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COMPARING COLLABORATIVE CAD MODELLING PATTERNS OF HIGH-PERFORMING AND LOW-PERFORMING TEAMS

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ABSTRACT

The development of cloud-based Computer-aided design (CAD) enabled real-time CAD collaboration between multiple designers. While this technology has great potential to change the way CAD work is done, it is still little explored. This paper presents a case with two high-performing and two low-performing three-member teams monitored with non-invasive methods (log data) during a six-week design project. The results show that high-performing teams focused more on the editing of assembly, while low-performing teams focused on creating and editing a part. Furthermore, high-performing teams tended to perform consecutive deleting actions and to transition to creating and editing classes of CAD actions after performing viewing actions. Two modelling approaches which lead to high-quality CAD models were identified. One approach is characterized by frequent use of transitions between editing and Organizing-Design (collaborative actions) classes, while the other between creating, editing and reversing classes. Presented results allow design teams to gain insight into sequential patterns which led to the generation of a high-quality CAD model and to better understand the CAD modelling process.

Keywords: Computer Aided Design (CAD), Virtual Engineering (VE), Collaborative design, Non-invasive monitoring, Sequence analysis

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1 INTRODUCTION

CAD models are one of the primary artefacts in the design process (Chandrasegaran *et al.*, 2013). They enable designers to straightforwardly develop, exchange, and collaborate on design concepts as part of the design workflow. Generated CAD models can be stored for future reference, therefore building up a rich source of information related to CAD modelling. Other benefits of using CAD models in a design process include great visualization, ease of generating technical documentation and the possibility of conducting various analyses (Um, 2015). Building on said capabilities, the current CAD paradigm follows an industrial trend which includes more frequent use of collaborative tools, enabling thus a virtual collaboration between designers (Deng *et al.*, 2022). While these technologies enable new ways of working, it remains unclear how to best utilise their potential. Hence, it is essential to examine the possibilities of a collaborative CAD environment, which enables the simultaneous collaboration of design team members and simplifies real-time data sharing.

As CAD has a central role in the design process, the efficacy of user interaction with CAD needs to be considered (Gopsill *et al.*, 2016). This encompasses methods and approaches to the generation of digital CAD models while taking into consideration how models can be manipulated, edited, re-used, modified, combined and post-processed. Furthermore, CAD users might generate different CAD model structures (for same design), which are resembled in varying sequences of CAD actions performed during the design process (Rosso *et al.*, 2021). Therefore, it is essential to better understand how to identify and analyse patterns of CAD actions.

During the designers' involvement in a design process, they look to improve their current design by performing sequential and iterative actions while navigating their way through the design space. Namely, sequence information may lead to identifying the strengths and weaknesses of taking actions in a certain temporal order (Atman *et al.*, 2007). Furthermore, designers learn which sequences of actions are optimal to use during the design process, which is essential due to sequential decision-making impacting the quality of the design outcomes (Rahman *et al.*, 2018). To successfully facilitate the design process, a deeper understanding of designers' behaviours, as well as the sequential actions they carry out are of great importance to the improvement of design processes and modelling patterns.

Given the potential of collaborative CAD features, coupled with the importance of performing sequences in an order suited for the design process, it is necessary to identify sequences of CAD actions which lead to high-quality CAD models. Therefore, this paper gives insights into the following research question: "*What insights can be gathered from the comparison between CAD actions of high- and low-performing design teams?*"

To answer the question, this paper gives an overview of previous work in Section 2, describes the context and methods used to gather and analyse the data in Section 3, presents results in Section 4, and discusses findings and implications in Section 5. Finally, Section 6 concludes our findings and provides implications for future work.

2 LITERATURE REVIEW

Cloud-based CAD enables new means of collaboration by introducing a real-time collaborative CAD environment (Deng *et al.*, 2022). Moreover, cloud-based CAD offers state-of-the-art modelling features which further enhance collaboration. It is capable of a non-invasive way of collecting data on performed user actions, which serve as a proxy for the design process. Data collection enables automated storage of designer CAD action data within the CAD environment without impacting or interfering with the modelling process. However, to successfully identify sequences of CAD actions which are present in high-performing design teams, these capabilities are yet to be fully explored and utilized. Researchers have already begun to explore the collaborative capabilities of cloud-based CAD. Namely, Eves et al. (2018) compared a cloud-based multi-user CAD (MUCAD) environment with a traditional, solitary one. It was revealed that MUCAD users were more aware of the actions performed by their colleagues. Furthermore, the final CAD models of the MUCAD teams, which used more collaborative and advanced features (e.g., *modelling-in-context*, *versioning*, etc.) resulted in higher quality than the others. However, the study also identified certain levels of frustration of individual users due to the distribution of activities within the team and differences in the modelling skills of individual team members. Furthermore, research was conducted relating to the potential of non-invasive data gathering. Gopsill et al. (2016) evaluated the potential of providing a non-obtrusive sensor for the monitoring, assessment and evaluation of engineers and the engineering design process. They discovered that inexperienced designers tended to delete the entire geometry rather than edit existing geometry. Another research relating to CAD performance was conducted by Ahmed-Kristensen et al. (2003) who analysed different approaches towards design tasks between novice and expert users and identified their differences. They found that experienced users used particular design strategies (e.g., referring to past designs, considering issues, etc.), while novice users tended to use a particular pattern of trial and error.

