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The multi-user computer-aided design collaborative learning framework

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ABSTRACT

New developments to computer-aided design (CAD) software transform a once solitary modelling task into a collaborative one. The emerging multi-user CAD (MUCAD) systems allow virtual, real-time collaboration, with the potential to expand the learning outcomes and teaching methods of CAD. This paper proposes a MUCAD collaborative learning framework (MUCAD-CLF) to interpret backend analytic data from commercially available MUCAD software. The framework builds on several existing metrics from the literature and introduces newly developed methods to classify CAD actions collected from users' analytic data. The framework contains two different classification approaches of user actions, categorizing actions by action type (e.g., creating, revising, viewing) and by design space (e.g., constructive, organizing), for comparative analysis. Next, the analytical framework is applied via a collaborative design challenge, corresponding to over 20,000 actions collected from 31 participants. Illustrative analyses utilizing the MUCAD-CLF are presented to demonstrate the resulting insight. Differences in CAD behaviour, indicating differences in learning, are observed between teams made up entirely of novices, entirely of experienced users, or a mix. In pairs of experts and novices, we see both a perceived high-satisfaction apprenticeship experience for the novices and preliminary evidence of an increase in expert design behaviours for the novices. The proposed framework is critical for MUCAD systems to make the most of the educational possibility of combining technical skill-building with team collaboration. Preliminary evidence collected in a fully-virtual design learning activity, and analyzed using the proposed MUCAD-CLF, shows that novice students gain advanced CAD design knowledge when collaborating with experienced teammates. With the user data captured by modern MUCAD software and the MUCAD-CLF presented herein, instructors and researchers can more efficiently assess and visualize students' performance over the design learning process.

1. Introduction

Since computer-aided design (CAD) was first developed in the 1950s, its capabilities have been continuously extended and diversified in different application design domains, such as mechanical, electronic, architecture, and so forth [1]. CAD has been used as an essential tool in engineering design to support detailed design for product development. Being an indispensable design tool in the industry, CAD has long been part of the university engineering curriculum [2]. While three-dimensional geometric and structural modelling remains the core of CAD programs, recent CAD technological advancements focus on "virtualization" and "collaboration" [1]. As virtual collaboration has long been an essential topic of research [3], and modelling is an indispensable part of engineering education [4], we are particularly interested in exploring the potential of improving modern pedagogy on CAD modelling with the collaborative nature of cutting-edge multi-user CAD (MUCAD).

With the commercialization of CAD software in the 1980s, industrial CAD systems, or what we refer to as Traditional CAD, have employed solid and parametric modelling techniques. Subsequently, developments continuously improved the virtual representations of curves and surfaces in Traditional CAD [5]. Notably, Traditional CAD operates in standalone computers, which makes file sharing between designers time-consuming and complicated. Driven by the growing complexity of modern product design and the improvements in geometric computing algorithms, collaborative CAD is becoming the state-of-the-art evolution in CAD design [6], which we refer to as Modern CAD in this paper. While preserving traditional parametric modelling techniques, Modern CAD

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migrates locally-installed Traditional CAD systems to the cloud. In contrast to Traditional CAD, advancements in cloud computing help Modern CAD users achieve more efficient file access and sharing.

With the standalone nature of Traditional CAD installations, all Traditional CAD software is effectively single-user CAD. However, cloud-based Modern CAD opens opportunities for multi-user CAD (MUCAD). In a MUCAD environment, geographically distributed engineers can virtually contribute to one CAD model simultaneously, where edits are instantly updated for every user viewing the design. Designing in a MUCAD environment can be described as an analogy to simultaneous text-editing in a Google Docs file, and the collaborative design principles in MUCAD are also deemed similar to the ones in Minecraft [7]. In order to provide real-time synchronization, MUCAD must be supported by a sophisticated collaborative software architecture system, such as conflict-free replicated data type [8]. Importantly, the MUCAD platform is expected to enhance virtual collaboration and stimulate more innovative ideas during the design process [9,10].

From Traditional CAD to Modern MUCAD, research with data analytics and multi-party collaboration has always been part of the efforts of improving design quality and efficiency with CAD. In the architecture, engineering, and construction (AEC) industry for example, there is an increasing demand for higher computing power, such as cloud computing and distributed data management, to achieve effective collaboration [11]. Specifically, Gao et al. examined the interoperability between CAD-based building information modelling (BIM) and operation and maintenance (O&M), and they found that this integration remains a challenge due to inefficiencies in information exchange [12]. With traditionally geometric-centered mechanical CAD on the other hand, new developments of semantic and textual representation of features aim to enhance the cognitive understanding of the designed product [13,14]. To further improve the design efficiency, common design structures can be identified from large CAD databases, such that skillfully reusing these structures can reduce redundant modelling time [15]. Data analytics have played an important role in the development history of CAD. While behaviours in CAD are traditionally hard to quantify, data mining of user behavioural analytics has the potential to improve modern research; such success has been reached in other fields, such as via the construction of recommender systems in learning social information [16]. However, there currently exists little work to explore the application of data analytics in CAD education.

Passow and Passow’s systematic review of the literature revealed that the most critical competency to be learned in undergraduate engineering programs is “coordinating multiple competencies to accomplish a goal,” and they further assert that “engineers’ technical work is inseparably intertwined with team-player collaboration” [17]. In other words, effective teamwork skills are essential for students to develop in the engineering design process [18]. MUCAD presents the opportunity for teamwork to be incorporated deeper in the engineering design process, into the step of detailed engineering design. From the literature, we expect that students will perform better when learning engineering concepts with collaborative interactions [19]. In brief, we expect the adoption of MUCAD for CAD teaching to effectively foster collaborative learning in modern engineering curriculums, especially since engineering education is increasingly emphasizing teamwork and collaboration.

The transformation from Traditional CAD to MUCAD, which includes real-time collaborative capabilities, is a relatively recent phenomenon. Therefore, little research has been done to examine if MUCAD indeed provides a more efficient platform for engineers to work together. Previous studies show that engineers often need to seek help from other professionals when learning new feature-rich software in the industry [20], and computer mediated collaboration can often be more effective than face-to-face communication [21]. We are thus interested in examining how students would incorporate similar learning methods in a virtual design challenge setting while developing effective teamworking skills.

In this paper, we first examine the modern teaching of Traditional CAD and how CAD analytics has been studied in academia, in Section 2. In the next section, we propose a MUCAD collaborative learning framework (MUCAD-CLF) with a set of metrics based on backend user analytics from the CAD software to analyze MUCAD learning. The framework combines metrics adapted from the literature with novel methods of analysis. Moreover, the framework provides a systematic data mining approach to study CAD users’ backend behavioural analytics. With data collected from a design challenge, we demonstrate the MUCAD-CLF and present our results in Section 4, illustrating the framework’s feasibility. Finally, we discuss promising potential for future application of the framework, motivating educators and researchers to build on this work with future research regarding CAD learning and team collaboration.

2. Background

As MUCAD is a relatively new innovation in CAD modelling, few researchers have focused their studies on team collaboration in the MUCAD environment. Those studies that do exist look at traditional product design outcomes and industry settings rather than learning outcomes and educational contexts. One study derives implications for MUCAD instructions from interviews with industry users [22], suggesting that there are features of MUCAD that require changes to the way CAD is taught in post-secondary education. The authors find that instruction should prepare students for the flexible modes of working that MUCAD affords, and that teamwork in the detailed design phase requires both standard workflows and a culture of psychological safety to take full advantage of the potential for collaboration. Phadnis et al. test the applicability of pair programming - a common approach to coding where two coders work together in real-time – to pair CAD, as facilitated by MUCAD [23]. The researchers suggest that the outcomes found previously in the pair programming literature, such as higher quality outputs and more satisfied collaborators, hold when pair CAD users are compared to individual users. Further exploring the comparison of paired versus individual MUCAD designers, Zhou et al. find that paired designers experience a higher level of emotion during the design process than individual users, which may indicate a more engaging work experience [24]. Eves et al. conducted experiments to find that teams using MUCAD had a greater awareness of teammates’ activities and increased communication between team members [9]. Similarly, Stone et al. found the potential of MUCAD to accelerate the modelling time for time-constrained activities [10].

These studies primarily focus on communication and other qualitative observations of the teams’ design process using MUCAD; the potential of insights from the rich data sets available via the MUCAD’s backend user analytics has not yet been fully explored. Further, recent developments of built-in data collection features in a commercial CAD software open up new opportunities for more efficient academic research, whereas in the past, researchers had to build their own programs to collect similar data [9,10,25–29]. In computer programming education however, Blikstein et al. have already demonstrated the potential of examining students’ process of programming using learning analytics [30]. With backend analytics that record all user actions available in a MUCAD software, we can now use quantitative data to examine user behaviours further and better understand collaboration. We do not compare Traditional and MUCAD in this paper because we did not collect data from Traditional CAD in this study; the methods and analysis included are specifically built for research in MUCAD. We do, however, anticipate an inevitable shift away from Traditional CAD towards MUCAD in the future, especially in educational settings like universities.

2.1. Modern teaching of traditional CAD

Researchers have put forward new theories or strategies to improve the learning experience of Traditional CAD. Besides teaching CAD as a solid modelling tool, CAD has also been used as a platform to teach engineering design through modelling and simulation [29]. Huang et al. found that applying the cognitive apprenticeship teaching method - demonstrating the thinking process of a CAD design while teaching fundamental CAD features - helped students develop the ability to apply their knowledge and problem-solving skills more effectively [31]. Meanwhile, others argue that overemphasizing CAD modelling features may lead to detrimental neglect of the functional design considerations, resulting in poorly constructed CAD models [32]. The recent emergence of direct modelling methods, a method that allows greater modelling flexibility by simply pushing and pulling geometric entities, is found to be particularly important to remind designers the associativity between parts [33]. Given that students have different collaboration styles during CAD design, Ellis et al. attempted to characterize students in groups based on their approach to collaboration, implying tailored instructions should be given to students depending on their teamwork preference [34]. Similarly, Hamade developed a set of survey questions to understand the backgrounds, attitudes, and preferences of CAD learners prior to training sessions [35], such that it would be possible to anticipate which students might encounter more difficulties during their CAD learning experience and could therefore be pre-emptively given additional support. In order to convey design quality requirements more efficiently, Company et al. attempted to develop embedded rubrics to guide CAD trainees, enforcing quality modelling [36]. While much can be learned from this Traditional CAD literature, a corresponding body of knowledge related to teaching and learning in MUCAD is lacking. This leaves the opportunities for research to examine if novel teaching and learning methods are required and beneficial in a MUCAD environment.

