Information Visualisation for Project Management: Case Study of Bath Formula Student Project

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This paper contributes to a better understanding and design of dashboards for monitoring of engineering projects based on the projects' digital footprint and user-cantered design approach. The paper presents an explicit insight-based framework for the evaluation of dashboard visualisations and compares the performance of two groups of student engineering project managers against the framework: a group with the dashboard visualisations and a group without the dashboard. The results of our exploratory study demonstrate that student project managers who used the dashboard generated more useful information and exhibited more complex reasoning on the project progress, thus informing knowledge of the provision of information to engineers in support of their project understanding.

Introduction

Organizations across diverse sectors are increasingly turning to information visualisation tools to leverage the growing availability of large data sets for insights to improve their work practices and performance [17], [28], [31], [2], [10]. Within the engineering domain, projects are becoming ever more complex and highly distributed, creating immense digital footprints as part of their project lifecycle [3], [11]. Unsurprisingly, research has begun exploring ways to leverage that digital footprint through analytics and information visualisation as a means to monitor engineering activity and progress

[11], [33] to support project delivery on time and at cost. Certainly, the use of such analytics and information visualisations can be particularly beneficial for managers in better understanding organizational processes, performance and improve their decision-making [23], [30].

However, researchers and practitioners alike have been calling for the establishment of information visualisation appropriate evaluation methods and guidelines. An often-recurring critique is the lack of rigorous qualitative user-centred design approaches being applied in the design and evaluation of information visualisation [1], [14], [26]. In line with this, user-centred design studies have become increasingly popular in problem-driven visualisation research; whereby researchers work with real users to understand the context of their problem, the tasks and data they work with, implementing and evaluating a visualisation solution in a practical context [25].

The process of evaluating information visualisation tools, both in examining the usability of the visualisations as well as the utility of the tool to support complex user processes or tasks, is an imperative and often difficult step, see e.g [9], in validating and encouraging wider adoption of those tools. In systematic reviews of the evaluation practices in the visualisation and information visualisation research community over the past 10 years, Lam et al. [16] and Isenberg et al. [14] uncovered a striking trend in evaluation techniques. Both sets of authors found that the majority of evaluation research has focused on understanding the visualisation systems and underlying algorithms, for instance through user and algorithm performance, accuracy and efficiency metrics. On the other hand, they found there were surprisingly low instances of evaluation approaches which focused on understanding the user's process. These include evaluation methods which aim to uncover how visualisation tools can be integrated and used in the user's work environment, and how user-centric tasks such as reasoning, knowledge discovery, or decision making is supported by visualisation tools [16], [14].

While the more frequently undertaken evaluation of visualisation and algorithm systems, largely quantitative controlled experiments using predetermined tasks, can help us understand the boundary factors for a visualisation tool's capabilities; successful application and adoption of these tools lies in grounding evaluation in the contextual needs and tasks of the end user. [14], [21]. In Isenberg et al.'s review [14], they suggest three pathways to aid in the wider uptake of grounded evaluation approaches: 1) less emphasis on quantitative significance testing, and greater acceptance and application of qualitative evaluation methods, 2) more detailed reporting about the methods used to gather insights from expert users, and 3) more rigorous and in-depth evaluation of feedback from users. Encouragingly, there is an increasing body of work highlighting the potential benefits of integrating

qualitative enquiry into visualisation research (e.g., [15], [25], [32]. Particularly, in insight-based evaluation methods and frameworks.
The aim of this work is to evaluate the effect of a dashboard visualisation tool on engineering project progress understanding and knowledge discovery. To achieve this, we briefly discuss information visualisation evaluation approaches and propose an insight-based evaluation framework for visualisations geared towards the engineering domain. This framework was applied in a case study with an engineering project management team, in which information visualisation tools were evaluated on how they supported user understanding of project activities and events. The results of the study are presented, followed by a discussion of the proposed framework and its implications in how information visualisation is applied to support engineering project activities.

Insight-based evaluation

The main tenant of visualisation is to display data in a way that maximizes comprehension [8] and enables the viewer to gain insight into the data [4], [27]. Though there are a few definitions of insight extant in the information visualisation (InfoVis) literature, the concept of insight is still not well understood [34]. North [20] argues that if the purpose of visualisation is to provide insight then evaluations of visualisation should aim to understand the degree of insight achieved by the end user. Towards this end, North [20, p.20] broadly characterised insights as:

- **Complex**: Insight is complex, involving all or large amounts of the given data in a synergistic way, not simply individual data values.
- **Deep**: Insight builds over time, accumulating and building on itself to create depth. Insight often generates further questions and, hence, further insight.
- **Qualitative**: Insight is not exact, can be uncertain and subjective, and can have multiple levels of resolution.
- **Unexpected**: Insights is often unpredictable, serendipitous and creative
- **Relevant**: Insight is deeply embedded in the data domain, connecting the data to existing domain knowledge and giving it relevant meaning.