Various researchers identified typical sequences of actions within the design process. McComb et al. (2017a) adopt data-mining techniques to quantitatively study the processes that designers use to solve configuration design problems. They used Markov chains to extract beneficial design process heuristics. Their finding was the difference between the low- and high-performing designers with the latter directing their focus more towards assembly design, especially earlier in the design process, and incorporating parameter operations in states that were otherwise dominated by topology operations. This allowed high-performing teams to better estimate the final quality of early concepts. In a related study (McComb *et al.*, 2017b), it was found that the first-order Markov chains are a better indicator of designers' sequential actions than higher-order Markov chains in configuration design problems. Additionally, they simulated a task of designing a truss by using CAD software between teams employing a non-sequential design approach (a zero-order Markov model) and a sequential design approach (a first-order Markov model), which they validated by using a leave-one-out cross-validation. They found that the sequential design approach produced solutions with higher quality. Hence, they concluded that exploring design sequences is a beneficial for better understanding of the design process.

While researchers analysed CAD actions and identified certain sequences in the design process, it remains unclear if high- and low-performing teams can be differentiated by the CAD action sequences.

3 RESEARCH METHODS

In this section, we present a case study in which the design teams developed a CAD model of a baby stroller during a design project course. Each CAD action they performed during the design course was tracked and stored. This enabled the data analysis to be conducted, which aim was to identify the patterns within sequences of gathered CAD actions.

3.1 CAD project course

The study was conducted during a CAD project course, where the main goal was to familiarize students with CAD tools in the context of generating a functional CAD model. While working on the development of their solutions, students develop teamwork, problem-solving and time-management skills. As part of the course, 42 undergraduate engineering students were divided into 14 teams and assigned with modelling a CAD model of baby strollers, shown in Figure 1. During the course, students were able to reach out to a teaching assistant for instructions and guidelines related to their design task.

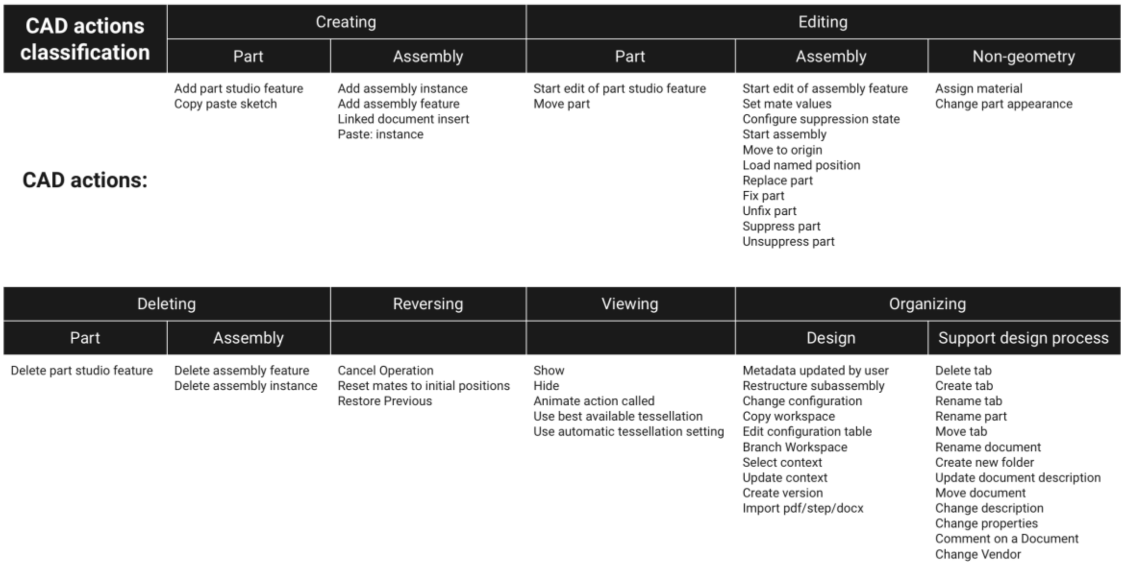
Figure 1. Final CAD models generated by analysed teams

