Skolkovo Institute of Science and Technology

Improving Collaborative Engineering Design and Learning through Feedback Systems in the Age of Digitalization and AI

Doctoral Thesis
By
Sabah Farshad

Doctoral Program in Engineering Systems

Supervisor
Professor Clément Fortin

Moscow, 2024

I hereby declare that the work presented in this thesis was carried out by myself at Skolkovo Institute of Science and Technology, Moscow, except where due acknowledgement is made, and has not been submitted for any other degree.

Sabah Farshad

Prof. Clement Fortin

Improving Collaborative Engineering Design and Learning through Feedback Systems in the Age of Digitalization and AI

By

Sabah Farshad

Submitted to the Skoltech Center for Digital Engineering on 20th June, 2023, in partial fulfillment of the requirements for theDoctoral Program in Engineering Systems.

Last updated on 6th February, 2024

Abstract

Collaborative engineering is one of the fundamental elements of developing complex engineering systems. Designing and developing most engineering projects/products is impossible without collaboration among teams from diverse disciplines. While substantial evolution of technical aspects of collaborative design such as web and cloud-based technologies has significantly facilitated communication, information flow, and remote teamwork in recent decades, poor collaboration remained one of the main factors of project failures. At the same time, compared with research on technical elements of collaboration, little has been done to understand the non-technical aspects of collaborative engineering design and learning.

This research aimed to further identify non-technical and human-centered challenges of collaborative engineering design and learning, expand the understating of collaborative engineering design frameworks and concepts, and suggest solutions based on state-of-the-art technology to address the challenges. Mainly, to formulate measures and indicators of collaborative design and learning that are both helpful in collaboration management/improvement, and understandable to machines with two goals; firstly, to employ cutting-edge technology capabilities in improving collaboration by overcoming the limitations such as scalability and cost. Secondly, to develop the basis for more effective human-AI collaboration.

Using a systematic iterative approach in the research methodology, this work is based on several iterations of literature review, case study, and validation. A set of five successive case studies and a systematic review have formed the building blocks of the work, where each case creates the basis for the next one. All the cases have been conducted during Project-based Learning (PBL) in engineering design courses at Skolkovo Institute of Science and Technology (Skoltech). I developed a novel system to measure, visualize and monitor Active Engagement (AE) in cloud-based PBL in engineering design activities. Then I tested the methods validity in practice, after examining a complementary communication strategy to enhance the results, later in a collaborative work with data-science experts we designed and developed a Machine-Learning (ML) algorithm to predict AE in text-based communions.

The results of this study indicate that; (1) the increasing dominance of cloud-based and online collaboration platforms marks a transformative shift in the collaborative design and learning landscape. This shift provides opportunities for data-driven interventions. (2) Active Engagement (AE) is one of the major constructs of collaborative design and learning. (3) It is evident that learners do not participate at PBL with the same level; a notable disparity exists in their levels of AE. This unbalanced AE is a serious challenge within PBL; the conventional focus to provide feedback on deliverables/outcomes does not distinguish between more and less responsible participants in a collaborative effort. (4) AE is measurable through data driven analysis based on data-log records in cloud-based platforms. (5) Using a process-oriented feedback mechanism to reflect AE to teams is an effective way to moderate the issues of unbalanced AE; however, a conflict management strategy is required to enhance the design outcomes. (7) ML techniques based on text-classification methods are able to predict AE in BPL team's communication; in addition, cutting-edge technology in Artificial intelligence (AI) and Natural language processing (NLP) has the potential to play a game-changer role to address the issues of a process-oriented feedback such as scalability and limited resources.

Finally, future studies could extend this work to better understand and enrich the implication of the research findings in different areas. First, this work opens the doors for further research on human-AI interactions in collaborative design and learning; for example developing chatbots that are able to detect the team members' engagement and start interacting with designers/learners through communication strategies that have been investigated in this research. Second, the application of process feedback mechanism in design learning within PBL settings, e.g., how using gamification methods would affect the results of a feedback system. Third, to repeat the research in real-work design teams.

Publications

Main author

1. Sabah Farshad and Clement Fortin. 2021. “Distributed Cognition Transformation in Complete Online System Engineering Design Teaching.” *Proceedings of the Design Society, Volume 1: ICED21, August 2021, pp. 1313 - 1322*. https://doi.org/10.1017/pds.2021.131

2. Sabah Farshad and Clement Fortin. 2022. “A Novel Method for Measuring, Visualizing, and Monitoring E-Collaboration.” *International Journal of E-Collaboration* 19 (1): 1–21. https://doi.org/10.4018/IJeC.317223.

3. Sabah Farshad and Clement Fortin. 2023. “Active Engagement in Collaborative Design: How to Measure and Use It in a Feedback System?” *Proceedings of the Design Society , Volume 3: ICED23 , July 2023 ,* pp. 455 – 464*:* DOI: https://doi.org/10.1017/pds.2023.46

4. Sabah Farshad, Yana Brovar, and Clement Fortin. 2023. “Enhancing Collaborative Design through Process Feedback with Motivational Interviewing: Can AI Play a Role?” [Presented at *IFIP 20th International Conference on Product Lifecycle Management 9-12 July 2023, Montreal, Canada*]

5. Sabah Farshad, Evgenii Zorin, Nurlybek Amangeldiuly, and Clement Fortin. 2023. “Engagement assessment in project-based education: A machine learning approach in team chat analysis.” *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12381-5

THIS PAGE INTENTIONALLY LEFT BLANK

Acknowledgments

Concluding my doctoral journey has been a meaningful and enriching adventure, and I owe thanks to those who played a pivotal role in this accomplishment. My family has provided a reliable foundation of support, and my friends, some despite the distance, have been a constant source of encouragement.

Special appreciation goes to Professor Clement Fortin, my doctoral advisor, for providing me with the opportunity to pursue research aligned with my goal of enhancing engineering teamwork and collaborative learning. His ambitious vision and consistent encouragement motivated me to strive for excellence.

I would like to thank my community fellows and all Systems Thinking Group (STG) members for their constant inspiration and encouragement. I also wish to acknowledge Dr. Dominik Knoll, whose well-structured PhD thesis inspired me in the organization and formatting of my thesis.

This journey has reinforced the importance of embracing diverse perspectives and fostering a culture of professional growth, even in the face of contrasting examples. I offer my profound thanks to those individuals who, directly or indirectly, have become a source of inspiration and learning. Those who, by any means, have reminded me of the importance of openness and flexibility.

Finally, I express my sincere appreciation to the committee members, reviewers of my work, and jury members who played a crucial role in evaluating and shaping the outcome of my thesis. Their valuable insights and constructive feedback have been essential to refining my work, and I am genuinely grateful for their time and expertise in contributing to the success of this academic effort.

Note: In some portions of this document (15% - 25% of the entire text); Artificial Intelligence assistant, particularly Generative AI, has been used to improve, rephrase, shorten, or summarize the content. The technologies used include ChatGPT-3.5, Claude, Grammarly, Perplexity, and Bing AI.

Contents

List of Figures

List of Tables

Glossary

Active Engagement (AE) – The involvement and contribution of team members in a collaborative project or task. Composed of Active Participation and Shared Responsibility (p. 3, 4, 17, 18, 29, 45, 65, 77, 79, 80, 81, 87, 88, 90, 104, 105, 110, 118, 121, 123, 124, 132, 133, 135, 140, 141, 142, 145, 146, 147, 149, 152, 153, 154, 155, 156, 157, 158).

Active Participation (AP) – Team members contribute equally and accept specific roles, encompassing shared problem-solving, cooperation, and active engagement in the process. (p. 45, 57, 70, 73, 108, 109, 110, 136, 142, 149, 161).

Artificial Intelligence (AI) – Simulation of human intelligence processes and capabilities by machines (p. 4, 7, 29, 54, 67, 73, 90, 117, 126, 146, 148).

Chatbot – An artificial intelligence system designed to simulate conversation with human users via text or speech (p. 4, 28, 29, 31, 55, 67, 73, 130, 156).

Cloud-based– A web-based platform or service hosted on remote servers and accessed via the internet (p. 3, 4, 22, 40, 79, 101, 116, 132, 155).

Collaborative Learning – A pedagogical approach emphasizing learning through collaboration among students from diverse disciplines and backgrounds (p. 16, 21, 22, 28, 29, 31, 32, 50, 57, 58, 59, 60, 67, 68, 69, 73, 74).

Computer Supported Collaborative Learning (CSCL) – The use of technology to enhance and facilitate collaborative learning activities and experiences (p. 21).

Common understanding – Members of the team communicate and understand each other (p. 20, 45, 70).

Critical Design Review (CDR) – A formal review session to evaluate the maturity and completeness of the design solution (p. 96, 118, 120, 128).

Data Log – Record of user activities and metadata on a digital platform (p. 4, 51, 108, 116,).

Design Research Methodology (DRM) – A systematic framework for conducting design research involving clarification, descriptive study, prescriptive study, and descriptive study II (p. 32, 76, 78, 91).

Distributed Cognition – A theory proposing that cognition processes can be distributed across members of a group, internal and external structures, and over time (p. 87, 93, 94, 95, 103, 141, 145, 153).

E-Collaboration – Collaboration among individuals to achieve common goals using electronic technologies (p. 38-40, 42, 43, 50, 51, 71, 72, 84, 104, 114, 117, 123, 124, 146, 150).

Feedback System(s) – A system that provides input about performance, actions, or engagement back to an individual or team to guide improvements (p. 18, 29, 33, 35, 55, 58, 69, 73, 74, 77, 81, 84, 85, 88, 90, 104-109, 115, 123-125, 144-158).

Human-Computer Interaction – Interaction between users and computing devices and systems (p. 17, 36, 37, 70, 73, 93, 94).

Machine Learning (ML) – Algorithms and statistical models that allow computers to perform tasks effectively without explicit instructions, through learning from data patterns and experiences (p. 65, 85, 86, 90, 117, 125, 126, 132, 137, 141, 149, 154, 158).

Motivational Interviewing (MI) – An evidence-based communication strategy focused on strengthening motivation for change by addressing ambivalence in a collaborative, goal-oriented style (p. 17, 18, 52, 68, 72, 80, 89, 90, 125, 126, 131, 132, 141, 147, 148, 150, 154, 156).

Mutual respect – To value skills, competence, and knowledge of others (p. 46, 70).

Natural Language Processing (NLP) – A field of artificial intelligence focused on enabling computers to understand, interpret, and analyze human language (p. 4, 29, 55, 90, 117, 125, 126, 141, 149, 145).

Open communication – Open, honest, and transparent sharing of ideas helps prevent unnecessary conflicts (p. 45, 70)

Preliminary Design Review (PDR) – A formal review session to evaluate the maturity of the preliminary design solution (p. 96, 118, 120, 128).

Process Feedback – Feedback provided based on behaviors, actions, and engagement throughout a process (p. 17, 18, 56, 59, 64, 73, 80, 81, 85, 88, 89, 118, 119, 120, 123, 125, 126, 130, 141, 147, 153-156).

Project-Based Learning (PBL) – A pedagogical approach centered on learning through collaborative, real-world design projects (p. 28, 31, 57, 60, 68, 69, 73, 89, 11, 123, 131, 142, 148, 154).

Sentiment Analysis – The use of data mining and machine learning to identify and categorize opinions and emotions based on text data (p. 54, 55, 68, 73, 74, 125, 126-131, 141, 154, 158).

Shared decision-Making – The process in which the team systematically gathers input from all team members, fostering active participation throughout the decision-making process (p. 45, 70).

Shared Responsibility (SR) – Team members contributing based on their abilities and experiences with defined roles and a sense of mutual ownership (p. 45, 70, 108-110, 136, 142).

Shared goals – Mutually determined goals by the team in order to carry-out mutual outcomes that the team agreed-upon (p. 45, 70)

Telegram – A cloud-based instant messaging application used for communication (p. 41, 94, 99, 101-103, 115, 134).

Text Classification – Categorization of text documents into different classes based on their content (p. 28-31, 133, 137, 158).

Trust – Trust is built through the investment of time, effort, and energy in developing an effective communication system (p. 39, 46, 56, 70).

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 1

Introduction

To stay competitive in designing and developing complex systems on a global scale, relying on collaborative engineering is inevitable in today's highly connected technology-driven economy (Lu et al., 2007). Collaborative engineering involves multiple specialists working together to design and develop a system, subsystem, or component. In the last decades, digitalization has reshaped collaboration practices, and web-based technology has transformed interaction styles. Geographical limitation is no longer a serious barrier to forming teams of engineers or remotely participating in collaborative learning activities. However, despite the technological developments, poor collaboration remains one of the main factors of project failures (Boucher, 2020).

In recent years, the COVID-19 crisis significantly exacerbated the trends of online collaborative engineering and design teaching. This unprecedented shift raised the question of how it has led to a different approach among engineers and engineering students. Should we review the design strategies connected to teaching, collaborating, or managing the design process?

In the field of systems engineering and design, normally information at the level of systems and subsystems is distributed across a variety of specialists, and intensive cognitive work is needed to organize and integrate the data into a cohesive design successfully (Greene, Papalambros, & McGowan, 2016). Nevertheless, we are facing a major change in the trends of human-computer interaction, which brings even more complexity in the system engineering and design teams' collaboration, communication, and interplay. Engineering design professionals more and more facing the need to adjust themselves to interdisciplinary working conditions and multicultural team interactions (Gereffi et al., 2008). These are also valid for engineering students who are learning design in collaborative course.

The importance of preparing engineers for these complex working conditions is not a new concept. The first UNESCO report on engineering in 2010 suggested that universities need to transform their curricula and pedagogy to support more project and problem-based learning, just-in-time approaches, hands-on application, and less formulaic approaches that turn students off (Lima et al., 2012). The report highlighted that relevance works, and the future of the world is in the hands of young engineers who need support in facing the challenges of the future.

While poor collaboration remains one of the main reasons for project failures, little has been done to understand the non-technical aspects of collaborative design and collaborative learning. This research aims to identify challenges of collaborative engineering design and learning and suggest solutions based on state-of-the-art technology. This study systematically examined the following research questions, which, through successive iterations, underwent detailed process of refinement and development:

(1) How the new norms of web-based collaboration formed different patterns of information flow and distributed cognition in collaborative engineering design and learning?

(2) How to design a data-driven dashboard to measure, visualize, and monitor active engagement as an essential construct of collaboration?

(3) How a process feedback on active engagement lead to a more balanced engagement and a better design?

(4) How a communication strategy such as Motivational Interviewing contributes to

a better outcome in the process feedback?

(5) How AI and ML can measure and improving active engagement in feedback systems in collaborative engineering design and learning?

In pursuit of answers to these questions, the investigation leads to the formulation of the following hypotheses.

(1) The emergence of new norms in web-based collaboration (exacerbated by the Covid-19 pandemic), significantly shapes different patterns of information flow and distributed cognition in collaborative engineering design and learning teams.

(2) A data-driven dashboard can measure, visualize, and monitor active engagement, by analyzing data-logs and tracking online activity records during collaborative works.

(3) The implementation of a process-oriented feedback mechanism that focused on active engagement leads to a more balanced distribution of engagement levels and improves collaboration.

(4) Using communication strategies, particularly Motivational Interviewing, during a feedback experience positively influences the outcomes and more effective and constructive feedback loops.

(5) AI and ML techniques can facilitate the feedback mechanism by automatically analyzing log data and providing personalized feedbacks.

During several iterations of literature review, case study, validation the results show that process feedback based on data-driven dashboards is an effective system to moderate poor involvement issues. However, a conflict management strategy is required to enhance the design outcomes. In addition, cutting-edge technology has the potential to play a game-changer role in addressing the issues of process feedback such as scalability and limited resources. At the same time, this work opens the doors for further research on Human-AI interactions in collaborative design and learning.

The rest of this chapter first discusses the main keywords of the research. Then, the scope, relevance, research methodology, and the thesis structure are explained.

1.1 Collaboration

Collaborative Engineering Design

Collaborative engineering design is a process that involves multiple stakeholders from various disciplines or organizations who work together to develop and design products or systems. According to (Fu et al., 2013) the aim of this approach is to enhance productivity, decrease development cycles, and improve overall design quality. Integration of diverse tools and systems such as video conferencing, instant messaging, and CAD systems is often necessary to facilitate communication and collaboration among team members. Collaborative engineering design also identifies potential conflicts and offers solutions to ensure smooth cooperation among participants. Various frameworks, such as socio-technical frameworks and co-construction models, can be used to model and analyze the collaborative design process, thereby providing a better understanding of the process and supporting its execution (Jing & Lu, 2011). Collaborative engineering design distinguishes itself from concurrent engineering by emphasizing the significance of communication, complexity management, and semiotics in the design process (Putnik et al., 2021).

Several researchers have sought to develop collaborative design processes, as noted by Pimapunsri (2007). Lu (2006b) proposes a new approach to collaborative engineering design using a Socio-Technical Framework (STF), which incorporates a basic questioning method, 3W1H. The questions "Who" (referring to the designers involved), "What" (the goals to be achieved), "Why" (the stakeholder rationales), and "How" (the proposed approach) are considered essential for successful collaboration. Lu uses these questions to create two axes: [What -> How], called "technical design decisions," and [Who -> Why], called "social interaction of design team." Figure 1.1 (a) illustrates the architecture of the sociotechnical framework and its use in iterative decision-making. The four parameters are used to map the "Who -> What -> Why -> How" process for collaborative engineering. [Who -> What] represents social interactions among participants, [What -> Why] establishes a common understanding of task work, and [Why -> How] establishes a consistent group preference. The next stage involves systematic negotiation of a joint decision (team agreement) by all participants in the collaborative design team. The new procedure for collaborative engineering design can be broken down into four stages, as shown in Figure 1.1 (b). The initial stage focuses on managing and guiding social interactions, establishing team goals, and clarifying resources and constraints. The understanding stage calibrates, eliminates, or minimizes the diverse understandings of stakeholders to obtain a common understanding. The preference stage rates and captures the relative strengths of individuals' preferences to establish the group preference. Finally, the decision stage involves comparing and negotiating preferences to make joint decisions that lead to a robust team agreement.

