,(2010). In this instrument, students rated their self-efficacy across eight common engineering design stages. It offers a systematic approach to collect information related to self-efficacy, and although it was developed for engineering design it was applicable to the students of all domains who are involved in the design process.

[3] https://www.asp-poli.it/

The post-course data collection was done at the end of the last day of the course after the final presentations and it had questions to record individual characteristics and individual behaviour (Figure 4- 1 above). A 4-point categorical scale was used for the questions related to the individual behaviour to maintain consistency with the ASP school grading system, which classifies students only at 4 levels: excellent, satisfactory, sufficient and insufficient. These questions aimed at capturing the behaviour of an individual after being influenced by the influencer(s) in the team. The mentors of courses communicated the team performance results daily on a 4-point.

Table 4- 1 Questionnaires elements during the empirical study 1

| *Respondent's answer context* | *Elements* | *Scale* | *Min-Max* |
|---|---|---|---|
| Pre-course data collection questionnaire | | | |
| Individual respondent data its self-efficacy (Carberry, et al., 2010) | Confidence | 0-100 scale | 0 = least value<br>100 = maximum value |
| | Motivation | | |
| | Believing in the success of the project | | |
| | Anxiety | | |
| Additional questions in post- course data collection questionnaire | | | |
| Individual respondent data on its perceived degree of influence in its team | Perceived degree of influence in the 8 common engineering design stages as used by (Carberry, et al., 2010) | 0-100 scale | 0 = least influence<br>100 = maximum influence |
| Individual respondent data on its perceived number of influencers in its team | Perceived number of influencers | Open-ended (numeric) | - |
| Individual respondent data on its behaviour in the team | Frequency of ideas produced by a respondent | 4-point Likert scale | 1 = never/least number of times produced ideas<br>4 = all the time produced ideas |
| | Frequency of the selection of respondent's own ideas by others | 4-point Likert scale | 1 = never/least number of times they selected ideas<br>4 = all the time they selected ideas |
| | Frequency of the selection of ideas from others in the team by the respondent | 4-point Likert scale | 1 = never/least number of times demotivated<br>4 = all the time felt demotivated |
| | Frequency of demotivation when a respondent's ideas were not selected/appreciated by others in its team | 4-point Likert scale | 1 = never/least number of times selected ideas<br>4 = all the time selected ideas |
| | Respondent's own assessment of its team's performance | 4-point Likert scale | 1= worst performance<br>4 = best performance |

| | | | |
|---|---|---|---|
| Team performance | Daily given by the mentors of the course based on teams' daily performance | 4-point Likert scale | 1= worst performance<br>4= best performance |

## 4.1.2 Results 1

In order to provide validation of the assumption (A1.1), the data related to individual characteristics were analysed. In general, it was found that self-efficacy changes during the design project (Figure 4-2) and there was a significant difference in the self-efficacy recorded pre and post-course (Wilcoxon signed-rank test W= 972, p-value<0.001). It was also seen that male and females and individual backgrounds perceive influence and number of influencers differently in teams Figure 4- 3.

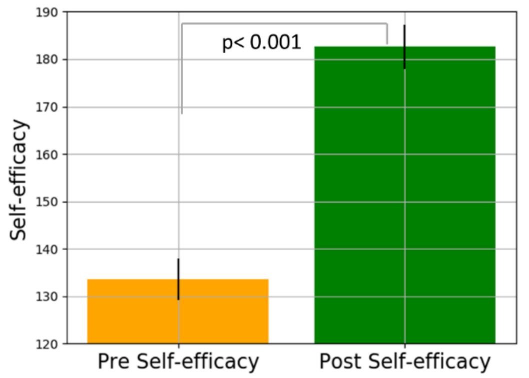


Figure 4-2 Self-efficacy before and after the workshop

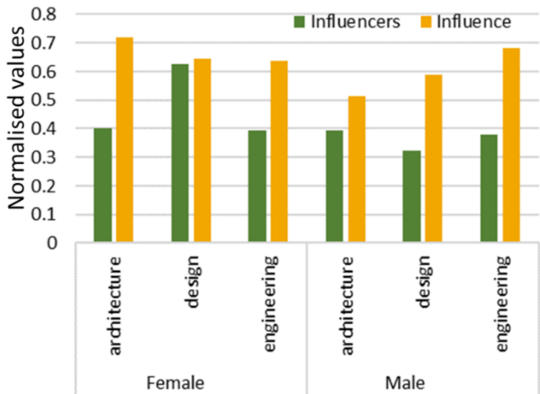


Figure 4-3 Gender and Educational background with respect to no of influencers and degree of influence

A similar relationship between the four self-concepts (confidence, motivation, expectation and anxiety) considered for determining self-efficacy, as proved in the past literature (Carberry et al., 2010; Bandura,1977) was found (Figure 4- 4).

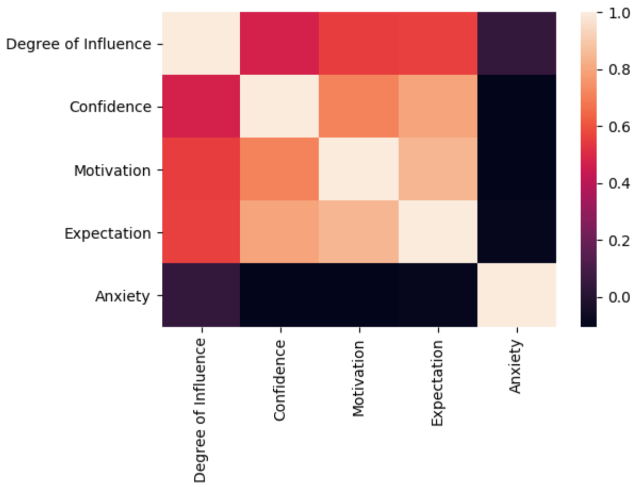
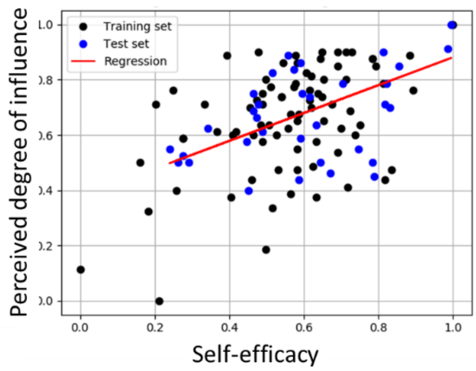


Figure 4-4 Correlation matrix for the four self-concepts (confidence, motivation, expectation, anxiety) and degree of influence

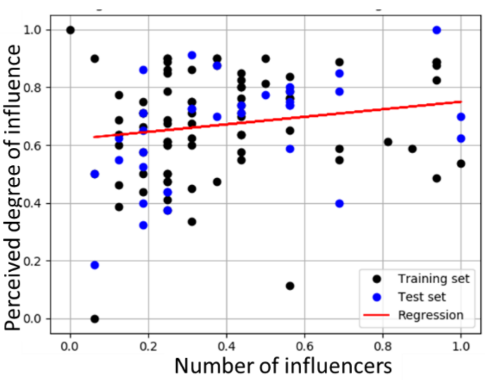



Coefficients: 0.5
Mean squared error: 0.02
$R^2$: 0.19

Figure 4-5 Linear regression between post-course self- efficacy and degree of influence

The correlation matrix in Figure 4- 4 shows the Pearson's coefficient, with lighter hues indicating positive correlations and darker hues indicating negative correlations. It clearly shows a positive relationship between the degree of influence and the three self-concepts (confidence $\rho = 0.48$, p-value < 0.001, motivation $\rho = 0.56$, p-value < 0.001 and expectation $\rho = 0.56$ , p-value < 0.001). This means that if 4 self-concepts that determine self-efficacy (in the post-course data) are correlated to the degree of influence. In other words, individuals who have high self-efficacy also perceive high influence from others (Pearson' ρ = 0.5, p-value < 0.001). The degree of influence has no correlation with anxiety (ρ = 0.04, p-value =0.6). This could signify that individuals with or without anxiety were both influenced by the influencers in the team.

The self-efficacy of the participants recorded after the course also showed a positive linear relationship with their perceived degree of influence from their team members (Figure 4- 5). However, there a very weak positive linear relationship between the degree of influence and the number of influencers (Figure 4- 6) was found with a Kendall correlation coefficient τ = 0.22 p=0.008. One reason hypothesized is that one influencer with a high degree of influencing power or multiple influencers with influencing powers might have had the same impact on the team processes.




Coefficients: 0.13
Mean squared error: 0.03
$R^2$: 0.12

Figure 4-6 Linear regression between number of influencers and degree of influence

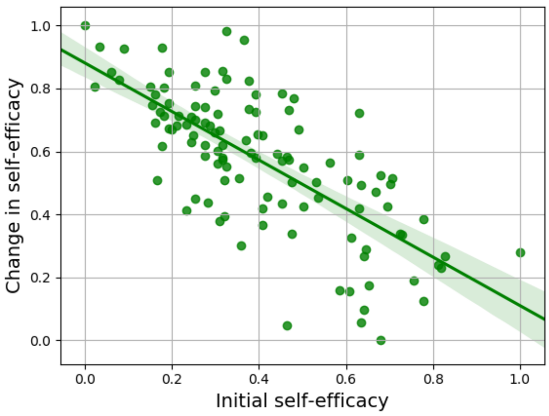



Figure 4-7 Negative relationship between pre-course self-efficacy and change in an individual's self-efficacy

Hence, the results supported *P1.1* i.e., part validation of A1.1 that self-efficacy is one of the characteristics responsible for influencing and being influence behaviour in teams. The *P1.2* of empirical study 1 was to provide logical verifications to various elements of the model formation.

A high negative correlation was found between the change in self-efficacy and the initial value of an individual's self-efficacy (Pearson's ρ= -0.7, p-value < 0.001) at the beginning of the course (seen in Figure 4- 7). This means that the individuals with high self-efficacy get to have less change in their self-efficacy (increase or decrease) than individuals with low self-efficacy. Thus, verifying that the change in self-efficacy logic implemented in the model that there is *less change for those having high self*-efficacy than those with lower.

The other verification was needed to show that the individuals' self-efficacy and influence affect their behaviour during engineering design activities. This was achieved by analysing individual behaviour post-course data as seen from Figure 4- 8 that shows Kendall's correlation coefficient of significant values (i.e., p-value <0.05). Participants who perceived more influence positively correlates with their behaviour to appreciate more ideas (τ = 0.4, p-value< 0.001). This case could also be explained as Normative Social Influence in which team members conform because they want to be liked or accepted by others in the team (Deutsch & Gerard, 1955). Those having high self-efficacy are likely to be slightly correlated to proposing more ideas to their team (ρ = 0.2, p-value=0.001). It could be because confident individuals are more effective in communicating, hence proposing more ideas than someone with low confidence. Besides, these results that helped to verify the model formation logic that individuals' self-efficacy and influence affect their behaviour during a design activity, some additional insights (like the ones mentioned in the following paragraph) were gained that supported the model.

An individual proposes more ideas when its team members (TM) appreciate its ideas more often ($\tau = 0.6$, p-value$< 0.001$). This could be due to the increase in one's intrinsic motivation, which depends on internal praises or appreciation by team members (Ryan & Deci, 2000). It was also found that an individual often appreciates ideas from its team members when they frequently appreciate or selects its ideas ($\tau = 0.4$, p-value$< 0.001$). This behaviour could be explained by the 'norm of reciprocity', which is a behaviour in social psychology where individuals feel obligated to return the favours that are done for them by others (Gouldner, 1960). Another finding to support Figure 4- 7 above was found that showed that individuals with high self-efficacy are slightly correlated to less demotivated ($\rho = -0.23$, p-value$< 0.001$).

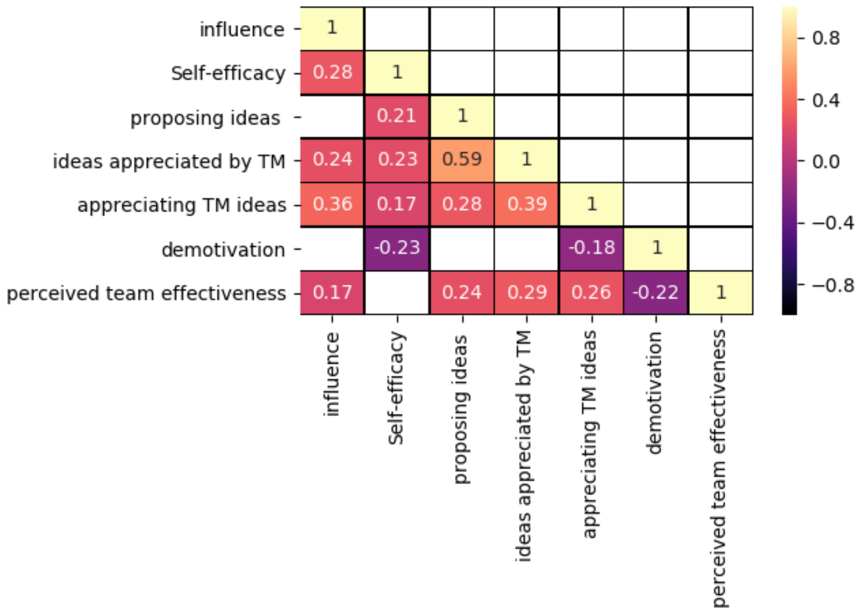



Figure 4-8 Correlation matrix for individual characteristics and behaviour during the course with significant p- values (TM = team member)

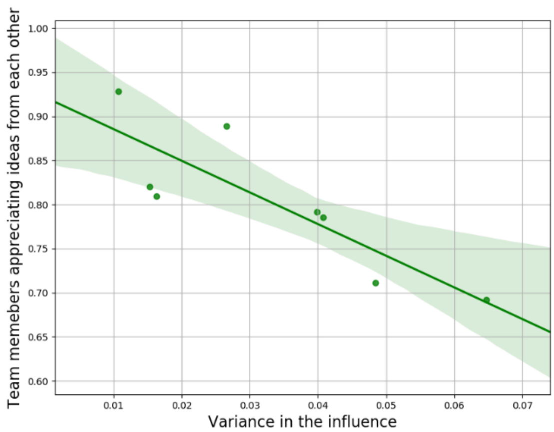



Figure 4-9 Correlation between the distribution of influence in teams and team members behaviour of appreciating ideas from each other

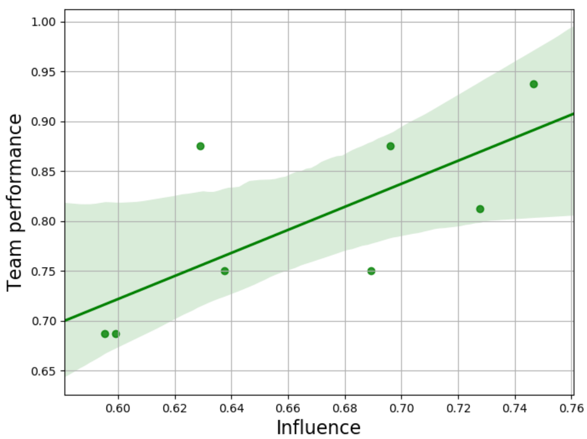



Figure 4-10 Correlation between the amount of influence perceived by team members in the teams and teams' performance

The results from empirical study 1 also showed some team-related behaviour. For example, from Figure 4- 9 it could be seen that teams that have high variance in the influence values perceived by their team members, tend to appreciate fewer ideas (Kendall correlation coefficient $\tau$ = -0.86, p-value=0.002). In other words, teams where only some individuals are perceived as highly influential, have a tendency to appreciate fewer ideas from each other. This could mean that team members frequently go along with the ideas of the influencer(s) and do not support ideas proposed by other low influential team members. Lastly, (as seen from Figure 4- 10) it was found that teams where their team members perceived high influence, performed better (Kendall correlation coefficient $\tau$ = 0.64, p-value=0.03). Thus, supporting *P1.2* in verifying that the degree of influence from influencers in teams affect team performance.

## 4.2 Empirical study 2

Empirical study 2 was used to support the RQ1 and had the following purposes:

Purpose 1 *(P2.1)*: Validate the assumption (A1.1) that self-efficacy and trust could be the individual characteristics responsible for the influencer effect. Due to insufficient work done in the past to reveal the qualities of an influencer(s) in design teams, the experiments were conducted to get some initial insights.

Purpose 2 *(P2.2)*: Logical verification of the model such as trust and familiarity relationship was verified by the empirical study done in the 'real world'.

### 4.2.1 Set-up 2

The experiment was set up to monitor semester-long design teams working on a task given by a company. There were 10 teams of 4 master's degree students of mechanical engineering in each of them. Working on a design problem was a part of the curriculum of their course 'Methods and Tools for Systematic Innovation' at Politecnico di Milano, Italy.

The data was collected when the students in the teams had started working together and the questions were related to the (1) individuals' data like self-efficacy, problem-solving attitudes and a number of perceived influencers, and (2) individuals' peer evaluation (Table 4- 2). The information on their self-efficacy used four self-concepts (confidence, motivation, expectation and anxiety) for engineering design by Carberry et al., (2010). The questions related to the problem-solving attitude aimed to capture an individual's approach when handling a design problem[4]. A similar set of questions were used by Becattini & Cascini, (2016) to assess the characteristics of creative instruments for problem-solving in students. The 4-point scale was used here instead of 10 point scale used by Carberry et al., (2010) to match the scales used for problem-solving questions by Becattini & Cascini, (2016). The peer evaluation was used to collect information about how participants feel about their team members and the questions were about trust, familiarity and influence The peer evaluation questions for determining the degree of influence were inspired by Ohland et al., (2012).

Table 4- 2 Questionnaires elements during the empirical study 2

| *Respondent's answer context* | *Elements* | *Scale* | *Min-Max* |
|---|---|---|---|
| Individual respondent data its self-efficacy | Confidence | 4- point Likert scale | 1 = least value<br>4 = maximum value |
| | Motivation | | |

[4] Problem-solving attitude was not considered for the model, but the insights were extracted for future analysis and implementation.

| | | | |
|---|---|---|---|
| (Carberry, et al., 2010) | Believing in the success of the project | | |
| | Anxiety | | |
| Individual respondent data its problem-solving attitudes (Becattini & Cascini, 2016) | Considering similar problems in different fields | 4- point Likert scale | 1= not at all agreeing with the statement<br>4 = agreeing strongly with the statement |
| | Neglecting the elements that are not directly involved in the problem | | |
| | Tackling unfamiliar tasks | | |
| | Considering the most desirable solution even if not technically feasible | | |
| | Considering the impact of design choices on all the requirements | | |
| | Always focusing on the structure/layout of the technical system | | |
| | The necessity to find the best compromise among system requirements | | |
| | Trying to modify the system as little as possible | | |
| Individual respondent data | Perceived number of influencers | open-ended (numeric) | - |
| Respondent's data for each of its peers for evaluating its degree of influence (Ohland, et al.2012) | Contributing to the team's work | 5-point Likert scale | 1 = least value<br>5 = most value |
| | Interacting with teammates | | |
| | Keeping the team on track | | |
| | Expecting quality | | |
| | Having relevant knowledge, skills, and abilities | | |
| Respondent's data for each of its peers | Perceived degree of influence from its peer[5] | 5-point Likert scale | 1= least influential<br>5 = most influential |
| | Trusting its peer | 5-point Likert scale | 1= least trustful<br>5 = most trustful |
| | Familiarity with its peer | 5-point Likert scale | 1= least familiar<br>5 = most familiar |

### 4.2.2 Results 2

To fulfil the P2.1 (i.e., to validate the assumption (A1.1) that self-efficacy and trust could be the individual characteristics responsible for the influencer effect), It was found that the difference in an individual's self-efficacy with respect to their peers is responsible for that individual's perceived degree of influence from its peers (Pearson $\rho = 0.41$, p-value= 0.014 ). This means that individuals with low self-efficacy perceive higher influence from individuals with higher self-efficacies in the team. Secondly, it was validated that trust plays important role in determining influencers. It was found that the perceived degree of influence by an individual from its peer is highly positively correlated with the

[5] Degree of perceived influence was also asked in the form of a direct question to see if there is any difference in the understanding of a respondent for the term 'influential' to the characteristics described in the other question to determine the perceived degree of influence. A strong correlation between the two influence value (indirectly and directly asked) was found (Pearson $\rho = 0.74$, p-value $< 0.001$), hence the two are used interchangeably and for the later empirical studies respondents were asked to directly fill the influence value for their peers.

trust between them (Pearson ρ = 0.7, p-value < 0.001). The linear regressions between the normalised values of the perceived degree of influence and the difference in self-efficacies and trust could be seen in Figure 4- 11 and 12. The linear regression model predicted a weak linear relationship between the difference in self-efficacies of the two individuals and the degree of influence as seen in Figure 4- 11. While the regression model predicted a strong relationship between trust and influence (Figure 4- 12). Hence, the results of this empirical study helped in supporting the assumption (A1.1) for the RQ1 that trust and self-efficacy are some of the characteristics that are considered in the study for determining the influencer effect.

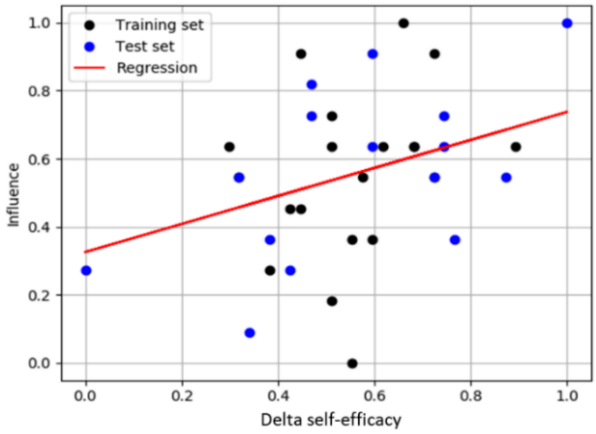



Figure 4-11 Linear regression between delta self-efficacy and influence

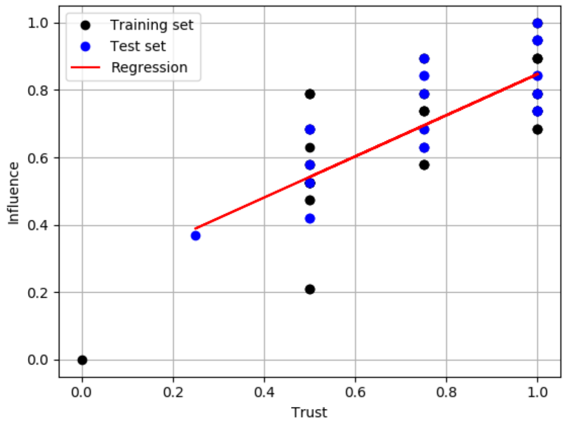



Figure 4-12 Linear regression between trust and influence

Coefficients: 0.41
Mean squared error: 0.04
$R^2$: 0.30

Coefficients: 0.61
Mean squared error: 0.01
$R^2$: 0.62

As seen from Figure Figure 4- 13 that negligible difference can be seen in line and curve of degree 1.5 (the red line is hidden by the green polynomial curve of 1.5) and no other curve fitted the data. Hence, for the model $I \propto \Delta SE^{1.5}$ was considered.

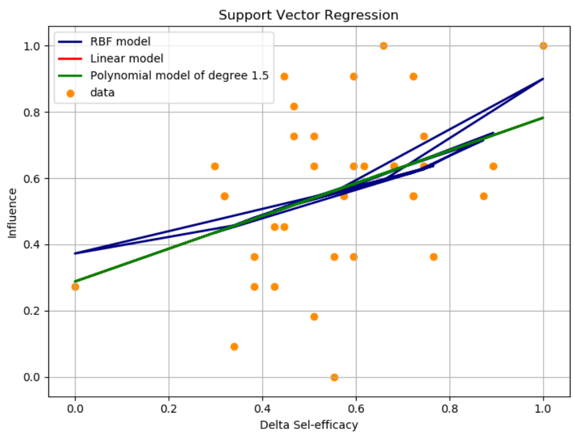



Figure 4- 13 Curve fitting for the data points

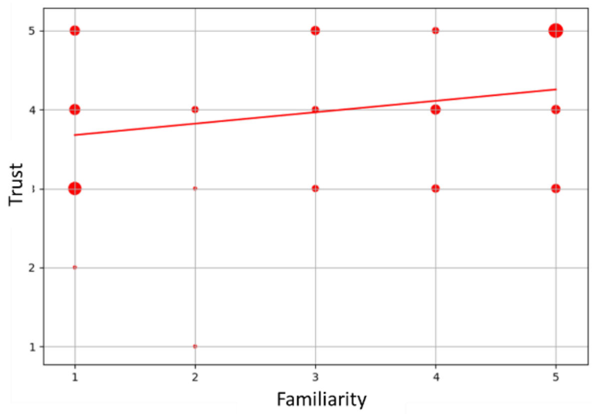



Figure 4- 14 Correlation between trust and familiarity

The second purpose *(P2.2)* of the empirical study was to provide a logical verification of the features behind the model. Here (in the questionnaire) ‘familiarity’ between the two individuals was asked as it is known that that trust depends on how well the two individuals know each other (Granovetter, 1973). It can be seen from Figure 4- 14 that a positive relationship between trust and familiarity (Pearson ρ 0.3, p value= 0.02) exists between the two individuals in a team. Thus, supporting the model formation that familiarity between the two individuals also affects trust between them.

## 4.3 Empirical study 3

The empirical study 3 was used for addressing the RQ1, hence had the following purposes:

Purpose 1 *(P3.1)*: To provide logical verification of the two social factors (majority and influencer effect) considered in the model in the real-world idea selection.

Purpose 2 *(P3.2)*: To validate assumption A1.1 that self-efficacy could be one of the characteristics determining influencer effect. As well as *A1.2* behind the research question 1, i.e., the perceived degree of influence by an individual and the past agreement its peer had with him/her, are some of the factors affecting its agreement when evaluating the proposed solutions by its team members.

### 4.3.1 Set-up 3

The empirical study 3 was done as an exploratory study done during the EU's Erasmus+ project called ELPID[6] where 5 teams of 8 students from different universities worked on a design task for a period of 3 days. The workshop was a sprint to introduce students to ideation techniques. Though the teams were under observation throughout the workshop, the data collection was done once (at the end of Day2). Each team had students from different universities, working on a design problem after attending lectures on concept generation. The design problem was to propose an entertaining system that could integrate with the existing university infrastructure to help the students on campus to relax.

The data collection was done in the form of a short Likert scale survey (1 being the minimum and 5 being the maximum score). The paper survey questions were direct and less effort demanding from participants. It was not mandatory for the participants to take part in the surveys. To maintain the anonymity of the participants, colour codes were used. For example, team C had pink, yellow, blue, green, pastel pink and so on as its members and the participants referred to these colour codes while answering questions about their peers. The questionnaire collected information related to decision making during idea selection as seen from Table 4- 3:

Table 4- 3 Questionnaires elements during the empirical study 3

| *Respondent's answer context* | *Elements* | *Scale* | *Min-Max* |
|---|---|---|---|
| Individual respondent data for itself | Self-efficacy | 5- point Likert scale | 1= least self-efficacy<br>5 = maximum self-efficacy |
| | Perceived number of influencers | open-ended (numeric) | - |
| | Why did the respondent agree with its peer when he/she proposed a solution? | open-ended (text) | - |
| Respondent's data for each of its peers | Perceived degree of influence from its peer | 5-point Likert scale | 1= least influential<br>5 = most influential |
| | Trusting its peer | 5-point Likert scale | 1= least trustful<br>5 = most trustful |

[6] ELPID: E-learning Platform for Innovative Product Development. Available at: http://www.elpid.org/

| | | | |
|---|---|---|---|
| | Agreeing with its respective peers when they proposed their solutions | 5-point Likert scale | 5 = agreeing most of the time<br>1= never agreeing |
| | Peers agreeing with the respondent when he/she proposed its solution | 5-point Likert scale | 5 = agreeing most of the time<br>1= never agreeing |

## 4.3.2 Results 3

The results of the study showed that a slightly negative correlation (Kendall correlation coefficient $\tau$ = -0.3, p-value 0.03) was found between the individuals' self-efficacy and the number of perceived influencers in their team (Figure 4- 15). The negative correlation could be because individuals with high self-efficacy are more likely to perceive others with high self-efficacy as influencers. This could be supported by the other findings such as the relationship between individuals' self-efficacy and the degree of influence by them. A positive correlation (Kendall correlation coefficient $\tau$ = 0.32, p-value 0.012) was found between the individuals' self-efficacies and their degree of influence as perceived by others (Figure 4-16).

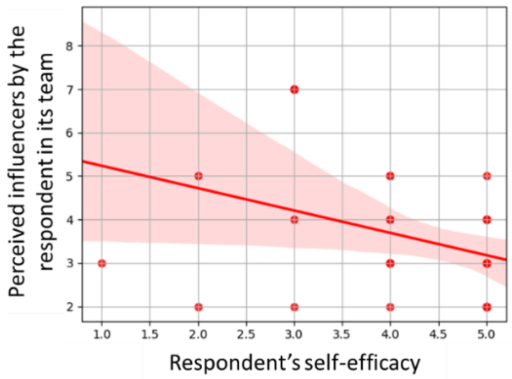


Figure 4-15 Correlation between self-efficacy and perceived number of influencers[7]

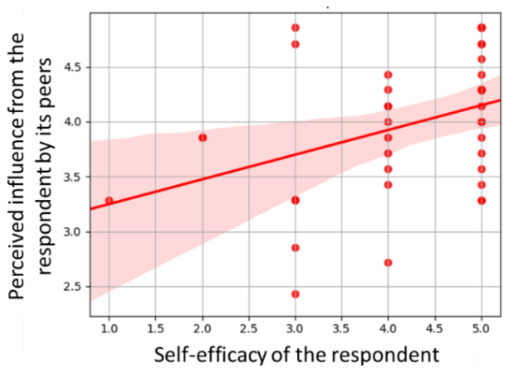


Figure 4-16 Correlation between self-efficacy and perceived influence

Results addressing the P3.1 of the study supporting A1.2 (i.e., to verify the logic behind the model that the two social factors; majority and influencer effect are present during the real-world idea selection) were obtained by analysing the open-ended questions where the participants (Why did the respondent agree with its peer when he/she proposed a solution). From the empirical study, 40 responses were collected but only 29 participants filled last the open-ended question. The analysis of the text-based answers to the open-ended question in the survey was done using the python programming language's Natural Language Processing Toolkit (Bird et al., 2019).

The text data was cleaned from non-alphabetic characters and stop words (like 'on', 'is', 'the' and so on) before lemmatizing it (Bird et al., 2019). The n-grams that are all combinations of adjacent words of length n that can be found in the given source text were used to capture the language structure from the statistical point of view determining the word that is likely to follow the given one (Jurafsky & Martin, 2019). In this case, as the responses were short, word-level bigram (where n =2) that is most used and is successful for smaller corpora was used than trigram used for larger corpora (millions of words). Using a bigram model, a sequence of two adjacent elements was extracted and the pair counts were plotted for Figure 4- 17. Figure 4- 17 shows the pairwise count of the words that occurred while analysing the opened ended question about what makes an individual agree with the other when he/she

[7] Heteroscedasticity (in similar figures) could have distorted the results and p-value might be lower than actual.

proposes a solution to the team. It can be seen from the pairs which popped out that ‘similar thinking’, ‘good idea’, ‘thinking good’, ‘good communication’ and ‘idea similar’ were the most commonly perceived answers by the respondents. Two things could be inferred from these word pairs:

Word pairs like ‘similar thinking’, ‘idea similar’ or ‘thinking similar’ clearly indicate that individuals go with the idea proposed by the other individual when they think it is similar to the one they thought. Hence, justifying the formation of coalition groups based on similar ideas (Cartwright, 1971).

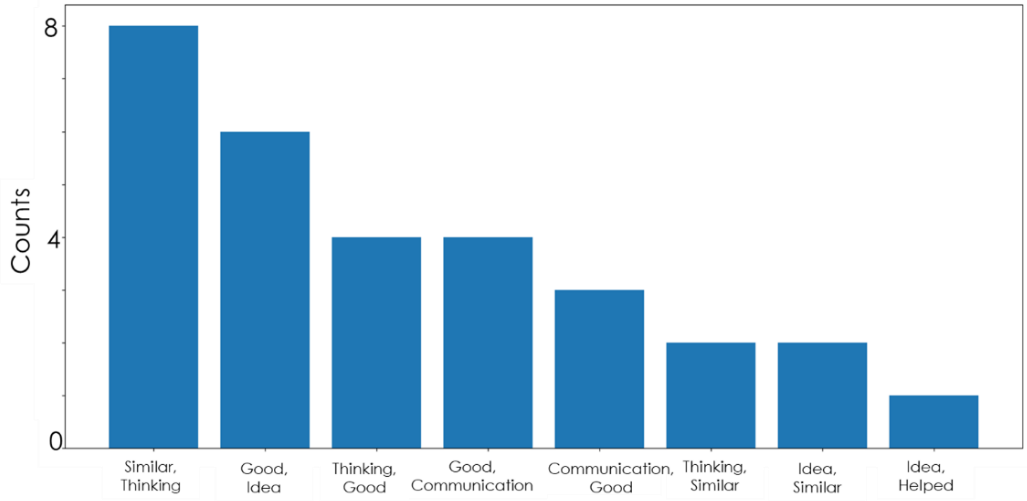



Figure 4-17 Pairwise count of the words that occurred when analysing answers to the open-ended question

Word pairs like ‘good idea’ and ‘thinking good’ show that an individual will agree with the other’s proposed solution when he/she perceives it to be ‘good’. This shows the presence of Informational influence which occurs when an individual looks to other team member’s guidance as he/she is uncertain about his/her opinion, hence, the effect of influencer prevails (Deutsch & Gerard, 1955). From the other word pairs like ’good communication’ or ’communication good’, it can be deduced that effective communication is a key trait of individuals who are confident (Cao et al., 2020), and it is known that self-efficacy is one of the characteristics of an influencer (Singh et al., 2020). Hence, the individuals’ decision-making was affected by the influencer(s) ‘good communication’.

