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IDENTIFYING COMPUTER-AIDED DESIGN ACTION TYPES FROM PROFESSIONAL USER ANALYTICS DATA

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ABSTRACT

Inspired by popular personality type indicators, we develop a framework for classifying individuals by their computer-aided design (CAD) behaviours. We are motivated by the trend of modern CAD software towards cloud platforms and expanded collaborative features. Cloud-CAD platforms enable collaboration by increasing access, and reducing conflicts and barriers to file-sharing.

In order to generate insight to support CAD collaboration, we analyze the real-world data from an industry partner's product development project, consisting of eight professional designers working on a cloud-CAD platform. This data corresponds to more than 1,420,000 actions over a span of eight months. Via hierarchical clustering, we group 79 unique CAD activities into 14 categories of CAD action groups, such as Part Studio, Assembly, Comment, View/Scan and Export. Next, we identify the degree to which each of the eight designers performs activity in these CAD action groups. We demonstrate the usefulness of this framework by highlighting insights revealed by the CAD action group mapping, confirmed via discussion with the industry partner. This CAD-type behaviour framework provides a tool for assessment and reflection on the types of behavioural tendencies present or missing on a team of designers. It can assist CAD educators and trainees in understanding their comprehensive CAD learning trajectory. Future extensions of the framework could leverage artificial intelligence techniques to provide real-time feedback on designer roles.

Keywords: computer-aided design; CAD; personality types; analytics; clustering

1. INTRODUCTION

When building a collaborative engineering team, it is crucial to recruit new hires that complement the existing team. Previous studies have considered the influence of personality traits and types on design-team success [1–4]. For this reason managers often use personality tests, such as the Myers-Briggs Type Indicator (MBTI) questionnaire, to identify an individual's work preferences [5–7]. Relying on self-reported responses, these tests provide a basis for understanding how an individual may behave in certain situations by categorizing their behaviour tendencies.

Inspired by personality tests, we propose a practical framework to analyze team member contributions to computer-aided design (CAD) work. In other words, we seek a "CAD type indicator," categorizing the behaviours of designers and their contributions to CAD models.

This framework is particularly relevant at this moment in time for two reasons: first, because of the increasing prevalence of cloud-CAD software and its accompanying collaboration features; second, because cloud-CAD software enables the collection of large-scale user analytics, providing the data necessary to generate and classify relevant CAD behaviours.

By better classifying CAD behaviours, our framework allows CAD designers, and engineering managers, to better delegate and coordinate their work, and to better chart their learning trajectories.

2. BACKGROUND

2.1 Cloud-CAD: Collaboration

Computer-aided design (CAD) is software used by engineers to create models, test simulations, and distribute ideas with teammates. Previous studies have examined CAD artifacts in order to draw conclusions and propose prescriptions for the design process [8,9].

CAD work has become synonymous with solitary work because its traditional form has a rigid sharing structure in which active contributions are limited to one computer at a time [10]. Until the current editor chooses to release their models, these changes are not propagated to the entire team. Modern cloud-CAD stores changes and commands directly to the cloud,

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making edits visible in real-time from any computer [11–13]. Thus, cloud-CAD supports the transition of CAD modelling and assembly from an individual- to a team-based endeavour. Recent works have explored the new working styles enabled by cloud-CAD, with data collected via controlled experiments [14–19]. Our approach uses data from real industry environments rather than simulated ones. With this information, we seek to identify varying CAD user behaviours.

2.2 Personality Types

Perhaps the most widely used personality test, the Myers-Briggs Type Indicator was developed as a means to understand how individuals would behave, as categorized by four personal tendencies. These four groupings are extraversion/introversion, sensing/intuition, thinking/feeling, and judging/perceiving [5–7]. Individuals take a self-assessment in which they choose one of two ways they will behave in specific scenarios. Based on their responses, an individual is placed in one of 16 MBTI types, with their specified type expressing characteristics that the individual would likely exhibit.

While managers will often use this approach as a tool for team and leadership development, these tests face criticism for their lack of proper psychological fundamentals. Some innate flaws with the tool derive from self-reported answers, vague personality assignments, and misleading interpretations [6,20]. These concerns introduce forms of bias that obscure the results and can oversimplify the complexities behind one's behaviours. Therefore, the categorizations should not be seen as absolute but rather as opportunities for individuals to develop self-awareness and self-reflect on their actions. With such an introspective look, individuals can use the information to exercise behaviours and actions that may differ from the norm, allowing them the opportunity to grow.

Our premise is that a framework similar to personality tests, applied to CAD work, will provide the same helpful introspection to designers as they increasingly work together on teams with cloud-CAD.

