ACTIVE ENGAGEMENT IN COLLABORATIVE ENGINEERING DESIGN: HOW TO MEASURE AND USE IT IN A FEEDBACK SYSTEM?

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ABSTRACT

Engineering design is typically a collaborative process, and in the era of digital engineering, online collaboration platforms are increasingly being used to perform the work. Despite the development of e-collaboration technologies, there is a significant gap between actual collaboration and what is really needed. However, improving collaboration requires a proper measurement system. Yet, the common methods to measure and improve collaboration are challenging, usually not compatible with digitalized collaboration, and have limited scalability. This paper presents a new data-driven method for measuring, visualizing, and monitoring Active Engagement (AE) in web-based teamwork, which is a key element of effective collaboration. We applied the method in a case study of four engineering teams during a Technology Planning and Road-mapping course. The results suggest that measuring AE in web-based teams, with an available history log, is technically feasible and can meaningfully represent the team's collaboration. The presented approach can be used to upgrade e-collaboration platforms as a toolkit or for further investigation on improving web-based collaborative design and learning through monitoring dashboards and feedback systems.

Keywords: Collaborative design, Teamwork, Case study, Digital engineering, E-collaboration

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Cite this article: Farshad, S., Fortin, C. (2023) 'Active Engagement in Collaborative Engineering Design: How to Measure and Use It in a Feedback System?', in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.46

1 INTRODUCTION

Teams, through collaborative problem solving, perform much of the complex work in the modern world (Graesser et al., 2018). However, today's teamwork, particularly engineering teams, relies on digital technologies and online collaborative platforms more than ever with a growing trend (Boughzala and de Vreede, 2015; Farshad and Fortin, 2021). According to Fortune Business Insights (FBI, 2022), by 2028, the global market for team collaboration software will be valued at $40.79 billion, up from $17.15 billion in 2021, which indicates a 230% larger market size. However, despite the significant development of communication and collaboration platforms, in terms of collaboration quality, there is plenty of room for improvement (Hihn et al., 2011; Ho et al., 2019; Rometty, 2006).
Fischer (Fischer, 2004) discussed collaborative design barriers and its core limitation in several dimensions; (A) Spatial, indicating inability to meet face-to-face and low density of shared interests. (B) Temporal, refers to the design and use time (i.e., who is expected to do the work? and who benefited from it?). (C) Conceptual, within and between domains, referring to limitations in establishing group thinking and shared understanding while dealing with different expertise levels. (D) Technological, stating requirement for fluency in interacting with digital environments. Some of the spatial limitations are addressed partially through computer-supported collaborative design technologies, and teams are able now to collaborate across borders (Brisco et al., 2018). Improving digital fluency is possible through developing frameworks that foster agility in the technological societies (Lang, 2021). Temporal and conceptual barriers, on the other hand, due to socio technical, cognitive, and interpersonal challenges, are more complicated. At the same time, Lazareva and Munkvold (2017) believe that improving interactions across team members is an effective way to improve engineering web-based collaboration. However, usually, the administration is not aware of the exact quantity/quality of interactions, collaboration, and the level of engagement of individuals. Moreover, engineering teams do not receive feedback on team interactions and individual levels of Active Engagement (AE) in the project. However, a mechanism that enables the team to remain aware of each other's activities, engagements, or status, regardless of their physical location, could mitigate these problems by creating an awareness system (Markopoulos and Mackay, 2009).
Nonetheless, without a clear metric to measure collaboration, it is difficult to overcome collaboration challenges and improving it, as one of the most well-known and influential management thinkers, Peter Drucker, once said (Kihlstrom, 2021): *"If You Can't Measure It, You Can't Improve It"*. Current methods of measuring collaboration often rely on questionnaires and/or direct observation by an agent (Tausch, 2016; Thomson et al., 2007; Zumbach et al., 2006); these methods are usually time-consuming, sometimes complicated, and qualitative, which might also face the issue of scalability in large-scale projects. This paper aims to address these challenges by formulating a measurement of team engagement that can be implemented through an algorithm to provide visual, automatic, on a real-time basis, and quantitative reports to be used in a monitoring/feedback dashboard. Even though online work has numerous difficulties, it has created the opportunity to analyze the data from recorded activities that leads to these questions; how can a data-driven measurement of AE in web-based collaborative engineering design is feasible; and how is it possible to use this measure in a feedback system?
In the next sections, together with discussing the literature, first the background and logic of the work are presented, then, the measurement criteria and the main hypotheses of the study are described. Section 4, addresses the validity of the approach by reporting the results of a case study. The discussion section outlines the approach pros and cons, and a method for integrating collaboration in various platforms. Finally, we conclude the study, as well as our outlook for future work.