Indeed, a more insight-based evaluation of visualisations has recently received a lot of interest, with researchers and practitioners championing qualitative evaluation methods [1], embedding evaluation in relevant domain impact [25], and exploring how to leverage the unexpected [32]. Unsurprisingly this increase in insight-based evaluation has led to the proposal of several frameworks to help categorise and quantify user insights in a meaningful way. For instance, [6] proposed a generalised non-domain specific 'fact taxonomy' drawn from literature review, user studies and expert reviews from a wide range of domains. The authors generated 12 different categories for characterising user insights, including trend, clustering, distribution, outliers, ranking, and associations. Similarly, [7] identified 8 categories of the types of insights generated by participants presenting visualisations of personal data from self-tracking technology. Similar to [6], insight categories were largely based on how data points were discussed. For instance, categories included data summary, distribution, trends, comparison, and outliers [7]. While these frameworks certainly contribute to a better understanding of different ways visualisation data is leveraged to reach insights, we argue that these frameworks tell us very little about how visualisation generated insights may support domain specific, in our case engineering, tasks and knowledge discovery-as outlined by North [20].

Saraiya et al. [24] developed a more domain specific compared to North [20] insight-based coding framework which utilised an open-ended user testing approach. Specifically, the authors asked users familiar with biological data analysis to explore bioinformatics visualisation tools. Rather than asking users to follow a strict protocol or to complete pre-determined tasks with the tool, the authors encouraged the users to explore and analyse the data represented in the tool as they normally would in their roles. Users were asked to think aloud throughout this process and verbalise their thoughts and findings about the data set. By inductively categorising user comments from this open-ended analysis process, the authors developed eight broad insight dimensions that focused more heavily on user's work processes, behaviour, and domain value. We argue this method, and resulting insight framework, is more in line with a context-driven evaluation approach.

Therefore, we adopted Saraiya's methods to formalise an insight-based evaluation framework for the engineering domain, particularly, to evaluate the project analytics visualisation tools we developed and their ability to support insight generation for engineer project managers. We introduce the engineering user group and project management visualisation tools evaluated within the case study below, and describe the development and application of our engineering domain insight evaluation framework to better understand how project analytics visualisations can support project management.

Case study: engineering project management – Bath Formula Student

This case study is focused on understanding and utilizing the digital footprint generated by engineering project work, such as digital communications (e.g., email, social media), records (e.g., reports, documents, presentations) and design representations (e.g., Computer-aided design (CAD) models) in the context of the Language of Collaborative Manufacturing (LOCM) project [1]. Using this low-level output data to provide student project managers from the University of Bath with dashboards supporting high level insights into project changes and progress, we evaluated the effect of an information visualisation tool on project progress understanding and knowledge discovery.

Participants
This evaluation work was performed with a project team of the University of Bath engaged in Formula Student (FS) competition [13] – Team Bath Racing. The FS is a yearly international competition where project teams of approximately 25 multi-discipline engineering university students design, manufacture, and race a single-seat racing car. This user group was selected as it encompassed an entire engineering project lifecycle, and its related digital outputs, in a rapid time-frame (22 weeks) and re-occurs annually. Six project managers, all male, from one team took part in the study. Each manager was responsible for managing different sub-teams across the project. Participants received £10 for each session they took part in.

Project Management Dashboard Tool
An FS team will generate approximately 8-9 terabytes of project related data over the course of their project lifecycle. In developing a dashboard tool, our aim was to develop automated analytic and information visualisation approaches using this low-level output data to provide project managers with dashboards supporting high level insights into project changes and progress. Ultimately, to support informed decision making towards optimal performance and productivity. In the development of the project management dashboard analytics, for explorative purposes we used project data generated across three different FS project teams over a three year period . Exploration of this dataset was undertaken by engineering researchers to understand what type of data was created and how it was organised.

[1] http://locm.blogs.ilrt.org/

The monitoring of the digital footprint was performed using a custom software tool that monitored the activity of the Formula Teams shared network drive (https://www.npmjs.com/package/fal). Over the course of the project, 129,377 files were created and 870,134 updates made. This includes the creation, deletion and modification of the files on the shared drive. The shared drive contains files pertaining to all activities of the project. The files were further classified by engineering activity defined by file type, with activities associated with engineering activities where software use is specific to an activity type (e.g. CAD files – Design), or to a general form of activity where software use may be for multiple purposes (e.g. documents, presentation slides – Documentation). Table 1 shows the volume and level of activity in each area.

Table 1. Number of files on the shared drive and their updates per project activity.

Activity	Number of Files	Number of Updates
Simulation	23,694	103,481
Software	4,755	15,762
Spreadsheet	2,282	11,938
Testing	868	5,226
Video	452	1,804
Website	290	1,102
Design	12,590	53,665
Documentation	7,220	23,993
Images	21,539	90,895
Management	36	231

In addition to the shared drive, the Social Media communications of the team were also recorded. This was achieved by recording the public tweets and Facebook posts of the team and placing them in the context of all other FS national teams. A total of 1341 public tweets were captured for all teams during this project.