It can be seen that a positive relationship appears between an individual’s agreements on the other individual’s proposed solution and perceived influence from the other individual in the team (Kendall correlation coefficient $\tau = 0.52$, p-value <0.001), hence validating the assumption and $A \propto I$. Thus, complimenting the study where ‘high social rank’ individuals have a larger effect on opinion formation than individuals with low rank (Wu & Huberman, 2004). Complementary findings by Thomas-Hunt et. al.,(2003) also stated that socially connected group members evaluate individuals more positively whom they favour. In addition to the perceived degree of influence, the agreement also depends on the amount of agreement the other individual had when the individual (who is deciding) proposed its solution (Kendall correlation coefficient $\tau = 0.55$, p-value <0.001), hence $A \propto$ *Past Agreement (PA)* (as seen in Figure 4- 19). This may be evidence of the 'norm of reciprocity', behaviour in social psychology where individuals feel obligated to return the favours that are done for them by others (Gouldner, 1960).

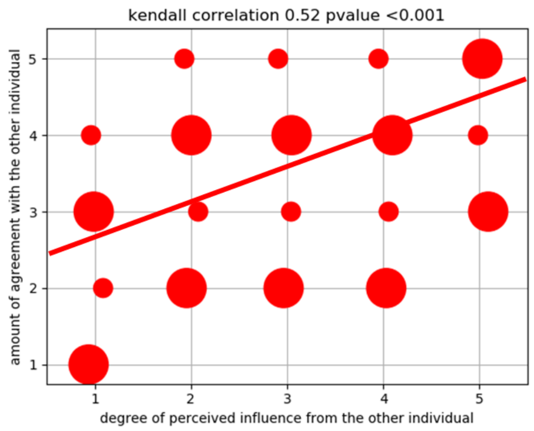



Figure 4-18 Correlation between agreement and influence (it shows the best fit line and the size of the dots that indicate the number of data points)

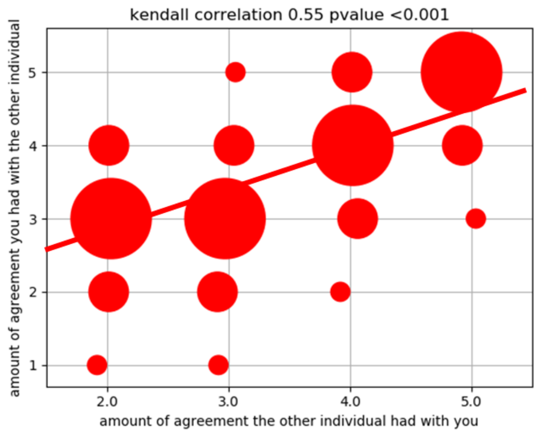



Figure 4-19 Correlation between agreement and past agreement (it shows the best fit line and the size of the dots that indicate the number of data points)

To address research question 1, P3.2 of the empirical study validated assumption A1.2. This could be seen in Figure 4- 18 and Figure 4- 19.

Another interesting thing to notice in this study was that familiarity between the two individuals was not directly asked as the 8 members in a team (2 from each from the 4 different universities; Italy, Croatia, Slovenia and Austria) met for the first time. However, each team had two team members from the same university, (i.e., two familiar individuals). Familiarity here refers to the state where two individuals belong to the same institution and have been introduced to each other prior to working collaboratively with other individuals (from different institutions) on a design project. The individuals from different institutions have not met or known each other before the design project, hence, were referred to as non-familiar. It was found that familiar individuals rated each other higher (for the sum of all the peer evaluation elements asked in Table 4- 3 ) than the non-familiar individuals (Figure 4-20). The sum of the scores for all the peer evaluation elements varied more than the non-familiar ones than familiar individuals (Figure 4- 21). A positive Point-Biserial correlation between familiar and non-familiar with respect to the sum of the values entered by the respondent showed that a non-familiar is more likely to be scored lower than the familiar individual from the same university ($\rho$=0.4 and p-value = 0.002). Hence, demonstrating that familiarity is an important characteristic in team processes and should be considered when modelling socio-cognitive collaborative teams.

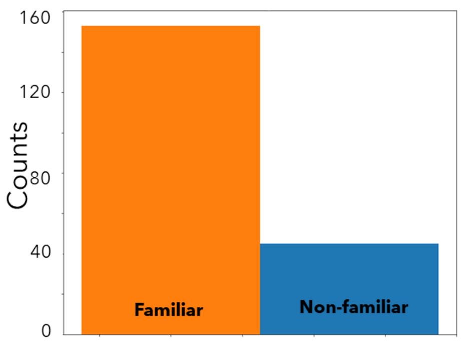



Figure 4-20 Number of times when a familiar individual was rated higher than the non-familiar ones

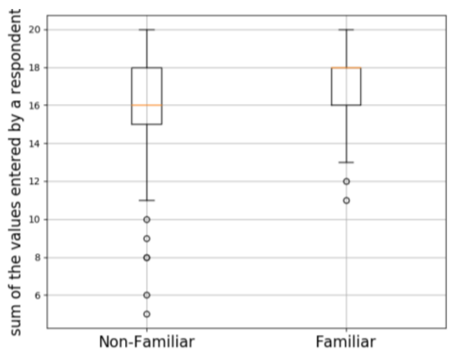



Figure 4-21 Boxplot where non-familiar individuals are more likely to get lower scores than familiar

## 4.4 Empirical study 4

The purpose of the empirical study 4 was:

Purpose 1 *(P4.1)*: To provide logical verification that the model parameters considered for the face-to-face collaboration behave differently during virtual team collaboration.
Purpose 2 *(P4.2):* To address the assumption behind the RQ3 (*i.e., A3.1: The effective communication between individuals plays a significant role during virtual team collaboration as it impacts model parameters*)

### 4.4.1 Set-up 4

To fulfil the *P4.1*, empirical study 4 uses the data from empirical study 2 (above) for comparing it to the data collected in the same settings but the teams collaborated virtually on the design project (in the year 2020). For the year 2020, in the same master's degree course (Methods and Tools for Systematic Innovation at Politecnico di Milano, Italy), there were 15 teams of 4 mechanical engineering graduate students that were working on a semester-long design task given by a company. The company and the design task were also the same as in the year 2019 for empirical study 2. The data was collected twice in the form of online surveys. The data collection and comparison to fulfil the purpose of the study was done as shown in Figure 4-22.

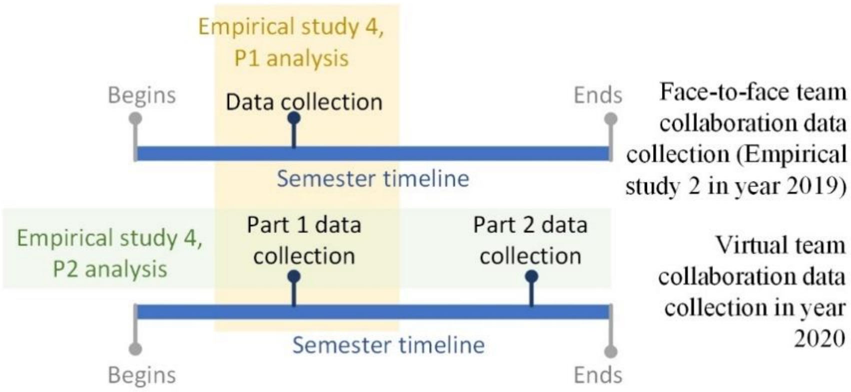



Figure 4-22 Data collection and analysis layout for the empirical study 4

The similarities, differences and additions to the questionnaire used for the empirical 4 (with respect to that of empirical study 2) are shown in Table 4-4.

Table 4- 4 Questionnaires elements during the empirical study 4

| **Common elements of the 2 questionnaires (face-to-face and virtual team collaboration)** | | | |
|---|---|---|---|
| | *Elements* | *Scale* | *Min-Max* |
| Individual respondent data for itself | Self-efficacy | 4 and 5- point Likert scale | 1= least self-efficacy<br>4,5 = maximum self-efficacy |
| | Perceived number of influencers | open-ended | - |
| Respondent's data for each of its peers | Perceived degree of influence from its peer | 5-point Likert scale | 1= least<br>5 = maximum |
| | Trusting its peer | 5-point Likert scale | 1= least<br>5 = maximum |
| | Familiarity with its peer | 5-point Likert scale | 1= least<br>5 = maximum |
| **Additional elements of the virtual team collaboration questionnaire** | | | |
| | Communication effectiveness | 5-point Likert scale | 1= least<br>5 = maximum |

| | | | |
|---|---|---|---|
| Individual respondent data for the team | Number of conflicts | 5-point Likert scale | 5 =least<br>1= maximum |
| | Task cohesion | 5-point Likert scale | 1= least<br>5 = maximum |
| Respondent's data for each of its peers | Agreement with its peer | 5-point Likert scale | 1= least<br>5 = maximum |
| | Communication with its peer | 5-point Likert scale | 5 =least<br>1= maximum conflicts ineffective communication |

These parameters were considered for the empirical study as they form the basis of collaboration affecting socio-emotional processes (Isohätälä et al., 2017) such as social influence in design teams that give rise to influencers (Singh et al., 2020). The self-efficacy questions for the face-to-face collaboration were the same as Carberry et al., 2010 but the scale was changed from 10 to 4-point. As the survey needed to be short and precise, the virtual collaboration questionnaire consisted of a direct self-efficacy question. The question format for recording respondent's trust, familiarity, degree of influence, agreement and communication with each peer was inspired by Ohland et al.(2012). The additional parameters were added to the virtual collaboration questionnaire based on González et al., (2003)

### 4.4.2 Results 4

The major difference between face-to-face and virtual collaboration could be seen in the individuals' perception of the number of influencers in a team (Figure 4- 23). It can be noticed that individuals have a lower mean perception of those controlling the team processes when face-to-face than virtual. Kruskal-Wallis H-test on the number of perceived influencers during face-to-face and virtual collaboration has the H =26.61, p-value<0.00, indicating that the two groups have statistically significant differences. This could mean that due to stronger social interaction in face-to-to-face meetings, social influence from some peers was felt more than the others, hence a lower number of perceived influencers. While during virtual team collaborations, the social interaction was weak hence the influence was perceived equally among all team members.

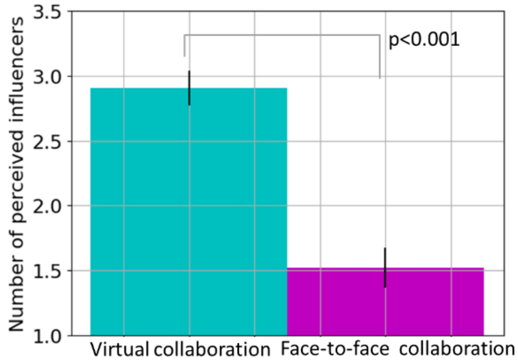



Figure 4-23 The difference in the perceived number of influencers in the face-to-face and virtual collaboration

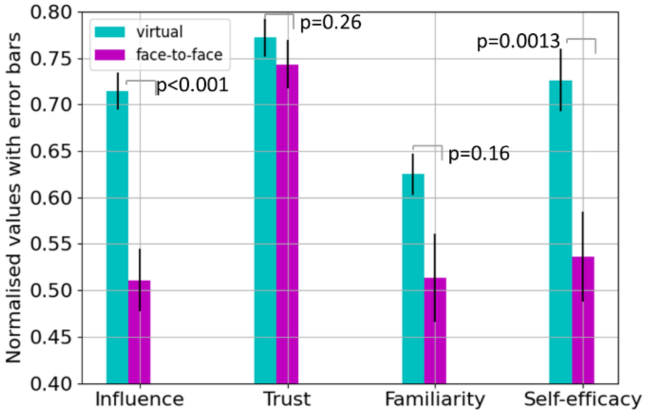



Figure 4-24 The difference in the model parameters in face-to-face and virtual collaboration during data analysis

It is clear that the parameters shown in Figure 4- 24 behave differently when the collaboration mode changes from face-to-face to virtual. Figure 5 shows the normalized values and p-values of the Kruskal-Wallis H-test. The parameters like self-efficacy and perceived degree of influence between the two individuals have a higher value for the virtual collaboration. This could be due to the efficient collaborative environment (Francescato et al., 2006). However, familiarity among the individuals seems to be higher in virtual team collaboration is not significantly different from face-to-face collaboration. Hence, conforming to the studies that suggested that familiarity is not moderated by the extent of virtualness (Stark & Bierly III, 2009). Trust, on the other hand, did not significantly differ in virtual and face-to-face collaborations. Studies suggest that trust, which is built through social interaction in face-to-face meetings, might not necessarily hold true for virtual team collaborations (Berry, 2011). Wilson et al., (2006) also discovered that trust in computer-mediated teams was lower but gradually increased to levels comparable to those in face-to-face teams over time. Thus, the above results helped in fulfilling the first purpose of empirical study 4 (P4.1, i.e., to provide logical verification that the model parameters considered for face-to-face collaboration behave differently during virtual team collaboration).

Communication is key in any collaborative work and successful project (Maier et al., 2009). In teams at the same place and collaborating face-to-face, communication is more likely to be initiated due to a higher probability of chance encounters (Axtell et al., 2004). Studies in the past showed that virtual team collaboration suffers from effective communication (Axtell et al., 2004) that give rise to team conflicts (Hinds & Bailey, 2003) that affects design outcomes. This might not be necessarily true as Figure 4- 25 (left) shows a weak positive impact of effective communication on the number of conflicts arising in the team (Kendall correlation coefficient $\tau$=0.32, p-value 0.05) when analyzing Part1 data of the virtual team collaboration and no relationship between the two for Part2.

However, a stronger relationship can be seen between task cohesion (i.e., *an individual's attraction to the team because of a liking for or a commitment to the group task* (González et al., 2003) and effective communication (Kendall correlation coefficient $\tau$=0.5, p-value = 0.004) during the end of the design project (Figure 4- 25 right). This means that effective communication helps in resolving conflict or in enhancing clarity that prevents conflicts when the teams start working on a design project. While towards the end of the project, effective communication does not have any effect on the number of conflicts in a team but improves task cohesion. Hinds & Mortensen, (2005) found in their study that communication moderates the relationship between team distribution and conflict.

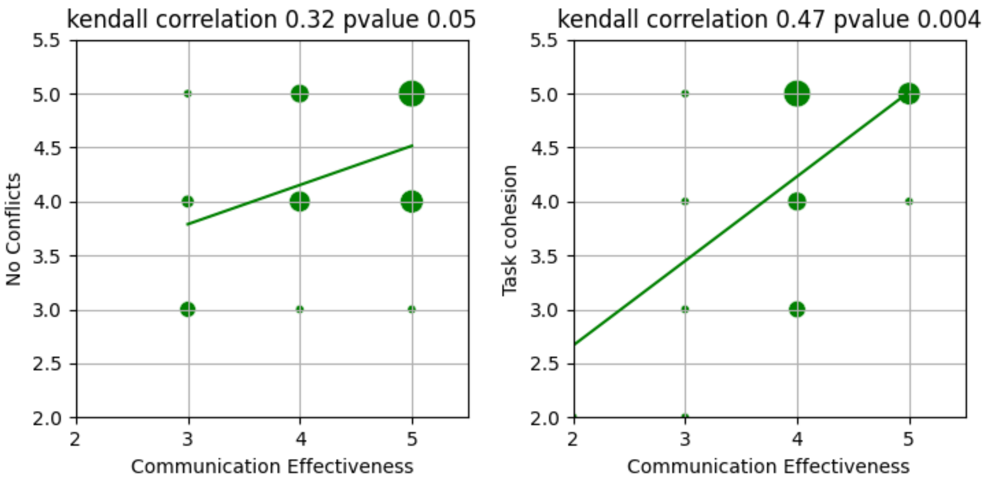



Figure 4-25 Communication affecting other additional parameters of the virtual team collaboration questionnaire like conflict (left) and task cohesion (right)

When further investigating the impact of respondent's quality of communication (i.e., the number of conflicts and the clarity) with its individual team members, the difference in their self-efficacies might have mediated the resolution of the differences between them (Figure 4- 26). The individuals who had higher self-efficacy than their peers (delta= positive) entered higher value for effective communication with their peers, hence low conflict probability. However, no significant difference (Kruskal-Wallis H-test p-value =0.2) was found between the communication values entered by a respondent for its peers and the difference in the self-efficacies. The chi-square test ($\chi^2$) results (on Part 2 data)[8] showed an association between respondents' communication with their peers and the difference in the self-efficacies with a significance value of 0.016 (critical =9.4 and stat =12.14). In order words, it might be possible that there is a higher probability of disagreement between the two individuals when they both have similar and high self-efficacies (Figure 4-26). While when the difference in their self-efficacies was not zero, there is a lower chance of having a conflict between the two individuals. Studies in the past have confirmed that self-efficacy affects an individual's conflict style (Desivilya & Eizen, 2005), where low self-efficacy is usually associated with conflict avoidance.


Figure 4-26 Difference in the self-efficacies and communication quality between the respondent and their peers

Additionally, it was also found that a respondent's communication with its team members affects model parameters (Figure 4-27). The relationship between communication value entered by a respondent and the other values like trust, influence and agreement for each of its peers exists both in Part1 and 2 data. Familiarity between the two individuals appears to be affected by communication towards the end of the project (as seen only in Part 2). A stronger correlation between communication and model parameters for Part2 data was found. Hence showing that with time individuals form stronger relationships and communication plays important role in the development of social-emotional factors in the team.

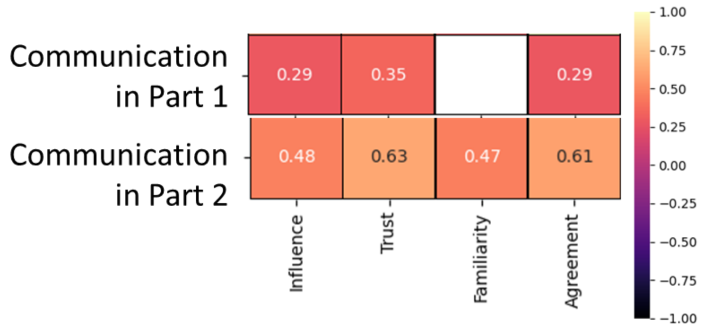



Figure 4-27 The effect of communication on the model parameters showing Kendall correlation coefficient of the significant p-values

The interpersonal attraction of a group member as described by González et al., (2003) is considered a crucial variable when the teams are collaborating at a distance. Similarly, as seen from

[8] Part 1 data had chi-square test significance value of 0.07

Figure 4-27, a respondent's perceived degree of influence from its peer that is considered for the current study is also affected by communication between them (Kendall correlation coefficient τ=0.5, p-value<0.001). The trust and familiarity between the respondent and its peers also increase with better communication (Kendall correlation coefficient τ=0.6 and 0.5 respectively with p-value<0.001). This could be due to the individuals are better at communicating, had more convincing power, hence the increase in trust. Lastly, the amount of agreement a respondent had with its peers also increases with communication between them (Kendall correlation coefficient τ=0.6, p-value <0.001) as effective communication leads to clarity and conflict resolution (Hinds & Mortensen, 2005). Thus, these findings of the empirical study 4 aided in fulfilling the second purpose (P4.2,i.e., validating RQ3 assumption that effective communication between individuals plays a significant role during virtual team collaboration as it impacts model parameters)

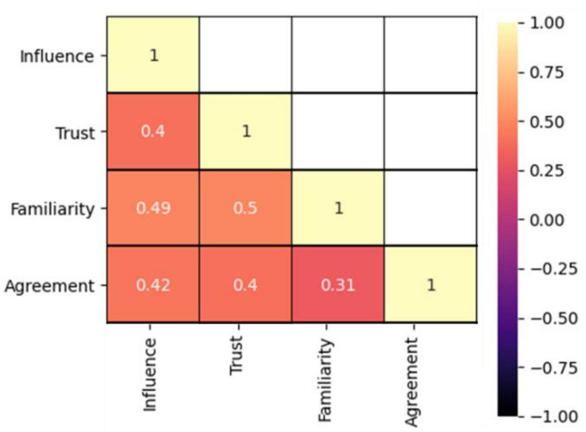



Figure 4-28 The relationship among the model parameters at the beginning of the course Kendall correlation coefficient of the significant p-values

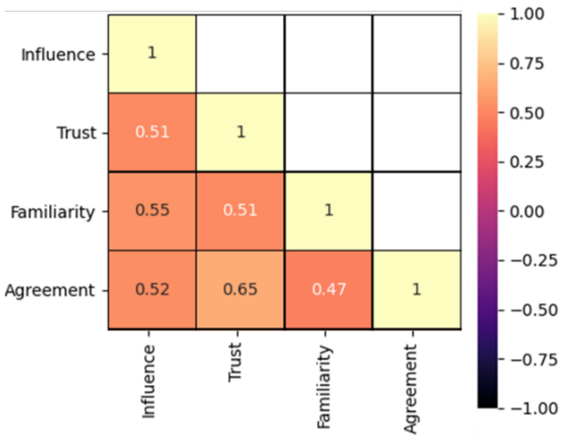



Figure 4-29 The relationship among the model parameters at the end of the course Kendall correlation coefficient of the significant p-values

Another interesting thing to note from Figures 4- 28 and 29 is that the correlation between the model parameters changes with time. The parameters show a stronger relationship towards the end of the project than at the beginning.

## 4.5 Summary

The summary of outcomes from different experiments that fulfilled their respective purposes to support the research questions and the model formation logic are given below in Table 4-5.

Table 4- 5 Insights from the observation experiments that were used in the model

| **Research Objectives →**<br>**Empirical studies ↓** | *Validate the assumptions* | *Logical verification* | *Additional insights* |
|---|---|---|---|
| *Empirical study 1* | Individuals who had higher self-efficacy were correlated to high perceived influence, hence, $I \propto SE$. Thus, partially validating A1.1. | High self-efficacy individuals get lesser change in their self-efficacies (increase and decrease) than the ones with lower self-efficacies. $SE \propto (\delta SE)^{-1}$ (*SE* is self-efficacy on an individual at a given time $t$ and $\delta SE$ is the change in self-efficacy at a time t and t +1,i.e. $SE_{t+1}$ - $SE_t$).<br><br>It was also supported by the finding where individuals with high self-efficacy are less demotivated. | A weak positive relationship between the degree of influence and the number of influencers was present as there could be one influencer with a high degree of influencing power or multiple influencers with influencing powers might have had the same impact on the team processes. Thus, supporting the argument that the influence is not evenly distributed in the teams. |
| | | Individuals who perceived more influence also tend to appreciate more ideas in the team. | Individuals propose more ideas when their team members appreciate their ideas more. |
| | | High self-efficacy individuals often propose more ideas to their team than those with low. | Teams with high variance in the influence, or in other words teams where only some individuals are perceived as highly influential, have a tendency to appreciate fewer ideas from each other. This could be because members frequently select ideas of the influencer(s) and do not |
| | | An individual often appreciates ideas from its team members when they frequently appreciate or selects its ideas. | |

| | | | |
|---|---|---|---|
| | | Teams where their team members perceived high influence, perform better. | support ideas proposed by other low influential team members. |
| *Empirical study 2* | The difference in an individual's self-efficacy with respect to its teammates is responsible for its perceived degree of influence. $I \propto \Delta SE$ (*I* is the perceived degree of influence and $\Delta SE$ is the difference between the self-efficacies), hence further supporting *A1.1* | Trust depends on how well the individuals know each other. $T \propto f$ (*T* is the Trust and *f* is familiarity between the two individuals). | The correlation between the parameters showed that the relationship between trust and influence is stronger than self-efficacy and difference in self-efficacies. Therefore, from Equation 10 (in Chapter 3), $w_1$=0.3, $w_2$=0.3, $w_3$=0.4,<br>The relationship between trust and familiarity was weaker than originally thought, hence in Equation 3, $w_4$= 0.7 and $w_5$ = 0.3 |
| | The amount of trust between two individuals is also responsible for the influence they perceive from each other. $I \propto T$ (*I* is the perceived degree of influence and *T* is the Trust), validating *A1.1* of *RQ1*. | | |
| *Empirical study 3* | High self-efficacy individuals also had an influence on other high self-efficacy individuals hence, conforming to the finding in empirical study 1. It further supports *A1.1* that self-efficacy could be one of the factors affecting the influence, $I \propto SE$ | The presence of coalition groups that are formed based on the similarity of solutions/opinions that lead to the majority effect. Influencer effect was also present when individuals were agreeing with others' proposed solutions based on an individual's effective communication (a key trait of individuals who are confident,'influencer'). Hence verifying the two social factors considered in the model during decision–making in idea selection | Individuals with high self-efficacy perceive fewer influencers than those with lower. |
| | Perceived degree of influence affects an individual's agreement ($A \propto I$). Besides an individual's *(j)* perceived degree of influence by an individual *(i)*, agreement of *i* with *j* also depend on the *j's* past agreement when *i* proposed its solution ($A \propto P_A$). Thus, revealing | | Familiarity is an important characteristic in collaborative team activities as it affects socio-cognitive team processes. |

| | | | |
|---|---|---|---|
| | another factor affecting an individual's agreement during idea selection. | | |
| *Empirical study 4* | Communications in teams play a significant role during collaboration as it impacts model parameters like influence, trust and conflicts. | Nearly all the team members were considered influencers when teams collaborated virtually while only a few influencers are perceived when collaborating face-to-face. | The parameters that are considered in the model show a stronger relationship towards the end of the project than at the beginning. In order words, the correlation among the model parameters increases with time. |
| | | The model parameters considered in face-to-face collaboration behave differently during virtual collaboration. Thus, providing the hint to alter the model parameters considered for face-to-face collaboration to simulate various virtual scenarios. | The number of conflicts arising in the team is related to the effectiveness of team communication. |
| | | | The difference between the self-efficacies of the individual mediates the quality of the communication between them. In other words, the probability of having a disagreement or conflict is less when the difference is the self-efficacies is less. |

# Chapter 5

# Model simulation details

Setting an agent-based model where the complexity of the agents' behaviour and the system they represent also rely on the computational resources (such as memory and processing power). A simple agent-based model could be capable of exhibiting complex behaviour patterns and information about the dynamics of the system that it mimics from the real world (Bonabeau, 2001).

This chapter presents the simulation tools and environments used in the study. It also shows the functionality of the model by presenting the results related to agent learning and comparing them to the literature. It ends with a description of the measures that were used to evaluate the design outcome in Chapter 6.

## 5.1 Simulation tools and environment

The computational model is implemented in the Python programming language as an agent-based system. Building a custom model in Python from scratch provided complete control over the model. Although, agent-based modelling framework in Python called Mesa is available but it wasn't very efficient and is still developing. Using python over other frameworks like NetLogo allowed more flexibility for modelling choices. Pre-existing platforms (like NetLogo) lack standard software development tools like the testing feature which is much simpler when coding from scratch in Python using an editor like Visual Studio. These pre-existing platforms often are not suited for optimized simulations such as running simulations in parallel, unlike Python where a multiprocessing package supports spawning. Since, Python is a user-friendly, high-level and widely used language, debugging the code was simple. Due to the object-oriented programming (OOP) aspect of python, properties and behaviours related to the individual agents could be easily controlled. Various libraries are available in python that was used for analyzing data without changing the environment.

Since, many of the parameters in the model are related (for example, an agent has its self-efficacy, influence value and other features in a session, which are updated in the other session. Therefore, an agent's characteristics are linked to a particular session which in turn is linked to a project), the relational database was used to store the key elements of the model that could provide insights. In order to extract and store the data related to individual agents at each step, session and at a project level, a database toolkit for python called SQLAlchemy was used (SQLAlchemy, 2021). SQLAlchemy is an Object Relational Mapper (ORM) that provided the advantages of SQL (Structured Query Language) and stored the data in SQLite, a relational database management system (SQLAlchemy, 2021). The model data from the SQLite database was then queried into CSV (comma-separated values) file format for analysis. The public repository of MILANO python code is available on Bitbucket[9].

## 5.2 Details of agent learning

The comparison of the solution quality of the agents for over 1000 simulations (for 3 peaks in design space) that learn from their past experience (i.e., learn from their positive and negative events without the effect of the influencers) with those that do not, could be seen in Figure 5- 1. This shows that the model functions as intended and the agents learn from their past experience which results in better solution quality. The increase in the quality of solutions with each session could be due to recall, which is correlated with the number of ideas generated (Dugosh & Paulus, 2005).

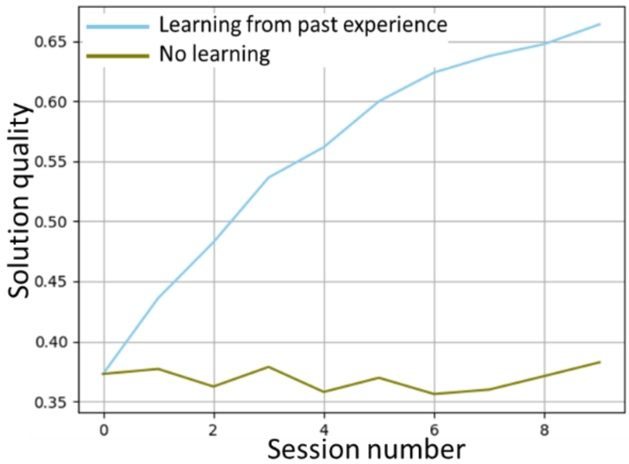



Figure 5- 1 Agent learning from past experience

The way an agent with high self-efficacy (but lesser than the self-efficacy of an influencer) behaves during idea generation, is different from an agent with low self-efficacy in a team where there is an influencer Figure 5- 3 shows how low and high self-efficacy agents behave during idea generation based on Figure 5- 2 that shows the flowchart of the extraction of the required data from the simulation. The figure shows the distance between the solutions of a low and high self-efficacy agent with respect to an influencer (here the maximum sessions were 20). It could be inferred that a high self-efficacy agent (but lesser than the self-efficacy of an influencer) explores solutions differently than an Influencer while a low self-efficacy agent (is the one with the lowest self-efficacy in the team) generates solutions closer to that of an influencer. Thus, it backs the formation of the model as it functions as intended. This aligns with expectations on the nature of influence in design teams and

[9] Link: https://harshika02@bitbucket.org/harshika02/milano.git

corresponds to Brown & Pehrson, (2019), where it was stated that some individuals are more influenced by the influencer(s) than others.

The learning that is modelled in this work could be associated with Associative Learning that states that *ideas and experiences reinforce each other and can be mentally linked to one another* (Paivio, 1969). This type of learning is a form of conditional learning that is based on the theory, which states that an individual's behaviour could be modified or learned based on a stimulus and a response (Paivio, 1969). For example, if an agent's solution was bad (i.e. it got poor feedback from the controller agent) (stimulus), it will not produce similar solutions (response) (i.e. avoiding that area on the solution space). Based on the relationship between the two stimuli (current and recalled events), associative memory can be called (Paivio, 1969). The agent uses both the positive and negative reinforcers (stimuli used to change behaviour), to modify the way they generate their current solution. Figure 5- 4 and Figure 5- 5 below show agents with the lowest self-efficacy in teams with a varying number of influencers learn from their successes and failures for a design task with five best solutions. Learning from success and failure has been explained in the Model description, where agents avoid the failures they have committed in the past and tend to follow the path that led to previous success.

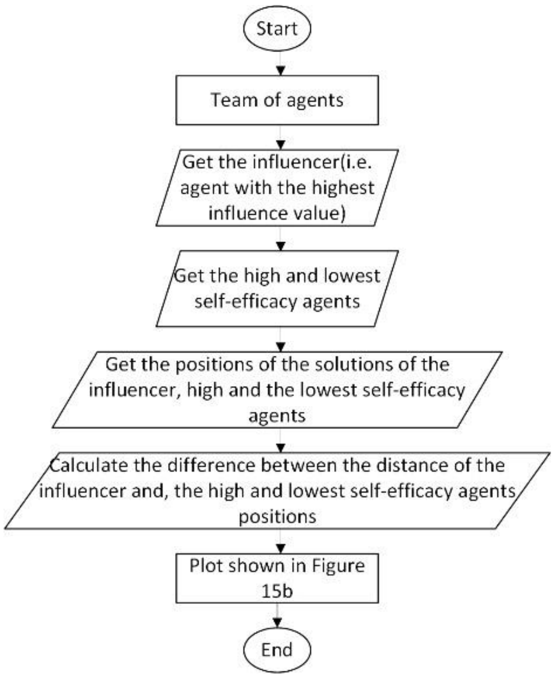



Figure 5- 2 A flowchart showing the steps taken to plot Figure 5- 3

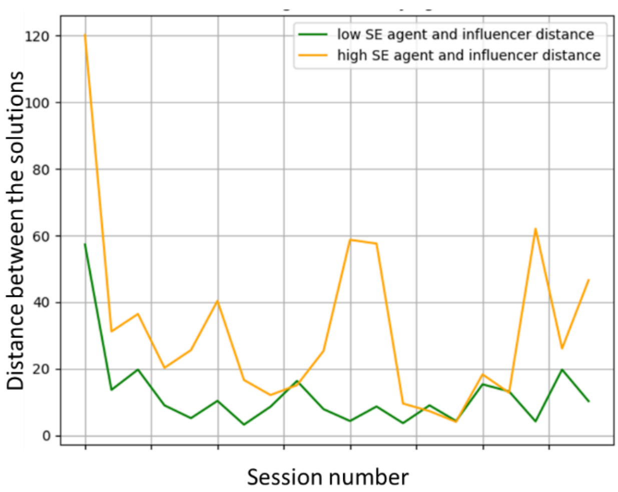



Figure 5- 3 Distance between low and high self–efficacy agents from the influencer (for maximum sessions = 20)

The curves obtained in the results shown in Figure 5- 4 similar to the learning curves described in Leibowitz et al.(2010). There is not much difference in the success learning curves (Figure 5- 4), with the lowest self-efficacy agents in teams of all influencers learning slightly more from their success than other team combinations. The failure learning results shown in Figure 5- 5 are more divergent and agents in the teams when all agents start at high self-efficacy ('All influencers') have the least ability to learn from failure than the other combinations tested. Concerning learning from failure, all the agents in the team with 'No influencer','1 influencer' and '3 influencers', learn more from their failures towards the end of a project. In general, it could be seen from Figure 5- 5, that the learning from failure becomes steady towards the end of a project. The slope of the failure learning curves (failure rate) exhibit somewhat similar behaviour of the 'early failure' phase (widely used in reliability engineering)

(Wilkins, 2002), where the rate of failure decreases with time, hence the system improves (Proschan, 2012).

