Virtual and face-to-face team collaboration comparison through an agent-based simulation

Singh, Harshika[1]
Department of Mechanical Engineering
Politecnico di Milano
Milano Bovisa - Via La Masa 1
Milan, Italy
harshika.singh@polimi.it
000103631459

Cascini, Gaetano
Department of Mechanical Engineering
Politecnico di Milano
Milano Bovisa - Via La Masa 1
Milan, Italy
gaetano.cascini@polimi.it

McComb, Christopher
Department of Mechanical Engineering
Carnegie Mellon University
Pittsburgh, PA, USA
ccm@cmu.edu
Member, ASME

ABSTRACT

The ongoing COVID-19 pandemic has accelerated the acceptance of virtual team collaboration as a replacement for face-to-face collaboration. Unlike face-to-face collaboration, virtual collaboration is influenced by unique factors, such as technology mediation. However, there is a lack of rigorous research that assesses the impact of virtual collaboration on the engineering design process. Therefore, the current study investigates the effect of virtual team collaboration on design outcomes by means of the MILANO

[1] Harshika Singh, harshika.singh@polimi.it

(Model of Influence, Learning, and Norms in Organizations) framework. To tailor MILANO for virtual collaboration, this paper first presents an empirical study of human design teams, which shows how model parameter values for face-to-face collaboration (like self-efficacy, perceived influencers, perceived degree of influence, trust and familiarity) differ from appropriate parameter values for face-to-face collaboration. The simulation results for both virtual and face-to-face collaboration show how design outcomes differ with collaboration mode. Unlike teams with a few well-defined influential individuals, the mode of collaboration does not have a significant impact on teams where all individuals are equally influential. Virtual collaboration also results in lower exploration and variety than face-to-face collaboration.

INTRODUCTION

The COVID-19 pandemic has accelerated a transition from face-to-face to virtual team collaboration [1]. A report by McKinsey found that there are positive aspects to this transition: people enjoy the added flexibility, they are more productive, and organizations have fewer locational constraints [2]. For these reasons, virtual team collaboration is likely to continue after the pandemic is over. However, there is little research on the behavior and performance of virtual teams in engineering design. This work presents insights from MILANO (Model of Influence, Learning, and Norms in Organizations), an agent-based model that is tailored in this work to simulate various virtual team collaboration scenarios.

A variety of terms have been used to describe the process used by a team that does not work face-to-face, including distributed teams, computer-mediated collaboration, or online collaboration [3]. The current work uses the term *virtual team collaboration* to describe the state when the team is not working face-to-face at the same location [4]. Virtual team collaboration (a term contrary to face-to-face or co-located collaboration) can be characterized by the percentage of time spent working apart and the level of technological enablement [5]. In this work, virtual collaboration and face-to-face collaboration are being referred to as the two collaboration modes.

Virtual teams face unique challenges [6] such as trust-building and knowledge sharing [7]. In addition, communication in virtual teams may affect social influence or giving rise to more conflicts [8], and the participation of expert members in the team may not guarantee good project outcomes [9]. These challenges, if not addressed and managed appropriately, can affect the performance of virtual teams [10]. Therefore, the purpose of the current work is to examine how design outcomes are affected by virtual team collaboration.

Studies have shown that virtual collaboration has unique drawbacks, especially in terms of lower collaborative behavior in teams [15] which leads to lower cohesion and weaker relationships in team members [16], which in turn negatively affects team performance [17]. Moreover, task- and relationship-related challenges in virtual team collaboration can further provide a hindrance to team performance [18]. For example, team members may react differently in unexpected new situations due to external stimuli when collaborating virtually, hence affecting relationships with the other team members [18]. Virtual teams often face difficulties in communication due to issues with technology. As these teams solely rely on technology to conduct any form of communication, it is crucial to consider the technology medium as an important attribute of virtual collaboration [19]. Any problem in the technology medium (e.g., internet, servers, collaboration software) directly affect communication among the team members. This deterioration, in turn, may increase the probability of a conflict due to misunderstanding or miscommunication [20]. Although face-to-face discussions are more effective in overcoming conflicts [13], they may lead to group coalitions [14].

Other factors are also crucial for collaboration, like trust, perceived influence, cohesiveness, and social interaction [11]. It is known that face-to-face collaborations are more powerful in developing social norms, authority, group culture, and commitment [12]. As in face-to-face collaboration, virtual collaboration also benefits from relationships, shared understanding, and trust [21]. These socio-emotional factors that affect the collaborative process should be considered when studying a collaborative learning environment [22]. 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) [23]. Virtual collaboration models like the ones proposed by Alsharo et al. [7] and Choi and Cho [24] suggest that knowledge sharing positively influences trust and collaboration among members, but trust does not have any significant impact on team effectiveness. Other studies showed that there is lower trust in virtual than face-to-face collaboration, but the level of trust increases towards the end of a design activity [25]. In contrast to face-to-face collaboration, research has shown that virtual team collaboration reduces the effect of personality, power or group formations within teams [26] but could result in the polarization of the decisions [27]. From the past studies, it is clear that the performance of face-to-face teams differs from virtually collaborating teams [17] as the elements that are useful in one collaboration mode might not be effective in the other [6].

While virtual team collaboration is increasingly popular, there is little research on the behavior and performance of virtual teams in engineering design. In contrast to the rich literature found on the face-to-face collaboration environment, few studies examine how virtual collaboration affects design team performance. Out of these few studies on virtual collaboration, most have explored collaboration through software tools like virtual worlds that assist designers [28,29]. Others have studied collaboration in a distributed environment based on agent interaction or studied negotiation or conflict resolution during co-design sessions [30,31]. 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 [6]. For example, certain collaboration elements might result in better virtual team collaboration outcomes than in face-to-face. Hence, a wider research question is identified that considers the effect of the individual, team, and task attributes during virtual collaboration:

What is the effect of the two collaboration modes (i.e., virtual and face-to-face) on design outcomes and design process?

This question is answered by using insights derived from an empirical study to inform simulations in an agent-based model. The remainder of the paper is organized as follows (see Figure 1). The paper begins with a description of the initial MILANO modeling framework from prior work, which was built to simulate face-to-to-face collaborations. The next section presents an empirical study designed to support the modification of existing elements of MILANO to suit the virtual team collaboration setting. The model is adjusted based on the empirical study and the existing literature, to simulate virtual team collaboration. Test cases are defined, and the comparison of the results of the virtual and face-to-face collaborations are presented to answer the research question.

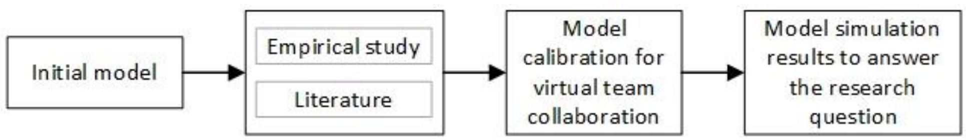

Fig. 1. The current work layout

MODEL DESCRIPTION

Agent-based models have often been used to represent actual design sessions [53, 57]. Such models have been built in the past to study different aspects such as interactions [58, 59] and collaborative methods [60]. They have been also used to simulate teamwork for different team types [54] and team structures [72]. The design problem characteristics [61], problem-solving styles [53] and decision-making behavior in agents during the early design phase [67] have been simulated to see the impact of various model parameters on the team performance. Some models have varied the agent characteristics like talkativeness, intelligence, and credibility to see their effect on the emergence of leaders in teams [68]. As well as different types of learning have been simulated in agents, for instance, collective learning where design team agents use input knowledge, environmental information, and design goals [69], learning from experience in agents [70] and social learning in agents [71]. From these studies, it is clear that features that were crucial to fulfilling the aim of the work were considered as implementing all of them would increase the computational load and would make it more challenging to draw strong inferences.

The current work makes use of the Model of Influence, Learning, and Norms in Organizations (MILANO) for simulating idea generation sessions [32] and concept selection during co-design [33]. Like the real world, a MILANO simulation starts with a design project that consists of multiple idea generation and selection sessions. Figure 2 shows one of these sessions in which designer agents generate solutions to a design problem and propose a final solution to the controller agent (equivalent to a project manager or similar) at the end of each session. The feedback from the controller agent helps designer agents to learn and accordingly propose solutions in the following session. The rest of this section details how design problems are represented in MILANO, how designer agents carry out concept generation and selection, and how designer agents with varying degrees of experience may be constructed.