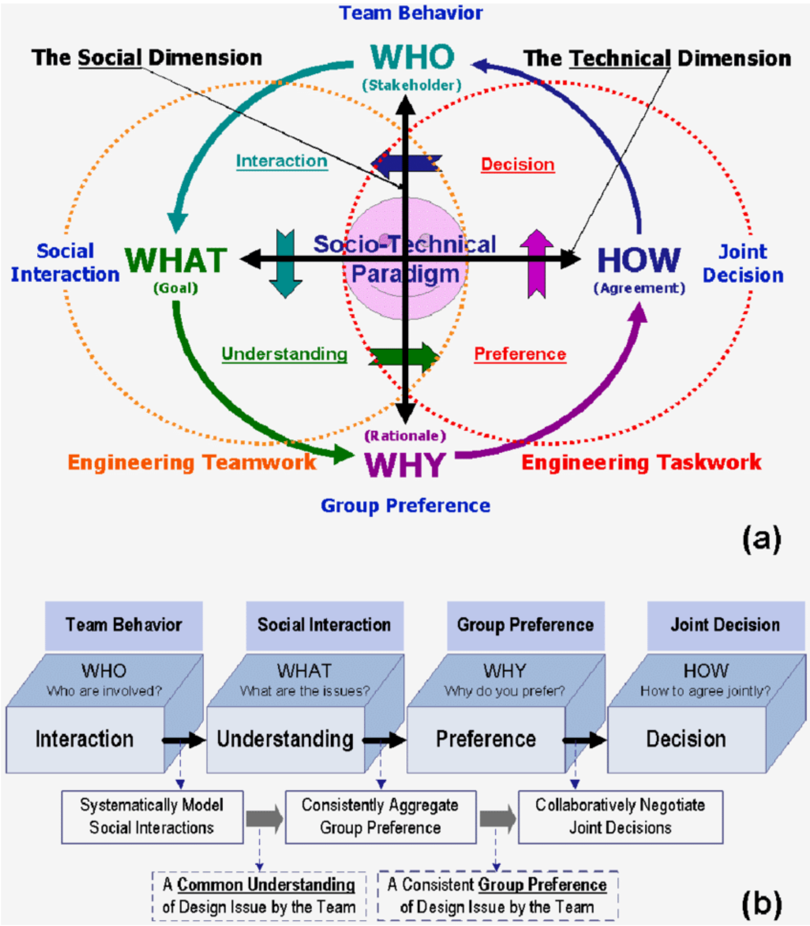


Figure 1.1: A socio-technical schema of collaborative engineering design [Lu, S. 2006] adapted by Pimapunsri (2007)

Collaborative Learning

In the field of engineering design, collaborative learning refers to a pedagogical approach that emphasizes the acquisition of deep knowledge and skills through the collaborative efforts of students from different disciplines and backgrounds. This approach leverages students' domain knowledge and experiences to address real-world challenges in team-based project settings (Ramasamy et al., 2022). Collaborative learning practices involve the use of a range of teaching and learning strategies that promote active learning and engagement, including problem-based learning, case studies, and group projects. Such practices enable students to develop and apply critical thinking skills, as well as learn how to work effectively in a team (Ramasamy et al., 2022).

Computer-supported collaborative learning (CSCL) is an integral component of collaborative learning in engineering design. CSCL refers to the use of technology to support and enhance collaborative learning activities. CSCL tools and platforms facilitate communication, collaboration, and knowledge sharing among students, especially in distance learning scenarios and helps students overcome challenges associated with language barriers and time and space constraints, enabling them to collaborate effectively in virtual teams (E. M. Nolan, 2021; Edmund Nolan, 2021; Ej Nolan, 2021, 2021).

The ultimate goal of collaborative learning in engineering design is to promote knowledge co-construction, reflection, and critical thinking among students (Finger et al., 2006). Collaborative learning practices provide opportunities for students to share their knowledge and experiences, engage in discussion and debate, and provide constructive feedback to one another. These activities encourage students to think deeply about the subject matter, develop a broader perspective on engineering design issues, and enhance their problem-solving skills. In summary, collaborative learning is an effective approach to engineering design education, promoting active learning and knowledge co-construction among students.

Cloud-based collaborative learning is an emerging area of interest in educational technology. A systematic review of cloud computing tools for collaborative learning activities suggests that certain cloud computing tools can be employed to support collaborative learning activities (Baanqud et al., 2020). Such cloud-based collaborative environments offer cost-effective, efficient, and flexible online course provision between universities. These tools aid students in engaging in reflective thinking, knowledge sharing, cognitive engagement, and cognitive development. Figure 1.2 shows an example of collaborative learning activity in Google Drive (Baanqud et al., 2020).

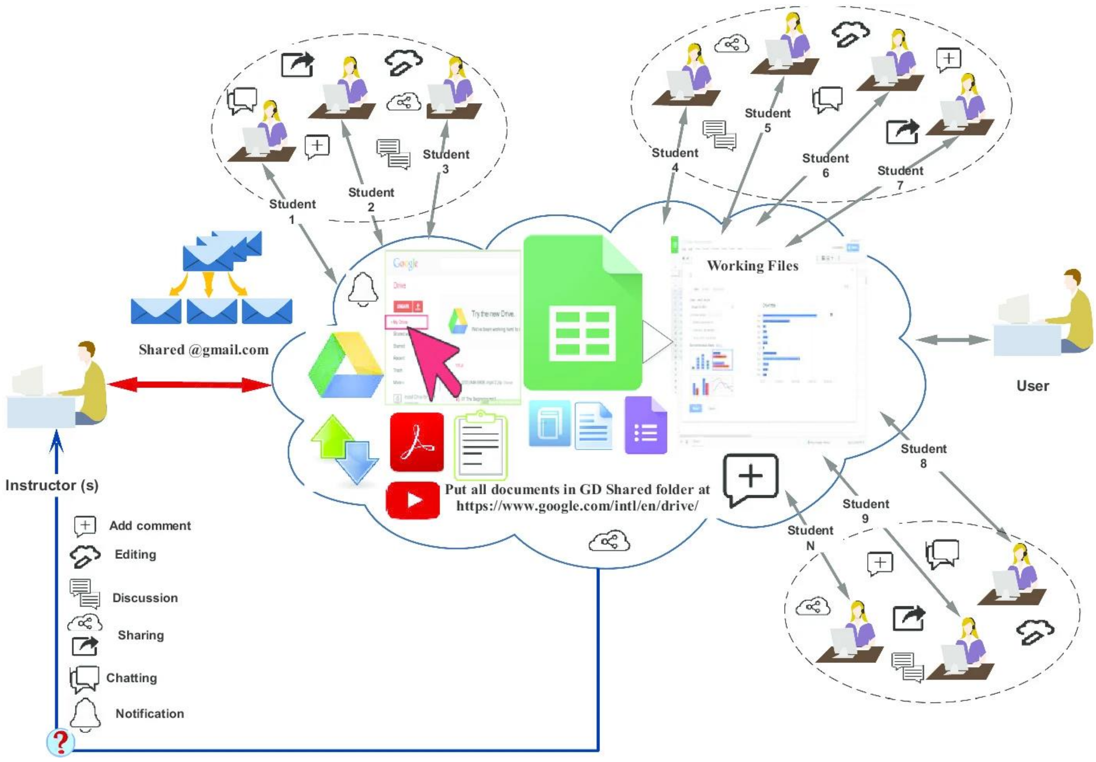


Figure 1.2: An illustration of the collaborative learning activity in cloud-based platforms (Baanqud et al., 2020)

Poor Collaboration

Effective collaboration is crucial for the success of engineering projects. Poor collaboration, on the other hand, can have several detrimental consequences. One of the most significant consequences is cost overruns, which may arise when team members do not communicate effectively or share information promptly. As a result, critical project milestones may be missed, and resources may be wasted

(Cheng et al., 2023). Moreover, rework due to poor collaboration can be quite costly, as it involves repeating work already done and may require the purchase of additional materials or resources.

Another significant consequence of poor collaboration is project delays. These delays can occur when team members do not work together effectively, which may cause tasks to take longer to complete, and the overall project timeline may be extended (Cross & Carboni, 2020). Such delays can lead to increased costs, lost opportunities, and damage to a company's reputation. Furthermore, quality issues can arise due to poor collaboration among team members. In such cases, critical details may be overlooked, or problems may not be identified promptly, leading to rework, additional costs, and delays. Quality issues can also affect the safety and reliability of the final product, which may have severe consequences (Bikard et al., 2023).

To mitigate the consequences of poor collaboration in engineering projects, several measures can be taken. Firstly, effective communication should be established among team members (Herbsleb & Roberts, 2006; Weger et al., 2022). This includes clear communication of project objectives, roles and responsibilities, and deadlines. Ongoing communication throughout the project can ensure that all team members are up to date, and any issues are addressed promptly. Secondly, project management tools can be employed to facilitate collaboration among team members (Pan & Rao, 2021). Such tools can help track project milestones, assign tasks, and monitor progress. Additionally, web-based collaboration tools and collaborative platforms can be used to facilitate communication among team members (Wahl & Kitchel, 2016).

Encouraging team members to work together, actively engage, and take responsibility, to solve problems and share knowledge is another way to mitigate the consequences of poor collaboration. This can be achieved through regular team meetings, training sessions, and team-building activities. However, using a regular feedback might also be effective. While this aspect has been investigated, establishing a culture of collaboration and knowledge sharing among team members can improve the quality of the final product and reduce the risk of delays and cost overruns.

It is evident that poor collaboration can have significant consequences on the success of engineering projects. To mitigate these consequences, companies should focus on effective communication, project management tools, and establishing a culture of collaboration and knowledge sharing among team members. By doing so, companies can reduce the risk of project failures and improve the quality of their final products.

Examples of Poor Collaboration Consequences

Poor collaboration is often cited as a leading reason for project failures; that can lead to misunderstandings, conflicts, and distance between team members, which can significantly influence project processes and lead to project failures (Banihashemi & Liu, 2014; Lubis et al., 2011). In contrast, effective collaboration can help teams provide more complex, innovative, and comprehensive solutions to problems (Hwang & Zhang, 2019).

The challenge of collaboration extends beyond the domains of engineering and design and encompasses various sectors and disciplines; one study found that open source drug discovery projects, which encourage collaboration and open access, have the potential to significantly increase research capacity and lead to new and inexpensive drugs (Årdal & Røttingen, 2012).

As another example, poor collaboration among medical staff can have serious consequences, including the death of a patient in a hospital (Fujino et al., 2020; Trivate et al., 2019); for example, lack of communication and coordination among medical staff can lead to medical errors, misdiagnosis, delayed treatment, and other issues that can compromise patient safety and health outcomes. In addition, medical staff who are hesitant to speak up about poor quality of care or safety risks may contribute to a culture of silence and complacency that can perpetuate poor collaboration and lead to adverse events (Berry, 2021). Psychological case conferences and other initiatives that encourage reflection, sharing of experiences, and emotional support among medical staff may help alleviate conflicts and prevent burnout, which can ultimately improve collaboration and patient care. Therefore, effective collaboration and communication among medical staff are essential for ensuring patient safety and quality of care in hospitals.

Poor collaboration in project management can have significant consequences, including project failures, delays, and cost overruns (Abedi et al., 2013, 2016; Lubis et al., 2011; Luwanda & Stevens, 2015; Silungwe et al., 2015). Poor communication skills can cause misunderstandings, conflicts, and distance between team members, which can significantly influence project processes and lead to project failures. In addition, poor collaboration can lead to improper planning and scheduling, poor production timing, poor coordination, lack of good communication among parties, wrong deliveries, poor control and supervision, and other issues within the project supply chain. These issues could result in adverse consequences for the objectives and success of the project, including quality shortfalls, disputes, time and cost overruns, and reduced productivity and efficiency. Therefore, effective collaboration and communication are essential for successful project management.

The subsequent sub-sections delves into more comprehensive descriptions of example failures in engineering design.

An Example of poor collaboration in space engineering (The Mars Climate Orbiter)

The Mars Climate Orbiter (MCO) project failure occurred due to a critical error in the spacecraft's trajectory calculations (Figure 1.3). The root cause of the failure was the use of non-metric units in the coding of a ground software file, Small Forces, which was used in trajectory models. This mistake led to the loss of the spacecraft during its Mars Orbit Insertion (MOI) maneuver in September 1999. The MCO was intended to orbit Mars as the first interplanetary weather satellite and provide a communications relay for the Mars Polar Lander. The failure of the

MCO project has since informed improvements in systems engineering for subsequent Mars missions, such as the Mars 2020 Perseverance Rover (Board & Eddington, 2013; Siegfriedt et al., 2022).

MCO project is a clear example of an engineering project failure where poor collaboration was identified as a reason behind the failure. The MCO was a spacecraft that NASA launched to study the Martian climate and atmosphere. However, the spacecraft was lost shortly before entering Mars' atmosphere in 1999. A subsequent investigation into the failure found that poor collaboration among the project's teams was a significant factor (Brady, 2002).

Specifically, the investigation found that the spacecraft's navigation software used metric units of measurement, while another team responsible for providing navigation data to the spacecraft used imperial units. This resulted in the spacecraft's navigation system providing incorrect data to the flight software, causing the spacecraft to enter Mars' atmosphere at too low an altitude and be destroyed (Brace et al., 1999).

The MCO project failure is a prime example of how poor collaboration, including communication, coordination, and standardization of units of measurement, can have disastrous consequences for an engineering project. The incident highlights the importance of effective collaboration in all aspects of engineering projects, from design and development to launch and operation. It also emphasizes the importance of thorough testing, quality control, and risk management to mitigate potential issues that could arise from poor collaboration.

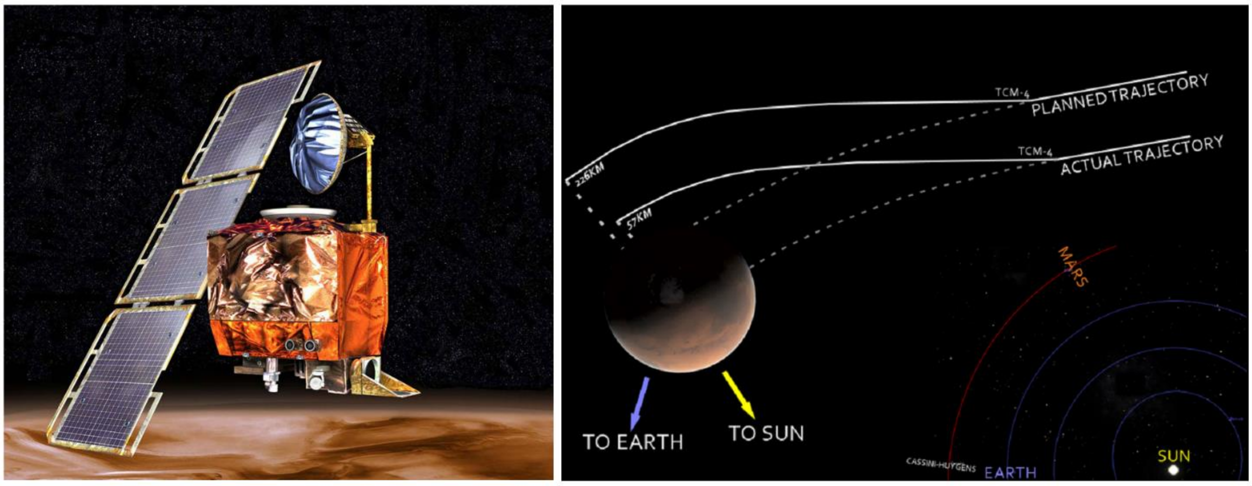


Figure 1.3: Left- An artist's concept of NASA Mars Climate Orbiter. Credit: NASA/JPL-Caltech; Right- Comparison of Actual and Planned Trajectories. Source: https://degiuli.com/

Recent global surveys on poor collaboration

According to a recent global survey on workplace collaboration (Elsie Boskamp, 2022), 39% of surveyed employees feel that their peers don't collaborate enough. The majority of employees feel that workplace collaboration is lacking at their company. Only 9% of surveyed employees reported that their place of employment had very effective sharing and collaboration tools and systems in a Deloitte study. An additional 39% of respondents said that their company's collaboration methods were somewhat effective. Research suggests that an overwhelming lack of incentives and rewards is the most common explanation for the lack of workplace collaboration. Although there can be some drawbacks to workplace collaboration, like stress and a lack of recognition for team achievements, more than half of the labor force in the United States relies on collaboration at work and rates teamwork as being very important to career success. In fact, most employees blame workplace failures on the lack of collaboration.

According to another recent global survey conducted by Corel Corporation (Corel, 2023), 54% of office workers believe that poor employee collaboration within hybrid and remote work environments is costing organizations revenue. The survey polled 2,027 office workers from the US, UK, Germany, the Netherlands, Italy, and Australia. The respondents identified a range of causes for the collaboration crisis, including a decrease in productivity, poor functionality of collaboration tools, and inadequate training to use the tools. The survey highlights the importance of investing in simple and intuitive collaboration tools that enable multiple team members to work on the same project at the same time and allow collaboration on any device.

1.2 Scope

This interdisciplinary PhD thesis encompasses four fields of knowledge (see Figure 1.4): Engineering Design (particularly through a systems engineering process), Engineering Education (with a specific focus on collaborative learning and Project-based Learning or PBL), Technology (involving AI, NLP, text classification, and chatbots application), and last but not least Collaboration and Teamwork. The thesis aims to advance our understanding of the complex interplay between these fields and explore their synergistic potential to improve collaborative engineering design and learning processes in the age of digitalization and AI.

Engineering Design and Systems Engineering

The thesis investigates the principles and methodologies of engineering design, with a particular emphasis on systems engineering, including the process such as designing complex engineering systems, problem definition, ideation, prototyping, testing, etc. A way to achieve this goal is by incorporating case studies into system engineering courses. By examining engineering design through an interdisciplinary lens, the research aims to uncover innovative approaches and frameworks that enhance the efficiency, effectiveness, and innovation of collaborative engineering design processes.

Engineering Education; Collaborative Learning and Project-Based Learning (BPL)

Within the realm of engineering education, this thesis focuses on collaborative learning and PBL as pedagogical approaches. It explores how these methodologies can foster interdisciplinary competencies, effective communication, and collaborative problem-solving skills among engineering students. The research aims to identify the non-technical and human-centered challenges that hinder successful collaborative learning and project-based activities. By examining the integration of these approaches with engineering design, the thesis seeks to develop strategies and recommendations to enhance collaborative engineering education in PBL.

Technology: AI, NLP, Text Classification, and Chatbots

This works explores the application of cutting-edge technologies, such as artificial intelligence (AI), natural language processing (NLP), text classification techniques, and chatbots to enhance collaborative engineering design and learning. The research investigates how these technologies can be leveraged to support and augment interdisciplinary collaboration, facilitate information retrieval and analysis, automate routine tasks, and enable effective communication and knowledge sharing among team members. The focus is on understanding the potential of these technological advancements to enhance collaborative engineering design and learning processes.

Collaboration and Teamwork

In the context of interdisciplinary engineering design and learning, this thesis examines the dynamics of collaboration and teamwork. It delves into the factors that influence effective collaboration, including Active Engagement, Feedback Systems, Communication strategies, and Conflict Resolution mechanisms. By investigating the non-technical aspects of collaboration and teamwork, the research aims to identify barriers and challenges that impede successful collaborative engineering design and learning. The thesis also explores strategies and frameworks that promote effective collaboration, foster a positive team climate, and enhance interdisciplinary collaboration outcomes.

By exploring the interconnections between these fields of knowledge, this PhD thesis aims to advance our understanding of collaborative engineering design and learning processes. The research findings will contribute to the development of practical frameworks, methodologies, and recommendations for practitioners, educators, and researchers in these fields. Ultimately, the thesis seeks to drive improvements in interdisciplinary collaboration, engineering design, engineering education, and the effective integration of technology to propel advancements in the age of digitalization and AI.