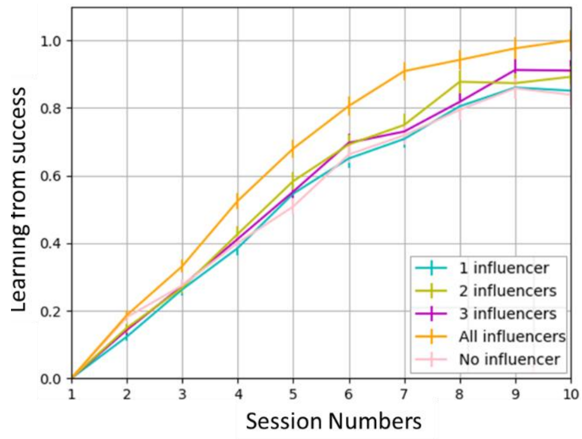



Figure 5- 4 Learning from Success

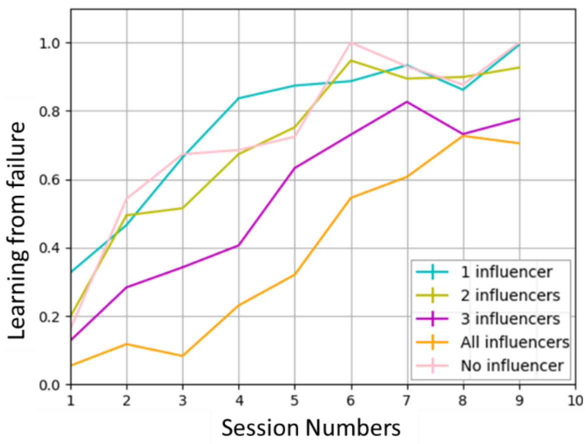



Figure 5- 5 Learning from failure

Social influence, which leads to the imitation in individuals to modify opinions, attitudes, and behaviour similar to the others they are interacting with, is referred to as social learning. As it could be seen from Figure 5- 6, the influence of individuals is unevenly distributed in a team, consequently, is social learning. The amount of social learning in the teams where the ratio of influencers to non-influencers (i.e. low self-efficacy agents) was half and agents in teams with ‘All influencers’, social learning could be seen high throughout the project, while minimum when all agents have low self-efficacy when they start working (Figure 5- 6). Social learning curves are similar to the ones obtained in other domains of study such as online gaming (Landfried et al., 2019) or during diffusion of innovation (O’Brien & Bentley, 2011).

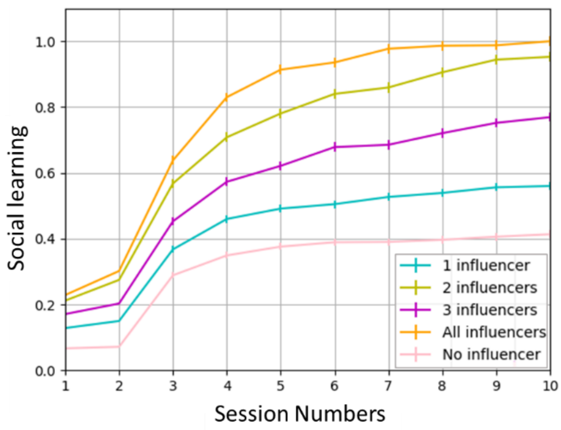



Figure 5- 6 Social Learning

## 5.3 Measuring design outcome

The design outcomes or the effectiveness of the design solutions could be measured in various ways. For example, quality (or in order words utility, usefulness or value), exploration (in terms of variety of solution) and surprise (or unexpectedness) are some of the commonly used measures (Kazjon & Maher, 2019; Shah et al., 2003; Dorst & Cross, 2001). Others like Clevenger & Haymaker, (2011) have defined dimensions of a design process (like strategy, challenge and exploration) to assess guidance in design. They defined design space from the perspective of objective space, alternative space, impact space and value Space. The alternative space which is most similar to the design space definition considered in MILANO consists of all the alternative solutions for a given task and includes explored and unexplored solution alternatives. Impact space analysis the impact of alternative solutions and determines whether they are acceptable or not. This in MILANO is determined by the controller agent. Considering the nature of this research (i.e., mimicking the design team collaboration in various scenarios), quality and exploration would be most useful to measure the design outcome. The quality or exploration could be used to evaluate design outcomes after idea generation or selection (Figure 5- 7). Given below are the explanations of these measures.

## 5.3.1 Quality measures

Studies in the past have measured the novelty and usefulness of the ideas or solutions and have emphasised creativity as means to solve complex problems where there is often not a single correct solution (Perry-Smith, 2006; Perry-Smith & Shalley, 2014). Thus, a similar concept of quality that is equivalent to the value or usefulness of a solution is considered in this study.

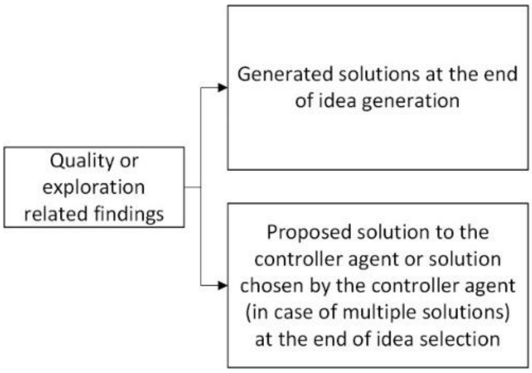



Figure 5- 7 Quality or exploration related findings could be obtained during idea generation and selection

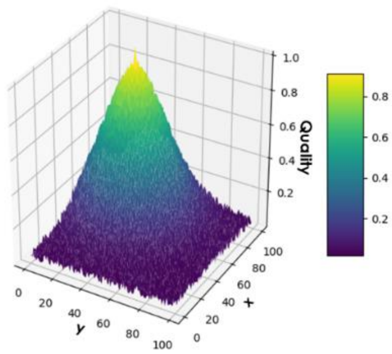
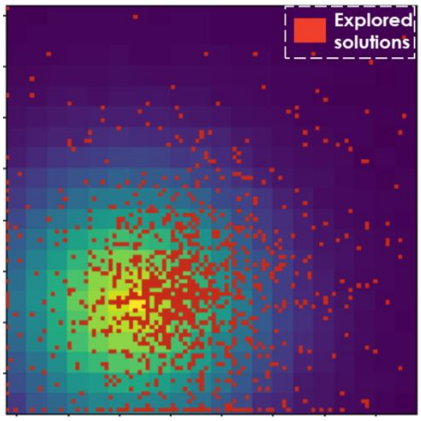



Figure 5- 8 Quality of solutions on a one peak design space

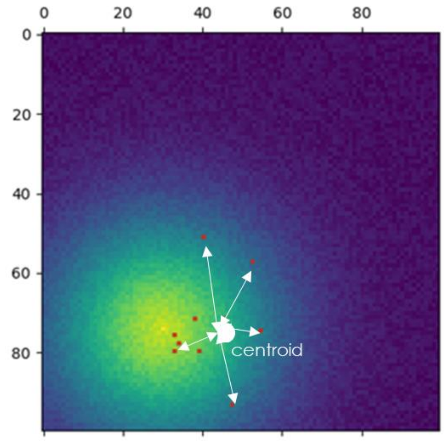
Quality represents a value of an objective function and is the most common measure used by the agent based-models in that have simulated design activity (Singh et al., 2011; Sayama et al., 2010; McComb et al., 2017; Cao et al., 2020). Similarly, the quality of the solution is the value of a point on a design solution space (shown in Figure 5- 8). The quality of the final solution is the value of the single solution that the team of agents proposed to the controller agent or the best solution according to the controller agents in case of multiple solutions.

## 5.3.2 Exploration related measures

Some similar exploration measures used by Song et al., (2021) where they evaluated the effectiveness of the solutions proposed by the human designers using an AI platform. They evaluated how specific drone designs differed from the basic drone and all other drones by comparing the similarity between a concept pair (similar to spread and EI below).




Exploration Index (EI)




Spread of the solutions

Figure 5- 9 Some of the exploration related measures of design outcome

*Exploration index*:

The exploration index is the number of points (solutions) explored when generating solutions on a lower resolution solution space ($Soln_{lowr}$) to the area of this lower resolution space ($Area_{lowr}$), an example can be seen in Figure 5- 9 (left) and is given in Equation 26. The lower resolution of solution space means that the original solution space (100×100 units) is decreased in size by a factor (5 in this case) so that the resultant is a smaller space (20×20 units). This means that if an agent explores solutions within 5 units of neighbouring cells, it is counted as one-unit exploration. It was done to avoid having an inaccuracy that could arise; e.g., when an agent explores immediate neighbour cells to an agent exploring 5 cells at a larger unit distance.

**Equation** 26
$$EI = \frac{Soln_{lowr}}{Area_{lowr}}$$

*Exploration Quality Index (EQI):*

Value space by Clevenger & Haymaker, (2011), is the measure of the values generated during an exploration, which is captured in MILANO in the exploration metric defined as EQ1. Ehrich & Haymaker, (2012) called a similar metric as objective space quality (OSQ) for evaluating design space exploration in their model that measured the quality of the design process exploration. Moreover, the design space sampling (DSS) metric defined by Ehrich & Haymaker, (2012) measured the *fraction of alternatives considered divided by the total number of alternatives possible*. Similarly, the exploration quality index (EQI) combines the idea behind OSQ and DSS in a single measure and gives the idea of the quality values of the explored cells (EI). EQI is the ratio of the number of solutions proposed on a lower resolution solution space ($qSoln_{lowr}$) above a certain threshold, $t$ (in this case t is above 0.5, where 0 is a minimum and 1 is a maximum solution quality value) to the total number of solutions ($qTotSoln_{lowr}$) available on the design solution space greater than the threshold value (Equation 27). Similar to EI, the solution space the original solution space (100X100) is decreased in size by a factor (5 in this case) so that the resultant is a smaller space (20X20). This means that if an agent explores 5 neighbouring solution cells, the average quality of these 5 cells is considered.

**Equation** 27
$$EQI = \frac{qSoln_{lowr}}{qTotSoln_{lowr}}$$

*Local Exploration Quality Index (LEQI ):*

Local exploration quality index is the ratio of the number of solutions proposed (*solns*) that are above a certain threshold, $t$ (in this case t is above 0.5) to the total number of solutions proposed (*totSoln*) (Equation 28).

**Equation** 28
$$LEQI = \frac{solns}{totSoln}$$

*Spread:*
It is the dispersion of the solutions (as seen in Figure 5- 9 right), studies like Song et al., (2021) have also used this measure to calculate variety in their solutions generated by the designers. It is calculated by getting the distance between each solution from the centroid of all the solutions on design space. The variation in these distances (i.e., the distance between a solution and centroid) gives the idea about how the solutions are located on design space. The spread shows how different the solutions are from each other; in other words, it exhibits variety in the solutions. If S is a set of n proposed solutions on a design space having 2 design variables, $S = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$. The coordinates of a centroid $c = (c_1, c_2)$, are calculated as $(c_1, c_2) = (\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i)$. The average distance μ from that centroid is $\mu = \frac{1}{n}\sum_{i=1}^{n} ||S_i - c||$, where $||S_i - c||$ is the Euclidean distance $d$ given as $d = \sqrt{(x_i - c_1)^2 + (y_i - c_2)^2}$. The spread or the variety among the solutions can be calculated as the standard deviation of these distances from the centroid (as given in Equation 29). Where *N* is the total number of distances between the solution coordinates and the centroid.

**Equation** 29
$$Spread = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(d_j - \mu)^2}$$

### 5.3.3 Additional team behaviour related measures

Other parameters like agreement and contribution were extracted from the simulation to determine team behaviour as they helped in explaining the reason behind the design outcome values. Agreement in teams is crucial in understanding how team members are behaving over the proposed solutions. Agreement in the model is the amount an individual agrees with the other's proposed solution (as calculated in Equation 16). Contribution, on the other hand, is an important element for early teamwork and may change over time (Thomas-Hunt et al., 2003). There might be a reduction in the contribution of isolated individuals as the motivation to communicate might change (Worchel, 1996). Hence, the contribution of agents in teams could help in understanding the behaviour of various team compositions. In the context of the model, the contribution is defined as the number of times an agent proposed its solution to the other team members, which was important in knowing team behaviour. Low contribution distribution would indicate that more or less all agents equally proposed solutions in the team. On the other hand, a high value of contribution distribution indicates that only some agents often proposed solutions.

# Chapter 6

# Research findings

Social Turing test method was proposed by Carley & Newell, (1994) to assess the effectiveness of a computational model and to determine the reliability of its results simulating social behaviour. The following points need to be fulfilled to meet the Social-Turing test: "*Construction of the artificial social agents with features that make them social in a social situation based on the hypothesis. Recognising the social behaviour that emerges from the computational model. There could be many aspects that were not included in the hypothesis, which can be determined at will. These aspects should be based on human data or handled through the Monte Carlo approach. The behaviour of the computational model could vary widely with such specification, but it should remain recognizably social*". Keeping this in mind, the agents in MILANO were given features that are responsible for the social nature and were place in a team (i.e., a social situation). The results presented in this chapter from the computational model address the three research questions to gather information about team behaviour (i.e., social behaviour). Lastly, empirical studies in Chapter 4 were used to gather insights into various aspects of human behaviour in design teams. Moreover, the results were extracted after a certain number of simulation runs, following the Monte Carlo logic where the computer simulations are done several times to reduce the effect of randomness. The results presented in this chapter are based on 200 simulations as they were reaching convergence after 150 simulations (i.e., 25, 50, 75, 100, 125, 150, 175 and 200 simulations were performed and after 150 simulations the deviation in the results was within one standard deviation).

## 6.1 Research questions and the simulation details

There are several parameters present during a collaborative activity (Singh et al., 2019), however only the ones relevant to the goal of each research question were considered. At the beginning of the simulation self-efficacies of the agents were controlled (i.e., each agent was allotted self-efficacy), the agent self-efficacy along with familiarity, trust and reputation are dynamic and change with sessions

(Figure 3- 9). This was done to controlled the number of influencers in a team to see their effect on the design outcomes. Except for the experienced agents, all the other novice agents (or simply when referred to as agents) did not have any previous experience of working on the given task. The parameters which were varied in the simulation for each research question will be described when addressing the research questions in the following parts. The preview Table 6- 1 that shows which sub-sections contain the results related to the

Table 6- 1 Research questions and simulation details preview table

| **Model parameters →** | | **Total number of agents** | **Number of defined influencers (i.e., high self-efficacy agents)** | **Number of experienced agents** | **Number of best solutions** | **Type of the curvature of the peaks** | **Team virtuality level** |
|---|---|---|---|---|---|---|---|
| **Research Questions** | **Simulation results sub-sections** | | | | | | |
| **RQ1** | 6.2.1 | 6 | 0-6 | 0 | 5 | standard | 1 |
| | 6.2.2 | 3,6,10 | half | 0 | 1 and 12 | standard | 1 |
| **RQ2** | 6.3.1 | 6 | 3 and 6 | 1 and 3 | 1 and 5 | standard | 1 |
| | 6.3.2 | 6 | 6 | 1 (routine and non-routine experience) | 5 | standard | 1 |
| | 6.3.3 | 6 | 6 | 1 | 5 | standard, steep, curved and mixed | 1 |
| **RQ3** | 6.4.1 | 6 | 3 and 6 | 1 | 5 | Standard and steep | 5 |

## 6.2 Answers to the research question 1

### 6.2.1 Varying the Influencers in design teams

**Set-up**

The purpose of the model is to simulate influencers in teams and see their effect on the design outcomes (RQ1). There are independent, intermediate and dependent parameters that are present when teams collaborate in a design session, however; only the ones relevant to the purpose of the work are considered (Singh et al.,2019). As seen from the model description, influence depends on both self-efficacy (self-efficacies of the agents were controlled i.e. each agent was allotted self-efficacy at the beginning of the simulation to control the number of influencers in the team) and trust (that emerges with other parameters like familiarity and reputation (Singh et al.,2020)). Other independent parameters like the number of agents, design task, length of idea generation and agent past experience were kept constant for the simulation to see the effect of intermediate parameters on the design outcome.

Two cases were designed to extract simulation data that could answer this research question (Figure 6- 1). The first case tested the situation where the distribution of self-efficacy in the teams is not uniform i.e. some agents have high self-efficacy and others low when they start working on a design task. This provided more control over the number of influencers in a team, hence seeing the effect of influencers emerging based on their high self-efficacy (as discussed above) on design outcome. Three sub-cases here were:

1.1 One agent with high self-efficacy and others with low (i.e., 1 influencer)
1.2 Two agents with high self-efficacy and others with low (i.e., 2 influencers)
1.3 Half of the agents with high self-efficacy and others with low (i.e., 3 influencers)

The case scenario tested the situation when the team has a uniform distribution of self-efficacy in its agents, i.e. all agents either have high or low self-efficacy when they start working on a design task. Two sub-scenarios here were:

2.1 All agents with low self-efficacy (i.e. no influencer)
2.2 All agents with high self-efficacy (i.e. all influencers)

These cases were designed to gain clear and accurate insights by controlling the dynamicity of the model processes. Thus, by assigning different self-efficacy combinations at the beginning of the simulation, the various number of influencers were to be formed and allocated to each influencer-team composition (1.1-1.3). In the other case where the teams had uniform self-efficacy (i.e., no well-defined influencer(s)), some agents may emerge as influencers as the team works from one session to another (2.1-2.2).

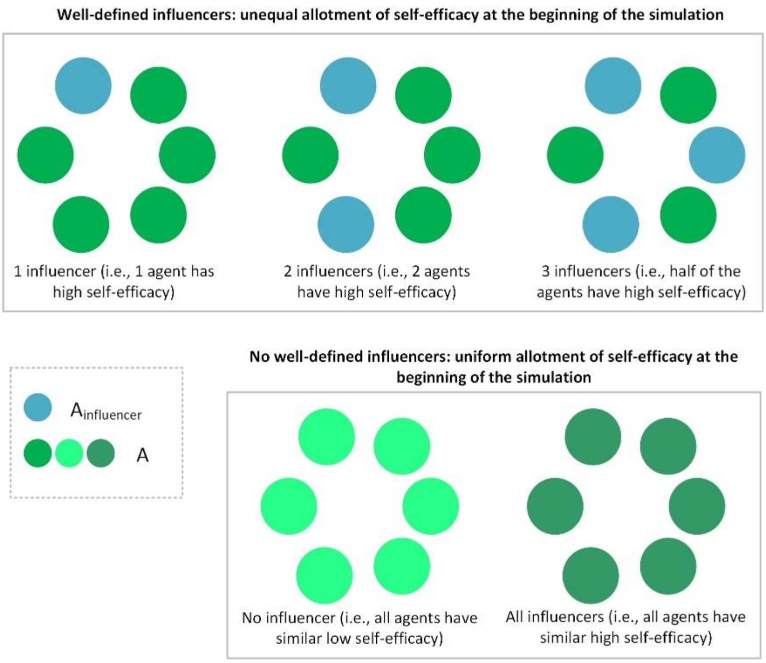



Figure 6- 1 Different case for simulating influencer-team compositions

### The impact of influencers on individual thinking outcomes during idea generation

To answer the first part of research question 1 i.e., *what is the impact of influencers on individual thinking outcomes during idea generation?* simulation results here provided some insights.

*Quality findings*

The results related to design quality for a 5-peak configuration of a design task with respect to different influencer/non-influencer team compositions could be seen in Figure 6- 2. In general, the quality of solutions increases with the idea generation sessions with minor divergence. The ANOVA results showed that the solution values generated by all the agents in the team with the various number of influencers during idea generation differed significantly ($F= 34.02$, $p < 0.001$). In other words, the two test scenarios with varying levels of influence in teams affected idea generation. However, in order to know how the pairwise test cases differ, a posteriori (post hoc) analysis was done. Figure 6- 3 shows significant p-values of post hoc T-test results for pairwise comparisons. It can be seen that all pairwise comparisons have a significant p-value except 1 and 2 influencers pair.

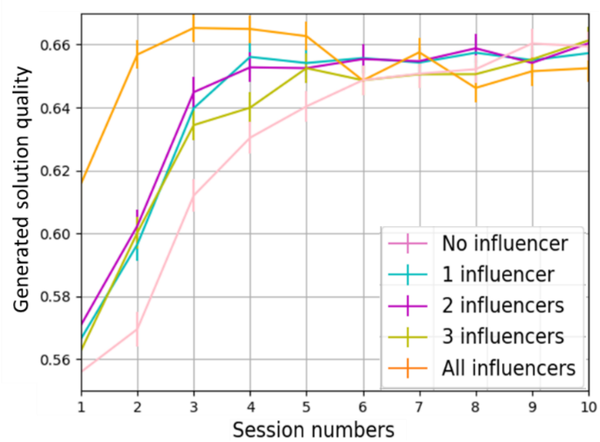



Figure 6- 2 Mean quality of the generated solutions by the individual agents in a team

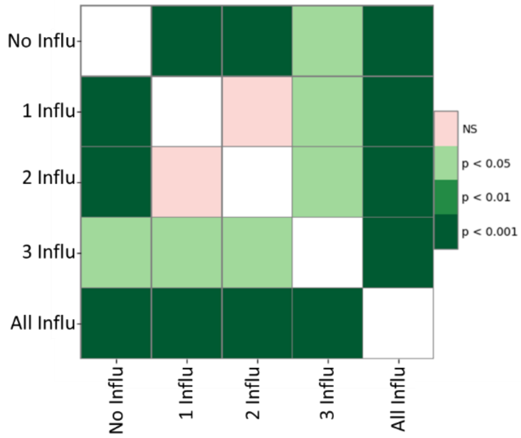



Figure 6- 3 Post hoc pairwise T-test for comparisons on the quality of the generated solutions by the individual agents in a team

Figure 6- 4 shows the quality of solutions of the lowest self-efficacy agent in different team compositions. It could be seen that this lowest self-efficacy agent in a team of all influencers, produces the worst quality of solutions than that of 1 influencer towards the end of a project. However, no such significant difference was found (Kruskal-Wallis H= 4.75, p= 0.31). This shows that agents with low self-efficacy behave similarly when generating solutions, irrespective of the influencer-team composition.

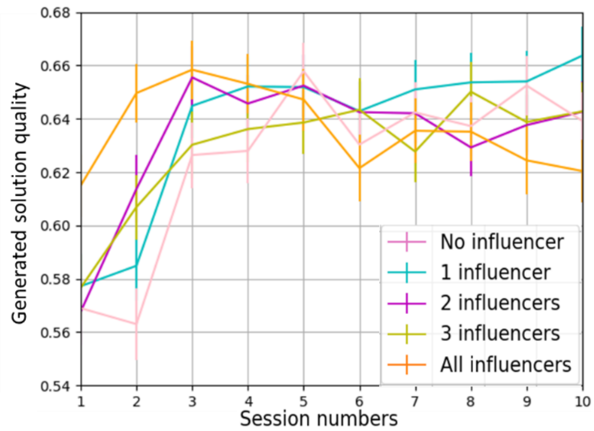



Figure 6- 4 Mean solution quality of the lowest self-efficacy agent in a team

*Exploration findings*

The exploration rate, which is the number of solutions in a design space explored during a session, without considering the ones in the previous session could be seen from Figure 6- 5. In general, the exploration rate during sessions 3-5 is lower than in other sessions in the teams of no and well-defined influencers. While agents in a team with all high self-efficacy (all influencers) start exploring more and more somewhat after the middle of the project. Agents in the teams with well-defined 1 influencer have the least exploration rate than other teams towards the end of a project

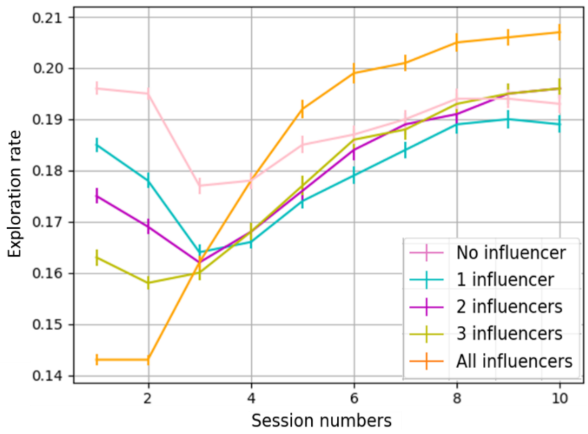



Figure 6- 5 Session-wise exploration rate

In order to understand how agents moved on the design space when generating solutions, Figure 6- 6 and Figure 6- 7 provide some insights. Figure 6- 6 shows the dispersion of the solutions during idea generation. In order words, variety, which increases with the number of influencers in the well-defined influencer compositions. However, in the case with no-well-defined influencers, no influencer teams had the least variety while all influencers had the most variety. This means that agents when generating solutions produce more diversity with the increase of influencers or when all the agents are equally influencing (all influencers). The diversity in the generated solutions in all the cases differs significantly (Kruskal-Wallis H= 84.78, p<0.001). After conducting a pairwise comparison (Figure 6- 8), it was found that agents in the teams with few well-defined influencers (1 and 2 influencers) behave similarly when generating a solution (i.e., follow the influencer). Agents with all low self-efficacy (no influencer) also behaved similar to the 1-2 influencer team agents. While agents in teams were half influencer and all agents with high self-efficacy generate more diversity in the solutions as seen from Figure 5- 3 that high self-efficacy agents are not afraid to explore on their own.

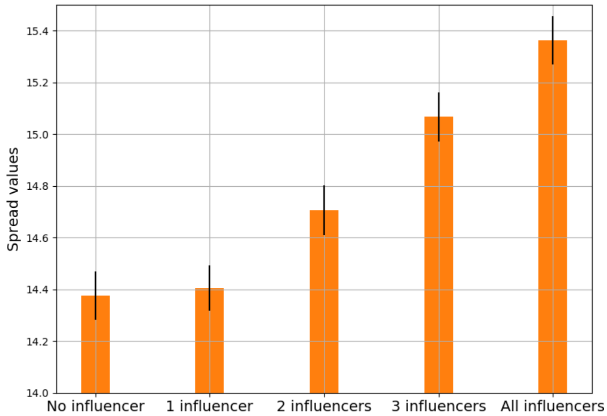



Figure 6- 6 Spread of the generated solutions

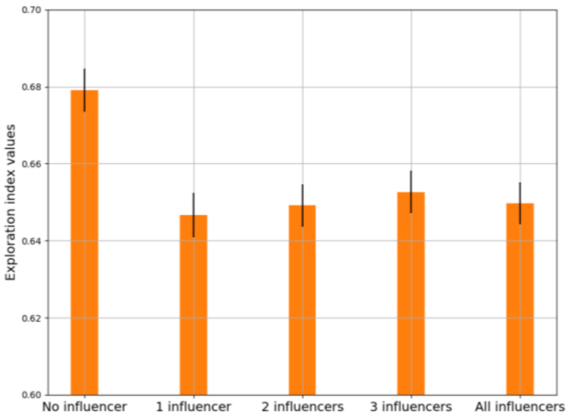



Figure 6- 7 Exploration index of the generated solutions

The EI value from Figure 6- 7 gives an idea about the exploration and it could be seen that the exploration value of no influencer team was the highest. This could mean that the agents in the no influencer teams explored more of the design space while the explored solutions were at a somewhat equal distance from the centroid, hence low dispersion value. The exploration of solutions on the design space by all the teams differs significantly (Kruskal-Wallis H= 18.70, p<0.001), however, when conducting a pairwise comparison Figure 6- 9, agents in all other teams behave significantly differently from no influencer composition.

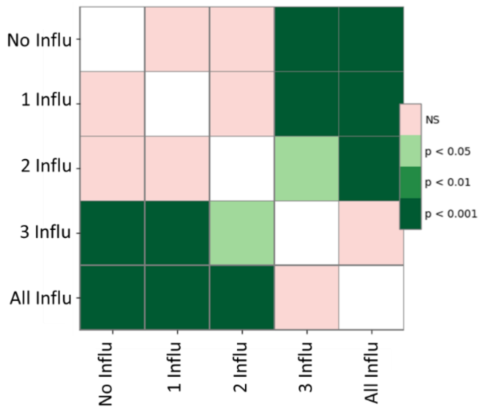



Figure 6- 8 Post hoc Conover’s test used after Kruskal-Wallis to do pairwise comparisons on the variety

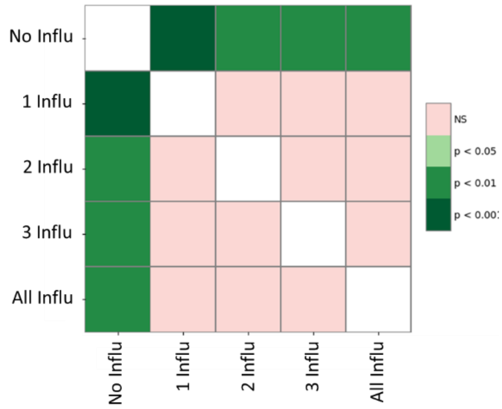



Figure 6- 9 Post hoc Conover’s test used after Kruskal-Wallis to do pairwise comparisons on the EI

## The impact of influencers on idea selection outcomes

The purpose of the model is to simulate idea selection in design teams while keeping in mind the factors that affect the decision-making (i.e., agreement with the proposed solutions) when selecting solutions. To answer the second part of research question 1 i.e., *what is the impact of influencers on individual thinking outcomes during idea generation?* simulation results here provided some insights.

*Quality findings*

Figure 6- 10 shows the final solution quality over the sessions and the difference between the final solution that was sent to the controller agent and the minimum and maximum solution values of the other proposed solutions during team interaction.

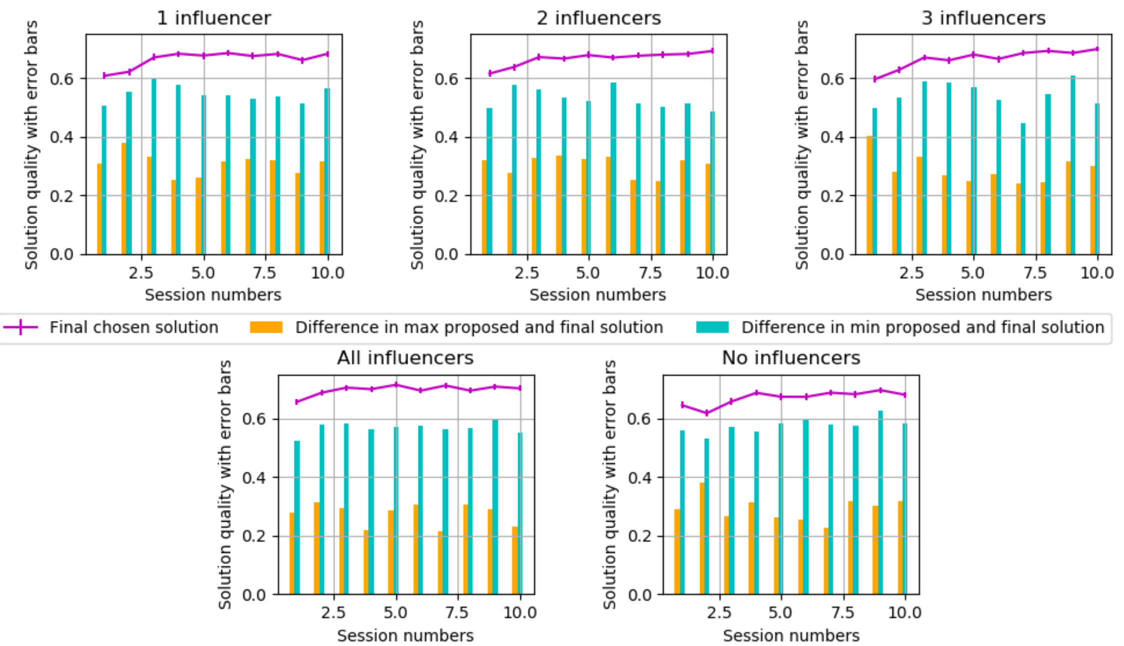



Figure 6- 10 Final solution and the difference in the maximum and minimum solution values of the proposed solutions

The quality of the solution is the value of a point on a design solution space. The quality of the final solution is the value of the single solution that the team of agents proposed to the controller agent or the best solution according to the controller agents in case of multiple solutions. The final solutions in the various team composition differed significantly in the quality values (Kruskal-Wallis H= 15.35, p=0.004). It can be seen from Figure 6- 11 that all influencers team had the best quality of the final proposed solutions throughout the design project, while the other team compositions had minor differences. However, not much difference can be seen towards the end of the project. From Figure 6-12, it can be noticed that the quality of the final solutions by all influencer teams differ significantly from other team compositions. The difference in the quality values of all influencer teams was comparatively lesser with the teams where agents had no well-defined influencer and all had low self-efficacy (i.e., no influencer) and the teams where half of the agents had higher self-efficacy than others (i.e., 3 influencers) than the teams with well-defined influencers especially 1 and 2 influencers.