Design task

The design task drives many aspects of the simulation and should resemble real world aspects of design. For instance, designers are often not immediately aware of the quality of their solution and proceed by trial and error [32]. In this way, designing a product resembles a search task where designers aim for acceptable solutions rather than mathematical optimized solutions [66] like in the study that found that designers tend to choose ‘satisficing’ solution concepts even when they were flawed [74]. Another key aspect is that design tasks often have many below-average solutions with a few solutions that have the highest value [32]. These characteristics of real-world design tasks were considered in the construction of the computational design task solved within the model.

In the model, a design task for which designer agents seek solutions is computationally represented as an N-dimensional function where each dimension denotes a design aspect (see Figure 2). Any point in the design space is a potential solution and can have a value in the range [0, 1]. The design solution space 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 (example can be seen from Figure 2). An agent moves from one point on the design space to another and this step taken by an agent is analogous to a designer exploring alternative solutions. The results of the design outcome presented in the paper are related to the design space with 5 peaks where peaks denote the best alternative options. The number of best solutions or peak is analogous to the ease of finding a good solution for a conceptual design problem (more details on this representation are provided in [32]). In this work, 2 aspects of a design (N=2) are considered for the prudent utilization of computational resources and clear understanding of the designer agent teams. A similar design problem representation was adopted for simulating teamwork based on differences in cognitive style [53]. Other studies in problem-solving have also used a similar 1-D and 2-D representation of the problem with peaks and valleys [54, 55].

The other parameter considered while representing a design problem is the curvature of the peaks (steep or curved) which is analogous to the necessary level of refinement or optimization during detailed design (as seen in Figure 3). Therefore, having steeper peeks in the solution space would require additional detailed design effort and increase the difficultly of a design task. Being able to modify the design task in this way is crucial, as it is known that the nature of the task given to the participants affects their performance [34].

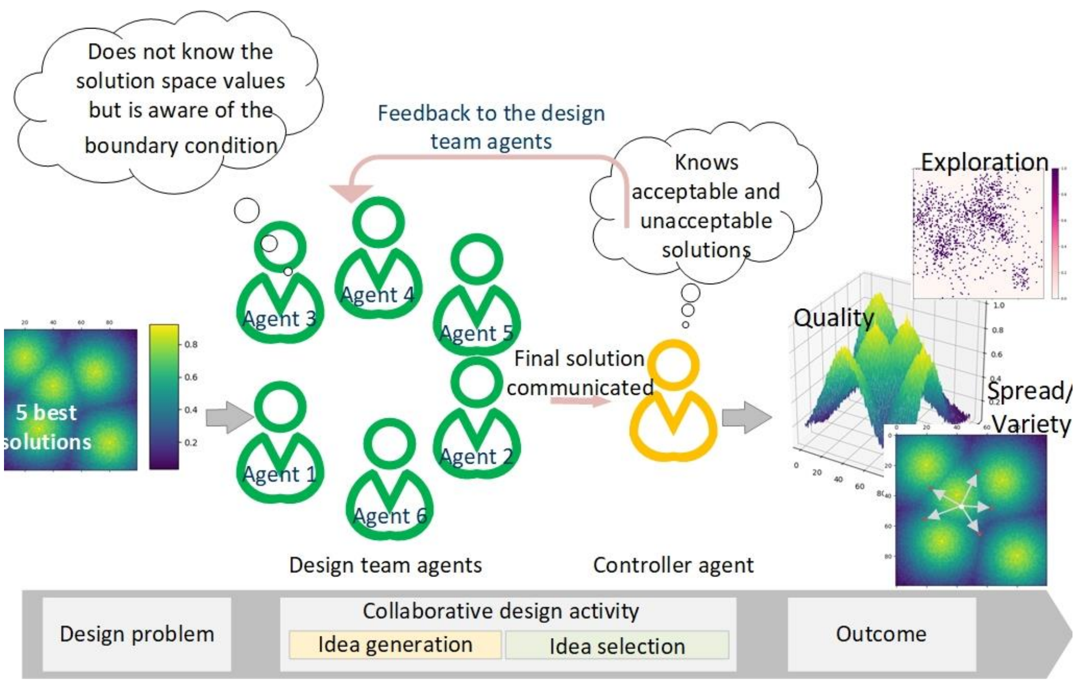

Fig.2. Milano framework

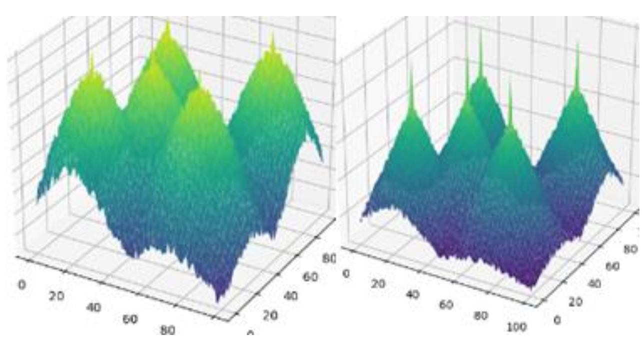

Fig. 3. Standard 5 peaks (left); steep 5 peaks (right)

Designer agents generating and selecting solutions

After the design task is given to the design team agents, they start generating solutions. The designer agents individually generate solutions based on a detailed process described in Singh et al. [32] and then propose the solutions to the team for further processing [33]. All the designer agents are given the same set of rules that determine their design behavior. However, this behavior is governed by the attributes of the designer agents, including self-efficacy, influencing power, reputation, familiarity, and trust. The influencing power perceived by an agent from its peer agent depends on self-efficacy and trust between them, where trust is further affected by an agent's reputation and familiarity (for more information on agent attributes see [32]). Each agent explores the solution space based on its mental energy which decreases with the length of an idea generation session. This results in a reduction in the size of steps taken by an agent as it explores the design space, as the agent nears the end of a session. Designer agents store both positive and negative experiences based on feedback from the controller agent in past sessions. An agent learns from these experiences by avoiding the area of the failures and moving in the direction of past success. Designer agents also learn from their peers, based on a model of social influence which is built on the differential self-efficacy and trust between the two designer agents. Trust in turn is based on an agent's reputation (i.e., the ratio of the number of accepted solutions to the total number of proposed solutions) and familiarity (i.e., the number of sessions the two agents have in common). Influence, trust, and self-efficacy are all dynamic across sessions. However, for the current work, influence values are pre-defined to create a controlled environment. As mentioned earlier that influence depends on self-efficacy and trust, since trust between the designer agents develops gradually with the design sessions, self-efficacy value allotted to the designer agents at the beginning of the simulation created influencers (i.e., designer agents having significantly higher self-efficacy than other team agents were called influencers). More details on agent behavior are provided in [32].

Idea selection follows idea generation as seen in Figure 2 [33]. In idea selection, the designer agents propose their solutions to the team and the team collaboratively decides which final solution to communicate to the controller agent. The probability of an agent being selected to propose its solution depends on how the self-efficacy is distributed in the team. An agent with high self-efficacy has a higher probability to communicate their solution. Similar to real-world brainstorming sessions where similar ideas may be combined, the designer agents in the model also combine their similar proposed solutions. The computational similarity between the solutions is defined by the distance between the solution points in the design space. The decision-making during idea selection is affected by the presence of a highly confident individual in the group as well as the majority effect 'caused by the presence of a critical mass of laypeople sharing similar opinions [14]. For example, individuals having similar thinking may strengthen their opinion and self-efficacy, hence, the majority effect. 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 the influencer effect. This gives rise to a coalition group in teams as the opinions of individuals that are close to each other tends to dominate the group judgment process. The cumulative self-efficacy of these coalition groups is a major factor that decides the amount of agreement a team has on the proposed solutions. The solutions with the maximum agreement are communicated to the controller agent. Depending on the quality of the solution proposed, a controller agent provides feedback to the team.

