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Designing Together: Exploring Collaborative Dynamics of Multi-Objective Design Problems in Virtual Environments

The pace of technological advancements has been rapidly increasing in recent years, with the advent of artificial intelligence, virtual/augmented reality, and other emerging technologies fundamentally changing the way human beings work. The adoption and integration of these advanced technologies necessitate teams with diverse disciplinary expertise, to help teams remain agile in an ever-evolving technological landscape. Significant disciplinary diversity amongst teams, however, can be detrimental to team communication and performance. Additionally, accelerated by the COVID-19 pandemic, the adoption and use of technologies that enable design teams to collaborate across significant geographical distances have become the norm in today's work environments, further complicating communication and performance issues. Little is known about the way in which technology-mediated communication affects the collaborative processes of design. As a first step toward filling this gap, the current work explores the fundamental ways experts from distinct disciplinary backgrounds collaborate in virtual design environments. Specifically, we explore the conversational dynamics between experts from two complementary yet distinct fields: non-destructive evaluation (NDE) and design for additive manufacturing (DFAM). Using Markov modeling, the study identified distinct communicative patterns that emerged during collaborative design efforts. Our findings suggest that traditional assumptions regarding communication patterns and design dynamics may not be applicable to expert design teams working in virtual environments. [DOI: 10.1115/1.4063658]

Keywords: collaborative design, computer-aided design, decision theory, design methodology, design representation

1 Introduction

As design and manufacturing technologies continue to advance and evolve at break-neck speeds [1,2]; these technologies are fundamentally changing the ways design teams design [3–5], and necessitate interdisciplinary teams [6] capable of adapting to an ever-evolving technology landscape. Design teams with team members from distinct disciplines, or high levels of disciplinary diversity, benefit from more diverse perspectives and approaches to problem-solving [7,8], resulting in a larger solution space [9], more innovative outcomes [9–12], and reduced risk [13–15]. Prior work has demonstrated the utility of concurrent engineering practices to leverage cross-functional teams to produce more innovative final products [9,16].

However, team science also points to diversity as a "double-edged sword" [17], with differences between team members acting as a barrier to effective teamwork [18]. Specifically, disciplinary diversity can introduce significant barriers to team communication, as team members must negotiate disciplinary boundaries by building a fundamental understanding of technical jargon and disciplinary norms [19]. Further, experts' perceptions of collaborations can threaten the collaboration itself. For example, a perceived

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loss of autonomy in decision-making and perceptions that disciplinary knowledge is not valued [20] can lead to the disintegration of the collaboration itself [21].

While we know design is a team sport, most studies have focused on individual expert strategies [12,22–24] to derive heuristics for effective problem-solving. This work aims to understand fundamentally how experts from disparate fields collaborate on a multi-objective design problem, to build foundational knowledge regarding the efficacy of these collaborations. We specifically study the interactions between additive manufacturing (AM) experts and non-destructive evaluation (NDE) methods as a representative case study in multi-objective design.

Advancements in AM have resulted in increased speed of production of additively manufactured parts and also made it possible to create intricate and complicated structures [25–28]. However, post-processing and inspection of AM parts can significantly increase the manufacturing process's overall costs and time to market [29]. While advantageous, the increased geometric complexity offered by AM, can also present new challenges for industries where component qualification and inspection are necessary before use [30–32]. Although AM technologies are reaching high technological readiness levels (TRL) ranging from 6 to 9 [33–35] (nine being the most mature technology), the NDE techniques needed to inspect complex parts manufactured with these technologies remain at lower maturity, ranging from TRL 3 to 6 [36,37]. While AM and NDE operate in intertwined domains, they remain professionally distinct, a perspective supported by the recruitment process from specialized channels like ASME, ASA, NIST, and NASA. NDE's focus largely resides in on-process and post-process AM inspection [38], whereas literature reveals a limited overlap with early-stage design for additive manufacturing (DFAM) considerations by NDE researchers [39]. This inherent distinction, corroborated by industry insights, emphasizes the pressing need to bridge these complementary areas for comprehensive manufacturing advancements. Therefore, we argue that investigating interdisciplinary collaborations between AM and NDE experts is not only timely but can yield valuable insights for integrating NDE considerations into AM design.

The COVID-19 pandemic has accelerated the adoption of virtual collaboration tools, which offer numerous benefits but also pose challenges, such as the absence of social cues [40,41]. While research by Maznevski and Chudoba has highlighted that this can result in a lack of trust and cohesion [42], virtual collaborative computer-aided design (CAD) software, notably cloud-CAD platform ONSHAPE, has demonstrated effectiveness in enabling distributed teams to collaborate on intricate design projects [43]. This study provides a comprehensive understanding of how experts collaborate using collaborative CAD software in a virtual environment. Using our Markov model, we found that experts exchange knowledge before transitioning to an action-oriented phase, where they remain. Unlike traditional applications of C–K theory, we observed that experts tend to stay in one phase before transitioning to the other, rather than alternating rapidly when solving a design problem. While prior team science literature suggests that communication patterns can predict problem-solving behavior, our findings show few linkages between communicative patterns and design dynamics, possibly due to a lack of research in virtual settings or CAD environments. Importantly, this work contributes novel insights into our understanding of how designers collaborate in virtual environments with an initial focus on dyads to elucidate foundational communication dynamics before advancing to larger, interdisciplinary teams; this is particularly critical given the wide-scale adoption of virtual technologies and the shift toward hybrid work environments.

2 Background

2.1 Interdisciplinary Collaboration in Design. Designing a solution to a complex interdisciplinary problem is dependent upon collaboration quality between team members. Disciplinary experts must work together to find solutions that balance competing objectives, requiring team members to engage in frequent communication to understand the tradeoffs of design choices. Prior work from team science points to linkages between team conversational dynamics and team performance [44–47]. For example, Nemeth and Staw [48] found that groups with a dominant member generated fewer and less varied ideas, leading to a reduced ability to generate diverse solutions. Similarly, Paulus and Dzindolet [49] examined social influence and team productivity and found that dominant individuals in conversations can significantly influence the group's ideas, and if their impact is negative, it may inhibit the group's creative potential.

Generally, a team's performance can be negatively affected by misinterpretation between team members due to differences in disciplinary discourse, norms, or jargon [21]. In a study examining the collaboration between engineers and biologists, Hashemi Farzaneh [50] underscored the importance of communication and mutual understanding between the two fields. Findings from this study indicate that such collaboration can improve analogical transfer, which refers to the process of applying knowledge from one domain (in this case biology) to a different domain (engineering), and result in more innovative design solutions. Sieffert et al. [51] highlighted the success of a workshop-style curriculum that aimed to bridge the gap between architects and civil engineers by fostering collaboration focused on sustainable construction using repurposed materials. Through this approach and training workshop, the architects and engineers were compelled to think critically to incorporate each other's disciplines, leading to a more holistic and innovative approach to building design. Kuusinen [52] investigated the collaboration and communication between user-experience specialists and developers in agile software development projects, identifying the critical role of effective task allocation, which highlights the need for clear communication and mutual understanding between team members. For large complex engineering systems, establishing collaboration strategies is critical to the management of the project itself. For instance, a NASA case study showed that coordination strategies, such as division of labor, coordination mechanisms (e.g., regular meetings and shared workspaces), and a shared understanding of project goals and requirements among team members, were effective in managing interdependent tasks, aligning stakeholders' goals, and addressing communication challenges [53].

Collaboration through virtual tools has become increasingly popular, particularly due to the COVID-19 pandemic [40,41]. Despite the prevalence of geographically distributed teams, strategies for effective team functioning in virtual environments are not well understood [54]. Technology-mediated communication across video conferencing platforms can make the interpretation of nonverbal and paraverbal cues (e.g., voice pitch, pauses, or inflection) difficult for remote workers; in in-person settings, these cues facilitated turn-taking (TT), conversation flow, and "mind reading" in group interactions [55–57]. Collaborative design tools may help teams overcome the challenges of virtual collaboration. Emergent work has demonstrated that collaborative CAD software tools such as ONSHAPE effectively enable distributed teams to work together on complex design projects [43]. For instance, Zhou et al. [58] examined the emotional experiences of designers in both traditional and collaborative CAD environments such as ONSHAPE. Their findings suggest that virtual collaborative tools can have a positive impact on communication and collaboration. Further, Phadnis et al. [59] compared the working styles of individuals versus pairs within a cloud-CAD platform and found that, while individuals were faster than pairs, pair work with a single shared input led to higher-quality final models. The use of virtual collaborative tools, such as collaborative CAD systems, can help design teams promote effective virtual interdisciplinary collaborations.