2.2. CAD analytical frameworks

As Vieira et al. summarized in a systematic literature review [37], although educators and researchers have been integrating educational data mining and learning analytics in education with various objectives, the affordances of this powerful integrative field have not yet been exploited. For education in Traditional CAD design specifically, researchers have been exploring applications of backend analytic data towards understanding students' learning behaviours. With all actions made by individual students visualized along a time series, Xie et al. examined the efficacy of technical instructions and support given to students during their design process through observing variations in the numbers of actions along students' CAD logs [26]. Further analysis was achieved with a more detailed classification of CAD actions in building-related and revision-related actions, modifying or deleting previously built structures. Then, researchers can statistically determine if a student has possessed a more reflective design process by having made a more significant proportion of revision-related actions, and iterative designing cycles can potentially be identified [28]. Similarly, Gopsill et al. further classified such analytic data in six command types for a typical CAD design process [38], which concluded with more detailed observations in the transition patterns between action types. With a CAD-based experimental platform developed specifically for research in learning analytics, Rahman et al. studied students' design thinking by coding different design actions with the Function-Behaviour-Structure ontology [27]. Meanwhile, it was also shown that analysis of exit surveys, the actual final CAD models, and students' self-reports were also valuable for research, supplementing the quantitative analysis of the learning analytics [26,28,29].

Building on this foundation of CAD analytic frameworks, commercial MUCAD software provides a mature commercial platform for analytic data collection, and more accessible and standardized analysis methods are now possible with data mining. In addition, analytics now give access to more behavioural data, providing us insight on collaboration, along with traditional data that record users' constructions only.

2.3. Gender difference

Some previous research suggests that there could be a difference in spatial reasoning ability between genders [39], one of many contributing factors leading to the under-representation of women in science and engineering. However, research has also shown that such ability differences result from societal exposure and opportunities for learning [39] and can be effectively minimized with spatial strategy instructions [40,41]. Previous work in the context of CAD has used gender as a lens for reporting differences. Xie et al. had found that male students tended to produce more complex designs that simply look "cool" but do not necessarily meet the design specifications; and female students tended to pay more attention to design specifications while spending more time on revising their designs [28]. When working in an engineering design team, Laeser et al. observed that gender composition does affect both the interactions between team members and the quality of the team's final reports [42].

Further related to gender, we propose our MUCAD-CLF as an alternative to popular self-assessment and peer-assessment of contribution scores for teamwork. The framework can deliver empirically-derived contribution scores that are not vulnerable to previously reported gender bias [43]. As gender differences can sometimes lead to important research questions and results, we have incorporated the exploration of gender-related research questions in our proposed framework.

2.4. Study aim

Our study aims to develop a collaborative learning framework for MUCAD which exploits user analytic data, the feasibility of which we next illustrate with data from 31 students who participated in a collaborative, virtual, design learning activity.

3. The MUCAD collaborative learning framework

The complete design process of a typical CAD model likely requires hundreds, or even thousands, of user actions (or clicks); the manual analysis of data of such scale is daunting. Further with our application in mind, large class sizes in schools and universities will certainly result in more collaboration and even larger datasets. Consequently, a more efficient approach to process these data is required. In the MUCAD-CLF, we combine several analysis methods and metrics adapted from the literature with new methods we developed. All analytic data were processed through self-built Python scripts, now shared open-source online [44]. The two classification methods presented in this section, as well as their potential applications illustrated in a case study in Section 4, make up the proposed Multi-User Computer-Aided Design Collaborative Learning Framework (MUCAD-CLF). An overview of the MUCAD-CLF is provided in Fig. 1.

3.1. A MUCAD platform

A first requirement of the MUCAD-CLF is a MUCAD platform. In this study, we use Onshape [45] as the MUCAD tool. Onshape was selected as the CAD platform in this paper because of its mature MUCAD environment and its ability to collect and present backend analytics for efficient research analysis. Access to these analytics also brings insight on behavioural actions for quantitative research to better understand collaboration. Onshape is one of the very first commercially available cloud-based Modern MUCAD software programs in the market. It is accessible from any computer, and even smartphone, with connection to the internet. Users design in Onshape by collaboratively contributing to the same document, which contains and organizes Part Studios, Assemblies, and Drawings as tabs, similar to a web browser. While multiple Part Studios, Assemblies, and Drawings can be created and used within one document, a typical design will start with part designing in several separate Part Studios, and parts are then assembled in an Assembly.

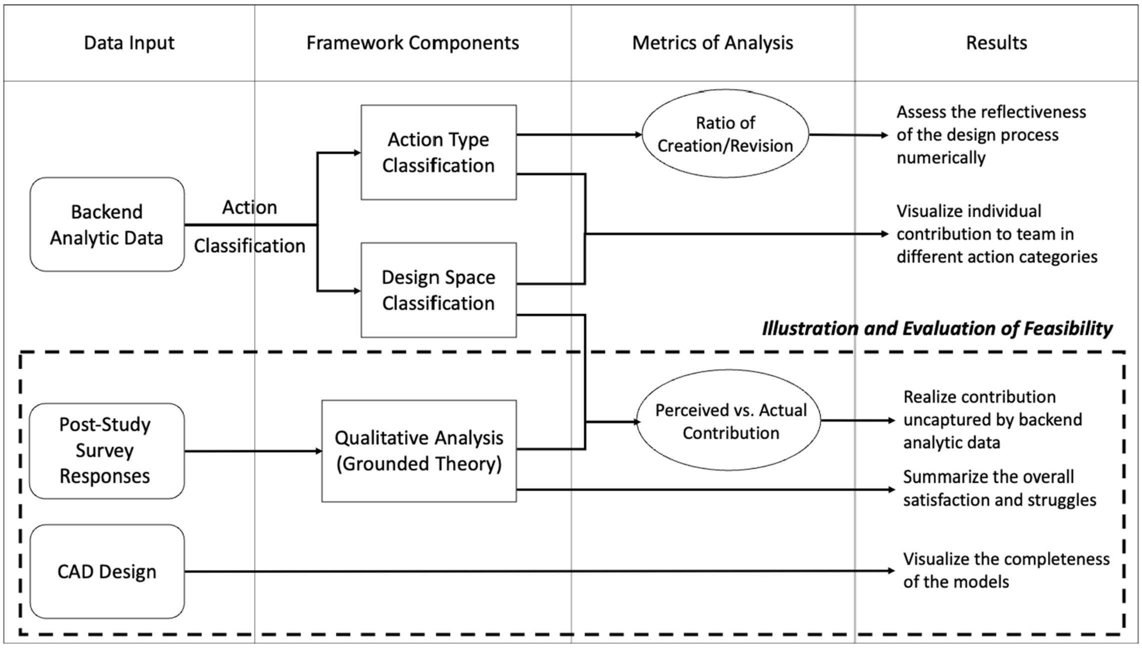

Fig. 1. An overview of the Multi-User CAD Collaborative Learning Framework and the additional data collected in this study as an illustration of feasibility.

Meanwhile, Drawings are used to produce technical engineering drawings for manufacturing but are not used and studied in this paper. When multiple users are working simultaneously in an Onshape document, they can make synchronous edits on the same part; they can work separately in different Part Studios and see progress in other Part Studios; and they can even follow others' view angle to see exactly what their teammate is viewing.

In addition, the Enterprise version of Onshape automatically records all edits made by each user within a document as a chronological audit trail. These backend analytic data record constructions and modifications to any features in the CAD document (e.g., creating a sketch, deleting a part, etc.) and any behavioural actions (e.g., switching a tab), which are essentially every click that a user commits. These analytics are visible to all administrators of the Enterprise account.

3.2. Design space classification

In general, designs are mainly constructed in two design spaces: Part Studios and Assemblies. Users start designing individual parts and make detailed modifications to existing parts in a Part Studio. Then, they assemble parts from different Part Studios in an Assembly with various available mates, constraining the relative motions of individual parts. Within each design space, there are unique features available to the specific design space (e.g., Extrude in Part Studios and Fastened Mate in Assemblies). In Part Studios, a part is usually constructed by first creating a new 2D sketch, which is then transformed into a 3D solid through various 3D features. Whereas in an Assembly, users need to first insert parts from different Part Studios that they want to assemble, then they constrain relative motions of different parts using Mating features.

Following the design architecture of the Part Studio and Assembly spaces, a method for classifying analytic actions was developed, as summarized in Table 1. This classification method first separates constructive actions that make visible modifications to the design from organizing actions that are more behavioural. Within the constructive action category, actions are further classified into their design space: Part Studio and Assembly. Sketching-related and 3D Features-related actions are deemed to be the two most distinguishable action types in Part Studios, hence forming two independent action groups in Part Studios. Similarly, Mating features-related and Visualizing-related actions form the other two action groups under Assembly. Organizing actions are split into Browsing, the most common organizing action types, and all other organizing actions.

3.3. Action type classification

The second classification method was adapted from Gopsill et al. [38], where analytic actions are categorized into six command types for a typical design process: creating, editing, constraining, deleting, reversing, and viewing. However, constraining actions that define the sketched geometry with precise dimensions cannot be isolated from Onshape's audit trails, as they are considered parts of editing actions to existing sketches or features. Therefore, the adapted version of this classification method in our framework contains five categories proposed by Gopsill's paper and an "Other" category, containing all actions

Table 1
Design space classification.

Design Space	Constructive Actions				Organizing Actions	
	Part Studio		Assembly			
Action Type Name	Sketching	3D Features	Mating	Visualizing	Browsing	Other Organizing
Summary of Sample Actions	Add/modify a sketch Copy/paste a sketch	Add/edit a Part Studio feature * Delete a sketch/Part Studio feature	Add/delete a part from Part Studios Insert/edit/delete an Assembly feature	Drag parts/ workspace Call animate actions	Create/delete/ rename a tab Open/close a tab	Create/merge version/ branch ** Undo/redo/cancel an operation

* Deleting a sketch is classified under 3D Features-related actions because a sketch is considered to be a part studio feature in Onshape Analytics once it is created.
** Undo/redo/cancel operations are included under Other Organizing actions because they are recorded unlinked from design spaces.

that do not fit in any of the other five action types. A summary of this classification method, along with some sample actions, is presented in Table 2.

