Enhancing Collaborative Design through Process Feedback with Motivational Interviewing: Can AI Play a Role?

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Abstract. Collaborative design is a key element in Product/System development. However, delivering true collaboration in multidisciplinary teams is challenging. Feedback systems are one of the solutions to improve collaboration; although teams normally receive feedback on outcomes, the collaboration process itself is neglected. During a PBL course, 40 engineers from 22 disciplines and 12 countries were distributed in six teams. In addition to receiving outcome feedback, we used Motivational Interviewing (MI) techniques to provide process feedback for half of the design teams whereas the other half only received outcome feedback. At the same time, we employed a pre-trained Machine Learning (ML) technique to compare the teams' progress through teams' communication and sentiment analysis. Our results show that; (i) adding process feedback in the early stages of the design process enhances the collaborative design. (ii) ML algorithms can predict the progress. We suggest further research using Natural Language Processing (NLP) and supervised ML techniques for designing a new AI team-mate and mentoring assistant, as well as fostering Human-AI interaction styles via MI methods.

Keywords: Collaborative Design, Feedback, Machine Learning, Motivational Interviewing, PBL

1 Introduction

In the universal competition between companies, developing new products has become a tough challenge where innovation and collaboration in the design process are two primary keys to success, and design projects depend on controlling the collaboration among the multidisciplinary actors [1]. According to surveys [2], 40% of engineering time is directly impacted by the ability to work together. Moreover, engineering efficiency as a top goal for product development success is significantly dependent on effective collaboration. In addition, many companies struggle with poor collaboration and its cost has never been higher. However, in the process of product and system development, which is following the Systems Engineering (SE) methodology, the issue of ensuring effective team collaboration is rarely addressed even though it is widely accepted as necessary [3]. SE aims to enable the successful realization, use, and retirement of engineered systems. Still, in the SE models (e.g., V-model) the focus is on the baselines, documents, reviews, and audits of the technical process [5], not on the collaboration process. Based on such a procedure, reviews and feedbacks target the evaluations of the design to ensure compliance with the technical requirements (Verification), and the stakeholders' needs (Validation), while the team interactions are not reviewed. In general, in design teams and PLM systems, no feedback is provided on the collaboration process of the design team itself. At the same time, interaction issues appear to be the most fundamental arguments concerning collaborative design, particularly when computer systems such as PLM systems are used in the process [6]. One of the effective strategies to improve interaction is MI, a guiding and mentoring style of communication [7] that is not sufficiently covered in engineering and design studies. Meanwhile, Artificial Intelligence (AI) is able to identify emotions and intentions of human interactions through ML using NLP techniques [8]. Now the question is how can we improve collaborative engineering design using AI capabilities, interaction improvement techniques, and process feedback in SE and PLM systems environments? To address this question, in this study we employ MI to empower team members to facilitate the process of collaboration during an SE project. Then we compare the progress in a case study including two groups of test and control teams to examine the effectiveness of MI in a team process feedback on the engagement and the final SE project outcome. At the same time, we test the predictability of the process through pre-trained machine learning techniques that opens doors for further development of team support through intelligent systems, particularly in collaborative design learning. This is important because in large-scale engineering design projects where hundreds and sometimes thousands of collaborators are working on the same project, the use of human support interventions through human agents are, if not impossible, very costly and difficult to scale. However, an AI agent that can handle this progress can possibly turn it into a cost-effective and highly scalable approach. Based on these, the hypotheses of this research are: (1) Using MI as a method in process feedback can significantly improve collaborative design in a design project. (2) AI can predict the progress through pre-trained ML and NLP techniques by teams’ sentiment analysis.

2 Literature review

This section first summarizes evidence on the improvement of collaborative design. It then explains the use of the MI and its significance. Next, the AI capabilities in detecting interaction sentiment are described. Finally, some research on using AI for the application of MI in human-AI interaction is explored.