2.3 CAD Analytics

Traditionally, personality tests rely on self-reported answers to a pre-determined set of questions. Similarly, previous work has explored questionnaires for classifying CAD trainee expertise to eventually predict performance [21].

An alternative to self-report questionnaires for generating CAD classification data is to observe the controlled behaviours of CAD designers via experiments. Recent progress has been made to develop and validate platforms for gathering data for in-person CAD work [22–25]. These platforms provide detailed and multi-modal data, but at the expense of natural working environments.

Rather than relying on self-reports or experimentally derived data, we can instead exploit real CAD work from expert designers in industry, as extracted via user analytics from the CAD software itself. CAD analytics have been explored in the past; Xie et al. first generate their own CAD analytics logging system to do time series analysis [26]; next, they explored how CAD analytics may be used to assess learning in engineering design projects [27]. Modern cloud-CAD systems make CAD data even more accessible and reliable, and as such is the approach we take for data generation in this paper.

3. METHODOLOGY

3.1 Data from Industry Partner

We worked in conjunction with an industry partner to receive historical CAD activity from an authentic work situation rather than a simulated one. The industry partner is a company that focuses on building automated robots that clean large commercial spaces such as airports, shopping malls, and hospitals. In April 2020, the company began transitioning to the cloud-CAD software Onshape, to facilitate data management and control over their workflow. Currently, the team consists of eight individuals who use the software to varying degrees to fulfill their responsibilities. One individual was the internal champion of the new software platform, the first to learn the tool and explore many of its functionalities. Another individual was the manager, with responsibilities to review and approve CAD models. The remainder of the designers' roles are mechanical designers, who contribute both to digital modelling as well as prototyping and testing. The eight users have been anonymized and are represented as users 'A' – 'H'.

3.2 Onshape Analytics

One of the management features available to Enterprise users of Onshape is Analytics, which records all events that take place within the server. Events are the actions that an Onshape user performs within the software. These events are divided into two categories: 'document' and 'user'. 'Document' events refer to actions that cover a document's lifecycle and its parts (e.g. Create/Open/Delete tab), while 'user' events refer to actions regarding the lifecycle of a user (e.g. Login, Add User). The data is presented as an audit trail which provides the timestamp, user, and document location for any given event.

Within the audit trail, several events and definitions are Onshape-specific. Unlike traditional CAD software, documents in Onshape are bins of information that can contain a variety of elements. Elements refer to the different workspaces such as part studios, assemblies, and drawings. Often, these elements are presented as tabs at the bottom of an Onshape document.

For the purposes of this study, we examine the frequency and occurrence of these events within the private enterprise cloud-CAD account of our industry partner.

3.3 Analysis

The ianalytics data comprised of an audit trail with 1,420,234 events. We began by using the statistics package Minitab to perform an overview analysis of the data to view general patterns in activity. From a preliminary analysis, we identify high level trends and themes. We then performed hierarchical clustering to reveal relationships between our users and events.

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Rather than group events from logical understanding of the activity, we proceed with clustering based on the data to determine which events are more likely to be used concurrently in practice, rather than in theory. Hierarchical clustering is a method that creates groups according to the common shared characteristics between observations. Clusters are formed using the similarity between these characteristics [28], which in our case was the proximity of time between events in the observations. Variables being grouped closely together indicates that these variables are more likely to occur in sequence with one another. These groupings are presented in dendrograms which give a visualization of the data. To determine the number of clusters, we identify sections with relatively large changes in similarity, serving as potential cutoffs. We supplement this information with a logical understanding of the group contents to determine the appropriate cutoff for the data. The process for selecting the cutoff for the user clusters can be seen in the Appendix. Given the relatively small sample size of the variables and users, this clustering approach allows us to visualize the groupings and draw conclusions from the dendrograms.

We begin by creating a dataset of event counts for each user, and via hierarchical clustering, we separate the users into three distinct groups. To better understand these cluster assignments, we then focus on understanding the relationship between events. This method highlights which events are more likely to be used concurrently in practice.

To prepare our data for variable clustering, we filter the observed event types from 157 to the 79 that were most prominent in the dataset; the omitted events were either committed by only one user or were used a negligible amount. Given that users ‘F’, ‘G’, and ‘H’ were less active, they were omitted from variable clustering to focus on those who regularly used the software. Events are grouped according to frequency in which they appear concurrently in an observation, therefore focusing on a smaller window of time presents more coherent groups. At first, we observed each user's monthly activity, but to achieve a higher granularity level, we pivoted to weekly activity before finally deciding to observe the daily activity. With each iteration, the logical coherence for each cluster became more defined.