2.2 Design Problem-Solving Strategies Employed by Experts. As the need for interdisciplinary teams grows, it is critical to understand disciplinary expertise and the fundamental ways experts solve problems collaboratively. Within design theory and methods, researchers have studied the problem-solving strategies of experts for some time, deriving heuristics, tools, and methods from patterns of expert behavior. However, much of this work has investigated experts working alone. For example, prior work by Damen and Toh [60] explored the information representation and structuring techniques used by expert designers during the design process. The study found that experts employ their experience and various knowledge transfer tools, such as sketching, diagrams, mind maps, and lists, for problem-solving and transforming resulting information into insights that facilitate effective communication with stakeholders [60]. Similarly, Ericsson and Lehmann [61] explored how experts and exceptional performers adapt to task constraints for optimal performance in the fields of music and chess. In this work, they identified cross-cutting adaptive strategies used by experts, such as chunking (breaking down large amounts of information into smaller, more manageable units or “chunks”), pattern recognition, and deliberate practice, to optimize their performance under different task constraints.

A significant body of work has explored the differences and similarities between experts and novices, often with the intent to develop tools to support novice problem-solving. For example, Ahmed et al. [62] conducted a study of novices and experienced designers and found that novices follow a trial-and-error approach, while experts evaluated their initial decisions and employed an integrated design strategy. Additionally, Ho [23] conducted a protocol analysis to investigate the problem-solving strategies used by novices and experts in design thinking. The study revealed that experts utilize a more systematic approach to problem decomposition, employing mental simulation, analogical reasoning, and abstraction techniques, while novices did not show such a structured approach. Further, Gosnell and Miller [63] found that compared to novices, experts rated concepts more strictly and gave less favorable ratings overall.

In the context of the current work, we view expert behavior through the lens of C–K theory. C–K theory introduced by Hatchuel and Weil [64] suggests that designers rapidly alternate between the concept space (C-space) and knowledge space (K-space) during design problem-solving. In this dynamic process, designers explore novel ideas in the C-space and draw on their existing knowledge in the K-space to refine and implement these concepts. For instance, Hatchuel et al. [65] demonstrated the effectiveness of C–K theory in the case of the Mg-CO_2 engine design for Mars missions, showcasing how the approach facilitates the development of innovative solutions by seamlessly integrating creativity and established domain knowledge.

Problematically, these studies often investigate designer behavior in isolation. Relatively little work has explored the interactions and strategies exchanged between experts during collaborative events. Within the team science literature, researchers have explored the factors that contribute to or detract from effective collaborations for teams of interdisciplinary experts [45–49,61]. Studies of evolving models of multidisciplinary collaboration emphasize the importance of communication, collaboration, and mutual understanding in promoting creativity and innovation [10]. Together, these studies suggest that *effective* collaboration among dyads/teams in multi-objective design problem-solving is essential for promoting creativity, enhancing learning outcomes, and developing useful solutions.

2.3 Synthesis of Prior Work and Context of the Current Study. While prior work has explored the problem-solving strategies of experts working independently, little work has identified the fundamental ways experts collaborate, particularly in the context of virtual work environments. The shift to virtual and hybrid modes due to the COVID-19 pandemic has made virtual teams and digital platforms the new norm for collaboration, highlighting the need to understand how these elements contribute to effective team collaboration.

Effective communication and knowledge exchange are crucial to forming a shared understanding among interdisciplinary team members. Misinterpretation between team members due to differences in disciplinary discourse, norms, or jargon can negatively affect the team’s overall performance. Studies have shown that collaboration and mutual understanding between different fields can improve analogical transfer [50], which is the process of applying knowledge from one domain to another, and results in more innovative design solutions. In addition, effective task allocation, clear communication, and mutual understanding are essential for collaboration and communication between team members, as identified by studies investigating collaboration and communication in different contexts [51–53,66]. Moreover, as geographically distributed teams become increasingly prevalent due to the COVID-19 pandemic, strategies for effective team functioning in virtual environments are critical. However, technology-mediated communication across video conferencing platforms can make the interpretation of nonverbal and paraverbal cues difficult, which are essential for effective communication and collaboration. Collaborative design tools, such as cloud-CAD platform ONSHAPE, can help teams overcome the challenges of virtual collaboration. In summary, collaboration and communication are critical for interdisciplinary teams to form a shared understanding of the design space, and the exchange of knowledge and effective communication is necessary for successful collaboration.

In the current work, we specifically focus on the collaboration between experts from two complementary yet distinct fields: AM and NDE. We highlight this as a prime case study to explore expert collaboration, as ensuring consistent quality in AM parts is a pervasive challenge [37,67]. Prior literature indicates NDE research primarily delves into in-process and post-process inspections within AM [68,69], and scant literature points to NDE researchers engaging with early-stage DFAM [39]. Although NDE professionals are familiar with AM, their expertise in DFAM principles is often limited, making these fields complementary yet distinct [70]. Similarly, while DFAM experts are starting to consider NDE, there has been limited research in early design processes focused on inspectability. Hence, while there’s a perception of overlap between AM and NDE due to their intertwined operations in manufacturing settings, a deeper dive reveals marked distinctions in their professional realms. Consequently, we argue that there is an emergent and pressing need to bridge these complementary areas for manufacturing advancements. Motivated by this, we aim to explore the communication and design patterns that emerge as dyads, consisting of one expert in AM and one expert in NDE, working in a collaborative CAD environment.

3 Research Objectives

> RQ1: How do experts collaborate on a multi-objective design problem in a collaborative CAD environment?

The first research question sought to identify the underlying collaborative process employed by dyads navigating a design challenge in a collaborative CAD environment. Specifically, we sought to understand the linkages between the way experts exchange knowledge and make design decisions by using a Markov model to derive higher-level collaborative processes from dyadic interactions.

> RQ2: What is the relationship between the conversational dynamics of dyads and the design dynamics produced during the dyadic interaction?

The second research question of this study sought to understand the linkages between conversational dynamics and design dynamics. Specifically, we explore the relationship between turn-taking, conversational dominance (CD), and silence; CAD efficiency (CE), CAD dominance, and CAD complexity. Prior work has demonstrated that the conversational dynamics of a working group, e.g., conversation dominance, is negatively correlated with the creative output of the team (e.g., fewer and less varied ideas [48,49]).

However, little work has explored what links exist between conversational dynamics and design dynamics in more complex design tasks, such as CAD modeling, during virtual collaborations.

4 Methods

4.1 Participants. A total of 30 experts and quasi-experts were recruited; 15 participants held expertise in NDE techniques and 15 participants held expertise in DFAM. Demographic information, including participants' experience with CAD, AM, and NDE techniques, was gathered through a comprehensive pre-study survey. This enabled us to effectively categorize the participants into two distinct groups: experts and quasi-experts. Quasi-experts were defined as senior Ph.D. students with at least 4+ years of practical experience in either AM or NDE. Experts were defined as industry professionals or faculty members with a minimum of 8+ years of experience in either AM or NDE; these definitions are in alignment with prior work in design studies [71,72]. Overcoming the inherent challenges associated with recruiting participants from specialized areas such as AM and NDE, we successfully employed purposeful and snowball sampling methods. Specifically, we relied on recommendations from professors to identify suitable Ph.D. students who met the criteria for being considered quasi-experts, a practice supported by existing literature [73]. Hence we categorized participants as quasi-experts if they have significantly more experience in an area as compared to novices but are not yet recognized as experts, e.g., senior-level Ph.D. candidates [73]. We categorize participants as experts if they possess significant knowledge, skills, or expertise in a specific field of study, which can be attributed to their research, professional experience, or occupation, e.g., Professors and Industry Professionals [22]. In total, 20 quasi-experts and 10 experts were recruited. Table 1 breaks down the participants' demographic data and expertise information.

Recruitment was done in accordance with the Institutional Review Board practices. The participants were recruited independently; none of the dyads had collaborated before the experiment. Each participant would receive a compensation of $25 Amazon gift card for participating in the study. We employed purposeful sampling to recruit individuals that are notably knowledgeable about a subject [74,75] and snowball sampling, in which current participants identify or recommend additional participants for recruitment [76,77]. These methods were used to specifically recruit individuals with areas of expertise in DFAM or NDE; where AM experts demonstrated knowledge of various DFAM principles [78], including designing for support structures, lightweight parts using lattice structures, and optimizing design orientation; and, the NDE experts exhibited expertise in or experience using NDE techniques [37,38], such as pulse echo ultrasonic inspection, X-ray diffraction analysis, or computed tomography (CT).