Gopsill's framework allows us to systematically examine a metric put forward by Xie et al. [28] by incorporating the concept of the ratio of building/revision to compare the ratio of creating versus revising actions (e.g., resizing, reshaping, and deleting built structures) for different designers, as a metric of determining how iterative a design process is. Xie's paper pointed out that a lower ratio of building/revision indicates a more iterative/reflective design process, whereas a high ratio indicates a more complex design, as designers continue building new structures and/or features [28]. With this second classification method of analytic actions, participants' designing behaviours during the design challenge can be further investigated. We have slightly modified this ratio as the ratio of creation/revision, where revising actions are the sum of all editing, deleting, and reversing actions, and creating actions contribute to the numerator of the ratio.

4. Case study of a collaborative learning activity

To illustrate and evaluate the feasibility of the proposed framework, we collected data from a teaching activity and conducted analysis with the dataset as a case study. In this section, we first outline the details of the collaborative educational design activity used to generate the data to be analyzed via the framework. Next, we will demonstrate some analysis performed using the novel MUCAD-Collaborative Learning Framework. With survey responses collected from the learning activity, we compared survey responses and results analyzed through the framework to discuss the feasibility of the framework.

4.1. Demonstration data collection

The experimental data for this study was collected via a teaching activity conducted with the Tufts University Centre for Engineering Education and Outreach in the summer of 2020. The teaching activity initially aimed to provide an opportunity for incoming undergraduate summer research students of the lab to familiarize themselves with each other and other graduate students of the lab and be introduced to Onshape, the MUCAD software they would be using for their summer research projects. The teaching activity took place as an open design challenge, where participants were asked to build a playground in Onshape with their assigned teammate(s) in a maximum of one and a half hours. The task was open-ended; there were no intentions to appraise a winner of the design challenge, nor were there any incentives for students to create the best design. During the design challenge, the data analyzed in this paper were recorded for internal feedback. After the activity, consent from willing participants was collected after research ethics review approval was granted to use these data for research purposes.

4.1.1. The design activity

Before the design challenge, a pre-study survey was sent out to all potential participants through a Google Form. The survey asked participants to self-identify their gender and background CAD experience as either expert ("I am an Onshape pro"), intermediate ("I have used CAD but never used Onshape), or beginner ("I have never used CAD software"). For analysis, all experts (e) and intermediate (i) participants are considered to be experienced (E) participants, and all beginners (b) are considered to be novices (N). All teams have been randomly given a label from Team A to Team P, while members of every team have been given labels as X#, where X is the letter of the team's label, and # is a sequential number assigned to individual members of the team. For example, Team A had members A1 and A2. For analysis, teams are considered to be either EE (all experienced participants), NE (a mix of novices and experienced participants), or NN (all novices) teams.

The design challenge was held on the online conference platform Zoom, where all participants joined the meeting room virtually through their own computers. All participants were randomly grouped into fourteen teams of two and two teams of three by the organizer, where each team contributed to one design in one shared Onshape document, and teammates' changes show up in real time. During the design challenge, each team was either placed into their own Zoom breakout room or a breakout room with another team (which we call discussion rooms); eight randomly chosen teams were placed into four discussion rooms. Within each Zoom breakout room, participants were free to communicate through virtual video and audio conversation, text chat, and screen sharing. In discussion rooms specifically, members from the two separate teams within the breakout room were also able to communicate with each other. As an assistance for new users to Onshape, a website link [46] was explicitly mentioned by the organizers and provided to all participants before the design challenge started, where some tips on using Onshape and ideas on playground design were demonstrated on the website, created by the organizers. Besides this website, participants were also free to seek help from any resources from the internet and other participants in their assigned Zoom breakout room.

While all participants communicated with their teammate(s) through their assigned Zoom breakout room, they collaboratively contributed to one shared CAD document in Onshape, which contains all Part Studios and Assemblies the team creates. After participants were distributed to their assigned breakout room and started their work, one organizer entered each breakout room to ensure all technology was functioning as expected and asked for verbal permission to record their breakout room for internal feedback. As requested by some participants, the organizer also gave a quick demonstration on building a slide in Onshape through screen sharing, instructions for which were also available on the given website at the beginning of the design challenge.

After approximately one and a half hours of design time, all participants stopped designing and returned to the Zoom main room. The organizer opened each team's CAD document and showcased every team's design to all participants, and each team had the chance to describe their design briefly. None of these demonstrations were aimed for any kinds of formal assessments. After the teaching activity, a post-study survey was sent out to all participants to collect their reflections for the design challenge through another Google Form. The post-study survey was mainly designed to be used for internal training feedback, not explicitly designed for research purposes. Nevertheless, post-study survey questions on overall satisfaction and team contribution provide data which aids in the illustration of our proposed framework and are therefore reported in this paper. The relevant questions from the survey are summarized in Table 3. Questions were asked on five-point rating scales along with optional space for open responses.

Table 2
Action type classification, adapted from Gopsill et al. [38].

Action Type Name	Creating	Revising			Viewing	Other
		Editing	Deleting	Reversing		
Summary of Sample Actions	Add a sketch/Part Studio feature/Assembly feature Add a part from Part Studio in Assembly	Edit a sketch/Part Studio feature/Assembly feature	Delete a sketch/Part Studio feature/Assembly feature Delete a part in Assembly	Redo/undo/cancel an operation	Open/close a tab Call animate actions	Create/delete/rename a tab Create/merge version/branch

Table 3
Post-study survey questions.

Question	Statement	Five-Point Rating Scale	
		1 Point	5 Point
1. Overall Satisfaction	I enjoyed my experience today.	I didn't like it at all.	I liked it a lot.
2. Learning Experience from Teammate(s)	I learned from my teammate.	I didn't learn anything.	I learned a lot.
3. Team Contribution	Regarding my and my partner's contribution to our playground:	I contributed a lot less.	I contributed a lot more.
4. Future Interest in Onshape	I am interested in using Onshape in the future.	I'm not interested at all.	I am very interested.

4.1.2. Experimental data

After receiving approval from research ethics review and consent from participants, the research team was given access to (1) the actual CAD designs in Onshape created during the design challenge, (2) participants' responses to the two surveys mentioned above, (3) video recordings of Zoom breakout rooms where verbal consents were given to the organizers at the time of the design challenge, and (4) backend analytic data automatically collected by Onshape during the design challenge. For this research, all analytic data were downloaded and analyzed for each participant separately in the form of audit trails (chronological sequences of CAD activities) in CSV format, where all analytic actions were recorded in chronological order with corresponding timestamps to each action. The readily downloadable analytics from the platform itself featured some missing data, and therefore, for this research project, the researchers acquired complete data from the software provider via database query. This data set included some duplicate or redundant actions which were identified and removed by the research team (for example, when switching between tabs, the user technically closes a tab then opens a tab, but actually only takes one action). Although we collected recordings for several Zoom breakout rooms during the design challenge, they have not been analyzed for this paper.

In total, we collected consents from 31 out of the 34 participants. Table 4 summarizes the demographic composition of the participants that have been included in the analysis for this paper. Meanwhile, consents were not provided by the teammates of three of these thirty-one individuals, restricting us from analyzing those three participants' data at the team level. Data for the other 28 participants come from 13 teams: seven EE teams, four NE teams, and two NN team; eleven teams of two, and two teams of three. Of the 31 participants included in the analysis, 27 of them provided pre- and post-study survey responses.

All survey responses were organized into a spreadsheet and imported into NVivo, a qualitative analysis computer software, for open coding using the grounded theory method. Meanwhile, with access to the final CAD designs created during the design challenge, we examined these designs to aid our quantitative analysis and possibly explain any exceptions that may have emerged from the analysis results. For example, Fig. 2 shows a screenshot of the final assembly of the playground designed by Team A (an EE team), whose design stands out in terms of its complexity when compared to Fig. 3, the parts designed by Team M (an NN team), who did not even attempt to assemble their parts in the Assembly. Moreover, several error messages are also noticeable in red in Fig. 3, indicating that the team had not fully understood how those features work and left the design challenge without resolving the issues.

Table 4
Demographics of participants in the case study analysis.

	Expert (e)	Intermediate (i)	Beginner (b)	Total
Male	1	10	3	14
Female*	2	7	8	17
Total	3	17	11	31

* The female category contains all non-male-identifying participants in order to preserve privacy of identity.

4.2. Demonstration of analysis utilizing the MUCAD-CLF

In this design challenge, over 20,000 actions were recorded from 31 participants. In this section, results are first presented by applying each classification method in the proposed MUCAD-CLF individually. Then, analysis comprising multiple classification methods and post-study survey feedback are also conducted.

4.2.1. Analysis of actions classified in design spaces

For inter-team analysis of action count, we normalized by team size to account for the fact that some teams were three and others were two. In Fig. 4, the counts of constructive actions per member in each team are plotted to compare teams in the three team types (EE, NE, and NN). As an obvious trend, EE teams had performed more constructive actions than NE and NN teams. However, it is also worth noting that Team H, as an NN team, performed more constructive actions per member than all NE teams, being close to an EE-team level. However, constructive actions of an NN team may also comprise a large amount of deleting and reversing actions as they tried to explore different features of the program, which will be further analyzed below. As shown in the NE category of Fig. 4, the average constructive actions performed per member in most NE teams consist of greater contribution from the experienced members, potentially signifying their leadership over the construction of the CAD model.

As each team's distribution of actions in the two design spaces (i.e., Part Studios and Assemblies) are plotted in Fig. 5, it is noticeable that Team M, an NN team, performed no edits in Assemblies. In general, most EE teams spent a greater proportion of their actions in Assemblies. However, although Team P performed a larger-than-average proportion of actions in Assemblies as an NE team, its total number of actions was small, and its number of actions in Assembly was even lower than the average number of other NE teams. In addition, Team G had a much lower-than-average number of actions in Assemblies as an EE team. After examination of Team G's CAD design, it was found that the team had not used any mates or animation in Assemblies but simply inserted the two parts they had created in the Assembly and focused most of their efforts on changing the appearance of different parts created. On the other hand, Team A had design lots of animation in their Assembly, and Team L had used multiple Assemblies to organize their parts. Hence, different teams may have different foci and modelling approaches when designing, and some designs may not require as many assembling actions as others for the desired visual presentation. For example, one modelling approach is to create multiple parts in one single Part Studio, where geometries are cross-referenced between different parts, such that all the parts are already roughly "assembled" in the Part Studio. Alternatively, with a top-down modelling approach, the design is decomposed and delegated to team members in different Part Studios before being inserted into the final Assembly. This modelling approach would then result in more Mating actions in Assembly.