Using the newly formed variable clusters, we created distributions for each user; these breakdowns revealed potential explanations for their assignment during user hierarchical clustering. After analyzing the information, we regrouped with our industry partner to learn more about their CAD behaviours. This discussion corroborated our initial conclusions by revealing how the team collaborated, highlighting the roles that specific users had on the team, and explaining anomalies that were found during analysis.

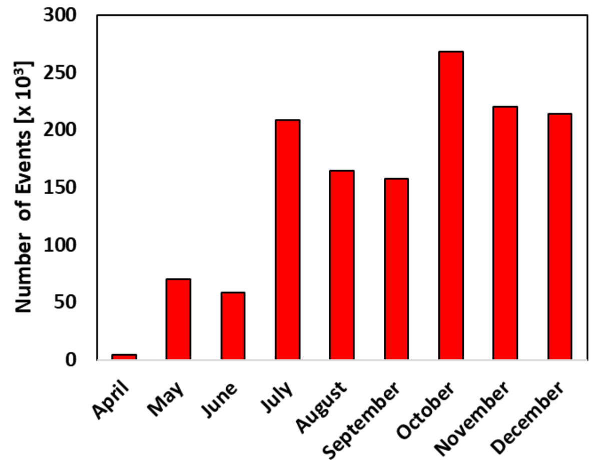
4. RESULTS

An initial review of the data revealed that activity started relatively low in the initial months and gradually built up until the first peak in July. After a slight drop, we then encounter a second peak of CAD activity in October, observed in Figure 1A. Additionally, Figure 1B shows the user distribution of CAD activity in 2020, with user ‘A’ performing the most actions. Conversely, users ‘F’, ‘G’, and ‘H’ contributed the least to the CAD modelling activities.

4.1 User Clustering

We created an array in which each row had the user event count during 2020. The users are divided into clusters based on the similarity of their variables. As seen in Figure 2, user ‘A’ has behaviour that differs from that of the rest of the team. We also notice that ‘B’ and ‘C’ are paired, while users ‘D’ – ‘H’ are grouped separately. To better understand the user assignments, we next aimed to identify how the variables influenced the groupings.

A



B

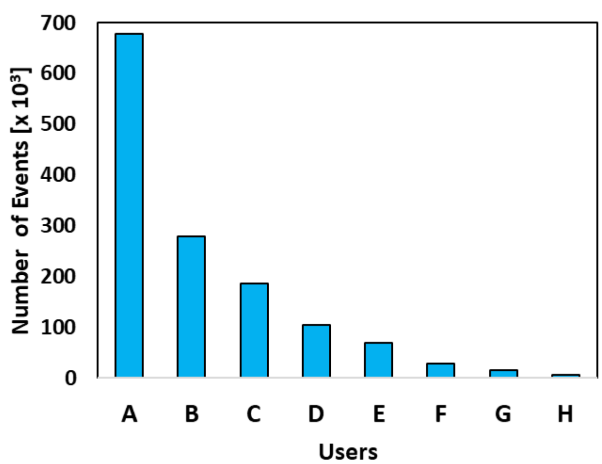


FIGURE 1 A and B: (A) MONTHLY CAD ACTIVITY BREAKDOWN OF ALL DESIGNERS AT INDUSTRY PARTNER IN 2020. (B) INDIVIDUAL USER CONTRIBUTIONS TO CAD SERVER ACTIVITY

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4.2 Variable Clustering

By grouping variables into clusters, we can identify 'types' that describe higher-level activities in which the corresponding variables are being used. To better identify the correlation between different events, we gathered counts of the events that a user performed each day. Given that users 'F', 'G', and 'H' made relatively fewer contributions than their teammates, we focused on analyzing activity from users 'A' - 'E', resulting in 737 instances of daily activity with 79 unique variables. The variables were then clustered together, resulting in the dendrogram shown in Figure 3, which shows the overall variable separation.

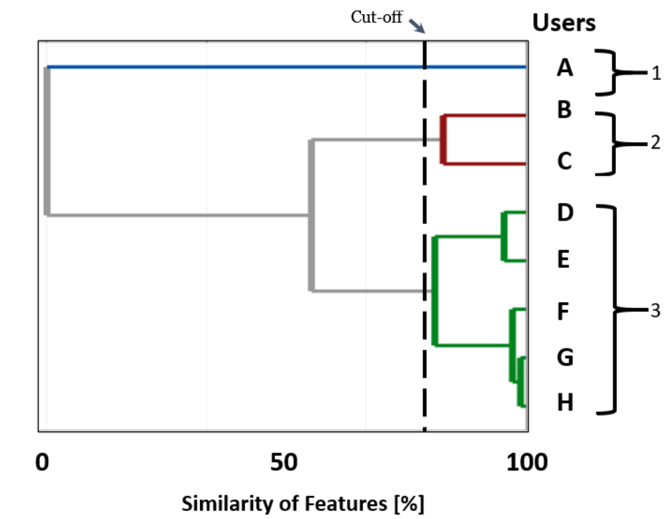

FIGURE 2: DENDROGRAM SHOWING CLUSTERS FOR ONSHAPE USERS. COLOURS INDICATE 3 CLUSTERS.