4.2 Data Collection. To conduct our laboratory-based mixed-methods study, collaborative CAD software, ONSHAPE, was used because not only is it synchronously collaborative [79], but it generates an audit trail of every CAD action taken by the users in the software platform, allowing the research team to explore patterns in CAD construction data. Audit trails capture every event that occurs within a specific document or for a specific user within a specified time [79,80]. For the purposes of our study, we will consider these audit trails as data logs that document actions taken within each dyadic CAD session. Essentially, audit trails record the event time, document name, ONSHAPE tab (e.g., part studio or assembly), username, and a brief description of the event, as illustrated in Fig. 1. The event time is recorded in universal time, with a resolution of 1 s, which is sufficient for our study. The event time recorded in audit trails serves as a reference point for corresponding sections in our video footage. These backend audit trail data were downloaded for each dyadic team separately in CSV format.

The study was divided into four sections: (1) pre-study steps and pre-study survey, (2) ONSHAPE training exercise, (3) design challenge, and (4) post-study survey. Figure 2 shows the timeline of the study.

As the aim of this study is to understand how experts collaborate on a multi-objective design problem, participants were paired within groups (experts and quasi-experts) according to their area of expertise (i.e., DFAM or NDE). Specifically, participants with expertise in NDE were paired with participants with expertise in DFAM, and participants with quasi-expertise in NDE were paired with participants with quasi-expertise in DFAM. Prior literature has documented the power dynamics between graduate students and professors, with various studies emphasizing the notable disparities in authority and influence between these two groups [81–83]. To mitigate potential confounding factors due to perceived power differentials, the research team deliberately paired quasi-experts with other quasi-experts. This pairing not only avoided conflation of results but also enabled the team to effectively control for the variable of power differentials in their study.

Following the pairing process, participants were provided with a pre-study survey and instructions to setup an ONSHAPE account; participants were instructed to setup their individual profiles to ensure effective backend audit data trail generation. The pre-study survey gathered demographic information, and experience levels. Participants were required to complete the survey before participating in the study.

Once the survey was completed, the research team selected a mutually available date and time for the virtual study to take place. As experts were geographically dispersed, the research team used the Zoom video conferencing tool [84] to facilitate the collaboration. At the start of the study itself, participants were informed that the entire session would be recorded, including all verbal communication and participants' laptop screens (via screen share tool).

The study began with a 20-minute individual training exercise in which participants were given a two-dimensional drawing and instructed to create a three-dimensional CAD model using

Table 1 Participants' demographic data and expertise information

Participants with DFAM expertise				Participants with NDE expertise			
Gender	Ethnicity	Profession	Count	Gender	Ethnicity	Profession	Count
Woman	White	Senior Ph.D. student	3	Woman	White	Senior Ph.D. student	3
Woman	Black	Senior Ph.D. student	1	Woman	Asian	Senior Ph.D. student	2
Man	White	Senior Ph.D. student	3	Man	White	Senior Ph.D. student	3
Man	Asian	Senior Ph.D. student	3	Man	Asian	Senior Ph.D. student	1
				Man	Prefer not to answer	Senior Ph.D. student	1
Woman	White	Professor	1	Woman	White	Professor	2
Man	White	Professor	1	Man	White	Professor	1
Man	Asian	Professor	1				
Woman	White	Industry	1	Man	White	Industry	1
Man	White	Industry	1	Man	White	Industry	1
	Total DFAM participants =		15		Total NDE participants =		15

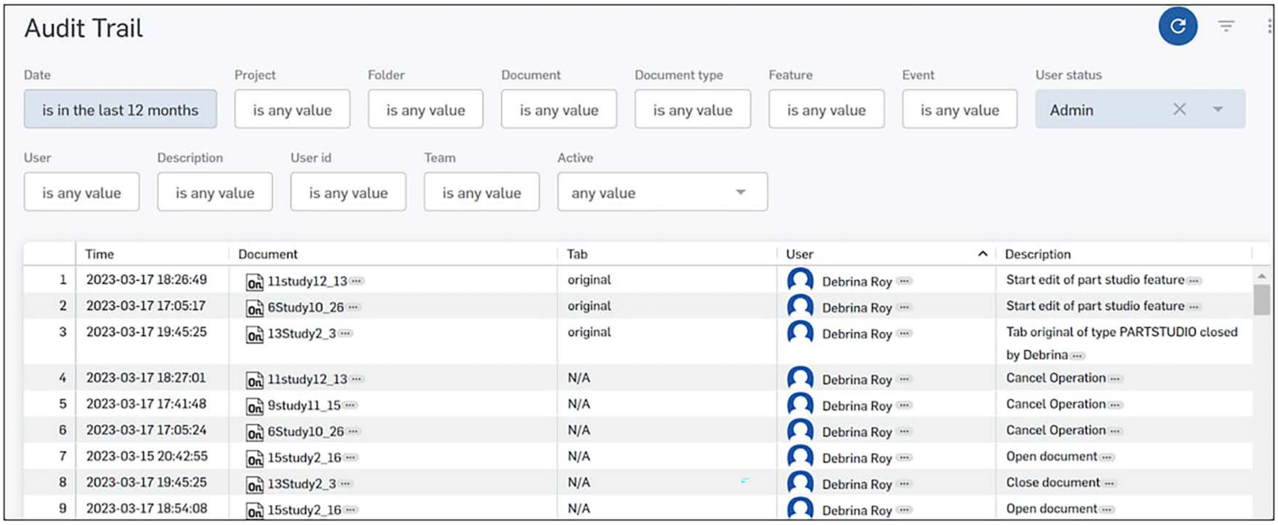


Fig. 1 Audit trails as data logs

ONSHAPE, as shown in Fig. 3 [85]. Once the model was complete, participants were instructed to assign a material (here titanium) to the part and then view the mass properties of the part. This exercise was designed to help participants become familiar with the ONSHAPE CAD environment and ensure participants were able to complete the fundamental CAD actions needed for the primary design challenge.

Following the training exercise, participants were briefed on the design challenge and were introduced to their partners. Participants were instructed to work collaboratively in CAD using the ONSHAPE platform. For the design challenge, the GE titanium bracket parametric model [86] was shared within ONSHAPE and the following design prompt was provided to participants:

> "*For the second task, a CAD model will be provided, and the challenge is a reduction of the part's mass by 50% while adhering to the principles of DFAM and NDE. It is imperative that the location of the four bolt holes remain unchanged, and the four loading conditions and bracket location are to be considered for the visualization of the part. To summarize, the primary objectives of this design prompt are: (1) achieving a 50% mass reduction, (2) ensuring that the final part meets DFAM and NDE requirements, and (3) retaining the size and location of countersinks and bolt holes.*"

In addition to this written prompt, a member of the research team remained in the Zoom room for the entirety of the experiment; using a verbal script the researcher encouraged dyads to work together to produce a design that met the stated design objectives (mass reduction) while remaining mindful to the opportunities and constraints inherent to both AM and NDE technologies.

Participants were also provided with four different loading conditions [86] the part would undergo, along with multiple images [87] highlighting the use of the component (see Fig. 4).

The design prompt was adapted from the GE Jet engine bracket challenge [86] to include explicit criteria related to the viability of the component to be inspected using traditional NDE techniques. This design challenge has been used in prior experiments to identify heuristics designers may use to increase the inspectability of designed components [39]. The participants were given 75 min to produce a design; dyads were allowed to end the study early if both team members were satisfied with the design. After the study, the researchers collected and stored the CAD models and the audit trail.

4.3 Metrics. Audio, video, and CAD data collected through the study were transformed into several key metrics to inform our understanding of the collaborative dynamics between experts. These metrics were calculated based on prior research [88–96] and are defined in the following sections.

4.3.1 Qualitative Coding of Video and Audio Data. To build a fundamental understanding of the way experts collaborate, we developed a simple coding schema to capture participant actions. The first author immersed themselves in the audio and video data, employing an open and axial coding approach [97] paired with constant comparative methods to generate a coding schema of expert actions. The first and second authors then reviewed the coding schema and refined the categories identified using constant comparative methods [98,99] with prior work [88]. Specifically, we draw from Hatchuel and Weil's C–K theory [64], which conceptualizes design as the interaction between two distinct spaces, the concept space and the knowledge space. The knowledge space refers to all known or true propositions, which conceptualizes design as the interaction between two distinct spaces, the C-space and the K-space. The K-space refers to all known or true propositions, while the C-space refers to concepts that are unknown or undecidable propositions in the K-space. C–K theory models the design process as the dynamic transformation of objects in the C-space into known entities in the K-space via emergent design information that becomes known through design actions. Based on this theory, the researchers formulated the coding schema shown in Table 2.