Further investigation into the detailed distribution of actions in Part Studios and Assemblies respectively reveals a noticeable unexpected trend that all teams had similar proportions of Sketching and 3D features in Part Studios, and Mating and Visualizing features in Assemblies. This observation is surprising, as different team types had varied proportions of actions in Part Studios versus Assemblies. In Fig. 6, it is shown that teams spent an average of 32.5% of their actions in Sketching and the other 67.5% in 3D features while designing in Part Studios. Similarly, it is also shown that teams, excluding Team M and Team G, spent an average of 19.6% of actions in Mating features and the other 80.4% in Visualizing-related actions in Assemblies.

Organizing actions are behavioural actions that could further differentiate experienced CAD users from novices, where experienced participants may spend more effort on renaming features/documents

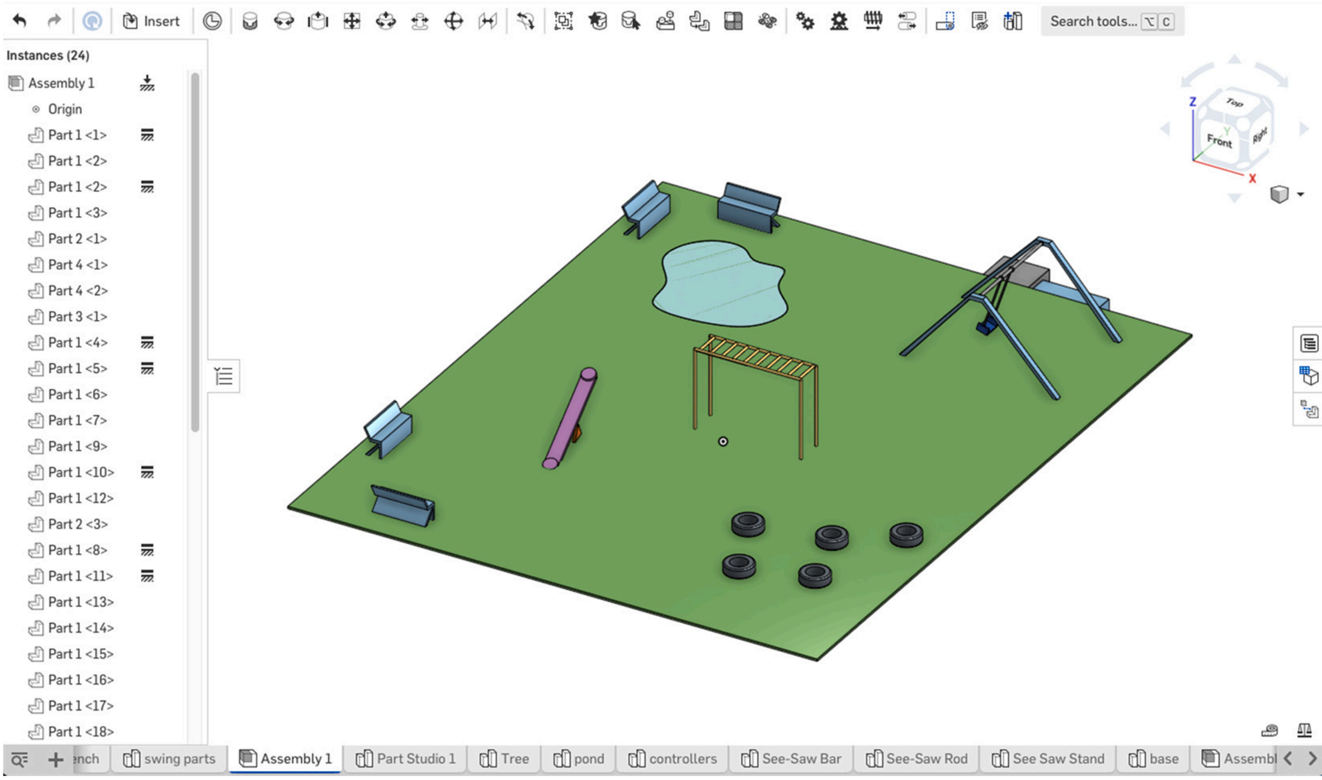

Fig. 2. CAD design of EE Team A in a final Assembly, with 11 Part Studios used.

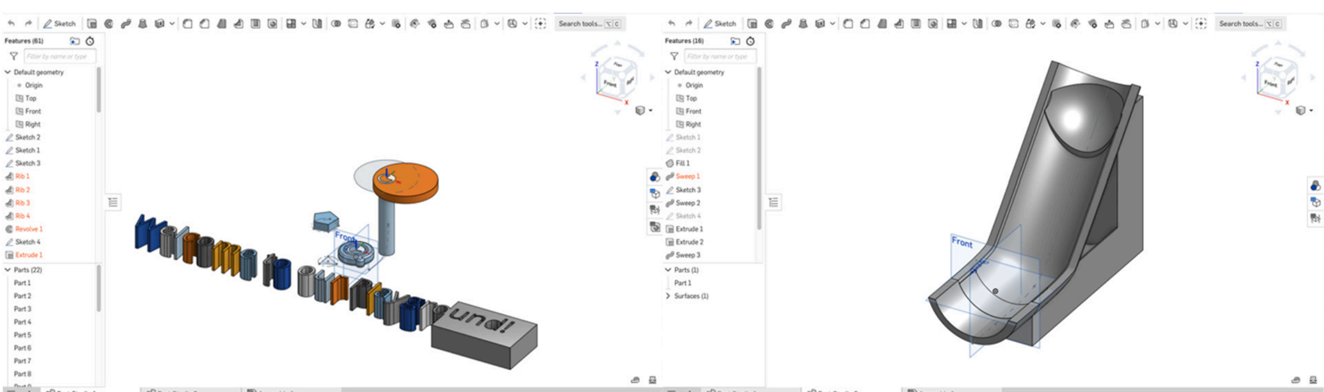

Fig. 3. CAD design of NN Team M, in separate Part Studios, without any final Assemblies.

and creating versions, branches, etc., for better organization. Particularly, NE teams were expected to have performed more Browsing-related actions as the experienced participants in an NE team needed to assist novice team members by browsing between different Part Studios and/or Assemblies. Examining in Fig. 7, the amount of Browsing-related actions alone shows that, as one might expect, an increase in Part Studios being used in the design generally required more browsing actions. As plotted in Fig. 7, the locations of the data points with respect to the trend line could be a good indicator of the teams' relative efficiency of workload and workflow design of any teams that participated in the design challenge. For teams located above the trend line, they may not have had efficient workload distribution as they frequently required to switch between Part Studios to finish their designs, wasting a significant amount of design time on browsing. On the other hand, teams located below the trend line should have had efficient workload distribution, managing different Part Studios with fewer browsing actions than other participated teams. At the same time, it was also a trade-off for participants to balance the time they spent on constructing their own designs and building better awareness of other parts of the design built by their teammate(s).

4.2.2. *Analysis of actions classified in action types*

Using the Action Types Classification method, analysis can be performed in a similar way to the previous classification method. Comparing different teams' distribution of actions in the six action types in Fig. 8, it is noticeable that NE and NN teams have greater proportions of reversing actions than EE teams, potentially confirming the assumption stated previously that a larger-than-average amount of creating actions may have been taken for exploration of different features of the program. Examining the average of all experienced (E) and novice (N) individuals in NE teams, it is noticed that experienced participants spent a greater proportion of activity on viewing related actions than novices, which could reflect the assistance provided by the experts to the novices in the team. Team M, an NN team, had a much greater-than-others

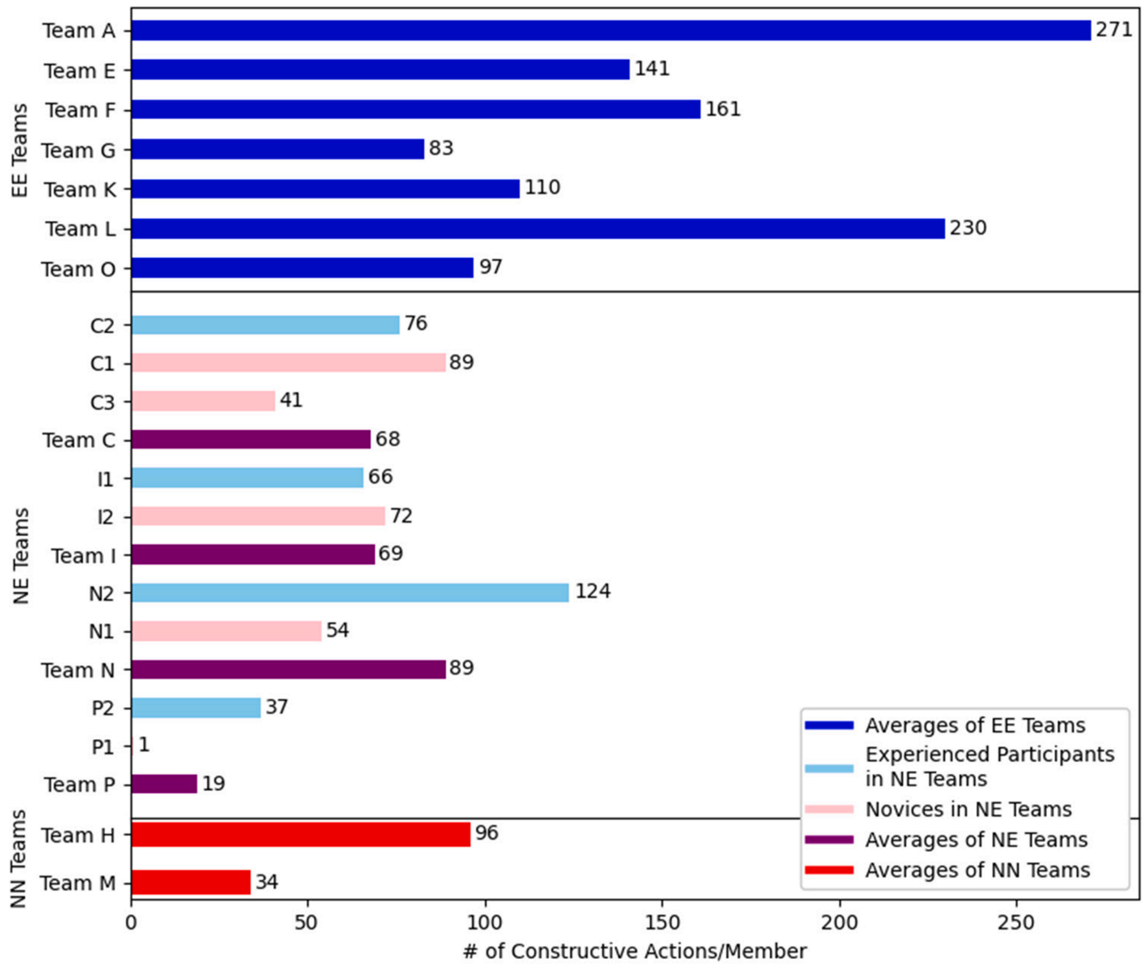

Fig. 4. The number of constructive actions per member by team types.

proportion of creating actions and smaller-than-others editing-related actions, which may indicate that they only focused on building new structures or trying out different features without carefully revising them for a better design. As previously shown in Fig. 3, a number of errors remained unresolved in Team M's final CAD model.