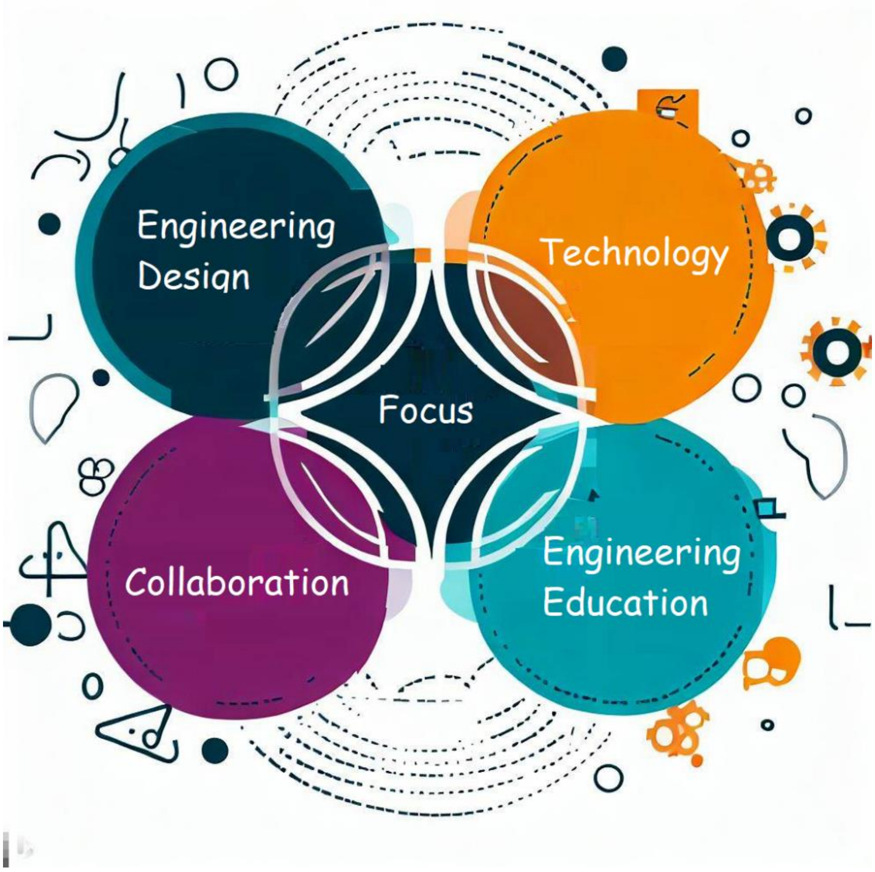


Figure 1.4: The work's relation to fields of knowledge (The artwork is a modified version of a design that produced through Microsoft Bing AI)

1.3 Relevance

The interdisciplinary nature of this PhD thesis is of significant relevance in the current landscape of engineering practice and education. This section highlights the relevance of the research by outlining the significance and potential impact of each field discussed in the scope section.

Relevance with Engineering Design and Systems Engineering

Engineering design plays a pivotal role in the development of complex engineering systems. As the complexity and interdisciplinarity of engineering projects continue to increase, understanding effective collaborative design principles and methodologies becomes crucial. Engineering design faces challenges due to outdated tools and systems, resulting in failures to fulfil expectations. The complexity of collaboration processes involving various disciplines and designers from different organizations further complicates the situation (Ambler, 2015). By exploring systems engineering principles, this thesis aims to enhance collaborative engineering design. This is especially relevant given the growing demand for interdisciplinary collaboration in addressing contemporary engineering challenges.

Relevance with Engineering Education: Collaborative Learning and Project-Based Learning

Engineering education is undergoing a paradigm shift, shifting from traditional teaching to technology oriented teaching (Malhotra et al., 2020). Collaborative learning and project-based learning have emerged as effective pedagogical strategies that promote interdisciplinary competencies, critical thinking, and problem-solving skills (Alves et al., 2018; Hussein, 2021). By focusing on these educational approaches, the thesis aims to enhance collaborative engineering education and prepare students for the demands of real-world collaborative engineering design projects.

Relevance with Technology: AI, NLP, Text Classification, and Chatbots

Technological advancements, particularly in AI, NLP, text classification, and chatbots, have revolutionized various industries, including engineering (Samarakou et al., 2015; Sasmita & Mulyanti, 2020; Xie et al., 2020); These technologies offer opportunities to improve collaboration, communication, and information processing in engineering design and education. By leveraging these advancements, the thesis explores the potential of AI and related technologies to overcome challenges like limited resources and scalability in monitoring collaborative processes and providing necessary feedback.

Relevance with Collaboration and Teamwork

Collaboration and teamwork are essential for successful engineering design projects, as they involve individuals from diverse backgrounds and disciplines (Sujan et al., 2020; Tan, 2020); Understanding the dynamics and factors contributing to effective collaboration is crucial for achieving project objectives and mitigating conflicts. This work investigates the non-technical aspects of collaboration and teamwork, aiming to identify challenges and develop strategies that promote effective collaboration and foster a positive team climate. Such insights are valuable for engineering practitioners and educators as they contribute to developing cohesive and high-performing interdisciplinary teams.

The relevance of this interdisciplinary PhD thesis lies in its potential to advance knowledge and practice in collaborative engineering design and learning. By integrating the fields of Engineering Design, Engineering Education, and cutting-edge technology with Collaboration and Teamwork, the research aims to bridge disciplinary boundaries and provide a comprehensive understanding of the complex interactions among these areas. This thesis's findings can potentially inform and guide engineering practitioners, educators, and researchers searching for improved collaborative engineering design and learning processes.

1.4 Overview of Research Methodology

In this research, I found Design Research Methodology (DRM) from Blessing and (Chakrabarti2009) an appropriate approach as the research method. DRM is a framework for conducting research in the design field and is used to guide research in various design-related fields. DRM involves a cyclical process of problem identification, solution generation, and evaluation, with the goal of creating new knowledge that can be applied to design practice. The cyclical process occurs through following stages:

Research Clarification

First, I reviewed the literature about collaborative design and collaborative learning in engineering and non-engineering fields. However this process was iterative and in each cycle new information was added, e.g., Feedback Systems, or the application of AI. The outcome of this stage is contained in chapter 2.

Descriptive Study I

To understand the challenges of collaborative design, after the global pandemic entirely changed PBL, I conducted an ethnography study in a rocket engineering student team. The insights gained into the actual practice include what team members face during a fully online design activity. The results of the study can be found in chapter 4, and parts of it were published (Farshad & Fortin, 2021).

Prescriptive Study

Based on the insight from the first study and information gathered from literature, I formulated and designed a data-driven dashboard to facilitate web-based collaborative design. I tested the methods validity in a questionnaire after applying it to an available dataset of engineering design works done by PhD and Master's student in a technology planning and rod-mapping course. The results of this effort published by (Farshad & Fortin, 2023).

Descriptive Study II

The designed method were verified through a comparative case study. I tested the methodology and tool on nine conceptual design studies of space systems, all of which are described in the next chapters.

1.5 Thesis Structure

The diagram in Figure 1.5 illustrates the flow of information through the structure of the thesis.

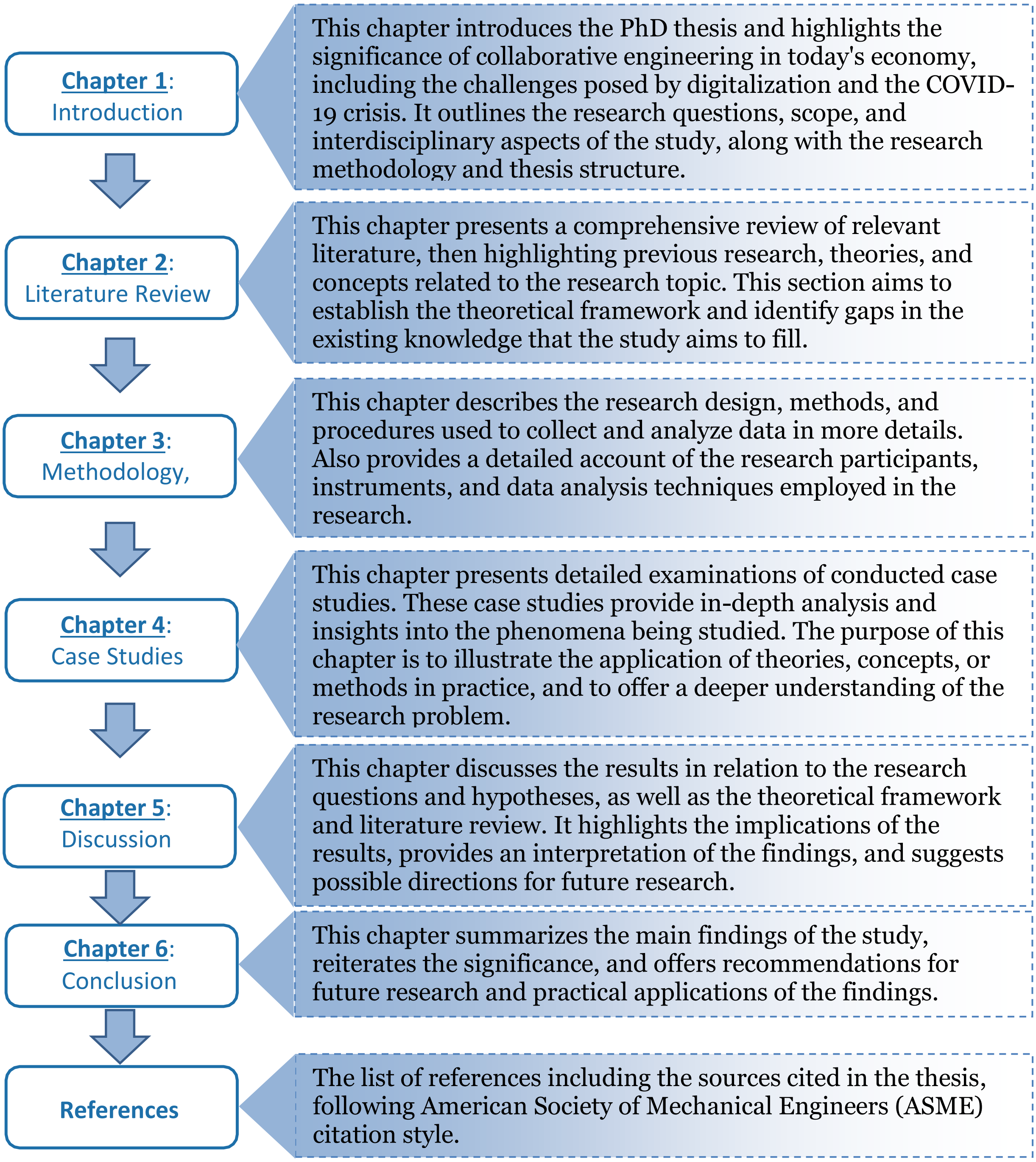


Figure 1.5: Thesis structure

Chapter 2

Literature Review

This chapter serves as a basis framework for the research study undertaken in this PhD thesis, with the aim of exploring approaches to enhance collaborative engineering design and learning within the context of digitalization, while focusing on the potential of feedback systems and cutting-edge technologies. As technology continues its rapid advancement, the landscape of collaboration and learning undergoes a profound transformation. Consequently, it becomes imperative to meticulously examine the current state of the art in collaborative engineering design and learning, and to explore avenues for fortifying these processes through the seamless integration of feedback systems.

2.1 Adapting to the New Normal in Collaborative Engineering Design and Learning

The COVID-19 pandemic has left no choice but to a significant shift towards remote teaching and online design activities in the field of engineering. This sudden and unforeseen change has prompted a reevaluation of the approaches employed by engineering teams and students in various aspects of the design process, including teaching methodologies, collaboration strategies, and project management techniques (Ahmed & Opoku, 2022; London et al., 2022). Particularly in the realm of systems engineering and design, the distribution of information across specialists and the subsequent cognitive effort required to organize and integrate this data into a cohesive design have always been challenging (Greene, Papalambros, & McGowan, 2016). However, the Covid-related circumstances introduced additional complexity to the collaboration, communication, and interplay within system engineering and design teams, driven by the evolving trends in human-computer interaction.

The implications of this transformation are equally relevant for engineering students who are learning design in distributed teams. A comprehensive review by Marinova (2020) highlights a range of emerging trends in remote work, which have become more prominent in 2020. As depicted in Table 2.1, some key insights from the report are summarized below. Notably, the statistics indicate a growing prevalence of online work as the preferred mode of operation. In a report published by Gartner (2020), it was revealed that 74% of companies have developed plans to transition a portion of their workforce to remote work permanently, extending beyond the immediate challenges posed by the pandemic.

Table 2.1: Remote work trends in 2020

Subject	Statistic	Source
Companies that reported an increase in web conferencing time	67%	Statista
The inclination to continue online working to some extent	99%	Buffer
Workers with an option of remote work, who plan to work remotely more systematically in the next five years	42%	Owl Labs
Forecast of the teams with remote teammates by 2028	73%	Upwork
Young managers who support their teams working remotely	69%	Upwork

Zoom has been one of the most widely-used applications to meet the virtual collaboration requirements during COVID-19	300 million daily participants reported	Zoom
The population of remote workers before the pandemic	4.7 million	Flexjobs
Percentage of worldwide companies that made it mandatory or supported their workers to work remotely during the pandemic.	88%	Gartner
Remote employees' opinion about their productivity when working from home (Accomplishing more in the less or same time, willing to work longer, and less likely to take time off)	77% believe they are more productive	CoSo Cloud
Work-related stress change based on telecommuters experience	80% reported less stress	Amerisleep
The distraction rate of people who work from home	75% reported fewer distractions	Flexjobs
U.S. telecommuters view as the main benefit of remote work	53% pointed flexible scheduling	Statista
The rise in Google search about "team-building" after the pandemic	9% increase	Think With Google

These reports acknowledge the need to rethink the off-site design activities. However, we first should understand the trends of the changes, find effective tools, review emerging procedures and recognize different patterns, and then re-plan accordingly. We had the opportunity to look closer into these challenges for a team of students learning system engineering and practising system development online.

Back at the early 2000s, while explaining a progressive framework for research on Human-Computer Interaction, James Hollan and colleagues (2000) talked about the importance of changing distributed cognition among human and computers because of the new era of technology:

> "*We are quickly passing through the historical moment when people work in front of a single computer, dominated by a small CRT and focused on tasks involving only local information. Networked computers are becoming ubiquitous and are playing increasingly significant roles in our lives and in the basic infrastructures of science, business, and social interaction*"

Regardless of their notable insight, neither Hollan and colleagues nor anybody else could predict how a virus would speed up the transformation of human interaction with the environment, including human-computer and, human to human relatedness, leading to different cognitive models in activity systems and extending minds.

2.2 The Evaluation of E-Collaboration Technologies, the Challenge of Poor Collaboration, and the Potential of Log Data

E-collaboration refers to utilizing electronic technologies in collaborative activities (Kock, 2005). Following an exceptional evolution in just a few decades, e-collaboration is a common and widespread practice nowadays. Rutkowski et al (2002) believe that e-collaboration is more than only a technological trade-off for traditional face-to-face collaboration. By focusing on the communicative dimensions of e-collaboration over a period of four years, Rutkowski and others developed a project with hundreds of participants from different national backgrounds working during six weeks of collaborative work. They used different interventions including IT setups and interviews based on which they concluded that: First, the evolution of e-collaboration is transforming the nature of teamwork, its functionality, and its productivity. Second, geographical distances between team members or time zones, no longer form a barrier to remote collaborations. Third, the fast spread of information and decentralized communication enables both problem solving and creativity. Further, it is necessary for the organizational structures to support e-interactions as a central element to efficient online teamwork. In addition, after removing the basic technical barriers, the main challenges in collaboration to deal with are organizational and social issues. Since Rutkowski et al's study, technical barriers have been significantly minimized and e- collaboration technology has continued to advance, however, as the study concluded, organizational and social challenges related to collaboration appear to remain central factors in teamwork failures. In this study, we intend to deal with technical methods that can help us to overcome the challenges of poor e-collaboration. For this purpose, in this section, we will first discuss the history of e-collaboration evolution, its current scope, and existing challenges, then we expand the concept and our solution in the next sections.

The idea and history of e-collaboration date back decades ago. Christopher Allen (2004) has traced its evolution from the very beginning till the 2000s; we have re-shaped and summarized Allen's work in Table 2.2: to portray the evolution of the e-collaboration basis, and then discussed the current status. We will next touch on evidence suggesting that technological development has not necessarily ended up with the same improvement in collaboration quality.

Table 2.2: Tracing the Evolution of E-collaboration

Year	Authors /Inventors	Names /Brands	Application /Capabilities	Highlights /Notes
1940's	Vannevar Bush	Memex	To stores books, records, and communications, as an enlarged intimate supplement to the memory	The idea were way before its time and never caught on.
1960's	ARPA and J.C.R. Licklider	ARPANET	To use computer as a remote communication device to collaborate in teams	ARPA or Advanced Research Projects Agency formed by the US as a response to the USSR launching Sputnik.
1960's	Doug Englebart And ARPA at SRI	Initially: NLS (oNLine System) Later: Office Augmentation	Integrating psychology and organizational development with the advances in computing technology in order to augmenting human intellect	Doug inspired by V. Bush's idea, but it seems that later on, the term 'augmentation' replaced with 'automation', and the idea were lost
1970's	IBM	Office Automation	To broaden the scope of IBM's 'word processing' products to all aspects of the office.	Ideas of collaboration got lost in the plan of process and automation
1970's	IBM, AT&T, Annenberg Trust, NSF and the New Jersey Commission of Science and Technology	Electronic Information Exchange System (EIES)	The first major implementation of a collaborative platform, including: threaded-replies, polling, anonymous messages, etc.	While there were references from that time to terms such as 'computer-mediated communications', 'decision support system', and 'collective intelligence', none of these was broadly adopted.
1980's	Peter and Trudy Johnson-Lenz	Groupware (1)	Person-to-person collaboration that is facilitated by computer.	Outside of the EIES community, 'groupware' was not widely adopted.
1980's	MIT's Irene Greif and DEC's Paul Cashman	Computer-Supported Collaborative Work (CSCW)	To develop new theories and technologies that can aid in the coordination of work groups.	In general, CSCW has never been truly adopted by anyone other than academics.

1990's	Robert Johansen	Groupware (2)	Computer support for business teams. A distinction between time and place for different types of collaboration was a unique contribution of the idea.	Emerging of Lotus Notes, Microsoft Exchange Server, and Outlook
	Ted Nelson and Phil Salin	Xanadu and AMIX	The origin of social software: The abilities of working with links and filtering, supporting collaborative development of modelling, games, and simulations.	The 'social software' term did not take off in that period. While Wiki was created in 1995, inventors did not define it as social software initially.
2000's	Clay Shirky	Social Software Summit	Evolution of Social Software Tries to converge existing technologies to support e-collaboration	
	Social software is re-defined as "software that supports group interaction" Web 2.0 created a network of cloud-based applications that enabled more collaboration, community-building, and other types of interaction.			