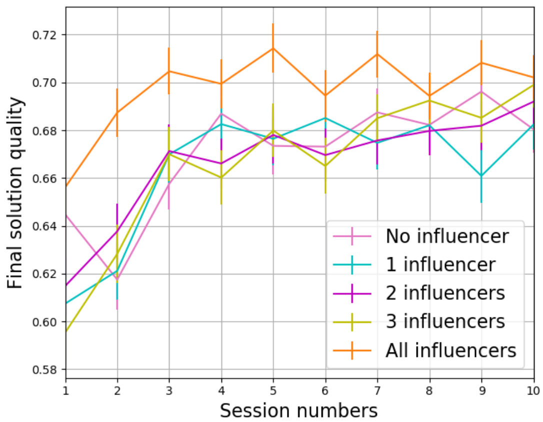



Figure 6- 11 Final quality of the solution with the standard error of the teams with different number of influencers

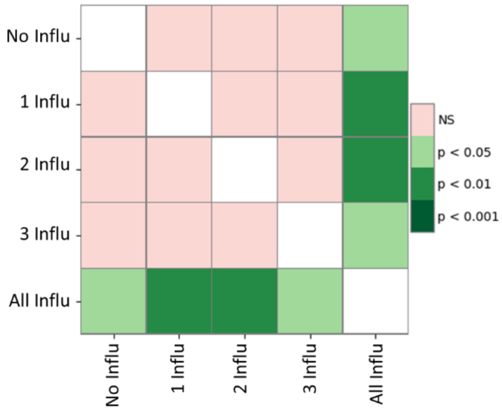



Figure 6- 12 Post hoc Conover's test used after Kruskal-Wallis to do pairwise comparisons on the final quality values

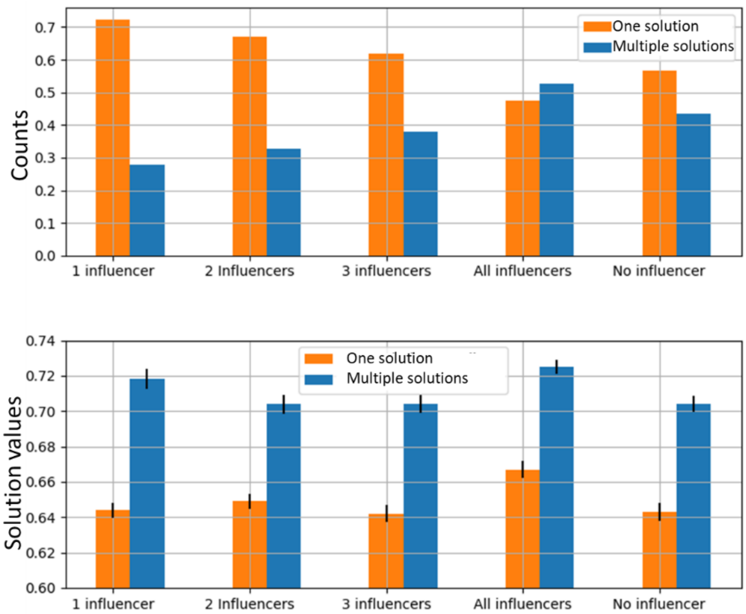



Figure 6- 13 Single vs multiple solutions (3) final solution count (top)and quality (bottom)

As discussed in the Model Description section that depending on the disparity in the total agreement value, a team could propose single or multiple solutions to the controller agent. Figure 6- 13 (top) shows the number of times the teams proposed multiple solutions alternatives (in this case 3) or single solutions to the controller agent. All influencer team proposed more multiple solutions to the controller agent while other team compositions mainly proposed single solutions. Proposing multiple solutions results in better solution quality as the controller agent has the liberty to select the most promising solution out of the multiple alternatives proposed (Figure 6- 13 bottom). The solution quality differed significantly when different teams proposed single (ANOVA F= 4.22, p=0.002) or multiple solutions to the controller agent (ANOVA F= 4.64, p< 0.001).

This difference in the quality was significant between all influencer team and other team compositions when they proposed single solutions to the controller agent (Figure 6- 14). The difference in the quality of the solution when multiple solutions were proposed was most significant between all and no influencer teams and teams with 2 or 3 influencers (Figure 6- 15). An interesting thing to see in (Figure 6- 15) is that no significant difference in the multiple proposed solution quality between all and 1 influencer was found.

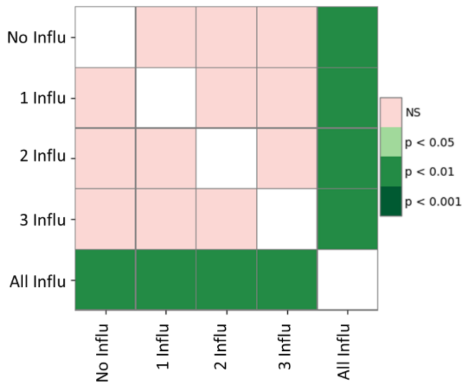



Figure 6- 14 Post hoc pairwise T-test of the quality of the single proposed solutions to the controller agent

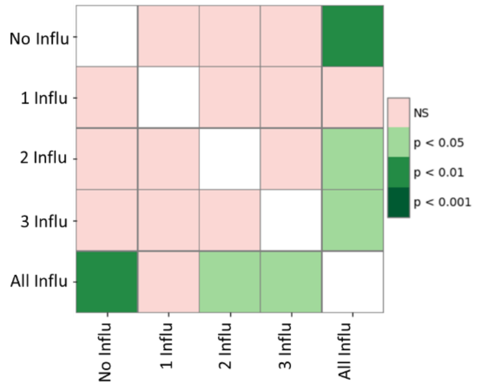



Figure 6- 15 Post hoc pairwise T-test of the quality of the multiple proposed solutions to the controller agent

*Exploration findings*

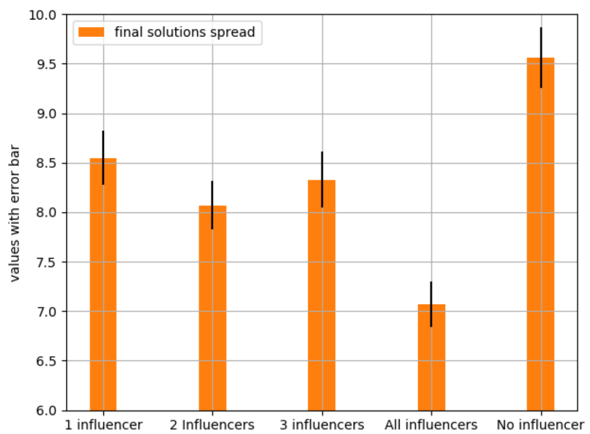



Figure 6- 16 Spread of the proposed final solution

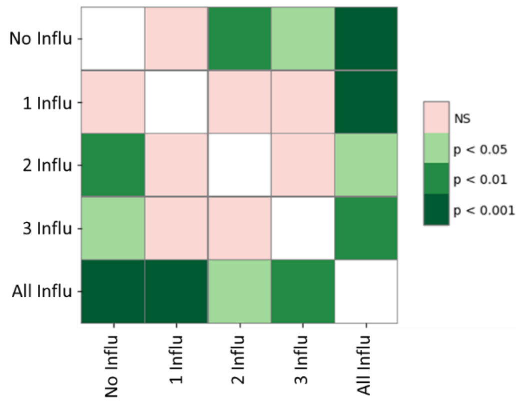



Figure 6- 17 Pairwise T-test after ANOVA to do pairwise comparisons of the spread values

Figure 6- 16 shows a different spread or the variety of the final selected solutions for various influencer-team composition (ANOVA F =11.24, p<0.001). The pairwise difference comparison in the spread values can be seen in Figure 6- 17. In general, it can be noticed that teams will no well-defined influencers (i.e., the second scenario with no and all influencers) behave differently than the teams with well-defined influencers (i.e., 1,2 and 3 influencers) in their spread values (having p<0.05). Even though the teams with no influencer have the most variety, they do not differ significantly from the teams of 1 influencer in their proposed solution spread values. The teams with well-defined influencers behaved similar to each other in the exploration of the design space when proposing their solutions to the controller agent, hence no significant difference could be seen in their spread values. Teams where all the agents had similar and high self-efficacy (i.e., all influencers), produced the least variety in their

proposed solutions. The all influencers team's variety values differ significantly from the rest of the influencer-team compositions.

Figure 6- 18 shows the EQI and LEQI values. Even though it can be seen that the EQI of the teams with no well-defined influencers had more alteration (i.e., all influencers had the highest and no influencers had the lowest EQI), there was no significant difference in the EQI values for all the team compositions (ANOVA F= 1.66, p= 0.16). LEQI on the other hand for all the team compositions differ significantly (ANOVA F= 3.399, p= 0.009). This significant difference in the LEQI values was mainly due to all influencer teams who had the highest LEQI. The all influencer team's LEQI differed significantly in comparison to the other teams with well-defined influencers and also with teams with no influencer (Figure 6- 19). LEQI of the teams with well-defined influencers and no influencer had no significant difference in their values.

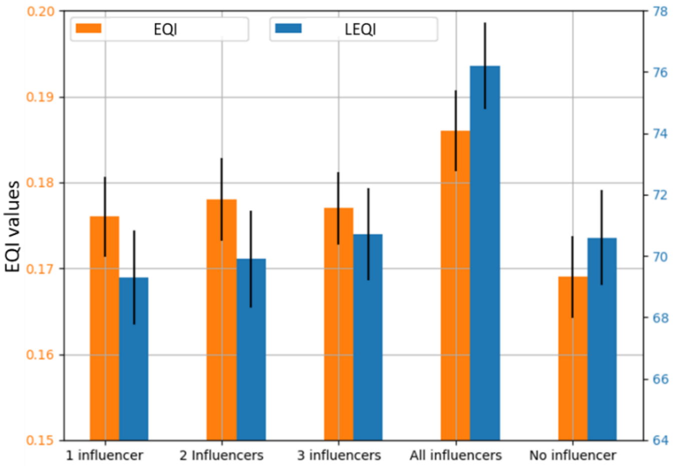


Figure 6- 18 EQI and LEQI of the teams with different influencers

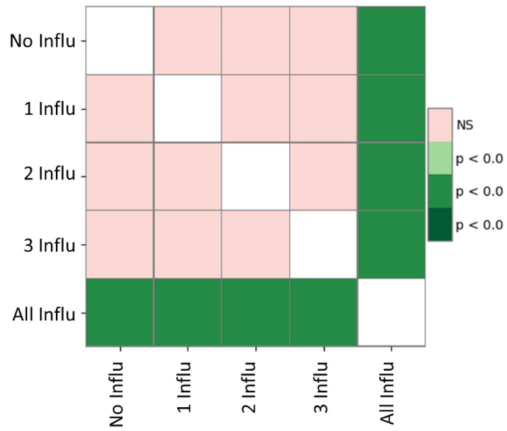


Figure 6- 19 Pairwise T-test after ANOVA to do pairwise comparisons of the LEQI of the proposed solutions

*Additional findings*

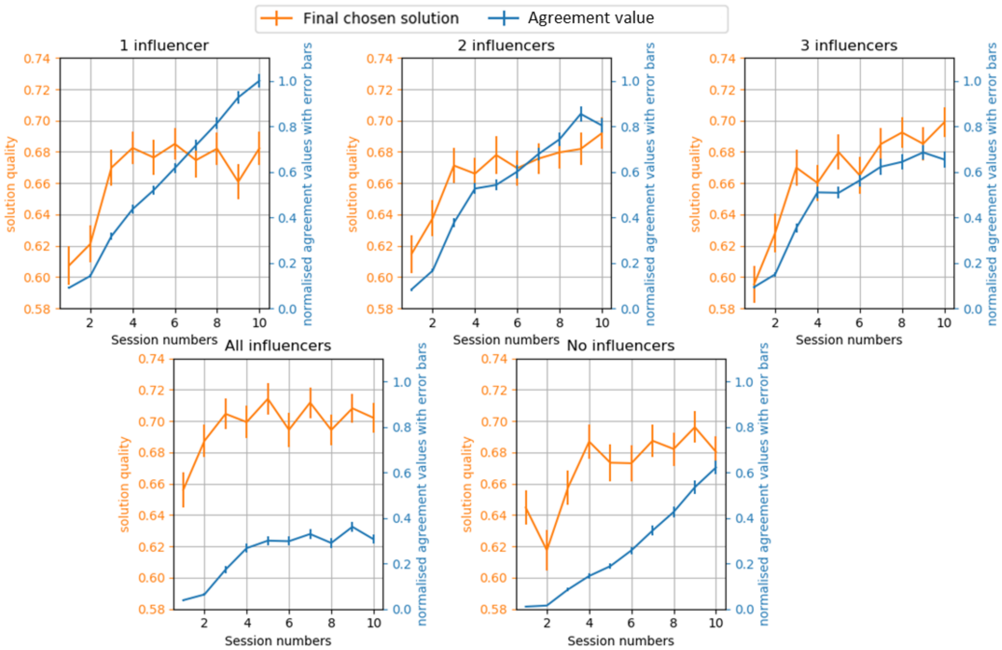



Figure 6- 20 Agreement values and final solution quality throughout the sessions

Agreement, as described in the Model description, is the amount an individual agrees with the other's proposed solution. The mean agreement value in the teams of different compositions changes throughout the project as seen in Figure 6- 20 (Kruskal-Wallis H= 13.5, p= 0.009). Teams with well-defined influencers have higher and a different pattern of agreement values than in teams with no well-defined influencers. However, a very weak correlation could be found between agreement values and solution quality of these teams (Kendall correlation coefficient $\tau$ = 0.2, p-value= 0.04). In general, it can be seen from Figure 6- 21 that more agreement values occur when the solution quality goes above average towards the end of a project.

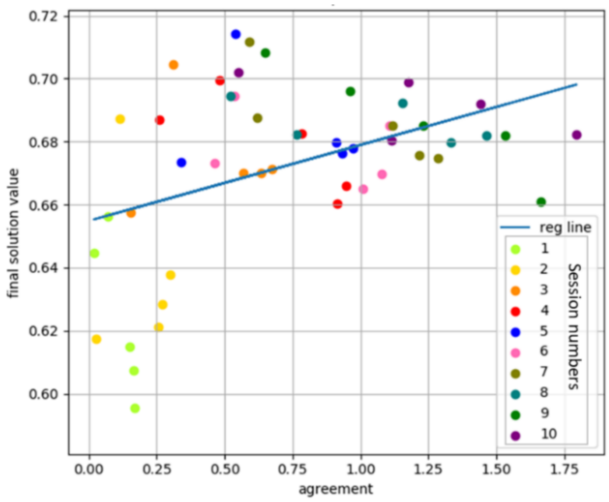



Figure 6- 21 More agreement values occur when the solution quality goes above average

In the context of the model, the contribution is defined as the number of times an agent proposed its solution to the other team members, which was important in knowing team behaviour. Low contribution distribution as shown in Figure 6- 22 indicates that more or less all agents equally proposed solutions in the team. On the other hand, a high value of contribution distribution indicates that only some agents often proposed solutions as seen from all influencers and 3 influencers team compositions. The values of the distribution of agents' contribution in various team composition differ significantly (Kruskal-Wallis H= 27.06, p<0.001). However, this significant difference is in the contribution distribution values is due to the all and 3 influencers team composition (Figure 6- 23).

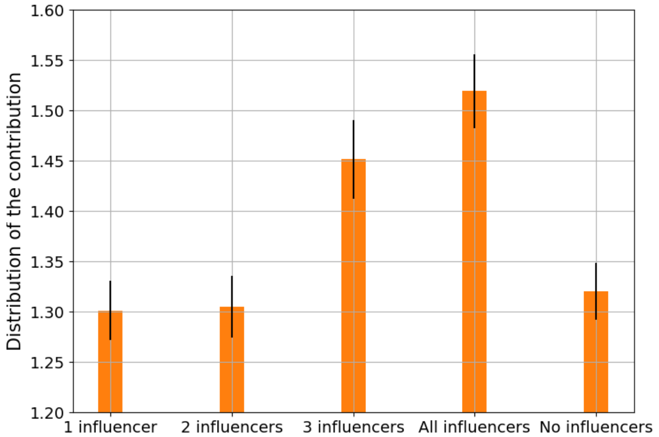



Figure 6- 22 Contribution distribution and average quality of the final solutions

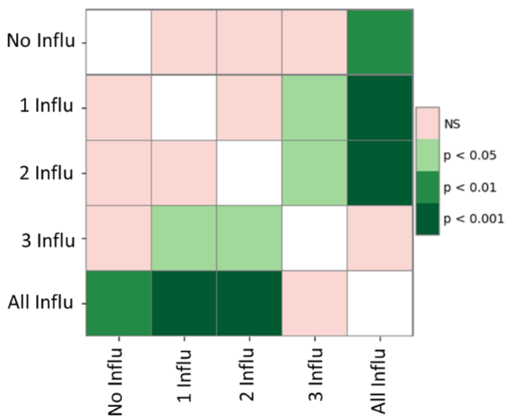



Figure 6- 23 Post hoc Conover's test used after Kruskal-Wallis to do pairwise comparisons on the contribution distribution values

Unlike the significant difference with teams of 1 and 2 influencers, 3 influencer team and teams with no-well defined influencers did not differ in the distribution of the contribution by their agents.

However, within the no well-defined influencer setting, all and no influencer teams behave significantly different from each other in the contribution by their agents. The agents contribute similarly in the teams with well-defined influencers (especially, 1 and 2 influencers) and no influencer, hence no significant difference in the contribution distribution values.

### Comparing idea generation and selection

As it was discussed in Chapter 2 that factors that facilitate idea generation (generation of alternative solutions by individual agents ) may not facilitate idea selection (selection of the best-proposed solutions by the team) (Toh & Miller, 2016). This could be clearly seen from simulation results extracted after the individual agents have generated solutions and after the team of agents have proposed their final solution to the controller agent. It can be seen from Figure 6- 24 that the solutions that were generated and then proposed by the agents to their team members differ significantly from the final solution that was prosed to the controller agent or selected by the controller agent in case of multiple solutions (F=15.39, p <0.001).

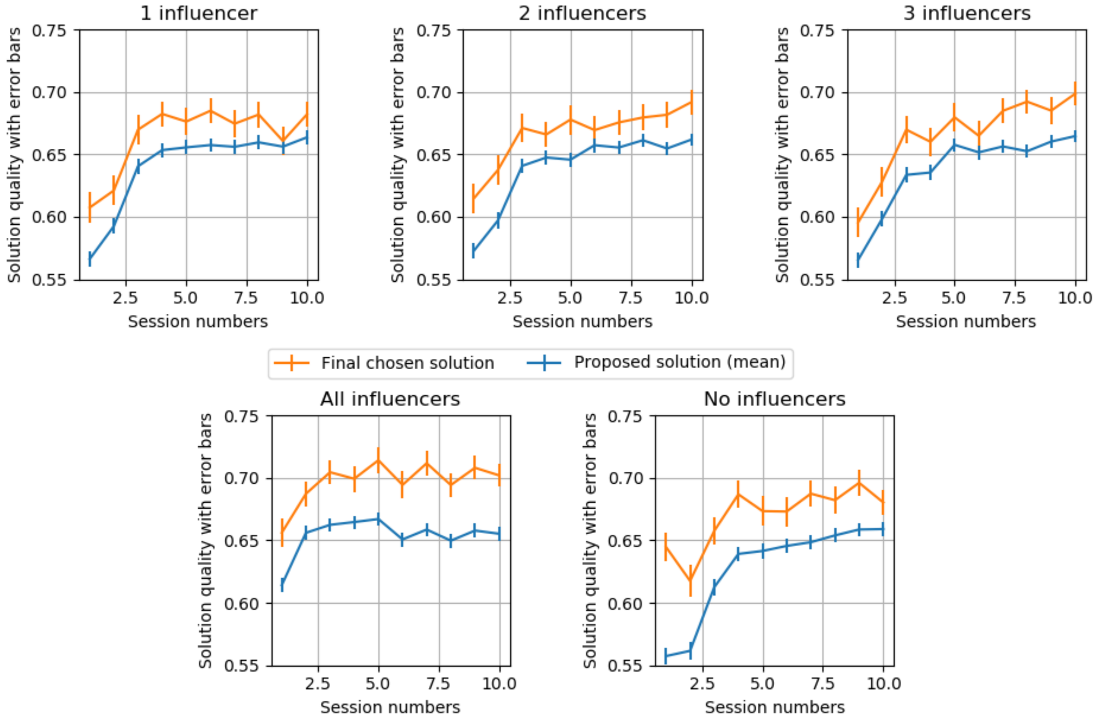



Figure 6- 24 Final solution and the mean value of the proposed solutions by the agents

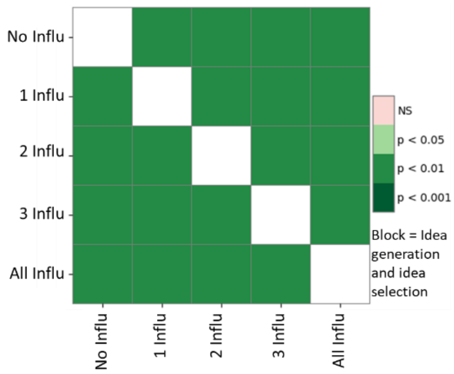



Figure 6- 25 Post hoc Nemenyi Friedman test p-value plot (block = idea generation and idea selection) for the solution quality

On comparing pairwise differences between the solutions generated and selected by various influencer-team compositions during the collaboration design activity (using post hoc Nemenyi Friedman test[10]), all pairs had a p-value <0.01 (Figure 6- 25). This means that agents in the teams with well and not-well defined influencers behave differently during idea generation and selection.

The difference could also be seen in Figure 6- 26 in the diversity of generated solutions by the agents and in the team's proposed final solutions to the controller agent (Kruskal-Wallis H= 1110.02, p<0.001). Teams whose agents had the highest variety when they generated solutions like all influencer teams, had the least variety in their final solutions. While agents in a team with all low self-efficacy had lesser variety in their generated solutions but produced higher variety in their final solutions than the rest of the team compositions. Similar, behaviour could also be seen from agents in the team of 1 influencer. The pairwise difference comparison as seen in Figure 6- 27 shows significant values for all the pairs in the two different blocks (idea generation and selection) and for the various influencer-team compositions. This could be because in general, idea selection results in convergence while idea generation is a divergent process, hence the values of spread in the two processes are expected to differ. However, comparing the individual values of these teams in the two process, highlighted their exploration behaviour.

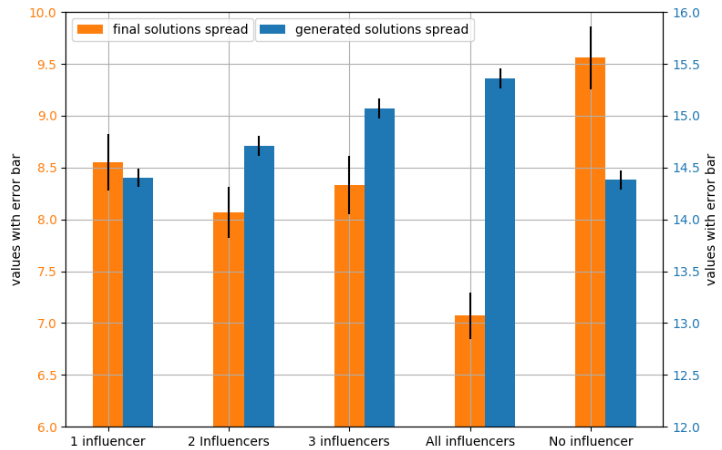



Figure 6- 26 Final solution and the generated solutions diversity comparison

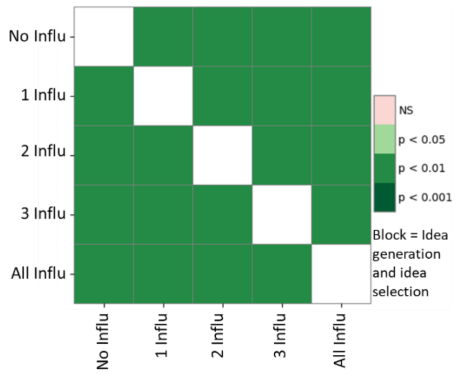



Figure 6- 27 Post hoc Nemenyi Friedman test p-value plot (block = idea generation and idea selection) for the solution spread

## 6.2.2 Varying design peaks and team size with same well-defined influencers

### Set-up

In order to see how team size and the nature of the task might affect the design outcomes of the teams with the same (roughly same as a team with the 3 agents has 1 influencer) ratio of influencers. The cases as seen in Figure 6- 28 consists of small, standard and large teams with design space filled with design peaks and the other with the only single best solution. This was done to chose extreme scenarios ranging from a small team working on a complex design task (i.e., single best solutions hence, the difficulty of finding the only best solutions is more than design space packed with best solutions) to a large team working on an extremely simple design task, while placing well-defined influencers in them.

[10] Block in Nemenyi Friedman test is referred to a blocking factor is also called a nuisance factor, and it is usually a source of variability that needs to be accounted for (https://scikit-posthocs.readthedocs.io/en/latest/tutorial/).

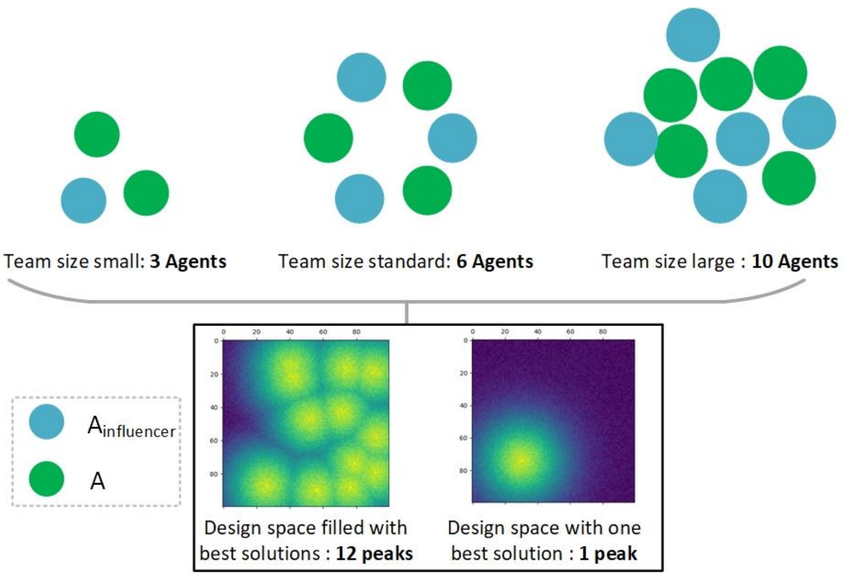



Figure 6- 28 Different cases for simulating influencer effect with varying task and team size

## The impact team size and number of peaks on the design outcomes

*Quality findings*

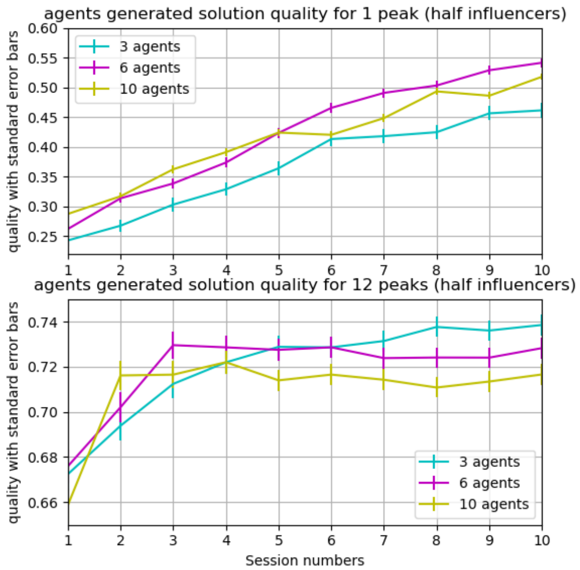



Figure 6- 29 Generated solution quality by the agents in the teams of various sizes

The quality of the solutions generated by the agents in the teams of size 3,6 and 10 Figure 6- 29) differ significantly from each other when working on a least complex design task (i.e., filled with peaks) (ANOVA F= 86.08, p<0.001) as well as on a complex design task (i.e., one peak) (ANOVA F= 24.94, p<0.001). However, in the pairwise analysis (Figure 6- 30 and Figure 6- 31), it could be seen that the team of 3 and 6 agents do not differ significantly in their generated solution quality values when the design task is least complex.

The solutions generated by the lowest self-efficacy agents in these teams (3,6 and 10 agents) behave similarly in their quality scores when the design task is complex (Kruskal-Wallis H= 2.42, p= 0.3). While for a least complex design task, the lowest self-efficacy agents in the teams of various size generated slightly significantly different solutions (Kruskal-Wallis H= 7.43, p= 0.024). This difference is due to the lowest self-efficacy agents in the small and large teams (i.e., 3 and 10 agents) that differ significantly in their solution quality (Figure 6- 32).

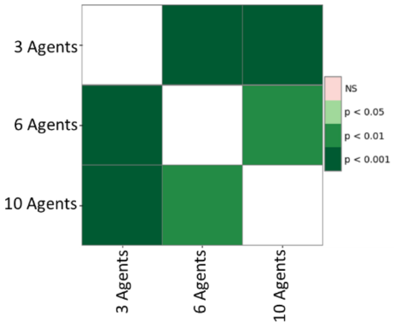



Figure 6- 30 Post hoc pairwise T-test p-value for one peak comparison for the generated solution quality

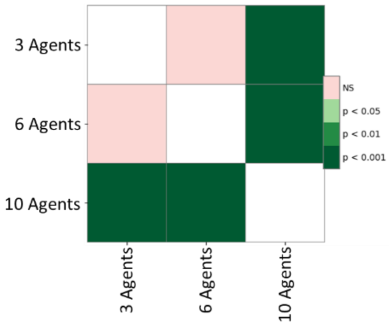



Figure 6- 31 Post hoc pairwise T-test p-value for 12 peaks comparison for the generated solution quality


Figure 6- 32 Post hoc Conover test p-value for 12 peaks for the generated solution quality by the lowest self-efficacy agent

The final solution selected and proposed to the controller agent (or selected by the controller agent when multiple solutions are proposed) could be seen in Figure 6- 33. Though it appears that standard size team (i.e., 6 agents) produce better final solution quality, no significant difference could be found for both 1 (Kruskal-Wallis H= 3.72, p=0.15) and 12 peaks (ANOVA F= 1.17, p= 0.3).

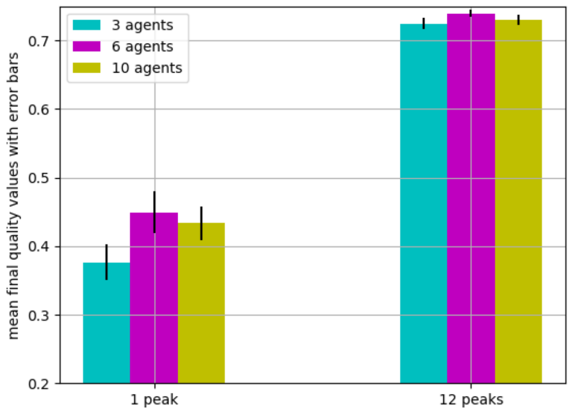



Figure 6- 33 Final solution quality for various team sizes

*Exploration findings*

The exploration rate of the three teams working on the design task with 1 peak and 12 peaks design space could be seen from Figure 6- 34. It could be seen that small teams had a higher exploration rate than very large teams and design space filled with best solutions results in more exploration rate. This means that small teams explore more unique solutions all over the design space even when the design space is packed with the best solutions than large teams. The exploration (EI) of the three teams in 1 peak design (ANOVA F= 334.68, p<0.001) and 12 peaks solution space (Kruskal-Wallis H= 434.27, p<0.001) when generating solutions differ significantly from each other. This means that the agents in the small and larger teams. The pairwise comparison (Figure 6- 35) also showed that the agents in these teams behave differently from each other during exploration, both when the design space has one best solution and when it is filled with the best solutions.

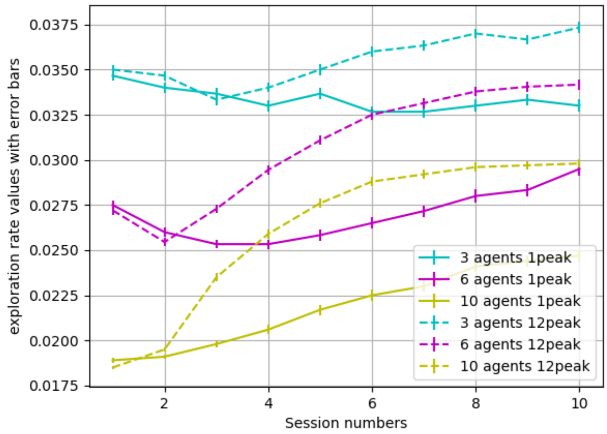



Figure 6- 34 Exploration rate of teams with various sizes on different design space

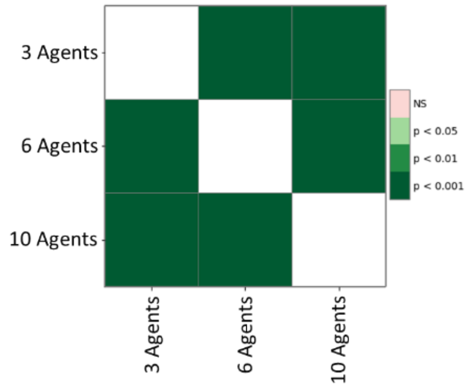



Figure 6- 35 Post hoc p-value plot (pairwise T-test for 1 peak and Conover test for 12 peaks) comparison for the EI of the generated solutions

The diversity in the final solutions (Figure 6- 36) that were proposed to the controller agent by the team of 3,6 and 10 agents, differed significantly from each both the case of 1 peak (Kruskal-Wallis H= 29.83, p<0.001) and 12 peaks (ANOVA F= 11.38, p<0.001) design space. Small teams tend to produce more variety in their proposed solutions than other team sizes. When performing the pairwise comparison (Figure 6- 37), it could be seen that the diversity in the proposed solutions for the teams with 6 and 10 agents was not significantly different from each other, while small team behaviour during idea selection differs significantly from the others.