Comparisons of individual participants' creation/revision ratios can potentially provide a better understanding of the design behaviours of participants with distinct previous CAD experience and different genders. In Fig. 9, it is first found that quite a few female participants had higher ratios of creation/revision than male participants in both experience categories, indicating those female members of the teams contributed more to the construction of the CAD model. Although there is a perceived difference in the ratio between experienced users and novices, the difference is not clear for both male and female participants of different skill levels in this design challenge. Nonetheless, averages calculated from this dataset (0.688 for experienced males; 0.677 for experienced females; 1.08 for male novices; and 0.814 for female novices) do show that experienced participants had undergone a more iterative design process than novices.

Linking the two classification methods of analytic actions introduced above, Fig. 10 plots the relationship between the number of constructive actions per member of a team and the team's ratio of creation/revision. With a negative relationship suggested by the trendline, the plot indicates that a larger proportion of constructive actions is more likely to be revision related actions as the number of constructive actions performed in the design process increases. Alternatively, one may conclude that all teams actually required only a similar amount of creating actions to construct all structures of their playground design, despite the difference in complexity, and the rest of the time and efforts were mostly spent on revising the created design. Teams with more background CAD experience performed more additional constructive actions, which may imply that they spent most of their actions revising their constructed features to perfect their designs. However, it is also noticeable that an NN team in Fig. 10 was a clear outlier from the general population. This observation could be explained as novices may have conducted a large number of random actions to explore and test the functionalities of different features in the CAD software.

4.2.3. Analysis of team contribution

We next compared participants' self-evaluated team contribution scores with their analytically-derived contribution of different types of actions. An assumption we have made for the visualization and analysis in this section is that a five-point team contribution score on the post-study survey (i.e., "I contributed a lot more than my teammate") would correspond to a 100% contribution of actions, meaning they have almost done all the work for the team. Although "contributed a lot more" would not necessarily mean 100% contribution to the team, we are exaggerating the contribution in this analysis for the ease of comparing between self-evaluated contribution and calculated contribution based on analytic data. Again, we have normalized team sizes to account for the fact that some teams were three and others were two.

In Fig. 11, a comparison between participants' self-evaluated team contribution score and their corresponding percentages of different types of actions contributed to their teams is made in terms of participants' genders and background CAD experience. In general, most experienced male participants seemed to over-evaluate their

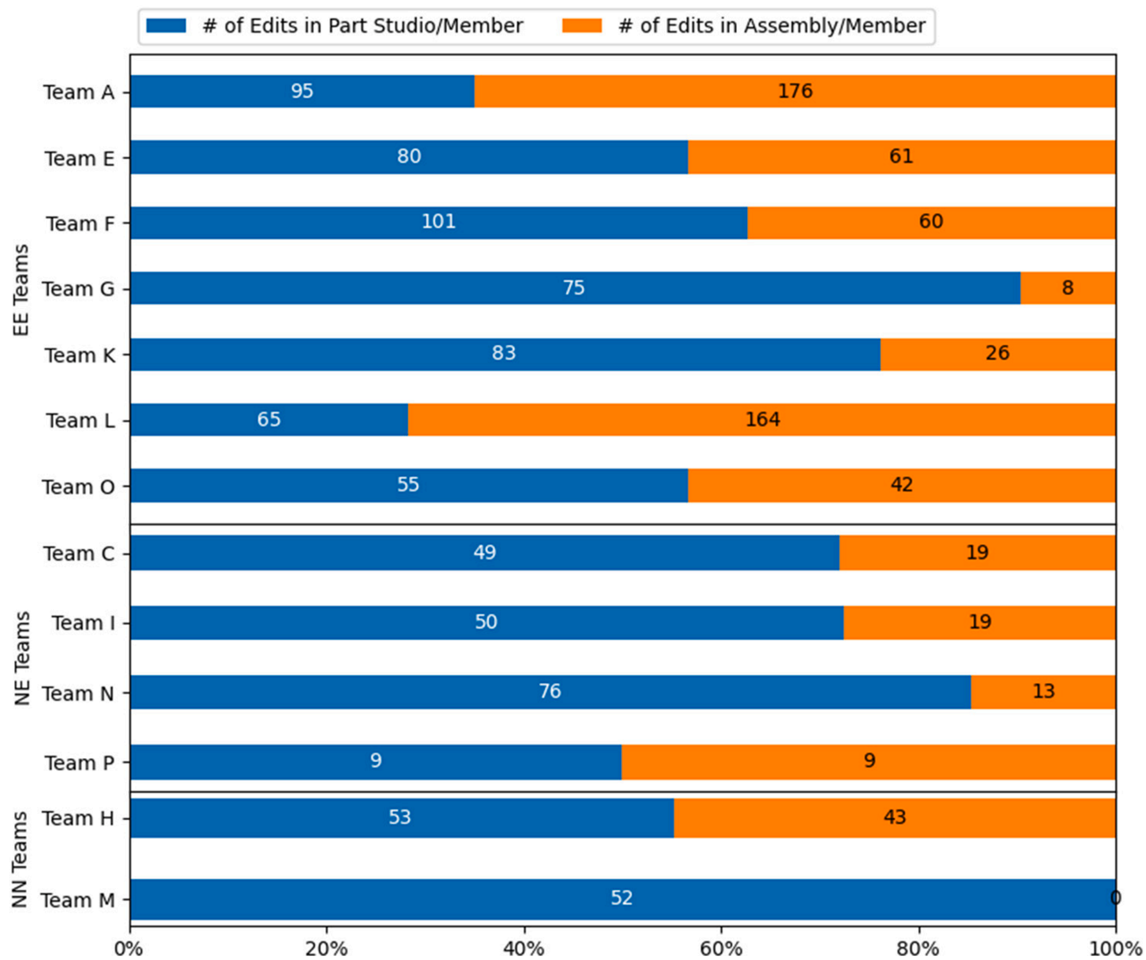

Fig. 5. Team distribution of constructive actions in design spaces. Number labels on bars represent the raw count of actions.

contribution compared to the analytic data, and most novices and most female participants have either accurately or under-evaluated their contribution.

In order to further investigate how participants rated their contribution to the team differently when they were placed in different types of teams, a different comparison is made in Fig. 12. In EE teams, most male participants over-evaluated their contribution of actions to their teams, whereas females' self-assessments were slightly more accurate than males. When experienced participants were paired with novices, experienced participants were able to accurately evaluate their contribution in terms of analytic actions, while novices tended to under-evaluate themselves. However, the analytic data does not fully capture assistance provided by the experienced participants, such as verbal instruction and idea generation. In the two NN teams analyzed, however, most participants' self-evaluated contributions do not match with the analytically-derived percentage of actions contributed to the team.

With the question of which type of action should be the best metric to evaluate one's contribution to the team, comparisons between participants' self-evaluated team contribution and the three types of analytic actions (constructive, organizing, and total actions) contribution are shown in Fig. 13. In general, no action types demonstrate a more consistent rating trend than others, and consistently, participants with higher self-evaluated contribution ratings did indeed contribute more actions in all types. However, there is not an obvious way for us to define a contribution grade to a participant simply based on their actions contributed to the team, since different self-evaluated contribution ratings were reported by participants with the same real percentage contribution of actions, and vice versa, as seen in Fig. 13. This therefore may indicate that a better classification method of analytic actions is required, or that we should not only consider a single type of actions contributed to the team when rating a participant's contribution.

4.2.4. *Post-study survey summary*

All participants' post-study survey responses were analyzed via open coding with the grounded theory, the results of which are summarized in Table 5. In general, participants reflected satisfying experiences from the design challenge, where only three participants (of 27 analyzed) reported a satisfaction rating below three (i.e., felt frustrated). Most participants also liked the teamwork arrangement for the design challenge, as teammates introduced more knowledge and ideas, making it a more enjoyable learning experience than self-exploration of the CAD software. However, sufficient communication appears to be crucial for a good teaming experience. Moreover, novices seemed to require more guidance to approach the CAD software, even when help from the experienced participants in an NE team were available. As participants were asked to self-evaluate their contribution to the team, it is noted that 16 out of the 27 participants reported equal contribution between their teammate(s) and themselves (i.e., a team contribution rating of three), and greater contribution gaps existed between members in NE teams.