The course starts with the introduction of the CAD modelling tool used during this course - *Onshape*. *Onshape* offers state-of-the-art collaborative features which include *versioning*, *branching*, *merging* and *editing-in-context. As such, it* enables designers to work on a shared CAD model in different workspaces, with the possibility of saving their work at a certain point and merging their designs. After teaching students how to navigate the design space of the tool, they were instructed on different aspects of CAD methodology. Students were taught methods of part and assembly design. To evaluate their knowledge, they were tasked with generating a CAD model based on a 2D sketch. After completing the task, groups of 3 students were formed and assigned tasks in the form of patent sketches based on which the students modelled a functional CAD model of the product. The deadline for the submission of the CAD model of the product was six weeks, after which the final CAD assemblies, shown in Fig. 1, were reviewed by teaching assistants and senior engineers from industrial companies. The review involved examining if the CAD model fulfils the task requirements and whether the CAD model is functional, ergonomically designed, and suitable for manufacturing. Teams were graded based on the quality of their CAD models in the context of adhering to the task's requirements. The points they were evaluated with range, from 28.67 to 44, out of possible 45.

For the purposes of this study, a theoretical sampling approach called *Polar types sampling* is used. The objective of this approach is to observe contrasting patterns in the data in a simpler manner by sampling extreme (e.g., very high- and very low-performing) cases (Eisenhardt and Graebner, 2007). Therefore, out of 14 design teams participating in the design project course, two of the best-performing teams, as well as two of the worst-performing teams were further analysed for the purposes of this paper.

3.2 Data collection and analysis procedure

Data was collected in a non-intrusive manner by tracking and storing information related to CAD actions performed by users within a MUCAD environment. This was enabled by the usage of *Onshape* which allows non-intrusive data capturing by storing every performed CAD action in an audit trail. Data is gathered and stored in a structured way adequate for data analysis. In this case, the gathered dataset consists of a timestamp when the action was performed, a document and a tab in which it was performed, the designer who performed it and the name of the action itself. Furthermore, some of the gathered actions were not performed by the designers themselves but were rather automatically stored by the software (e.g., *Update Metadata*, *Content update*, etc.). Given that the focus of this paper was on designers' actions, automatically generated actions were excluded from the dataset. Moreover, redundant actions clustered by timestamp values were identified. Redundant actions occur, e.g., when a user inserts a sketch, namely, *OnShape* then registers four actions – *Add part studio feature*, *Commit add or edit of part studio feature*, *Insert feature: Sketch*, *Add or modify a sketch*. As this would lead to inaccurate results of the data analysis, redundant actions were excluded from the analysed dataset. Finally, actions related to the generation of technical documentation were also excluded due to the emphasis of this study being on the modelling of parts and assemblies. The remaining actions were then classified using a classification of CAD actions based on Gopsill et al. (2016), Deng et al. (2022) and Celjak et al. (2022). The classification enables the data analysis on different levels of granularity as it may be conducted on class, subclass or action level. The classification includes six general classes of CAD actions: *Creating*, *Editing*, *Deleting*, *Reversing*, *Viewing*, and *Organizing*. *Creating*, *Editing*, and *Deleting* were further divided on a *Part* and A*ssembly* level, while *Editing* also to *non-geometry*, and *Organizing* was split into *Design* and *Support design process* (the former is related to CAD model and workspace, while the latter is related to CAD files). This classification (Figure 2) separates constructive actions that make direct, visible modifications to the design (e.g., *Creating*, *Editing*, etc.) from *Organizing* and *Viewing* actions that are related to the process. Hence, it serves as a basis for further data analysis.



CAD actions classification	Creating		Editing		
	Part	Assembly	Part	Assembly	Non-geometry
CAD actions:	Add part studio feature Copy paste sketch	Add assembly instance Add assembly feature Linked document insert Paste: instance	Start edit of part studio feature Move part	Start edit of assembly feature Set mate values Configure suppression state Start assembly Move to origin Load named position Replace part Fix part Unfix part Suppress part Unsuppress part	Assign material Change part appearance

Deleting		Reversing	Viewing	Organizing	
Part	Assembly			Design	Support design process
Delete part studio feature	Delete assembly feature Delete assembly instance	Cancel Operation Reset mates to initial positions Restore Previous	Show Hide Animate action called Use best available tessellation Use automatic tessellation setting	Metadata updated by user Restructure subassembly Change configuration Copy workspace Edit configuration table Branch Workspace Select context Update context Create version Import pdf/step/docx	Delete tab Create tab Rename tab Rename part Move tab Rename document Create new folder Update document description Move document Change description Change properties Comment on a Document Change Vendor

Figure 2. Classification of CAD actions (based on Deng et al. (2022) and Celjak et al. (2022))

The goal of data analysis was to better understand the design process and identify patterns within performed CAD actions. Analysis of classes of performed CAD actions was conducted using the class distribution of design teams' CAD actions and Markov chain transition matrices. Class distribution of CAD teams' actions provided insight into the usage percentage of various CAD action classes of different design teams. Transition matrices allowed us to explore the number of occurrences of one action or class of actions transitioning into another action or class of actions. Subsequently, they also provide an insight into the spectrum of CAD actions used by designers. Finally, the most common sequences between classes of CAD actions performed by design teams during an overall design process have been identified by dividing the number of each transition by the total number of recorded transitions.