2 BACKGROUND, LOGIC AND THE DESIGN

During the last decades, a large body of research from healthcare to engineering, investigated the importance and need for improving collaboration. Depending on the field and context, there are different approaches to improve collaboration. For example, Benz et al., (1995), emphasize stakeholders' analysis and detailed surveys to improve collaboration between schools and vocational rehabilitation. Pirkis at al., (2004), believe that promoting systems-level and cultural change, improving service delivery, supervision and training, are efficient ways in dealing with poor collaboration in the public mental health sector. Fernandes et al., (2012), conclude that gamification is a successful method to enhance collaboration in Requirements Elicitation practice. Ferme et al., (2018), suggest that developing longterm relationships between project stakeholders through early contractor involvement (ECI), advances collaboration in Green Building Projects. According to Duehr et al., (2021), agile working practices have a great potential to improve collaboration in product development teams. The common area in the mentioned methods is that they all rely on a network of different variables with a need for human-agent observation and interpretation, which makes it very difficult to computerize.

Another method that has received less attention in improving collaboration is feedback systems. We believe that this method has the potential to be reiterated through algorithms and machine language. In a detailed doctoral thesis, Sarah Tausch (Tausch, 2016) worked on the influence of feedback on collaboration, and shows that providing feedback on collaboration for teams, particularly through a computer-mediated system, can effectively improve the problem-solving results. She utilized group mirrors/social mirrors techniques to provide feedback on collaborative activities in the group processes. By referring to Jermann et al. (2001), Tausch distinguishes three different feedback systems; mirroring techniques, metacognitive tools and guiding systems (see Figure 1). Collecting data about collaborative processes is the common feature of all these tools. Mirroring systems reflect the current state to the group using the aggregated data. Metacognitive tools, through comparing the current state versus the desired state and presenting it to the team members, go one step further, and guiding systems provide advice for the team. The system we are proposing here, can benefits from all three approaches together through four main steps (Figure 1 and 2): First, collecting data from the history log of the operating platform and create a dataset. Second, analyse the data, measure contributions based on the defined formula, and create a report. Third, create the visual report as the feedback and compare members' activities. Forth, the possibility to provide advice for each member and the team in general.

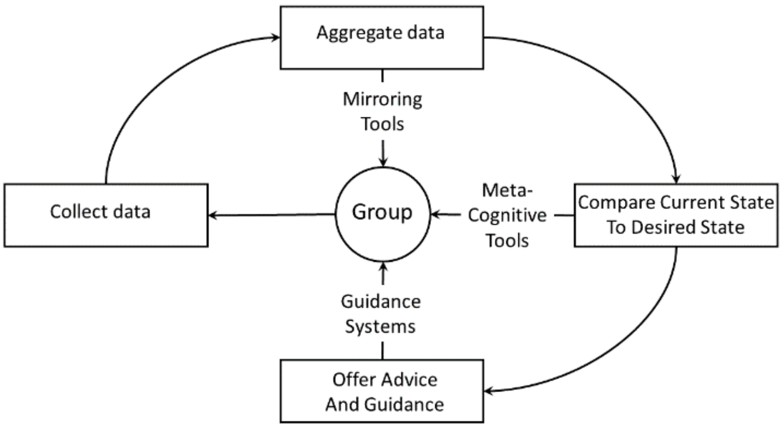

Figure 1. Mirroring, meta-cognitive and guiding systems according to Jermann et al. (2001) and Streng et al. (2009), as cited in (Tausch, 2016)