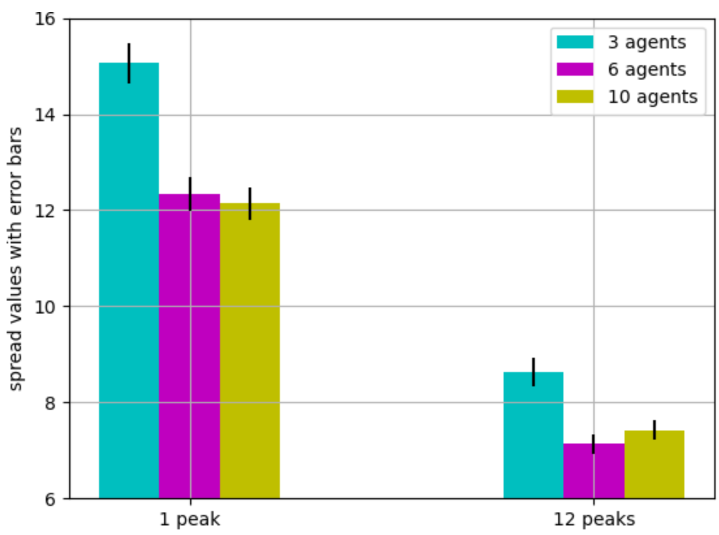



Figure 6- 36 Spread of the final proposed solutions to the controller agent for different team size and design space

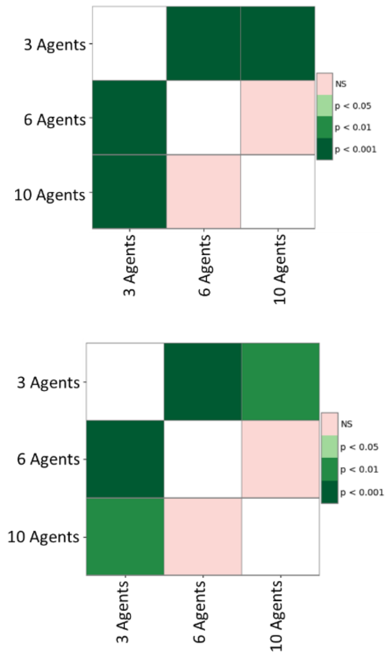



Figure 6- 37 Post hoc p-value plot (Conover test for 1 peaks Top and pairwise T-test for 12 peaks Bottom ) comparison for the spread of the final solutions

The contribution of agents in the teams of different sizes with a similar ratio of influencer agents for the two design tasks (extremely simple and very complex task) could be seen from

Figure 6- 38. It could be seen that teams working on a complex design task (i.e., 1 peak) had a more uniform contribution by their team members than the teams working on a very simple design task (i.e., 12 peaks). In general, in standard size teams (in this case 6 agent teams), some agents tended to contribute more, hence more distribution value than the teams with 3 or 10 agents. The distribution contribution in all the cases differed significantly (Kruskal-Wallis H= 58.99 $p<0.001$) and the pairwise difference comparison could be seen from Figure 6- 39.

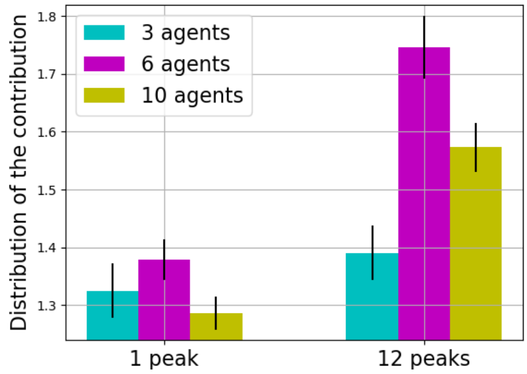



Figure 6- 38 Contribution distribution for different team size and design space

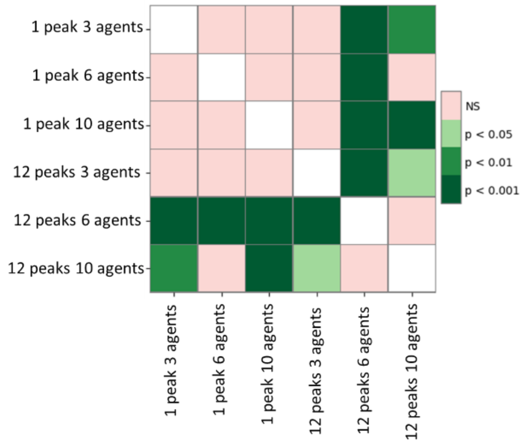



Figure 6- 39 Post hoc Conover test p-value comparison for the contribution distribution for different peaks and team size

It could be seen from Figure 6- 39 that the contribution by the agents in the teams working on a complex task did not differ significantly from each other. In the case of a very simple design task, the contribution by the agents in very small teams differ significantly from those with 6 and 10 agents. The contribution by the agents in large teams did not differ significantly from the teams with 6 agents for both simple and complex tasks.

## 6.3 Answers to the research question 2

### 6.3.1 Varying the number of experienced agents and number of peaks

**Set-up**

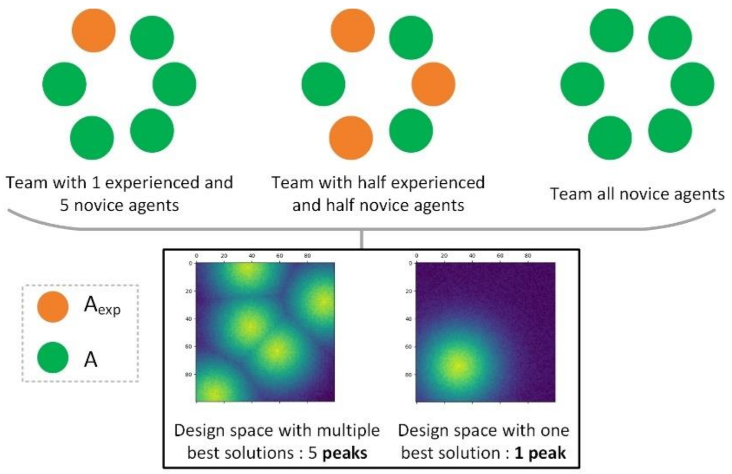



Figure 6- 40 Different cases for simulating different experienced-novice team composition with two types of the design task

To explore research question 2, three scenarios were framed and tested (Figure 6- 40). The first scenario tested the situation when the team has only one experience agent with novices. The second case is when half of the team is experienced and the other half is a novice, and the last case is when all the agents in a team are novices. All of the novice agents have similar self-efficacy when they start working on a design task while the experienced agents have higher self-efficacy.

## The impact of experienced- novice agents on the design outcome

*Quality findings*

The solutions generated by agents in the different experienced-novice agent team compositions could be seen in Figure 6- 41. In the case of a complex design task (i.e., one peak), agents in the team with 3 experienced agents produced the highest solution quality throughout the sessions, while all new agents produce the least. The generated solution quality by these team compositions for 1 peak design space significantly differ from each other (ANOVA F= 3807.27, p<0.001). When the design task was moderately complex (i.e., 5 peaks), the solutions generated by agents in the teams of 3,1 and no experienced agent in them, differ significantly (ANOVA F= 473.07, p<0.001). It could be seen that the generated solution quality becomes stable after some sessions when experienced agents are present in the teams, while for all new agent teams, it gradually increases. The pairwise comparison in Figure 6- 42 also showed that the agents in teams with 3,1 and no experienced agent in them differ significantly from each other when working on a design task with a single peak and 5 peaks. However, agents in the teams of 3 and 1 experienced agent have a lesser significant difference in their generated solution quality than with all new agent teams when working on a moderately complex task (Figure 6- 42 bottom).

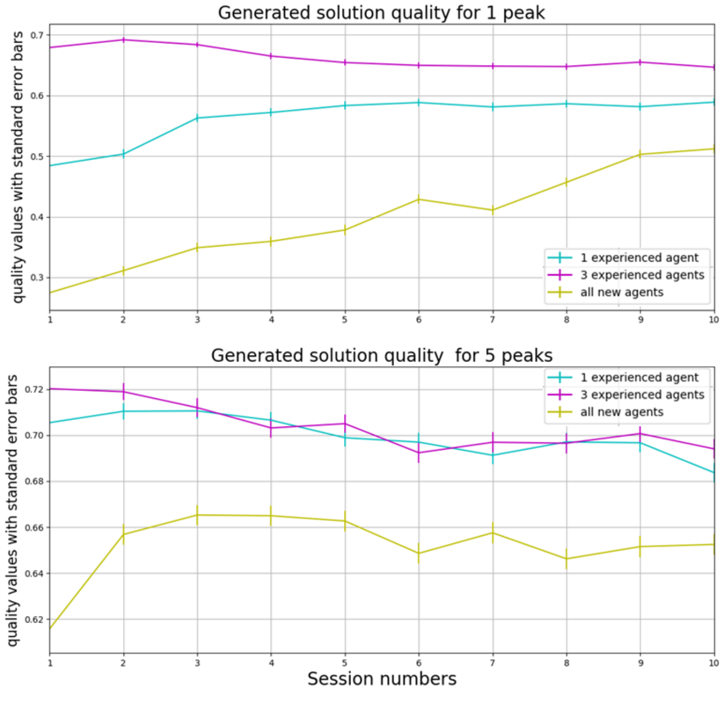



Figure 6- 41 Generated solution quality for different experienced- novice team compositions

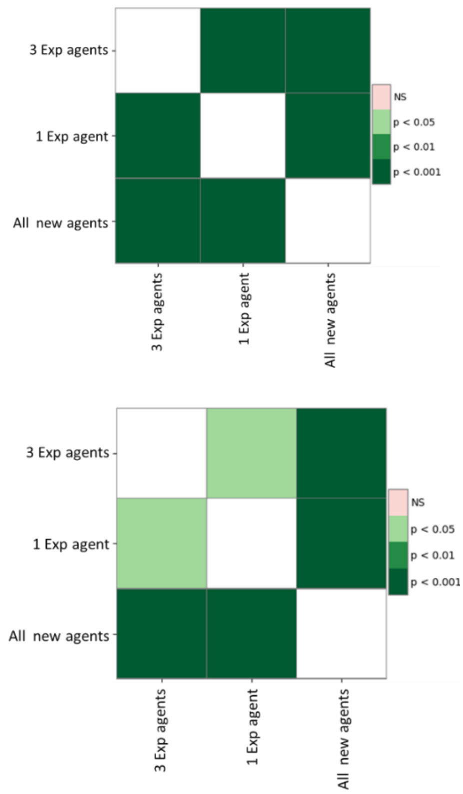



Figure 6- 42 Post hoc pairwise T-test p-value for 1 peak (Top) and 5 peaks (Bottom) comparison for the generated solution quality

The final solution that was selected by the team and proposed to the controller agent (or selected by the controller agent when multiple solutions were proposed), could be seen in

Figure 6- 43. Teams with 3 experienced agents produced the highest final solution quality for both 1 and 5 peaks while all novice agent teams had the least. The final solution quality by all the team composition significantly differ from each other (Kruskal-Wallis H= 25.06, p<0.001 for 1 peak and H= 20.31, p<0.001 for 5 peaks). The pairwise comparison (Figure 6- 44) also showed that the teams with a different number of experienced agents and all novice agents differ significantly in their solutions. The difference in the final solution quality between the 1 and 3 experienced agent teams for multiple solution design space was lesser than with all novice agent teams (Figure 6- 44 bottom).

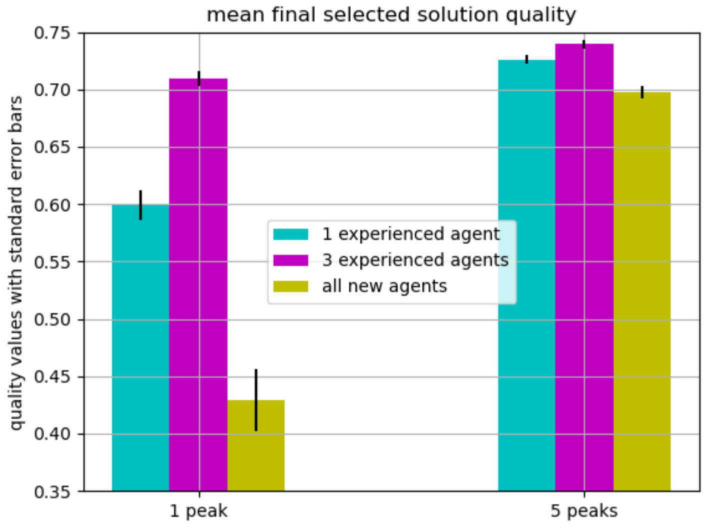



Figure 6- 43 Overall final solution quality for one best solution and multiple best solution problems

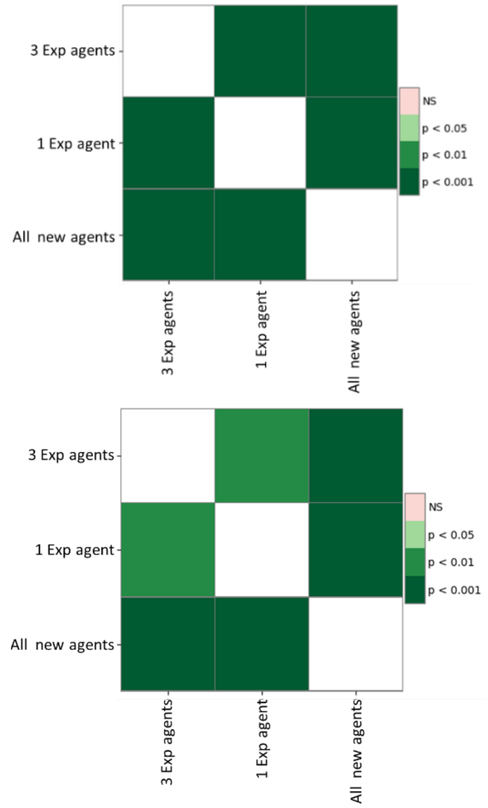



Figure 6- 44 Post hoc Conover test p-value plot for 1 peak (Top) and 5 peaks (Bottom) comparison for the final solution quality

*Exploration findings*

Figure 6- 45 shows the exploration index when agents were generating solutions. It could be seen that the teams with experienced agents in them (1 and 3 experienced agents) had a lesser exploration index when there was only one best solution than multiple best solutions. Teams with all novice agents explore more when the task is more complex (i.e., one best solution present). In the case of moderately complex task (i.e., the task with multiple best solutions), teams of experienced agents (especially, 3 experienced agents and 3 novice agent team), explore the most, while all novice agent teams explore the least. The EI of all the teams significantly differ from each other (Kruskal-Wallis H= 44.4, p<0.001 for 1 peak and H= 160.75, p<0.001 for 5 peaks). However from the pairwise comparison of the difference in the EI in Figure 6- 46 showed that teams with 1 and 3 experienced agents in them, showed no significant difference in their EI than with all novice agent team when working on a complex task (Figure 6- 46 top). The pairwise difference in the EI values for all the team combinations is quite significant for a moderately complex task (Figure 6- 46 bottom).

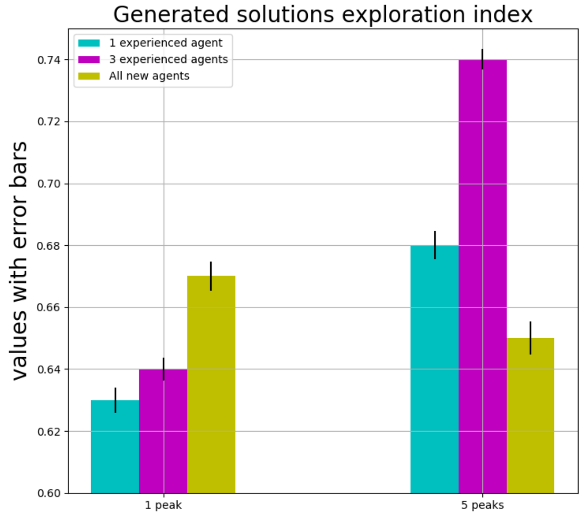



Figure 6- 45 Exploration Index for of the generated solutions for 1 and 5 peaks

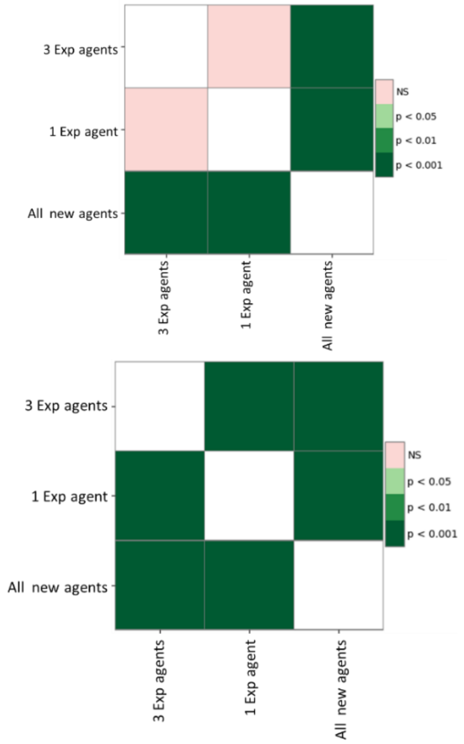



Figure 6- 46 Post hoc Conover test p-value plot for 1 peak (Top) and 5 peaks (Bottom) comparison for the generated solution EI

Although the agents in the teams explore the design space while generating solutions, it is not necessary that they have a high variety in their final proposed solutions. It could be seen from Figure 6- 47 that in general, the spread values for 5 peaks were lesser than one peak design space. Figure 6- 47 also shows that all novice agent teams had the highest variety in their proposed solutions when the task was complex (i.e., 1 peak). The team with the one experienced agent had more diversity in their solutions than the team with three experienced agents for a complex task. A more significant difference could be seen in the team behaviour when selecting the final solution for the design task with a single best solution (Kruskal-Wallis H= 117.25, p<0.001) than that with multiple solutions (Kruskal-Wallis H= 0.81, p= 0.67). The pairwise comparison for the spread values (Figure 6- 48) showed that teams with experienced agents behave differently in their final solution diversity than the team with all novice agents. However, the difference in the diversity of final solutions is less significant for the team with 1 and 3 experienced agents.

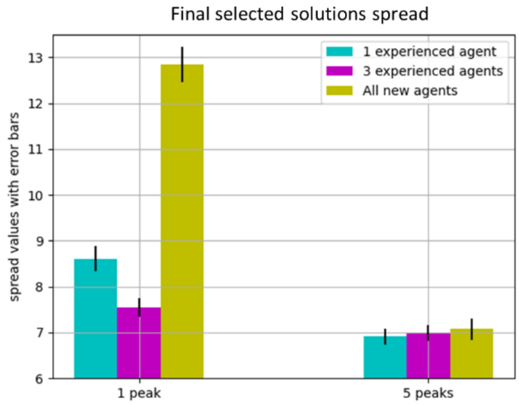



Figure 6- 47 Spread of the final proposed solutions for 1 and 5 peaks

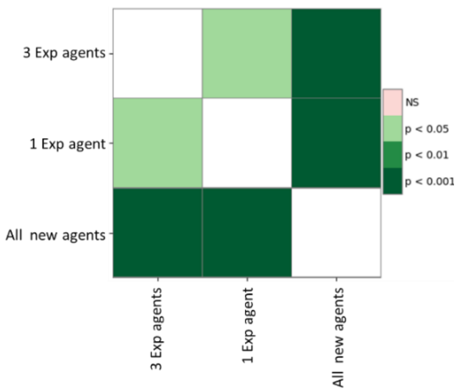



Figure 6- 48 Post hoc Conover test p-value plot for 1 peak comparison for the final solution diversity

The contribution by the agents in the two team compositions working on different tasks could be seen from Figure 6- 49. In general, the distribution of the contribution differed significantly (Kruskal-Wallis H= 70.55 p<0.001), but from the pairwise difference comparison (Figure 6- 50), it could be seen that the contribution by agents in the teams with experienced agents (1 or 3) did not differ significantly from each other except the teams of all new agents. Only some agents in the teams with experienced agents continuously proposed solutions, hence high distribution value than the teams of all new agents.

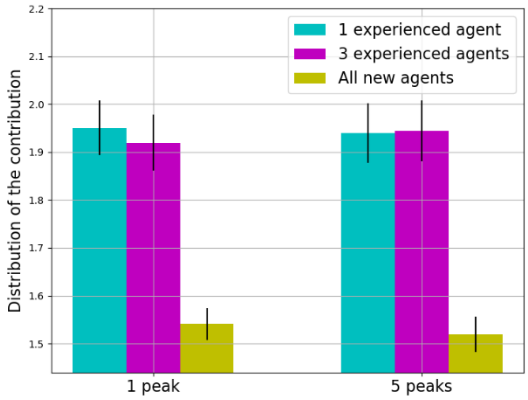



Figure 6- 49 Contribution distribution for different team composition and design space peaks

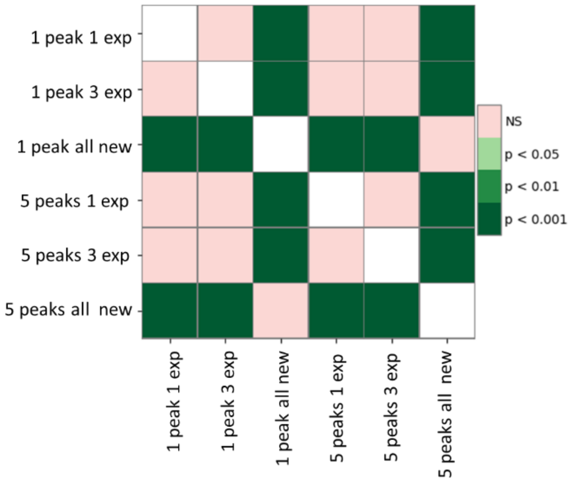



Figure 6- 50 Post hoc Conover test p-value comparison for the contribution distribution for different peaks

## 6.3.2 An experienced agent with routine and non-routine experience

In the above cases, the experienced agent was familiar with the design task (i.e., the agents gained their experience by working on a task similar to the current task). The results from the case where the experienced agent is placed in a team that works on a slightly different (unfamiliar) design task are given below in this section.

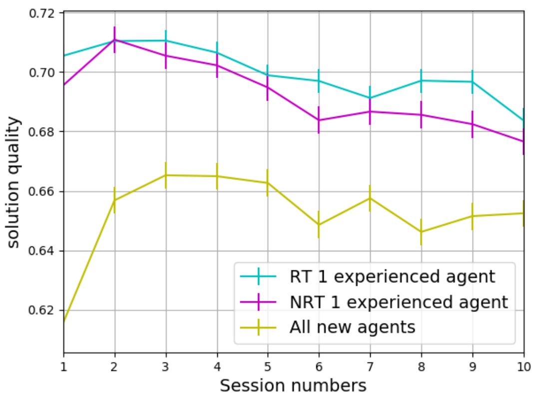



Figure 6- 51 Session wise generated solution quality for RT, NRT and all new agents


Figure 6- 52 Post hoc pairwise T-test p-value comparison for the generated solution quality

The quality of the solutions generated by the agents for a moderately complex task (i.e., 5 peaks) in the team of agents with one experienced agent who is working on a non-routine task (NRT), one experienced agent who is working on a routine task (RT) and a team of all novice agents show that they behave differently (ANOVA F= 397.57, p <0.001) could be seen in Figure 6- 51. As expected, the agents in the team with an experienced agent who is working on a familiar task (RT), generated better solution quality than the NRT agent team throughout the sessions. However, the quality of their solutions seems to be decreasing after mid-session. The pairwise comparison plot in Figure 6- 52 also shows that these agents in these teams behave differently from each other when generating solutions.

The exploration values of the generated solutions could be seen in Figure 6- 53. The exploration index values differed significantly (Kruskal-Wallis H= 19.25, p<0.001). However, the pairwise difference comparison for the exploration index was not significant for NRT and RT experienced agent teams (Figure 6- 54 top). The difference in the EI value for the NRT experienced agent team and the all new agent teams were lesser than all new agent teams and RT experienced agent team. Similar to the generated solution quality, EQI values also differed significantly (ANOVA F= 161.57 p<0.001). The pairwise difference comparison plot in Figure 6- 54 (bottom), also shows that all the pairs had p<0.001.

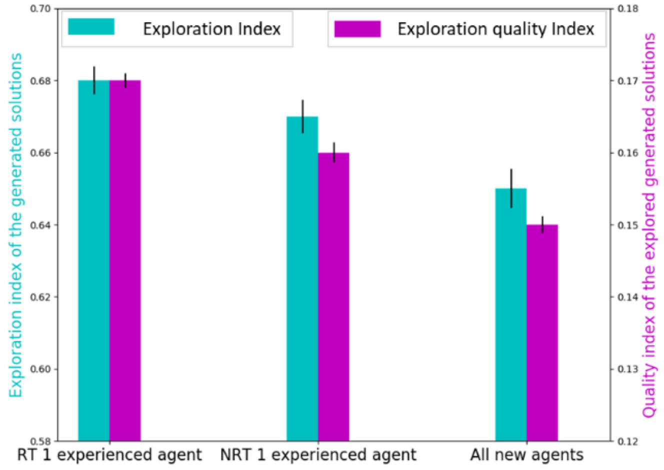



Figure 6- 53 Exploration Index and exploration quality index for of the generated solutions for RT, NRT and all new agents

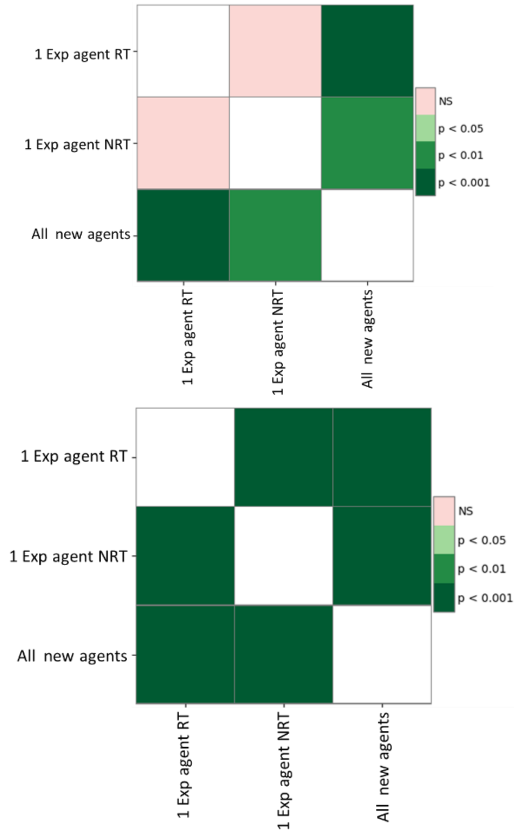



Figure 6- 54 Post hoc p-value plot with Conover test for EI (Top) and pairwise T-test for EQI (Bottom) for the exploration values of the generated solutions

The mean final solutions quality on which the teams received feedback from the controller agent could be seen in Figure 6- 55. The final solutions quality for the three teams differed significantly (Kruskal-Wallis H= 15.24, p<0.001). This difference was clarified through the pairwise comparison (Figure 6- 56). It appears that a team where the experienced agent was familiar with the design task produced better final solution quality, but no significant difference was found with respect to the teams where the experienced agent was not familiar with the design task. Nevertheless, both the teams with an experienced agent (RT and NRT) produced better final solution quality than the all novice agent team. The spread of the final solutions (Figure 6- 55) for these did not differ significantly (ANOVA F= 0.128, p=0.87).

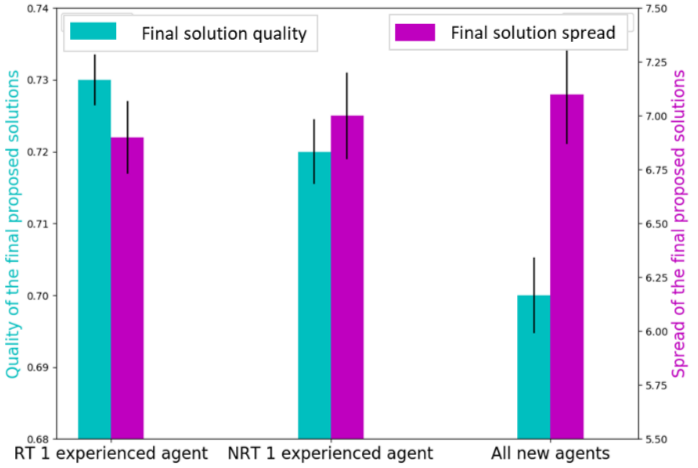



Figure 6- 55 Solution quality and the diversity in the quality of the final solution for RT, NRT and all new agents teams

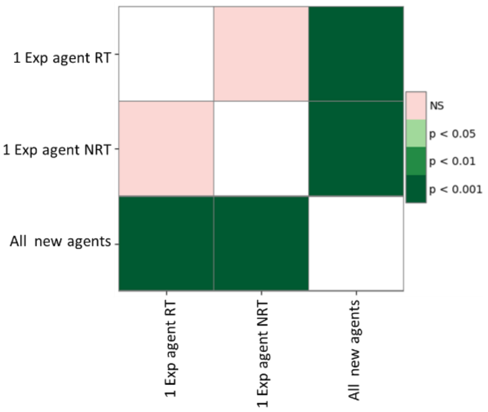



Figure 6- 56 Post hoc Conover test p-value comparison for the final solution quality

## 6.3.3 Varying the task complexity in terms of peak curvature

### Set-up

The curvature of the peaks represents the ease of refining the best solution. Thus, for the steeper peaks (for the same number of peaks), it is more challenging to find an above-average solution in the vicinity of the best solution. On the contrary, curved peaks have more above-average solutions surrounding the best solutions. The mixed peaks, however, have some peaks that are steep (some best solutions that have fewer above-average solutions surrounding them) and some peaks that are curved (some best solutions that have several above-average solutions surrounding them). In order to see the effect of different curvatures of the peaks while having an experienced agent in a team on the design outcome, the cases shown in Figure 6- 57 were designed. The curvature of the peaks was regulated by controlling the landscape function *f(x)* in Equation 1. This was done by modulating the distance *D* that represents the distance between the random point (*x1*,*x2*) and the nearest best solutions. For example, *D-2* was used for standard peaks, while *D-3* and *D-1* resulted in curved and steep peaks. By using *D-3* for some and *D-1* for the other best solutions, a design space with mixed peaks was obtained.

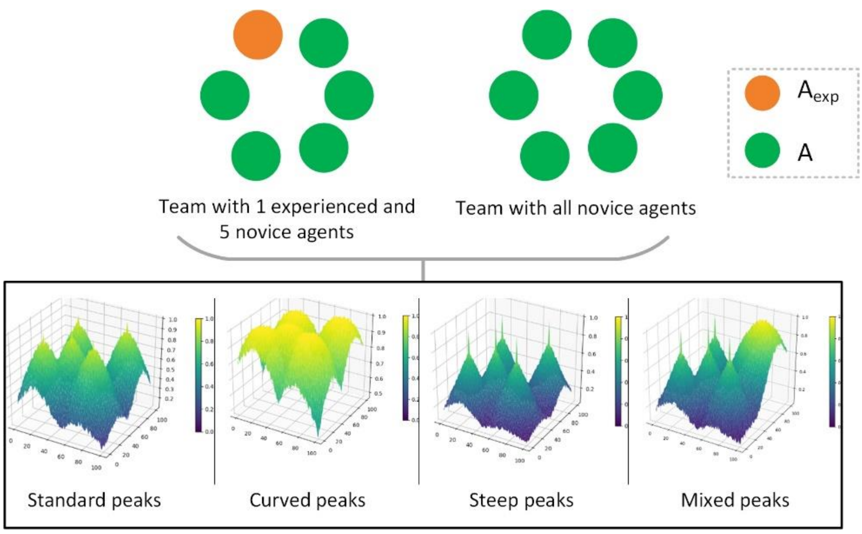



Figure 6- 57 Different cases for simulating the effect of peak curvature with experienced and non-experienced agent teams

### Team collaboration (i.e., virtual and face-to-face) affecting design outcomes

*Quality findings*

As seen from the above section that having an experienced agent in a team increases the quality of the generated solutions. Similarly, from Figure 6- 58 it could be seen that the experienced agent teams in various types of design peak curvatures, produce better solution quality than the agents in the teams of all novice agents. It could be seen that when the design task is less complex (i.e., easy to refine, with curved peaks), the solution quality becomes stable. While in the complex tasks (i.e., hard to refine, steep peaks) the solution quality increases gradually. The teams in mixed peak case showed in-between behaviour (i.e., the solution quality increases and then becomes stable after mid-session). As expected, the solutions generated by agents have higher quality values for curved than steep peaks, while mixed and standard peaks generated in-between values. The generated solution qualities of the two teams in the four peak conditions significantly differed from each other (ANOVA F= 9769, $p<0.001$) and could be seen in Figure 6- 59.