Data analysis was conducted using the Python programming language and its libraries. As shown in Figure 3, the first two phases of the process involve initializing and reading the dataset, which is followed by filtering the aforementioned undesired CAD actions from the dataset. Furthermore, variables related to CAD actions and classes have been defined. Consequently, the process of iterating through the dataset is initialized and CAD actions are mapped. This is followed by generating results which are then prepared for visualization. Finally, the results of this coding process are displayed in the form of a quadratic transition Markov matrix which provides insight into the probabilities of transitioning from one state to another, as well as in form of a stacked bar chart which gives insight into the class distribution of design teams' CAD actions.

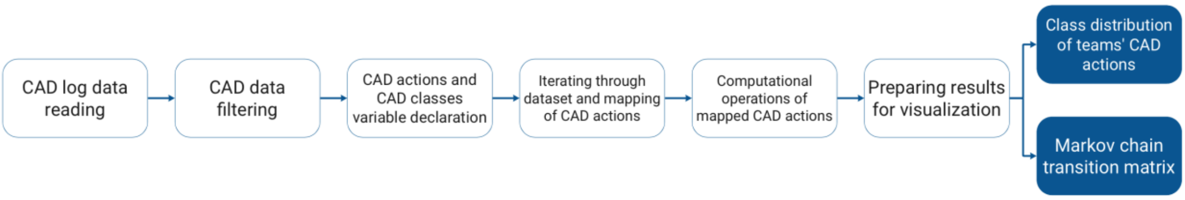


Figure 3. Data analysis and visualization coding process

4 RESULTS

The data analysis was conducted by using the collected data about CAD actions performed by two high-performing and two low-performing teams during the design course. The four analysed design teams performed a various number of CAD actions. The high-performing teams recorded 14264 (Team HP1) and 8601 (Team HP2) actions, while low-performing teams recorded 3049 (Team LP1) and 5460 (Team LP2) actions. The results are structured in the following way. Firstly, the distribution of classes of CAD actions performed by each team is shown in a grouped bar chart. Secondly, Markov transition matrices are used to show the probability of each team transitioning from one class of CAD actions to another. Finally, the most commonly used sequences of classes of CAD actions are shown.

4.1 Class distribution of design teams' CAD actions

The distribution of classes of CAD actions provided insight into how the design teams divided their work during the modelling process. Furthermore, it showed similarities and differences in the approach to the modelling process between the design teams. Namely, as can be observed from Figure 4, the most used class of CAD actions by each team was *Editing-Part*. Furthermore, low-performing teams frequently used *Reversing* and *Creating-Part* classes of CAD actions. A similar tendency is observed in the case of one of the high-performing teams (Team HP1). Contrary, Team HP2 frequently performed CAD actions classified within *Organizing-Design* and *Editing-Assembly* classes. On the opposite side of the usage spectrum, *Editing-Non-geometry* was the least frequently used class of CAD actions in the case of each observed team. High-performing teams also less frequently used *Organizing-Support design process* and *Deleting* classes of CAD actions, while low-performing teams tended to less frequently use *Editing-Assembly* class. Moreover, Team LP2 rarely used *Organizing-Design* class, while Team LP1 rarely used *Viewing* class of CAD actions.

Similarities between high and low-performing teams emerge in *Deleting* class as each team recorded 3-5% usage. Conversely, dissimilarities between high and low-performing teams include *Creating*, *Editing* and *Organizing-Support design process* classes. Namely, both low-performing teams recorded 17% usage of *Creating-Part* CAD actions. Contrary, high-performing teams recorded notably lower 9% usage in the case of team HP2, and slightly lower 15% usage in the case of team HP1. Consistency between high and low-performing teams can be observed in the case of *Creating-Assembly* class as the former recorded 10% usage, while the latter recorded 13% (LP2) and 15% usage (LP1). Furthermore, 25% of the CAD actions performed by low-performing teams are attributed to the *Editing-Part* class. High-performing teams recorded slightly lower values with 18-20% usage. *Editing-Assembly* equates to 14% of overall performed CAD actions by Team HP2, which is two times more than Team HP1 and almost five times more than the low-performing teams' record. *Organizing-Support design process* class of CAD actions is used more by low-performing teams which recorded 7% usage, compared to the usage of high-performing teams which is halved.