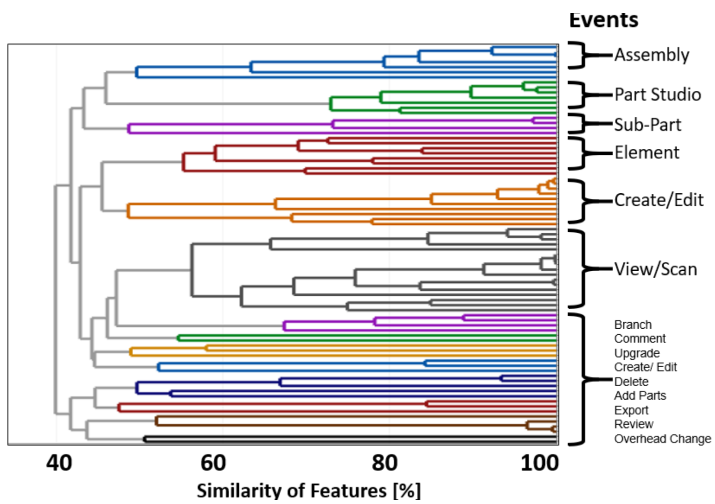

FIGURE 3: DENDROGRAM SHOWING OVERALL CLUSTER BREAKDOWN FOR 79 VARIABLES. COLOURS INDICATE 14 CLUSTERS.

We use the plateaus of similarity as a reference to determine where to create groups. After observing the resulting groups, we identified 14 logical cluster names. Figure 4 and Table 1 further display the breakdowns.

4.3 Cluster Breakdown (Type Breakdown)

Using the newly formed clusters, we found the total number of events each user performed in each cluster. These counts were then converted to a percentage distribution per user to determine an individual's activity and CAD task distribution. As seen in Table 1, 'Element' and 'View/Scan' comprise most of the CAD activity, with users 'A'-'C' scoring higher in the former. User 'E' scores highest in 'View/Scan'. There are more active commands from clusters 1 – 3, whereas 4 – 14 display a mix of passive/reaction ones.

5. DISCUSSION

5.1 Cluster Coherence

The identified type clusters have varying coherency levels. The logical association between variables can be seen within such clusters as 'Part Studio'. The instances within 'Part Studio' either refer to Part Studio by name or are associated with Part Studios, such as 'Add or modify a sketch'. This trend also continues within our 'Assembly' cluster, in which events directly relate to assembly activity. While these clusters have a logical cohesion, others do not experience as much harmony. Our largest cluster, 'View/Scan', is a conglomerate with a level of congruency that is disturbed by a few extraneous events. Six of the variables contain the phrase 'Open' or 'Close'. The association between these events implies a situation in which a user's main actions are simply viewing a document and its components. While these actions describe passive commands, the 'Update Metadata' events imply more actionable behaviour.

Additionally, our smaller clusters require a looser interpretation because the variables do not have an immediate connection to one another, making it somewhat challenging to provide a proper label. This disparity is particularly noticeable in cluster '10', comprised of the two variables, 'Delete Workspace' and 'Comment on a workflowable object'. Despite being labelled 'Delete', the two cluster '10' events do not have an immediate logical connection. Such groupings are likely a result of the relatively small user dataset. While we observed 737 instances of daily behaviour, these actions were still only performed by five distinct users.

5.2 Validation with Industry Partner

After analyzing the audit trails and clustering observations, we returned to our industry partner to discuss the company's experience and habits using CAD software. This discussion provided context to the data and provided explanations for our observations.

Our industry partner revealed that the transition to Onshape had been a gradual one, with users adopting the software at various points in the year. Several of our observations were corroborated within this discussion. Our analysis revealed that user 'A' exhibited vastly different patterns than their peers. Our industry partner revealed that one particular user – identified as 'A' - wanted to familiarize themselves with the software and experimented with the software's different features. This individual also took the responsibility of transferring legacy data to the current software, explaining why they exhibit unique

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behaviour. Additionally, they disclosed that two teammates, who we labeled as ‘B’ and ‘C,’ were responsible for the CAD design of a new product in advance of an October milestone. While these two worked on the same project, they split the tasks in half and designed components independently before integrating them in the end. The legacy data transfer and project modelling align with the July and October peaks, which were initially identified in Figure 1, respectively. Further, without knowing the document or project details – only the actions - we were able to identify users ‘B’ and ‘C’ as having quite similar CAD histories reflecting their split of the modeling work, indicating that they had taken on similar work behaviours.