From this initial exploration, nine broad data analytic metrics emerged (discussed further in [11]), which could be leveraged to support the monitoring of project activities. Through a series of iterative user-centred design interviews, focus groups and workshops with stakeholders and FS user-groups, a suite of initial interactive information visualisations were designed and developed using free Tableau software [29] for data visualisation. Dashboard design requirements and principles were formulated based on users needs and available data. A dashboard consisted of five data tabs with one data visualization tab presented at a time via a web-based Tableau application. The tabs were presented in the following order: Raw Folder Activity,

Activity, Activity Drill Down, Twitter, Facebook (see Figures 1-4). The users were able to navigate through the tabs at the bottom of the display in order to access different data analytics and visuals developed from the data on the project digital footprint. The dashboard was presented on a laptop computer with the 27" touchscreen monitor during interviews with half of the project managers (Dashboard experimental group).

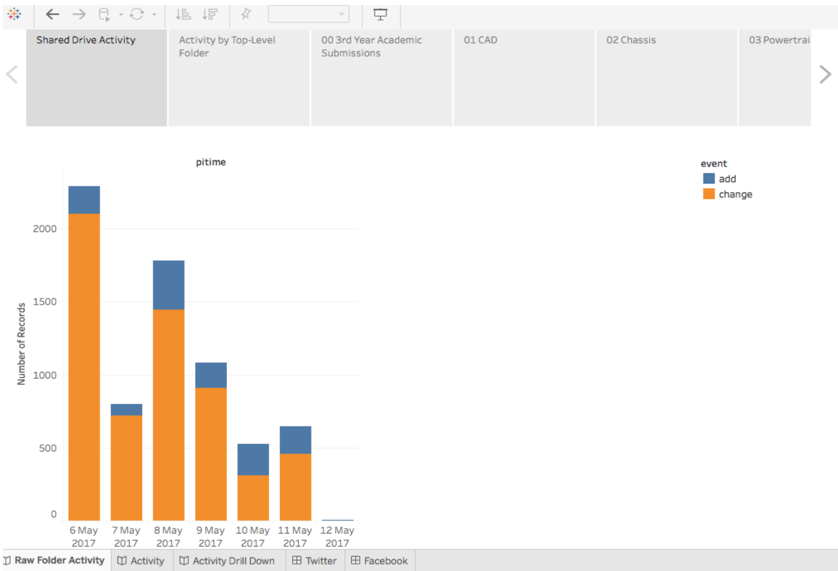

Fig 1. Total files added and changed on the shared x-drive by day.

The following information on the project digital footprint was presented to the users: **Raw Folder Activity tab -** total files added and changed on the shared X-drive by day (bar chart – see Figure 1), number of files added in the previous week - top and sub-level folders (heat map - see Figure 2), activity by top and sub-folders and the number of files added or changed for each top and sub-level folder, time spent on activity types and number of files worked on – top and sub-folder (heat map similar to the one in Figure 2), **Activity tab -** type of activity analytics by day derived from the files extensions, including time spent on activity and number of files worked on (line graph, see Figure 3), **Activity Drill Down tab -** with information on time spent on activity and number of files worked on within sub-folders (line graph similar to the one in Figure 3), **Facebook** and **Twitter tabs -** information on social media which consisted of Facebook and Twitter dashboards. On the Facebook tab: impact (likes and shares), engagement (comments) across 43 FS teams' posts, trending words/topics being used by Formula Students in the last month (tree map). On the twitter tab: the top

Formula Student Accounts currently being followed (tree map), network of top users interacting with @TeamBathRacing handle (EgoNet), reach (retweets) and size of reaction (favourites) across 43 FS teams' tweets. An example of Facebook activity visualisations is represented in Figure 4. A visualisation similar to Figure 4 was developed for Twitter related analytics.

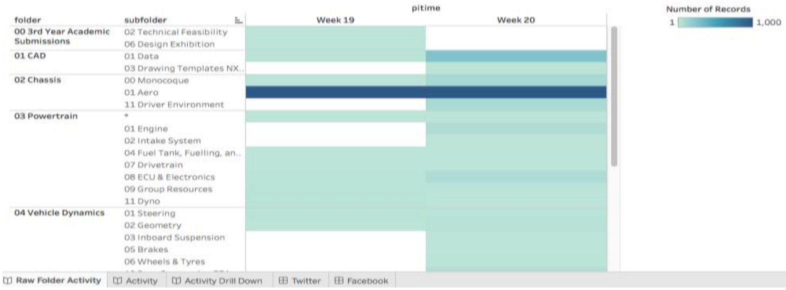

Fig 2. Number of files added in the week - top & sub-level folders.

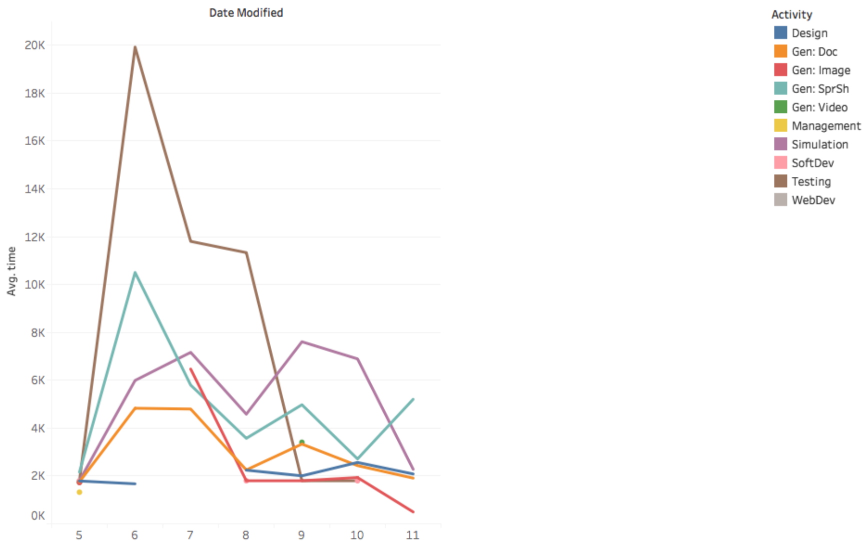

Fig 3. Type of activity by day: design, reports, images, video, management, simulation, software development, testing, web development.

