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DOES SYNCHRONOUS COLLABORATION IMPROVE COLLABORATIVE COMPUTER-AIDED DESIGN OUTPUT: RESULTS FROM A LARGE-SCALE COMPETITION

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ABSTRACT

With the growing demand for distributed collaboration for large and complex design in modern engineering, the collaboration inefficiencies of traditional computer-aided design (CAD) tools are increasingly conspicuous. Emerging cloud-based multi-user computer-aided design (MUCAD) platforms bring a new working style for CAD in the form of real-time synchronous collaboration. Little research exists to characterize collaboration in CAD, and specifically the synchronicity of collaboration has yet to be examined. In this study, we analyzed the backend action logs of 101 teams' design processes from a large-scale virtual robotic design competition, where all designs were modelled in a commercially available MUCAD platform. Metrics of interest were analyzed with regression and mediation analyses to uncover factors that correlated to a team's success in the competition. Results show that team size is a positive predictor of team performance. Large teams, which tend to see a large amount of time commitment from members, were more likely to perform more CAD actions and achieve high scores from the competition. This suggests that the benefits of collaboration (e.g., economies of division of labor, learning) outweigh the potential downsides (e.g., coordination overhead, free riding) in this context. While controlling for team size, increased synchronous collaboration occurrences were observed to negatively correlate to teams' performance – a novel finding which we discuss in detail. Thus, we conclude that although large teams benefited from the MUCAD environment, a tendency for synchronous real-time collaboration did not coincide with higher performance. This study provides important evidence in the ongoing design and innovation research fields aiming to better understand collaboration. Future research should investigate the characteristics of effective collaboration strategies in MUCAD environments to develop best practice for the increasing number of design teams moving to such tools.

Keywords: computer-aided design, multi-user CAD, synchronous collaboration, user analytics

1 INTRODUCTION

In modern engineering design and product development processes, distributed collaboration is increasingly demanding for large and complex design projects, requiring support from appropriate design tools [1]. Computer-aided design (CAD), on the other hand, has traditionally fostered a solitary working style [2]. Driven by innovation in digital technologies such as additive manufacturing, virtual and augmented reality, advanced simulation, and broad trends towards digitization as a means of organization resilience, CAD is increasingly important [3–5]. While CAD modeling is an indispensable part of the product development process, the incapability of efficient collaboration in traditional CAD platforms hinders improvements in design quality as the scale and complexity of projects grow. With the emergence of cloud-based collaborative CAD, or multi-user CAD (MUCAD), the traditional design process in CAD is expected to be revolutionized towards enhanced collaboration [6].

Access to traditional CAD software often requires local installations and licenses for each contributor to a design. Meanwhile, file transfer between collaborators can be time-consuming and prone to compatibility errors, resulting in numerous copies of the same design file, the potential for costly rework, and the need for conflict resolution [7]. Migrating both the CAD platform and data storage to the cloud, the efficiency of product development management is expected to be improved with instant access to others' designs for reference. At the same time, MUCAD cloud-based platforms enable synchronous CAD collaboration, where multiple designers can access and make edits in the same file simultaneously with immediate updates of others' edits, similar to text editing in a Google Docs file. While synchronous collaboration has been studied in other disciplines and contexts, such as pair-programming [8], computational notebooks [9], and collaborative writing [10,11], there exists little research to extend this knowledge to computer-aided design. As a cloud-based MUCAD platform enables both instant file access and synchronous design collaboration, this study primarily focuses on the collaboration aspect of the platform and its correlation to design outcome.

We conducted our research based on a dataset collected from a large-scale, fully virtual high-school robotics design competition using a multi-user CAD (MUCAD) tool. While past large-scale studies of design competitions focused on idea generation [12–14], to our knowledge, our study is the first of its kind to look at a CAD competition specifically. As similar research often examined collaboration quality with a simplified or artificial task in a non-naturalistic environment [15], our research also benefits from our non-intrusive data collection method -- backend analytic data that are automatically logged during the design process. We analyzed data from 101 teams competing in the design competition who used a cloud-based CAD platform with synchronous collaboration capabilities. We first tested relationships between performance and important variables of interest such as effort and team size in this context. Next, we tested a unique collaboration feature – a measure of synchronous collaborative work – and its relationship to team performance.

Our analysis finds that the synchronous design and collaboration capability of MUCAD is a negative predictor for team performance. We identify a trend where increase in synchronous collaboration does not generally lead to team success but the opposite, while controlling for team size and time spent on the CAD model. This finding has important implications for both engineering design and management research. This study is the first to explore the real-world ramifications of the changes afforded by this new multi-user and multi-tenant approach to mechanical design. As CAD increasingly moves to this cloud-based realm, this research points to the importance of understanding the affordances of how individuals and teams approach multi-tenant design activities.