Experience in designer agents

Once the model is formed, it can be used to simulate different collaboration scenarios by varying model parameters. For example, it is known that novice and experienced individuals differ in their idea generation strategies [35]. In MILANO, a novice agent is one that lacks exposure to problems or tasks which are similar to the one currently being solved. In contrast, an experienced agent is one which has encountered similar tasks before and therefore has extra knowledge of failure points. 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 recalls those experiences when working on the current problem [35]. Novices, on the other hand, use trial-and-error techniques to solve the current problem [35]. This may cause novices to take more time to reach a satisfactory solution, as shown in prior work [36]. Designer agents who have worked on a design task were stored in a pool as experienced agents. Then a few agents from this experienced agent pool and some newly created agents were placed together in a team to work on a design task (more details on the representation of experience in MILANO are provided in [36]).

Like any other agent-based model that aims to mimic human activities, MILANO also had some assumptions for example the most confident and trustful individuals were considered influencers [32], the agreement in teams is affected by the influencers [33] and experienced agents know the design space based on their past experience [36]. It should be noted that MILANO was originally conceived and implemented for simulating face-to-face teams. Therefore, in order to understand and add some crucial elements of virtual team collaboration, the following empirical study and some supporting literature (as given in the virtual Team collaboration model section) were used to adjust the original MILANO implementation.

EMPIRICAL STUDY

As stated above, MILANO was initially constructed to simulate face-to-face teams. Therefore, an empirical study was designed to expose the differences between virtual and face-to-face collaboration, enabling these differences to be represented in MILANO.

Experimental set-up

During the study, teams of 4 mechanical engineering graduate students worked on a semester-long design task given by a company for a master's degree course on Methods and Tools for Systematic Innovation at Politecnico di Milano, Italy. The design task for both the years 2019 and 2020 was about addressing the issues related to electro-domestic appliances like washing machines, dryers, dishwashers, refrigerators and air conditioners. The teams had to choose one of the several design problems themes given by the company (Appendix A). The structure of the course offers students to apply their knowledge gathered from the lectures related to systematic innovation to a real-world problem given by a company. The teams started with problem clarification, solution generation and the idea selection phase where they selected the best solutions. These teams were supervised by the teaching staff and received regular feedback from the company experts during the design reviews throughout the semester. The design process followed by the teams consisted of a typical divergent and convergent process (generating and selecting solutions) for efficient problem-solving. The end outcome was at least one conceptual design solution that aimed to solve one of the problems related to electro-domestic appliances. The design scenario (lecture content and design review dynamics) was kept similar for face-to-face and virtual collaboration settings.

Data was collected from 10 teams collaborating face-to-face in 2019, and for 15 virtual teams in 2020. For each team, the data was collected in the form of online surveys. The data collection was done as shown in Figure 4.

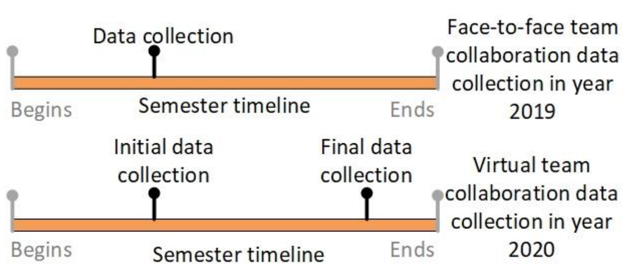

Fig. 4. Data collection

This information was collected for the empirical study (as seen in Table 1) as it forms the basis of collaboration affecting socio-emotional processes [22] such as social influence in design teams that give rise to influencers [32]. As such, they are important factors in the MILANO framework. The self-efficacy questions for the face-to-face collaboration were the same as [37] but the scale was changed from 10 to 4-point to match the scale of the problem-solving attitude questions (not presented in this paper). 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 respondents' trust, familiarity, degree of influence, agreement and communication with each peer was inspired by [38]. The additional parameters were added to the virtual collaboration questionnaire based on [23] as seen from Table 1 (more details could be seen in Appendix B).

Table 1. Questionnaires elements during the empirical study

Common elements of the 2 questionnaires (face-to-face 2019 and virtual team collaboration 2020)			
	Elements	*Scale*	*Range*
Individual respondent data for itself	Self-efficacy	4 and 5- point Likert scale	1= least self-efficacy, 4 or 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, 5 = maximum
	Trusting its peer	5-point Likert scale	1= least, 5 = maximum
	Familiarity with its peer	5-point Likert scale	1= least, 5 = maximum
Additional elements of the virtual team collaboration questionnaire in 2020			
Individual respondent data for the team	Communication effectiveness	5-point Likert scale	1= least, 5 = maximum
	Resolution of the conflicts	5-point Likert scale	1 =least, 5= maximum
	Task cohesion	5-point Likert scale	1= least, 5 = maximum
Respondent's data for each of its peers	Agreement with its peer	5-point Likert scale	1= least, 5 = maximum
	Communication with its peer	5-point Likert scale	1=least, 5= least or no conflicts and very efficient communication

In the following part of this section, the results from the individual data analysis from the years 2019 and 2020 are discussed.

Empirical study findings

When analyzing the data from face-to-face and virtual collaboration, initial data collected in 2020 was used as it matches the data collection time with the year 2019 (Figure 4). The difference in the information considered in face-to-face collaboration and virtual collaboration can be seen in Figure 5. It is clear that the parameters shown in Figure 5 behave differently when the collaboration mode changes from face-to-face to virtual. Figure 5 shows the normalized values and p-values of the Mann Whitney U-test. The parameters like self-efficacy and perceived degree of influence between the two individuals have a higher value for the virtual collaboration. One reason for this trend could be due to the efficient collaborative environment [39] where individuals feel more confident about themselves than in classrooms or the better disposition of the participants when collaborating remotely during the pandemic.

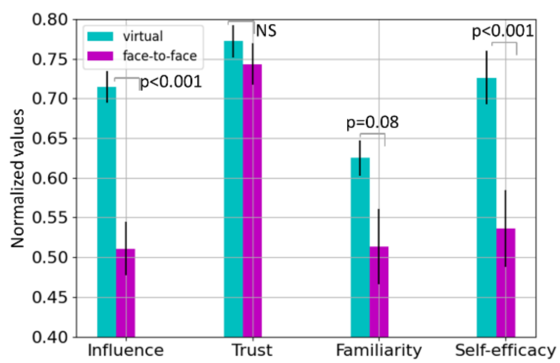

Fig. 5. The difference in the information in face-to-face and virtual collaboration during data analysis (NS = not significant)

However, familiarity among individuals seems to be higher in virtual team collaboration and is not significantly different from face-to-face collaboration. These results conform to the studies which suggested that familiarity is not moderated by the extent of virtualness [40]. In contrast, the trust 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 be true for virtual team collaborations [41]. Wilson et al. discovered that trust in computer-mediated teams was lower but gradually increased to levels comparable to those in face-to-face teams over time [42]. Since the presented empirical study has a low temporal resolution, no conclusions can be drawn on trust-building in teams over time.

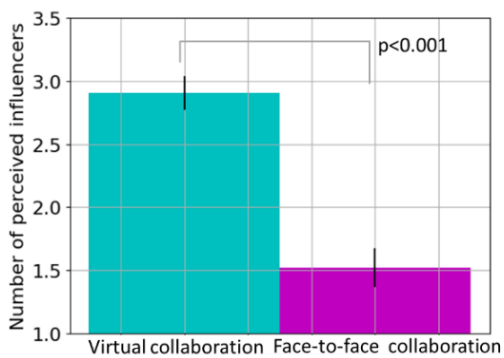

Fig. 6. The difference in the perceived number of influencers in the face-to-face and virtual collaboration

The major difference between face-to-face and virtual collaboration is in individuals' perception of the number of influencers in their team (Figure 6). Specifically, individuals report fewer influences when face-to-face than when virtual. The two groups have statistically significant differences (Mann Whitney U =140.5, p <0.001). This could mean that due to stronger social interaction in face-to-to-face meetings, social influence from a small number of peers was felt much more than the others, leading to a lower number of perceived influencers. In comparison, during virtual team collaborations, the social interaction is not physical, hence, and the influence from peers is perceived more uniformly.