The remaining classes do not show distinctive dissimilarities between high and low-performing teams, as certain values between the teams' usage of classes overlap. Namely, low-performing teams tended to frequently use *Reversing* CAD actions as they recorded around 20% usage. Team HP1 recorded similar usage to low-performing teams with 19%, while team HP2 recorded notably lower usage of 10%. Furthermore, *Organizing-Design* class of CAD actions is barely used by Team LP2, however, teams HP1 and LP1 recorded 5% usage, while Team HP2 was an outlier with 19% usage. *Viewing* class of actions shows Team HP1 recording 12% usage compared to Team LP1 which recorded just 1% usage, while teams HP2 and LP2 both recorded roughly 7%.

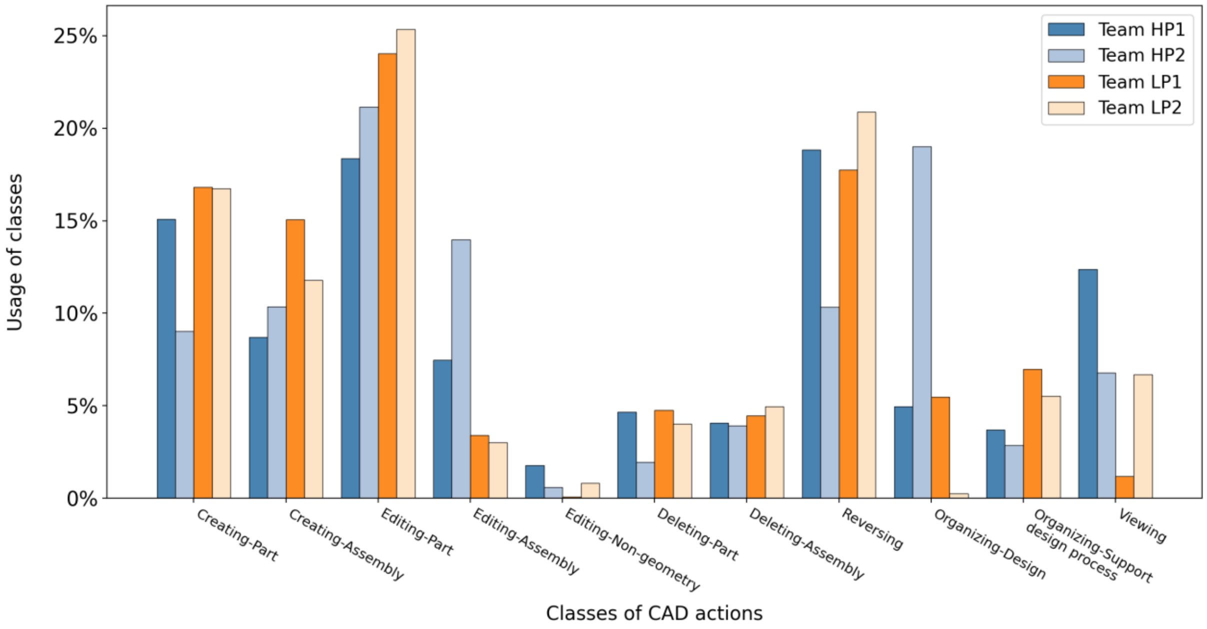


Figure 4. Class distribution of design teams' CAD actions

4.2 Markov chain transition matrices between classes of CAD actions

Generated matrices implicitly show different approaches towards CAD modelling between high and low-performing design teams as they record different transitions between classes of CAD actions. These transitions are depicted in Figure 5 by four Markov chain transition matrices with the upper ones representing the design process of high-performing teams HP1 and HP2, and the lower ones representing the design process of low-performing teams LP1 and LP2. The matrices consist of values which represent the probability of one unique class of CAD actions transitioning into another. Higher colour intensity suggests a higher probability of transition from a class of CAD actions defined by the row of observed value to the one defined by the column. For example, the probability of Team HP1 transitioning from the *Creating-Assembly* to the *Reversing* class of CAD actions is depicted by the $a_{2,8}$ element in the upper left matrix of Figure 5 and is equal to 0.45 (45%). Empty or white elements of the matrix suggest the transition from the class of the initially performed CAD action to the class of the CAD action which followed has never occurred.

Both high and low-performing teams show similarities in their respective transitions between classes of CAD actions. However, some transitions show major dissimilarities between teams of identical performance. Moreover, certain transition frequency is not exclusively linked to high or low-performing teams but occurs in both high and low-performing teams. Therefore, transitions between classes of CAD actions could be divided into several categories. The first category includes consistent similarities between high and low-performing teams (i.e., where both high-performing teams record similar transitions, which are also similar to those of both low-performing teams). The second category encompasses consistent dissimilarities between high and low-performing teams (i.e., where both high-performing teams record similar transitions, which are dissimilar to those of both low-performing teams). The third category is characterized by inconsistent dissimilarities between high and low-performing teams (i.e., where there are no distinctive similarities between teams of identical performance, nor is there a distinctive difference between high and low-performing teams).