These findings open a new and vital direction for future work, to better understand the affordances of cloud CAD, and ultimately to generate improved CAD models and products.

2 BACKGROUND

Research towards understanding and improving collaboration has long been an important direction of inquiry in engineering, management, economics, and psychology. In general, the study of team productivity is challenging because observational studies face a complication of confounds that may be hard to measure, and lab experiments generally rely on simplified tasks to test specific hypotheses. Therefore, the literature shows mixed results in the myriad of studies investigating the link between team size and productivity or comparing individual to team performance. The theoretical benefits and costs of collaboration are well discussed by Mao et al.: teams can benefit from division of labor and learning; teams can also suffer from costs of communication and coordination, the potential for free riding, herding and groupthink [16]. Their study found that as team size increases for a complex task (defined as one that comprises multiple, partially interdependent subtasks and relies on both coordination and division of labor), there is a positive correlation with collaboration within teams, leading large teams to outperform an equivalent number of individuals. Further, a larger team has the potential to be more diverse, which can be functionally beneficial to groups in several ways (see thoughtful discussion in [17]). These findings are relevant here as our study benefits from a unique context: we observe the team performance of a design competition with a complex task – a robot design challenge in CAD – with varying participating team sizes.

Looking to design-specific studies, when collaborating in small design teams, research found that individuals often outperformed teams in terms of design quality [18]. These researchers further found that guidance from a process manager could mitigate deficiencies. In the context of complex systems design, researchers found that as team size increases, collaboration effort also increases with added social sources of complexity, contributing significant time and cost to the design process [19]. To improve teams' performance, research findings also suggested enhancing the most proficient member of the team instead of the least proficient member [20].

Specific studies of collaboration in CAD have recently accelerated with the development of real-time collaborative CAD; these tools are called multi-user CAD (MUCAD), cloud-CAD, or multi-tenant CAD. These works provide preliminary insight into how collaboration may affect design outputs. When collaborating in a MUCAD environment with a partner as compared to individually, more emotion was also observed from the designers [21]. Studies of pair-CAD (inspired by pair-programming) show that speed and quality of outputs are different in a paired collaborative working style [22]. In another study, ensuring effective communication and grouping team members with similar spatial manipulation abilities resulted in better team performance [23]. Other researchers have attempted to establish relationships between the characteristics of a CAD part and the optimal number of collaborative contributors [24].

While these studies present interesting empirical results, they generally fail to explore the complex way in which MUCAD may affect collaborative design. Indeed, these new software platforms represent a major transformation of design and management capability; MUCAD's broad set of cloud-enabled features may influence the design output in varied ways and warrant a clarifying discussion. We therefore distill the expected benefits and drawbacks of MUCAD derived from our own experience, the MUCAD literature, and related studies of computer-supported collaborative work.

First, it is possible to collaborate in a modern MUCAD environment asynchronously; the cloud-based nature of the system architecture could in and of itself lead to some design benefits, including:

- Reduction of conflicts and rework because of a single source of truth model [7]
- Reduction in time spent on data transfer overheads, versioning [25]

Our study context allows us to explore the relationship between performance and the real-time synchronous capability of MUCAD (similar to Google Docs). This capability introduces additional potential design benefits, as well as drawbacks:

- Improved parallelization of design tasks [25]
- Enhanced communication and shared understanding, especially if the CAD is used as reference during reviews and meetings [25]
- Enhanced awareness of teammates' actions, leading to earlier detection of mistakes or divergent design choices, earlier identification of conflicts that need resolution via close collaboration, and ultimately a reduction in rework and integration challenges [22,25]
- Increased social presence or co-presence [26] and increased designer interaction may increase worker engagement [21].
- Improved learning and training [25]

Finally, there exist potential drawbacks of real-time synchronous capability:

- Challenges to coordination with decentralized authority
- Information overload [27] and increased distraction

The existing MUCAD literature predominantly involves small-scaled controlled experiments, lacking statistical significance from a large enough dataset. The unique context of our study, and the nature of our data, present the opportunity to investigate the multi-dimensional relationship between performance and various variables of interest, including synchronous real-time collaboration.

3 METHODS

For this research, data were collected from a large-scale virtual robotics design challenge, the 2020 Robot to the Rescue competition, where Onshape, a MUCAD platform, was used for design and collaboration. Statistical analyses were conducted between metrics of interest.