From a Human–computer Interaction (HCI) perspective, a feedback loop works like a self-correcting system (Dubberly et al., 2009); Information is flowing back and forth between the system and the person. The person acts to achieve a goal and provides input to the system; she measures the effect of her action through the system's feedback; then compares the result with the goal. The comparison directs her next action, starting the cycle again.

In a conceptual model of collaboration by Martinez at al., (2021), authors argue that the use of log data to identify key indicators of collaboration and teamwork has enabled new ways of predicting outcomes and personalizing feedback on a real-time basis. In their paper, by citing different publications, Martinez and colleagues provide many examples. For instance; Reimann, Yacef, & Kay (2011), used log data to understand the way of groups working in synchronous/asynchronous settings; Perera, Kay, Koprinska, Yacef, & Zaïane (2008) used data log to characterize effective collaboration; Rosé et al. (2008), applied log data in argumentation; and Kay, Maisonneuve, Yacef, & Zaïane (2006), used log data in teamwork. Previously, Schwind and Wegmann (2008) in the field of software development networks, used socio-technical network analysis as an approach to data-driven collaboration measurement. They extracted data from three sources; code classes, e-mail traffics, and versioning data derived from databases. We used a data-driven approach but a new straightforward design. Figure 2 represents the system schema; inputs are time, data, and attendance elements based on frequency and

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volume (See section 3), then Active Participation (AP) and Shared Responsibility (SR) which are crucial building blocks of collaboration (Griffiths et al, 2020) are calculated. In the next step, a visual quantitate report is available as feedback. We are expecting a higher level of collaboration and better teamwork results after utilizing these outputs. According to Griffiths A.J. (2020) AE is emerging from SR and AP. SR refers to the idea that each member of the collaborative design team contributes his/her own abilities/experience/knowledge with a unique role in preparing possible solutions for the project's sections. It defines personal roles and responsibilities for each member within the team with a sense of common ownership for the outcomes (Griffiths et al., 2020; Hallam et al., 2015; Tucker and Schwartz, 2013). AP refers to the acknowledgement and consideration of the inputs and opinions of the members who are part of the collaborative work, in which transparency and free exchange of information are required (Arias et al., 2016). SR involves each individual's unique role, AP needs that team members together contribute to providing necessary materials for the project (Cowan et al., 2004; Griffiths et al., 2020). The assumption is that, a feedback system improves AE and, therefore, the collaboration. Based on the discussed topics, this paper proposes and examines three main hypotheses: First, AE is meaningfully correlated with collaboration. Second, AE is automatically measurable through analysing log data in collaborative platforms. Third, visualized results from log analysis (hypothesis 2) is useful in preparing team performance reports and creating a computer-mediated feedback system.