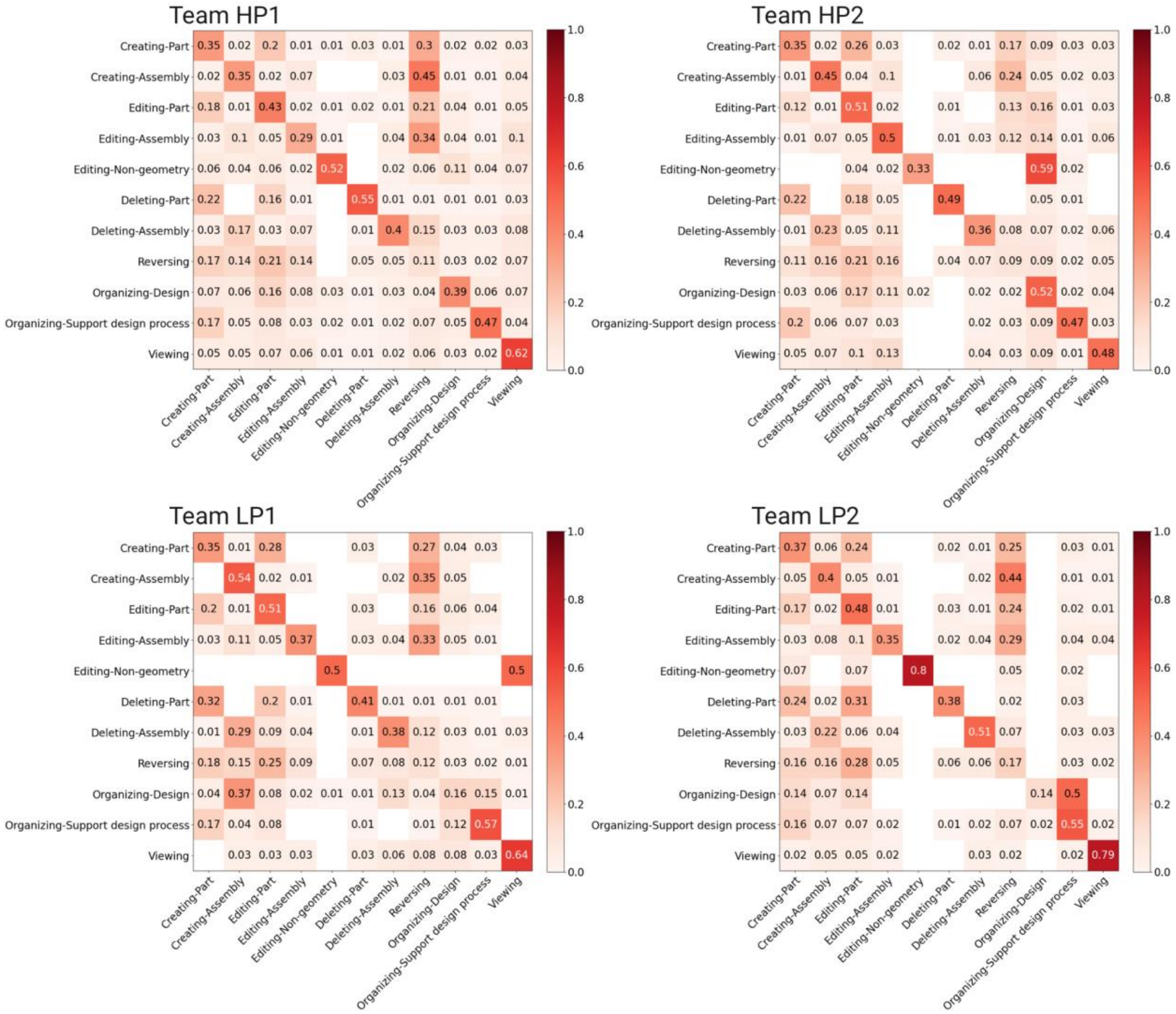


Figure 5. Markov chains in the context of CAD actions

The first category encompasses transitions occurring from *Creating-Part*, *Editing-Part*, *Deleting-Assembly* and *Reversing* classes of CAD actions. Transitions occurring from said classes record similar frequencies in the overall design process of each of the analysed teams. The second category includes transitions occurring from *Deleting-Part*, *Organizing-Design*, *Organizing-Support design process* and *Viewing*. High-performing teams tended to consecutively use *Deleting-Part* CAD actions 10-15% more than low-performing teams. Moreover, high-performing teams used consecutive *Organizing-Design* CAD actions 25-35% more than low-performing teams. Low-performing teams recorded 10% more consecutive *Organizing-Support design process* CAD actions. Finally, high-performing teams tended to transition from *Viewing* class to one of *Creating* and *Editing* classes on an average of 17% more frequently than the low-performing teams did. The third category, which encompasses inconsistent dissimilarities between high and low-performing teams consists of transitions occurring from *Creating-Assembly* and *Editing-Assembly* classes of CAD actions. Team HP2 tended to perform consecutive *Editing-Assembly* CAD actions from said classes on an average of 16% more frequently than low-performing teams. Moreover, they recorded consecutive usage of *Creating-Assembly* class 5% more than Team LP2, however, 9% less than LP1. Contrary, team HP1 tended to perform consecutive *Creating-Assembly* and *Editing-Assembly* classes of CAD actions an average of 8% less often than low-performing teams. Moreover, team HP1 recorded a high frequency of transitions to the *Reversing* class of CAD actions, similar to low-performing teams.