Each tab contained further up to 16 lower level sub-tabs. All main tabs except of Activity Drill Down were used by the participants, though only three types of data visualisations across all tabs were examined: activity type heat map, number of records by the shared X-drive folder structure over time and social media visualisations. The participants were only provided with the visualisations of the data from their project.

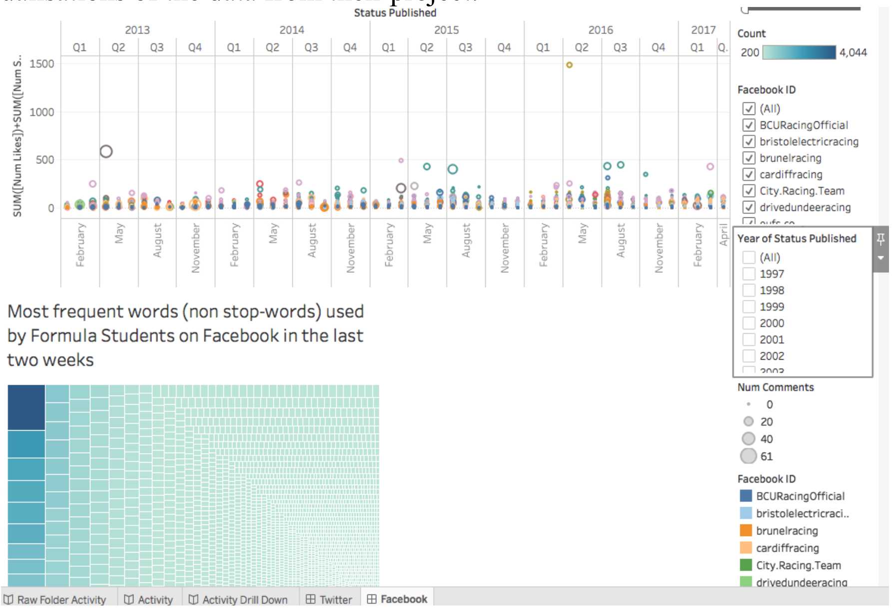

Fig 4. Facebook analytics dashboard: impact (likes and shares), engagement (comments) across 43 FS teams' posts, trending words/topics being used by FS in the last month.

Methods

The aim of the experiment was to evaluate how the provision of the project management analytics dashboard affected FS project managers' interpretation of project activities and events. A Dashboard present vs. absent mixed design was employed. The dashboard was tested with the help of semi structured interviews with 6 project managers. Managers took part in four evaluation sessions, one every two weeks over an eight week period. Each session comprised of a semi-structured think-aloud task in which managers were asked to consider and verbally walk through their thought process around the project's progress and performance over the past two weeks. Experimenter prompts contained project's main goal, activities and issues encountered. An example of the interview prompts is: 'What have been the main activities and goals you were working towards this week?'

As this type of project review activity was generally performed as a group within the team, half of the evaluation sessions were group sessions and were conducted with a maximum of four managers in the Dashboard present group, and maximum two managers in the No Dashboard group. Across the four sessions, the Dashboard present group had access to the developed dashboard and was encouraged to use and explore the data to help them reflect on project activities. Prior to the first session, this group was given a brief training session, walking them through what data and visualisations were available to them in the dashboard. Evaluated separately, the No Dashboard group did not have access to the dashboard and was asked to simply reflect on and discuss their project activities.

Each session lasted between 20-45 minutes, with both groups' comments audio recorded and the dashboard present group's interaction with the dashboard was video recorded using screen capture software.

Proposed insight framework

User comments recorded across the four evaluation sessions were transcribed for coding. An insight in this case has been defined as an individual observation about project activity by the participant [24]. An inductive and iterative coding process was used to develop the insight framework. Specifically, two coders used Saraiya et al.'s eight insight dimensions, which focuses on user's work processes, behaviour, and domain value, as an initial coding template. As categories of our users' domain specific processes and tasks emerged, insight dimensions were adapted and added to. This process led to the final insight-based evaluation framework, which included nine insight dimensions (see Table 2 below):

Table 2. Insight-based evaluation framework.