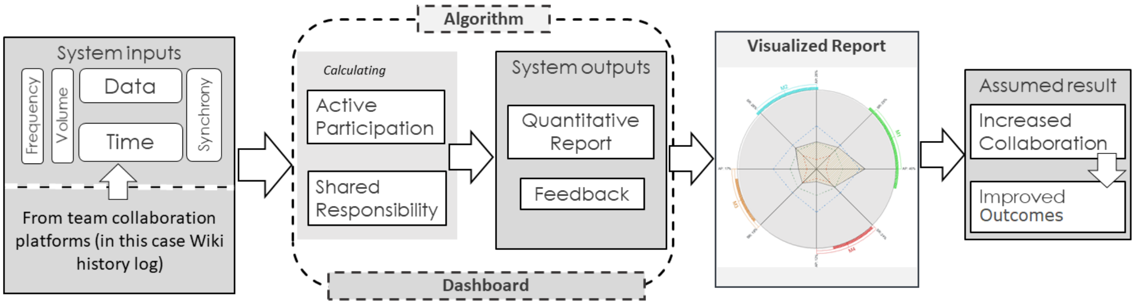

Figure 2. The system inputs and outputs

3 MEASUREMENT CRITERIA

Results from research suggest that work engagement positively relates to innovative employee behaviour, mediates the relationship of leader-member exchange and perceived organizational support with innovative work behaviour (A. Agarwal, 2014). As described in the previous section, AE includes Active Participation and Shared Responsibility. To calculate these two measures, we use data stored in the history logs. A history log of the collaborative platforms in which the team is working, provides detailed data of the person who did contribute to the document, including time, task, and volume of data. Table 1 summarizes all the criteria and formula to calculate each item. To define the weights, we interviewed a group of students (5 PhD and 5 Master engineering students) and asked them to weigh each item based on the importance from 1 to 4, in which 1 corresponds to a 25% weight, and 4 corresponds to 100%; after gathering opinions, we allocated the average defined weight to each item. In table 1, ID is an abbreviation made from the first letter of the criteria's column label (e.g. 'APD' represents 'A'ctive 'P'articipation in 'D'ata). In the last two rows, the equations to calculate the total engagement based on these criteria are presented.

Table 1. Measurements' details

Criteria	ID	Unit	Weight	Formula
Active Participation in Data	APD	Byte %	50%	The total volume of data in Bytes entered in the time period; date 1 to date 2 (e.g., one week from 8:00AM, 10/22/23 to 12:00PM, 10/29/23)
Active Participation in Time	APT	Day %	25%	The number of days that the contributor recorded an activity in the specified time period (e.g., if during a week a member worked on the project on Monday, Tuesday, and Friday, this measure is 3)

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Active Participation in Revision	APR	No.	25%	The total number of times that the contributor has edited the document and the log recorded an activity (e.g., if a member was active 10 times on Monday, 8 times on Tuesday and 5 times on Friday to save the document with changes, this measure equals to 10+8+5=23)
Shared Responsibility on Sections (Tasks)	SRS	%	25%	The number of tasks that a contributor worked jointly in the specified time period (i.e., the contributor recorded activities on the same task with one or more other contributors)
Shared Responsibility in Time	SRT	No.	25%	The number of times in which the contributor worked jointly on the same task in the specified period (i.e., the recorded log has the same time stamp(s) with one or more other contributors)
Shared Responsibility in Networking	SRN	%	50%	The total number of members who the contributor worked with in the same task in the specified period
Total Active Participation	AP	%	100 %	APD+APT+APR
Total Shared Responsibility	SR	%	100 %	SRS+SRT+SRN
Total Active Engagement	AE	%	100 %	(AP+SR)/2

4 CASE STUDY

To examine the validity and test the effectiveness of the method, we designed two case studies. In study one, we had access to the history log of four teams of engineering students in a technology planning and road-mapping course while documented all the project activities on a Wiki page as a collaborative platform for delivering the course requirements. In this section, we report the first study and its results. The second case study was designed to further validate the application of the method in a project-based learning (PBL) design course and the results are published in a journal paper (Farshad & Fortin, 2023).

4.1 Project and participants

In the first study, a group of PhD and MSc students in a learning-by-doing Model-based Systems Engineering (MBSE) course, had to define the technology planning and road mapping stages in a particular domain and document the entire progress in a collaborative Wiki page. The stages included the following tasks; defining the scope of the project, clarifying technology vision and current state of the art, creating a timeline, preparing the system model, defining figures of merit, doing the relevant literature review, exploring intellectual property databases, examining technical feasibility, conducting financial valuation and market research, doing risk and uncertainty analysis, and finally providing scientific references with citations.