It is known that communication is key in any collaborative work [43]. In teams collaborating face-to-face, communication is more likely to be initiated due to a higher probability of chance encounters [12]. Hence, communication data was not collected in face-to-face for its comparison with the virtual setting because it is already known that virtual team collaboration suffers from effective communication [12] that give rise to team conflicts [19] that affects design outcomes. Similarly, Figure 7 shows that those individuals collaborating virtually who rated higher values for communication in their teams also gave high scores to conflict resolution and task cohesion. Moreover, a positive impact of effective communication on the number of conflicts arising in the team (Kendall correlation coefficient $\tau=0.32$, $p= 0.05$) when analyzing initial data (at the beginning of 2020 in Figure 4) of the virtual team collaboration was found. However, no such relationship between the two (communication and conflict resolution) was found for data collected at the end of 2020 (Figure 4).

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 [23]) and effective communication (Kendall correlation coefficient $\tau=0.5$, $p = 0.004$) during the end of the design project (i.e., Final data collection Figure 4). 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 and Mortensen, found in their work that communication moderates the relationship between team distribution and conflict [44].

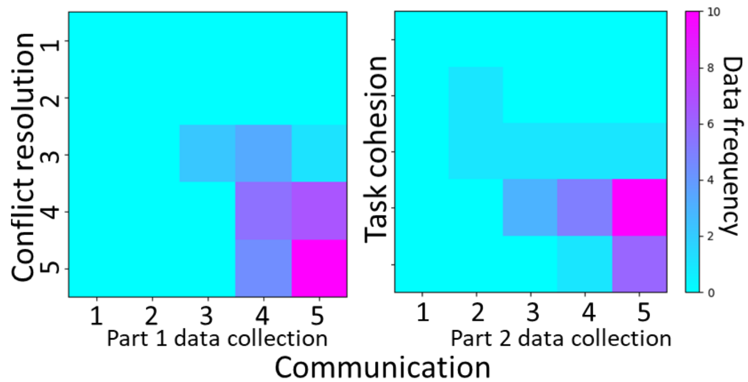

Fig. 7. Respondents' value counts of the communication and other additional parameters of the virtual team collaboration questionnaire

When further investigating the impact of respondent's quality of communication (i.e., the number of conflicts and the clarity) with its team members, the difference in their self-efficacies might have mediated the resolution of the differences between them. The chi-square test (χ^2) results (on Final data collection in Figure 4)[2] showed an association between respondents' communication with their peers and the difference in self-efficacies (χ^2 =12.14, p=0.016).

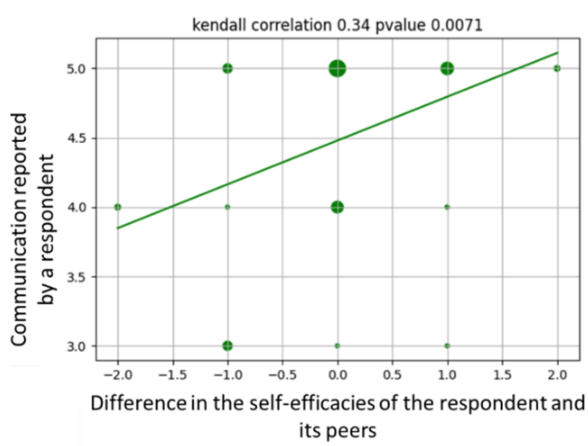

Fig. 8. Difference in the self-efficacies and communication quality between the respondent and their peers

[2] Initial data collected at the beginning of 2020 in Figure 4 had chi-square test significance value of 0.07.

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 (Figure 8). While respondents with lower self-efficacy than its peer entered lesser communication. Figure 8 shows a positive correlation between the difference in self-efficacies and communication (Kendall correlation coefficient τ=0.34, p =0.007). In other words, the chances of having a disagreement are more when the respondent and its peer have similar self-efficacies than when the respondent has higher self-efficacy than the peer. Studies in the past have confirmed that self-efficacy affects an individual's conflict style [45], where low self-efficacy is usually associated with conflict avoidance.

Additionally, it was also found that respondents' communication with their team members affected model parameters (Figure 9).

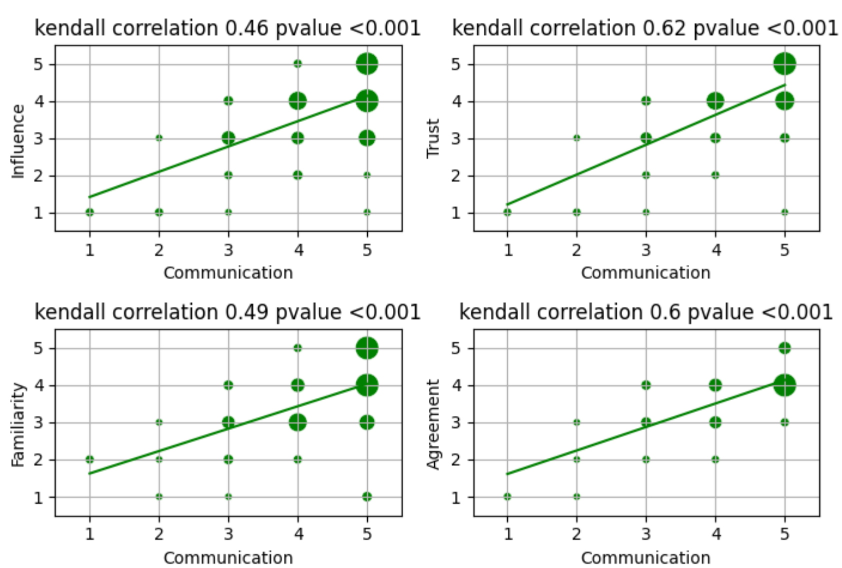

Fig. 9. The effect of communication of the model parameters

The relationship exists both in initial and final data (shown in Figure 4) but was stronger for the data collected towards the end of the semester as shown in Figure 9. The interpersonal attraction of a group member as described by [23] is considered a crucial variable when the teams are collaborating at a distance. Similarly, a respondent's perceived degree of influence from its peer that is considered for the current work is also affected by communication between them (Kendall correlation coefficient $\tau=0.5$, $p<0.001$). The trust and familiarity between respondents and their peers also increase with better communication (Kendall correlation coefficients $\tau=0.6$ and 0.5 respectively with $p<0.001$). Lastly, the amount of agreement a respondent had with its peers also increases with communication between them (Kendall correlation coefficient $\tau=0.6$, $p<0.001$) as effective communication leads to clarity and conflict resolution [44].

VIRTUAL TEAM COLLABORATION MODEL

The insights from the empirical study are critical for informing the modification of the MILANO framework [32-33] for addressing virtual teams. When considering the empirical study, it is clear that the behavior of face-to-face teams differs from virtual teams. The latter part of the empirical study also demonstrated how these relevant model parameters are influenced by additional virtual team collaboration variables like communication. The results of the empirical study were used to update the variable relationships implemented in the model and not the exact coefficient. The remainder of this section details several updates made to MILANO.

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 [46]. 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 [19]. These are taken into consideration in Equation 1, where communication effectiveness (η) depends on technology mediation (τ) and the degree of team virtuality (V_d), while ε is the shape parameter.

$$\eta = \frac{\varepsilon}{(\varepsilon-1)+e^{(\tau V_d)}} \quad (1)$$

τ 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 ε changes ranges between 1-2 times the s' (for example s' =10, in this case). This gives the desired behavior of least communication effectiveness when completely virtual team collaboration has the worst technology mediation. The model assumes that when the teams are face-to-face, the communication is most effective, thus the value of communication effectiveness (η) is close to 1 (i.e., maximum effective communication).

Communication affecting conflicts

The past literature showed that effective communication among the team members helps in resolving conflicts [44]. However, the empirical study 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 (ΔSE). This means that if the two individuals have similar self-efficacy

($\Delta SE \approx 0$), there is a higher probability of conflict or disagreement. Hence, Equation 2 can be formed to map this behavior, where the conflict factor (κ) depends on the effectiveness of the communication (η) and θ. θ governs the conflict factor based on the difference in the self-efficacies of the two designer agents (Equation 3).

$$\kappa = \frac{\theta}{(\theta - 1) + e^{\frac{\theta}{2}\eta}} \tag{2}$$

$$\theta = m + p\ \Delta SE_{i-j} \tag{3}$$

m in the above equation determines the slope of the curve and ranges from 0-2 (0 when the two designer agents (*i* and *j*) have similar high self-efficacies and 2 when one of the agents has higher self-efficacy than the other). To get the desired function value between 0-1, *p* was taken as 2 for the current model simulation. Conflict probability is determined by comparing κ to a random number between 0-1. If κ, which also depends on ΔSE_{i-j} is greater than the generated random number then the chance of having a conflict is more when the two agents have similar high self-efficacies. However, in this way, the model does not eliminate the chance of having any conflicts between a high and a low self-efficacy agent.