2.1 Improving Collaborative Design

Research on collaborative design mostly investigated the technical side of collaborative design such as design, engineering, and manufacturing through computer-aided approaches [9]–[11], web-based systems [12], [13], or information sharing systems and enterprise resource planning [13]–[15]. Management, social and cognitive aspects have also been studied [17]–[19]. However, evidence indicate that the non-technical dimension of collaboration is the main effective factor in engineering projects [20], it has also been documented that early in a project's life cycle, when the conceptual design is being developed, non-engineering factors are most likely to influence the system's design [21]. Wang et al. [20] showed that the team collaboration atmosphere is the most significant factor, followed by the ability of collaborators to learn in terms of team efficacy in collaborative design. Wang et al. suggest that the human interaction process is one of the most influential elements of collaborative design. Stempfle & Badke-Schaub [22] investigated collaborative design challenges, focusing on the cognitive processes of design teams during the design process. They analyzed the entire communication of three design teams and concluded that teams spent about 70% of their interaction on the content, and 30% on the group process.

2.2 Motivational Interviewing (MI)

MI is a communication strategy and mentoring style that has been investigated in various settings including leadership and management [23]–[25], sport and human coaching [26], healthcare [27], higher education and training [28] etc. MI is an evidence-based evolution of Rogers's person-centered counseling approach, a directive method to enhance readiness for change by helping people explore and resolve ambivalence [31]. The rapidly growing evidence for MI indicates its significant effectiveness in various systematic reviews and meta-analyses [30]–[34]. The high effectiveness of MI across various settings suggests a need to understand and apply this style in collaborative design and engineering. Miller & Rollnick [35] in their book "Motivational interviewing: Helping people change" define MI as follows:

"*MI is a collaborative, goal-oriented style of communication with particular attention to the language of change. It is designed to strengthen personal motivation for and commitment to a specific goal by eliciting and exploring the person's own reasons for change within an atmosphere of acceptance and compassion*."

The fundamental elements of MI consist of three qualities [36]: (i) MI is a guiding technique of communication that lies between active listening and guiding through giving information. (ii) MI is designed to empower people to change by discovering their own meaning, values, and capacity for change. (iii) MI encourages a natural changing process and respects individual autonomy through a respectful, curious approach. According to Miller & Rollnick, in the MI method, the mentor interacts with the person as an equal partner and avoids unrequested advice, directing, confrontation, warnings, or instructing. It is not a way to "get people to change" or techniques to push people and impose on the conversation. The principles and skills of MI can be applied in a variety of conversational contexts, but MI is especially useful in the following situations: (a) High ambivalence, where people are stuck with vague feelings about change. (b) Low confidence is when people have doubt about their ability to improve. (c) Low desire, when people are not sure if they want to make a change or not. (d) Low importance, when the advantages of change and the disadvantages of the current situation are not clear.

As cited in [37], based on the Miller and Moyers method, the acronyms OARS and EARS are used to summarize the idea for acquiring MI. OARS and EARS refer to Open-ended questions/elaborating, Affirmations, Reflective Listening, and Summaries.

Klonek & Kauffeld, [37] use a metaphor to describe the application of the OARS; the verbal skills of the MI idea can be compared to the oars on a boat, which the trainees use as dynamic micro-tools within verbal interaction (Figure 1). The OARS of a boat help the trainee safely go across the river, similar to basic communication skills that help interaction go smoothly. Dynamic interactions with a conversational partner are represented by the river. The rock in the river represents resistance to change. "To roll with resistance", not confrontation with it, is one of the main principles of MI.

Fig. 1. The metaphoric meaning of OARS as micro-tools to navigate through a dynamic interaction (i.e. river) in a conversation (Klonek & Kauffeld, 2015)

Klonek & Kauffeld [37], showed that MI is significantly effective in verbal communication skills, increases motivation to interact, and reduces the confrontational behaviors of engineering participants.

2.3 AI application in Sentiment Analysis

Sentiment analysis through conversations using AI is an emerging and yet challenging approach that aims to discover the emotional states and their changes in people participating in a conversation. There is a wealth of information in the interactions that affect speakers' emotions in a complex and dynamic manner, and in recent years many promising studies have been conducted on how to accurately and comprehensively model these complex interactions [38]. As chatbots are common in everyday life and their role in teamwork is becoming more important, in a study on emotion recognition through conversations sentiment, Majid & Santoso [39] developed a chatbot called Dinus Intelligent Assistant (DINA) to assist student administration services. The study used datasets of textual-based content of conversation dialogues. They preprocessed the conversations using sentiment analysis and then applied neural networks to categorize the emotions. The result showed an accuracy of 0.76, meaning that the algorithm can reliably recognize emotions from text-based conversations. Dehbozorgi [40] used sentiment analysis on verbal data from team discussions to create an indicator for individual performance. The study conducted a successful attitudinal components detection that correlates with performances through NLP algorithms.