After gathering the data from logs of projects and applying the method, we prepared a report and sent them to all team members. The definitions and graphs were presented to all the teams beforehand. In the reports, we did not include any name; instead, we used letters in alphabetical order and asked the team members to guess which letter is representing them and the other members' roles. To reduce the bias of answers, we promised a reward (the reward not mentioned) to correct answers. Figure 3 shows a sample report for one of the teams. Figure 4, presents questions and responses. The report included two pages; on the first page, they could find the project name, the graph with a guide and a short explanation of the performance of each member. On the second page, all the teams' graphs were pictured without additional information. Table 2 shows the projects and the teams. We used email to send the reports and a link to a Google form in which the questionnaire was designed. In the form, after filling in personal data and selecting the project name, the first question was the following: which letter in the report do you guess represents your role in the team? Answering by selecting a letter from A to D in a dropdown response (see Figure 3; Page 1/2). Question two, asks to guess the letters representing the other member's roles. These two questions allow us to assess the accuracy. If participants can guess the answers correctly, we can conclude that the measurement is more likely to represent the collaboration quality. In the next three questions (Figure 4), participants were asked to

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score the accuracy/usefulness of the metrics through a linear answer from 1 to 10. In the end of the questionnaire, participants were asked to comment if they wished. We received 8/15 answers and four comments, which will be discussed later in the paper.

Table 2. Projects and teams

Team	Project Name	Members			
		Gender	Degree	Field of Study	Age
1	Automatic optical waste sorting	F	MSc	Manufacturing Engineering	23-31
		F	MSc	Engineering Systems	
		F	MSc	Manufacturing Engineering	
		M	PhD	Data Science	
2	3D Printing In Space	M	MSc	Space Engineering	
		M	PhD	Mechanical Engineering	
		M	PhD	Materials Science	
		F	MSc	Manufacturing Engineering	
3	Mars Exploration Robots	M	PhD	Petroleum Engineering	
		M	PhD	Data Science	
		M	PhD	Engineering Systems	
4	Electrochemical Energy Storage	M	PhD	Data Science	
		M	PhD	Materials Science	
		M	MSc	Physics	
		M	PhD	Engineering Systems	

As shown in Figure 3, the report includes a visualized engagement level for each person and an explanation of each member's role. The colours also represent the level of engagement, from high to low respectively; Green, Cyan, Orange, and Red.