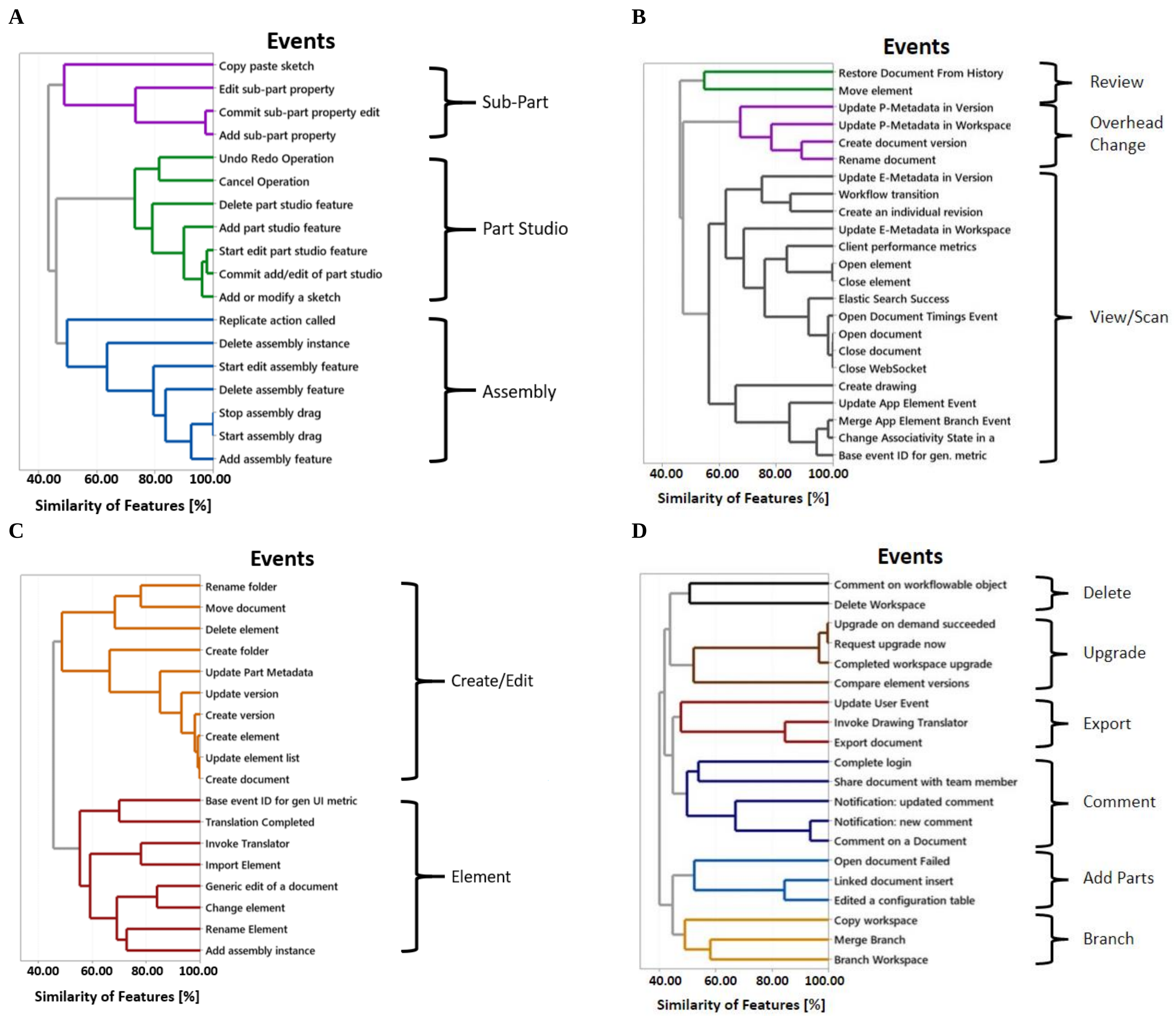

FIGURE 4 A, B C, and D: ALL 79 VARIABLES IN 14 CLUSTERS, REPRESENTED IN DENDROGRAMS

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TABLE 1: MAPPING OF VARIABLES TO CLUSTERS