Reduction in influence between team members

Factors like trust, positive mutual regard, mutual attraction, cohesiveness, and social interaction are crucial for collaboration [11] and some of these are affected by communication mediated by technology [19]. Research in the past has shown that physical distance reduces the development of friendships or attraction, making conflict more likely [19, 23]. It was also seen from the above empirical study that good communication between two individuals results in a higher influence value. Therefore, the model considers the conflict between the two designer agents (*κ*) and reduces the influence value as perceived by one agent from the other (Equation 4).

$$\Delta I_i^j = a \cdot \kappa^b \quad (4)$$

Where *ΔI* 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_i^j as given in Equation 5 for face-to-face collaboration is the influence value perceived by agent *i* from *j* [32]. Where ΔSE = difference in self-efficacy of agent *i* and agent *j*, and *T* is the degree of trust of agent *i* has on agent *j*. *SE* is the self-efficacy of an agent *j*.

$$I_i^j(\Delta SE, SE, T) = w_1(\Delta SE_{i-j})^{1.5} + w_2\left(SE^j\right) + w_3\left(T_i^j\right) \quad (5)$$

Therefore, the influence ${I_v}_i^j$ during virtual team collaboration is reduced by ΔI_i^j depending on the conflict and could be given as Equation 6. The weights w_1, w_2 and w_3 were taken as 0.3, 0.3 and 0.4 respectively. More details on influence and trust rationale could be found in Singh et al. [32].

$${I_v}_i^j = I_i^j(\Delta SE, SE, T) - \Delta I_i^j(\kappa) \quad (6)$$

Gradual trust in virtual team members

Trust is one of the most important antecedents of virtual collaboration and over time trust may change [21]. From the above empirical study, little difference could be seen in the mean trust values (*T*) for virtual and face-to-face collaborations. As the empirical study was done at specific times, 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 [42]. Specifically, they have found that trust 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. mentioned that trust develops slowly in virtual teams than in face-to-face teams [26]. Therefore, trust-building between the two designer agents for virtual collaboration (T_v) is lower and develops gradually than in face-to-face teams (Equation 7).

$$ {T_v}_i^j = \lambda \cdot T_i^j \qquad (7) $$

Where λ is a factor that results in gradual trust-building and lies between 0.7-1.0 (1 when the team is completely face-to-face).

SIMULATION METHODOLOGY

Studies in the past have shown that knowledge, skills, abilities, and other characteristics of individuals when working virtually differs from those working face-to-face [49]. Individual characteristics like personality and experience, team composition, and task features are also important in virtual team collaboration and their impact is different from face-to-face [50, 51, 52]. In order to assess the impact of collaboration mode (face-to-face and virtual) on design outcomes, the cases shown and described in Figure 10 were simulated through the model.

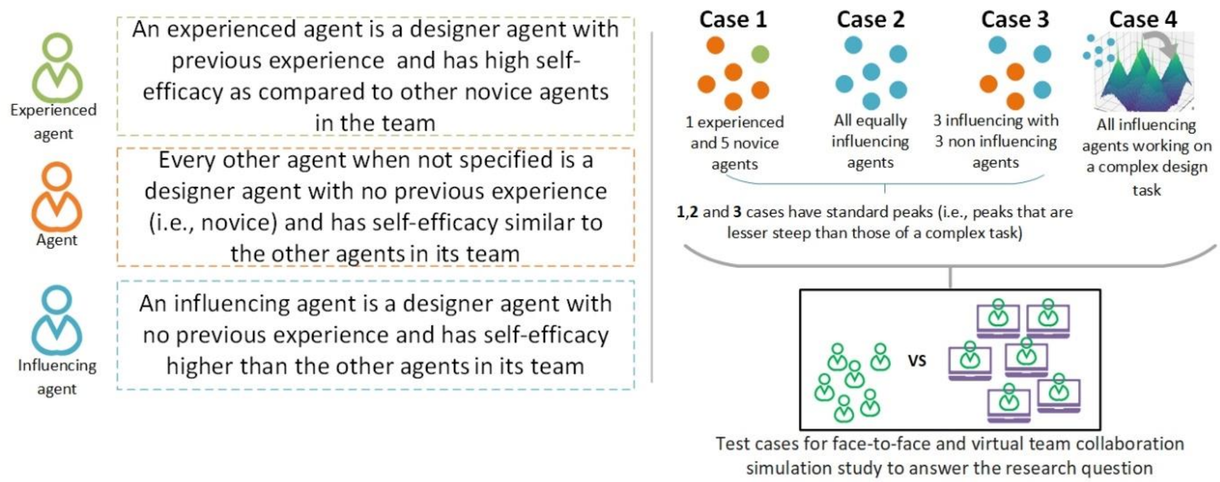

Fig. 10. Simulated test cases

These test cases were also recommendations by Powell et al. where issues related to input, output, task and socio-emotional processes during an early virtual team collaboration were identified [6]. As such, the cases used here represent common design team collaboration conditions. For example, the first test case as seen in Figure 10 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. The results in the following section are obtained and based on

200 simulations to reduce the randomness. The design outcome from the computational agent teams was measured in terms of quality solutions (value or utility) [47] and exploration [48]. The quality of the solution is the value of a point on a design solution space. Exploration on the other hand was further measured in three different ways as given below.

Exploration index (EI) is the of solutions explored on a lower resolution solution space (S_{exp}) to the area of this lower resolution space (A_{lr}). The resolution of the design space was reduced to avoid having an inaccuracy that could arise from near and far exploration; for example, when an agent explores 4 immediate neighbor cells to an agent exploring 4 cells at a larger distance.

$$EI = S_{exp}/A_{lr} \tag{8}$$

Exploration quality index (EQI) is the ratio of the number of the explored solution above a certain threshold, t (in this case t is 0.5, where 0 is a minimum and 1 is a maximum solution quality value) on a reduced resolution solution space (S_q) to the total number of solutions available on the design solution space greater than the threshold value (TS_{lr}).

$$EQI = S_q/TS_{lr} \tag{9}$$

Spread is the dispersion of the solutions. It is calculated by getting the distance between each solution from the centroid of all the solutions on a 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 a 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, $S = \{(x_1, y_1), (x_2, y_2), \ldots., (x_n, y_n)\}$. 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 10). Where *N* is the total number of distances between the solution coordinates and the centroid.

$$Spread = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(d_j - \mu)^2} \qquad (10)$$

RESULTS AND DISCUSSION

The simulation results related to the quality of the solutions generated by designer agents in the teams (of the 4 cases shown in Figure 10) in the two collaboration modes differed significantly from each other (Figure 11).