Moreover, from 2000 to 2023, there have been a number of prominent advancements in e-collaboration technologies. The below list summarized some of the key advancements during this period:

1. **Cloud Computing**: The rise of cloud computing has significantly facilitated e-collaboration. Cloud-based platforms and services allow users to access, store, and collaborate on documents and files with an internet connection without geographical limitations (Alam, 2020). This has made it easier for teams to work together in real-time and remotely.

2. **Video Conferencing**: The development of high quality video conferencing platforms has revolutionized e- collaboration. Tools like Zoom, Microsoft Teams, and Google Meet have become essential for online collaboration (Singh & Awasthi, 2020). These tools enable communication and screen sharing, while making collaboration and communication easier for teams.

3. **Project Management Software**: The advancement of project management software has remarkably improved e-collaboration for organizing, planning, and handling tasks in projects. Tools like Jira, Asana, and Trello provide features such as task assignment, file sharing, , and progress tracking (Milojević et al., 2023).

4. **Real-Time Collaboration Tools**: Real-time collaboration platforms such as Google Docs and Microsoft Office 365, allow multiple users to simultaneously work on the same document. These tools enable real-time editing, version control and commenting.

5. **Virtual Whiteboarding**: Virtual whiteboarding tools, like Miro and Mural, have gained popularity for facilitating collaborative brainstorming and visual collaboration (Jackson et al., 2022). These tools provide a digital canvas where team members can contribute ideas, create diagrams, and collaborate on visual content in real-time.

6. **Instant Messaging and Chat**: Instant messaging and chat applications, such as Discord, Slack, and Telegram, have become essential for quick and efficient communication among team members (Davis et al., 2022). These tools offer features like group chats, direct messaging, file sharing, and integration with other collaboration tools, enabling seamless communication and collaboration.

Zhang et al. as cited in (Jones, 2012), more elaborated the evolution of collaboration digital technologies by dividing them in two main categories; 1) Asynchronous tools, and 2) Synchronous. Each of these categories has subdivisions as follows:

1. **Asynchronous tools**

- Communication tools (including: Email, Newsgroups, Microblogs)
- Information Sharing tools (including: Blogs, Discussion, Forums, Wikis, Online, Documents, File sharing)
- Group Calendar tools
- Social Networking Tools
- Integrated Systems

2. **Synchronous**

- Whiteboarding
- Video Conferencing
- Instant Messaging (Chat)
- Short Message Service (SMS)

The path that collaboration technology has taken towards digitization has been very fast and impressive. However, looking at its evolution in Table 2.1 and the mentioned categorizations, it seems that developers' attention of e-collaboration has been more on technology and removing technical barriers than fostering collaboration essence. Over hundreds of thousands of years, if not millions, human has been engaged in collaborative activities in different ways. As cited in (Sewell, 2001), Lipnack and Stamps's (1994) by pointing to the collaborative nature of work in early human times argue that after the Industrial Revolution we have forgotten how and why we used to collaborate and work in teams: to achieve goals that bind mutually dependent small groups of people. Mentioning the prehistoric examples of hunter-gathering or farming, they argue that modern forms of cooperation have led us to refuse teams. We argue that the fast shift of traditional collaboration style to digitalized e-collaboration in the last two-four decades has even exacerbated this gap.

To understand the current situation of e-collaboration technologies and updated statistics, we searched for the latest valid surveys. In a recent article, Boskamp (2022) by citing Forbes, Fortune, Deloitte, Harvard Business Review, and some other widely known magazines/publications, broke down their data and illustrated remarkable statistics of work collaboration and the role of digital technologies in collaborative works. According to the article, over 50% of U.S. workers report relying on collaboration in their work, while 75% rate collaboration as a critical aspect. At the same time, 56% of employers utilize online collaboration techs. Furthermore, Fortune Business Insights (FBI, 2022) reported that the market for team collaboration technologies will be valued at $40.79 billion by 2028, which shows more than a 230% rise, compared with 2021. These data and the evolution of e-collaboration in the last 60 years are stunning, however, despite the impressive development of e-collaboration technologies, in terms of collaboration quality, there are significant gaps to cove (Hihn et al., 2011; Ho et al., 2019; Rometty, 2006). Based on the Boskamp work, lack of collaboration is cited as the leading cause of workplace failure by 86% of employees in leadership positions.

In summary, e-collaboration technology has grown rapidly and is now part of the daily lives of a significant number of teams across the world. Meanwhile, the quality of collaboration has a lot of room for improvement. The main objective of this study is to address the challenge of poor collaboration in teams that have a serious dependence on digital technologies for teamwork. We believe that, due to accessibility to recorded history logs and computerized procedures, e-collaboration provides a great potential to analyze team activities and suggest effective methods to improve them.

2.3 Definitions and constructs of collaboration

Wood and Gray (1991) suggest a notable definition of collaboration derived from a synthesis of conclusions from nine studies on the subject;

“Collaboration occurs when a group of autonomous stakeholders of a problem domain engage in an interactive process, using shared rules, norms, and structures, to act or decide on issues related to that domain."

They further highlight six elements in their definition: First, Stakeholders of a Problem Domain; referring to the groups with common and/or different interests. Second, Autonomy; meaning that stakeholders are independent decision makers. Third, Interactive Process; indicating the involvement of all stakeholders in a change-oriented relationship. Furth, Shared Rules, Norms, and Structures; referring to implicit or explicit agreements to govern the interaction process. Fifth, Action or Decision; showing that to reach the objectives the contributor must intend to “act or decide”, regardless success or failure in obtaining the objectives. Sixth, Domain Orientation; directing to the need that participants’ processes, decisions, and actions must be oriented toward to the problem domain that brought them together. Thomson et al. later expanded Wood and Gray’s definition and redefined it as follows (Thomson et al., 2007):

“Collaboration is a process in which autonomous or semi-autonomous actors interact through formal and informal negotiation, jointly creating rules and structures governing their relationships and ways to act or decide on the issues that brought them together; it is a process involving shared norms and mutually beneficial interactions.”

Rooted in a learning approach, Lai (2011) believes that collaboration is the “mutual engagement of participants in a coordinated effort to solve a problem together.” Lai further explains different perspectives and research paradigms in collaborative learning: The “effect” paradigm focuses more on outcomes than collaborative process itself, comparing group performance to individual efficiency. In the “conditions” paradigm individual characteristics, group heterogeneity and size, and task features are considered as moderators of the effectiveness of collaboration on learning. The “interactions” paradigm attempts to identify mediating mechanisms between outcomes and collaboration, developed as an answer to the complexities associated with the previous paradigm. And, the “computer supported” paradigm attempts to determine whether the theoretical basis of face-to-face collaboration can be realized in computer-mediated interactions.

Griffiths et al (2021) conducted a systematic review to map a conceptual framework of collaboration in the educational setting. To build a universal model, the review aims to identify the common constructs throughout different definitions of collaboration. Then authors developed the “building blocks” framework and identified the necessary steps to come into the position of true collaboration. The model underlines the iterative nature of the collaborative process and the significance of re-evaluating the basic elements of a collaborative development. Figure 2.1 shows the building blocks and Table 2.3 illustrates the definition for each term in the framework.

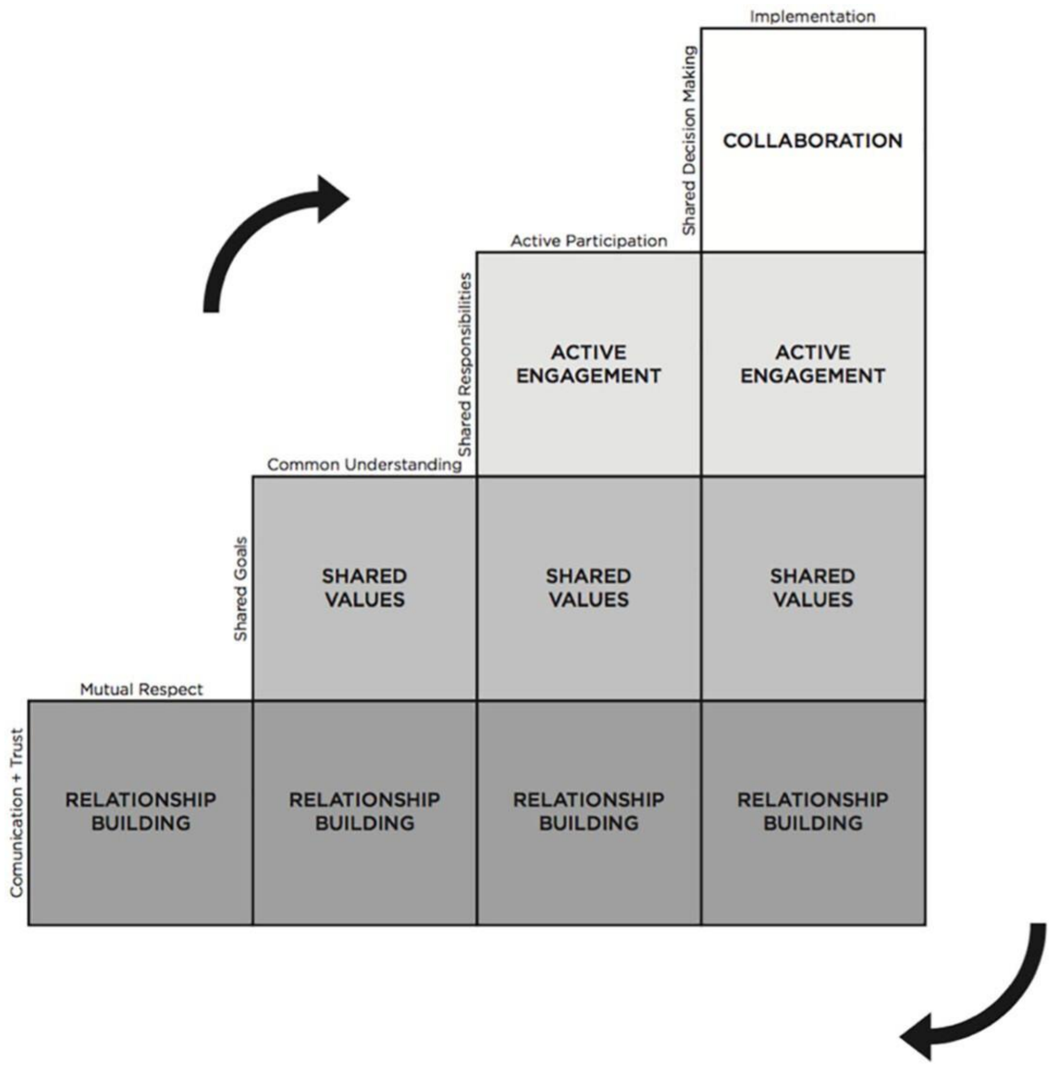


Figure 2.1: Building blocks of collaboration (Griffiths et al, 2020)

Table 2.3: Concepts and constructs of collaboration based on Griffiths et al work

Terms	Definition
Shared decision making	The process in which the team systematically gathers input from all team members, fostering active participation throughout the decision-making process.
Active participation	Team members contribute equally and accept specific roles, encompassing shared problem-solving, cooperation, and active engagement in the process.
Shared responsibility	The practical utilization of capabilities, the establishment of roles, ensuring equivalent contributions, and making productive use of members' strengths.
Shared goals	Mutually determined goals by the team in order to carry-out mutual outcomes that the team agreed-upon
Common understanding	Members of the team communicate and understand each other
Open communication	Open, honest, and transparent sharing of ideas helps prevent unnecessary conflicts.

Trust	Trust is built through the investment of time, effort, and energy in developing an effective communication system.
Mutual respect	To value skills, competence, and knowledge of others.

2.4 Improving collaboration

Over recent decades, a large body of research from engineering to healthcare investigated the importance and demand for improving collaboration. Depending on the discipline and context different approaches are being occupied to improving collaboration. For example, Willey & Freeman (2006) conducted a study in the field of engineering education to improve teamwork and engagement. They examined the benefits of self and peer assessment together throughout a multistage collaborative project. A confidential online tool was used to gather 180 participants receive self and peer-evaluation grading. The findings suggest that the method improved participants' engagement, collaboration, and satisfaction. Yin et al. (2011) in order to investigate how to measure and improve collaborative design performance, adopted a questionnaire survey and in-depth focus group interviews after critical literature reviews. They developed a design performance measurement (DPM) matrix that measures team members' performances in a collaborative design work through five DPM indicators and 25 DPM criteria. Indicators are innovation, efficiency, collaboration, effectiveness, and management skill. Their findings suggest that decision-making efficiency is the key DPM criterion for collaborative design efficiency. Clear team objectives for collaboration, the decision-making ability of managers, and competitive advantage in innovation are the next important criteria. Yin et al. believe that DPM is a useful tool for improving collaborative design performance. Alharthi et al. (2018) investigated the effect of cognitive styles in collaborative gaming activities. Players took part in the mixed methods user-study that were classified based on a cognitive style elicitation instrument. The analysis revealed that cognitive styles had an effect on performance; the mental load could result in different team collaboration (Alharthi et al., 2018). Hebert et al. (2014) in a social work context examined whether intensive inter-agency collaboration facilitated an effective collaboration for maltreated children in a pilot study of intensive family intervention. This qualitative study evaluated inter-agency collaboration through a semi-structured group interview format and thematic analysis. According to the analysis, the collaborative model is strongly endorsed. The authors indicated that the observed change may have been a result of the pilot program's unique structure and functioning, which encouraged high levels of team communication, strong client engagement, availability, and intensive treatment of mental health problems in children and parents. In a healthcare setting, Sandahl et al. (2013) conducted a study to investigate how simulator-based medical team training can improve inter-professional collaboration within an intensive care unit (ICU). During their case study over a period of two years, 135 members of the general ICU staff in a hospital received inter-professional team training. The findings showed that the training sessions (three times a week) was effective to improve the participants' understanding of fundamentals of collaboration. However, the findings indicate that the observed improvements is not sustainable without everyday use of the learned behaviours in work. In addition, there are other threats to sustainability such as overtime for staff, budget cuts, and poor communication.

One of the known methodologies to improve team performance is the Scrum framework, which is an agile project management framework that aims to improve team performance in both output and process (Sassa et al., 2023). According to Sassa and colleagues' review, Scrum is characterized by rituals such as Sprint planning, Daily stand up, and Retrospective meeting, which are intended to address and enhance team performance. Their research has shown that Scrum is an agile framework for empirical-based project development, that offers a flexible and adaptable methodology. In addition, a review of an agile software development methodology with Scrum and Extreme Programming emphasizes the customer-centric nature of agile methods, highlighting their ability to fulfill changing customer requirements (Sankhe et al., 2022). However, Scrum faces series challenges such as the difficulty in handling, adaptation Challenges, need for proper training, etc., (Akif & Majeed, 2012).

2.5 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 (Li et al., 2005; Qin et al., 2003; Zheng et al., 2011), web-based systems (Shen & Barthès, 1997; S. Zhang et al., 2004), or information sharing systems, enterprise resource planning (Numata, 1996; Roy et al., 1997; S. Zhang et al., 2004). Some studies tried to outline the architectural elements of design interaction (Simpson & Viller, 2004). Some other discovered the usage of multi-factor measures to improve collaborative design, for example Yuanyuan Yin et al. (2008) developed a model of improving collaborative design through a novel 3-dimensional performance measurement approach to help project directors improve team collaboration by indicating both strengths and weaknesses of team members during the project. Such studies focus on complexity of collaborative design that usually propose a multiple-criteria model to reflect the design dynamics. Meanwhile, management, social and cognitive aspects have also been studied (Cross & Clayburn Cross, 1995; Girard & Robin, 2006; Lang et al., 2002). However, the emphasis on technical dimensions have remained a pivotal theme of many collaborative design studies, for example Wu et al. (2022) to address the requirement for closer multidisciplinary collaborative design (MCD) and integration that the traditional design method cannot solve its interaction barriers, suggest a digital twin-enabled MCD approach. Such a digital-twin enables virtual verification, conceptual and detailed design in a multidisciplinary environment.

On the other hand, some research indicate that non-technical dimensions of collaboration is the main effective factor in engineering projects (Wang et al., 2021), also it has been documented that early in a project's life cycle, when the conceptual design is being developed, non-engineering factors are likely to influence the system's design most (Greene et al., 2003). Wang et al. (2021) showed that the team collaboration atmosphere is the most significant factor, followed by the collaborators' learning ability in terms of team efficacy in collaborative design. Their study aimed to identify the factors influencing teamwork efficiency in collaborative design. The study followed an input-process-output approach and initially established a hypothetical model. Using semi-structured interviews, questionnaire survey, and structural equation modeling, Wang et al suggest that human interaction process is one of the most influencing elements of collaborative design. They add that while existing literature has examined some technical and managerial factors of collaborative design, the area still lacks an overall coverage of non-technical factors. Klein et al. (2003) explored collaborative design dynamics from a negotiation perspective in complex systems such as airplanes that are defined via the interaction of multiple participants (sometimes thousands). This study reviewed research from the complex systems and negotiation literature and concluded that it has much to offer to improve the understanding of the dynamics of collaborative design. According to their results, collaborative design dynamics reflect two basic facts: (1) collaborative design is a form of a distributed network, and (2) involved agents respond to local incentives and are self-interested. Stempfle & Badke-Schaub, (2002) investigated collaborative design challenges with a focus on the cognitive processes of design teams during the design process. They analyzed the entire communication of three design teams through a model through a model to detect content, underlying basic thinking operation and process type (e.g. is it planning, decision, control, etc.). According to the conclusion on content- and process-directed activity: All the observed teams spent about 70% of their interaction on the content, 30% on the group process.

2.6 Improving e-collaboration, and using data-logs

Qiu (2019) in an online engineering education setting looked for a solution to facilitate learning engagement. Compared with the empirical studies of conducting hypothesis tests, Qiu worked on a practical, systematic, and model-driven approach to assessing and enhancing collaborative practices. After exploring the proposed framework through two tests (Pilot and confirming) the results suggest the approach is helpful to improve collaborative practices for retaining effective engagement in the online engineering education setting. Figure 2.2 shows an overview of Qiu's systemic approach. Online education is modelled as a socio-technical service system. Data collection on teaching/learning activities is the first step, the pre-processing, and mining. The next step includes analysing processed data using Structure Equation Modelling (SEM) and Social Network Analysis (SNA) tools to identify best practices and know transformative operations for improvement. The framework also relies on daily survey data in the Operations stage. According to Qui, the proposed systemic approach should be applied in an iterative and evolutionary mode, in order to continuously and adaptively leveraging collaborative learning in an online engineering education setting.