After finalizing the codebook, two researchers used the codebook to code randomly selected dyadic interactions of audio and video data using SOLOMON CODER, a behavioral coding software [100]. SOLOMON CODER chunks video data into 0.2 s segments and codes

Fig. 2 Study timeline

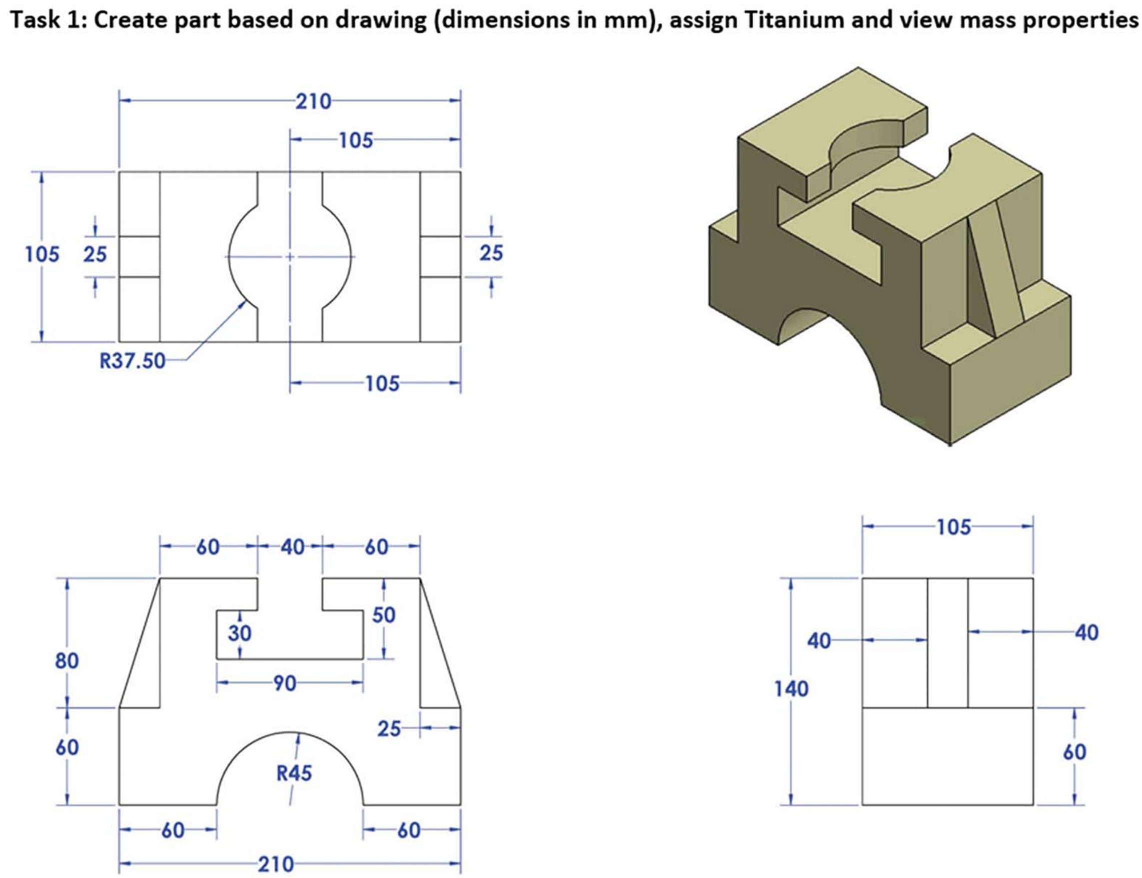


Fig. 3 ONSHAPE **training exercise**

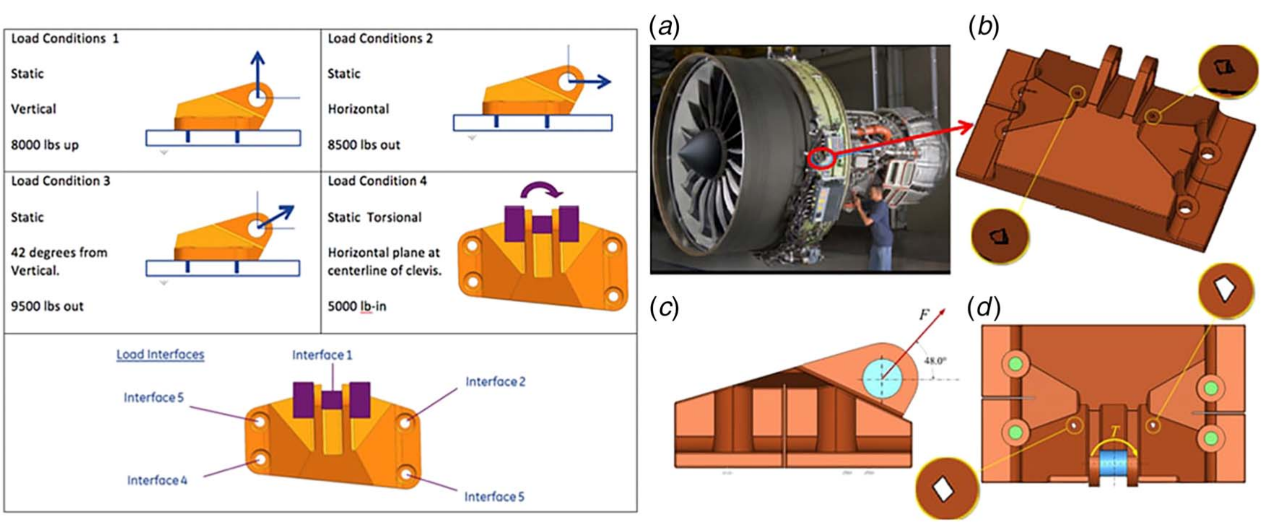


Fig. 4 Design challenge visualization aid [86,87]: (*a*) jet engine, (*b*) iso view, (*c*) side view, and (*d*) top view

were assigned based on the audio and video data for each temporal interval. Initial inter-rater reliability [101] was calculated and found to be insufficient with Cohen's $\kappa = 0.64$. Subsequently, the researchers discussed disagreements and reviewed the codebook and definitions together. An additional set of dyadic interactions were randomly selected and both raters coded the video and audio data. Inter-rater reliability was once again calculated and found to be sufficient, with Cohen's $\kappa = 0.81$, indicating acceptable agreement between raters. The researchers then proceeded to code the remainder of the video and audio data independently.

The outcome of this coding process, a vector of time-stamped coded actions per dyad was then used as input into a Markov model. A Markov model is a mathematical model that is employed to describe a stochastic process consisting of a finite number of states in which the system transitions between each state [102]. It is widely used in diverse fields such as demand predictions, decision-making analyses, chemical processes, and design research [103–105]. Markov modeling has been extensively applied to study the cognitive states of designers involved in problem-solving, to identify design heuristics, and to investigate team dynamics

Table 2 Codebook

Definition	Code	Example quote	Letter code
Knowledge share—sharing general information, principles, or knowledge from the individual's area of expertise.	DFAM knowledge share	"For it to print additively, it needs to have overhangs no more than 45 deg angles."	A
	NDE knowledge share	"If we go through the Ultrasound route then we need to make sure the part is simplified and has more flat and parallel surfaces."	B
Design decision—decision made about the design to meet either DFAM, NDE, or mass reduction design requirement.	DFAM design Decision	"I am going [to] fillet these sharp corners on this part right here."	C
	NDE design decision	"Yes, and then we can make the whole thing flat that way it will be easier to test."	D
	Mass reduction design decision	"We can cut out the bulk right here, should immediately remove some mass."	E
CAD action—observable actions taken in CAD environment by experts individually (NDE or DFAM) or collaboratively	NDE CAD action	"we could also extrude this down and then chamfer" (proceeds to extrude it down—performs the CAD action).	F
	DFAM CAD action	"I will cut that out with this circle"(proceeds to extrude it down—performs the CAD action)	G
	Collaborative CAD	"Ah while you are extruding that, I am adding back the chamfer next to the bolt holes."	H
	CAD action check (mass, measure)	"Okay, let's see where we are at now."	I

during concept generation [106–108]. By employing a Markov model, we can visually analyze observed interactions and interpret the dynamic nature of communication, leading to a comprehensive understanding of how participants collaborate and adapt during the design challenge.