5. Discussion

By proposing and applying multiple metrics of the MUCAD-CLF in this paper, we have demonstrated an approach for analyzing individual behaviours and team collaboration in the MUCAD environment with collected fine-grained analytic data. The results of this analysis could

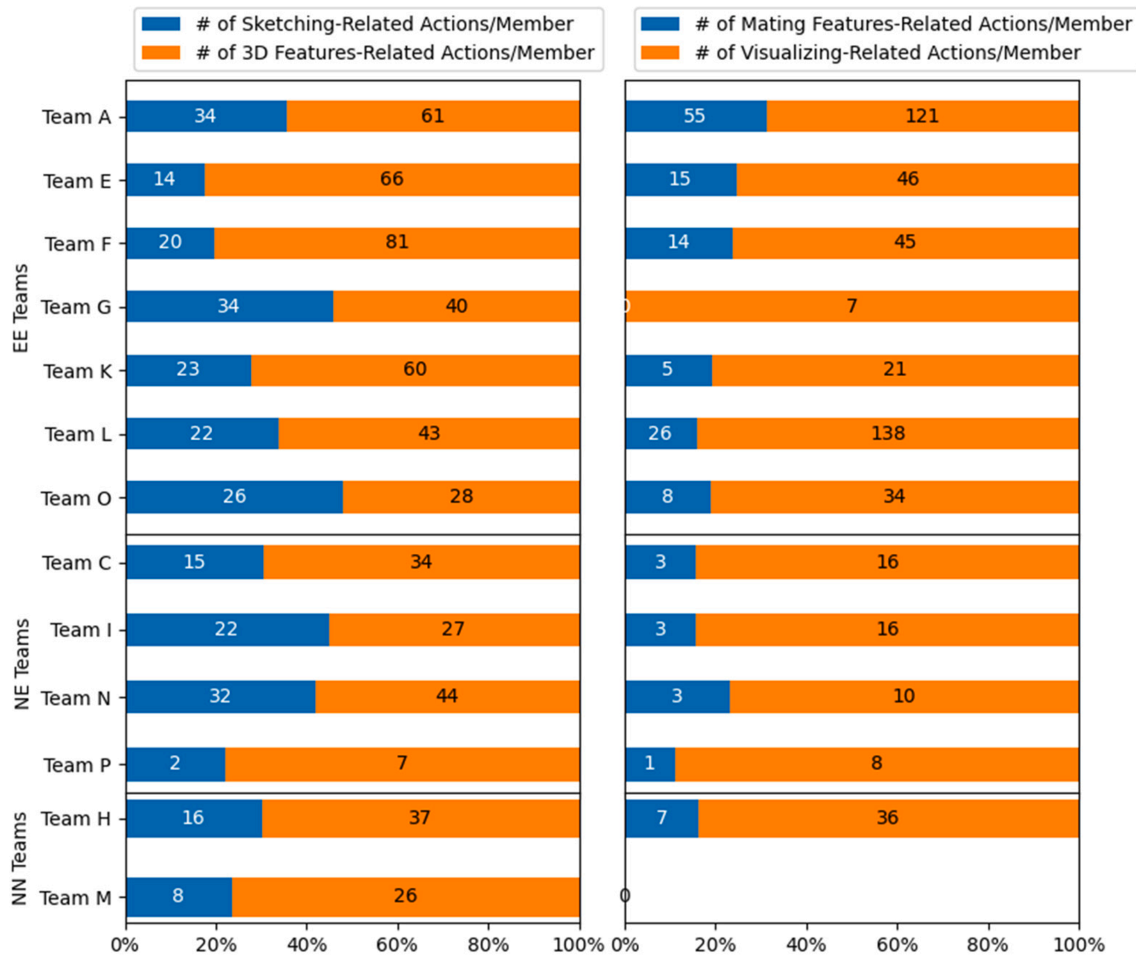

Fig. 6. Team distribution of constructive actions in design spaces.

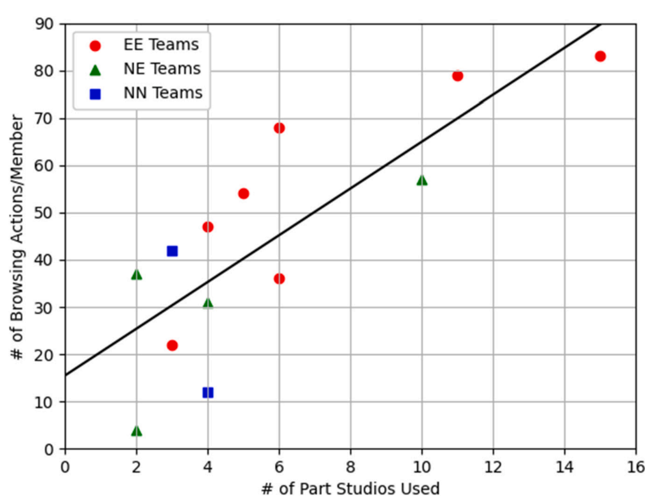

Fig. 7. The number of Browsing actions versus the number of Part Studios used, with a linear regression line of best fit.

potentially provide additional perspectives to educators/researchers on assessing and assisting students with CAD learning and teamwork. While the focus of this study is on collaborative CAD modelling, our work on developing categories for classifying actions is also applicable to comparisons between individual CAD users. Although the confidence level of the results presented in this paper may be limited due to the small sample size of the experiment and the unbalanced composition of participants (i.e., having few experts and NN teams decreases the confidence of the result), the MUCAD-CLF has revealed trends that certainly warrant further research and exploration.

Employing the MUCAD-CLF proposed in this paper, several behavioural trends of participants with different background CAD level are summarized: (1) teams and members of the team with more CAD experience tended to perform more constructive actions, contributing to the complexity and advancement of the design; (2) all participants showed similar behaviours in different design spaces (Part Studio and Assembly) based on analytic data regardless of differences in CAD experience; (3) participants with more CAD experience tended to undergo more iterative design processes; and (4) there is greater misalignment between novices' self-evaluated contribution and their analytically-derived contributions. More importantly, using a combination of multiple metrics from the MUCAD-CLF could be helpful for educators and researchers to visualize and assess individual students' CAD designing behaviours with respect to the class average and easily identify students that require additional assistance. For example, a comparison of Browsing-related actions versus Part Studios used in the design process could reveal the efficiency of workload distribution and workflow design of a team, as shown in Fig. 7. Also, linking the number of constructive actions performed by a team to the team's creation/revision ratio, as in Fig. 10, could be an informative metric to assess how well students carry out an iterative design process, which is deemed to be an important component in engineering design/education [28] and has been studied by researchers for many years [47,48]. While an instructor is monitoring a class learning to CAD model, students or teams that are advancing too fast with the design (i.e., they may lack sufficient

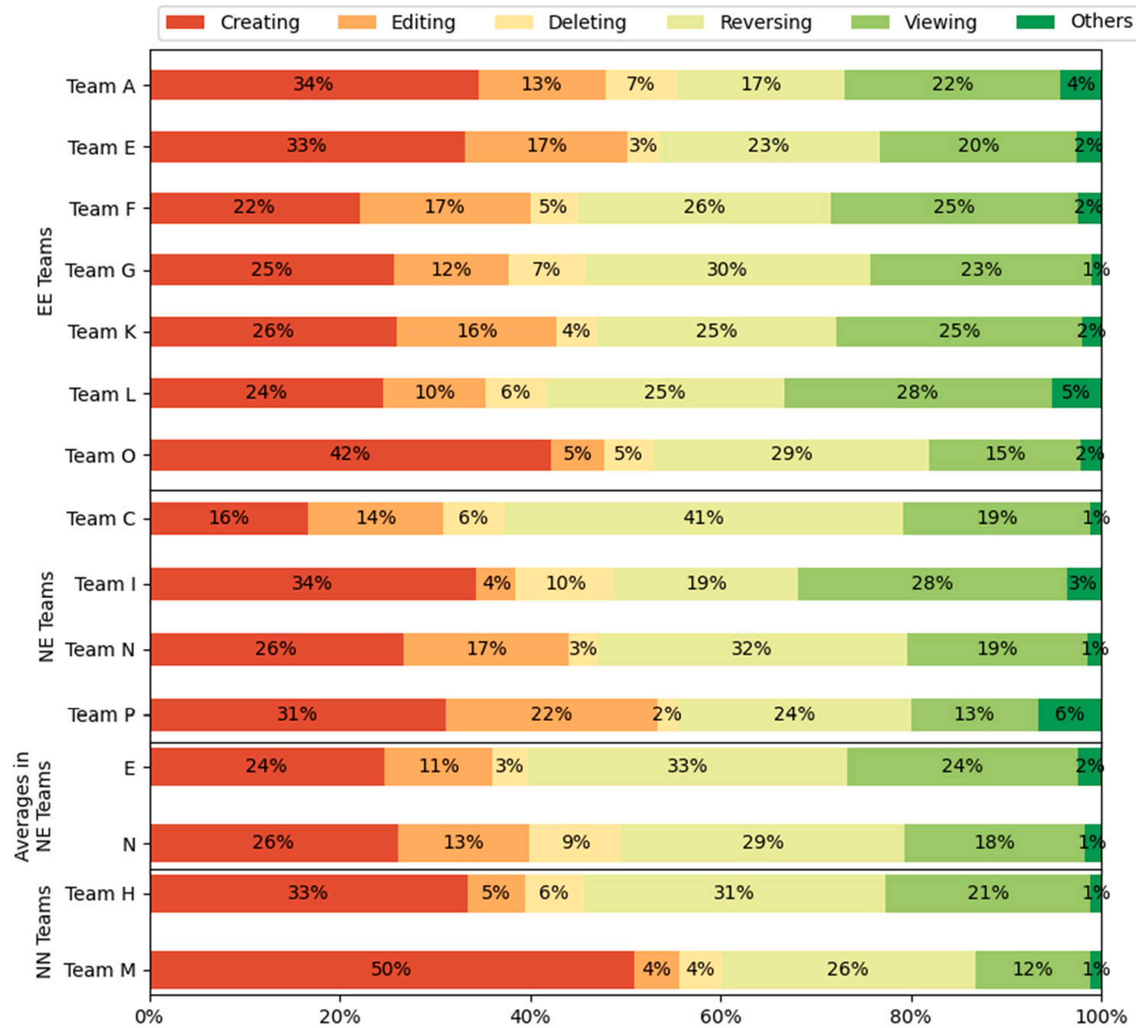

Fig. 8. Team distribution of actions in action types through the design process.

revision by missing constraints or fully dimensioned sketches) or too slow with the design (i.e., they may not have enough time to complete the design if they keep struggling) can be easily identified as they locate far away from the average trendline. Consequently, instructors can provide effective feedback during students' learning process.