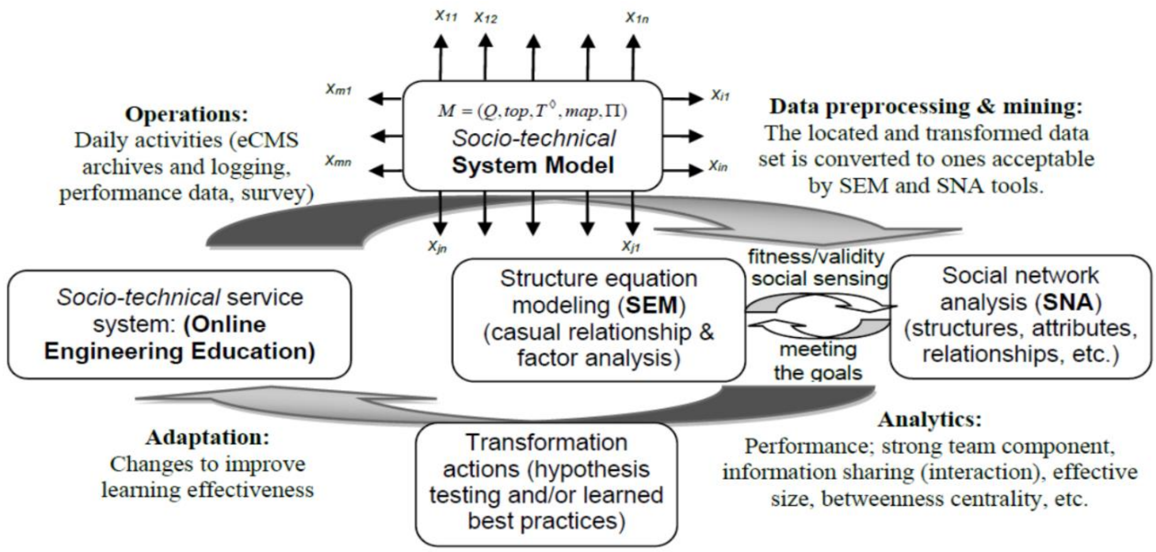


Figure 2.2: Qiu's approach to leveraging engagement in online collaborative learning (Qiu, 2019)

Belanger et al. (2022) studied difficulties of engineering design teamwork in the e-collaboration settings. They report that the rapid shift from co-located to distance collaboration during the pandemic caused dramatic challenges to many engineering students. With the aims to explore challenges of e-collaboration in engineering design teams, the authors observed teamwork difficulties through three datasets. (A) By collecting data through survey responses during in-class idea generation activities; (B) reflection essays about their team project at the final stage of the semester; and (C), individual reflections on the discussion panel during the whole semester. The study results show significant positive correlations between teamwork experience (e.g., perceived contribution, efficiency, and communication) and the number text-based idea generation, and significant negative correlations between teamwork experience and the number of ideas generated in a blend mode of sketches and text. These findings were unlike the classic findings that sketches improve performance. Moreover, the online environment intensified existing team challenges more than it formed new challenges. The e-collaboration challenges also dropped dramatically over time then remained steady. The challenges and their variable patterns indicate a great potential to improve web-based collaborative design.

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, they 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. Schwind and Wegmann (2008), also 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. Fan et al (2017) to address a gap in how specific collaboration process patterns affect teamwork performance in collaboration management, developed a Collaboration Process Pattern approach to analyse teamwork performance by mining collaboration system logs in software programming teams. The authors indicate that the research is novel in three ways. (1) It is fact-driven because the result is based on teamwork tracking logs. (2) The developed pattern mining approach is based on graph and sequence mining. (3) They used time-dependent regression, and the approach derives business insights from real-world collaboration data. The study showed that the effects of collaboration patterns differ based on the types of tasks. According to the authors, the findings are helpful in prioritizing the limited attention of managers on certain tasks for intervention.

2.7 Motivational Interviewing (MI)

MI is a communication strategy and mentoring style used in various settings including leadership and management (Marshall & Nielsen, 2020; Niesen et al., 2018; Organ, 2021), sport and human coaching (Wierts et al., 2019), healthcare (Simmons & Wolever, 2013), higher education and training (Ogles et al., 2021) and therapy, mental disorders treatment (Lundahl et al., 2010; Marker & Norton, 2018), and many more. 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 (Hettema et al., 2005). The rapidly growing evidence for MI indicates its significant effectiveness in various systematic reviews and meta-analyses (Hettema et al., 2005; Lundahl et al., 2010; Magill et al., 2018; Rubak et al., 2005; Schwalbe et al., 2014). The high effectiveness of MI across various settings suggests a need to understand and apply this style in collaborative design and engineering.

Miller & Rollnick, (2012) 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 (MINT, 2021):

- MI is a guiding technique of communication that is between active listening and directing through giving information.
- MI is designed to empower people to change by discovering their own meaning, values, and capacity for change.
- 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 engages with the person as an equal partner and avoids unrequested advice, directing, confronting, warning, 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 several different conversational contexts, but MI is especially useful when the following situations exist:

- High ambivalence where people are stuck with uncertain feelings about change.
- Low confidence is when people have doubt about their ability to improve.
- Low desire when people are unsure about whether they want to make a change or not.
- Low Importance where the advantages of change and disadvantages of the current situation are not clear.

As cited in (Klonek & Kauffeld, 2015) 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, (2015) use a metaphor to describe the application of the OARS; the MI idea verbal skills can be compared to oars on a boat, which trainees use as dynamic micro-tools within verbal interaction (Figure 2.3). The OARS of the boat help the trainee safely go through the river, similar to the basic communication skills that help the interaction goes smoothly. The dynamic interactions with a conversational partner are represented by the river. The rock in the river represents resistance against change. “To roll with resistance”, not confrontation with it, is one of the main principles of MI. The mentor needs to ask the right questions and effectively listen to avoid confrontation. To evoke self-motivational statements and move forward, the mentor uses open-ended questions. Reflections and summaries help to figure out the motivations in an empathic manner, and affirmations serve to build rapport.

Figure 2.3: The metaphoric meaning of OARS as micro-tools to navigate through a dynamic interaction (i.e. river) in a conversation (Klonek & Kauffeld, 2015)

In their study Klonek & Kauffeld (2015), by using an observation-based scientific approach, demonstrated how MI provides important skills for engineers. In a skill-based MI training, 25 engineering students took part with quality assurance assessment of the training, including systematic observations through interactions recording, self-reported, and standard performance evaluations. Participants showed a significant increase of verbal communications skills, and decreased confrontational behaviors. Results also indicate significant increases in motivation to interact with conversational partners in comparison to before the training. While the study's small sample size indicates a limitation, analysis showed large effects on verbal skills. The study suggests that MI is effective to deal with motivational challenges within the higher education of technical professions.

2.8 Artificial Intelligence (AI) and Sentiment Analyses

Sentiment analysis through conversations using AI is an emerging and yet challenging approach that aims to discover the emotional states and its changes in people participating in the conversation. There is a wealth of information in the interactions that affect speakers' emotions in a complex and dynamic manner, and many promising studies have been conducted in recent years on how to accurately and comprehensively model these complex interactions (Y. Zhang et al., 2020). As chatbots are often found in daily life, and their role in teamwork becomes more important, in a study on emotion recognition through conversations sentiment, Majid & Santoso (2021) 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 0.76 accuracy, meaning that the algorithm can reliably recognize emotions from text-based conversations. Dehbozorgi (2020) used sentiment analysis on verbal data from team discussions to create an indicator for individual performance. The study conducted a succefully attitudinal components detection that correlates with performances through Natural Language Processing (NLP) algorithms. Saura et al. (2019) performed a sentiment analysis with a supervised ML and text data mining techniques to detect indicators for startup business success. This research discovered some of the positive and negative feelings for the identification of key factors for the startup business success based on text sentiment analysis.

2.9 Feedback Systems

Sarah Tausch (2016) studied the effect of feedback systems on improving collaboration and shows that providing feedback on collaboration to teams, especially through a computer-mediated system, enhances problem-solving (Tausch, 2016). She employed group mirrors techniques (also known as social mirrors) to produce feedback on collaborative works in the group processes. Tausch by referring to Jermann et al. (2001) draws a distinction between three different feedback systems; 1) mirroring techniques, 2) metacognitive tools, and 3) guiding systems (Figure 2.4). A mirroring system reflects the existing state to the group using the aggregated data. A metacognitive tool by comparing the current state with the desired situation goes a step further, and a guiding system directs the team by providing advice.

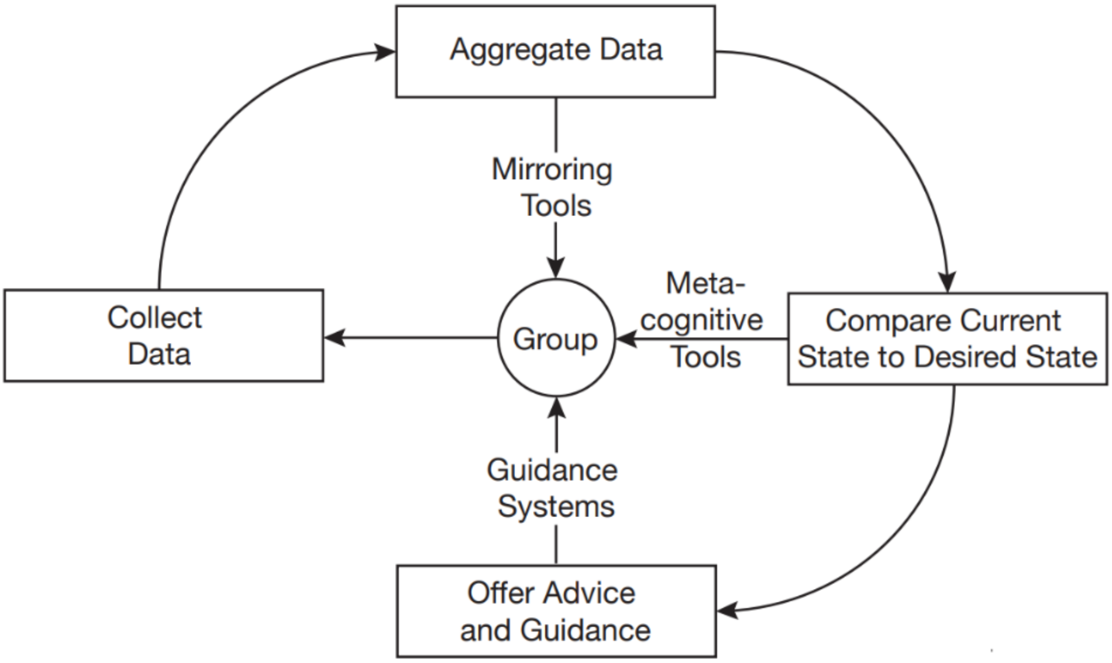


Figure 2.4: Mirroring, meta-cognitive and guiding systems according to Jermann et al. (2001) and Streng et al. (2009), as cited in (Tausch, 2016)

While literature on process feedback is less extensive than outcome feedback, evidence support the idea that process feedback can be as effective as outcome feedback to enhance performance (Earley et al., 1990; Geister et al., 2006; McLeod et al., 1992; Paulson Gjerde et al., 2017). Geister et al. (2006) to address the challenge of feedback deficit about team processes in virtual teamwork, provided feedback through an Online-Feedback-System (OFS). A longitudinal study of 52 teams was conducted, where motivation, interconnection aspects, and task-related aspects were observed. The results suggest that compared with the control groups that did not use the OFS, teams that used the OFS showed improved performance. Moreover, results indicate primary motivation as a moderating variable on the improvement prompted by the OFS. The less motivated team members were positively affected by OFS in both motivation and satisfaction. Furthermore, interpersonal trust was a mediating factor for less motivated team members.

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.

2.10 Collaborative learning in Project-based Learning

Engineering design professionals more and more facing the need to adjust themselves to interdisciplinary working conditions and multicultural team interactions (Gereffi et al., 2008). In the current accelerated progress toward digitalization and globalization, we require engineers, who no longer merely master the technical aspects, but are also able to involve their competencies in real-world situations (R. M. Lima et al., 2012). Referring to the first UNESCO's report 2010 on engineering, Lima et al. (2012) argue that these new requirements pose new challenges to engineering education models:

"University courses can be made more interesting through the transformation of curricula and pedagogy using such information and experience in more activity-, project- and problem-based learning, just-in-time approaches and hands-on application, and less formulaic approaches that turn students off. In short, relevance works! Science and engineering have changed the world, but are professionally conservative and slow to change. We need innovative examples of schools, colleges and universities around the world that have pioneered activity in such areas as problem based learning. The future of the world is in the hands of young engineers and we need to give them as much help as we can in facing the challenges of the future." [UNESCO (2010), p.32]

As an answer to those needs, collaborative design learning through Project-Based Learning (PBL) methods is well known as an effective way for students to learn design while experiencing design challenges by active participation in the real-world tasks (Kokotsaki et al., 2016; Volpentesta et al., 2012). It is an innovative design pedagogical approach that motivates and integrates learning through design projects (Kolodner et al., 2003). The significance of PBL is not limited to higher education, findings from high school studies indicate that scientific-technological PBL elevates pupils' motivation and self-image at all levels and meaningfully contributes to better learning outcomes and educational success (Doppelt, 2003). As a result of PBL experiences, students can enhance their cognitive abilities to work collaboratively, communicate effectively, and develop design thinking as important elements of the design process (Stozhko et al., 2015; Volpentesta et al., 2009). According to a recent systematic review, collaborative learning through PBL is significantly constructive in analytical thinking skills, students' communication, and learning outcomes (Hafeez, 2021). Studies not only show the effectiveness of PBL but also argue that it is increasingly popular as an educational approach worldwide and is becoming a permanent feature of the century (Larmer, 2018).

On the other hand, delivering a productive collaborative design learning in student teams is not easy. Particularly higher education, there are usually a wide range of engineering disciplines among students, as well as a spectrum of different personalities and cultural backgrounds, and clearly they represent different styles of thinking. Lee et al. (2015) summarized three types of intragroup conflicts in PBL team members; First, task-related conflicts that happens after disagreements arise regarding a collaboration task. Second, processor procedure-related conflicts that happens when the members are concerned about responsibilities and have different opinions about the collaboration process. And third, emotional-related conflict that happens when the group members have negative feelings towards each other when they have an interpersonal conflict that can be linked with relationship or personality too. At the same time, collaborative design courses usually are outcome-based; meaning that instructors' attention is on the project (deliverables) not the teamwork qualities, in case of paying attention to the process, it is usually limited to self or peer assessments (R. M. Lima et al., 2012).

One of the most serious issues of collaborative projects is unequal contribution or engagement, also known as the issue of free riders (James et al., 2002; Williams, 2017). The issue of free riders not only results in unfair grading (Gibbs, 2009; Sluijsmans et al., 2001) but also could lead to a frustrating and stressful environment in teamwork because of creating an extra workload for the rest of the team members (Strauss & U, 2007). A systematic review finding revels that, time, energy, and cost, on one hand, and lack of expertise, accuracy in measuring tools, design, and implementation of the measures, on the other hand, are serious issues that need to address in evaluating teamwork in engineering education (Cruz et al., 2020). In addition, while the detailed monitoring of team members' engagement and participation can be useful to evaluate the activities, a limited number of project supervisors hardly can assess a large amount of data in a PBL. This poses a scalability challenge if the number of PBL participants increases (Traverso-Ribón et al., 2016).

Further, the increasing dependence on digital technologies, which has become faster in recent years, transformed the educational settings. According to World Economic Forum (2020), the COVID-19 pandemic has changed education forever. However, this digitalization might be an opportunity to address some of the collaboration challenges in PBL through technological advances.

Extensive research investigated collaborative learning and PBL in recent years. While there has been much research on improvement methods, limited studies have addressed feedback on the engagement, and applications of state-of-the-art technology to address challenges such as the scalability of process feedback. This section continues with definitions of collaborative learning and PBL. Then advantages and challenges of PBL in the literature are summarized. Next, different approaches to improvement are explained. Finally, after discussing different feedback systems, the section is finished with a summary.

In general, collaborative learning refers to small group learning where each member actively supports the learning processes of its fellow members (Gokhale, 1995). The concept of collaborative learning is increasingly recognized as a way for students to engage in discussion and influence the group's learning outcomes through their own learning responsibilities (Gol & Nafalski, 2007). As a popular collaborative learning approach, Project-based learning (PBL) is a method of systematic learning and teaching that involves students in the real-world complex tasks, which usually results in a presentation with a prototype or product to an audience; this enables them to build up knowledge and life-enhancing skills (Barron & Darling-Hammond, 2008b; Thomas et al., 1999). The roots of PBL can be traced back over a century, to the work of John Dewey (1959), educator and philosopher at the University of Chicago (Krajcik & Blumenfeld, 2006). Dewey argued that if students are engaged in problem-solving activities that resemble what experts do in real life, they would develop a personal investment in the material. Recent findings such as a 20-year meta-analysis of journal papers on PBL, representing 12,585 students from 189 schools (Chen & Yang, 2019), confirms Dewey's original insights; according to the study, compared with traditional instruction, PBL significantly has a positive effect on students' academic achievements.

In the engineering design field, as a result of their study "A DECADE OF PROJECT BASED DESIGN EDUCATION – IS THERE A FUTURE?", Vukašinović and Fain (2014), discussed three key outcomes of PBL; First, outline of skills that students identified as relevant for their success as engineers. Secondly, identification of potential gaps between education and practice. And third, suggestions for future development. Based on interviewing with students and a survey, they also concluded that despite appreciating PBL, communication and teamwork are skills that need further development for successful practice.

It is widely reported in the literature that collaboration is a key characteristic of PBL, as all members need to contribute to the collaborative outcome, while students encounter difficulties and failures in their efforts to interact effectively (Helle et al., 2006; Kapp, 2009; Lau et al., 2013). However, ensuring collaboration among student who participated in the project during a PBL course is a significant issue (Hussein, 2021).

A number of studies have attempted to provide strategies to improve student engagement in PBL courses, for example Morais et al. (2021), in their experimental research, suggest at least two practices; first, providing training to the groups that enables them to carry out more independent peer reviews. An evaluation procedure can also be simplified with the use of a rubric that specifies criteria for each evaluation scale. Second, it will also allow us to enhance the development of teamwork skills, by reducing the negative effects of incomplete evaluations through the creation of five-student groups. The findings of another study suggest that in order to deal with inequality in engagement and free-riders challenges, students not only require instruction on teamwork skills and opportunities to practice them, but also a motivational systems and tightly designed assessment process, including self and peer-review evaluations (K Willey & Freeman, 2006). The problem with this approach is that it is not always possible to train students for a proper peer-review, or the educational rules have restrictions for this type of grading. At the same time, it is not always possible to divide groups into five people, sometimes due to limitations, it is necessary to form larger or smaller groups.