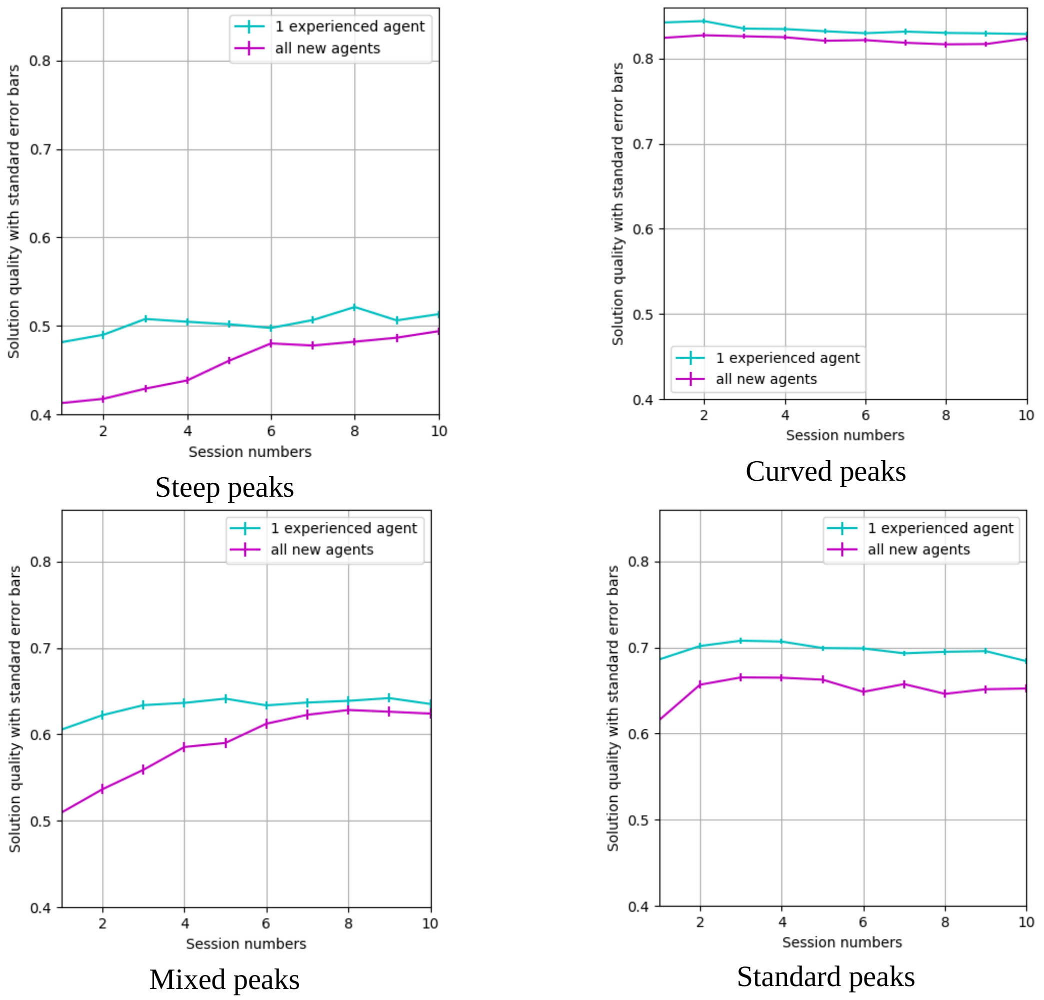



Figure 6- 58 Generated solution quality for different curvature peaks

The final solution that was selected and proposed to the controller agent (or selected by the controller agent when multiple solutions were proposed) by the teams and on which they received feedback at the end of every session, for the design task with different peaks, could be seen from Figure 6- 60. Similar to the generated solutions, a team with an experienced agent in them in all the design peak conditions had better mean final solution quality than all novice teams. The difference in the final solution quality was significant (Kruskal-Wallis H= 76.26, p<0.001) and could also be seen from Figure 6- 59.

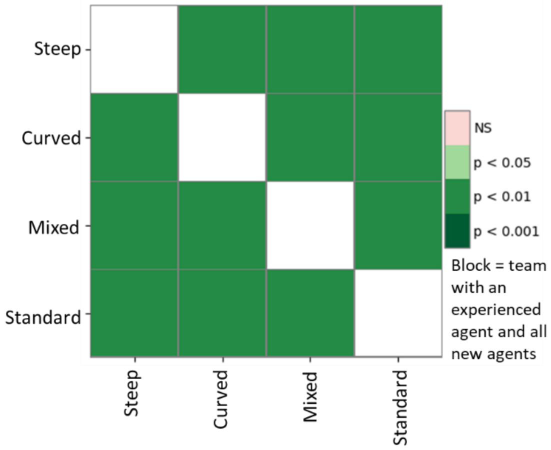



Figure 6- 59 Post hoc Nemenyi Friedman test p-value plot (block = experienced agent in a team) for the generated and selected solution quality for different peak curvatures

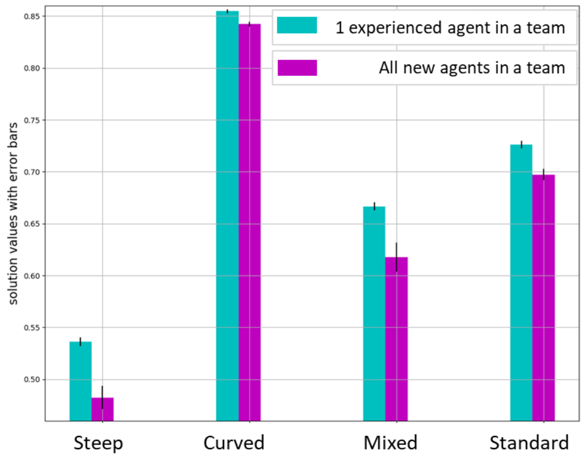



Figure 6- 60 Mean final solution quality for different peak curvatures

*Exploration findings*

The session-wise exploration (

Figure 6- 61) was more when the design space had curved peaks and least for steep peaks. In general, it could be seen that teams with all new agents explore less in each session than teams with an experienced agent in them. The exploration index (EI) for these teams for different design task peak configurations differed significantly (Kruskal-Wallis H= 320.94, p<0.001). From the pairwise difference comparison in Figure 6- 62, it could be seen that the EI for mixed peaks did not differ significantly for experienced and all novice agent teams. The exploration style for mixed and steep peaks as well as for standard and curved peaks of a team with an experienced agent in it did not differ significantly. All new agent teams, on the other hand, did not differ significantly in the exploration behaviour for steep and curved design space.

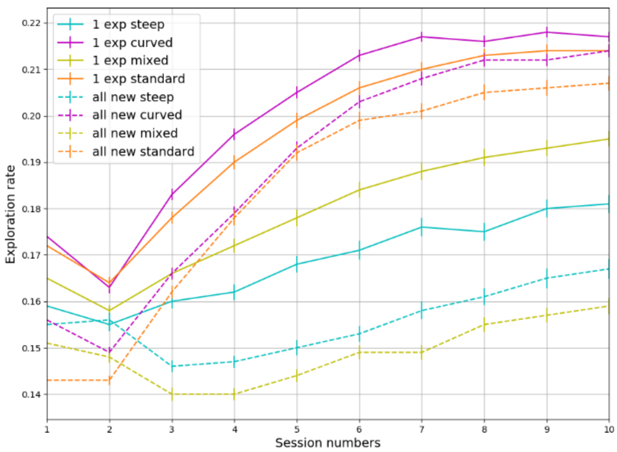



Figure 6- 61 Session-wise exploration rate for different peak curvatures

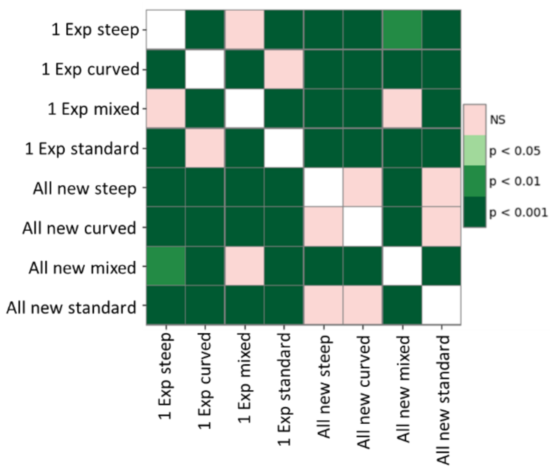



Figure 6- 62 Post hoc Conover test p-value comparison for the generated solution EI for different peaks

However, the exploration quality index (EQI) in Figure 6- 63 differed significantly (Kruskal-Wallis H= 877.27 p<0.001), where teams with an experienced agent had better EQI values. The pairwise difference comparison in Figure 6- 64 shows that the EQI for curved peak configuration did not differ significantly for the teams with and without an experienced agent. The EQI for standard and mixed peaks for teams with an experienced agent in it had no significant difference.

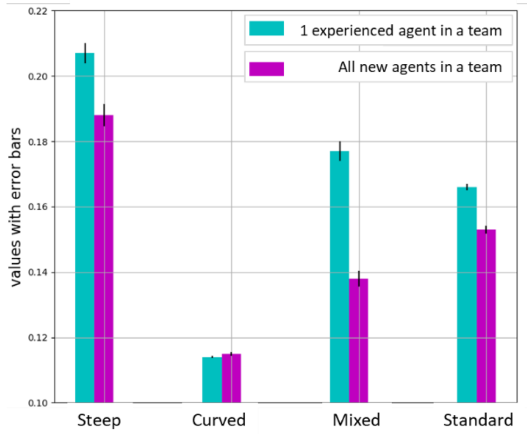



Figure 6- 63 EQI for both the teams for different design space peak configuration

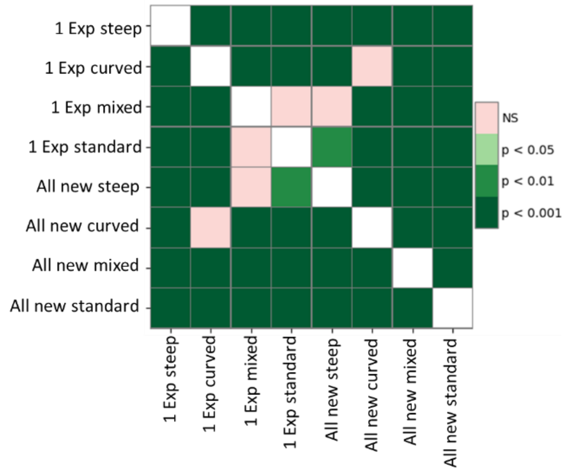



Figure 6- 64 Post hoc Conover test p-value comparison for the generated solution EQI for different peaks

The final solution diversity as seen from Figure 6- 65 was more for the all new agent teams for hard to refined design task (steep peaks ) and for mixed peak design task. When the design task was less challenging to refine (curved peaks), a team with an experienced agent in it, had better diversity. In general, the spread values differed significantly (Kruskal-Wallis H= 185.82, p<0.001). The pairwise difference comparison (Figure 6- 66) shows that teams with and without an experienced agent differ significantly in their final solution diversity for all the design peak configurations except for the standard peaks. The diversity in the solutions of teams with an experienced agent for various peak curvatures was not significantly different. While all new agents teams differed in the diversity of their final solutions for all the peak configurations except for the curved and standard peak curvatures.

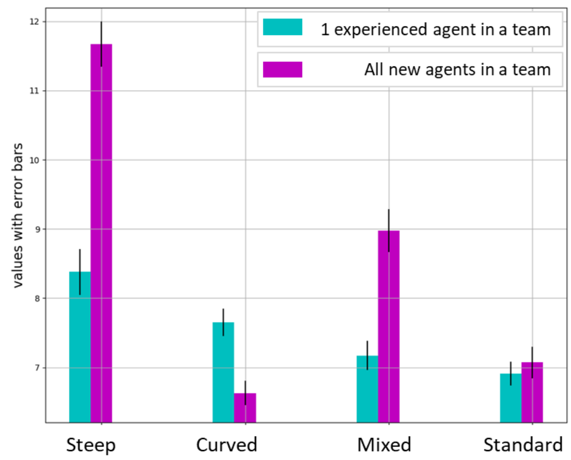



Figure 6- 65 Spread values for both the teams for different design space peak configuration

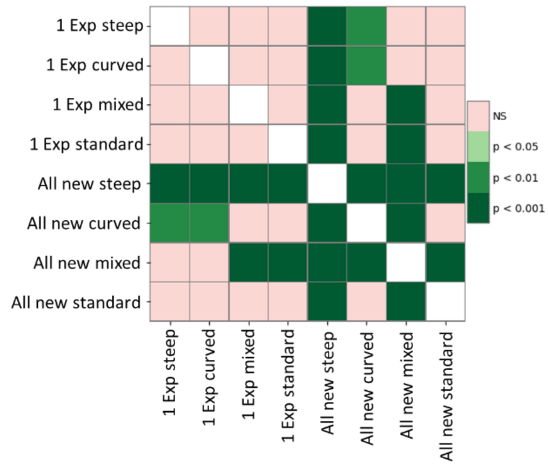



Figure 6- 66 Post hoc Conover test p-value comparison for the final solution diversity for different peaks

## 6.4 Answers to the research question 3

### 6.4.1 Team collaboration mode

**Set-up**

In order to assess the impact of collaboration mode (face-to-face and virtual) on design outcomes, the cases shown and described in Figure 6- 67 were simulated through the model. These test cases were considered based on recommendations by Powell et al.(2004) where issues related to input, output, task and socio-emotional processes during an early virtual team collaboration were identified (Powell et al., 2004). As such, the cases used here represent common design team collaboration conditions. For example, the first test case as seen in Figure 6- 67 consists of a very common scenario where a design team has one experienced individual in it. It would be interesting to see how the team in the first test case would function in different collaborating modes. Similarly, cases like the second and third simulate other commonly observed scenarios where the distribution of social influence (because of one's confidence and trust level) results in influencers. The fourth case sees the changes due to the design task with respect to the collaboration mode. The above test cases were simulated for virtual and face-to-face collaboration scenarios where the extremes were considered (i.e., the degree of team virtuality was maximum and technology mediation was bad with pure face-to-face collaboration) to observe more variation.

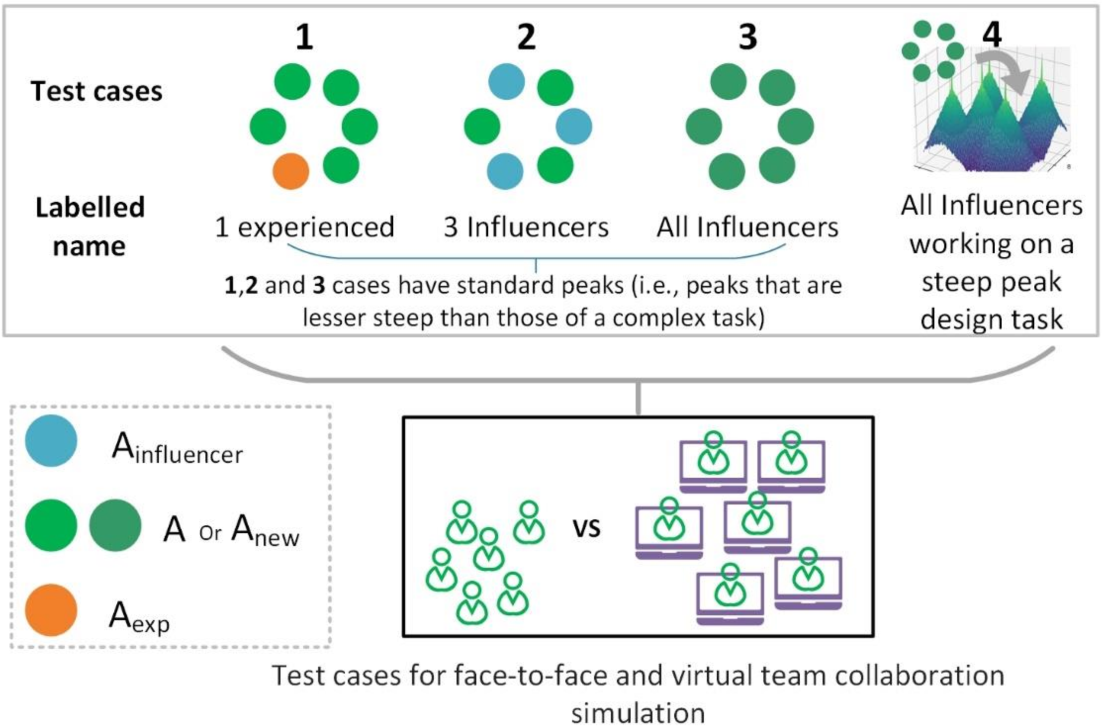



Figure 6- 67 Simulated test cases

## Team collaboration (i.e., virtual and face-to-face) affecting design outcomes

*Generated solution quality findings*

The simulation results related to the quality of the solutions generated by agents in the teams (of the 4 tested cases shown in Figure 6- 67) in the two collaboration modes differed significantly from each other (ANOVA $F= 5416.44$, $p <0.001$). The session-wise difference in the individual agents' generated solution quality in cases that were tested was lesser in virtual than face-to-face team collaboration (Figure 6- 68). The minor changes can be observed from Figure 6- 68 in the session-wise behaviour related to the generated quality of agents in all influencer teams both in virtual and face-to-face collaboration mode. Agents in an all-influencer team generate slightly higher solution quality when in virtual collaboration mode. As expected from the agents in the all- influencer teams in steep peak design space configuration produced the least solution quality (due to the nature of the design task). The session-wise difference in the behaviour of agents in the all-influencer teams when generating solutions to a design problem that is difficult to refine (i.e., all influencer in steep peaks) in both virtual and face-to-face collaboration is also trivial. One possible reason could be the similar state of agents (i.e., similar self-efficacy among all of them), which resulted in similar behaviour in individual agents when generating solutions. It could be inferred that if all individuals in a team are equally confident, the mode of collaboration does not have a significant effect on individual agents' idea generation quality

*Generated solution exploration findings*

The generated solution quality of the individual agents who have different cognitive state (i.e., unequal distribution of self-efficacy) in teams, is more diverse in both the collaboration mode. As expected, the agents in teams with one influencing agent who is also experienced, generate better solution quality than all other tested cases and this difference is significant when the teams are collaborating face-to-face. In general, virtual team collaboration might be more effective when the influencing power is in half of the team members (3 influencers) than face-to-face. While the opposite might be true when there is an experienced individual in a team.

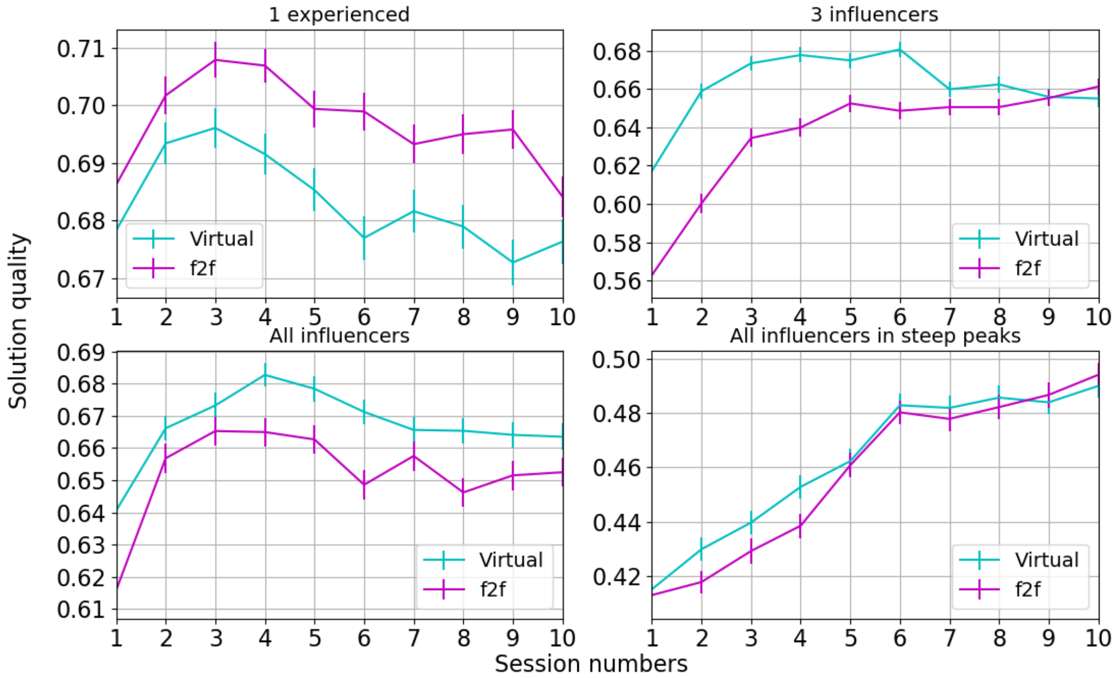



Figure 6- 68 Session-wise generated solution quality

The teams in the tested cases show different session-wise exploration rate patterns (Figure 6-69). Exploration rate can be defined as the number of unique solutions explored during a session. It can be seen that all influencer team's exploration rate increases drastically after initial sessions till mid-project and then plateaus for face-to-face collaboration. While in the virtual collaboration it gradually increases after initial sessions till the end of the project. For all influencer team in steep design space (i.e., complex design task) session-wise exploration rate in virtual collaboration decreases till the middle of the design project and then gradually increases later.

The session-wise exploration rate for teams with a well-defined one experienced influencer is higher (both in virtual and face-to-face) than other team compositions as the experienced agent knows which areas are safe to explore (Figure 6- 69). In general, a team with an experienced agent when collaborating virtually explores less towards the end of a project than when face-to-face. On the other hand, the team where half of the agents had higher self-efficacy than the others (3 influencers) explored the design space more when collaborating virtually. Another interesting thing to notice in the exploration rate is the similarity between the 3 influencers and all influencers team in the virtual collaboration after a few initial sessions. This behaviour requires further investigation.

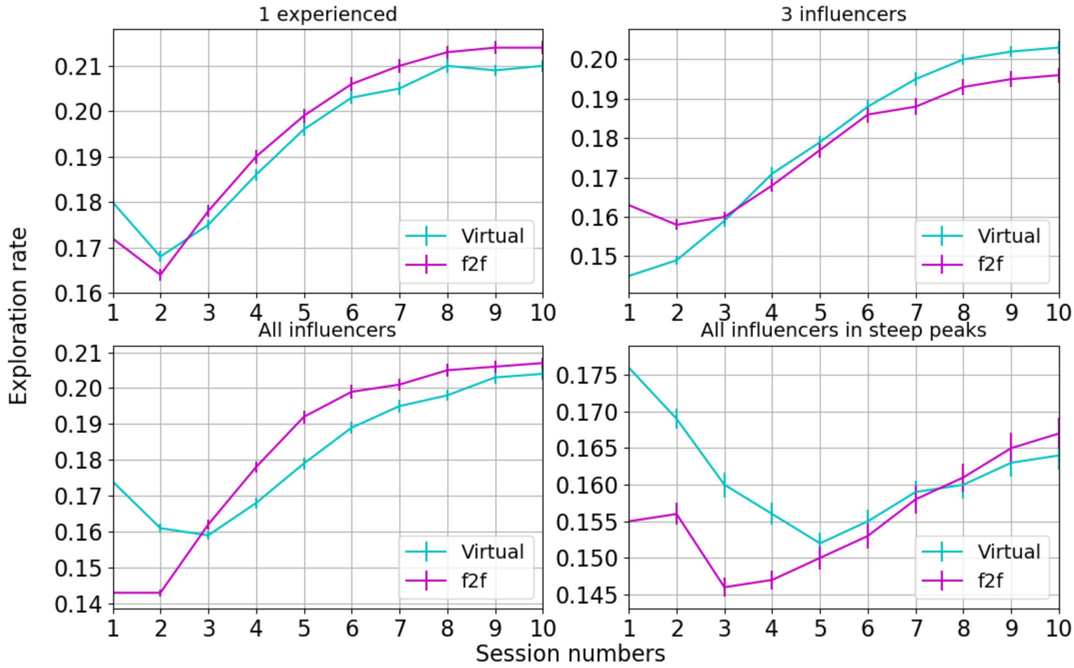



Figure 6- 69 Session-wise solution exploration rate

The exploration index (*EI*) and the exploration quality index (*EQI*) are seen in Figure 6- 70 and Figure 6- 71. It can be seen that the EI (Figure 6- 70) of the teams with 3 and all influencers differ significantly in two collaboration modes, where face-to-face collaboration had more exploration of the design space. While the teams with a well-defined one influencer with past experience (1 experienced) and teams working on a complex design task (All influencer in steep peaks) show a less significant difference in their exploration with respect to the collaboration environment. Figure 6- 71 (right) shows a significant difference in EQI values of all the team compositions in the two collaboration modes except teams working on a complex task. For a simple design task (design task with less steep peaks), face-to-face team collaboration results in a better quality of the explored solutions than virtual team collaboration.

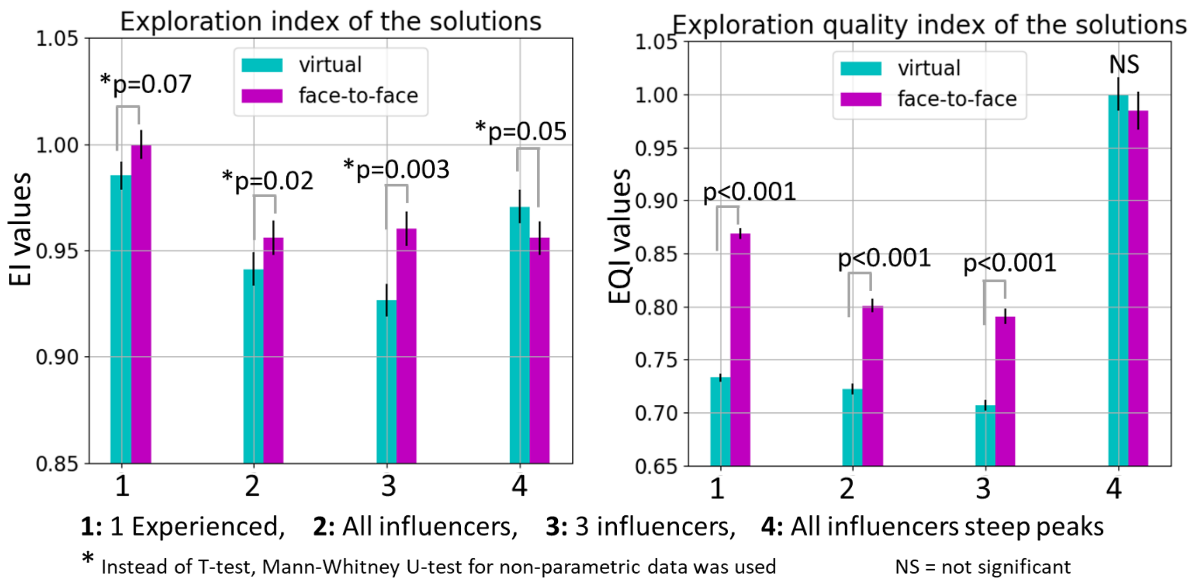



Figure 6- 70 Mean values of exploration index of the generated solutions

Figure 6- 71 Mean values of exploration quality index of the generated solutions

*Final solution findings*

Figure 6- 72 shows the bubble plot where the size of the bubble is defined by the number of times a team proposed single or multiple solutions to the controller agent and the quality of these solutions. Similar to the real design session as described in the idea selection that a team in the model could propose one (as in v one or f2f one) or multiple solutions (as in v multiple or f2f multiple) to the controller agent when the desired team agreement on a single solution is not reached. It can be seen from Figure 6- 72 that multiple solutions (in this case 3) when proposed to the controller agent results in better solution quality feedback in the teams of well-defined influencers (i.e., 3 influencers and 1 experience agent in a team). A team with 3 influencers has better solution quality of the multiple solutions when collaborating virtually. Having 3 influencers in a team results in more single solutions of lower quality when collaborating face-to-face. While 1 experience agent in a team proposes multiple better quality solutions when collaborating face-to-face.

From Figure 6- 72 a more distinct behaviour of teams with all agents having similar self-efficacy (i.e., all influencers) can be seen than those of the well-defined influencers. All influencer teams produce similar quality when proposing multiple solutions either virtually or face-to-face. These teams when working on a difficult design task (i.e., steep slopes where the solutions are hard to refine) show a slight difference in the quality where proposed multiple solutions in virtual mode have better quality.

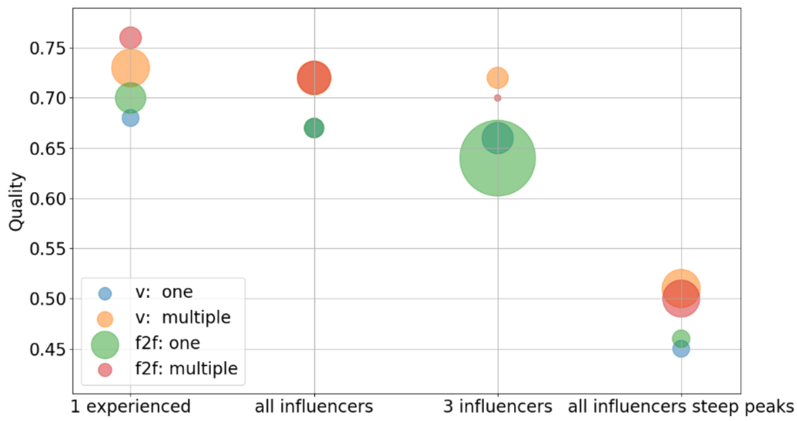



Figure 6- 72 A bubble plot showing the number of times 1 or multiple solutions (size of the dots) were proposed by a team and their respective quality (position on the vertical axis)

The evaluation of the final solutions that were proposed by the teams to the controller agents in terms of quality and diversity (spread) in them can be seen in Figure 6- 73 and Figure 6- 74. Similar to the generated solutions, no significant difference can be seen in the quality of the final solutions proposed (Figure 6- 73) by a team having similar self-efficacy (i.e., all influencers) in the two collaboration modes. This difference is also insignificant when the agents in all influencers teamwork on a complex design task. However, a significant difference can be seen in the teams with well-defined influencers. Teams with an experienced agent result in better solution quality when working face-to-face while those with half influencers produce better quality when working virtually.

The diversity in the proposed solutions by the teams (Figure 6- 74) differ significantly for the teams with well-defined influencers (1 experienced and 3 influencers teams), where face-to-face collaboration results in more spread. No or low significant difference can be seen in the spread values for the teams with no well-defined influencers (all influencers) when working virtually or face-to-face.

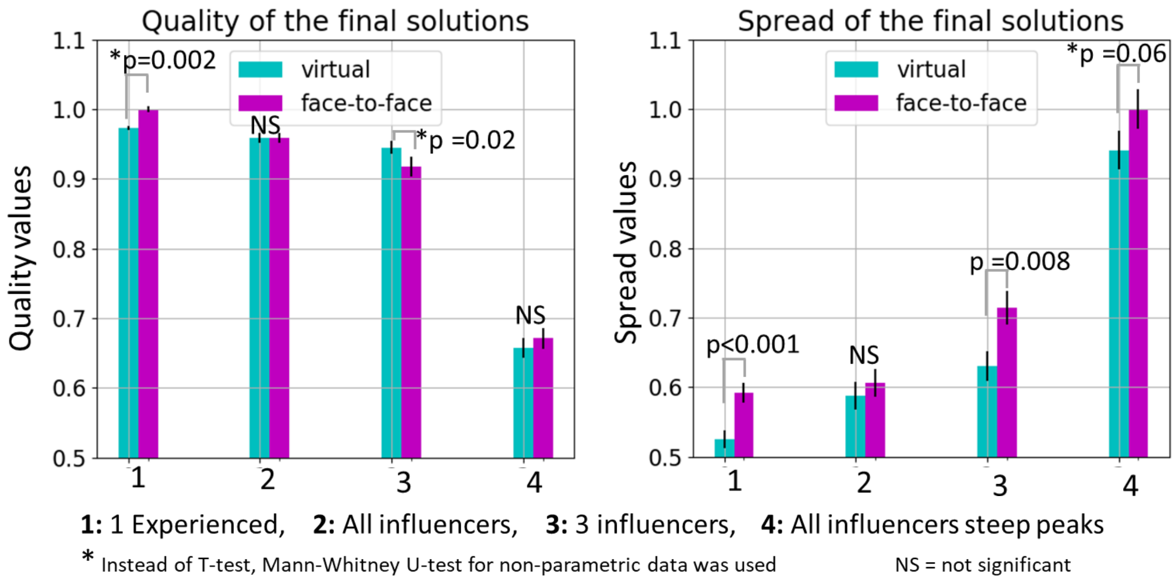



Figure 6- 73 Mean values of final quality

Figure 6- 74 Mean values of final solution spread

*Team contribution*

The contribution can be defined as the number of times an agent proposed its solution to the other team members. Figure 6- 75 shows the significant difference (T-test p values) in the contribution distribution in the teams in the two collaboration modes. In general, face-to-face team collaborations results in only a few agents continuously proposing solutions throughout a design project, hence higher distribution value. On the contrary, virtual team collaboration causes a more uniform proposing of solutions in its teams. This difference seems to be more significant in the case of well-defined influencers (1experienced and 3 influencers). Unlike, teams of agents with similar self-efficacies working on a complex design task (all influencers in steep peaks), these teams when working on a less complex task produce no significant difference in their team member contribution when the collaboration mode changes.

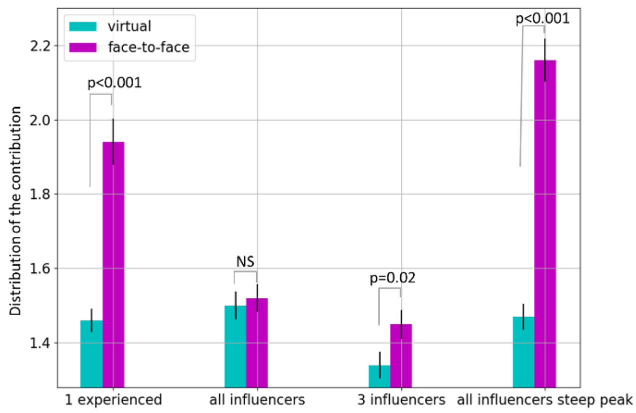



Figure 6- 75 The amount of contribution for face-to-face and virtual team collaboration

## 6.5 Discussion and interpretation of the research findings

### 6.5.1 Research findings for RQ1

The results related to research question 1, showed that the influencers affect design outcomes. The agents in the teams with different well-defined influencer compositions differ significantly from the teams without well-defined influencers when generating solutions. The teams with 1 and 2 well-defined influencers did not differ significantly in their generated solution quality. This means that having 1 or 2 influencers produce a similar effect on individual thinking when generating ideas.

The generated solution of the lowest self-efficacy agent in these teams had no significant difference in their quality values. This shows that all the low self-efficacy agents in the teams are learning, irrespective of the team composition. One possible reason for this could be because the individuals in teams compare their performance with the others in the teams, hence converge in their solution quality (Larey & Paulus, 1999). They are storing the events in their memory and recalling the ones associated with their current situation (explained in the Model Description above). Recalling these events and associating them to the current situation enhanced idea generation (Dugosh & Paulus, 2005). The quality results of the model are consistent with the study done by (Paulus, 2000; Brown et al., 1998), where it was shown that exposure to others' ideas, may increase the quality of ideas generated. However, this quality value increases gradually or becomes stable after some sessions when the influence in the team increases.