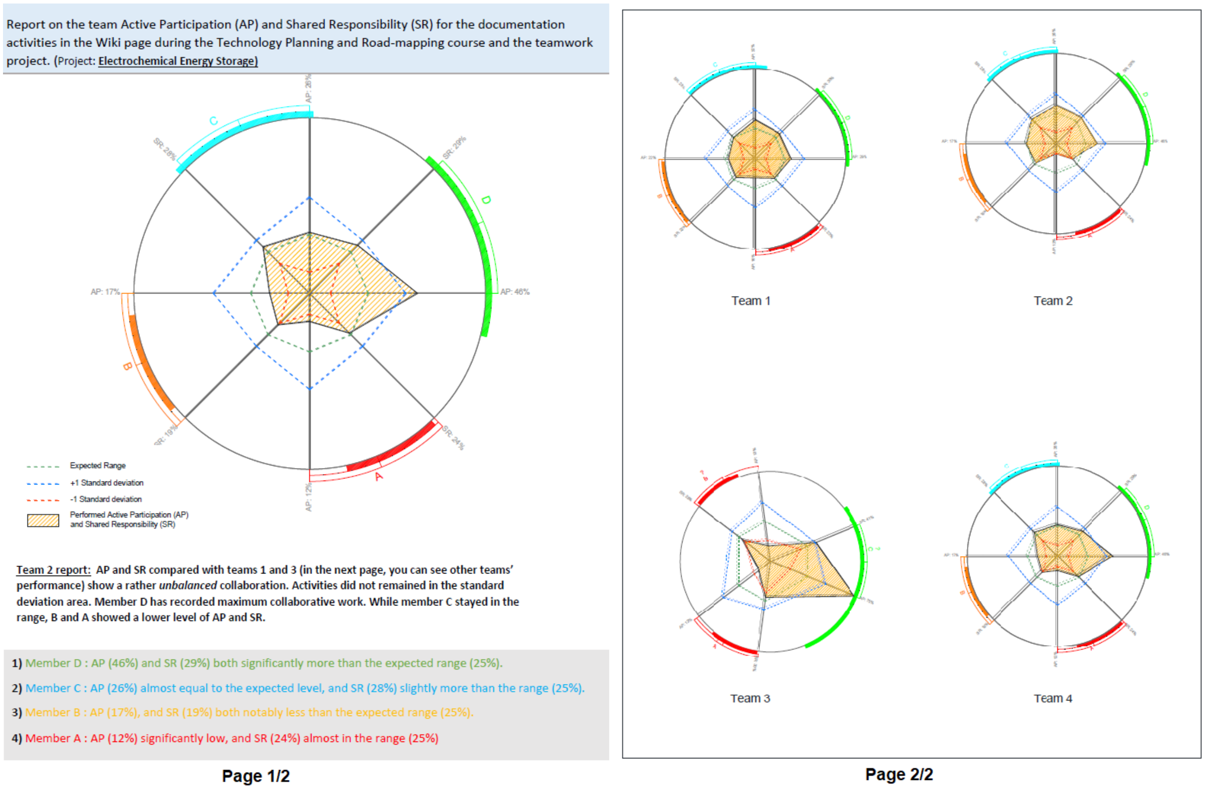

Figure 3. Page 1/2, a report of team collaboration performance. Page 2/2, all teams' graphs.

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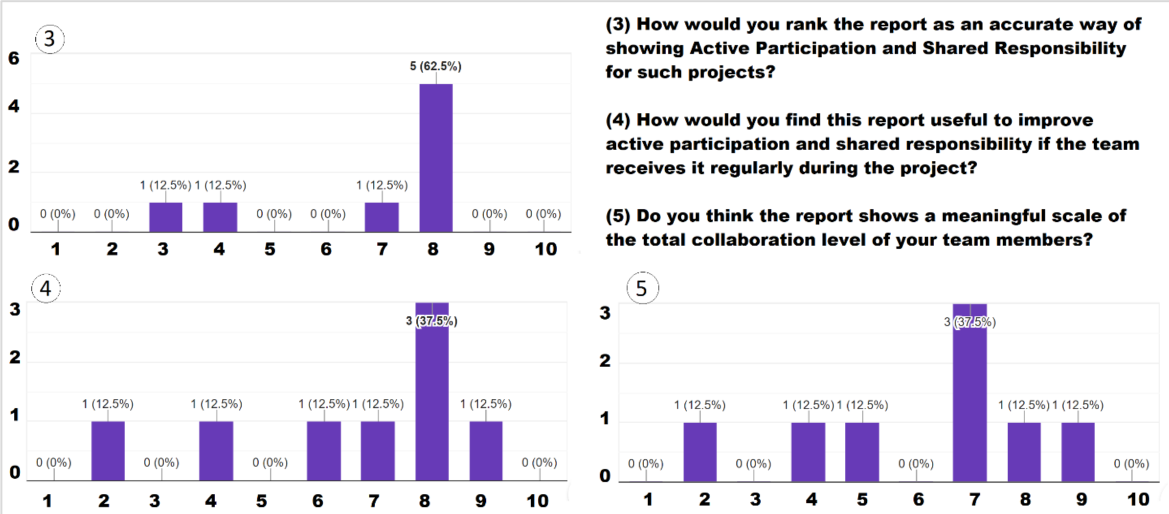