In this study, the coding of dyadic interactions resulted in a vector of codes for dyad; this vector was used as input into the Markov model for analysis, conducted in R studio version 4.2.3 [109] to examine the frequency and sequence of these actions, generating a transition matrix, following prior research on design actions using Markov models [110,111]. To enhance visibility, each Markov Chain, depicting the emergent pattern, was manually created, emphasizing transition probabilities higher than 0.15 and excluding lower probabilities due to their infrequent occurrence. In summary, combining this qualitative coding schema with Markov modeling enabled the research team to identify larger patterns of collaborations across all dyads.

In pursuit of exploring collaborative dynamics, we narrowed it down to conversational dynamics and design dynamics. The following information delves deeper into each of the metrics that contribute to these dynamics.

4.3.2 Conversational Dominance. Conversation dominance is a measure of the asymmetry of conversational dynamics in collaborative tasks and has been linked with both objective and effectual meeting outcomes [89]. In a dyadic collaboration, if both speakers contributed equally to the conversation and spoke for 50% of the time, the resulting dominance value would be zero, indicating no discernible dominance. Conversely, if speaker A spoke for 60% of the time and speaker B spoke for 40%, the dominance value would be 20%, indicating that speaker A is dominant by 20%. CD was calculated as shown in Eq. (1), where CD is equal to the absolute value of the difference between the time spent speaking by the first speaker (ST_1) and the time spent speaking by the second speaker (ST_2), divided by the total duration of the conversation (ST_{total}).

$$CD = \frac{|ST_1 - ST_2|}{ST_{total}} \tag{1}$$

4.3.3 Turn-Taking. Turn-taking in a conversation refers to the frequency of speaker changes, and has been found to foster equal participation opportunities among team members, encourage information sharing, increase engagement, stimulate creativity, and ultimately enhance overall team performance [90]. Turn-taking was calculated first by identifying unique speakers and speaking segments separated by at least 500 ms of silence. Silence duration of 500 ms is commonly used to define a turn boundary in conversational analysis research [89,112–114]. TT was then calculated by counting the number of speaker changes between speaking segments (T_n); this total was then divided by the total length of the study (T_{total}), as outlined in Eq. (2)

$$TT = \frac{T_n}{T_{total}} \tag{2}$$

4.3.4 Silence. Additionally, the ratio of silence over the total duration of the study was calculated. Prior work has demonstrated that sustained silence in collaborative problem-solving groups allows group members to process and integrate their individual ideas and perspectives, leading to a more efficient and effective group brainstorming session [91,92]. As outlined in Eq. (3), silence (S) was calculated by dividing the total time a single dyad was silent (T_s) by the total time of the study (T_{total}). Here the threshold for silence was determined to be any length of time greater than

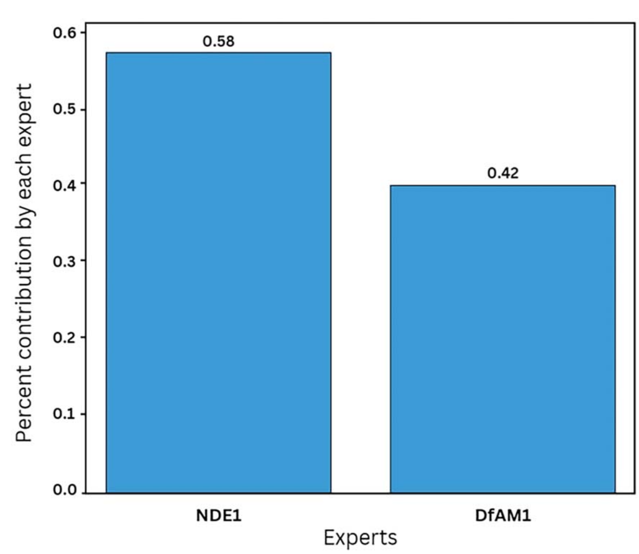


Fig. 5 CAD dominance from MUCAD_CLF generated percent contribution graph

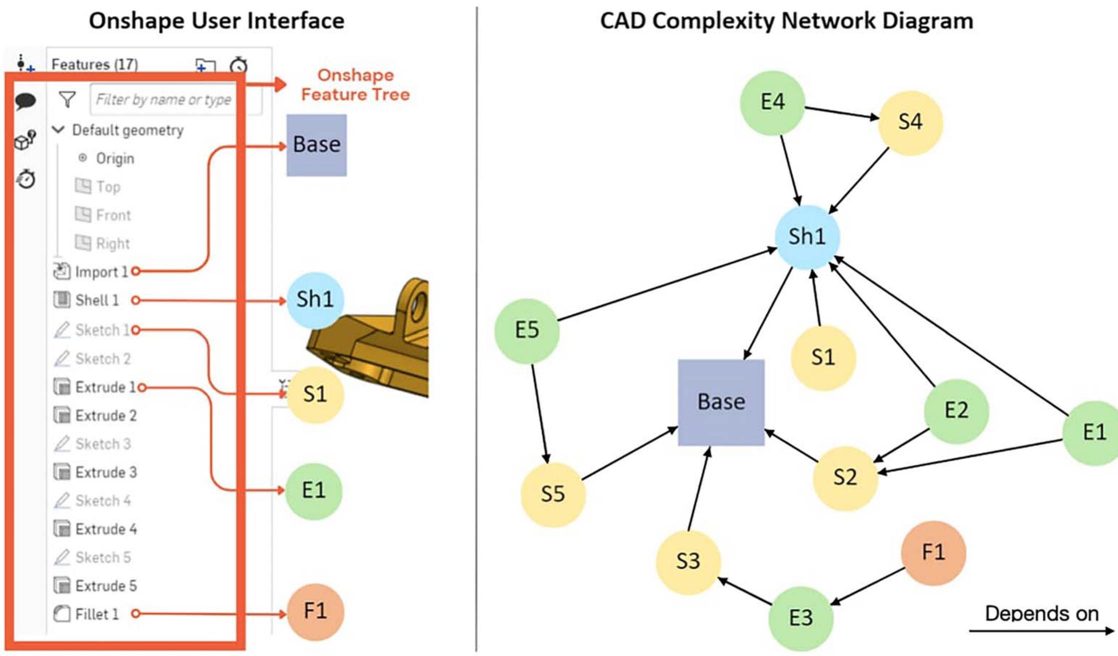


Fig. 6 ONSHAPE **feature tree (left) and the network graph formation (right)**

500 ms [89] during which no participant was speaking.

$$S = \frac{T_s}{T_{\text{total}}} \tag{3}$$

4.3.5 Computer-Aided Design Dominance. We defined "CAD dominance" as a metric used to understand the asymmetry of contributions to the CAD model during the collaboration. The multi-user computer-aided design collaborative learning framework (MUCAD_CLF) [93,115], was utilized to automatically calculate and graph the CAD contribution percentage of each dyadic collaboration. This framework analyzes individual behaviors and team collaboration in the MUCAD environment with fine-grained analytic data. The audit trails collected from ONSHAPE were downloaded in CSV format for each dyadic team which contained records of all analytic actions, recorded chronologically with corresponding timestamps, and then plugged into the MUCAD_CLF script. The script automatically derived the contribution of different types of actions, and the occurrences of each action corresponding to each participant. It further generated a graph, an example of which is shown in Fig. 5, displayed the percentage of contribution by each participant per dyadic team. For the purposes of this study, we were interested in the asymmetry of contributions to the CAD model during the collaboration, hence the delta of the percent contributions were calculated. The CAD dominance (C_dD) was calculated as the difference between the percentage contributions of the first expert (E_1) and the second expert (E_2) as shown in Eq. (4).