2.4 AI and MI

One of the advantages of MI is the possibility to employ its techniques through AI and ML in chatbots. Hershberger et al. [41] developed and tested a training tool to assess dialogue in MI that uses NLP to provide MI metrics. The study objective was to implement MI more widely in a manner that can provide immediate and efficient feedback for MI training. The results of this study that was conducted in a therapy setting, showed that MI metrics can be detected by AI. The developed model produces metrics that a trainer can share with a student, or clinician for immediate feedback, while it decreases the need to rely on subjective feedback and time-consuming review procedures. Almusharraf et al [42] trained, and tested an automated MI-based chatbot that is capable of drawing out reflection and generate MI-oriented responses in a conversation with cigarette smokers. The chatbot could stimulate reflections on the pros and cons of smoking through MI techniques.

3 Methodology

This study incorporates a multi and interdisciplinary research literature review, along with a case study conducted during an eight-week SE course, where we established a test-control group setup to compare and evaluate the effects of variables. To observe the normal distribution, the teams were equally distributed based on expertise, gender, project of interest, and nationality. The students went through an SE learning process, according to NASA and INCOSE handbooks using a Project-based Learning (PBL) approach. The test (experiment) group consisted of teams with lowest grades during the Preliminary Design Review (PDR). Pre and post-intervention results were compared using data graphs and statistical analysis by comparing the PDR with the Critical Design Review (CDR) grades. The intervention consisted of using MI techniques in the test group through brief interviews and short talks. The study was double-blind, meaning that neither the experiment/control group nor the review team was aware of the ongoing research. To compare the text-based sentiment of the teams, we used the Google Cloud Platform (GCP) to perform a sentiment analysis that evaluates a given text and identifies the overall emotional opinion within the text, particularly to determine a writer's attitude as positive, negative, or neutral [44]. We used the pre-trained Natural Language features of GCP. The document sentiment includes the overall sentiment of the text that consists of Score and Magnitude; a score of the sentiment ranges between -1.0 (negative) and 1.0 (positive) and corresponds to the overall emotional tendency of the text. The magnitude indicates the overall strength of the emotion (negative/positive) and, (Figure 2). At the end of the course, all participating teams were asked to export all chat conversations to a single file to be used in the analysis (Only if all team members agreed). The research team undertook to respect privacy so that the names are coded, and the conversations are not to be published without permission. One of the participating teams refused to share the content and is excluded from the study, but this issue did not have a negative impact on our study as both the test and control groups had three teams at the end. For each period, the entire conversation was analyzed and the average sentiment score for the given period was extracted.

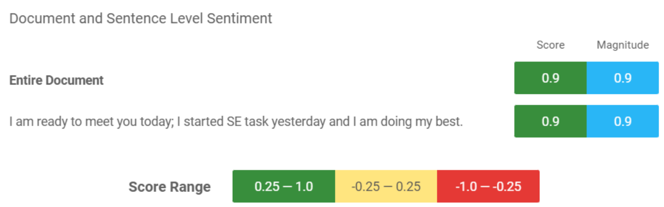

Fig. 2. An example of one sentence sentiment level (areas: Green; Positive, Yellow; Neutral, Red; Negative)

4 Case study

The Northern Sea Route (NSR) is a shipping route that crosses the seas of the Arctic Ocean. Annual cargo shipments on the NSR are up to 33 million tons mainly as an energy highway for the export of hydrocarbons and other natural resources [45]. The NSR has nine main ports, and each port has different levels of resources. With the aim of improving the shipping process on the NSR, the following SE projects were defined to the teams: (1) Spare part delivery from the main ports to ships with measurements of temperature, pressure, winds, and visibility on the route using Unmanned Aerial Vehicle (UAV). (2) Charging station, interaction with UAV, and navigation. (3) Port fuel transfer automated system in all weather conditions. (4) Ambulance system for emergency evacuation from ships based on a UAV system. (5) Emergency drug delivery to a ship or port based on a UAV system. (6) Coordination of various UAVs to carry out different tasks, to the ports and/or the ships; central coordination system. (7) Satellite communication and observation along the sea route in all weather conditions with monitoring of ice thickness and prevailing winds. Participants had the chance to select three projects of interest in order of priority. The deliverables for each review stage were according to the "V model" of SE. Totally, 46 engineers from 22 disciplines and 12 countries were distributed in seven teams after filing out a form containing their demographic information, degrees, expertise, and favorite project. Three teams were included in the test and four teams in the control group. One of the control group teams, consisting of six members, was excluded from the study. The final number of participants in each group was 20 individuals, organized into two teams of seven and one team of six.