Figure 4. Questions and responses to scoring the metrics

4.2 Results

Based on the received answers, except for one case, all the participants guessed their roles and other team member's positions correctly, which corresponds to 87.5% of correct answers. 75% of participants believe that the accuracy of the report for showing the team engagement level is 70 to 80%, while 25% believe it to be 30 to 40%. To determine the possible usefulness of the report, in case a team receives it gradually during a project, nobody thinks that it is completely useless and 75% believe that the usefulness is higher than 50%. At the same time, 62.5% see the report as a meaningful scale of total team collaboration, while 37.5% evaluated it at below 50%. We have noticed a notable difference in answers between the participants who recorded a high level of engagement with those counterparts who participated less; highly engaged members scored the report to be accurate, useful if they had it during the project, and meaningful to show the total collaboration. Moreover, recorded comments revealed some important points that will be discussed in the next section.

5 DISCUSSION

This study investigated the idea of measuring AE as an indicator to monitor and improve collaborative work. It also examined the feasibility of designing a collaboration measuring and monitoring toolkit in e-collaboration platforms. Next, it proposed a novel approach by designing a data-driven model. The results of the case study support the main hypotheses: First, we found a meaningful correlation between AE and collaboration in web-based engineering design teams working collaboratively on wiki platforms; this is in line with previous research that showed the possibility to monitor wiki-based team engagement over time (Berthoud and Gliddon, 2018). Second, AE is measurable through analyzing log data, with the possibility of an algorithmic procedure on a real-time basis. Third, teams welcome a feedback system illustrating team performance and engagement. While previous studies on evaluating collaboration, mostly relied on questionnaires, interviews, surveys, etc., (For instance, see: (Briggs and Murphy, 2011; Hamalainen, 2008; Jeffares and Dickinson, 2016; Marek et al., 2015; Prochaska et al., 2021)), we believe that data-driven analysis is a more optimum approach toward e-collaboration measurement in digitalized teamwork. The tendency towards a data-driven computer-based measurement is grounded on several reasons: first, although the increasing progress of web-based teamwork makes collaboration more complex, it creates an opportunity to access the needed data to analyze activities through recorded logs. Second, the report can immediately show the on-going status, anytime, anywhere. Further, it will facilitate research on e-collaboration. In addition, it makes computer-mediated feedback feasible, quick, and low-cost. Finally, such an approach paves the way for utilizing state-of-the-art technology and Artificial Intelligence systems to improve collaboration and teamwork.

The case study results showed that providing meaningful insight into the general state of team collaboration is possible through the analysis of log-data. Even though a significant percentage of the participants in the survey believe that receiving feedback is useful during teamwork, this aspect requires further investigation. The comments received from the participants are generally centred

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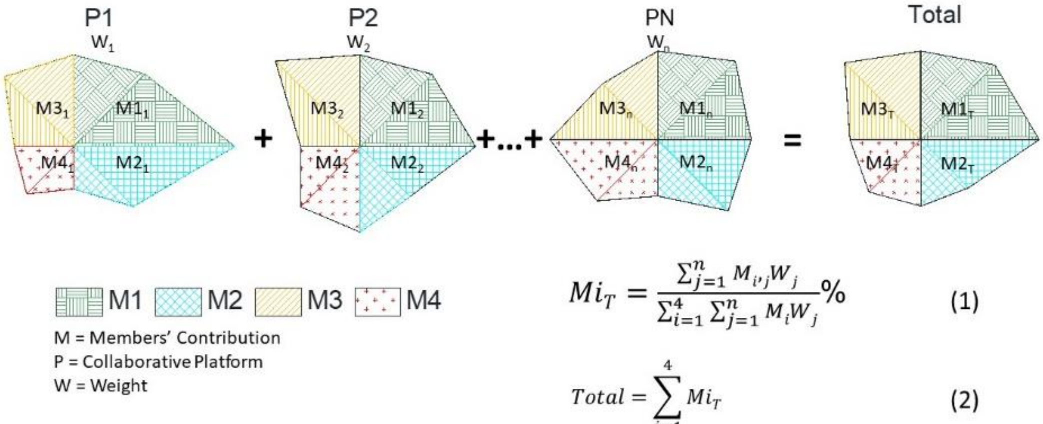
around the same concern: They believe that while the report gives an acceptable profile of working on the wiki page, it could not completely cover all the teamwork, because they had been active in other platforms as well (e.g. Google docs, Zoom session, Telegram chats, etc.). Our team was aware of this valid objection prior to the study, however, at least two points are worth mentioning here: (a) we had not intended to measure the entire collaboration; instead, we tested the feasibility of facilitating the measurement on a specific portion of the collaborative work and correlation of AE with the general collaboration. (b) If we could do the first step successfully and find meaningful correlations, then we will be able to expand the system outside of one specific platform. To achieve this, we propose to apply the approach to multiple platforms. To give an example, Figure 5 illustrates a team of four members working on N different platforms, each with a different pattern of engagement and different weight or importance, in which members can agree on the weights (W). Then, the performance of each member is determined for each platform. Finally, to define the overall scale of engagement, equation 1 will calculate the total activity, and equation 2 can be used to calculate the whole team performance.