3.1 The competition

The 2020 Robots to the Rescue (RttR) competition was a virtual design challenge held by PTC Inc. for FIRST Robotics [28]. FIRST Robotics teams are made up of high school students and are facilitated in school or structured afterschool programs.

The competition was first launched on April 4, and the deadline for all submissions was May 15. In this 41-day competition, teams collaborated virtually to design robots that solve real-world problems. At the end of the competition, each design was judged by three judges (a documentation reviewer, a CAD basics reviewer, and an Onshape expert reviewer) based on Problem Definition and Robot Design on a one to five scale under each criterion. For this study, we only consider criteria under the Robot Design category (summarized in Table 1) for all analyses and discussions because the excellence in Problem Definition cannot be assessed through the designed model.

Table 1. Judging rubric on Robot Design used in the competition.

Criteria	Description of full five-point score
Completeness and complexity of design	Assembly is complete. Uses complex mechanisms to allow for realistic motion.
Ability to solve the problem	Robot mechanisms are uniquely and innovatively designed to address all the requirements.
Feasibility	Design is complete with manufacturing documentation.
Utilization of FIRST components	Adheres to the robot requirements from the competition and FIRST. Innovative and unique usage of typical FIRST components.

3.2 The CAD platform

All teams in the competition were encouraged to use Onshape as the primary CAD platform for their design and were required to submit Onshape-based CAD models for the final judging. However, all participants were free to import parts from other CAD software and the public Onshape parts library. Different from traditional CAD software, Onshape provides a cloud-based multi-user CAD platform. Users can access CAD files through any device with internet access to view and edit the CAD model. Multiple users can also open and work on the same model synchronously to discuss ideas and collaborate on constructing the model in real-time, which enables our study on engineering collaboration. Apart from the synchronous editing feature, Onshape is similar to other traditional feature-based CAD programs.

As the teams designed in their Onshape documents, backend user analytics were logged automatically in the cloud, recording essentially every action the users committed in the document. Meanwhile, every action was recorded with a corresponding timestamp and the user who made the changes. Eventually, analytic data can be analyzed in the form of audit trails. In a previous work [29], we categorized actions in constructive actions (that make visible changes to the CAD model) and organizational actions (e.g., browsing between tabs, renaming features) for more efficient analysis of this rich database.

3.3 Participants

By the end of the competition, 151 robot designs with 70,833 unique parts were submitted from the participating virtual teams, coming from ten countries. Of these competition entries, teams with constructive action counts or total number of action counts below 5% of the average number of all participating teams were excluded from our analysis. Such that, we excluded teams that may have imported most of their parts from the public library with minimal edits, teams that constructed the majority of their parts in other CAD software before converting them into an Onshape document for submission, and teams with documents that may have experienced unexpected backend data loss. With this criterion imposed, 101 submissions with complete statistics of team composition (e.g., *Team Size*) were included for analysis. With 1,627,764 entries of backend analytic data collected from these 101 teams, 377,559 user actions were extracted for analysis. Among all the analyzed teams, *Team Size* ranged from four to thirty-two, and teams received *Points* from four to eighteen, where the maximum possible *Points* were twenty. Figure 1 shows the distribution of *Team Size* and *Points* received by the 101 analyzed teams, composed of 1254 individuals.

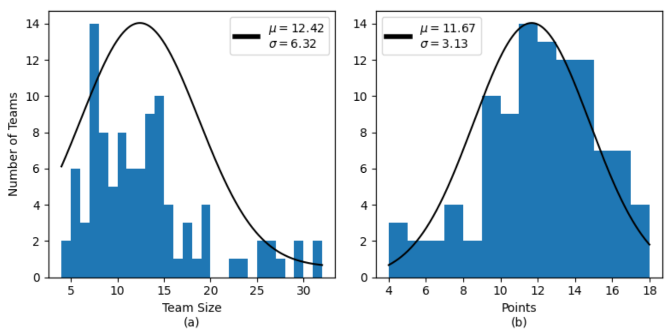

Figure 1. *Team Size* and *Points* of teams in normal distributions.

3.4 Data analysis

Besides the *Points* and the aggregate count of actions (*Total Actions*), we aimed to build a model from the analytics to capture the factors of interest discussed in the Background section. The limitations of these metrics as proxies are discussed later in the paper. Table 2 provides a summary of the metrics and their description. With all variables available, the Pearson correlation matrix between every pair of variables was first computed, and the correlation among variables were then further examined through regression analyses.