Dimension	Value	Description
Observation	Numerical	Frequency of insights made by the participants – this dimension is a direct match with an element of the framework of Saraiya et al. [24]
Comparison	Numerical	The insight discussed the similarities/differences between pieces of information (e.g. objects, people, activities, etc.) This insight dimesion is adapted from Saraiya 'category' characterisation [24], it is also critical for information processing in the context of engineering design [12]
Hypothesis	Numerical	Suggests an in-depth data understanding and inference; it is adapted directly from [24] and regarded as the most critical dimension according to Saraiya et al. [24]. Hypothesis can be:

		○ *Causal*: Linking pieces of information to explain causal relations, the ability of the individual to understand information [12] ○ *Proposed further enquiry*: generates or identifies a new question/hypothesis [24]
Judgement/valence	Numerical	Whether an opinion or judgement was made about the value of the insight made (e.g. evaluation of information, domain value of information [24], subjective interpretation [12]
Information granularity (breadth or depth)	Categorical	Indicates the level of granularity or detail in the statement (directly adapted from [24])
Project context	Categorical	Insights were grouped based on the area of the project that they pertained to. This dimension emerged in the process of interviews coding as domain specific project activities according to Saraiya's inductive coding methodology [24]
Project aspect (managerial or technical)	Categorical	Whether the insight was related to managerial or technical activities. This dimension also emerged in the process of interviews coding as domain specific project aspect according to Saraiya's inductive coding methodology [24]
Information usage behaviour (confirmatory or exploratory)	Categorical	Whether the dashboard is used to confirm an insight generated by memory; or the dashboard is used in an exploratory way unrelated to a priori ideas [24]. This insight dimension is relevant only to the Dashboard group
Information source (self or dashboard generated)	Categorical	Whether the user generated the insight from memory or from interacting with the dashboard. This description is relevant only to the Dashboard group. It emerged in the process of interviews coding as domain specific project activities according to Saraiya's inductive coding methodology [24]

Average Huberman's inter-coder reliability [18] across the first two sessions was 70% for the first four dimensions (*Observation, Comparison, Hypothesis, Judgement*) and 100% for the other, more straightforward dimensions.

Case study results

In this section comparison results between Dashboard and No Dashboard groups are presented across the nine insight categories pf the proposed framework. Further, a closer look is taken at the Dashboard group to investigate how they used dashboard visualisations. Note that the last two dimensions mentioned in the previous section – Information usage and Information source- refer only to the dashboard users as they characterise dashboard interaction behaviour.

Dashboard versus No Dashboard groups

Observation: In the Dashboard group 76 meaningful project-related observations with different topics were identified while in the No Dashboard group there were only 46 which is 40% less compared to the Dashboard group (see Figure 5 for the proportions).

Comparison: There are 15% more comparisons identified in the Dashboard group compared to the No Dashboard (see Figure 5).

Hypothesis: 13% more hypotheses were generated by the Dashboard group (see Figure 5).

Judgement/valence: 19% less judgmental statements were generated in the Dashboard group compared to the No Dashboard group (see Figure 5).

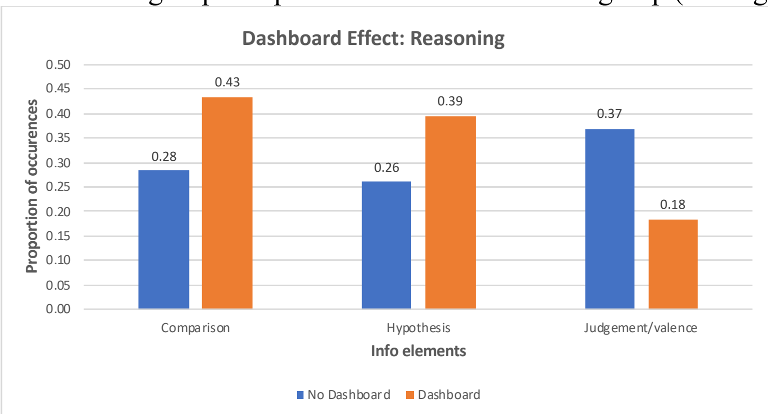

Fig 5. Proportion of occurrences of cognitive elements: comparison, hypothesis and judgement/valence - for Dashboard and No Dashboard groups.

Information granularity: there are 23% more occurrences of statements with specific information and 15% less occurrences with mixed (both specific and general) statements in the Dashboard group (see Figure 6). The difference for general information statements between the groups is not so substantial: there are 8% more general statements in the No Dashboard group.

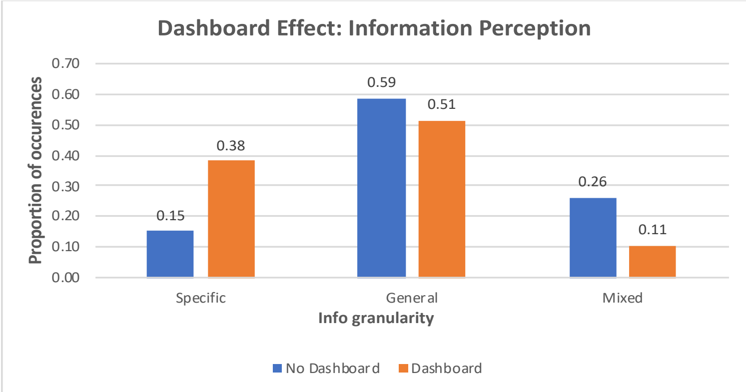

Fig 6. Proportion of occurrences of three types of information granularity: Specific, General and Mixed information - for Dashboard and No Dashboard groups.