Furthermore, any improvement and development rely on a proper measurement. In a cross-sectional descriptive study based on survey research, interviews, and team observations with a focus on the examination and measurement of face-to-face teamwork in a collaborative learning, De Hoyos Guevarra (2004) examined the validity of the Teamwork Assessment Scale (TAS). TAS is a paper and pencil instrument with 28 items that describe team interaction and engagement. They used measure such Team Flow and Team Synergy. Teams were observed while accomplishing their projects and four case studies provided an in depth view of the team dynamics and interactions. The results show that positive social engagement, keeping a positive and productive team environment through conflict management, and leadership determine team performance. Huyck et al. (2007) to assess teamwork effectiveness in academic PBL experiences, after collecting data of approximately 40 teams formed from 400 students developed several strategies: Self-assessment, knowledge test of teamwork concepts, surveys of assessing perceptions, and judge's teamwork scores in the end-of-semester presentations.

To improve teamwork the researchers designed two different intervention; (1) Feedback during weeks 5-8. (2) Gamification in team forming and teamwork awareness activities. A facilitator helped teams to understand and play the games and collected data by asking certain questions. Finally a group of judges provided feedback by observing their behavior and answers to the questions. The results indicate that students who attended the games experienced higher average grades, and felt more positive about the collaborative design learning, they were also more likely to feel positive about their team functioning. However, participation in the games was not correlated with a meaningful difference in mastering the teamwork. Besterfield-Sacre et al. (2007) argue that assessing teamwork outcomes is better accomplished by interpreting the process rather than the result. They further argue that although direct observation of 100% of student behavior is ideal, it is not cost-effective. The study suggests work sampling, an economic industry-based alternative, to follow the team's engagement processes. The study investigated a work sampling methodology to assess students engaged in teamwork by determine attributes of teamwork through time proportion. The results of testing in four learning environments robustness of work sampling indicate a statistically valid alternative for assessing teamwork. Ortiz-Marcos et al. (2015) in an engineering PBL study, measured team collaboration through direct behavior observation, peer-review, questionnaire, and quality of final presentations trough specific rubric criteria. Nearly 300 students in different groups participated in the study. Collected data from meetings participation, written work, and presentation during the PBL were analyzed. In a part of the study's conclusion authors believe that there is a clear need to strengthen the competence of communication, it is also important that feedback from instructors at the end of each presentation is not limited to the content, but on the structure itself.

Efforts to improve PBL have been diverse in terms of adopting approaches. To enhance PBL in an engineering design module, Chua et al (2014) used learning and facilitating methods such as mind-maps, analogies, and round-table discussions. 60 first-time PBL students participated in the study and were equally divided into two classes (experimental and control groups). The experimental group had a lower academic standing than the control. The rubric for the project-based module included a scenario-based oral examination and a written knowledge test to examine knowledge and problem-solving skills, and design. The finding suggests a significant improvement in knowledge scores, problem-solving ability, and design quality in the experiment group compared with the control group. Rodríguez Montequín et al. (2013) to investigate human factors and group dynamics in PBL used personality assessments, the Myers-Brigss Type Indicator (MBTI) in team forming. The purpose of the study was to understand the effect of combinations of student profiles in-group dynamics and at the same time, to predict the final success of a group. Eight different student groups were analyzed to study the influence of the MBTI profiles on the group's success. The final results suggest that the leadership style associated with the profile of the student in the role of the group coordinator and the members' profile combinations have an effect on the group's success.

Schaddelee and McConnell (2018) conducted a study to better understand what helps and what hinders the engagement of management students in a PBL setting; By investigating the students' perceptions of an interdisciplinary PBL course, and then taking action and responding to the students through a series of surveys over two years, students were asked to share their experiences. They found both positive and negative experiences in working in teams, the design of the program and the project, and how the program was communicated and integrated. The gathered comments and suggestions by students ended up in a set of recommendations to further improvement of student engagement and learning outcomes. They concluded that the effect of less committed team members on the group's marks needs to be addressed. Managing the engagement and involving all team members in the project is important and mentorship plays a significant role. They further discuss the role of the course design, peer-review usage, and a few other factors.

Traverso-Ribón et al. (2016), described a learning-oriented collaborative assessment method to facilitate the assessment process in engineering PBL and proposed an e-assessment strategy and a software architecture for evaluation.

They used three criteria; balanced engagement, usage of the tools, and task accomplishment. According to the study results, the experience has provided promising evidence for the development of sustainable evaluation procedures in PBL using e-assessment. However, team members needed training on using activity indicators to build up assessment recommendations.

Attempts to study and improve collaboration are not limited to the educational settings and engineering. A large body of research from engineering design to medicine and management employed different methods to target the same issue. For instance, to dealing with poor collaboration in the public mental health sector Pirkis at al., (2004) suggested promoting cultural and systems-level change, improving delivery of service, and using supervision and training. Fernandes et al., (2012), believe in the effectiveness of gamification to cope with collaboration problems in Requirements Elicitation practice. Duehr et al., (2021), suggest agile working practices to enhance collaboration in product development collaboration.

Using feedback is a common method in the evaluation and for improvement purposes, it has been forwarded that providing teams with feedback is a powerful practice to improve both their performance and learning (Gabelica et al>, 2014).

Paulson Gjerde et al (2017) distinguish between process feedback and outcome feedback in students' performance and perception in higher education. Their study explored how altering the feedback message might influence participants' learning and perception. They provided feedback on in-class quizzes in either the process part or the outcome part of the quiz. The results showed that process-oriented feedback is more positive on student performance than outcome-oriented feedback, it is also perceived more favorably by students both in terms of efficacy and in terms of impact on their learning.

To summarize, PBL as a learning-by-doing approach is a popular and effective strategy in collaborative design learning. One of the main issues, however, is providing active engagement in teams. Different approaches to assessing and improving team engagement and collaboration have been reviewed in this section. The mentioned methods, despite their relative efficiency, have drawbacks. Issues such as scalability, sustainability, and adaptability with digitalization have not been addressed properly. For instance, the work sampling method is vulnerable to error pronging because engineering teamwork is not linear, and to obtain an acceptable result we need to wait until the end of the process. Some approaches such as psychometric or personality tests might confront limitations such as privacy issues, rules and regulations, or ethical challenges. Full behavioral monitoring is not cost effective. Using interviews and surveys is slow and challenging.

WhilepPeer and self-review in both assessing and improving PBL appears to be one of the effective and most common approaches that have been repeated in many studies, students may allocate the same score to all the group members and/or give scores based on prejudices (Ortiz-Marcos et al., 2015). Also, free-rider participants do not take the opportunity of self-and peer assessment to benefit more from it (Keith Willey & Gardner, 2009).

Some studies have also been done using technological-based methods to improve collaborative learning, for example; Huang and Chuang (2008) in a study to support the development of collaborative problem-based learning with an intelligent diagnosis tool, used an open software e-learning platform, Moodle, and a learning diagnosis tool to alleviate the loading of the instructors. The posted transcripts of learners' on a discussion board and chat room were preprocessed by the learning parameter extraction module to reflect the learners' planning on the solutions to the problem. To examine the quality of the learners' suggestions, the extracted parameters were fed into a classification algorithm, and if necessary, appropriate feedback will be provided to the learners/instructor. The results showed that the text mining and machine learning techniques used in the study were effective in automatically providing useful feedback for the learners to progress through the problem-solving process.

Schwarz et al (2021) presented a dashboard, which enables teachers to observe the engagement of concurrent teams in which a single teacher could successfully orchestrate the progression of several groups working on geometry difficult problems.

Emerging New Performance Management Tolls with a Focus on Feedback, Personalization, and Data-Driven Insights

2.11 Emerging Commercial Team Services: A Focus on Feedback, Personalization, and Data-Driven Insights

Emerging commercial services for team and individual work performance analysis and improvement are undergoing a significant transformation, moving away from traditional annual performance appraisals to more frequent feedback mechanisms that align with the natural cycle of work. As a report by Harvard Business Review stated (Cappelli & Tavis, 2016), this shift is driven by the recognition that traditional appraisals, which emphasize individual accountability for past results, often neglect the crucial aspects of improving current performance and developing talent, thus hindering long-term competitiveness.

Organizations are increasingly focusing on creating personalized and authentic experiences to strengthen employee engagement and performance. According to McKinsey & Company (Emmett et al., 2021), this involves the use of digital portals, virtual focus groups, and rapid prototyping to design prototype solutions that cater to the specific needs of employees. Moreover, companies are leveraging technology to enhance the employee experience by identifying critical moments that matter, such as annual performance reviews, and providing context-specific personalization to guide and support employees in real time. Emmett et al. add that one of the key elements of the evolving commercial services is the emphasis on data-driven performance management, and companies are establishing centralized "commercial operations hubs" to integrate data, derive insights, and foster an action-oriented performance culture.

2.12 Research Gaps

Following research gaps identified in the literature, relevant with this work regarding collaborative engineering design and learning in the context of digitalization and AI, and communication strategies.

- Integration of digital technologies: While the shift towards digitalization and web-based collaboration has accelerated, there is a need to explore how to effectively integrate emerging technologies (e.g., artificial intelligence, web-based collaborative platforms, and chatbots) into collaborative engineering design processes and collaborative learning environments.

- Organizational and social challenges: Despite advancements in e-collaboration, there remain organizational and social challenges that can hinder effective collaboration. Research could focus on identifying and addressing these challenges to improve collaboration outcomes. For example, the challenge of unbalanced engagement or the issue of free-riders in the context of PBL.

- Quality improvement in collaboration: Although collaboration has been extensively studied, there is a need for research that specifically targets improving the quality of collaboration in teams heavily reliant on digital technologies. For instance exploring methods to analyze team activities, identify areas for improvement, and propose effective strategies or interventions.

- Non-technical dimensions of collaborative design: While technical aspects of collaborative design have received significant attention, there is a need to further explore and address non-technical dimensions such as team collaboration atmosphere, learning ability, cognitive processes, and negotiation dynamics. Understanding and improving these aspects can enhance collaborative design outcomes (e.g., Motivational aspects of team communication)

- Evaluation and assessment of teamwork: Developing effective evaluation and assessment methods for teamwork particularly in collaborative learning and project-based learning (PBL) settings remains a research gap. This includes finding reliable and valid measures to assess teamwork effectiveness, identifying strategies to address issues like unequal contribution and free-riding, and exploring innovative assessment processes that go beyond traditional approaches.

- Integration of motivational strategies: Motivation plays a crucial role in collaboration and learning. Further research is needed to investigate the integration of motivational strategies, such as Motivational Interviewing (MI), into collaborative engineering design and collaborative learning contexts. This research could explore the impact of motivational strategies on communication skills, engagement, and motivation to interact effectively.

- Sentiment analysis and emotional states: Although sentiment analysis and AI techniques have been applied to uncover emotional states in conversations, there is a need for research that focuses on understanding the emotional dynamics and their impact on collaboration within engineering design teams and collaborative learning environments. This could involve developing more accurate models for emotional analysis and exploring the implications for collaboration and performance.

- Feedback systems for collaboration: While feedback systems have been studied, there is an opportunity to further investigate their effectiveness in enhancing collaboration and problem-solving. Research could explore different types of feedback systems, their impact on collaboration improvement, and how they can be tailored to specific collaborative contexts.

- Scaling up collaborative learning approaches: While collaborative learning and project-based learning have shown promise, there is a need to explore strategies for scaling up these approaches to larger educational contexts. Research could focus on adapting collaborative learning methods to different educational levels, disciplines, and institutions, while maintaining their effectiveness and addressing scalability issues by using cutting-edge technology and advances in AI.

By addressing these research gaps, we can contribute to the growing body of knowledge surrounding remote teaching and online design activities in engineering fields. The findings can inform educators, designers, and policymakers in developing effective strategies, tools, and policies to enhance the quality and outcomes of remote engineering design education in the present and future contexts. In this work, however, this work will not cover items 5 and 6, while the other 4 aspects has been investigated completely or partially which is reflected in the case studies, discussion and conclusion sections.

Chapter Summary

This chapter formed a background from the relevant literature. It seems that there is no single and common definition of collaboration and opinions cover different characteristics depending on the context and discipline. However, engagement is a common element in the all above-mentioned definitions. While, wood and Gray (1991) define collaboration as an interactive process where autonomous stakeholders of a problem domain engage using shared rules, norms, and structures to act or decide on domain-related issues, Thomson et al. (2007) expanded this definition, emphasizing formal and informal negotiation, shared norms, and mutually beneficial interactions. Lai (2011) on the other hand, views collaboration as participants mutually engaging in solving a problem together. Griffiths et al. (2021) conducted a systematic review to develop a conceptual framework of collaboration in education, highlighting shared decision making, active participation, shared responsibility, shared goals, common understanding, open communication, trust, and mutual respect as key constructs. The framework emphasizes iterative collaboration and re-evaluating its fundamental elements.

As a result of digitalization, today's collaboration is relying on technology and web-based platforms more than ever. The shift towards digitalization and web-based collaborative design was significantly accelerated by the global pandemic started in the beginnings of 2020. This prompted a reevaluation of collaboration strategies, teaching methodologies, and collaborative design approaches. Systems engineering and design faced new trends in information flow and cognitive distribution. Remote work trends emerged, indicating a preference for online operations. Statistics highlighted increased web conferencing, remote work plans, and the rise of remote teams. Web-based communication tools became widely used for virtual collaboration. Remote work was found to increase productivity, reduce stress and distractions. Rethinking off-site design activities is crucial, considering trends, tools, and procedures. The new norms accelerated human-computer interaction transformation, shaping new collaboration models.

E-collaboration, the use of electronic technologies in collaborative activities, has undergone significant evolution and is now widely practiced. The communicative dimensions of e-collaboration have transformed teamwork, overcoming geographical barriers and enabling problem-solving and creativity. While technical barriers have been minimized, organizational and social challenges remain central factors in collaboration failures. Tracing the evolution of e-collaboration from the 1940s to date, it is evident that the focus has been on technology rather than fostering collaboration. Despite impressive developments, collaboration quality still needs improvement. The study aims to address the challenge of poor collaboration in teams heavily reliant on digital technologies, leveraging e-collaboration's potential to analyze team activities and propose effective methods for improvement.

Improving collaboration has been a subject of extensive research across various fields. Yin et al. (2011) developed a design performance measurement matrix to assess collaborative design work, highlighting decision-making efficiency as a crucial criterion. Willey and Freeman (2006) focused on engineering education and found that implementing self and peer assessment in a collaborative project enhanced engagement, collaboration, and satisfaction. Alharthi et al. (2018) examined the impact of cognitive styles on collaborative gaming activities and discovered that different styles influenced team performance. Hebert et al. (2014) studied inter-agency collaboration in a social work context and identified its effectiveness in supporting maltreated children. Sandahl et al. (2013) explored the use of simulator-based training to improve inter-professional collaboration in a healthcare setting, finding that while training was effective, sustained improvement required the regular application of learned behaviors. Challenges to sustainability included staff overtime, budget cuts, and communication issues.

Research on improving collaborative design has primarily focused on the technical aspects, such as computer-aided approaches, web-based systems, and information sharing systems. Some studies have explored the architectural elements of design interaction and employed multi-factor measures to enhance collaborative design. While technical dimensions remain a central theme, the management, social, and cognitive aspects have also been studied. Wang et al. (2021) emphasized the importance of non-technical factors, such as team collaboration atmosphere and learning ability, in influencing collaborative design efficiency. Klein et al. (2003) examined collaborative design dynamics from a negotiation perspective, highlighting the distributed network nature and self-interested behavior of participants. Stempfle & Badke-Schaub (2002) focused on the cognitive processes of design teams during the design process. Overall, the research in this area emphasizes the need to address both technical and non-technical dimensions to improve collaborative design.

Qiu (2019) proposed a systematic approach for improving collaborative practices in online engineering education through data collection, preprocessing, and analysis using SEM and SNA tools. Belanger et al. (2022) investigated the challenges of e-collaboration in engineering design teams during the pandemic, identifying correlations between teamwork experience and idea generation modes. Martinez et al. (2021) discussed the use of log data in predicting outcomes and personalizing feedback, citing studies that applied log data in understanding group work, characterizing effective collaboration, analyzing argumentation, measuring collaboration in software development networks, and assessing teamwork performance in software programming teams. These findings offer valuable insights for collaboration management and intervention.

Motivational Interviewing (MI) is an evidence-based communication strategy used in various fields, including leadership, coaching, healthcare, therapy, and more. It aims to enhance readiness for change by addressing ambivalence and empowering individuals to discover their own capacity for change. MI emphasizes collaborative, goal-oriented communication, respecting autonomy and promoting a respectful, curious approach. Key techniques of MI include open-ended questions, affirmations, reflective listening, and summaries. MI has demonstrated effectiveness in systematic reviews and meta-analyses. It has been applied in training engineers, leading to improved communication skills and motivation to interact effectively in technical professions.

Artificial Intelligence (AI) and sentiment analysis are emerging approaches aimed at uncovering emotional states and changes in conversation participants. These complex interactions contain valuable information that can affect speakers' emotions. Recent studies have focused on accurately and comprehensively modeling these interactions using AI techniques (Y. Zhang et al., 2020). In one study, Majid & Santoso (2021) developed a chatbot called Dinus Intelligent Assistant (DINA) to assist student administration services. They used sentiment analysis and neural networks to categorize emotions in conversation dialogues, achieving a 76% accuracy rate. Dehbozorgi (2020) utilized sentiment analysis in team discussions to create an indicator for individual performance, while Saura et al. (2019) employed supervised ML and text mining to detect indicators of startup success based on sentiment analysis.

Feedback systems play a crucial role in enhancing collaboration and problem-solving within teams. Sarah Tausch (2016) investigated the impact of feedback systems, particularly computer-mediated ones, on collaboration improvement. She utilized group mirrors (social mirrors) to provide feedback on group processes. Tausch distinguished three types of feedback systems: mirroring techniques, metacognitive tools, and guiding systems. Research suggests that process feedback can be just as effective as outcome feedback in enhancing performance. Geister et al. (2006) implemented an Online-Feedback-System (OFS) to address feedback deficits in virtual teamwork, resulting in improved performance, especially among less motivated team members. From a Human-Computer Interaction perspective, feedback loops function as self-correcting systems, where information flows between the system and individuals, guiding their actions towards achieving goals (Dubberly et al., 2009).

Collaborative learning through Project-Based Learning (PBL) has gained recognition as an effective approach to education, particularly in the engineering field. PBL involves students working on real-world design challenges, promoting active participation and integration of learning. It not only enhances cognitive abilities but also fosters skills like collaboration, effective communication, and design thinking.

However, ensuring successful collaboration among students in PBL teams can be challenging due to the diverse backgrounds, personalities, and thinking styles of team members. Unequal contribution and free-riding also pose significant issues. To address these challenges, various strategies have been proposed, such as providing training on teamwork skills, implementing motivational systems, and designing assessment processes that include self and peer evaluations. Additionally, measuring and assessing teamwork effectiveness have been explored through methods like direct behavior observation, peer-review, questionnaires, and rubrics. Improvements in PBL have been achieved through the adoption of different approaches, such as mind-maps, analogies, and round-table discussions. Research efforts extend beyond education, with studies in fields like medicine and management aiming to enhance collaboration. Overall, collaborative learning and PBL hold promise for improving educational outcomes, but ongoing efforts are needed to address the associated challenges and further enhance the effectiveness of these approaches.