4 ANALYSIS AND RESULTS

In this section, we present our analysis and results that may uncover the factors that contributed to teams' success (measured by high *Points* in the competition) and factors that correlated to more effort invested in the competition (measured by large *Total Actions* in CAD). To provide an overview of the relationship between all variables, the Pearson correlation coefficients between variables were first summarized in a matrix, presented in Figure 2. None of the independent variables were highly correlated (>.8), and thus we proceed with the regression models.

Table 2. Metrics of interest.

Metrics	Description	Statistics
Points	The graded points teams received for Robot Design in the 2020 RttR competition, as detailed in Table 1.	$\mu = 11.7$ $\sigma = 3.13$
Bill of Material (BOM) Size	The size of the bill of material of the final assembly, counting the number of parts in the final model.	$\mu = 324$ $\sigma = 482$
Team Size	The number of people in the team, i.e., individuals who have access to the CAD document.	$\mu = 12.4$ $\sigma = 6.32$
Usage Time per User	Average amount of time (in hours) per team member interacted with the document, excluding inactive idle time ≥ 10 minutes.	$\mu = 6.94$ $\sigma = 4.33$
Collaboration Occurrence Ratio	The proportion of occurrences when one person opened the CAD document, one or more teammates were already working in the document.	$\mu = 0.37$ $\sigma = 0.26$
Total Actions	The number of actions (clicks) recorded by backend Onshape Analytics during the competition.	$\mu = 3738$ $\sigma = 2905$

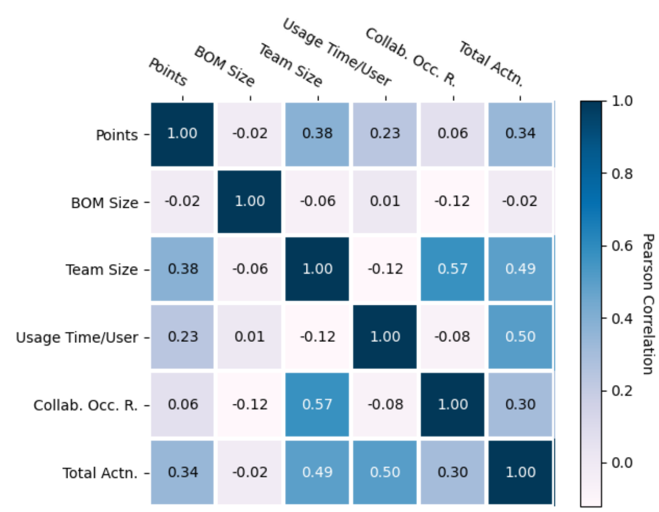

Figure 2. Pearson correlation matrix of all metrics of interest.