4.3 Most commonly used sequences of classes of CAD actions

The results of this section aim to provide insight into the most commonly used sequences of classes of CAD actions during the modelling process of design teams. This was enabled by dividing the number of each transition by the total number of recorded transitions. Consequently, the ten most common sequences between classes of CAD actions performed by design teams during an overall design process have been identified and are shown in Figure 6. Both high and low-performing teams recorded a high frequency of consecutive *Editing-Part* CAD actions performed, however, low-performing teams tended to do it slightly more often. Moreover, low-performing teams transitioned from *Creating-Part* to *Editing-Part* and vice versa around 4,5% of the time, while high-performing teams tended to do so around 3% (team HP1) or less than 3% (team HP2). Similarly, low-performing teams tended to transition slightly more frequently from *Creating-Assembly* to the *Reversing* class of CAD actions. Furthermore, team HP1 recorded a rather notable number of transitions to/from *Reversing* class of CAD actions. Contrary, team HP2 did not record any of those transitions, but rather a substantial number of transitions to/from *Organizing-Design* class of CAD actions. A transition specific to one of the low-performing teams includes team LP1 performing consecutive *Creating-Assembly* CAD actions 8,11% of the time.

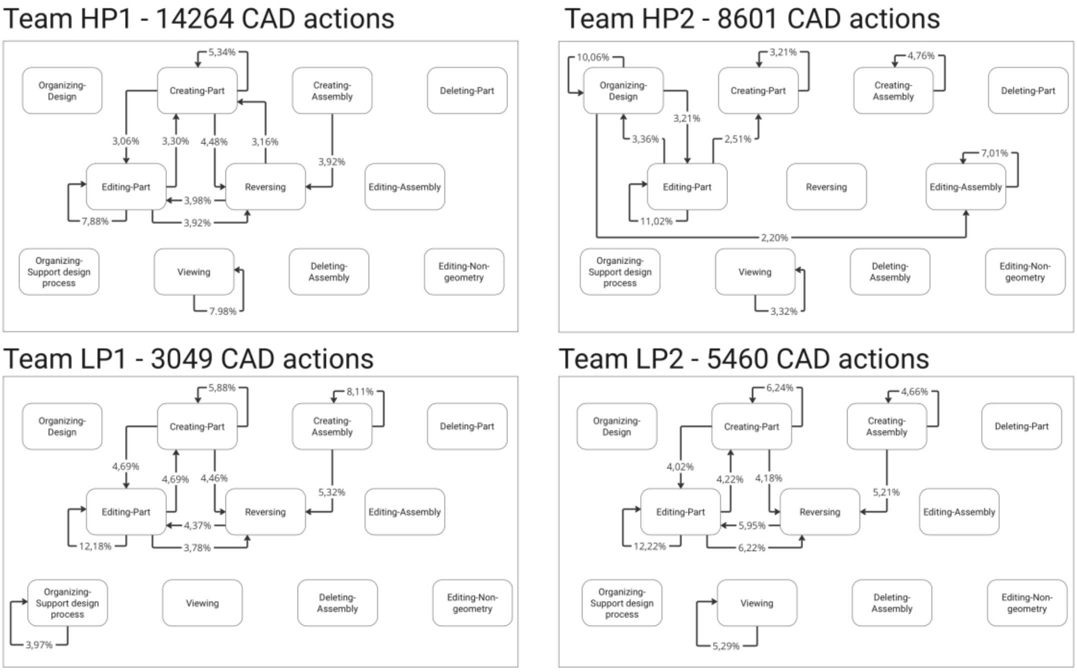


Figure 6. Most common transitions between CAD action classes

5 DISCUSSION

The results show that there is a major difference between the modelling patterns of high and low-performing teams in terms of using creating and editing classes of CAD actions. Namely, low-performing teams tend to focus more on creating a part or assembly and editing a part compared to high-performing teams. Contrary, high-performing teams register more usage of *Editing-Assembly* class of CAD actions than the low-performing teams. It might be that high-performing teams started earlier with the assembly design to better estimate the final quality of early concepts (McComb *et al.*, 2017a), which resulted in more editing of assembly later in the modelling process. Furthermore, it was observed that high-performing teams are more likely to perform consecutive *Deleting-Part* CAD actions than low-performing teams. Contrary to our finding, Gopsill et al. (2016) found this pattern occurring in the modelling process of novice design teams. They interpret it as a sign of participants having difficulties in both generating the geometry and the ability to constrain it appropriately so that it can be edited without causing issues with the model. These conflicting insights could be result of analysing different CAD complexities (single part vs multi-part product). We suggest that this tendency could also be attributed to high-performing teams starting earlier with the assembly design, where they experimented with different versions of the design, ultimately resulting in performing consecutive deleting actions.