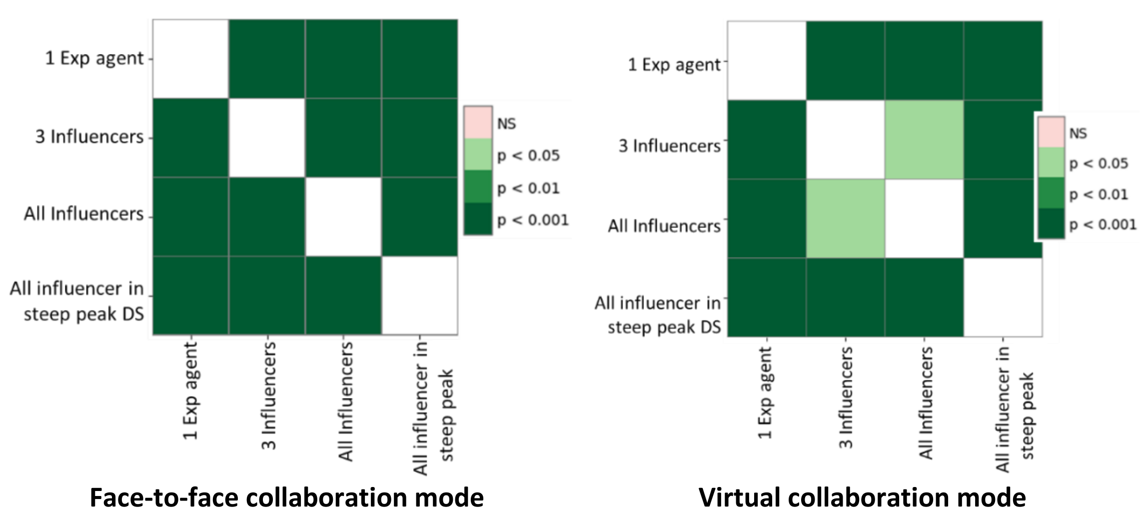

Fig. 11. Post hoc pairwise T-test p-value plot (after Holm correction) for generated solution quality during face-to-face (left) and virtual (right) collaboration mode

The session-wise difference in the individual designer agents' generated solution quality in cases that were tested was lesser in virtual than face-to-face team collaboration (Figure 12). The minor changes can be observed from Figure 12 in the session-wise behavior related to the generated quality of designer agents in all influencer teams both in virtual and face-to-face collaboration mode. Designer agents in an all-influencer team generate slightly higher solution quality when in virtual collaboration mode. As expected from the designer 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 behavior of designer agents in the all-influencer teams when generating solutions to a design problem that is difficult to refine (i.e., all influencers in steep peaks) in both virtual and face-to-face collaboration is also trivial. One possible reason could be the similar state of designer agents (i.e., similar self-efficacy among all of them), which resulted in similar behavior in an individual designer agent 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 designer agent's idea generation quality.

The generated solution quality of the individual designer agents who have different cognitive states (i.e., unequal distribution of self-efficacy) in teams, is more diverse in both the collaboration mode. Studies in past have shown that experienced designers who have task high proficiency drives the team design process and thus the team performance [62]. Similarly, as expected, the designer 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.

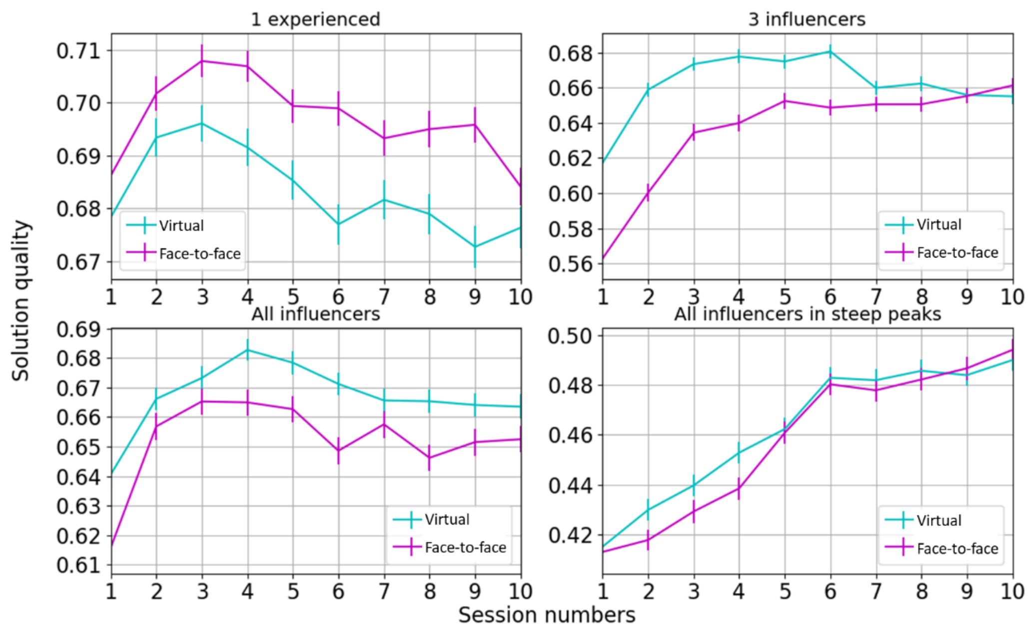

Fig. 12. Session-wise generated solution quality

The teams in the tested cases show different session-wise exploration rate patterns (Figure 13). The 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. 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 designer 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 behavior requires further investigation.

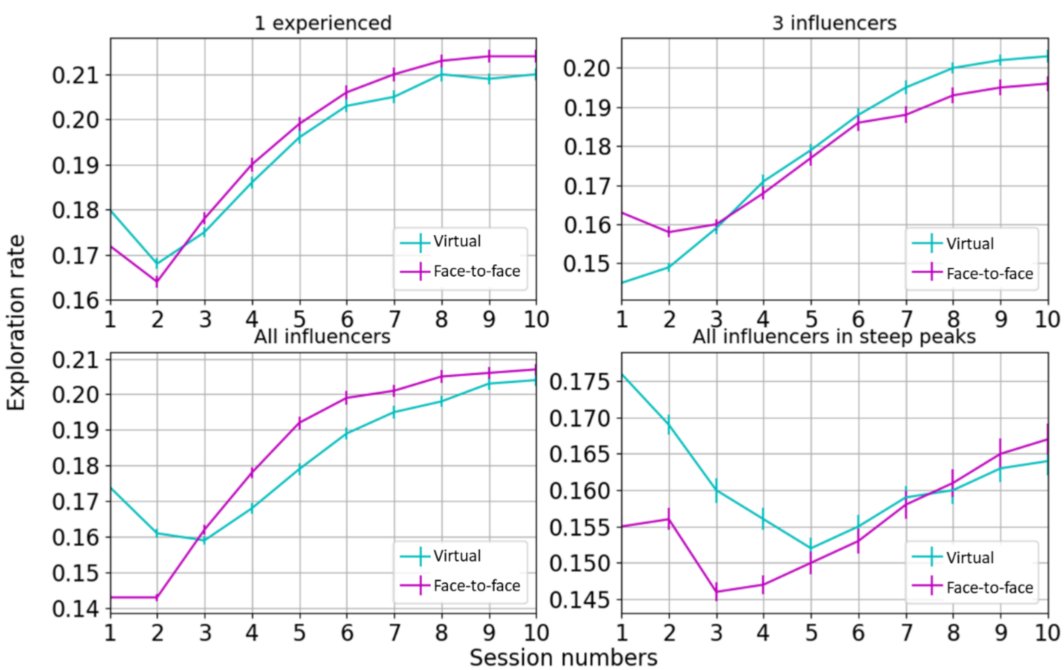

Fig.13. Session-wise solution exploration rate

Figure 14 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 by Singh et al. that a team in the model could propose single or multiple solutions to the controller agent when the desired team agreement on a single solution is not reached [33]. It can be seen from Figure 14 that multiple solutions (in this case 3) when proposed to the controller agent result 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.

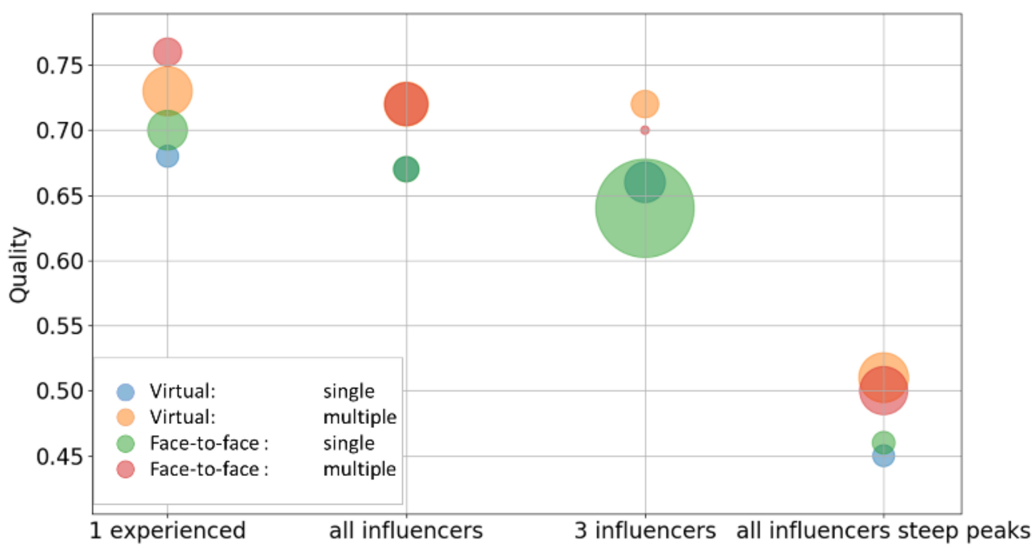

Fig. 14. A bubble plot showing the number of times 1 or multiple solutions (size of the dots) were proposed by a team and their respective quality (position on the vertical axis)

From Figure 14 a more distinct behavior of teams with all designer 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 (Figure 14). 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.