Based on feedback received from the post-study survey, it is observed that the MUCAD design challenge was favourable to the majority of students. Most students recognized this team exercise as a beneficial way for them to learn the CAD software, which signifies the opportunities for conducting similar activities with collaborative CAD modelling for future research. Further, based on survey responses, we anticipate that collaborative CAD designing has the potential to facilitate better the cognitive apprenticeship teaching method proposed by Huang et al. [31], which is beneficial in stimulating students' metacognitive behaviour, leading to success in problem-solving skills. It is important to note that in our study, we found that more guidance should be provided to novices at the beginning of the design challenge, in the form of a brief introduction to the software, or else meaningful collaboration is challenging, placing additional pressure on the more experienced member(s) of the team.

Meanwhile, several findings from this study may facilitate future research. While we observe that some female participants exhibited higher creation/revision ratios than did males in the design challenge, Xie et al. presented opposite findings when their students were asked to design in CAD individually [28]. Although we do not have a large enough data size to make a meaningful conclusion on the gender difference, the observed difference based on our preliminary data certainly suggests that past trends should be revisited and therefore gender is an important variable for future experiments with our proposed framework. Slight disagreement observed in this experiment could potentially be explained by examining differences between genders in a collaborative CAD environment, where the analysis of audio/video recordings in the form of case studies will be crucial [49]. Analysis of the audio/video recordings may also result in an understanding of the generally observed higher self-reported contribution level from experienced participants; this finding could indicate that there exist other factors of the contribution that are not captured by the collected analytic data, where the inclusion of more perspectives may yield better understanding on how students assess their own contribution to a team. As Stone et al. concluded, teams with different communication patterns tended to perform differently [10]. With low communication levels, the benefits of the collaborative nature of MUCAD are not realized, and consequently, we observed team members reporting more negative reflections after the design challenge.

Therefore, although analytic data provide novel and rich insights on students' design process for educators and researchers that are not captured by traditional CAD software, to best assess a student's CAD design learning, we should not solely rely on analytic data but also consider other factors, such as the quality and complexity of the actual designed product, the idea generation process, and communication during the design process.

As we have carried out our analysis solely relying on participants'

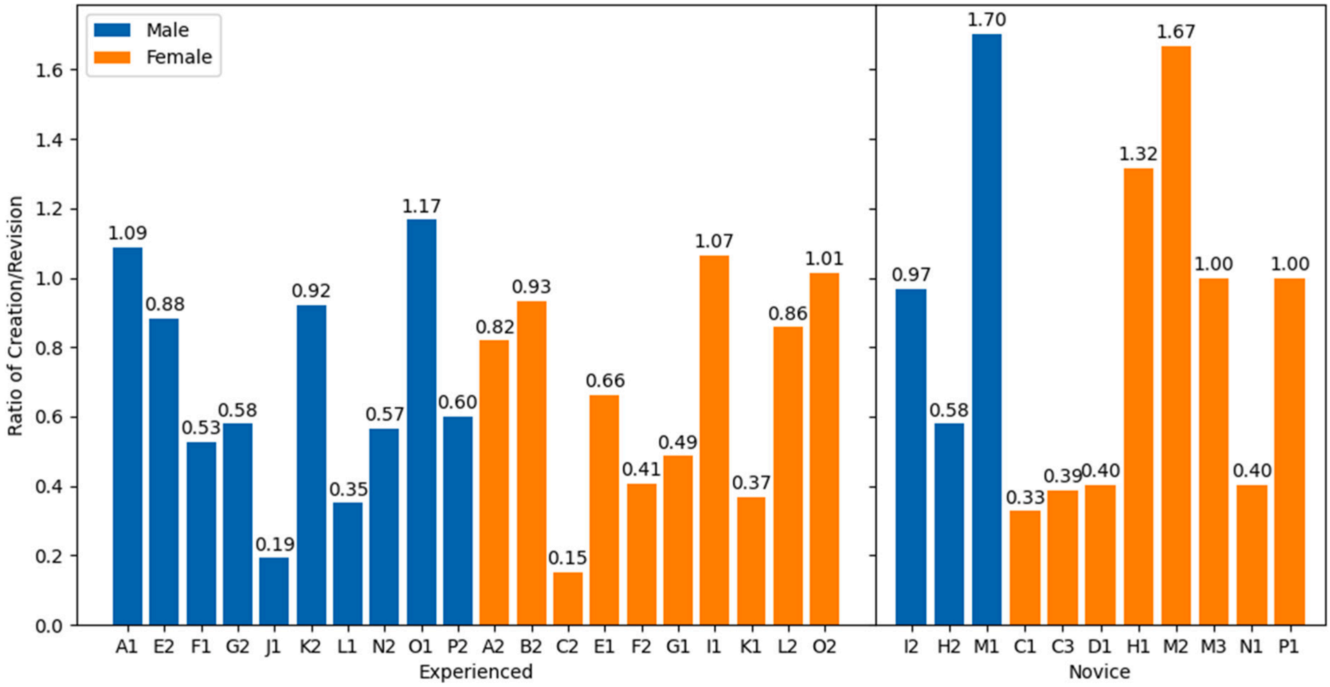

Fig. 9. Individual ratios of creation/revision. Note: research consents were not given from teammates of B2, D1 and J1.

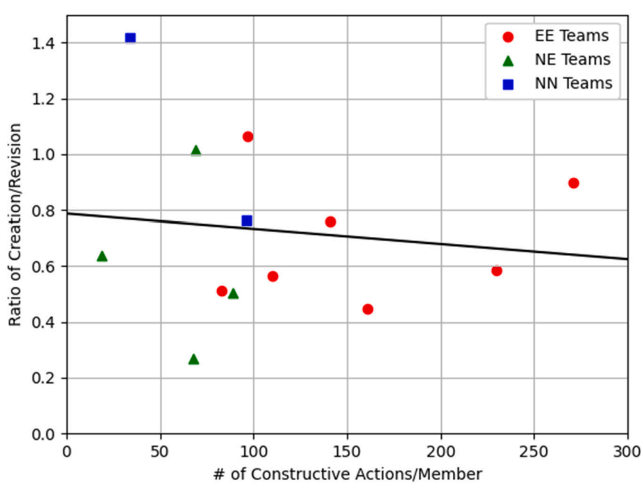

Fig. 10. The ratio of creation/revision versus the number of constructive actions, with a linear regression line of best fit.

self-evaluated CAD experience on the pre-study survey, we acknowledge that improvements are required for future work. As we asked experienced participants to classify themselves as either an intermediate ("I have used CAD but never used Onshape") or expert ("I am an Onshape pro") CAD user, there is no suitable category for participants with some Onshape experience but not yet professional. Also, the levels of experience participants have with other CAD software could also vary widely, which was observed in the post-study survey responses. Besides, early research showed that people's self-perception of CAD skills is deemed to be generally not accurate [9], or it could be described as a phenomenon of the Dunning-Kruger effect [50]. Hence, we would expect more accurate research findings with a more reliable CAD-skill evaluation rubric to be developed, which could involve more quantitative measurements that help students better assess their CAD expertise [35], or future research could simply define participants' expertise by counting the number of feature types that they have mastered to use during the design process.

While we study participants' design behaviour fully based on analytic data, we have not closely examined the resulting CAD model in the analysis. With future work on assessing the characteristics of the actual model (e.g., completeness, creativity, useability, etc.), the combination of data analytics with the graded models may yield informative implications on the types of design behaviour that may lead to a better designed product. While we have only analyzed the analytic data in aggregate counts of actions over the entire design process, future work can also examine the process in a time-series manner. CAD tools are increasingly seen as tools not only for detailed design (embodiment), but also for conceptual design [51]. However, the use of CAD tools in the conceptual designing phase of the design process may lead to premature fixation and bounded ideation, negatively impacting the team's creativity [52]. The use of our MUCAD-CLF to study the impact of different types of design behaviour in different stages of the design process, in particular with a creativity lens, is anticipated to provide better guidance for engineers on using CAD tools for enhanced visualization and structural accuracy while preserving designers' creativity, especially in the newly emerging MUCAD environment.

6. Conclusion

In this paper, we have proposed a MUCAD-CLF for educators and researchers towards understanding students' CAD design behaviours when working and learning individually or collaboratively in a MUCAD environment, based on the use of backend user data. By classifying designer actions into different categories using the MUCAD-CLF, comparisons between student groups based on one or multiple action categories can yield meaningful implications on how students with different levels of experiences, and potentially different genders, behave. We anticipate that the MUCAD-CLF will inform the best practices of teaching CAD with a quantitative assessment of students' learning process for more responsive feedback and learning CAD in a collaborative environment that enhances teamwork.

Although no statistically significant conclusions could be drawn from our study, we encourage future research to apply the framework to generate insight and inform best practices for learning CAD in team-based design activities. With data analyzed from a collaborative

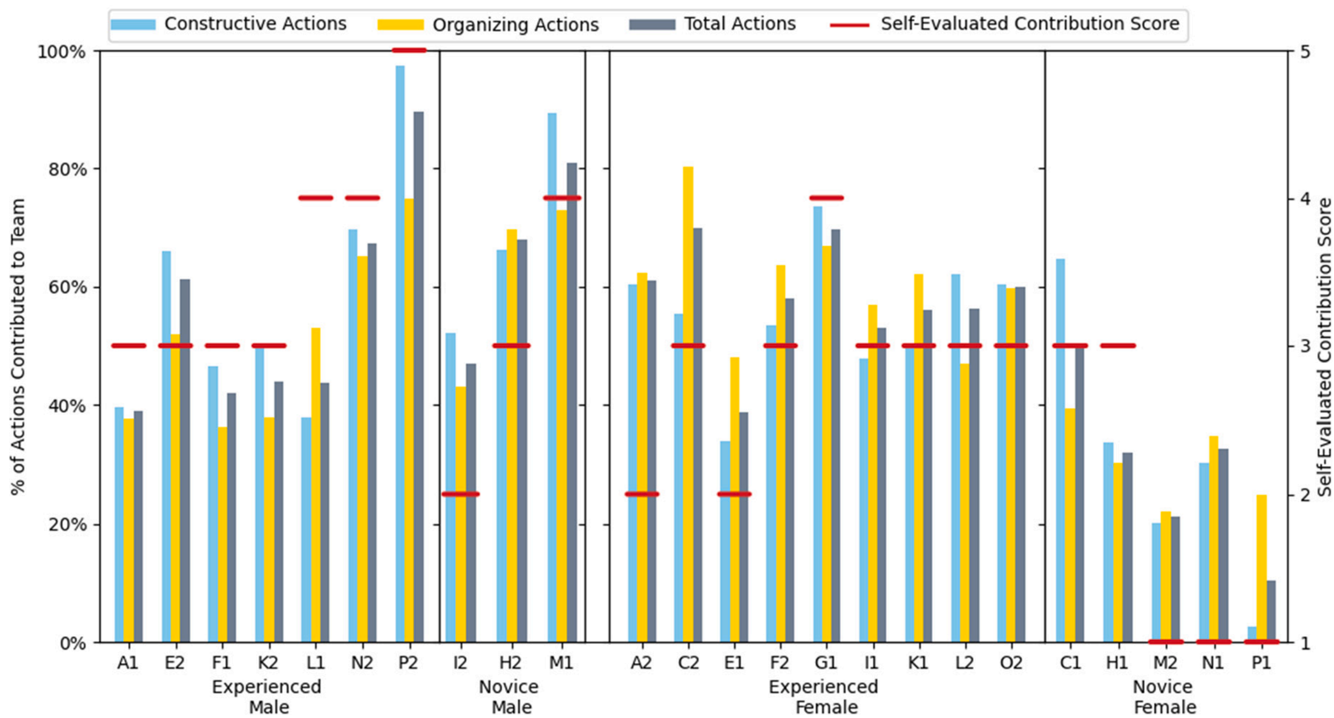

Fig. 11. Comparison between self-evaluated team contribution with analytic actions.