The section also addressed research gaps in collaborative engineering design and learning within the context of digitalization, AI, and communication strategies. The identified research gaps include the integration of digital technologies, organizational and social challenges, quality improvement in collaboration, non-technical dimensions of collaborative design, evaluation and assessment of teamwork, integration of motivational strategies, sentiment analysis and emotional states, feedback systems for collaboration, and scaling up collaborative learning approaches. By addressing these gaps, the study aims to contribute to the knowledge base in remote teaching and online design activities in engineering fields. The findings can inform educators, designers, and policymakers in developing effective strategies, tools, and policies to enhance the quality and outcomes of remote engineering design education.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 3

Research Methodology, Thesis Objectives, and Questions

Introduction

This research employs DRM, a Design Research Methodology (Blessing & Chakrabarti, 2009), to systematically investigate and develop measures and indicators of collaborative design and learning. The philosophical underpinnings of this research are grounded in the pragmatist paradigm, which emphasizes the practical application of knowledge and the importance of understanding the real-world implications of research findings. Pragmatism focuses on the usefulness and practicality of research outcomes, making it a suitable approach for investigating the challenges and potentials of collaborative engineering design and learning.

There are five main reasons why the DRM methodology is chosen: (1) A Systematic approach: DRM provides a systematic approach to design research and offers a structured framework, leading to reliable and valid results. (2) Flexibility: The purpose of DRM is to be versatile and capable of being adjusted to various design scenarios while maintaining effectiveness. (3) Iterative process: DRM employs an iterative process to enhance research quality and increase the chances of finding effective solutions. (4) Practical relevance: DRM aims to develop practical domain knowledge that applies research findings to design practice. (5) Scientific rigour: DRM emphasizes the formulation and validation of models and theories about design phenomena and the development and validation of methods and tools based on these theories.

The research questions are addressed through a systematic iterative approach, involving several iterations of literature review, case study, and validation. This approach allows for the continuous refinement of the research findings and the development of practical solutions to the identified challenges.

The philosophical underpinnings of this research also emphasize the importance of interdisciplinary collaboration and the integration of diverse perspectives in addressing complex engineering design and learning challenges. By adopting this approach, the study aims to contribute to the development of more effective and efficient collaborative engineering design and learning practices, as well as the advancement of Human-AI interaction in this domain.

Ultimately, this research on Enhancing Active Engagement in Collaborative Engineering Design and Learning with a special focus on the Role of Feedback Systems and Potentials of the Cutting-Edge Technology aims to address the non-technical and human-centered challenges of collaborative engineering design and learning by employing DRM as an iterative approach with a focus on validation through cases studies where each study builds a basis for the next study.

3.1 Methodology

This section describes the research methodology in two subsections: first, the holistic framework and approach of the entire study, and second, the research focus and validation strategy.

Framework and approach

This study has utilized a combination of different methodologies. In a holistic view, we modified the Design Research Methodology (DRM) by Blessing and Chakrabarti (2009) and integrated it with a validation approach that is explained in the next subsection. However, in each case study, a specific appropriate methodology has been adopted and explained in the corresponding section.
The DRM includes four stages: (1) Research Clarification, (2) The first Descriptive Study (3) Prescriptive Study, and (4) The second Descriptive Study. Figure 3.1 shows the connection between these steps in DRM framework.

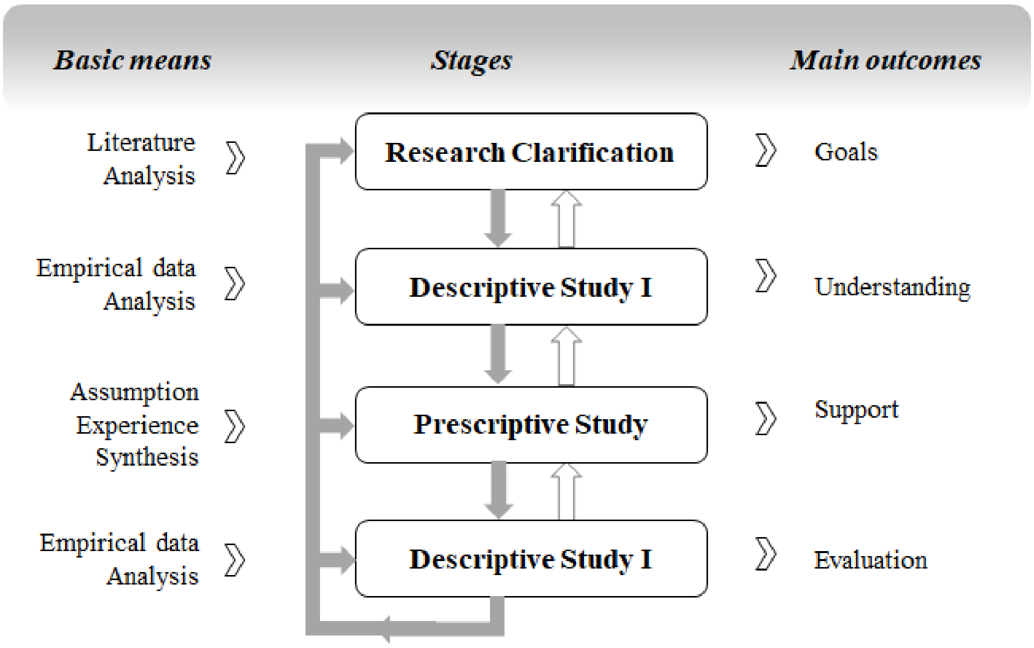


Figure 3.1: DRM framework; based on Blessing and Chakrabarti (2009)

The research started with the aim of improving collaborative engineering design in PBL (research clarification stage). Based on our understanding of learning-by-doing design courses, the underlying assumptions were the following: collaboration is a crucial element of design learning; improving the quality of collaboration will improve the design process and the learning outcomes; this will leads in a better and thus more successful PBL. Furthermore, we considered the currently collaboration level in PBL teams insufficient.

With the start of Study I, we searched the literature for additional influencing factors to elaborate the existing situation description. To improve collaboration, the description was meant to be detailed enough to identify the factors that should be addressed. However, the global pandemic changed the situation where most of the teamwork was done online. A literature search did not yield sufficient evidence to clarify crucial factors for improving collaboration in a fully online PBL. Before moving on to the next stage, we decide to carefully observe student engagement at an entire online engineering design PBL course in an ethnographic study. The analysis of the empirical data revealed a transformation in information flow and usage of cloud-based platforms in the online PBL course, as well as unequal engagement in collaborative tasks. After reviewing the description of the existing situation, we decide that our understanding is sufficient to launch the Prescriptive Study.

During Study II, we corrected and elaborated on our initial description of the desired situation based on our increased understanding of the existing situation. Based on the new vision for improving the current situation, we have described how addressing factors in the existing situation can lead to achieving our desired/improved situation. To address the poor involvement in collaborative design, we decided to work on improving the balance of active engagement. Our argument is that providing feedback on engagement should reduce the inequality of engagement, which in turn should reduce poor collaboration, which eventually should lead a better design and improve PBL. Now we had enough confidence to start the systematic development of a dashboard to improve collaborative design learning through a feedback mechanism. After clarifying the task and conceptualizing the design, we developed a concept for a system that would utilize data-logs to calculate and visualize active engagement in order to support improving collaborative design. Based on our evaluation of the concept and verification of the underlying assumptions, we decided to focus our implementation efforts on the core intention of the system. First evaluations showed that the system has been properly developed.

At this stage, we perform Study III to examine the impact of the system and its ability to achieve the desired state. In order to analyse the actual use of the system, we conducted an empirical study to evaluate the applicability of the system. The main question was whether feedback on engagement causes a more balanced active engagement, and how this contributes to the collaborative design. The results show regular mirroring of team engagement helps balance team involvement. While this positively contributes to the design outcomes, the improvement is not significant.

The fourth study was designed to evaluate the possibility of a complementary intervention to enhance collaborative design and learning. In this stage, another iteration of literature review conducted to answer following questions; (a) what other element(s) of teamwork can be compatible with process feedback on engagement? (b) What methods have been studied to improve this item, which has received less attention in engineering and PBL? (c) What are the challenges and limitations of this method? (d) Can state-of-the-art technology play a role?

Based on an interdisciplinary literature review, the fourth case study was implemented with these assumptions: (a) motivation and conflict management can play a complementary role to the process feedback (b) Motivational Interviewing is an effective tool to perform a. Evidence suggest that; (c) these strategies face limitations in scalability and cost; (d) AI has the potential as an alternative solution.

Finally, using the results and experiences from the previous cases, the research proceed to the last iteration, where we conducted Study V, to further touch on AI-ML-NLP in a proof-of-concept to shed more light on the cutting-edge technology to address the challenges.

Focus and validation

To find the research problem in each case we focused on the PBL ongoing courses. For example, while in a PBL course, different engagement levels can be seen in the teams, the question remains whether the pattern of engagement contributes to the design quality, the learning outcomes, or the final grades. Now, this scope needs to be established to validate the claim of "there is a meaningful correlation between a balanced active engagement and collaborative learning outcomes".

Another focus and contribution that essentially led us to drill down to the topic of feedback systems is the question of "How we can balance the engagement?". Once the problem has been narrowed down in scope, we developed the next assumption. For example, "a process feedback improves engagement" now we can test the claim verification and validate of the proposed solution through an empirical study. Figure 3.2 shows the iterative cycle of narrowing down to the research claim in each case, which is a simplified version of the Sargent (2013) model of design validation as further developed by Isaksson et al (2020). According to Isaksson et al., based on Asimov (1962) the model also shows the inherent similarity between design research and design problems, where an analysis-synthesis-evaluation loop is needed to identify the underlying challenge that can be addressed by the design within the means and capabilities of the designer.

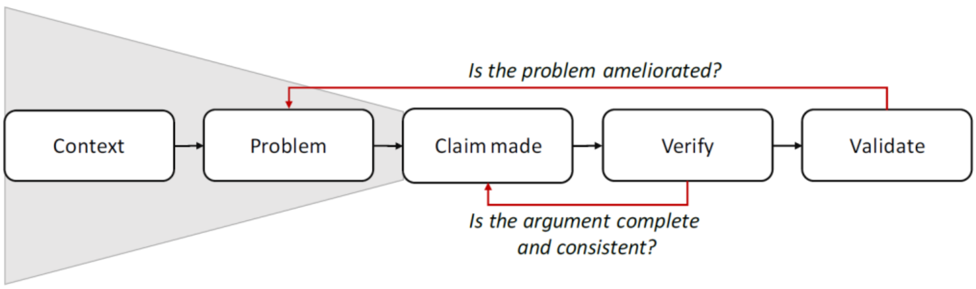


Figure 3.2: Focusing to enable verification and validation (Isaksson et al., 2020)

The research is carried out in a practical context of PBL courses with a context of collaborative engineering design and learning, where the research team had a track record of working on design education. This brings a specific theoretical lens for each study through which we look at practical problems. Within these research themes, we identified a research gap where we can make a contribution to knowledge. We did not assume to address the identified research gap in its entirety; rather we found a focus for each case study. The focus originated in the practical problem we wanted to address.

Within the particular research focus, we identified research questions, which we could address within the allocated time (usually during a semester for gathering data and 3-6 months of analysis, interpretation, and repot/publication).

For each case study, this research included the steps shown in Figure 3.3, but the emphasis in each step varied, and the balance between the research and application sides was different. Validation has been a part of both the contribution to knowledge and practice. As Figure 3.3 indicates, once research hypotheses are defined, there is an iterative loop between the research questions, the study, and the results as a verification process.

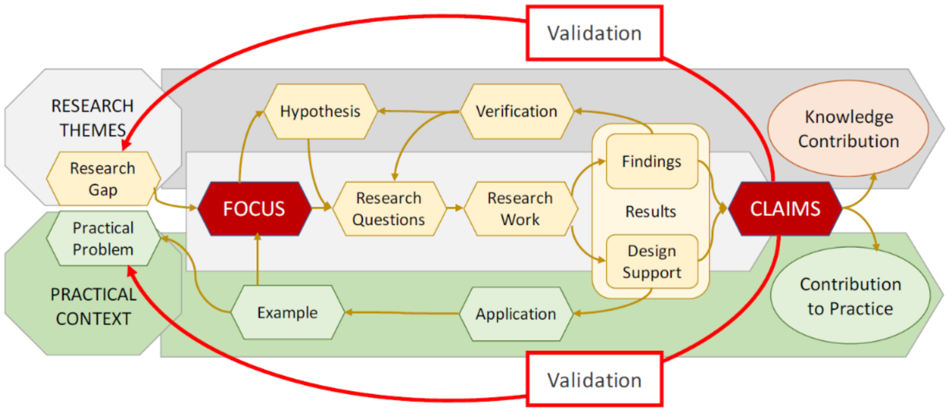


Figure 3.3: Journey to validation (Isaksson et al., 2020)

3.2 Goals

This research pursuits multiple goals. **First**, it aims to provide a better understanding of the collaborative engineering design and collaborative design learning and their dynamics, key elements and challenges. **Second**, to design and propose supporting technology-based tools/dashboards and measurement approaches of collaboration constructs that meet web-based team activities, while understandable, and applicable by machines. **Third**, to propose human-centered approaches that not only enhances the collaboration but also lead in significantly better outcomes. And, **last** not least, to explore the potentials of cutting-edge technology and AI advances in order to overcome the challenges and limitations with a focus on Human-AI collaboration.

Improving understanding

The significance of establishing a scientific foundation for collaborative engineering cannot be overstated. Lu et al. (Lu et al., 2007) shed light on several key points that emphasize its importance. (i) in today's globally connected and technology-driven economy, industries must embrace collaborative engineering to maintain competitiveness in designing, manufacturing, and operating complex systems. However, despite its undeniable significance, collaborative engineering currently relies more on skillful artistry than on well-defined scientific principles. (ii) to meet the challenges of complex tasks and increasing social responsibilities, a deeper understanding of how engineers should collaborate is essential. It is crucial for collaborative engineering to evolve into a rigorous discipline rooted in scientific principles. To address these needs, Lu et al. propose the development of a human-centered engineering approach that generates valuable knowledge for educating students and empowers engineers to become effective collaboration leaders.

In a recent systematic review and critical analysis conducted by Varela et al. (2022), the central role of humans in collaborative engineering was further emphasized. The study underscored the importance of comprehending the fundamental aspects of collaborative engineering to enhance its practice. By merging scientific principles with practical guidelines, collaborative engineering can grow as a discipline and empower engineers to effectively lead and contribute to collaborative endeavors. Consequently, achieving a comprehensive understanding of collaborative engineering design is a crucial step towards improving its application and advancing innovation in complex systems.

Proposing supporting tools

Despite the significant development in e-collaboration technologies, lack of true collaboration remained one of the main reasons for project failures. To discuss the importance of supporting collaborative design Kolfschoten et al., (2014) reported lessons from a case study at the ESA concurrent design facility and present a set of challenges and guidelines for effective collaborative design and engineering. The study emphasis on the importance of Group Support Systems, collaboration support (Computer Supported Collaborative Work) tools and principles, to a better collaborative engineering procedure.

A paper by Buchal & Lu (2011) existing computer tools do not provide adequate support for collaborative knowledge building and that better tools are needed based on the specific requirements to improve engineering design education and practice. According to Bavendiek et al. (2016) supporting collaborative design by digital tools has potentials and challenges. They argue that while the application of modern digital tools for information representation and exchange as well as the use of design methods in distributed teams can support a wide range of the tasks, for a successful collaboration, new competencies are required for efficient work among team members.

Using the tools in a feedback system

Feedback systems in teamwork allow for the assessment and improvement of teamwork processes and outcomes. For example, Real-time language feedback is a system that monitors the communication patterns among team members and provides real-time instructions to shape the way the group works together to improve the way groups work together (Tausczik & Pennebaker, 2013). Another example is multimodal data labeling that is semi-supervised machine learning method that helps with manual data labeling of multimodal data in a collaborative virtual environment (CVE). This method can be used to train teamwork skills, and a feedback system based on that can predict human behavior and provide feedback to scaffold skill learning (Plunk et al., 2023).

The current feedback systems in engineering design and learning are mostly outcome-based, this work has a special focus on process feedback. However, while process feedback is not easy because of scalability issues, AI might have the potential to cover this aspect. These are basis for the next goals.

Human-centered approaches

Collaborative engineering design and learning can benefit greatly from focusing on the human aspect of collaboration over the technical parts. This is because effective collaboration requires experts from various disciplines to ensure sub-systems' interoperability and include customers, users, and other stakeholders in the design. A collaborative approach to design and engineering is critical. However, gaps in current practices need to be addressed, including the lack of adequate support for collaborative knowledge building and the need for better tools to support it that focus on human aspects. To address these gaps, there is a need for more research into collaboration support for effective collaborative design and engineering and for the development of better tools to support collaborative knowledge building and effective communication. In addition, there is a need to leverage recent approaches and technology for enabling or promoting collaboration, such as human-centered and human-machine interaction approaches.

On the other hand, recent studies show that graduates and undergraduate students in some engineering fields often lack the collaboration and communication skills necessary for agile methods and, thus, are not yet well enough educated for approaches that intensely relies on collaborative engineering design. Therefore, new approaches or more adequate educational methods for teaching the necessary communication and collaboration skills need to be developed (Kropp et al., 2014).

The potentials of the cutting-edge technology

Recent advance in AI and Machine Learning technologies such as Language Models provide a great opportunity to improve collaborative engineering design and learning. Language Models are advanced AI algorithms that can process and understand natural language at an unprecedented level with many possible applications in engineering design and human-AI collaboration. For example, socially embodied AI refers to the state an AI-based agent takes on when embedded within social and technologically nonpartisan "bodies" and contexts that creates a social form of human-AI interaction (HAII) (Seaborn et al., 2020). These technologies can cover the scalability problems and limited while facing large amount of data.

Computational linguistics is another example: Recent advances in computational linguistics, including cloud computing, and Big Data, that uses AI, ML, and deep learning, are able to understand the structure of human language and its use in social settings. Computational linguistics can help researchers and engineers overcome linguistic barriers, and facilitate communication (Lin et al., 2023).

3.3 Research Questions

Improving understanding

RQ1 *"How the new norms of web-based collaboration formed different patterns of information flow and distributed cognition in collaborative engineering design and learning?"*

Answering this question provides us with a better understanding of collaboration dynamics in engineering design and learning during the global pandemic. Case study one designed to answer the question. We employed an ethnography methodology to observe the entire process of a rocket engineering process. Ethnography is a qualitative research methodology that involves studying people and is a type of field research that involves observing and interviewing individuals in their work/life settings to gain an understanding of their perspectives and behaviors where the researcher can is a member of the group (Goldman, 2011; Rashid et al., 2015). At the same time we used another mythology called Distributed Cognition for Teamwork (DiCOT). Blandford and Furniss (2005) developed DiCoT as a method and representational system to support the analysis of Distributed Cognition within small working teams. By using these two methodologies in the first case study we gained insights that paves the way to the next goals.