1 Assembly	2 Element	3 Part Studio	4 View/Scan	
Add assembly feature	Add assembly instance	Add or modify a sketch	Base event ID for generic metrics	Open document
Delete assembly feature	Change element	Add part studio feature	Change Associativity State in a Drawing View Event	Open element
Delete assembly instance	Generic edit of a document	Cancel Operation	Close WebSocket	Update App Element Event
Replicate action called	Import Element	Commit add or edit of part studio feature	Close document	Update Element Metadata in a Version Event
Start assembly drag	Invoke Translator	Delete part studio feature	Close element	Update Element Metadata in a Workspace Event
Start edit of assembly feature	Rename Element	Start edit of part studio feature	Create an individual revision	Client performance metrics
Stop assembly drag	Translation Completed	Undo Redo Operation	Create drawing	Elastic Search Success
	Base event ID for generic UI metrics		Merge App Element Branch Event	Workflow transition
			Open Document Timings Event	

5 Sub Part	6 Branch	7 Comment	8 Upgrade	9 Create/Edit
Add sub-part property	Branch Workspace	Comment on a Document	Compare element versions	Create document
Commit sub-part property edit	Copy workspace	Share document with team member	Completed workspace upgrade	Create element
Copy paste sketch	Merge Branch	Complete login	Request upgrade now	Create folder
Edit sub-part property		Notification about a new comment	Upgrade on demand succeeded	Create version
		Notification about a updated comment		Delete element
				Move document
				Rename folder
				Update Part Metadata
				Update element list
				Update version

10 Delete	11 Add Parts	12 Export	13 Review	14 Overhead Change
Delete Workspace	Edited a configuration table	Export document	Move element	Rename document
Comment on a workflowable object	Linked document insert	Invoke Drawing Translator	Restore Document From History	Update Part Metadata in a Version Event
	Open document Failed	Update User Event		Update Part Metadata in a Workspace Event
				Create document version

Lastly, regarding Table 2, we generated a breakdown of the user activity by cluster. Users ‘B’ and ‘C’ exhibit comparable distributions, further emphasizing why the two were grouped in our initial analysis. The table also shows likely why users ‘D’-‘H’ were grouped closely together, with each of these users having their ‘View/Scan’ type outweigh their ‘Element’ contribution. Such a categorization implies a more passive CAD role which the team corroborated. User ‘E’ was identified as having the reviewer role for the team. The distribution table corroborates this role because user ‘E’ has the highest ‘View/Scan’ score and the second highest ‘Comment’ score. Scoring high in ‘View/Score’ is indicative that this individual does not necessarily create the initial documents but will review others’ work. Additionally, having a relatively higher ‘Comment’ score suggests that an individual who reviews work is more likely to question or provide feedback on the project.

Using analytics, we predicted potential roles and habits; upon further discussion, we found that our observations aligned with the team’s process and timeline. Despite access to only limited information about the team’s CAD practices, we could pinpoint certain design behaviours from only the analytics data.

5.3 Application of Type Breakdown

Personality tests provide an insight to an individual’s work habits. Inspired by the application of these tests, we developed a framework that creates newly identified types that serve as a basis for understanding CAD behaviours in industry users. From meeting with our industry partner, we were able to corroborate our findings and provide additional context to the data developing a framework that can be applied in a larger scope.

We propose that type breakdown can be a tool for onboarding. For example, new employee ‘X’ is unfamiliar with cloud-CAD and is given a week to learn the software. After this period, the team lead reviews the new user’s breakdown, which can be seen in Table 3, finding that ‘X’ performs similarly to user ‘E’, who serves as a reviewer. However, user ‘X’ was hired to join the designer team. When comparing their activity to that of ‘B’ and ‘C’, the team lead can provide recommendations on which events the new user should focus on learning and implementing. The team lead identifies ‘Assembly’, ‘Part Studio’ and ‘Element’ as areas in which user ‘X’ is currently lacking. By focusing and strengthening their knowledge in these areas, ‘X’ works to meet the habits of that of a designer. This tool is beneficial for newer members to have a system that pinpoints which areas need attention to achieve their desired role. If ‘X’ intended to join the team as a reviewer, the team lead could determine that they are on the right trajectory to meeting the role’s responsibilities from a quantitative perspective.

5.4 Limitations and Future Work

Given that the industry partner is still in their initial stages of transition to the cloud-CAD software, future audit trails may

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contain more mature and representative information. Currently, we examine activity primarily from five users. We anticipate that as our industry partner develops more projects and individuals become more familiar with the software, we may observe changes in the observed type distributions.

Additionally, this research focused on activity counts without considering collaboration. After identifying similar behaviours through analytics, we can add a layer of complexity by considering each event's document location. By including document ID information, we can observe user interactions, identifying proactive or reactive actions. The collaboration was reasonably limited in this study as work was primarily independent. To further expand the analysis, the research will benefit from analyzing audit trails from additional companies. Such observations will indicate whether companies have a unique ‘footprint’ regarding CAD or if type distribution is consistent and perhaps universal.