Results also show that low-performing design teams tend to use a high percentage of *Reversing* class of CAD actions after creating or editing a part or an assembly. This may be attributed to users adjusting to the use of new CAD software or lack of design knowledge and general idea. Similarly, Ahmed-Kristensen et al. (2003) identified this pattern during the design process of novice users and defined it as a *trial-and-error* pattern. Notably, one high-performing team also registers a high percentage of reversing CAD actions used, therefore, the same could be implied for them. However, as they generated almost 15000 CAD actions, and relating to the previous finding, this can be attributed to them generating various versions of the product. Although the CAD has traditionally been used in the detailed design phases, these results suggest that it could also bring benefits in the earlier design phases. This could be related to new CAD features (e.g., versioning, branching, merging and editing-in-context), and new collaborative working practices (Deng *et al.*, 2022; Horvat *et al.*, 2021). Moreover, this high-performing team also shows similarities to the low-performing teams in the context of *Organizing-Design* class as they show very limited usage of CAD actions within the said class. Contrary, the other high-performing team tends to use advanced modelling features such as *creating versions* and *modelling-in-context*, while also often transitioning into *Organizing-Design* class after *Creating* and *Editing* classes. Implementation of these features in their modelling process allowed them to conveniently collaborate on a shared CAD model. This suggests that the use of advanced collaborative features relates to the quality of the overall CAD model, which corresponds to the findings of Eves et al. (2018), who drew identical conclusions during their research when they compared traditional and collaborative CAD.

Finally, the analysis of the most common transitions between classes of CAD actions identified two different modelling approaches that high-performing teams utilise. It was observed that one approach most frequently used *Organizing-Design* class, with the most common transitions to/from *Editing* classes. The other approach is characterized by frequent use of transitions between Reversing and Editing- and Creating-Part classes. While both approaches are valid, the high-performing team which utilised the latter approach recorded almost 6000 more CAD actions than the other team. Findings of this study could indicate that different modelling approaches could affect the overall number of performed CAD actions and, consequently, efficiency of CAD modelling.

Many unanswered questions still exist regarding the quality of CAD work in collaborative CAD. Certain limitations of the current research need to be overcome to achieve more generalisable results. The first limitation is related to the small sample size in terms of involved teams. Another limitation of the study was the lack of design experts as participants. Future research should find ways to involve such individuals, as this will likely result in more complete and usable overall CAD models and, therefore, associated sequences of CAD actions leading to those models. Furthermore, some sequences of certain individuals within the design teams may have notably varied from other individuals, therefore hindering the results. Hence, a similar analysis should be conducted on the individual level.

6 CONCLUSIONS

This research has provided some initial insights into the potential of utilizing non-intrusive data logging to identify CAD modelling sequential patterns and better understand the design process. Using *Onshape* as CAD modelling software for the design project has simplified the process of data gathering. Furthermore, the adopted classification has consolidated individual CAD actions into different classes and enabled the conduction of analysis on multiple levels of granularity. The analysis of two high-performing and two low-performing teams showed similarities and differences in class distribution and design sequences of performed CAD actions. The results have shown two different approaches towards CAD modelling. High-performing teams were oriented towards editing of assembly more than the low-performing teams. Furthermore, one high-performing team shows a tendency to use advanced actions such as *versioning* and *modelling-in-context*. Moreover, both high-performing teams tended to transition to *creating* and *editing* classes of CAD actions after utilizing the viewing capabilities of the software. However, this was not the case for the low-performing teams. Finally, high-performing teams displayed a tendency to perform consecutive deleting actions.

Scholars and educators can utilise these results to analyse actions performed by students in the design project course and to better understand the CAD modelling process. The results presented in this paper could be helpful for engineers and educators to gain insight into sequential patterns during the design process which could potentially be linked with quality of CAD model in further studies.

Future work should aim for a deeper understanding of the design process by implementing time variables (e.g., duration of a modelling process, timestamp of a specific action) in the analysis. Moreover, to identify the optimal sequences in the design process, additional data about CAD modelling has to be collected (to enable triangulation). Furthermore, the implementation of machine learning algorithms could be used to process said data and enable analysis of the CAD collaboration in a more detailed manner.

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