Project context: in both groups 8 project-related topics, or activities, were identified: social media, manufacturing, simulation, general trends, academic/Final year projects (FYP), Computer-aided design (CAD)/Design, Static events such as business, finance, design reports etc. and administration related events (see Table 3). The heat map of proportions occurrences of these activities in the interview scripts of both Dashboard and No Dashboard groups is represented in Table 3.

The majority of statements in the No Dashboard condition mention manufacturing: 39% of statements. 20% of statements in the same group contain information about static events, such as business, finance related events or design reports. Within the Dashboard group, only 29% of statements mention manufacturing activity and the general distribution of project activities is more even compared to the No Dashboard group. If we compare proportions of occurrences of different project activities discussions across the two groups, it can be seen in Table 3 that the biggest differences are related to such activities as social media, manufacturing and admin events (10% difference per each of these three activities).

Project aspect: there is no substantial difference across the two groups with respect of two main project management areas: technical aspects are mentioned 4% less times in the Dashboard group and managerial aspects are mentioned 6% more in the Dashboard group (see Figure 7).

Table 3 Heat map of project related activities proportions mentioned in the statements in Dashboard and No Dashboard conditions.

Project Activities	Dashboard	No dashboard	Difference
Social media	0.21	0.11	0.10
Manufacturing	0.29	0.39	-0.10
Simulation	0.07	0	0.07
General trends	0.07	0.04	0.03
Academic/FYP	0.03	0.02	0.01
CAD/Design	0.08	0.09	-0.01
Static events	0.21	0.2	0.01
Admin events	0.05	0.15	-0.10

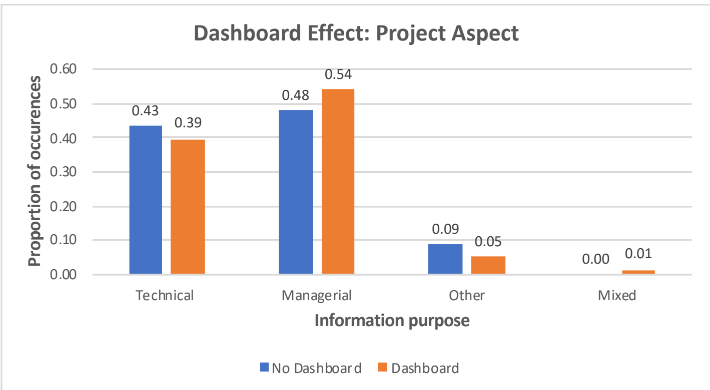

Fig 7. Proportion of occurrences of three types of information granularity: Specific, General and Mixed information - for Dashboard and No Dashboard groups.

Dashboard group

Information usage behaviour and **information source** dimensions of the evaluation framework refer only to the Dashboard group since they describe how users interact with the dashboard. Dashboard exploratory behaviour contained more comparisons and hypothesis and statements generated without using the dashboard contained more subjective judgements and evaluations (see Figure 8).

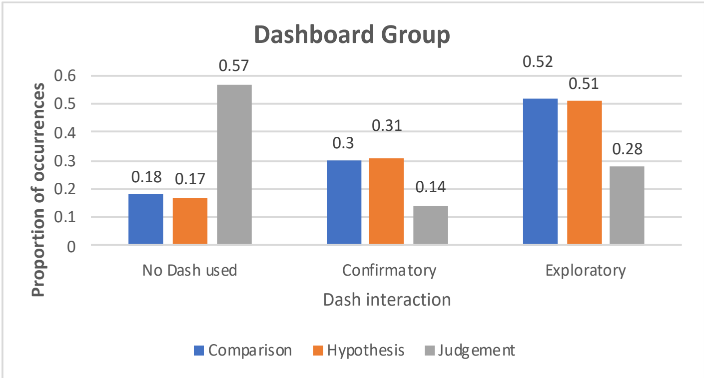

Fig 8. Proportion of occurrences of cognitive elements: comparison, hypothesis and judgement/evaluation - across three types of Dashboard interaction behaviour (no dash, using to confirm information, using to explore) within the Dashboard group.

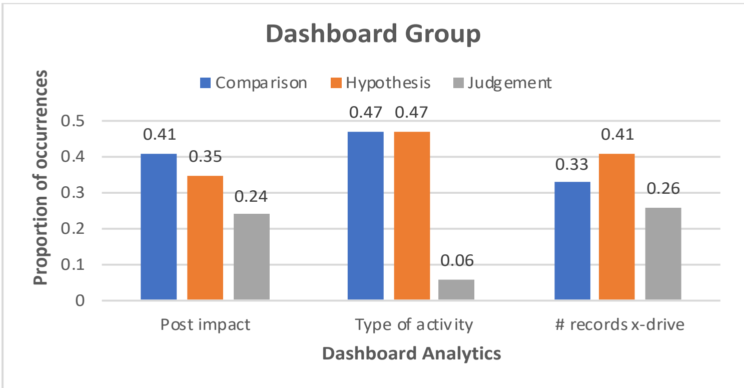

Fig 9. Proportion of occurrences of cognitive elements: comparison, hypothesis and judgement/evaluation - for Dashboard group across three types of analytics used by the participants.