The exploration index (EI) and the exploration quality index (EQI) are seen in Figure 15. It can be seen that the EI 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 influencers in steep peaks) show a less significant difference in their exploration with respect to the collaboration environment.

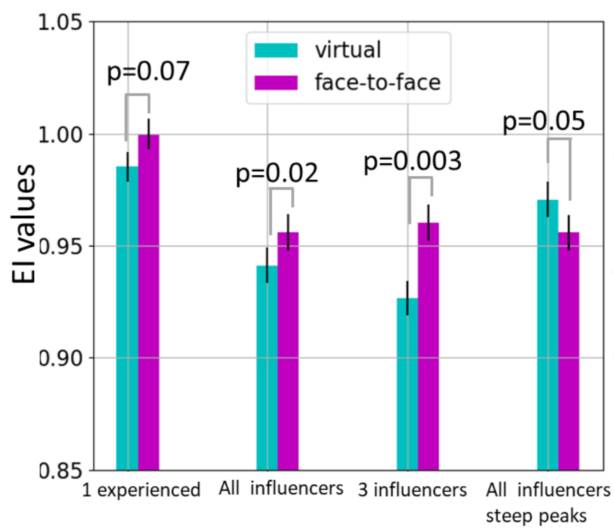

Fig. 15. Mean values of EI for face-to-face and virtual team collaboration with p-values of Mann-Whitney U-test

Figure 16 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.

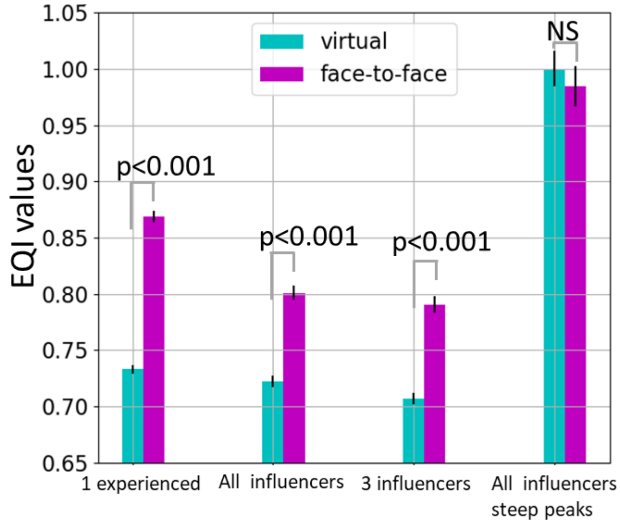

Fig. 16. Mean values of EQI for face-to-face and virtual team collaboration with p-values of T-test (NS = not significant)

The evaluation of the final solutions that were proposed by the teams to the controller agent in terms of quality and diversity (spread) in them can be seen in Figures 17 and 18. Similar to the generated solutions, no significant difference can be seen in the quality of the final solutions proposed (Figure 17) by a team having similar self-efficacy (i.e., all influencers) do not differ in the two collaboration modes. This difference is also insignificant when the designer agents in all influencers team, work 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.

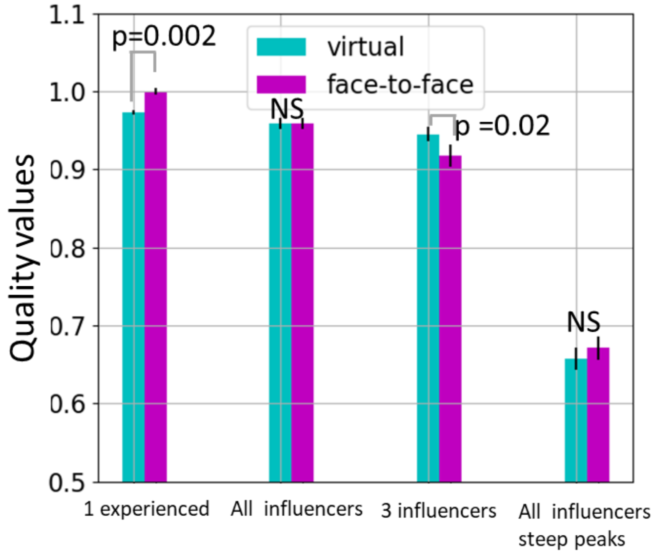

Fig. 17. Mean values of final quality for face-to-face and virtual team collaboration with p-values of Mann-Whitney U-test (NS = not significant)

The diversity in the proposed solutions by the teams (Figure 18) 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.

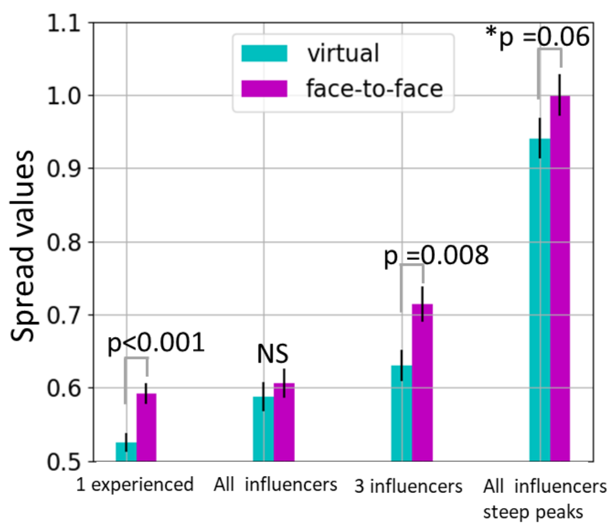

Fig. 18. Mean values of final solution spread for face-to-face and virtual team collaboration with p-values of T-test (p* is of Mann-Whitney U-test, NS = not significant)

The contribution can be defined as the number of times an agent proposed its solution to the other team members. Figure 19 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 designer 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 designer 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. Some studies in the past also found that virtual teams distributed the contributions among the team members and only a few selected team members contributed in the collocated teams [56].

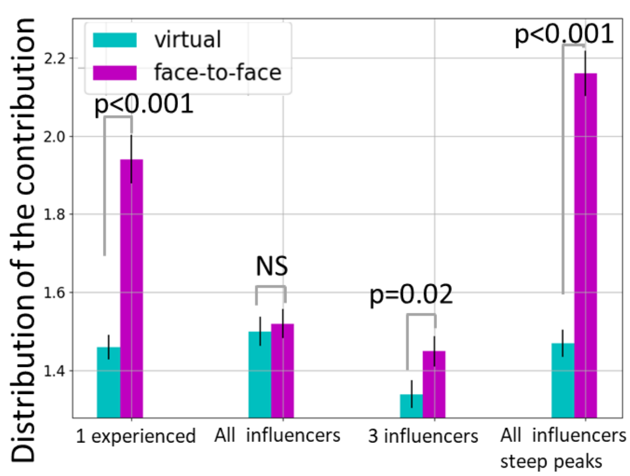

Fig. 19. The distribution of the contribution for face-to-face and virtual team collaboration with p-values of T-test (NS = not significant)

CONCLUSION

Virtual team collaboration has the potential to revolutionize work as it offers levels of flexibility and convenience that are not present in traditional face-to-face collaboration. This work sought to answer the research question: What is the effect of the two collaboration modes (i.e., virtual and face-to-face) on design outcomes and design process? In doing so, an agent-based model was constructed based on empirical study results that showed that face-to-face model parameters used in MILANO differed from those needed to simulate virtual collaboration. The empirical study found that communication in virtual collaboration affects other MILANO parameters. These results facilitated the simulation of both face-to-face and virtual teams. The primary results from those simulations are:

- When self-efficacy is equally distributed in a team, the impact of the collaboration mode (i.e., virtual and face-to-face) on idea generation and selection is minimized. The solution quality of the teams with consistent high self-efficacy individuals in virtual collaboration was comparable to that achieved in face-to-face settings. This effect was robust across different levels of design task complexity.
- The effect of design team collaboration mode (i.e., virtual or face-to-face) is more prominent when the influence is not uniformly distributed in teams. The impact of an influencer who is also experienced is more evident in the face -to face collaborations than virtual. However, when half of the small design team members are more confident than the others, virtual collaboration mode results in better quality.