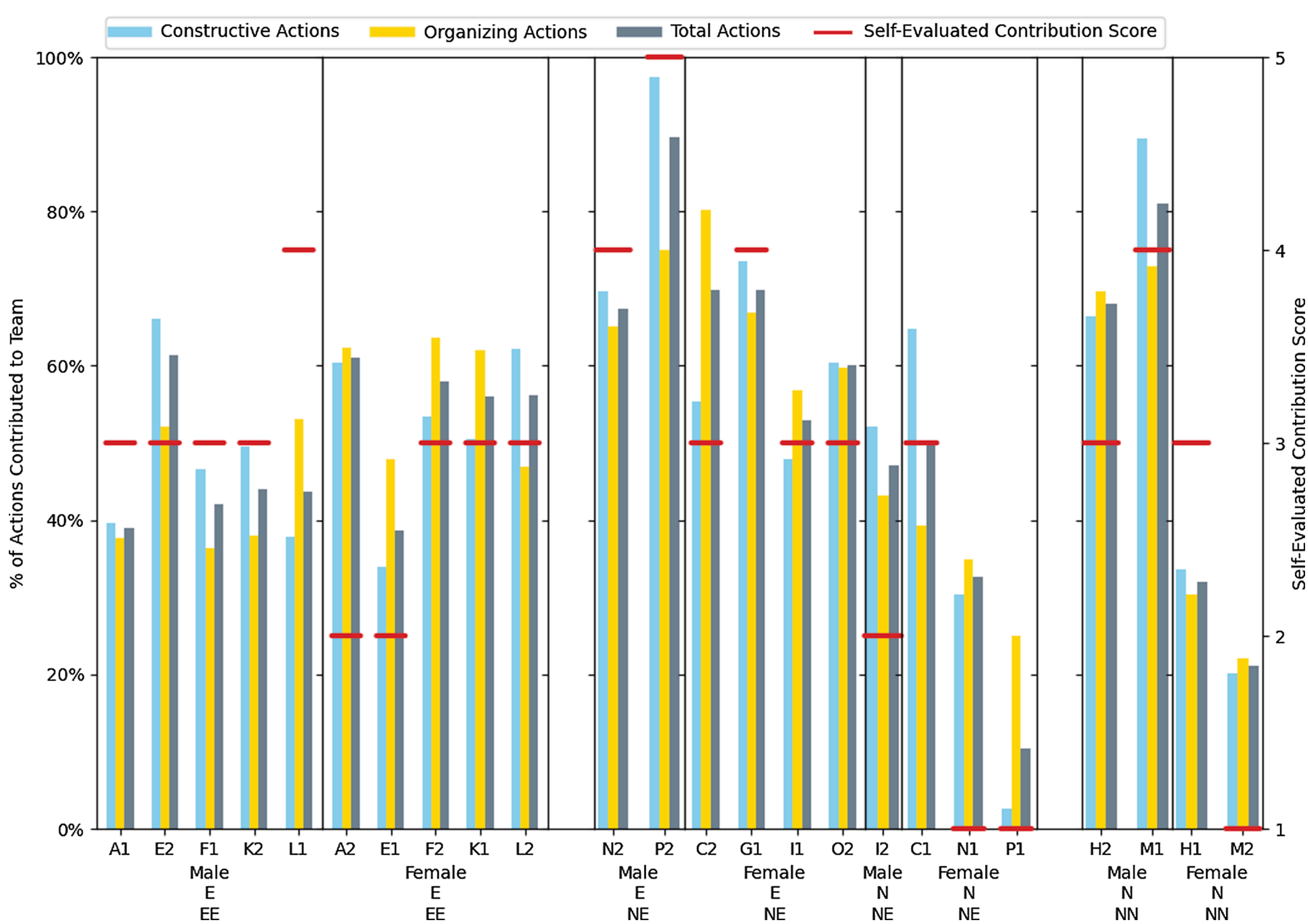

Fig. 12. Comparison between self-evaluated team contribution with analytic actions by team types.

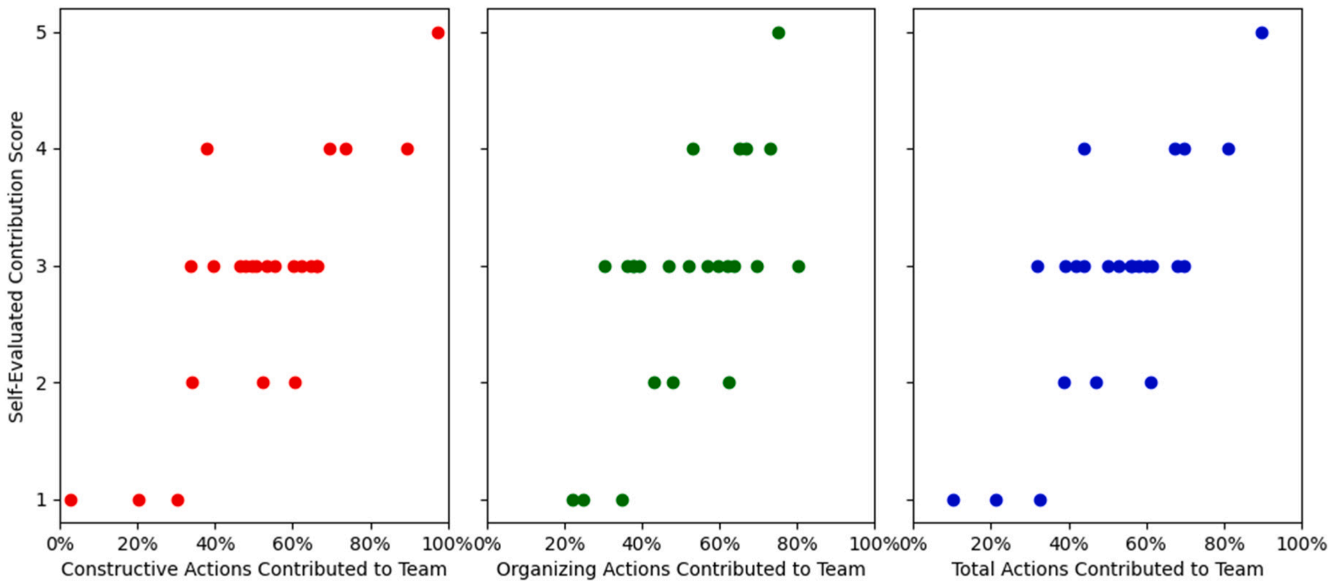

Fig. 13. Comparison between self-evaluated team contribution and action type contribution.

Table 5
Summary of post-study survey responses for 27 participants.

Category	Key Summary	Most Frequently Mentioned Positive Comments	Most Frequently Mentioned Negative Comments
Overall Satisfaction	The majority of participants enjoyed the design challenge (x24 ratings $\geq$ 3); only a few intermediates and beginners felt frustrated (x3 ratings $<$ 3).	– Onshape was fun to play with (x13) – Like this as an introduction to Onshape (x4) – Learned through collaboration (x4)	– Could not find a way to start (x8)
Learning Experience from Teammate(s)	Most participants did learn from their teammate(s) (x23 ratings $\geq$ 3), but members of NE teams had a greater disagreement (i.e., the N learned a lot, but the E did not).	– More knowledge presented in a team (x11) – More efficient to learn as a team than self-exploration (x6)	– Insufficient communication (x4) – Wasting too much time on teaching novices (x2) – No idea on how to start as a team (x2)
Team Contribution	Many participants reported equal contribution (x16 ratings = 3); and greater disparity exists in NE teams.	– Experienced participants contributed more when paired with novices (x5)	– Spent too much time on exploring Onshape (x3) – Novices required more time on building features (x1)
Future Interest in MUCAD (Onshape)	All participants expressed strong interest, except one frustrated beginner.		

MUCAD design challenge, we demonstrate the utility of the proposed MUCAD-CLF via results of its application. In even a limited demonstration application, the proposed framework generated evidence to confirm that experienced CAD participants exhibit more obvious leadership in teams and desirable iterative design behaviour.

While traditional assessments for CAD learning mainly rely on qualitative information, quantitative data analysis provides a complementary and potentially more objective lens for educators and researchers, being reflective of the real user actions. Integrating the MUCAD-CLF with a commercially available CAD platform may allow this data-based analytical framework to be more accessible to other educators and researchers. As all analytic data are automatically collected and obtained from the cloud, educators and researchers can monitor and assess without physically being in the same place as the designers. Once the data are examined with the MUCAD-CLF, results can be easily visualized. With increasingly prevalent work and study from home, establishing learning activities on a cloud-based MUCAD environment has the potential to lead to better learning outcomes for students in both CAD skills and teamwork.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alison Olechowski reports financial support was provided by PTC Inc. Matthew Mueller reports a relationship with PTC Inc that includes: employment.

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