$$C_dD = \%E_1 - \%E_2 \tag{4}$$

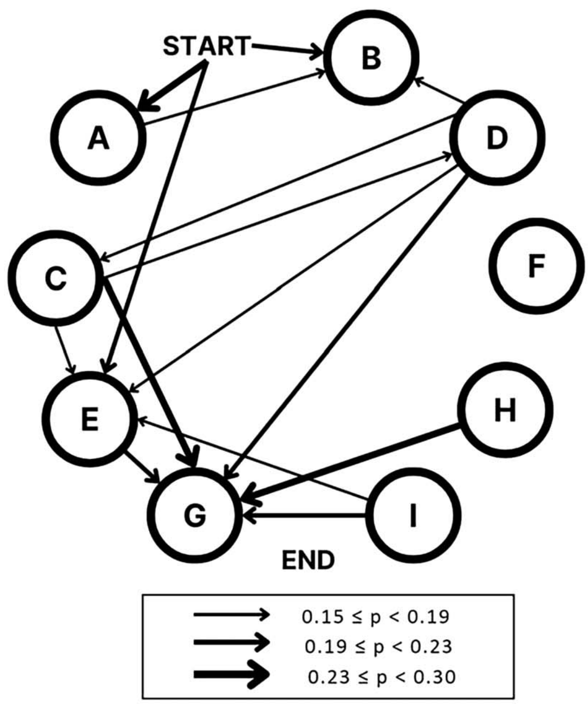
4.3.6 Computer-Aided Design Efficiency. CAD efficiency was conceptualized as a metric to evaluate the efficiency of the participants in the CAD environment. Specifically, this metric provides insight into the dyad's number of CAD actions and task completion time. When time is held constant, higher efficiency corresponds to fewer CAD actions, indicating that the dyad completes the CAD task in fewer steps. Conversely, if the number of actions remains constant, dedicating more time to the task results in higher CAD efficiencies. As outlined in Eq. (5), CE is equal to the total time taken to finish the design task (T_f) divided by the total number of CAD actions taken (CA_n). This equation was motivated by a method developed by Mišić [116] which was used to measure CAD efficiency and identify areas for improvement in CAD software design, particularly in terms of user interface design [94].

$$\text{CE} = \frac{T_f}{\text{CA}_n} \tag{5}$$

4.3.7 Computer-Aided Design Model Complexity. Prior work done by Camba et al. [95] and Hennig et al. [96] explored methods to analyze and quantify CAD model complexity. Camba et al. investigated feature complexity, specifically the number and type of design elements such as extrusions, fillets, and chamfers, and their interconnectedness using network graphs to analyze CAD model complexity. Hennig et al. proposed frameworks for benchmarking complexity measures using measures from network graphs to detect systematic variation in complexity growth. From Hennig et al.'s work, we adopted the Halstead-derived volume measure complexity (HVM) to quantify CAD complexity in our study. We defined CAD complexity as the degree of interdependence among the design elements of a CAD model. To calculate CAD complexity, we utilized the HVM equation (Eq. (6)), which takes into account the total number of features (N), node connectivity dependencies (E), unique number of interfaces (E_u), and unique number of components (N_u) identified from the network graphs.

$$\text{HVM} = (N + E) * \text{Log}(N_u - E_u) \tag{6}$$

To generate these network graphs, we started from the "base" of the feature tree, which represents the original CAD model imported into ONSHAPE, and stacked up the features based on their dependent sketches and features, as shown in Fig. 6 (left). Each item in the feature tree is considered a "component" of the overall CAD model. The dependencies between components are unidirectional, meaning that changes made to one component will affect a dependent component, but not vice versa. For example, in Fig. 6, changes made to F1 (fillet 1) will not impact E3 (extrude 3), but changes to E3 will affect F1. Following this, we calculated the HVM CAD complexity. From Fig. 6 (right), we can see the total number of features N (E1, F1, S1, …, etc.) = 12 and node connectivity dependencies E (the lines connecting the features) = 16. To determine the number of unique components (N_u), we counted each unique type of CAD feature (e.g., sketch, extrude, fillet) present in the CAD model, resulting in N_u (S, Sh, E, F) = 4. Similarly, we determined



Codebook	Letter Code	Probabilities within State	
DfAM Knowledge Share	A	A → A	0.48
NDE Knowledge Share	B	B → B	0.57
DfAM Design Decision	C	C → C	0.18
NDE Design Decision	D	D → D	0.17
Mass Reduction Design Decision	E	E → E	0.23
NDE CAD Action	F	F → F	0.38
DfAM CAD Action	G	G → G	0.41
Collaborative CAD	H	H → H	0.43
CAD Action Check (mass, measure)	I	I → I	0.12

Fig. 7 Markov model representation

the unique number of interfaces (E_u) by counting each unique dependency between two types of CAD features; for example, an extrude that depends on a sketch is considered as one unique interface. From Fig. 6, we found $E_u = 7$. In summary, we analyzed each CAD model produced by the dyadic teams by first generating network graphs and then calculating the HVM CAD complexity.

5 Results

To address our research questions regarding how experts from distinct backgrounds collaborate, we performed a Markov model analysis and conducted a Pearson's correlation to understand the linkages between conversational dynamics and design dynamics. By analyzing both verbal and CAD-based metrics, we were able to gain a more comprehensive understanding of how experts from different domains work together and how they coordinate their actions.

5.1 How Do Experts Collaborate on Multi-Objective Design Problem in a Collaborative Computer-Aided Design Environment? To understand how experts collaborate in a collaborative CAD environment, a Markov model was generated to illustrate the actions taken by expert dyads during the design challenge and to show the likelihood of transitioning from one action to the next based on the previous action. Figure 7 presents the resulting transition diagram, which displays the various collaborative actions taken by the expert dyads. The arrows in the diagram indicate the movement between different actions, including knowledge sharing (DFAM or NDE), design decision (DFAM or NDE), and CAD actions (DFAM, NDE, collaborative, or checking measures). The thickness of the lines indicates the probability of a transition. For greater clarity, only transitions with probabilities greater than the median, 0.15, are indicated.

We can discern general trends in collaboration by analyzing Fig. 7. Expert dyads were most likely to start their collaboration by discussing "DFAM knowledge" (A). This suggests that in the dyadic interactions, the DFAM experts were most likely to initiate the collaboration and began sharing knowledge and principles relevant to the DFAM design constraints. Analysis of the conversational dominance solely as illustrated in Fig. 8, indicated, on average NDE experts contributed 54% of the conversation, while DFAM experts contributed 46%. This means that although DFAM experts played a significant role in initiating the discussion, both experts made nearly equal contributions to the overall conversation dynamics, i.e., neither group dominated the conversational dynamics. This is further bolstered by Fig. 7, where we see the dyads were likely to alternate between "DFAM knowledge share" (A) and "NDE knowledge" (B), suggesting that during the start of the collaboration, experts tended to exchange knowledge from their areas of expertise. We hypothesize that experts were formulating a common language or, from the perspective of C–K theory, were working to determine the set of known propositions in the knowledge space that would inform the creation of partially known propositions in the concept Space.

Our analysis also revealed that the dyads were very likely to move from "DFAM design decisions" (C), "NDE design decisions" (D), "mass reduction design decision" (E), "collaborative CAD" (H), and "CAD action check" (I) to "DFAM CAD actions" (G). These findings suggest that regardless of which expert (i.e., NDE or AM) made the design decision, DFAM experts were more likely to take charge of the CAD environment, capitalizing on emergent information about model performance from mass reduction design decisions (E), collaborative CAD (H), and CAD action checks (I). This suggests that DFAM experts may dominate collaborative CAD environments. When examining CAD dominance alone, as depicted in Fig. 9, DFAM experts contributed 68% on average, while NDE experts contributed 32%, thereby supporting our hypothesis.

Upon reviewing video data, we also note that NDE experts preferred to wait until the majority of the design objectives had been achieved—namely that the DFAM principles had been met and mass reduction design decisions had been made—before initiating discussions about NDE techniques for inspecting the part. For instance, after the CAD part was modified to meet DFAM principles and mass reduction objectives, the NDE expert might suggest that the part needs to have a minimum thickness of 6 mm to be inspected using X-ray CT based on their experience or recommend increasing