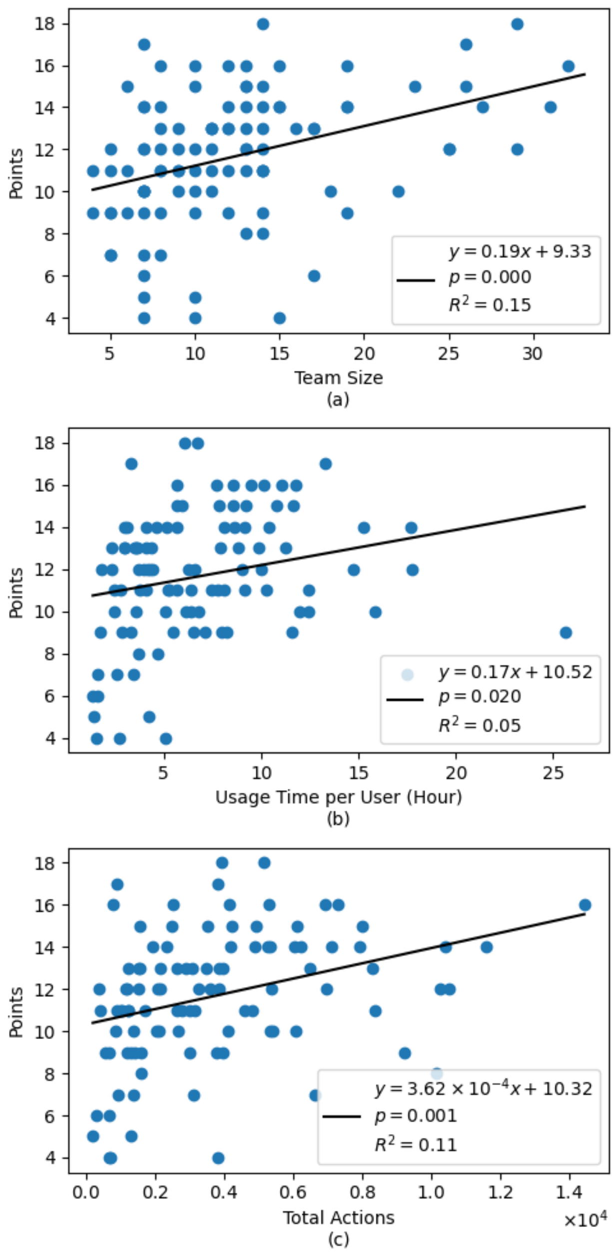

Figure 3. Regression models between *Points* and *Team Size*, *Usage Time per User*, and *Total Actions*; p-values of the slope terms of the equations are reported.

4.1 Investigating variables of interest and performance

From the correlation matrix in Figure 2, *Team Size*, *Usage Time per User*, and *Total Actions* were the three variables with the highest Pearson correlation coefficient with *Points*. Then, linear regression models between *Points* and these three variables are plotted in Figure 3. In Figure 3(a), the regression model suggests an increased probability of achieving better performance as *Team Size* grew, while it is also worth noticing that even small teams were able to achieve high *Points* in this competition. In Figure 3(b), the model suggests another positive correlation between *Points* and *Usage Time per User*, meaning that better performance was generally achieved with greater average time commitment from team members. However, it is also widely observed that teams with lower-than-average time commitment could also result in high performance, and high time commitment also did not guarantee a high return in team performance. In Figure 3(c), higher *Points* were generally achieved with more actions recorded from the design process, as suggested by the model. However, outliers were also widely observed in the plot. In other words, many teams achieved high *Points* with an average amount of *Total Actions*, while many teams that performed a large number of CAD actions had poor achievement.

4.2 Investigating variables of interest and effort

As the final CAD model was the only deliverable in the Robot Design virtual design challenge, the number of actions largely reflected a team's effort in this competition. Based on the correlation matrix in Figure 2, *Team Size*, *Usage Time per User*, and *Collaboration Occurrence Ratio* were identified as the three most statistically significant factors related to *Total Actions*, and a linear regression model for each of the variables is shown in Figure 4. As suggested by Figure 4(a), larger teams were more likely to perform more actions in the CAD model. However, quite a few medium-size teams also had high number of actions committed to their design. In Figure 4(b), we see a positive correlation between the amount of *Usage Time per User* and the number of *Total Actions*, suggesting that an increase in average time commitment of team members could result in greater team effort investment. Figure 4(c), a weak correlation between *Collaboration Occurrence Ratio* and *Total Actions*, suggesting frequent simultaneous collaboration in MUCAD generally led to more actions committed to the CAD design. In summary, greater effort investment was likely correlated to large *Team Size* and large individual time commitment in a team. Meanwhile, frequent collaboration could also potentially encourage more effort commitment.

4.3 Mediation analysis on effort to performance

As *Team Size* and *Usage Time per User* both had positive relationships with *Total Actions* and *Points*, mediation analyses were performed to test if *Total Actions* mediated the impacts of both *Team Size* and *Usage Time per User* on *Points*. As shown in Figure 5, the indirect effect (also known as the average causal mediation effect, or ACME) between *Team Size* and *Points* was not statistically significant but close to the 0.05 threshold acceptance value. In fact, bootstrapping with different randomized initial values sometimes showed statistical significance during our analysis process for some trials. Thus, the model suggests a weak partial mediation of *Total Actions* between *Team Size* and *Points*. In other words, *Total Actions* can only partially explain the increase in *Points* led by the increase in *Team Size*, where there exist other factors that could also mediate the increase. As shown in Figure 6, on the other hand, there exists a complete mediation effect on *Total Actions* between *Usage Time per User* and *Points*. While there were a statistically significant indirect effect and a statistically non-significant direct effect (also known as the average direct effect, or ADE), it is concluded that the increase in *Usage Time per User* led to an increase in *Total Actions*, which thus resulted in higher *Points* for teams in the competition.