Broadly speaking, agents when generating solutions produce more diversity with the increase of influencers or when all the agents are equally influencing (all influencers). As agents in all and 3 influencer teams have the highest diversity and behave similarly in the variety of the generated solutions. As in quality values, well-defined agents 1 and 2 influencer teams do no significantly differ in the diversity of their generated solutions. This could be because, with few influencers, agents explore the solutions close to that 1 or 2 influencers. Paulus & Dzindolet (2008) stated that due to social comparison, individuals tend to move towards the direction of the social comparison referent (influencer(s)) and mimic the performance of their collaborative workers. As there are fewer influencers in '1 influencer and 2 influencer teams', the other non-influencers follow these influential agents, hence lesser spread than the other team compositions. Teams without well-defined influencers (all and no influencers) differed in their spread and the exploration index (EI) values. The team with all agents with low self-efficacy and without well-defined influencers (no influencers) had the least variety but the highest EI. This shows that no influencers explore more and had solutions equally scattered than all influencers teams whose solutions are scattered unevenly on the design space. No influencer team behave significantly different in exploring design space from the other teams. Having more influence in teams restricts exploration similar to having a hierarchy of authority in teams that reduces direction and breadth of solutions (Keum & See, 2017).

Idea selection results showed that the final solutions that were proposed to the controller agent (or selected by the controller agent in the case of multiple solutions), differed in their quality values in the teams with and without well-defined influencer teams. On the other hand, no influencer teams who had the same distribution of low self-efficacy, behaved similar to 1 influencer team in their final proposed solution diversity. While EQI is not affected by the presence of influencers in the team (i.e., teams with and without well-defined influencers had the same EQI), LEQI of the team with all agents having the same and high self-efficacy, differ significantly from the other team compositions. This shows that the teams where all agents have similar and high self-efficacy produce better solution quality than the teams with influencers. The empirical study observation by Singh et.al.,(2020) found that teams with high influence in them performed better, however, the distribution of the influence was unclear.

Proposing potentially good alternatives during decision-making is crucial (Keeney, 1996), but it is often seen that individuals and organizations often consider only one alternative (Nutt, 1998). Limiting the alternatives or final selected solution when proposing to the controller agent (project manager, team leader and similar ones) is a common mistake (Keeney, 2002). Thus, proposing multiple final solutions alternatives (in this case 3) to the controller agent resulted in better solution quality. All influencers teams proposed more multiple final solution alternatives which could be of the reasons why they performed better in terms of their final solution quality. It was seen that the teams with well-defined influencers have higher and a different pattern of agreement values than in teams without well-defined influencers. This could be because influencers (who are perceived as more influential than other members) have more influence value that affects agreement with them on their proposed solution, hence resulting in higher agreement values in well-defined influencer teams. The agreement values on the proposed solutions in all influencers teams were significantly lower than other well-defined influencer team compositions, which might have caused the team to proposed multiple final solution alternatives than a single solution.

An increase in the number of influencers or the agents having high self-efficacy in the team decreased team agents' contributions. In all influencers and 3 influencers team compositions, only some agents often proposed solutions than all the team members. In teams with well-defined influencers and no influencer team (where an influencer emerges as the team works from one session to another), the contribution by their agents was more uniform. As it is known from the model description that the probability of a high self-efficacy agent to propose a solution is more than that with lower and a certain number of agents are defined to propose their solution. Hence, in the teams with 3 and all influencers, most or all the agents proposing solutions have high self-efficacy. When the solutions of these agents are selected, their self-efficacy is further increased, therefore resulting in only some agents regularly contributing (hence, also decreasing the variety in their solutions). Similar to the real world where individuals are often fixated on their own ideas, which produce fewer variations in designs (Neroni & Crilly, 2019). The team with all influencers where only some agents regularly proposed solutions, performed better than the other team compositions. A rather similar phenomenon was demonstrated by a contribution model for engineering design teams where team members had unequal effects on team performance and enhancing the contribution by the most proficient member of a team is likely to increase team performance (Brownell et al., 2021).

Idea generation is a divergent process while idea selection is a convergent one. It is not necessary that the teams who generate creative ideas also select creative ideas as there are plenty of factors that affect decision-making in idea selection (Toh & Miller, 2016). Similarly, the model simulation results showed that the quality of the solutions during idea generation differed significantly from the final solution quality proposed, contrary to the studies that have found that the difference in the individual and the group final idea quality was minimal (Rietzschel et al., 2006).

### Impact of model parameters: team size and design task in terms of number of peaks

When changing some of the model parameters like team size and complexity of the design task (i.e., number of peaks on a design space) while keeping the allotted number of influencer the same (i.e., half of the team members as influencers), it was found that that the generated and selected solution quality significantly differed from each other. For the least complex design task (i.e., filled with best solution peaks), agents in the very small and standard size design teams behaved similarly while differed significantly from the large teams. While for the complex task, agents in all three teams of various sizes behaved differently when generating solutions. The exploration behaviour of these teams differed significantly from each other on the two design spaces. The diversity value in the final solutions of the 6 and 10 agent teams. Very small teams showed higher diversity in their proposed solutions and had the highest EI in all the sessions, hence, contradicting the studies that stated that small teams will lack the diversity of viewpoints (Jackson, 1996). Many research in psychology have suggested that a large team size (10-12) results in social losses due to social loafing or conformity, decision-making becomes tedious, hence the quality of task decreases (Latané et al., 1979). However, here these teams of various sizes working on the two extreme design tasks did not select any significantly different final solutions in terms of their quality value.

The impact of model parameters like team size and complexity of the design task (i.e., number of peaks on a design space) on the design outcomes could be seen in the paragraphs below. As expected, when the number of agents is increased in a team, exploration increases as there are more agents to explore the design space as seen in Figure 6- 76 (Kendall correlation coefficient τ= 0.84, p-value<0.001). Not only having a larger team increases exploration but also it produces a higher quality of the explored solutions (Figure 6- 77). It could be inferred that increasing the team size helps in exploring the design space where higher exploration also results in a better quality of the explored solutions while generating ideas. An empirical study done by Pacheco & Soares, (2018) showed that larger teams have higher performances even though, large teams perceive lower collaboration when compared to smaller teams.

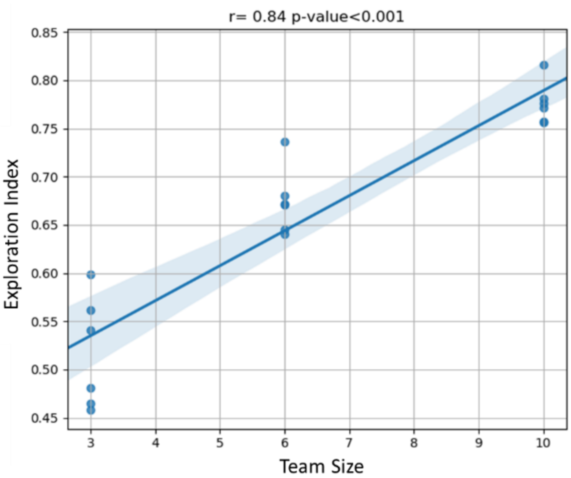



Figure 6- 76 Team size positively affecting exploration index

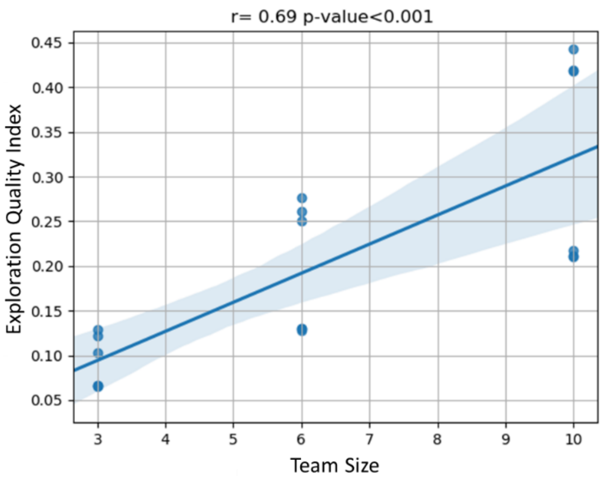



Figure 6- 77 Team size positively affecting exploration quality index

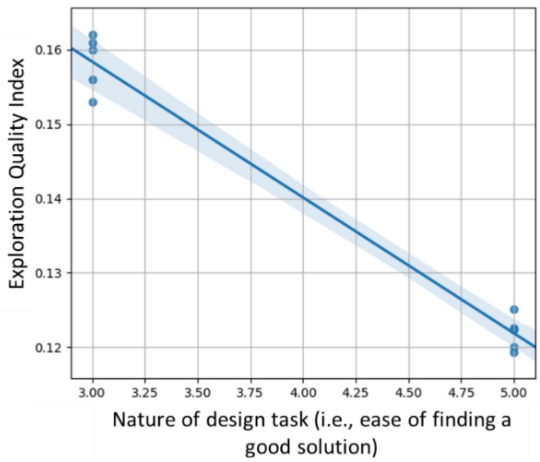



Figure 6- 78 Nature of the design task (number of peaks) negatively affecting EQI

The nature of the design task based on the number of best solution peaks in a design affects the design outcome. Figure 6- 78 shows that as the number of best solution peaks are increased in a design space, the chances of having a better EQI (exploration quality index) decreases (Point Biserial correlation coefficien= -0.99, p-value <0.001). In order words, the agents explore less because they become confined to an area as soon as they find a good solution (when no experienced agent is present), hence reducing the exploration value with respect to the greater number of above-average solutions available in a design space. Thus, having a design task with multiple peaks does not ensure higher exploration quality.

Overall, it could be seen from Figure 6- 79 and Figure 6- 79 that the final design outcomes proposed by a team also vary with the nature of the design task. It can be seen from Figure 6- 79 that as the ease of finding a good solution increases (i.e., more number of peaks in a design space), the quality of the final selected solution that is proposed by a team to the controller agent also increases (Point Biserial correlation coefficient = 0.97, p-value < 0.001). As expected, when the design task is difficult (i.e., the number of good solutions are less), the quality of the final solution is also low because the probability of finding an above-average solution on a design space is less.

Similar to the EQI of the generated solutions that decreases as the number of peaks is increased, the diversity in the final proposed solution is also negatively affected by the number of peaks (Figure 6- 80 which shows the Point Biserial correlation coefficient = -0.85, p-value = 0.002). This suggests that agents in a team propose and select solutions from limited areas of design space that have previously given successful results, irrespective of the number of actual best solutions that might be present in a design space.

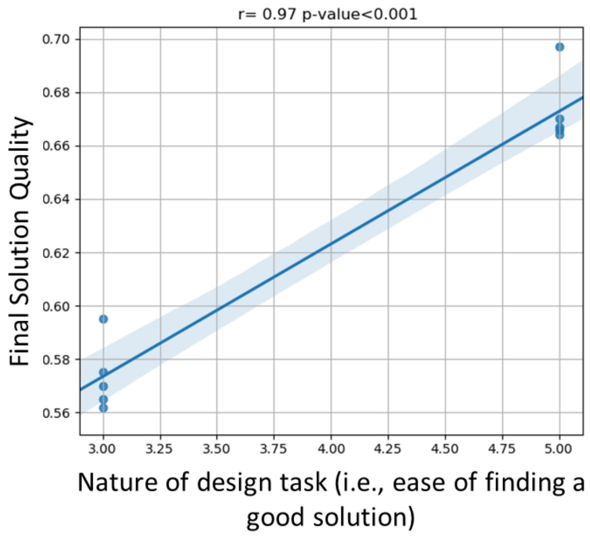



Figure 6- 79 Nature of the design task (number of peaks) positively affecting the quality of the final solutions

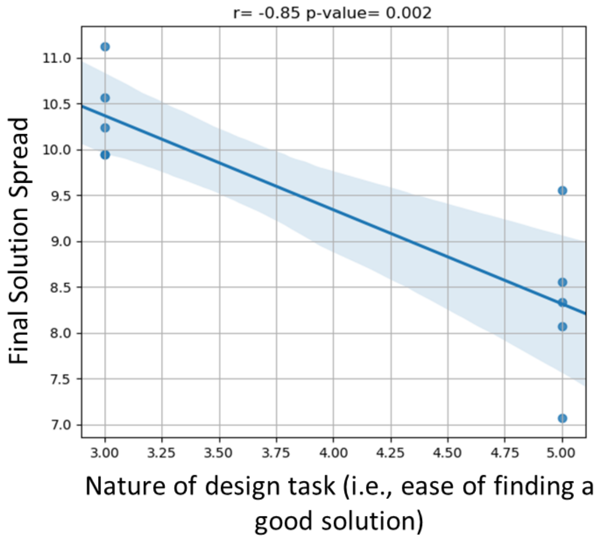



Figure 6- 80 Nature of the design task (number of peaks) negatively affecting the diversity in the final solutions

## 6.5.2 Research findings for RQ2

The quality of the solutions generated by agents in the teams with an experienced agent in them was better than all new agent teams. This is likely observed because novices socially integrate with experienced individuals in teams, they tune their activities on the levels of experienced individuals (Fronza et al., 2011). Similar results were found in Atman et al., (1999) where novices did not produce quality design solutions. This could be because of the obvious reason that the experienced agents are aware of the failure zones and success points of the design problem. Experienced agent teams (both 1 and 3 experienced agents) behave similar to those of the experienced individuals in the real- world who start solving a problem from a 'higher place' or start the session with superior quality because of their ability to recall meaningful information before beginning the current task (National Research Council, 2000).

Though the solution quality of the final solutions by the experienced agent(s) in teams with novices was constantly better, it gets stable after some sessions, while all novice team continuously improves their solution quality. As the experienced agent teams (1 and 3 experienced with novices) immediately start producing above-average solutions, hence they receive good feedback from the controller agent. This makes the team propose solutions close to the previous ones which result in less change in the quality after some sessions. This behaviour indicates ‘fixation’ as found by Ball et al. (1994) in their study. The agents in the all novice team behave differently when the tasks become difficult (i.e., one peak), they take more time (sessions) to reach an above-average solution (Perišić et al., 2018), hence a gradual improvement in their solution quality.

A larger difference in the quality of the solutions among the three-team compositions was seen when there is one best solution than multiple best solutions in a design space. Since there are multiple best solutions in the design space with 5 peaks, all the team compositions produce better solution quality than when there was one peak. This difference in performance (when working on a difficult task and a task with multiple alternatives) could be seen most in the all novice agent team.

Figure 6- 81 shows that the distribution and mean of the final solutions proposed by the teams of no experienced agents (i.e., all novice), novice agent teams with one experienced and novice agent teams with 3 experienced agents for all types of the design task. Besides having lower variability in the final solution qualities of teams with 3 experienced with 3 novice agents, they also have a higher quality mean than the other compositions. Teams with all novice agents produce larger variability in the final solution values and have the lowest quality mean. This shows that teams with varying experienced-novice composition behave differently also during idea selection. Despite Figure 6- 81showing, that experience agents in a team produce better final solution quality no such significant correlation could be found (Pearson’s correlation coefficient = 0.95, p-value = 0.21). One reason could be the mediating nature of the design task.

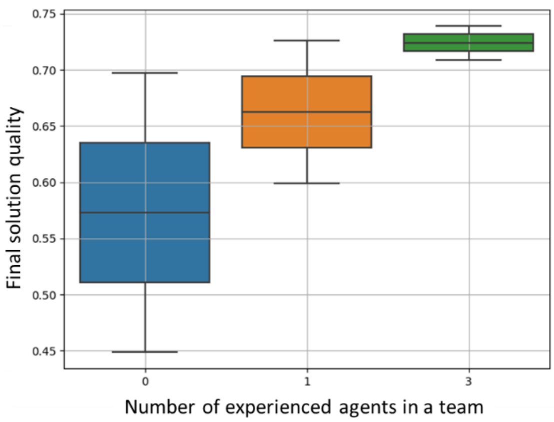



Figure 6- 81 Number of experienced agents and the final solution quality

The teams with experienced agents in them (1 and 3 experienced agents) explore less when there was only one best solution than multiple best solutions. This is because they had experienced agents who were aware of the failure and success points on the solution space, they consider fewer options than novices (Björklund, 2013). Hence, when the number of best solutions increased, their exploration increased (Chen, 2001). On the other hand, the team of all novice agents did not know about the position of the one best solution on the design space, hence they use ‘trial and error’ techniques for generating solutions (Ahmed et al., 2003). In the case of a difficult task (i.e., one peak) kept exploring and have a higher exploration index than other team compositions for one peak. On the contrary, all novice agent team were not aware of the positions or the fact there are multiple solutions so when they find one of the best solutions of the five peaks solution space, they stop exploring other areas and explore lesser than the teams with experienced agents. A similar finding was found in the study done by Christiaans & Dorst, (1992) where some junior students while solving a simple problem did not gather much information as they were unaware of a lot of potential criteria and difficulties on the solution space.

Authors like Fricke, (1996) explained that when designers produce good early concepts, they need not radically alter them when further exploring solutions, hence good designers have less diversity, similar to the teams with experienced agents in them. Since it is more probable to propose a solution of high quality when there are multiple best solutions, it is easier for those agents proposing the solutions to become even more confident, hence more influential. This makes the same agents often propose solutions close to their past successful solutions and the rest of the agents agreeing with them due to their influential nature. All novice agent teams, on the other hand, had the highest variety in their proposed solutions. As explained above that as the team of all novice agents were not aware of the position or the area of the only best solution present (for one peak design space) so they proposed solutions from all over the design space to the controller agent, hence they the highest variety or spread of their solutions. The team with the one experienced agent had more diversity in their solutions than the team with three experienced agents as the degree of influence reduces the variety of solutions, especially when the design task is more complex. Teams with both experienced and all new agents teams had similar diversity in their solutions when the design task had multiple best solutions.

Experienced agent in a team who is familiar with the design task (routine task, RT) and an experienced agent who less familiar with the design task (non-routine task, NRT) affects idea generation solution quality. As expected, the EQI of the teams with NRT experienced agent is lower than the teams with RT experienced agent. Nevertheless, both the teams with RT and NRT produced had better final solution quality than all new agent teams.

### Impact of model parameters: design task in terms of peak curvature

A weak positive correlation was found (Point biserial correlation =0.092, p-value <0.001) between having an experienced agent in the team and the individual agents' generated solution quality. Hence, clearly stating that the design task (in this case the curvature of the peaks) play a significant role. On further analysing the relationship of the curvature of the peaks with the design outcomes as be seen from Figure 6- 82, Figure 6- 83 and Figure 6- 84. The curvature of the peaks also had the same effects as the number of peaks (i.e., number of best solutions) on EQI and spread.

It can be seen from Figure 6- 82 and Figure 6- 83 that as the curvature of the peaks increases (i.e., the refinement of the conceptual solutions becomes easier), the agents stop exploring and become confined to specific areas on design space, hence reducing EQI and diversity in their solutions (Kendall correlation coefficient $\tau= -0.85$, p-value<0.005 and $\tau= -0.62$, p-value<0.041 respectively). However, the quality of the final proposed solution increases with the curvature of the peaks as the refinement of the solutions becomes easier as seen in Figure 6- 84 (Kendall correlation coefficient $\tau= 0.9$, p-value=0.002).

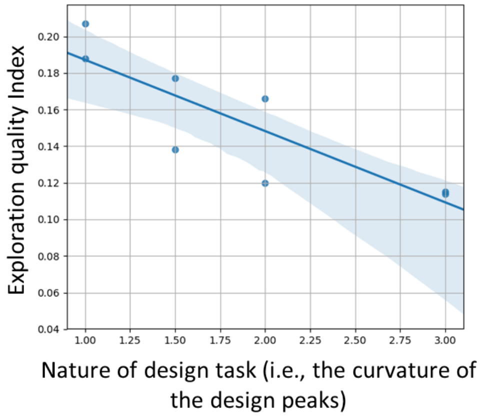


Figure 6- 82 Nature of the design task (curvature of the peaks) negatively affecting EQI

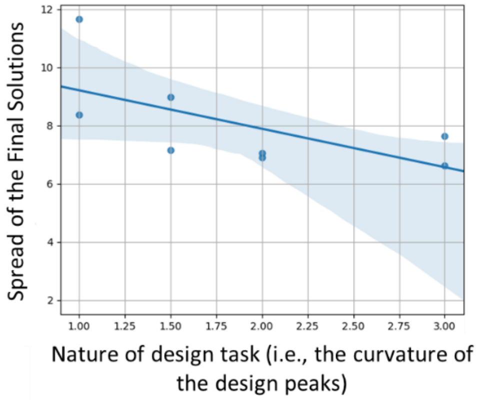


Figure 6- 83 Nature of the design task (curvature of the peaks) negatively affecting diversity in the final solutions

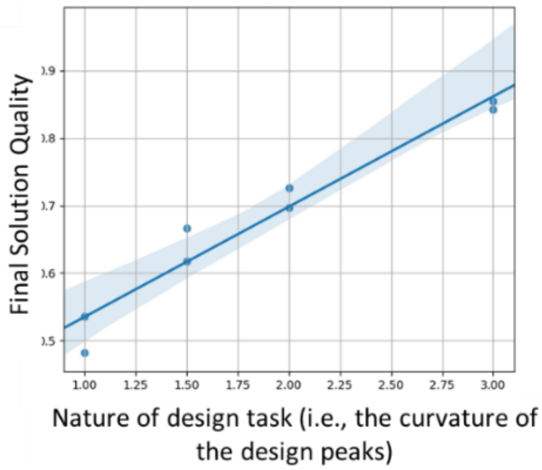


Figure 6- 84 Nature of the design task (curvature of the peaks) positively affecting final solution quality

Thus, supporting the findings related to RQ2 *(i.e., How do different experience- novice agents in teams affect design project outcomes with respect to the design task? )* were presented.

### 6.5.3 Research findings for RQ3

From the results in Chapter 4, no direct relationship could be found between collaboration mode and design outcomes as for some cases virtual collaboration might is better while face-to-face for the others. However, some generalisations can be made based on Figure 6- 85 and Figure 6- 86. It can be seen from Figure 6- 85 that not only the median of the final solution quality of the teams in virtual collaboration is slightly less but also, they are less dispersed than the teams collaborating face-to-face. The distribution of the spread of the final solutions (i.e., diversity) also differs in the two collaboration modes (Figure 6- 86) The median of the final solution spread during virtual team collaboration is slightly lesser than face-to-face collaboration that is skewed right, however, Kruskal-Wallis H-test shows no significant difference (H =0.75, p= 0.38). These broad findings of the research do not conform to the past research that stated that either face-to-face or virtual team collaboration results in better performance (Malhotra & Majchrzak, 2014). While supporting the studies that have shown in their findings that asynchronous collaboration is as effective as face-to-face collaboration in terms of solution quality (Ocker & Yaverbaum, 1999) (Ocker et al., 1995). Hence, suggesting that no clear differences in the two collaboration modes can be made without considering their impact on the individual test cases.

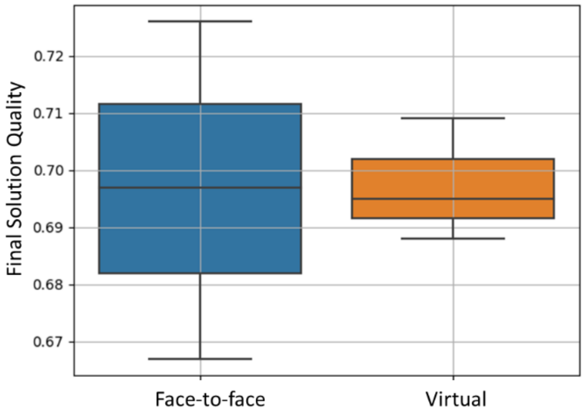



Figure 6- 85 Collaboration mode and the final solution quality

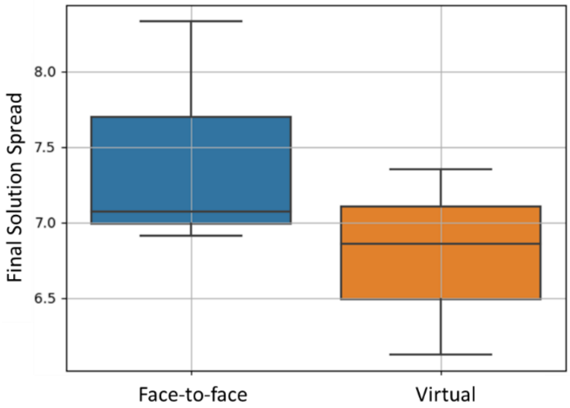



Figure 6- 86 Collaboration mode and the spread of the final solutions

It is clear from the results presented in Chapter 4 that virtual and face-to-face teams behave differently. The ANOVA results of the generated solutions by agents in the 4 cases (i.e., (i) teams with an experienced agent, (ii) half of the team with high self-efficacy,(iii) all agents with same self-efficacy and (iv) all agents with same self-efficacy working on a complex design task) differ from each other for virtual ($F= 6567.6$, $p<0.001$) and face-to-face collaboration ($F = 6149.32$, $p <0.001$). It could be inferred that the teams in the 4 test cases behave differently from each other when generating and selecting final solutions during face-to-face collaborations. However, was found that teams like half agents with high self-efficacy (3 influencers) and all agents with similar high self-efficacy (all influencers) had a less significant difference in their generated solution quality (Figure 6- 87 and Figure 6- 88) and behave similarly when proposing final solutions (Figure 6- 89 and Figure 6- 90) when collaborating virtually. Hence, supporting the RQ3 by demonstrating that team, task and individual factors have a different effect when collaboration mode is changed (i.e., virtual or face-to-face collaboration).

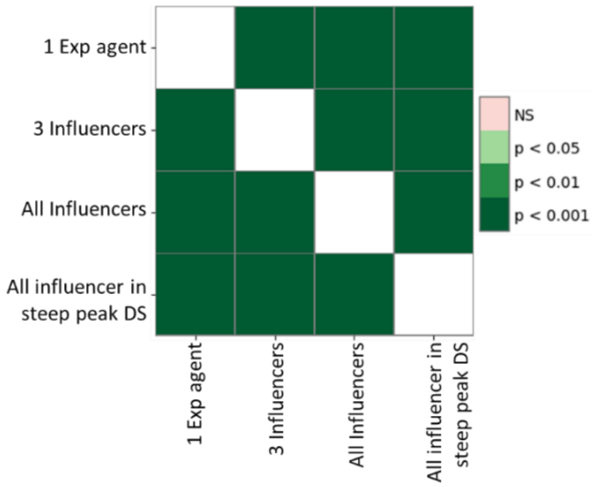



Figure 6- 87 Post hoc pairwise T-test p-value plot for generated solution quality during face-to-face collaboration

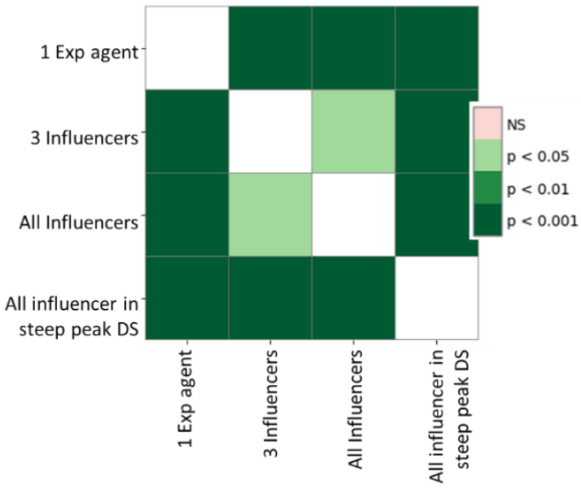



Figure 6- 88 Post hoc pairwise T-test p-value plot for generated solution quality during virtual collaboration

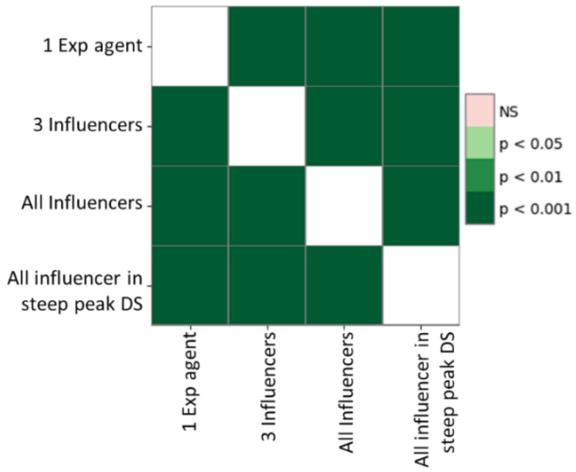


Figure 6- 89 Post hoc Conover's test p-value plot for selected solution quality during face-to-face collaboration

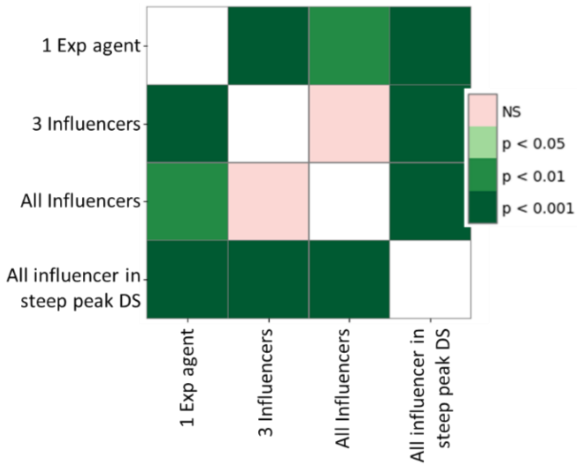


Figure 6- 90 Post hoc Conover's test p-value plot for selected solution quality during virtual collaboration

As highlighted by Pinar et al., 2014) that there is a gap in the literature that has focused on studying the performance and success of virtual teams. Studies like Liao, (2017) suggested that the effect of a leader like behaviour on individual processes and outcomes was stronger in highly virtual teams because of difficulties in communication, some individuals may take initiative and assist the team. However, the results presented above show that the teams with one influential experienced individual perform better in face-to-face collaboration mode while with many influencers (3 or all) perform better virtually. The teams with one influential experienced individual performed better both in face-to-face and virtual team collaborations. A similar conclusion was reached by Hoch & Dulebohn, (2017) where that high performing virtual teams had a more powerful and influential individual (strong leader) than low performing virtual teams that had no such defined leader. The exploration of the design space is lesser when the teams are collaborating virtually especially when working on a moderately complex task. This could be because of less social influence which might have caused the agents to be a move towards their own solutions rather than being attracted by others' proposed solutions. Reduction in EI also resulted in lesser EQI values. The diversity in the proposed solution is also lesser for virtual collaboration than face-to-face team collaboration for a moderately complex task for well-defined influencer cases (1 experienced and 3 influencers). Studies like Potter & Balthazard, (2002) found that CMC (computer-mediated communication) leads to social inhibitions and increases radical opinions, equality of participation and a reduction of status differences between members. Similarly, the model results show that contribution in virtual teams is more uniform than face-to-face collaboration as the impact of social influence is weaker.

Overall, it could be inferred that the teams where the influence is unevenly distributed (due to unequal distribution of self-efficacy and experience) are more prone to collaboration environment effect than the teams with equal distribution of self-efficacy. The design task type also affects virtual team behaviour. Hence, the findings support research question 3 (i.e., '*How does virtual team collaboration affect design project outcomes with respect to face-to-face collaborations*') by clearly showing the comparison between face-to-face and virtual team collaboration.

## 6.6 Practical implications

The study deals with an agent-based model for simulating collaborations of a team when working on a design task. One advantage of such models is that they can be easily modified based on the goal of the study. Thus providing a wider perspective to its practical implications.

The research started with exploring the role of influencers in design teams and how they impact design outcomes. The empirical studies conducted to validate model assumptions showed that self-efficacy and trust between the two individuals give rise to the influencing and being influence phenomenon. The other parameters like familiarity and agreement between the two individuals are also present and influence design outcomes. Hence, the study revealed that when conducting and investigating collaborative teams, it is important to consider various socio-cognitive phenomena that are affecting design outcomes. The model simulation results related to RQ1 showed that unequal distribution of social influence or in other words, influencers affect individual thinking of other designers during idea generation. A designer with low self-efficacy produces solutions close to the influencer while a high self-efficacy individual is more confident to explore on its own. Thus, having a various number of influencers in a team results in different behavioural patterns (for example, having 1 or 3 or no well-defined influencers). On the other hand, low self-efficacy individuals conform easily to the influencers while it is hard for a high self-efficacy individual to do so. It may be difficult for a team with all similar high self-efficacy to converge to a single solution while individuals in a 1 influencer team may always follow the influencer. Thus, when studying idea selection parameters (like influence or past agreements between the two individuals) should be considered to understand the choices made during decision-making. The results also imply that the effect of influencers differs when a team or task characteristics are changed. Team managers, leaders, or others in similar roles should consider these factors when forming a team for better team member experience as well as for obtaining desired outcomes.

The research findings related to RQ2 which studies the effect of having various combinations of novice-experience designers in a team on the design outcomes. The results clearly imply that having experienced individuals in teams with novices could be more useful when the design solutions are difficult to find and refine (i.e., one and steep peaks on a design space). All novice designers generated high variety but low quality when the task was difficult. However, having high variety and exploration in the case of one best solution is not useful as it leads to wastage of resources. Therefore, all novice individual teams working on a project whose design task has fewer alternatives might not be efficient. In case a design problem has multiple alternative solutions, any team composition would produce similar variety and quality results. Therefore, when forming a team with novice and experienced designers, researchers and practitioners should consider the nature of the design task at hand for better yields.