6. CONCLUSION

We developed and demonstrated a framework for classifying individual designers by cloud-CAD behaviours. The framework was developed via the analysis of 8-months of real-world product development CAD data from an industry partner. We first clustered the eight designers by their CAD activity. Next, we clustered the CAD activity, consisting of 79 actions, revealing 14 action groups that tended to occur together. Finally, we present how the eight designers contribute actions to each of the action groups. Observed trends were confirmed with discussions with the industry partner.

With this large-scale CAD analytics data, we are able to classify “types” of the individual designers and action groups where some designers contributed more deeply than others. The analytics provided the industry partner team with insight that was previously inaccessible.

Our framework facilitates self-assessment and awareness for individual designers. It can help managers and supervisors generate constructive feedback, onboard new people, identify team strengths and weaknesses, and ultimately build a well-rounded CAD team. Future extensions of the framework could leverage artificial intelligence techniques to provide real-time feedback on designer roles. This work can lead to more effective and efficient CAD modelling, and ultimately, higher quality products in less time.

TABLE 2: BREAKDOWN OF TEAM MEMBER (A-H) PERCENTAGE CONTRIBUTIONS IN EACH OF 14 CLUSTERS OF CAD ACTIVITIES. COLOUR DEPTH CORRESPONDS TO MAGNITUDE OF PERCENTAGE.

	1 Assembly	2 Part Studio	3 Sub Part	4 View/ Scan	5 Element	6 Branch	7 Comment	8 Upgrade	9 Create/ Edit	10 Delete	11 Add Parts	12 Export	13 Review	14 Overhead Change	Total
A	3.16	2.54	0.04	32.97	44.21	0.03	0.3	0.01	13.83	0	1.41	0.08	0.04	1.37	100
B	3.17	8.26	0.13	29.74	45.23	0.02	0.13	0	11.58	0	0.62	0.22	0.06	0.83	100
C	4.17	13.39	0.02	17.58	55.54	0.02	0.19	0	8.29	0	0.26	0.08	0.03	0.42	100
D	5.4	6.26	0	38.97	35.8	0.13	0.83	0.1	7.96	0.02	2.95	0.16	0.06	1.34	100
E	4.85	4.49	0.02	58.62	24.54	0.11	1.23	0	4.61	0.24	0.35	0.48	0	0.44	100
F	3.54	6.35	0.33	41.26	36.09	0.08	0.37	0.02	4.09	0.01	7.03	0.22	0.06	0.55	100
G	4.17	4.68	0	52.96	31.15	0.13	1	0.02	4.33	0.04	0.32	0.43	0.02	0.74	100
H	3.9	4.41	0.14	50.79	32.56	0	1.76	0	4.96	0	0	1.35	0	0.14	100

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TABLE 3: SAMPLE DISTRIBUTION OF USER X. THEIR BEHAVIOUR MATCHES THAT OF A REVIEWER BUT NEEDS FOCUS ON ACTIVE EVENTS TO MATCH THAT OF A DESIGNER.

	1 Assembly	2 Part Studio	3 Sub Part	4 View/ Scan	5 Element	6 Branch	7 Comment	8 Upgrade	9 Create/ Edit	10 Delete	11 Add Parts	12 Export	13 Review	14 Overhead Change	Total
New Employee															
X	1.12	3.26	0.14	52.79	28.64	0.47	2.74	2.78	4.46	0	0	1.37	2.1	0.14	100
Designers															
B	3.17	8.26	0.13	29.74	45.23	0.02	0.13	0	11.58	0	0.62	0.22	0.06	0.83	100
C	4.17	13.39	0.02	17.58	55.54	0.02	0.19	0	8.29	0	0.26	0.08	0.03	0.42	100
Reviewer															
E	4.85	4.49	0.02	58.62	24.54	0.11	1.23	0	4.61	0.24	0.35	0.48	0	0.44	100

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APPENDIX

Dendrogram Clusters

To identify the number of clusters in our dendrograms, we review our Minitab output which reveals the changes in similarity as new clusters are formed. We look for relatively large changes in similarity to serve as our cutoffs. In Table A1, we have the Minitab output for our users dendrogram; there are relatively large changes at 2 and 3 clusters, with similarity differences of 55.2% and 22.5%, respectively. In Figure A1, we have a visual representation of how these differences translate to our dendrogram. These serve as potential cutoffs for our dendrogram, with the former creating two groups and the latter creating three groups. To achieve a greater level of granularity, we proceed with the latter. Using this method, we use Table A2 to determine the number of groups for our events dendrogram. Starting from Number of clusters = 1, we experience relatively large similarity jumps at 2 (1.62%) and 4 (1.01%) clusters; however, we continue to expand the number of clusters because the current group contents lack coherence. At 13 and 15 clusters, we see similarity differences of 0.97% and 1.01%, respectively. We inspect the event clusters from 13 to 15 to identify whether the groups have logical coherence. We determine that 14 is the appropriate number of clusters for this dataset as we can define the context in which the events are being used. While we could further break down these clusters, we risk overdefining our data and create clusters that contain few unrelated events.