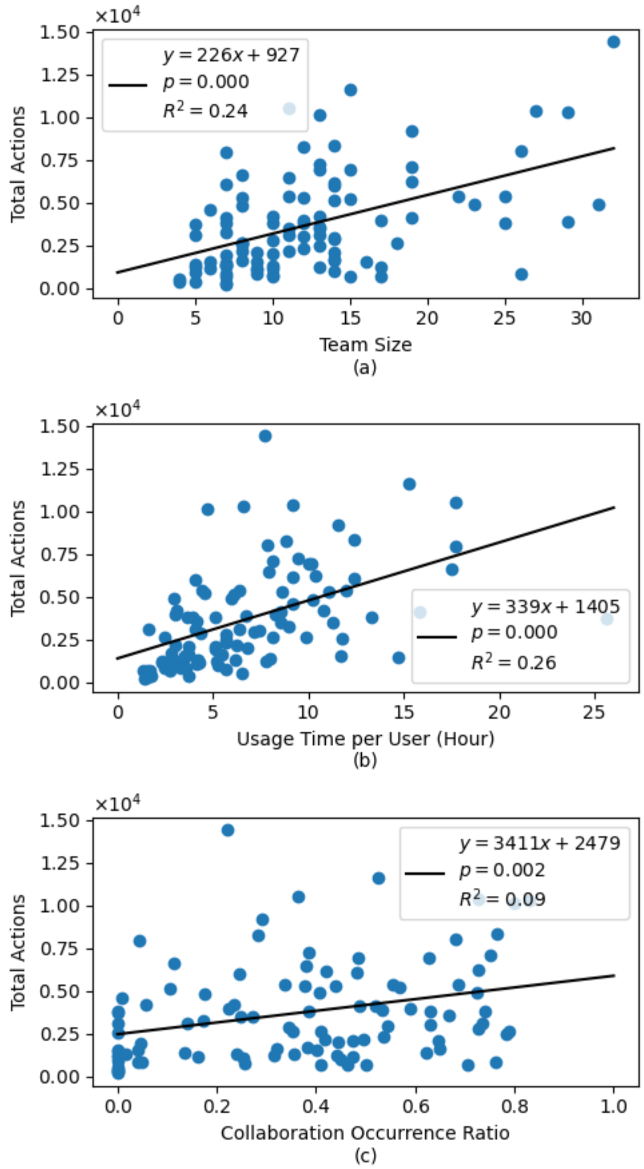

Figure 4. Regression models between *Total Actions* and *Team Size*, *Usage Time per User*, and *Collaboration Occurrence Ratio*; *p*-values of the slope terms of the equations are reported.

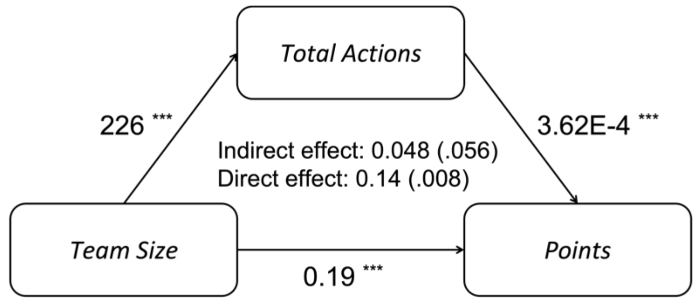

Figure 5. Mediation analysis of *Total Actions* on *Team Size* and *Points*. Coefficients are reported with *p* values in parenthesis, and *** indicates $p < .001$.

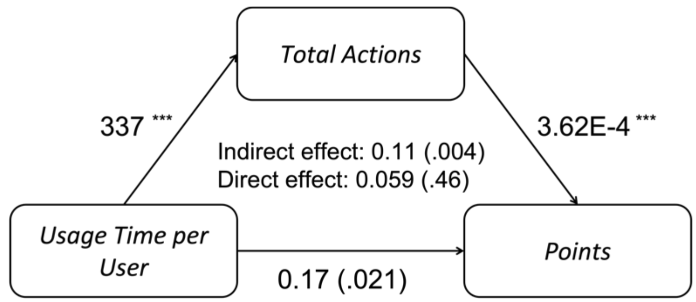

Figure 6. Mediation analysis of *Total Actions* on *Usage Time per User* and *Points*. Coefficients are reported with *p* values in parenthesis, and *** indicates $p < .001$.

Table 3. Coefficients of hierarchical regression analysis for variables predicting *Points*.

	A	B	C	D	E
(Constant)	10.3 ***	9.14 ***	9.14 ***	9.43 ***	9.56 ***
Total Actions	4e-4 **	2e-4	2e-4	2e-4	
Team Size		0.14 **	0.14 **	0.21 **	0.25 ***
BOM Size			-1e-5	-1e-4	
Collab. Occ. Ratio				-2.96 *	-2.86 *
R^2	.113	.174	.174	.213	.182
Adjusted R^2	.104	.157	.148	.180	.165
F-statistic	12.6	10.3	6.81	6.48	10.9

*, **, *** indicate $p < .05$, $p < .01$, and $p < .001$, respectively.