$$Mi_T = \frac{\sum_{j=1}^{n} M_{i,j} W_j}{\sum_{i=1}^{4} \sum_{j=1}^{n} M_i W_j} \% \qquad (1)$$

$$Total = \sum_{i=1}^{4} Mi_T \qquad (2)$$

Figure 5. An example of four team members working in N number of collaborative platforms.

With an Application Programming Interface (API), we can integrate and unite all the platform results. One of the problematic issues is computing data from communication platforms; we are currently working on a machine-learning technique to address this issue through tracking the conversations and mapping the engagement based on text-classification approaches and online communication features such as word counting, replies, file sharing, etc.

Regarding security and confidentiality concerns, the data log used in this study did not contain any of the design detail or documentation content. This type of log record only contains meta-data, such as names, data volumes, time stamps, and the titles of the tasks (sections). However, to secure their identity, team members are able to create a desired username to stay anonymous from external viewers. At the same time, an access control model with specific policy enforcement will increase the security of meta-data in cloud-based collaboration (Spyra et al., 2016).

Although the study is novel and the findings show promise, it faces limitations. Technically, the equation to measure AE (through AP and SR) on some occasions might return inaccurate results. For example, when a contributor frequently adds wrong information and another team member corrects all the wrong statements at once. However, this can be addressed through a revision tracker mechanism, where the first contributor's acceptance of the revision would lead to an extra score for the second member. Another issue might happen when teams are made up of different roles; in this case, a weighting strategy for each role or a coefficient factor based on a predefined measure for different responsibilities/work types would mitigate likely misevaluations. Another issue might occur when the team members are located in different time zone, though an automatic time converter to Coordinated Universal Time (UTC) would solve the problem. Furthermore, cited by Driskell et al. (2010), McGrath (1984) describes four major types of team tasks in a team task taxonomy: (1) choosing or decision-making tasks, (2) negotiating tasks, (3) executing tasks, and (4) generating tasks. This study may have primarily targeted executing tasks, where performing a manual or psychomotor task by the team members is required; however, we do not know how the other three tasks may or may not have been reflected in the measurement.

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6 CONCLUSION AND FUTURE WORK

The importance of collaboration to solve today's complex problems is evident, and e-collaboration is becoming the dominating practise of teamwork due to the rapidly growing trends of digital engineering practices. We believe that our approach and the presented model facilitate designing and implementing data-driven dashboards in e-collaboration tools, as well as opens the door for more investigation on different aspects of improving e-collaboration.

Our case study represents a first step to implement such an approach and more in-depth work is required to improve the approach validity. At the same time, technological advances in artificial intelligence, machine learning, and natural language processing techniques may help to improve the solution. Integrating the measurement from multiple resources to obtain a comprehensive collaboration level is another open area for research. Further research is also required to investigate how feedback on engagement helps teams to develop better designs and solutions for our world's crucial problems.

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