TABLE A1: MINITAB OUTPUT OF SIMILARITY LEVELS FOR DENDROGRAM OF USER CLUSTERS.

Number of clusters	Similarity of feaures [%]	Similarity difference from previous cluster [%]
1	0.00	x
2	55.24	55.24
3	81.04	25.81
4	82.79	1.74
5	95.46	12.68
6	97.21	1.75
7	98.89	1.68

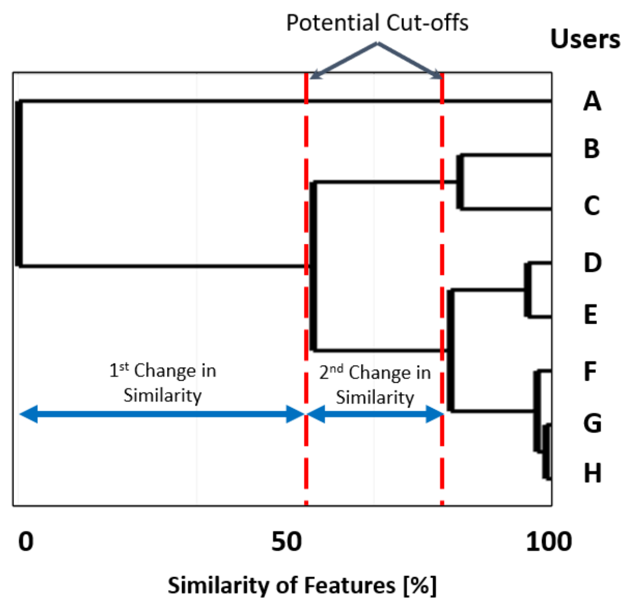

FIGURE A1: DENDROGRAM OF USER CLUSTERS SHOWING THE POTENTIAL CUTOFFS.

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TABLE A2: MINITAB OUTPUT OF SIMILARITY LEVELS FOR DENDROGRAM OF EVENT CLUSTERS.

Number of clusters	**Similarity level [%]**	**Similarity difference from previous cluster [%]**	**Number of clusters**	**Similarity level [%]**	**Similarity difference from previous cluster [%]**
1	46.26	x	**40**	75.81	0.31
2	47.88	1.62	**41**	76.01	0.20
3	47.91	0.03	**42**	77.58	1.57
4	48.92	1.01	**43**	78.43	0.85
5	49.28	0.36	**44**	80.23	1.80
6	49.62	0.34	**45**	80.30	0.07
7	50.15	0.53	**46**	80.53	0.23
8	50.44	0.29	**47**	81.16	0.64
9	50.49	0.05	**48**	81.52	0.36
10	51.25	0.76	**49**	83.24	1.72
11	51.67	0.42	**50**	85.25	2.00
12	51.82	0.15	**51**	85.39	0.14
13	*52.79*	*0.97*	**52**	85.59	0.21
14	53.05	0.26	**53**	85.92	0.33
15	*54.06*	*1.01*	**54**	86.06	0.14
16	54.12	0.06	**55**	86.21	0.15
17	54.35	0.23	**56**	86.51	0.30
18	54.98	0.63	**57**	86.59	0.08
19	55.01	0.03	**58**	90.05	3.47
20	55.83	0.81	**59**	90.84	0.79
21	57.08	1.26	**60**	92.23	1.39
22	57.33	0.24	**61**	93.10	0.87
23	58.63	1.30	**62**	93.69	0.59
24	59.43	0.80	**63**	94.08	0.40
25	60.00	0.57	**64**	94.76	0.67
26	60.91	0.90	**65**	96.47	1.72
27	62.42	1.51	**66**	96.87	0.40
28	63.41	0.99	**67**	97.51	0.64
29	66.23	2.82	**68**	97.90	0.39
30	67.25	1.03	**69**	98.13	0.23
31	69.33	2.08	**70**	98.38	0.25
32	69.88	0.54	**71**	98.39	0.01
33	70.35	0.48	**72**	99.09	0.70
34	70.79	0.44	**73**	99.60	0.50
35	71.63	0.83	**74**	99.72	0.12
36	71.85	0.22	**75**	99.73	0.01
37	72.31	0.46	**76**	99.89	0.16
38	73.06	0.75	**77**	99.97	0.08
39	75.50	2.43	**78**	99.98	0.01

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