5 Results and analysis

While the PDR results of the test group with a mean grade of 68% were lower than in the control group which had a mean of 72%, this difference statistically is not significant (Independent T-Test with 95% confidence: 0.27>0.5). However, a comparison of the CDR results indicates that both groups showed improvement, but the difference is significant (Independent T-Test with 95% confidence: 0.017<0.5). Figure 3 shows the comparison of the two groups. The data-mining process for analyzing the text-based conversation reveals that both groups stayed in the Neutral area with no significant differences. The entire conversations of all teams from the start day to the PDR were analyzed and the average grade was calculated. The results show -0.08 and -0.04 respectively for test and control group. The same process was repeated over the time span from PDR to CDR. Figure 3 illustrates the results. As the graph shows, the results of text-based sentiment analysis using AI and the results of changes in scores in CDR are meaningfully correlated.

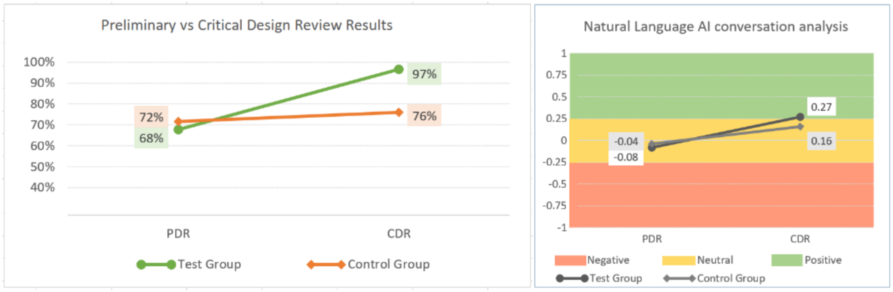

Fig. 3. Left graph: Test and Control groups' grades in PDR and CDR; Right graph: Sentiment Analysis with Google Cloud Natural Language

6 Discussion

While previous research to improve collaborative design in engineering has mainly focused on technical aspects, non-engineering factors are likely to influence system design the most, particularly in the early phases. On the other hand, positive interpersonal relationship enhances individuals' enthusiasm for collaboration. A large body of research confirms the significant positive influence of MI as a communication strategy and mentoring style. Although MI is effective, it is not easy to employ it in collaborative engineering projects or educational PBL with a large number of participants. However, AI advances using ML and NLP shows promise toward using an automated intervention through chatbots or other Human-AI interactions. However, this topic has not been studied in engineering, especially in the field of collaborative design and PBL. The case study results show a significant positive effect of MI in improving collaborative engineering design in SE and PBL outcomes. This is in line with previous systematic analysis about the positive influence of MI to improve interactions (e.g., [32] and [33]); however, the effect of using MI in a process feedback on collaborative design had not been studied before. This result supports the first hypothesis of the study. In addition, the second hypothesis is also supported by the results. This is in accordance with previous studies that investigated the application of speech analysis in predicting performance [46]. Although pre-trained AI detects the overall sentiment of the team, it is not able to recognize the engagement quality and collaborative process, however, a supervised ML that has been specified to classify speech according to collaboration activities, can increase the quality of monitoring.

7 Conclusion

Improving collaboration is a widely recognized need, however, it is challenging, expensive, and faces the issue of scalability. Improving interactions is one of the most effective ways to support team collaboration, and MI has proven to be an effective strategy for enhancing interactions. We also demonstrated its effectiveness in engineering design and PBL and suggested that state-of-the-art technology has the potential to further develop it. This paper is icebreaking from different perspectives and opens the door for future studies. First, it reveals the significant effect of Motivational Interviewing as a way to improve interaction and therefore the design in engineering collaborative design and project-based learning. Second, sentiment analysis is a powerful tool to recognize the team's challenges and track the changes after interventions. Third, the literature review results show a promising capability of AI as a new member of engineering teams that can monitor interaction and start mentoring through MI techniques, which is a part of our outlook for future studies. This point is also important in the Human-AI collaboration because it provides a basis to identify an effective interaction style of an intelligent machine with its human colleagues.

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