Participants in the Dashboard condition used only three types of analytics out of four given to them by the experimenters: types of project activity derived from X-drive files extensions, number of records by each x-drive folder and social media impact posts. The heat map in Table 4 demonstrates proportion of frequencies of project activities mentioned by the participants across these three types of visual analytics. As it can be seen in Table 4, posts impact visualization was used only in discussions about social media activity, project activity analytics was mainly used to discuss static events

(33%), general trends (25%) and simulation (25%) activities, number of records in folders on the shared X-drive analytics was used to discuss manufacturing and build activity (38%) and CAD design (19%).

The least number of judgemental statements were generated while using the visualisation on project activities (see Figure 9) compared to the other two visualisations.

Table 4. Heat map of project related activities proportions across three dashboard analytics used in the Dashboard condition.

Project Activities	Post impact	Type of activity	# Records by x-drive folder
Social media	1.00	0.00	0.00
Manufacture/Build	0.00	0.08	0.38
Static events	0.00	0.33	0.13
General trends	0.00	0.25	0.13
Simulation	0.00	0.25	0.06
CAD/Design	0.00	0.08	0.19
Admin - events	0.00	0.00	0.06
Academic/FYP	0.00	0.00	0.06

Discussion and conclusions

One of the findings of the current study is that only three types of dashboard analytics out of four available were used. It can be explained by the fact that the users selected those analytics which matched the questions of the interviewer. With these three dashboard analytics types for project management based on project digital footprint, there are some implications of a positive dashboard effect on participants' reasoning about the status of the project. The comparison results between Dashboard and No Dashboard conditions are summarized in Table 5 below:

Table 5. Comparison results across the seven out of nine insight dimensions for Dashboard and No Dashboard conditions.

Insight dimension	Comparison results
Observation	More in the **Dashboard** group
Comparison	More in the **Dashboard** group
Hypothesis	More in the **Dashboard** group
Judgement/valence	More in the **No Dashboard** group
Information granularity (breadth or depth)	More *specific* information in the **Dashboard** group, no difference for *general* information
Project context	The topics are more evenly distributed across all project areas in the **Dashboard** group, focused on one area (Manufacturing) in the **No Dashboard** group
Project aspect (managerial or technical)	No difference

The main positive effects of the dashboard tool can be summarised as follows:

- Dashboard visualisations possibly broadened participants' attention and attracted it to different project activities and aspects. This conclusion is based on the number of observations and topics distribution in Dashboard and No Dashboard groups (Figure 5, Table 3);
- Dashboard changed participants' reasoning and facilitated higher value reasoning elements, such as comparisons and hypothesis generation (Figure 5);
- Dashboard provided more specific information and helped to focus on lower granularity of information without losing general information of higher granularity (Figure 6).

Based on the above described findings of this exploratory study, we can suggest that digital footprint analytics has a good potential and can be a useful measure which can assist project managers and participants in project status analysis. The next steps for the future work can be the exploration of the effect a project digital footprint analytics dashboard on decision making and actual project outcomes. Cognitive benefits of using a dashboard in this study do not directly imply better project outcomes and more research is needed to examine this connection. Further, new project digital footprint analytics based on people and team aspects can be developed and tested.

There are several limitations of the current study which should be mentioned. First, this dashboard evaluation was conducted with a relatively novice and small team of engineers. Further work is needed to examine how the beneficial insights into project activity observed here may scale up to larger projects and organisations. Second, interview questions and prompts were mainly focused on project activities which could define the usage of specific dashboard analytics. Third, the present study might not represent naturalistic usage of project related dashboard analytics, but rather an off usage of dashboards. The study aimed to simulate relatively naturalistic review of project progress and activities for this user group (e.g. held in work environment, in groups rather than individually, applying an open-ended task methodology). However, based on user feedback and the real-time project statistics provided by the project status monitoring dashboard, this particular visualisation tool may have more impact on insight generation if interacted with more consistently over time. While this was not possible in this phase of testing due to the stability of the prototype dashboard, further evaluation of this dashboard tool will entail field trial testing in everyday usage of the tool.

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References

1. Arias-Hernandez, R. and Fisher, B. 2013. A qualitative methodology for design of visual analytic tools for emergency operation centers. In *International Conference on System Sciences*, 126-135.
2. Bačić, D. and Fadlalla, A., 2016. Business information visualization intellectual contributions: an integrative framework of visualization capabilities and dimensions of visual intelligence. *Decision Support Systems*, *89*, pp.77-86.
3. Briggs, D.: 2012, Data Distribution on the 787, Bringing Model Based Definition to the World, *Collaboration and Interoperability Congress,* May 21-23, 2012, Denver.