4.4 Predicting team performance via regression model

A hierarchical regression was conducted to test if the teamworking and structural characteristics significantly predicted teams' *Points*, the results of which are presented in Table 3. From model A to C, control variables for team effort (measured with *Total Actions*), *Team Size,* and model complexity (measured with *BOM Size*) were included successively. In model D, the *Collaboration Occurrence Ratio* was added, testing the effects of collaboration to *Points*, while controlling other variables shown to be influential to team performance in the existing literature. Finally, insignificant variables ($p \geq .05$) were removed from model D to form the final model E that best predicted the *Points* teams received in the competition.

The hierarchical multiple regression revealed increasing predictability of the models as additional control variables were added, except *BOM Size*. Using all the control variables only, model C accounted for 17.4% of the variation in *Points*. With the *Collaboration Occurrence Ratio* added in model D while controlling all other variables, the model's predictability improved, accounting for 21.3% of the variation in *Points*. As insignificant variables in model D were taken out, the final model E accounted for 18.2% of the variation in *Points*. Hence, we conclude that the performance of a team (i.e., *Points*) can be predicted based on its characteristics in such design competition with a mathematical model in the following form:

$$Points = f(\beta_0 + \beta_1 \cdot Team\ Size - \beta_2 \cdot Collaboration\ Occurrence\ Ratio) \tag{1}$$

In other words, the *Points* of a team can be estimated as a function (f) of *Team Size* and *Collaboration Occurrence Ratio*, and the β terms are positive coefficients that can be estimated with the regression model E in Table 3. Meanwhile, it is also worth noting that although *Collaboration Occurrence Ratio* was not significantly correlated to *Points* in Figure 2, it is a significant variable in the regression model when the other two significant variables are controlled. Also, while *Total Actions* significantly correlated to *Points* in Figure 2, it was not a significant variable in the model, potentially due to collinearity with other variables.

5 DISCUSSION

This research is the first to examine the affordance of a MUCAD platform from a large-scale competition through a non-intrusive approach. As virtual collaboration in CAD modeling is expected to be increasingly vital for future mechanical engineering design, we attempt to inform the best practices of employing a MUCAD platform for large and complex CAD designs with this study.

Several observations were made on the participating teams, with statistical analyses performed between metrics of interest. In general, larger teams tended to achieve excellence in team performance, even when effort was accounted for. This result does not align with what we might expect based on previous findings of design collaboration [18], where individuals have been found to outperform teams. This disagreement may be driven by differences in task complexity; in studies of collective intelligence, it has been found that interacting groups work quicker and more efficiently than individuals for complex tasks but not simple ones [30]. As reviewed in the background, the positive predictive power of team size to performance may be driven by efficiencies of division of labor, learning, and potential benefits of diversity [16].

Results presented in this paper reveal a significant relationship between performance in a collaborative CAD task and team size (positive) and synchronous collaboration (negative). This relationship persists even when we control for effort. Although increased synchronous collaboration indeed tended to occur with increased actions, it was also a significant negative predictor of points achieved in the competition. This novel finding suggests that team performance could be negatively correlated to simultaneous design collaboration as enabled by a MUCAD platform, and warrants discussion. A possible explanation for the trend of negative influence of synchronous collaboration relates to the approach to this new style of collaboration. In past studies of creativity, it has been found that for unstructured tasks (e.g., concept generation), rules or templates – in effect a structured process – lead to better outputs [31]. This resonates with best practice in the product design literature, which broadly affirms the importance of process [32,33]. Future studies should look to better understand the general approach to synchronous work, whether and how it was coordinated.

It will be important for future research in this area to more specifically understand the affordances realized via synchronous collaboration. We imagine this work-mode could be used not only for truly collaborative contributions to design, but for design reviews, training and learning, or simply by necessity of parallel access. For example, as a deadline approaches, synchronous collaboration may be the by-product of parallel design as many contributors attempt to finish the project. As Marion et al. suggested, digital tools can bring effectiveness and efficiencies to the design process, but they can also lead to negative consequences in the absence of strong management processes [34]. For example, synchronous collaboration may correlate with iterative design cycles; prior research has shown that iterations can be a 'double-edged sword.' While increased iteration creates more knowledge, excessive iteration can lengthen design times [35]. In fact, past research has revealed that despite effective iterations in the early stages of a design process, both students and professional designers were prone to design fixations towards the end of the project [36]. Managing design iteration has been shown to be a key attribute in project outcomes [37]. This research highlights the ongoing importance of better understanding individual and team approaches to effectively using and exploiting the potential advantages of MUCAD.