When addressing the RQ3 that explores the effect of virtual team collaboration on design outcomes while considering the team, task and individual parameters. It was clear from the empirical study that the model parameters considered for face-to-face collaboration behave differently in virtual collaboration. Communication mediated by technology effectiveness affects perceived influence in teams. Conflicts, on the other hand, are impacted by communication and difference in the self-efficacies of the two individuals. Therefore, this implies that future researchers should consider factors other than communication when studying conflict management in teams. When comparing the results of virtual team collaboration to face-to-face, it was evident that face-to-face collaboration not always result in better outcomes (as suggested in most of the literature). The results were suggestive of the fact that some teams might perform better when collaborating virtually than face-to-face. For example, when the influence is not uniformly distributed in teams (1 experienced and influential agent, and 3 influential agents in a team). The impact of an influencer who is also experienced is more prominent in the face - to face collaborations than virtual. While when half of the small design team members are more confident than the others, virtual collaboration mode is more beneficial. On the contrary, when self-efficacy is equally distributed in teams, the impact of the collaboration environment on individual thinking during idea generation is less. As virtual team collaborations are getting popular and effective (due to the advancements in technology), it is crucial to understand what makes virtual team collaboration projects successful. Thus, the research findings were suggestive of considering various individual, team and task parameters that results in effective virtual team collaboration.

## 6.7 Model Validation

“Closeness" to reality is an important concern for the computational models (Burton & Obel, 1995). The current model presented here has the elements of illustrative (or "intellective') simulation studies (i.e., *models that explore the implications of reasonable assumptions about behaviour, in order to determine what the world is like when these assumptions are true*) (Burton & Obel, 1995).

When it comes to the overall validity of the model, (i) content, (ii) construct and (iii) criterion-related validity provides a first-level reference for testing the validity of a computational model and helps to access if the research maintains a balance between realism, relevancy and computational modelling (Burton & Obel, 1995).

- Content validity: is obtained if the model captures the important aspects of the research goal and makes sense to a group of experts. In this case, the research was discussed and presented multiple times to a committee of professors at Politecnico di Milano and obtained good grades/remarks. Hence, accomplishing the content validity.
- Construct validity: is obtained if the model contains parameters, variables and relations which yield outcomes corresponding to the real world. In this case, the model parameters and the relationships among them were verified and validated through empirical studies and literature. Hence, fulfilling the construct validity.
- Criterion-related validity checks the real-world intent of the model and, how the model and its result are used. In this case, the presented model clearly shows its intent to simulate real-world collaboration activities. The model and the simulation results show how designers behave during a collaborative design and the impact on design outcomes when various team, task and individual parameters are changed. Some of these results conformed to the literature studies.

Burton & Obel, (1995) also highlights that there are trade-offs among the above validity criteria i.e., a model may not be able to fulfil all the criteria perfectly.

Agent-based models have an advantage over traditional models as they can capture individual-level details (for example varying self-efficacy, agreement, trust and so on at the individual level). But the results of ABM hold true within the limits of the model parameters (Rand & Rust, 2011). Figure 6-91 taken from Rand & Rust, (2011) shows the tradeoff between the analytical modelling and ABM.

As seen from above that computational studies are challenging to validate and these studies done using ABM add another layer of complexity for validation. Rand & Rust, (2011) suggested that researchers should use both ABM (when it comes to modelling individual characteristics to provide a layer of realism) along with analytical modelling methods to generate results that are both true (if the restrictive assumptions hold) and are built on assumptions (if the restrictive assumptions are not true). Since computational models come in various types, “*none are necessarily valid, nor invalid*”, instead “*simplicity and balance of purpose, computational model and experimental design provides a valid focus*” (Burton & Obel, 1995).

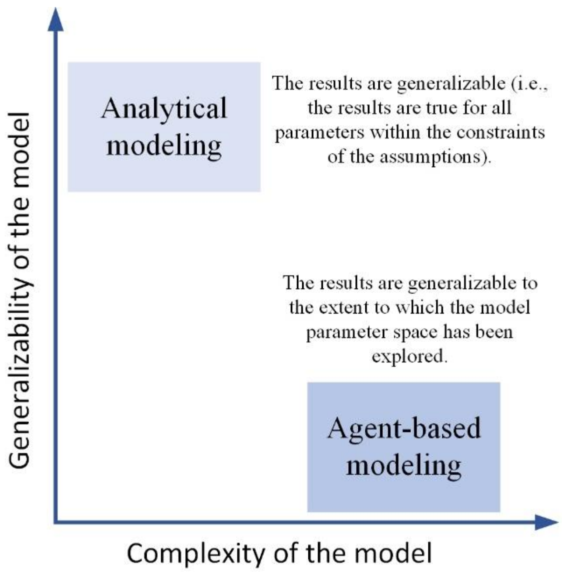



Figure 6- 91 Tradeoff between analytical modelling and ABM (Rand & Rust, 2011)

Considering the suggestions, the model is built on assumptions (as indicated in Chapter 2) that are validated and model formation logics are verified through empirical studies. The results from the model simulation that answers the research questions were partially validated through Literature studies. As indicated in Chapter 1 that the research falls into the Type 6 design research project (Blessing & Chakrabarti, 2009). Type 6 design research of DRM consists of a review based descriptive study (research questions and assumptions) which is followed by a prescriptive study (proposed model). These two phases of the research are followed by a comprehensive descriptive study II that evaluates using prescriptive study (empirical studies) and (or) a review-based evaluation (i.e., literature supporting the simulation findings).

Since ABM simulation results are difficult to validate through empirical experiments, the elements of the study as shown in Table 6- 2 were tested in parts. Model formation logic, in order words logical verification (Isaksson et al., 2020) was done through empirical studies. The assumptions behind the model were also validated through empirical studies. Hence, giving a partial validity to the model since the beginning. The other partial validity of the model was obtained when the results of the simulation conformed to the findings in the near and far domain literature. The evaluation criteria for agent-based simulation involving social science elements should be based on the research aims, method used and the domain of the study (Gilbert & Ahrweiler, 2006).

Table 6- 2 Validation and verification of the elements of the research

| **Elements of the research** | **Means of validation or verification** |
|---|---|
| Model formation logic<br>• Reduction in an individual's self-efficacy<br>• The less number of perceived influencers by those having higher self-efficacy<br>• Familiarity and reputation affecting trust<br>• The presence of influencer and majority effect during idea selection<br>• The parameters used for modelling face-to-face collaboration change during virtual collaboration | Empirical studies (Chapter 4) |

| | |
|---|---|
| Assumptions behind research questions<br>• A1.1 Self-efficacy and trust are some of the characteristics for influencing and being influenced behaviour<br>• A1.2 The perceived degree of influence by an individual and the past agreement its peer had with him/her, are some of the factors affecting its agreement when evaluating the proposed solutions by its team members<br>• A3.1 Effective communication between individuals plays a significant role during virtual team collaboration as it impacts model parameters | Empirical studies (Chapter 4) |
| Model simulation results | Review-based studies (Chapter 6) |

# Chapter 7

# Conclusions and future work

The aim of this research was to explore and improve the understanding of the design team collaboration under the influence of various individual, team, task and environmental factors. In doing so, the study built and used a computational framework called MILANO that was described in Chapter 3. The model consisted of a design problem and agents, that had their own attributes. The empirical studies were done during the research supported in validating the major assumptions and provided logical verifications for the model framework and was presented in Chapter 4. The agents in the model learned from their own past experienced and were influenced by others in the team. By altering the attributes of the team, agents, task and collaboration environment different collaborations scenarios were simulated. The results from the simulation answered the research questions identified at the beginning of the study. This chapter concludes the thesis by providing a review of the research objectives that were fulfilled and a summary of the outcomes that address the research questions. The chapter also states some limitations of the research along with the prospective future work.

## 7.1 Review of the research objectives

Referring to the objectives identified at the beginning that fulfilled the purpose of the study, given below is the review of how they were addressed during the research. To what extent they were fulfilled during the research, their status (open, partially and completely addressed) is indicated.

1. To identify the main components of the collaboration in design teams that affect design outcomes (was completely addressed).
   The elements that the previous computational model lacked and the need to build an agent-based model to study team collaboration was established. Based on the past literature and the research gap identified in Chapter 2, the main components of collaboration were identified that were related to the goal of the work. The main team collaboration design parameters were classified as dependent, intermediate and independent.

2. To develop a computational framework that captures the cognitive and social phenomenon of the individual in the design teams (was completely addressed).

   The computational model was formed based on past theories and literature as described in Chapter 3. It comprised of a design task that was given to a team of agents, who perform idea generation and selection in each design session. At the end of each session, a controller agent provided feedback to the team. The agents incorporate this feedback when generating solutions in the following design sessions by recalling these events and acting accordingly.
3. To develop a more comprehensive model of idea generation and selection in the design process by identifying the parameters that affect them (was completely addressed).

   The idea generation in an agent was influenced by its own learning from past experiences and due to the presence of influential team members. Learning from the past event was impacted by an agent's recall time, expertise level and intensity of the recalled event. While an agent's learning due to the degree of influence from other agent depended on the self-efficacy and trust between them. Idea selection was also had social factors like the influencer and majority effect. The agent's agreement with the other agent on its proposed solution was impacted by the past agreement value and the degree of influence perceived by the agent.
4. To design experiments with these parameters identified to validate the model assumptions (was completely addressed).

   Some of the major relationships among the model parameters were validated through empirical studies. The relationship between trust, self-efficacy and delta self-efficacy with the degree of influence was supported by the empirical studies. The empirical study also revealed that the past agreement and the degree of influence could be some of the factors affecting agreement during decision-making in the idea selection process. As it is a computational model, more empirical studies would have provided more
5. To investigate the effect of unequal distribution of social influence in teams on design outcomes by means of model simulations (was completely addressed).

   MILANO was used to simulate a common design team collaboration when it is often seen that certain individuals are more influential than others. Two broad cases were created where one case was about the unequal distribution of influence (i.e., well-defined influencers) and the other was about teams with equal distribution of influence (i.e., no well-defined influencers) at the beginning of the simulation. The results from these cases are summarized in the section below.
6. To deploy the model for simulating other collaboration scenarios by varying model parameters (was completely addressed).

   The model was used to simulate several collaboration scenarios by varying parameters like team size and design task (peaks and curvatures). The teams with a varying number of experienced and novice agents were also simulated to see their impact on the design outcomes. The experience in an agent was also altered in the form of routine and non-routine tasks. However, could be many more scenarios where the model for simulating these collaboration activities could be deployed.
7. To validate these results by means of literature (was partially addressed).

   Most of the simulations of different team collaboration scenarios were done for the first time, finding the exact results in the literature that supported or contradicted the model results was challenging. However, a few studies could be found that supported or contradicted the results at an individual behaviour level, mainly in the case of experienced and novice agent simulation.
8. To expand the model to accommodate the effect of environment on the mode of collaboration (virtual and face-to-face) by identifying roles and relationships among the main parameters affecting it through empirical experiments (was completely addressed).

   Lastly, the model was used to simulate a widely popular scenario where the team collaboration was done virtually, and the results were compared to the face-to-face collaboration setting. This was done by modifying the MILANO framework based on the past literature and the insights from the empirical study.

9. To analyse the data extracted from the model to provide some insights into the behaviour of the collaborative system and patterns in team outcome when subjected to a change in design parameters (was completely addressed).
   The results from the model simulation showed how teams with a varying number of influencers differed from the teams without well-defined influencers. It also showed how teams with different experienced- novice agent team composition differed in the behaviour when generating and selecting solutions. Finally, the results related to the virtual and face-to-face team collaboration showed how certain cases could perform better when collaborating virtually than face-to-face.
10. To discuss model results and their implications to propose further future research (was completely addressed).
   The results of the model were discussed, and their implications were highlighted in the previous Chapter 6. This chapter further summarises them (given below) and presents some of the potential future research areas and implementations in the model.

## 7.2 Summary of the findings

The results addressing the research questions could be summarized as follows:

Influencers in design teams:

- Influencers in the team affect idea generation as the agents in the teams with non-uniform distribution of self-efficacy (well-defined influencers) differed significantly from those in uniform distribution of self-efficacy (not well-defined influencers).
- Teams with uniform distribution of low self-efficacy behave differently from teams with uniform distribution of high self-efficacy. In these teams (uniform low self-efficacy distribution) an influencer might emerge after some sessions and their behaviour related to final solution quality and diversity becomes similar to well-defined influencer teams. They also had high exploration than other teams.
- Few well-defined influencer teams (1 and 2 influencers) had less diversity in the generated solutions. While as the influence increased (3 and all influencers), the diversity in the generated solutions also increased.
- The teams with uniform distribution of high self-efficacy (all influencers) produce better final solution quality and differed significantly from well-defined influencer teams.
- The variety in the final proposed solutions also differs significantly for well and not well-defined influencer team compositions except for no and 1 influencer teams (as no influencer teams might have an emerged influencer).
- The contribution in few well-defined influencer teams (1 and 2 and no influencers) was more uniform than teams where more individuals had high influence (3 and all influencers).
- Having a similar ratio of influencers in teams with varying sizes showed that the impact of team size is more significant when the design task is more complex. The idea generation behaviour of agents in the small to large teams differed significantly from each other in terms of solutions quality and exploration. Very small teams (3 agents) had the most variety in the final proposed solutions for both complex and extremely simple design tasks.
- The contribution by agents in teams of various sizes was more uniform when the task was complex. In an extremely simple design task, only a few agents continuously propose solutions (contribute more often) especially when the team size was standard (6 agents) or large (10 agents).

Design team with experienced and novice designers

- Agents in the teams with (1 and 3 experienced agents) and without experienced agents behaved differently when generating solutions for a complex and moderately complex design task. Unlike all new agents, teams with experienced agents in them generate better solution quality but the increase in their solution quality became stable after some sessions for a complex design task.
- Having more experienced agents in a team with novices for a complex task resulted in better quality. The difference in the final solution quality between all new agent teams and experienced agent teams (1 and 3) was lesser when the solution was moderately complex.
- Teams with 1 and 3 experienced agents behaved similarly when exploring the design space for a complex design task while all new agent teams explored the most. The team of all new agents generated high variety and low quality when the task was complex. Having a high variety and exploration index in the case of one best solution is not useful as it leads to the wastage of resources. Therefore, all novice individual teams working on a project whose design task has fewer alternatives might not be efficient. However, in the case of a design problem that has multiple alternative solutions, all the team composition produced similar variety results.
- Teams with an experienced agent who was familiar with the design task (routine task, RT) and teams with an experienced agent who was less familiar with the design task (non-routine task, NRT) did not differ in their idea selection behaviour. However, the agents in the teams with RT experienced agent had better exploration quality than NRT experienced agent teams.
- When changing the ease of refining the best solutions (i.e., varying the above-average solutions in the vicinity of the best solutions), teams with an experienced agent always performed better than all new agent teams. However, the quality of the explored solutions for simple to refine design task was not different for teams with and without an experienced agent.
- The agents in the teams with an experienced agent also had a higher exploration for all the sessions than all new agent teams for all the complexities of the design task. All new agent teams explore steep and curved peak design space in a similar fashion due to their lack of experience.
- The teams with all novice agents had more diversity in the final solutions for all the task types than the teams with an experienced agent. Teams with an experienced agent behave similarly during idea selection for all the task types, hence had similar diversity in their final proposed solutions.

Design team performance in different collaboration mode:

- When self-efficacy was equally distributed in teams, the impact of the collaboration mode (i.e., virtual and face-to-face) on idea generation and selection was minimized. The solution quality of the teams with consistent high self-efficacy individuals in virtual collaboration was comparable to that in face-to-face settings even when the nature of the design task varied in complexity.
- The effect of design team collaboration mode (i.e., virtual or face-to-face) was prominent when the influence was not uniformly distributed in teams (in this case 1 experienced and influential agent, and 3 influential agents in a team).
- The impact of an influencer who was also experienced is more evident in the face -to face collaborations than virtual. While when half of the small design team members are more confident than the others, virtual collaboration mode results in better quality.
- Patterns of exploration differed in the two collaboration modes. Specifically, less exploration in virtual mode than in face-to-face for a simple design task was observed.
- Virtual collaboration also resulted in less variety in the proposed solutions.
- Virtual team collaboration causes more uniform contribution by all team members than in face-to-face. This difference is more significant when the teams had well-defined influencers or work on a complex design task.

## 7.3 Strength and limitations

The main strength of the research lies in presenting a framework that could be extended and altered at an individual level to capture and represents systems at great depth. The model could be used to simulate several collaboration scenarios and could be calibrated according to the need (like the one presented here where the collaboration environment was altered). The model could be used as an alternative to laboratory experiments as it provides a faster approach to study team collaboration and performance, for instance, team size variation presented in section 6. Besides the model as a whole, the research also sheds light on some of the questions in team collaboration that were unattended in the past. For example, studying influencers in the design team, experienced- novice team compositions as well as comparing face-to-face collaboration by considering individual, team and task factors. In general, the results could be exploited by those studying or managing teams to understand and enhance team performance. The empirical studies that explored the elements like the majority and influencer effect or the factors affecting an individual's agreement, could serve as the starting point in the design research domain to build further investigations when studying concept selection.

Though the main capability of an agent-based model is to represent a system in a simplified form, this is also the main limitation of this research. Therefore, the results should be considered as insights instead of actual understandings, as they would vary with the complexity of the task modelled, the number of agents and learning rules. Due to a layer of complexity added by the agent-based models, validation of the entire simulation finding is challenging. It is important to be explicit on how far one can take the results presented in the model. The generalizability of the results from the agent-based model is low, however, the results are applicable in their respective parameter settings (Rand & Rust, 2011). They are not indicating the exact behaviour of influences, but rather they could be interpreted as indications of how influencers are affecting design teams. Undoubtedly, more work needs to be done to see how influencers in the design team affect team and organization creativity. Some of these limitations could be listed as follows: (1) As stated in the model description that 'k' in k-means clustering of similar solutions was chosen randomly whose value lied between the 2 and the total number of solutions proposed. This approach might not be effective when the team size is very large. (2) The two-dimension representation of the design space was done for simplification purposes as increasing the dimensions was drastically increasing the computational load. Here model adopts one of the ways to represent a design task as there are very limited guidelines given on how to computationally represent an actual design task relevant for industry, public, social design or innovation projects. (3) The limited number of steps assigned to the agents before they are ready to communicate their solutions. Increasing and decreasing the steps may affect how agents move on the design space, hence their solution quality. (4) There could be many factors that affect an individual's working in a team (such as motivation) that were unaccounted for in the study. Moreover, in the real world, the degree of influence perceived by other team members may depend on different factors for different individuals. Experience in agents was simulated by means of familiarity with the task. In the real world, experience is a meta-cognitive skill. (5) Agents move on the design space without being aware of their own solution quality, while in reality, a naive human designer has some idea about its solution that could be based on intuitions, long term memory or life experiences. (6) There are several other factors such as gender roles, informal communications and cognitive biases are present during a collaborative interaction and were not considered during investigating how influencers affect project outcome. It should also be highlighted that in the model the role of social aspects on idea generation events such as taking and giving ideas based on personal attributes is not much emphasized. (7) Coalition to form groups of agents was based on the similarity of their solutions/opinions which in the real world might also depend on physiological similarity, proximity, gender, team structure and so on. For the current work, behaviour and thinking in agents were not treated independently. For example, one could change their behaviour without necessarily abandoning their ideas (e.g., if someone simply wishes to avoid conflict). (8) The results shown in the empirical studies were based on self-reported data that were according to an individual's perception and more qualitative analysis should be done on a larger dataset. There could have been many unaccounted factors that could have influenced the result of the empirical studies (for example, an individual's perception of the 'good idea' could have been influenced by the presenter's nationality). The empirical studies lacked data related quality of solutions produced by individual team members, hence nothing could be said the quality of solutions generated in the empirical studies.

## 7.4 Future work

Considering the limitations identified above, the planned future work aims to address some of those, besides exploring new potential research topics. These include:

1. Design task:
    a. As mentioned above in the limitations that the simulation results were based on a design task that had two design variables (i.e., 2 dimensions), extending the design task function 3 or more dimensions would be the next step. This would provide us insights into the impact of design task variables on the design outcomes. Studies like Lapp et al., (2019) have used an objective function with multiple dimensions in their work, however, adding more dimensions in MILANO would increase computational resources. Thus, code structure and workstation requirements (memory and processing power) need to be adjusted. In the immediate future, a design task with more variables will be made and a possibility for agents to choose the desired design variables to generate solutions would be constructed.
    b. Currently, the design task resembles more a 'search task' with a fixed design space and variables (i.e., its dimensions). Computational representing a real-world design problem is quite challenging. So far, very limited work has been done to computationally represent actual design problems relevant for industry, public, or social design /innovation projects (Censi, 2016). This in general, could be a potential research domain that needs more attention.
    c. Co-evolution of the problem and solution space (Maher & Tang, 2003) was not considered in the current model, however in the future, it would be apt to consider a design problem that is not fixed, or the solution space evolves with a problem. The problem itself could be divided into sub-problems and could be distributed among the team members rather than all the team members working on the same problem at the same time. These sub-problems will have sub-solutions that when combined, should address the main design problem.
2. Agent learning:
    a. This feature of the model where 'the design team is not aware of the quality of their solutions...", was inspired from the real-world representation where, when the designers start working (and they have no past experience similar to the agents in this case), they go by trial and error. However, unlike humans who have an intuition or long-term memory that help them to get an idea about the quality value of their solutions, agents in the model are not capable of doing so. Therefore, in the future, the work would deal with building agents that have some idea about the solution quality. One way to achieve this could be by making all the agents aware of the solution space values with some noise that varies from agent to agent. This would further help in exploring the interplay between influence and solution quality.

   b. Since the work models' agents learn by following the 'influencers', imitation is the only form of social learning, that the model represents. Other types of learning such as instructional learning that consists of strategies that individuals select and use to accomplish a task that could be considered in future work. This would help in having more complex learning in agents.
   c. Currently, the agents in the model do not know anything about other agent's capabilities. Adding an attribute in agents where an agent knows about the other agent's capability (in terms of domain knowledge/skills) would be considered in the future as this feature might influence the degree of influence.
3. Using other evaluation metrics for evaluating the design outcomes could be considered in future. For example, measuring novelty (Kazjon & Maher, 2019) of the solutions produced the artificial design agents.
4. Simulating other collaboration scenarios like the implementation of the incubation period between sessions that would affect idea generation and agent attributes could be considered. Additionally, shuffling team members from one session to another would affect team familiarity at a given session.
5. Conducting more empirical studies to reveal factors that affect influence and enhance the understanding of the role of influencers in design teams, would be done continuously. The feedback from these experiments would aid in tuning the model.
6. The complexity of a design process is challenging to capture in a computational model. Therefore, in the future, a richer representation of communication and collaboration would be focused. Features like organic timing to propose solutions, proposing multiple solutions, the building of each other solutions and not just combing similar solutions would be considered for future work.

Though the agent-based modelling approach has often received criticism over simplification and validity, they are also widely appreciated for their ability to capture details at an individual level and representation of complex scenarios that are difficult to control in real-world settings. To conclude, design research has a fair number of agent-based models that have been used to study various aspects.

*"A good model is the one which meets its purpose, and we need to understand the purpose of the computational model"* - (Burton & Obel, 1995)

Now, at the end of this research, I recognize that there are many potential areas of improvement, additions in the model and questions that need to be addressed, hence I believe it is a start of research. At last, besides being an excellent learning experience, conducting this research was equally rewarding.

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# Glossary

**A**

| | |
|---|---|
| Agent | An agent is an autonomous entity that observes and acts in an environment (Russell & Norvig, 2002) (section 3.4). |
| Agent memory* | A simplified version of memory (storage) where agents store experience after working on the design task at the end of a session (Liew & Gero, 2004)(section 3.4.1). |
| Agreement* | It is defined as the situation in which an individual has the same opinion, or in which it approves of or accept something from its peer. Agreement in the model is what an individual agrees with the other's proposed solution (section 5.3.3). |

**C**

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| Coalition groups* | A coalition is an act that takes place when the judgements (opinions) of individuals are close to each other and it tends to dominate the group judgment process (Cartwright, 1971) (section 3.6.3). |
| Complexity of a task* | The complexity of a task is defined by the ease of finding an above-average solution (i.e., above 0.5) (section 2.7). The nature of the task in the model is mainly focuses on its complexity. |
| Contribution* | The contribution is defined as the number of times an agent proposed its solution to the other team members (section 5.3.3). |
| Controller agent* | The controller agent could be considered similar to an external leader in self-managing teams who is not directly involved in the team activities but provides feedback to the design team agents (Morgeson, 2005) (section 3.4). |

**D**

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| Decision making* | Decision making here is an idea selection activity that consists of a coalition of like-minded agents and agreeing on solutions (section 3.6.3). |
| Design collaboration* | It is a collaborative activity where designer agents work on a design task. In the context of the research, the term collaboration design is |

*This term is defined in the context of this study and does not indicate a broader meaning in the ordinary language

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| | used interchanging with design collaboration and design team collaboration (section 2.1). |
| Design outcome* | The output of the design activity (idea generation or selection) is called design outcome. Evaluating design outcome gives an idea about design team performance (section 5.3). |
| Design task* | Design task is a term that stands for how a task is expected to be done in the best possible way (i.e., to obtain the best solution values) (section 3.3).<br><br>It is computationally represented as a multi-dimension function. This function represents the goodness (value/performance) of the design solution given a certain number of variables to explore.<br><br>It is characterized by a number of peaks each with a certain curvature<br><br>The number of peaks could be analogous to the ease of finding a good solution for a conceptual design problem. The best solution or solution with the highest value is i.e. 1.0 (section 3.3).<br><br>The curvature of the peaks (steep or curved) could be analogous to the refinement or optimisation of detailed design activity. The peak curvature affects the gradient around the maxima (best solution values) (section 3.3). |

**E**

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| Energy to explore* | The way agents explore the solution space in the model depends on their attention energy that drops towards the end of the session as the recalling process becomes tiring (section 3.4.1) |
| Experienced agents* | Experienced agents are the ones having the knowledge of failure or error points, as they have worked on similar tasks before (section 3.7). |
| Expertise* | It means knowledge in a particular field. When an agent has a lower domain-expertise level, it will learn slower from its positive event (section 3.5.1). |
| Exploration* | Exploration of the design space can be measured in terms of the number of design alternatives discovered (Dorst & Cross, 2001) (section 5.3.2). |
| Exploration rate* | The exploration rate is the number of solutions in a design space explored during a session, without considering the ones in the previous session (section 6.2.1). |
| Extrovertism | It is a feature in agents that is mediated by self-efficacy (Stajkovic et al., 2018), thus, all individuals with more self-efficacy are likely to propose solutions to the team(section 3.6.1). |

**F**

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| Failure radius* | The failure radius or the size of the failure circle around the failure point depends on the learning capacity from a failure of an agent (section 3.5.1). |
| Familiarity* | Familiarity between two agents is defined as the number of sessions the two agents have in common (i.e., have worked together), therefore familiar with each other (section 3.4.1). |
| Feedback* | It is a score provided by a controller agent based on the quality of the solution proposed by a team (section 3.6.4). |
| Forgetting* | The experiences of an agent that are not utilised in the agent's current situation and are not recalled for a long time are forgotten from the memory (Oberauer & Lewandowsky, 2008) (section 3.4.1). |

**I**

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| Individual personality | According to personality psychology, individual personality refers to the individuals' characteristics of behaviours, cognitions, and emotions that evolve from environmental or biological factors (section 2.3.1). |
| Influence* | Influence (interchangeably used for social influence) is the power perceived by agents in the team from other agents (section 2.2.1, 3.4 and 3.5.2). It is the capability to affect other agents' opinions and thinking. |
| Influencers* | Influencers in design teams are individuals that have more capacity to affect (influence) some team members' thinking, attitudes, decision-making and behaviour more than the others (section 1.1). |

**M**

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|---|---|
| Majority influence | There are two subtypes of majority influence processes: coalition process and pure majority process (Cartwright, 1971). Coalition takes place when the judgements (opinions) of individuals are close to each other and it tends to dominate the group judgment process. Majority process is where the judgement of a larger (majority) group of individuals influences the judgement of other team members during decision-making (section 3.6.3). |
| MILANO* | The model proposed in this study is called MILANO (Model of Influence, Learning, and Norms in Organizations) (section 3.2). |
| Minority influence* | Minority influence is an influence that occurs when the cumulative self-efficacy of the coalition group is less than other groups/individual and causes the group to agree on the proposed solution of the minority (i.e., influencer(s)) (section 3.6.3). |

**N**

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| Negative event* | A negative event is an event that had below-average feedback (less than 0.4 in value). It will be stored as a failure in agents' memory (section 3.5.1). |
| Nomothetic | The nomothetic simulations assume the presence of laws or theory such as interaction among agents depends on the attributes of an agent and the environment (Gilbert & Ahrweiler, 2006) (section 2.7). |
| Non-routine task* | A task is said to be a non-routine task when it is not exactly similar to that of the experience of an experienced agent, thus referred to as a non-routine task (Ball et al., 2004) (section 3.7). |

**P**

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| Past agreement* | The agreement an agent's peer had with it when this agent proposed solutions in the past (section 2.7). |
| Positive event* | A positive event is an event that had above-average feedback (more than 0.4 in value). It will be stored as a success in agents' memory (section 3.5.1). |
| Project* | A project consists of several sessions of idea generation and idea selection and involves a set of design agents and a controller agent (section 3.2). |

**Q**

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| Quality* | Quality measures the usefulness (value) or the feasibility of an idea that satisfies the design specifications (Sarkar & Chakrabarti, 2011). Here it is represented as a value of a point on the design space. (section 5.3.1) |

**R**

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|---|---|
| Recall* | Recall here refers to the act of bringing a past event back into agents' current situation. (section 3.4.1) |
| Reputation* | Reputation is a perception created by agents through other agent's past actions (Mui et al., 2002). The reputation of an agent is the number of solutions that are accepted by the controller agent to the total number of the solutions proposed by an agent (section 3.4.1). |
| Routine tasks* | A task is said to be a routine task when it is exactly similar to that of the experience of an experienced agent, thus referred to as a non-routine task (Ball et al., 2004) (section 3.7). |

**S**

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| Self-managing teams | Self-managing teams consist of a group of individuals that have a shared leadership model, work to achieve a common goal and are |

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| | equally responsible for the project outcome (Magpili & Pazos, 2018) (section 3.4). |
| Self-efficacy | An individual's belief in their capability to achieve goals is taken as one of the characteristics that determine this behaviour (Bandura, 1977) (section 3.4.1). |
| Session* | A session is a part of a design project and consists of idea generation and selection processes. A design project may contain several sessions (section 3.2). |
| Social Influence | According to Bandura's Social Cognitive Theory, social influence is the process where individuals change their behaviour, attitudes, and opinions in the presence of social interaction (section 2.2) |
| Social learning | According to Bandura's Social Learning Theory, social learning is a learning process and social behaviour acquired by observing and imitating others.(section 3.5.2) |
| Spread* | Spread or variety in the solutions is the measure of how much the explored or final proposed solutions are different from each other. (section 5.3.2) |
| Step* | Idea generation in the model consists of several steps which are analogous to an agent thinking and exploring the solution space before proposing its solution to the team. A step is formed when an agent moves from one point on the solution space to another(section 3.2). |
| **T** | |
| Team size | Team size is the number of agents in a team who are working on a design task (section 2.3.2). |
| Trust | Trust is an individuals's confidence/faith/hope in a peer with its proposed solutions and ability to do design activities. (Costa et al., 2018) (section 2.3.1). |
| Virtual teams* | Virtual team collaboration was a term that was used contrary to face-to-face co-located collaboration. It can be described as a degree of a team's virtualness that is a function of the percentage of time spent working apart and level of technological enablement (Griffith & Neale, 2001) (section 2.3.4). |
| **W** | |
| "What if" scenarios | Hypothetical scenarios that are created by informal speculation about how a given situation might emerge based on the different variables that are difficult to control in real-world settings (section 2.7). |

# Appendix A

# Publications arising from this research

1. Singh, H., Cascini, G., Casakin, H. & Singh, V., (2019), “A Computational Framework for Exploring the Socio-Cognitive Features of Teams and their Influence on Design Outcomes”, *Proceedings of the 22nd International Conference on Engineering Design (ICED19)*. Delft, The Netherlands: The Design Society
2. Singh, H., Cascini, G. & McComb, C., (2020), “Analysing the Effect of Self-Efficacy and Influencers on Design Team Performance”, *Proceedings of the Design Society: DESIGN Conference*. Online.
3. Singh, H., McComb, C. and Cascini, G., (2020), “Modelling the Dynamics of Influence on Individual Thinking during Idea Generation in Co-design Teams”, *In Design Computing and Cognition DCC’20*, pp. 43-62, Springer
4. Singh, H., Cascini, G. & McComb, C., (2021), “Comparing Design Outcomes Achieved by Teams of Expert and Novice Designers Through Agent-Based Simulation”, *Proceedings of the Design Society: International Conference on Engineering Design (ICED 2021)*, Online
5. Singh, H., Becattini N. & Cascini, G., (2021), “How familiarity impacts influence in design team collaboration”, Proceedings of the Design Society: International Conference on Engineering Design (ICED 2021), Online
6. Singh, H., Cascini, G. & McComb, C., (2021), “Comparing Virtual And Face-To-Face Team Collaboration: Insights From An Agent-Based Simulation”, *Asme 2021 International Design Engineering Technical Conferences And Computers And Information In Engineering Conference*. ASME Digital Collection 2021
7. Singh, H., Cascini, G. & McComb, C., (2020), “Influencers in Design Teams: A Computational Framework to Study their Impact on Idea Generation”, *Artificial Intelligence for Engineering Design, Analysis and Manufacturing* (in press)
8. Singh, H., Cascini, G. & McComb, C., (2020), “Idea Selection in Design Teams: A Computational Framework and Insights in the Presence of Influencers”, *Design Science*, ($2^{nd}$ review)
9. Singh, H., Cascini, G. & McComb, C.,2021. Virtual and face-to-face team collaboration comparison through an agent-based simulation. *Journal of Mechanical Design* (under submission)