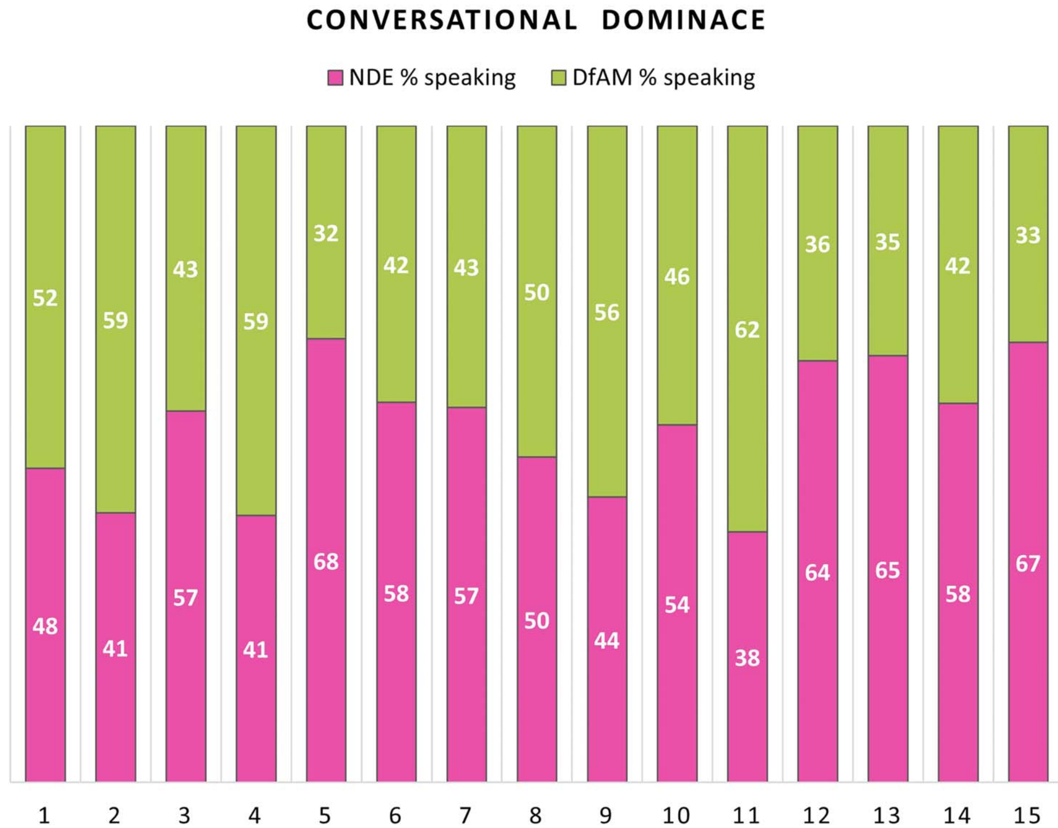


Fig. 8 Conversational dominance broken down by area of expertise

the number of parallel surfaces for optimal ultrasonic testing. This is an interesting observational finding and warrants additional investigation in future work, as it may indicate that NDE experts do not feel a strong sense of ownership over the model.

5.2 What Is the Relationship Between the Conversational Dynamics of Dyads and the Design Dynamics Produced During the Dyadic Interaction?

In pursuit of our second research question, we investigate the relationship between conversational

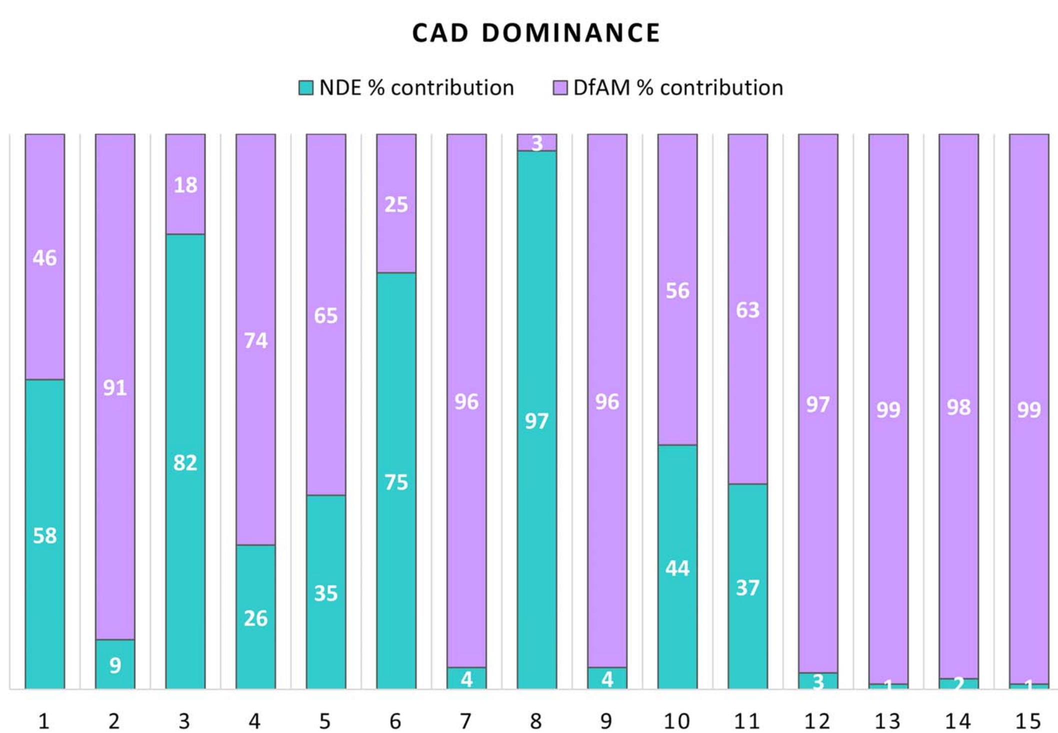


Fig. 9 CAD dominance broken down by area of expertise

Table 3 Correlation between conversational dynamics and design dynamics

	Conversational dominance		Turn-taking		Silence	
	r	p-value	r	p-value	r	p-value
CAD dominance	0.174	0.536	−0.009	0.974	0.032	0.910
CAD efficiency	0.064	0.821	−0.356	0.193	0.593	0.020[a]
CAD complexity (HVM)	0.143	0.609	0.307	0.265	0.074	0.794

Note: r = Pearson correlation coefficient.
[a]Correlation is significant at the 0.05 level (two-tailed).

dynamics and design dynamics, namely CAD efficiency, CAD dominance, and CAD complexity. Specifically, a Pearson's product-moment correlation was conducted to examine the relationship between conversational dominance, turn-taking, and silence and the design dynamics. The variables exhibited a linear relationship, and all variables were found to be normally distributed as determined by the Shapiro–Wilk test ($p > 0.05$). Additionally, box and whisker plots were visually inspected, and no outliers were found. Table 3 summarizes the Pearson correlation coefficients between the variables.

There were no statistically significant relationships between conversational dominance and CAD dominance, $r(13) = 0.174$, $p = 0.536$; CAD efficiency, $r(13) = 0.064$, $p = 0.821$; or CAD complexity, $r(13) = 0.143$, $p = 0.609$. Thus, our findings suggest that conversational dominance is not correlated with CAD dominance, i.e., although an expert may dominate the conversation it does not necessarily mean this same expert will be responsible for a majority of the CAD actions in a collaborative CAD task.

Additionally, there were no statistically significant relationships between turn-taking and CAD dominance, $r(13) = -0.009$, $p = 0.974$; CAD efficiency, $r(13) = -0.356$, $p = 0.193$; or CAD complexity, $r(13) = 0.307$, $p = 0.265$. It is noteworthy that our findings did not reveal significant levels of turn-taking, which typically leads to equal opportunities for all team members to participate in conversations to promote collaboration.

There were no statistically significant relationships between silence and CAD dominance, $r(13) = 0.174$, $p = 0.536$; and CAD complexity, $r(13) = 0.074$, $p = 0.794$. However, there was a statistically significant, moderate positive correlation between silence and CAD efficiency, $r(13) = 0.064$, $p < 0.05$. Based on prior works [91,92], which have demonstrated that silence is necessary for effective design decision-making in teams, we hypothesize that the dyads used the periods of silence to reflect on their design decisions and execute the CAD actions efficiently during these periods.

6 Discussion

The overarching aim of this work was to understand the fundamental ways virtual teams of experts from disparate fields collaborate on a multi-objective design problem in a collaborative CAD environment. Additionally, this study draws focus on dyads, particularly in a controlled environment, serving as a foundational step to understanding the broader complexities of "designing together" in virtual settings. While the dynamics between dyads offer invaluable insights, it is worth noting that real-world design teams often comprise more than two collaborators and are influenced by myriad external variables.