4. Card, S.K., Mackinlay, J.D., and Shneiderman, B. 1999. Readings in Information Visualization: Using Vision to Think. Morgan Kaufmann, San Diego, USA.
5. Carpendale, S. 2008. Evaluating information visualizations. *Information Visualization: Human-Centered Issues and Perspectives, 19-45.*
6. Chen, Y., Yang, J. and Ribarsky, W. (2009). Toward effective insight management in visual analytics systems. I*EEE Pacific Visualization Symposium 2009*, 49-56
7. Choe, E.K., Lee, B., and Schraefel, M.C. (2015). Characterizing visualization insights from quantified selfers' personal data presentations. *IEEE Computer Graphics and Applications*, 35 (4), 28-37.
8. Daintith, J. and Wright, E. (2008) A dictionary of computing (6 Ed.). Oxford University Press.
9. Ellis, G. and Dix, A. (2006). An explorative analysis of user evaluation studies in information visualisation. In *Proc. BELIV'2006*, ACM Press, 1-7.
10. Gaardboe, R., SVARRE, T. and Kanstrup, A.M., 2015. Characteristics of business intelligence and big data in e-government: Preliminary findings. *Innovation and the Public Sector*, p.109.
11. Hicks, B., McAlpine, H., Gopsill, J., and Snider, C. (2016). The digital footprint of engineering design projects: Sensors for project health monitoring. In *International Conference on Design Computing and Cognition (DCC 2016).*
12. Hicks, B.J., Culley, S.J., Allen, R.D., and Mullineux, G. (2002). A framework for the requirements of capturing, storing and reusing information and knowledge in engineering design. International Journal of Information Management, 22, 263-280.
13. IMechE (2017). Formula Student. Accessed December 14, 2017: http://events.imeche.org/formula-student
14. Isenberg, T., Isenberg, P., Chen, J., Sedlmair, M., and Moller, T. (2013). A systematic review on the practice of evaluating visualization. *IEEE Transactions on Visualization and Computer Graphics 19* (12), 2818-2827.
15. Jackson, B., Coffey, D., Thorson, L., Schroeder, D., Ellingson, A.M., Nuckley, D.J. and Keefe, D.F. (2012). Toward mixed method evaluations of scientific visualisations and design process an evaluation tool. In *Proc. BELIV'2012*, ACM Press, 4.
16. Lam, H., Bertini, E., Isenberg, P., Plaisant, C., Carpendale, S. 2012. Empirical studies in information visualization: Seven scenarios. I*EEE Transactions on visualization and computer graphics*, 18 (9), 1520-1536.
17. Lurie, N.H. and Mason, C.H., 2007. Visual representation: Implications for decision making. *Journal of Marketing*, *71*(1), pp.160-177.
18. Miles, M. B., & Huberman, A. M. (1994). Qualitative data analysis: An expanded sourcebook. Sage.

19. Munzner, T. (2009). A nested model for visualization design and validation. *IEEE Transactions on Visualization and Computer Graphics* 15(6), 921-928.
20. North, C. 2006. Toward measuring visualization insight. *IEEE Computer Graphics and Applications: Visualization Viewpoints, May/June 2006,* 20-23
21. Plaisant, C. (2004). The challenge of information visualization evaluation. IEEE Proc. In AVI'04, 109-116.
22. Plaisant, C., Fekete, J.D. and Grinstein, G., 2008. Promoting insight-based evaluation of visualizations: From contest to benchmark repository. *IEEE transactions on visualization and computer graphics*, *14*(1), pp.120-134.
23. Raymond, L. and Bergeron, F. 2008. Project management information systems: An empirical study of their impact on project managers and project success. *International Journal of Project Management* 26: 213-220.
24. Saraiya, P., North, C. and Duca, K. (2005). An insight-based methodology for evaluation bioinformatics visualizations. *IEEE Transactions on visualization and computer graphics*, 11(4), 1-14.
25. Sedlmair, M., Meyer, M., and Munzer, T. 2012. Design study methodology: Reflections from the trenches and the stacks. *IEEE Transactions on visualization and computer graphics*, 18(12), 2431-2440.
26. Shneiderman, B. and Plaisant, C. 2006. Strategies for evaluating information visualization tools: Multi-dimensional in-depth long-term case studies. In *Proc. BELIV'2006*, ACM Press, 1-7.
27. Spence, R. 2001. Information Visualization. Addison-Wesley.
28. Trieu, V.H., 2017. Getting value from Business Intelligence systems: A review and research agenda. *Decision Support Systems*, *93*, pp.111-124.
29. Tableau Software. 2013. "Technical Specifications—Tableau Desktop." Accessed December 6, 2017. http://www.tableausoftware.com/products/desktop/techspecs.
30. Watson, H.J. and Wixom, B.H (2007). The current state of business intelligence. *IEEE IT Systems Perspectives*, 96-99.
31. Wixom, B.H., Watson, H.J., Reynolds, A.M. and Hoffer, J.A., 2008. Continental airlines continues to soar with business intelligence. *Information Systems Management*, *25*(2), pp.102-112.
32. Woźniak, P., Valton, R. and Fjeld, M. 2015. Volvo single view of vehicle: Building big data service from scratch in the automotive industry. In *Proc. CHI 2015*, ACM Press, 671-678.
33. Wu, I. and Hsieh, S. 2012. A framework for facilitating multi-dimensional information integration, management and visualization in engineering projects. *Automation in Construction*, 23, 71-86.
34. Yi, J.S., Kang, Y.A., Stasko, J.T. and Jacko, J.A., 2008, April. Understanding and characterizing insights: how do people gain insights using information visualization?. In *Proceedings of the 2008 Workshop on BEyond time and errors: novel evaLuation methods for Information Visualization* (p. 4). ACM.