Model complexity, as measured by the size of the Bill of Material, was not found to have a statistically significant predictive relationship with performance. Past studies of collaboration that consider complexity have looked at task complexity [16], whereas our measure in effect represents solution complexity. Considering that designing a robot in CAD is a complex task by Mao et al.'s definition (one that comprises multiple, partially interdependent subtasks and relies on both coordination and division of labor [16]), our findings generally align with theirs, where large teams were outperformers. Our null findings on model complexity as a predictive factor in performance can be interpreted to mean that complex designs were not necessarily better in and of themselves – likely reflecting that effective design might best be done with a simple, elegant solution. Further, BOM size is an imperfect measure of solution complexity, as parts in the BOM table were not necessarily self-built, and the same part can be duplicated with minimum effort required.

Meanwhile, increased time commitment from the teams is found to first correlate to an increasing amount of CAD actions recorded during the design process, which then eventually leads to higher points received from the competition. At the same time, it is observed that larger teams tended to perform more CAD actions in total, and larger teams also statistically achieved higher points with their design. This finding provides evidence that the benefits of collaborative work outweigh the expected downsides such as coordination overhead and the phenomenon of free riding in this context [16]. Again, while traditional research often suggests increased challenges in effective collaboration for large design teams [38,39], this research suggests potential mitigation of such challenges in a MUCAD environment.

6 LIMITATIONS

We measured synchronous collaboration by counting the instances when more than one team member was simultaneously logged in the CAD document, which may be an imperfect measure. For example, designers could potentially be working individually in separate design "spaces" in the CAD document, essentially analogous to collaboration in a traditional CAD environment, where the potential of the MUCAD system is not fully realized. For future research, a more detailed analysis can be performed to differentiate collaboration strategies used by different teams and study the impacts of different strategies on the final team performance. For example, collaborators may all be working on the same part simultaneously, or there may exist a high-level reviewer that monitors the team as they distribute design in parallel.

Similarly, as we interpreted the number of actions and the length of usage time in the CAD design equivalently as the effort investment and time commitment of a user in the design, more accurate measurement of the two concepts can be explored in future work. For example, a large number of insignificant actions could be generated by randomly clicking and testing out different features of the CAD software, and a long period of aimless traversal through the CAD document can result in longer-than-actual design time recorded by the analytic data. While we had to assume that a similar amount of such behaviors, or noise, existed for every analyzed team, more accurate evaluations can be performed with more sophisticated definition of the concepts or even assistance from external data collected through other media.

Our study solely analyzed data collected from the CAD platform. Teams likely coordinated using additional tools, such as online chat platforms, virtual whiteboards, or video calls. This behavior was not considered in our study, and thus we may be missing collaboration-related data to better understand the complexity of virtual collaboration in multi-user CAD. We also aggregated our study statistics per team over the full design process, but the need for synchronous capability may vary from the start of a CAD design to the completion, and we did not capture this difference. Analytic data used in this study can also be analyzed in a time-series manner, visualizing the variation of different metrics of interest over the entire design process. The characteristics of high-performing teams' design processes may lead to the identification of best engineering collaboration practices at different stages of the design process.

As participants in this design competition were novice designers, their collaborating strategies do not necessarily represent the quality of industrial product development management. While we expect our study to provide insightful recommendations for professional designers to establish the best collaboration practices in MUCAD by observing students' performance, professional engineers may utilize a different approach. Further, we did not measure learning, which is a theoretically predicted outcome of synchronous work and may be an unmeasured confounding variable in our model. Finally, demographic data, such as participants' gender, is missing from this dataset; as design is a socio-technical phenomenon, we may thus be missing significant factors that affect teams' design outcomes.

7 CONCLUSION

By analyzing the performance of 101 teams in a large-scale robotics design competition, we identified a set of factors that correlated to the team performance in a cloud-based collaborative MUCAD environment. Specifically, larger team size and increasing time commitment from team members are correlated to more actions committed in CAD and higher performance achieved in the competition. More frequent synchronous collaboration occurrences tended to correlate to more CAD actions but worse team performance; we discuss several potential reasons why we might see this result, including a lack of organized coordination and team learning. While our study provides important evidence to explain team CAD performance, we point to a number of important areas of future work to more thoroughly understand this design style. With these research findings, improvements on future engineering collaboration in a MUCAD environment can be better tailored toward the above-mentioned factors.

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