With the growing prevalence of virtual teams and technology-mediated interactions, communication, and coordination of collaborative actions between team members have become increasingly complex [117,118]. Despite the prevalence of geographically distributed teams, strategies for effective team functioning in virtual environments are not well understood [54]. Further, little work has investigated the collaborative actions of expert designers in virtual team environments [43,119], and no work has explored how collaborative design platforms, such as collaborative CAD environments may contribute to or detract from the effectiveness of expert collaborations. This work sought to close these critical research gaps by answering two key research questions: (1) *how do experts collaborate on a multi-objective design problem*, and (2) *what is the relationship between the conversational dynamics of dyads and the design dynamics produced during the dyadic interaction?*

Our study revealed that dyadic collaborations exhibit unique communicative patterns, which are characterized by several elements that influence conversational dynamics and design dynamics. Based on prior work, which has established the criticality of knowledge sharing between experts to facilitate design decisions [88], we developed a qualitative coding schema to analyze dyadic interactions during a collaborative CAD task. Markov model analysis revealed emergent patterns in collaborations, suggesting that during a multi-objective design challenge, one area of expertise may dominate the knowledge exchanged and the decisions made. Specifically, we observed that dyads were most likely to begin the design challenge with the DFAM expert sharing relevant knowledge. Further, from the Markov model we observe some transitions between (C) and (D); each of these states refers to a design decision, either DFAM (C) or NDE (D). This indicates that as the dyads were working to converge on a design solution, the experts were collaboratively transitioning between areas of expertise to accommodate both the NDE and the DFAM constraints. Further, we also observe transitions between states (A) DFAM knowledge share and (B) NDE knowledge share, indicating experts exchanged expertise. Interestingly, we see few connections between knowledge-sharing states and action-oriented states, suggesting the presence of some incubation period between knowledge sharing and design actions. The collaborative process was observed to be more likely dominated by design decisions over NDE decisions after information exchange, consistent with expert behavior documented in the literature. The significance of domain expertise and heuristics in guiding decision-making during collaboration highlights their impact on communicative patterns and design outcomes. Additionally, the deferred testing approach, akin to the traditional V-model [120], emphasizes the significance of considering expert-driven decisions at later stages of the design process.

Evaluating our Markov model from the lens of C–K theory provides interesting insights. We conceptualize the K-space as both states (A) and (B) explicitly referring to "knowledge share." From the Markov model, we observed that if experts entered either state A or B they tended to remain there. In our study, we conceptualize the C-space as action-oriented design decisions, explicitly referring to states (C) and (D). The Markov model suggests that while dyads exchanged knowledge across areas of expertise (the K-space), it did not necessarily result in transitioning to the concept space (C-space). This is in contrast with C–K theory which suggests that design teams rapidly alternate between the C and K spaces, and emergent information in both spaces informs the development of known or partially known propositions in either the C or K space.

In pursuit of RQ2, *what is the relationship between the conversational dynamics of dyads and the design dynamics produced during the dyadic interaction*, we sought to understand the linkages between conversational dynamics and design dynamics. Specifically, we explore the relationship between turn-taking, conversational dominance, and silence to CAD efficiency, CAD dominance, and CAD complexity. Prior work has demonstrated that conversational dominance within problem-solving teams can have a negative impact on the team's creative output [48,49]. However, little work has explored what if any links may exist between conversational dynamics and design dynamics in more complex design tasks, such as CAD modeling, in virtual teams.

In our work, we explore the linkages between conversational dominance, silence, turn-taking, and design dynamics including CAD dominance, CAD efficiency, and CAD complexity. We found no linkages between conversational dominance and design dynamics; this is particularly interesting from the lens of conversational and CAD dominance. Although an expert may dominate the conversation it does not necessarily mean this same expert will be responsible for many of the CAD actions in a collaborative CAD task. This is contrary to studies that demonstrated team members that dominated communication channels tended to contribute more to project completion in high-tech teams [121–123]. Instead, this could suggest that conversational dominance and CAD dominance may reflect a type of division of labor, with one team member "driving" the CAD operation while the other "navigates" the software, aligning with prior work by Phadnis et al. [59] which demonstrates higher-quality work via division of labor and tasks in virtual teams.

There was also no evident relationship between turn-taking and design dynamics, meaning that more democratic turn-taking did not necessarily result in successful design dynamics. This contrasts a study by Haan et al. [90], which found that inclusive turn-taking, involving equal opportunities for all team members to participate in a conversation, can promote information sharing, engagement, and creativity, ultimately leading to improved team performance [90]. We also found a statistically significant positive relationship between silence and CAD efficiency. We hypothesize that dyads used the silence to reflect on their design decisions and execute the CAD actions more intentionally. This aligns with prior research that found that periods of silence allowed group members to process and integrate their individual ideas and perspectives, leading to a more efficient and effective group brainstorming session [91,92].

7 Limitations and Future Work

This study was circumscribed by several key factors. First, our study uses a limited sample size as recruiting participants with niche expertise in DFAM and NDE proved to be challenging. We overcame this by using snowball and purposeful sampling methods, and while most of our participants were quasi-experts, future studies could benefit from recruiting more field experts to solidify our current findings. Moreover, although all participants had previous CAD experience, not all were familiar with ONSHAPE. The training exercise aimed to acquaint them with the unique CAD environment, yet some may have needed additional in-depth training to improve their proficiency. Despite the infeasibility of recruiting a sufficient sample size with expertise in both DFAM/NDE and ONSHAPE, it's worth noting that participants' skills in ONSHAPE may have affected results. Specifically, if participants felt they lacked sufficient skills, they may have been less likely to participate in the CAD software itself, leading to a disparity in CAD dominance. Future studies should assess participants' perceptions of their CAD abilities post-task to better understand this potential confounding variable.

Further, our study specifically focuses on dyadic interactions within the realm of virtual design collaboration. While this emphasis offers valuable insights into the dynamics of two-person interactions, it is essential to recognize that the scope of design collaboration often extends beyond dyads. In practice, design collaborations frequently involve larger and more diverse teams, each bringing its unique dynamics, challenges, and collaborative synergies. By narrowing our lens to dyads, we potentially miss out on the multifaceted complexities and nuances inherent in broader team interactions. Consequently, the generalizability of our findings is primarily confined to dyadic settings. To obtain a more holistic and representative understanding of virtual design collaborations, future research should indeed delve deeper into larger team dynamics, examining the intricate interplay of individual roles, communication patterns, and collaborative outcomes. Such investigations will be paramount in bridging the existing knowledge gap and fostering efficient and innovative virtual design collaborations across diverse team configurations.

Another notable limitation of our study is the potential influence of participant compensation. All participants were informed prior to the study that they would be compensated regardless of their performance during the study. This guaranteed compensation likely contributed to a significant variance in participant motivation, as compared to more authentic in-situ designers and design teams, who are more authentically motivated to design optimal solutions to meet customer and/or stakeholder needs. While our setup aimed to foster participation, it might not have elicited the same level of dedication and effort as real-world scenarios where tangible consequences or rewards are present.

8 Conclusion

Multi-objective design problems require the collaboration of experts from distinct backgrounds. Collaboration across teams and dyads can be challenging, but effective communication, decision-making tools, and organizational support can facilitate the integration of diverse knowledge and perspectives. This study aimed to understand how expert dyads from disparate fields collaborate virtually on a multi-objective design problem in a collaborative CAD environment. By exploring the communicative intricacies within dyads this study offers a foundational perspective on understanding the wider spectrum of virtual design collaboration. The study addressed critical research gaps by investigating the communicative patterns and the relationship between the conversational dynamics of dyads and the design dynamics produced during the dyadic interaction. The findings revealed unique communicative patterns characterized by several elements that influence conversational dynamics and design dynamics. Markov model analysis identified emergent patterns in collaborations, suggesting that experts may not rapidly transition between concept and knowledge spaces, but instead allow knowledge to incubate as each expert learns the jargon and disciplinary norms from their counterpart. In addition, the study found few linkages between conversational dynamics and design dynamics. Overall, the study contributes to the understanding of effective team functioning in virtual environments, providing insights into the communicative patterns and design dynamics of expert designers in virtual team environments.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

Appendix: Markov Model—Transition Matrix

	A	B	C	D	E	END	F	G	H	I
A	0.4813	0.1493	0.0858	0.0373	0.0784	0.0075	0.0261	0.0896	0.0112	0.0336
B	0.0989	0.5714	0.0192	0.1181	0.0357	0.0165	0.0110	0.0989	0.0082	0.0220
C	0.0884	0.0221	0.1823	0.1768	0.1547	0.0000	0.0332	0.2652	0.0442	0.0332
D	0.0417	0.1563	0.1615	0.1667	0.1563	0.0000	0.0521	0.1979	0.0521	0.0156
E	0.0858	0.0901	0.0944	0.1331	0.2318	0.0000	0.0773	0.2146	0.0343	0.0343
END	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
F	0.0331	0.0397	0.0464	0.0464	0.1126	0.0133	0.3841	0.0729	0.1325	0.1192
G	0.0568	0.0917	0.0895	0.0437	0.0983	0.0044	0.0349	0.4061	0.0611	0.1135
H	0.0270	0.0068	0.0405	0.0743	0.0203	0.0000	0.1419	0.2365	0.4257	0.0270
I	0.1440	0.0720	0.0880	0.0480	0.1520	0.0240	0.0800	0.2320	0.0400	0.1200
START	0.4000	0.2000	0.0000	0.0000	0.2000	0.0000	0.0000	0.0667	0.0000	0.1333

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