- Patterns of exploration differ in the two collaboration modes. Specifically, less exploration was observed in virtual mode than in face-to-face for a simple design task. Virtual collaboration also tends to result in less variety in the proposed solutions.
- Virtual team collaboration encourages more uniform contributions by all team members. This difference is more significant when the teams have well-defined influencers or work on a complex design task.

The model considers some of the many parameters to capture the important differences between virtual and face-to-face design settings. As the complexity of an agent-based model increases, the generalizability of the model reduces. Therefore, it is important to be explicit on how far one can take the results presented through the agent-based model. The finding presented in the paper are based on certain model parameters and changing these parameters may vary the results. For example, the results were related to a design problem that had 5 best solutions, however, increasing the number of best solutions (for example to 12 peaks) or having only one best solution could produce different outcomes. The two-dimension representation of the design space used less computation power and was effective in visualization agent behavior. In the future, it could be expanded to more dimensions. The learning rules given to agents limit the exact imitation of human designers. While simulating virtual and face-to-face collaboration, factors such as gender roles, informal communications, experience, interaction style, and cognitive biases were not considered during this work. Moreover, the results shown in the empirical studies were based on self-reported data collected at specific times. This empirical data did not directly capture how many times the teams generated and selected ideas. In the future, this study should be replicated on a larger scale to reveal the impact of factors like the team demographic composition, size of the teams, and task complexity on the design process and outcomes. This is necessary to fully validate the results of this model as well as continuously improve the modelling approach.

The work showed that the mode of collaboration (virtual and face-to-face) has more impact on some teams than others. This unlocks the questions on combing the elements of virtual and face-to-face collaboration that could result in the best design outcomes. For instance, having face-to-face team collaboration before the same team starts working virtually could result in better cohesion as the team members get familiar with each other. At the same time, this setup could reduce social loafing (which mainly occurs in face-to-face collaboration) that lowers team performance. This aspect of successfully combining the elements of virtual and face-to-face collaboration should be studied in the future.

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Figure Captions List

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Table Caption List

APPENDIX A

Design Brief

Since the *company X*[3] was a leader in the production of the mechatronic components for household appliances in Europe, the design themes proposed by them consisted of the following:

Table 2. Description of the design themes during the empirical study

Themes for the year 2019	Platform	Current issue	Desired function	Conditions
No-Frost Refrigerator	Refrigerator	The moisture in the air freezes on the fridge surfaces.	A system should be able to differentiate the air coming from the freezer and deviate it to the desired zone.	Impact on individual outlets and all outlets of a refrigerator should be considered. Using just one actuator (12V) was allowed. The maximum power allowed was 4 W. The solution should have reasonable costs and must be able to fit in the

[3] The company name will be updated in the final draft

				available refrigerators.
Microplastics when washing	Washing Machine	The friction among clothes, and between the drum and the clothes shed microfibers in the water.	The system should be able to avoid the dispersion of trapped microfibres in the environment.	A solution should integrate into the appliance (i.e., the washing machine of volume = 200 l x 150 w x 100 h (mm)) The solution should trap microfibers (0.03 to 0.3 mm: Appreciable, and > 0.3 mm: Necessary).
Themes for the year 2020	**Platform**	**Current issue**	**Desired function**	**Conditions**
Dryer Fluff	Tumble Dryer	The user has to clean the fluff at the end of every cycle. Safety and efficiency issues.	Reduce the number of user interactions needed for fluff removing (from 1 to 10 drying cycles)	The overall dimension of the filters housings must be respected. Fluff cannot be drained in the water circuit.

Dishwasher Drying	Dishwasher	High energy consumption due to hot water usage. Water vapour is being released in the ambient.	The solution should result in low energy consumption drying.	Modification of components currently inside the dishwasher was allowed.
Air Conditioner Condensation	Air Conditioner	The drainage system has issues like stagnation, walls modifications and leakages.	The solution must avoid the formation of condensation and its accumulation on the splits.	Addition and (or) modification of the current splits were allowed. A non-invasive solution.
Washing Machine Paddles	Washing Machine	Paddles currently have a single function.	Additional useful functions for paddles.	Compatibility with the current system.
Open Theme	Any electrical appliance	Find and address the issues users/customers are currently facing when	Satisfy user/customer need	Modification of components currently inside the systems was allowed. However, the solution must have a

		operating these appliances		low impact on general platform design.

APPENDIX B

Table 3. Description of the elements in the questionnaires during the empirical study

Common elements of the two questionnaires	*Description*
Self-efficacy	It was explained as respondent's belief in its capacity to execute behaviors necessary to complete a task or achieve goals [32, 37]. Where; 5 = very confident in your capacity to execute behaviors necessary to complete a task or achieve goals. 1 = not at all confident in your capacity to execute behaviors necessary to complete a task or achieve goals.
Perceived number of influencers	It was explained as the number of team member that respondent thinks are most influential and are governing the team process the design activity [32,33]
Perceived degree of influence from its peer	It was explained as a peer's influential nature that causes a respondent to follow peer's actions of generating solutions and keeping into account the peer's proposed solution when the respondent is generating its own solutions [32,33]. Where; 5 = You follow his/her techniques and actions of generating innovative solutions. You always keep into account his/her proposed solution into

	account while generating your own solutions. You agree to him/her most of the time. 1= You never follow his/her techniques and actions of generating innovative solutions. You never consider his/her proposed solution into account while generating your own solutions. You never agree with him/her.
Trusting its peer	It was explained as having respondent's confidence/faith/hope in a peer with its proposed solutions and ability to do design activities [32]. Where; 5 = You feel assured and can rely on his/her character, ability or strength. You always place your confidence/faith/hope in him/her with his/her proposed solutions and the ability to do project activities 1= You never feel assured and can never place your confidence/faith/hope in him/her with his/her proposed solutions and the ability to do project activities
Familiarity with its peer	It was explained as the state of acquaintance between the respondent with its peer [73]. Where; 5 = You would consider yourself in close acquaintance with him/her and know his/her working style 1= You would consider yourself not at all acquainted with him/her and do not know his/her working style.
Additional elements of the questionnaire during virtual collaboration	*Description*

Communication effectiveness	It was explained as a process of sharing information (exchanging ideas, thoughts and knowledge) such that the purpose or intention is fulfilled in the best possible manner. Where; 5= Effective conversations when exchanging ideas, thoughts and knowledge during project work. You find the conversations clear. 1= Ineffective conversations when exchanging ideas, thoughts and knowledge during project work. You do not understand others when they are conversing their ideas.
Resolution of the conflicts	It was explained as the encounters or disagreements that occurred while doing the project activity. These could be related to the task (eg. disagreements on ideas, work distributions and so on) or emotional (annoyance, envy, or personality) [23]. Where; 5= The team never faced situations where the opposition of persons or forces gave rise to dramatic action. The team never had any serious disagreements or arguments 1= Many times the team faced situations where the opposition of persons or forces gave rise to dramatic action. The team had many serious disagreements or arguments
Task cohesion	It was asked as a respondent’s attraction to the group because of its liking for or a commitment to the given task (i.e. task-specific teamwork)[23]. Where; 5= Members demonstrate their desire to do well on the project and pull together to get the job done

	1= Members do not demonstrate their desire to do well on the project nor do they get the job done
Agreement with its peer	It was explained as the situation in which the respondent had the same opinion as of the peer, or in which it approves of or accepts something from the peer [33]. Where; 5 = You always agreed with him/her on his/her ideas and solutions 1 = You never agreed with him/her on his/her ideas and solutions.
Communication with its peer	It was asked to capture how often the respondent's communication with individual peers in the team was smooth (fluent) during the project activity. Where; 5 = You had no conflicts and were always able to understand him/her. 1 = You always had conflicts and were never able to understand him/her.