Proposing supporting tools

Seeking the answer of the previous question, we learned about the enormous use of some web-based collaborative tools and the challenge of unbalanced engagement of members in tasks and responsibilities. Now the attention goes to the tools and possible opportunities to design better collaborative tools.

These brought us to the following research question.

RQ2 *"How to design a data-driven dashboard to measure, visualize, and monitor active engagement as an essential construct of collaboration?"*

Our hypothesis is that a data-driven dashboard can measure, visualize, and monitor active engagement, by analyzing data-logs and tracking online activity records during collaborative works.

We designed a dashboard to test the hypothesis. The accuracy of the proposed dashboard to measure active engagement in a collaborative work is verified in case studies. Hence, through this the research work contributes to the knowledge on the interplay of processes and design tools in collaborative engineering design and learning. In addition, a data driven measurement tool will let us to employ technology-based interventions that meet the requirement of digitalized process.

An access to all the data logs of a technology planning and road-mapping course where teams of engineering students worked on a collaborative project provides us with the ability to design and validate the idea of a dashboard. Later when the system designed (based on the insights from the literature), we applied it to the available data and then through an online questionnaire the validation was examined.

Now the next question should address the usefulness and efficacy of the designed dashboard in a feedback system.

Feedback systems

When we made sure that, the system is accurate enough to reflect the engagement level of the members during a collaborative project; it is time to evaluate its efficacy to improve active engaging and the design outcomes.

RQ3 *"How a process feedback on active engagement lead to a more balanced engagement and a better design?"*

To answer this question, we designed a case study where half of the teams received a regular feedback con their engagement. We had a chance to compare the changes in the engagement pattern by comparing the experiment group with a control group containing teams that not received a process feedback. The feedback clearly had a positive influence on balancing the engagement, however, the improvement in the design was little. This shed a light on the next issues on how improving the outcomes too.

Human-centered approaches

A human centered approach focuses on understanding the needs, wants, and limitations of the people who will directly benefit from the solution while involving collaboration between the team members throughout the design process (Göttgens & Oertelt-Prigione, 2021). Motivational interviewing (MI) also is a person-centered approach to communication that aims to elicit and strengthen intrinsic motivation for behavior change (Bischof et al., 2021; Rubak et al., 2005). In the field of collaborative design, MI can be used to enhance organizational readiness and facilitate implementation efforts, MI can also be used to help staff to adopt new evidence-based practices in organizational settings (Arbuckle et al., 2020).

The solid evidence on the efficacy of MI, and the gap of using MI in the collaborative engineering design and learning from the question of how the outcomes of a collaborative design might influenced by a MI-based strategy.

RQ4 *"How a communication strategy such as Motivational Interviewing contributes to a better outcome in the process feedback?”*

To answer this question, in a case study we designed a double-blind methodology, where neither the participant teams nor the judges were aware of the ongoing research. We provide a process feedback using MI to half of the teams (experimental group) and then compared the outcomes with control teams that not received any feedback.

Although the results showed a significant improvement in both the team sentiment and the design, using such a communication strategy is not easy in large scale projects or large number of members, or educational settings that too many students are participating in an engineering course and Project-based Learning (PBL). These trigger the question about the potential of cutting-edge technology and AI advances to address the limitations.

Potentials of the cutting-edge technology

Several studies explored the use of AI to assist in applying MI and help people change.

In a study titled "Advancing Motivational Interviewing Training with Artificial Intelligence: ReadMI", Hershberger et al. (2021) developed a training tool called Real-time Assessment of Dialogue in Motivational Interviewing (ReadMI) that uses natural language processing (NLP) and ML to provide feedback to students, residents, or clinicians in a real-time basis. In another study titled "Technology-Assisted Motivational Interviewing: Developing a Scalable Framework for Promoting Engagement with Tobacco Cessation Using NLP and Machine Learning" Saiyed et al. (2022) developed a digital conversational agent called the Technology Assisted Motivational Interviewing Coach (TAMI) that incorporates machine learning models to help people engage with tobacco cessation. Now the promising evidence initiate the last questions of the current research.

RQ5 *"How AI and ML can facilitate the process of measuring and improving active engagement in feedback systems in collaborative engineering design and learning?"*

To answer this question, we used a retrospective methodology. Meaning that we employed ML models to predicted the results of the previous case studies by training and testing the model using the available data sets to create a proof-of-concept.

Chapter Summary

Chapter 3 of discusses the methodology, thesis objectives, and research questions employed in the study. The research methodology used is Design Research Methodology (DRM. The philosophical underpinnings of the research are grounded in the pragmatist paradigm, which emphasizes the practical application of knowledge and the importance of understanding the real-world implications of research findings. The research questions are addressed through a systematic iterative approach involving literature review, case study, and validation.

The research aims to address the challenges of collaborative engineering design and learning by employing DRM as an iterative approach with a focus on validation through case studies. The study emphasizes interdisciplinary collaboration and the integration of diverse perspectives to address complex engineering design and learning challenges. The ultimate goal is to contribute to the development of more effective and efficient collaborative engineering design and learning practices, as well as the advancement of technology in this domain.

The chapter also describes the holistic framework and approach of the study, which includes four stages: Research Clarification, the Descriptive and Prescriptive Studies. Each stage builds upon the previous one and involves refining the research findings and developing practical solutions. The research also focuses on validation and uses empirical studies to test and verify the proposed solutions.

The goals of the research are multi-fold. First, it aims to provide a better understanding of collaborative engineering design and learning and their dynamics, key elements, and challenges. Second, it aims to design and propose supporting technology-based tools and measurement approaches for collaboration constructs. Third, it seeks to propose human-centered approaches that enhance collaboration and lead to better outcomes. Lastly, it explores the potentials of cutting-edge technology and AI advances in overcoming challenges and limitations, particularly in the realm of Human-AI collaboration.

The chapter concludes by highlighting the research questions and the methods that we tried to address the questions.

Chapter 4

Case Studies

This section provides a comprehensive report of the five case studies I have conducted as a result of the iterative approach supported by the methodology. Each study builds upon an independent methodology, literature review, and previous literature review, and case studies (for case studies 2-5).

4.1 Case Study #1: Web-Based Collaborative Engineering Design and Learning

Engineering design teams, particularly in academic courses, were no exception to the consequences of the unknown virus and the global pandemic. Forced online teaching has influenced the way of using communication technologies. The information flow architecture of engineering design is also transforming due to the remote activities and the dominancy of web-based technologies. This transformation creates different patterns of distributed cognition within design teams. In the course of full remote teaching, we studied the entire information flow of a small and dispersed engineering team through the early stages of design for one month using the ethnographic method and Distributed Cognition analysis techniques. Our analysis, of the interdisciplinary design team during a rocket engineering project and system engineering teaching, shows the considerable role of different online data sharing and communications technology platforms in distributed cognition and collaborative problem solving within the team. These new trends create new challenges and opportunities, and in order to enhance collaborative design, these emerged out of the box trends require more attention and updating of existing strategies.

Introduction to study #1

The COVID-19 crisis has led to a surge in remote teaching and online design activities, impacting the approach of engineering students. This change necessitates a review of design strategies for teaching, collaborating, and managing the design process. Systems engineering and design typically involve distributing information across specialists and requiring cognitive work to integrate data successfully. However, the shift towards remote work and human-computer interaction adds complexity to collaboration, communication, and teamwork for engineering students. Reports indicate that remote work is becoming increasingly prevalent, even beyond the pandemic. This necessitates rethinking off-site design activities, understanding emerging trends, and adopting effective tools and procedures. This study explores the challenges faced by students learning system engineering and practicing system development online, utilizing the framework of distributed cognition. The study analyzes cognitive processes, information flow architecture, and communication platforms used in a multidisciplinary remote design project. The findings emphasize the role of simple communication platforms like Telegram, Google Docs, and Zoom, while discussing future directions for research in web-based collaborative design and engineering problem-solving.

Distributed Cognition

Despite the traditional view in the cognitive sciences that the individual's brain plays an exclusive role in the cognition process, Distributed Cognition Theory (DCT) developed a different and more modern perspective in which forms of the extended mind emerge, such as complex sets of connections between individuals and artefacts in a certain task (Hutchins, 1995). Hollan et al. (2000) believe that to design efficient human-computer interactions and to understand human cognitive functions, we must grasp the nature of these distributions of processes. In DCT, we expect to find a system that can run a dynamic self-configuration to coordinate subsystems to accomplish different functions. In fact, rather than through the elements' spatial colocation, a cognitive process is bounded by the functional links among the elements that engage in it. Based on the DCT principles to observe human activities, at least three kinds of cognitive process distribution are perceptible:

- Distributed cognitive processes across the members of a social group;
- Involved cognitive processes in coordination between both internal and external structures;
- Distributed processes through time in which the products of initial events can transform the nature of following events.

According to this view, in addition to the larger field of cognition processing, and the important role of communication between different elements in a system, one can note a particular focus on the way of transforming and propagating information within the system to deliver collaboration.

Different studies on teams of software development, co-located agile engineering, and transportation, have applied this approach to analyse the team performance and information flows (Sharp et al., 2006; Dreyfus, 2007; Sharp, Giuffrida and

Melnik, 2012; Andreasson, Jansson and Lindblom, 2019). Although a wide range of papers has used this approach to study a combination of remote and on-site engineering projects, the current situation of full-remote-work is new, and we could not find a study on completely online teaching/teamwork based on the same method.

The analysis in this study relied on DCT to explore how information flows in all directions during remote teamwork of a system engineering teaching and related design operations. Along with previous explanations of Distributed Cognition, we used the DiCOT technique to analyse the information flows of the team. In the next section, we briefly describe this method and then discussed it in detail in the next subsection

Distributed Cognition for Teamwork (DiCOT)

Blandford and Furniss (2005) developed DiCoT as a method and epresentational system to support the analysis of Distributed Cognition within small working teams.

The DiCoT technique includes three basic themes (Figure 4.1.1):

- The first theme is related to the physical environment of the cognitive system.
- The second theme focuses on the artefact's details.
- The third theme pays attention to information flow and the way that information flows within the cognitive system, the media or tools, which facilitate the transforming information process.

A set of principles obtained from Distributed Cognition are defined in DiCoT to map the three themes for a deeper investigation. In section 4, we explain these themes, their principles, and related analysis.

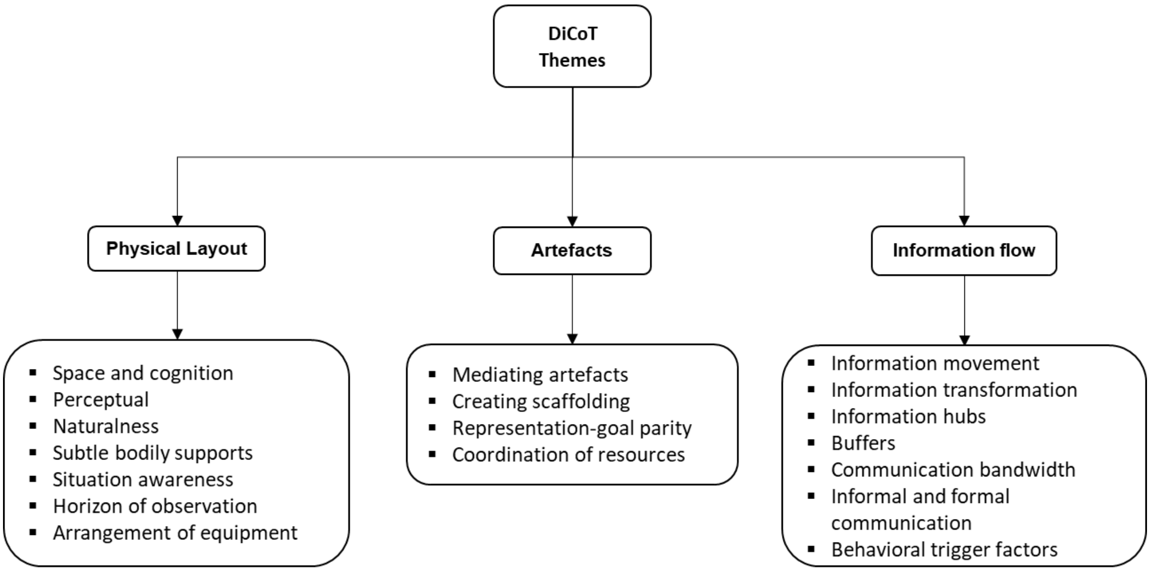


Figure 4.1.1: The DiCoT three basic themes

The Study

A team of students designing and developing a rocket for a rocket engineering competition (IREC, 2020) was studied. While learning the various stages of System Engineering (SE), the team must design, build, and launch a rocket carrying a payload of no less than 4 kg to a target apogee of 3 Km above ground level and land the rocket parts on the ground without any damage. The mission supported by Skoltech Space Centre and, participants were PhD and Master programs students from the SE course. The first phase of the system engineering development and design before the Preliminary Design Review (PDR), and Critical Design Review (CDR)observed in this study ran for one month during November 2020, and included; Mission Objectives, Concept of Operations, Mission Requirements, System Requirements, System Architecture, Product Breakdown Structure (PBS), Work Breakdown Structure (WBS), Stakeholder Analysis, Risk Analysis, and Preliminary Design.

The Team

The team involved in the project consists of three different groups: the main group, seven engineers from different disciplines; the second group, two mentors from the Space Centre Engineering at Skoltech. One of the mentors was the course instructor and the second mentor a member of the group as a technical advisor. The third group was composed of a network of external advisors with significant experience in this type of project. All groups were dispersed worldwide and had only online contact during the various stages of project development throughout the whole study. The team was a good example of absolute remote engineering design. An outline of the roles and countries of the main team members (the main team was the central focus of the study) is specified in Table 4.1.1 None of the members were native English-speakers, but the main language of the project, all documentation and communications were in English.

Table 4.1.1: The main team roles and countries

ID	Expertise/ Degree/Gender/Age	Role	Country	ID	Expertise/ Degree/G/Age	Role	Country
M1	Space Engineering/ MSc/Female/22	Coord.	Russia	M5	Space Engineer/ PhD/M/32	Mentor	Russia
M2	Engineering Systems/ PhD/Male (M)/41	System Engineer	Iran	M6	Mechanical Engineering/ M/26	Mechanical Design	Pakistan
M3	Robotic/ MSc/M/23	Mech. Eng.	Russia	M7	Electronic Engineering/ MSc/M/24	Electronics Design	Russia
M4	Aerospace/ MSc/M/24	Modeling - 3D	Egypt				

Data Gathering

We used the anthropology informed approach to gather data for our study (Bentley et al., 1992). One of the researchers is a member of the team under the study who participated as a system engineer. It is also an accepted method in virtual ethnography (Hine, 2000) and helped the researcher to have a better understanding of team members' viewpoints during virtual meetings.

The researcher is a member of the team virtual group and directly observed the members activities in text-based connections, during 62 hours of 27 video sessions, the design iterations, and preparation for PDR and CDR. We recorded all the sessions via 49 hours of video recording and six hours of voice recording. The researcher also had access to the pairing section recordings and text messages by uploading the backup of conversation to a virtual archive channel by the involved members who accepted to be observed throughout the study. The collected data included recordings, screenshots, observation notes, online documentation activities and text messages. Moreover, a brief questionnaire (Table 4.1.2) was answered by each team member about the details of the way and time in which they shared information.

Table 4.1.2: Questions about sharing information adopted and modified from Sharp et al (2012)

1. How do you share the project information with your teammates?
2. How often do you reach out your teammates, and how, e.g. WhatsApp call with M1 every day x times for x minutes?
3. Are there any information or files that you think do not need to share? Please outline examples with indicating why you believe so.
4. If you come across a situation you think you could act better in a face-to-face meeting. Please example and reasons. What you have done in such situations?

DiCOT Analysis

Physical Layout of the team members

The physical layout of all the team members' workspace was their home offices and varied in terms of the form of the space they used and how the working environment might help their work activities. The DiCoT framework of Physical layout parameters is summarized in Table 4.1.3.

Table 4.1.3: Physical Layout adopted from Sharp et al. with permission (2012; 2016)

Space and cognition	The use of space to support activity, e.g. laying out materials
Perceptual	How spatial representations aid computation
Naturalness	How closely the properties of the representation reflect those of what it represents
Subtle bodily supports	Any bodily actions used to support activity, e.g. pointing
Situation awareness	How people are kept informed of what is going on, e.g. through what they Can see, what they can hear and what is accessible to them.
Horizon of observation	what an individual can see or hear (this influences situation awareness)
Arrangement of equipment	How the physical arrangement of the environment affects access to Information.

Space and Cognition

Based on interviews with members, physical space was limited to the workers' desk during this project. Scattered notes in a notebook or scraps of paper were used temporarily and were not properly archived for later use. Schedules and important events were set up virtually.

One of the most used methods to ensure everybody had quick access and was made aware of new changes was pining a specific post in the virtual Telegram group. This approach corresponds to a physical bulletin board, where important announcements are pinned.

Perceptual and Naturalness

Relying deeply on working in the virtual setting has narrowed spatial perception that are affected by signals received from these information resources. In general, each person received information from three different monitors. Usually a laptop, a monitor in Extend Project mode, which connected to a laptop, and a personal smartphone (see Figure 4.1.2). For some members, more monitors were used. It is not easy to measure the naturalness principle of the physical layout, and difficult to evaluate how the presentation of data for members was natural, because most of the members were in their first experience for this type of project and environment.

Subtle bodily supports

Since all team-related activities took place in the virtual environment, there was no expressive physical gesture or movement that could be reported as a principle regarding subtle bodily supports. It is almost impossible to read the body language correctly in virtual space because there is no natural gesture in text-based conversations, and during video meetings, you can only see a face or mostly people tend to turn off their videos. Though tagging people in-group chat spaces or using emoji cartoons was very common, inferencing this kind of virtual gestures is not reliable as subtle bodily support for at least two reasons; first, they are quite limited and predesigned features, and second, we could not find solid evidence that has studied this area.

Situation awareness

The team members relied on Telegram group chat for meeting invitations, event reminders, link to documents, sharing resources and mandates, etc. Announcement on the Telegram instant messaging group is the primary mean of being aware of all project milestones and activities. The coordinator updates the situation after any change and posts it in the chat group to ensure everyone is aware of the situation. In necessary situations, tagging (using @+ID creates a signal notification for the person) is used to confirm the corresponding person has seen the post. According to observations, although the concurrent use of several artefacts and the instantaneity of announcements increases the cognitive load, which is a big challenge and needs investigation, situation awareness generally happens effectively.

Horizon of observation and arrangement of equipment

The members' horizons concerning this project and teamwork were clearly limited to the monitors in front of them. Given that 100% of activities under this study were performed remotely, and it was a temporary short mission, it was not possible to provide a specific physical horizon of observation. Figure 4.1.2 shows a typical horizon of observation and arrangement of equipment.

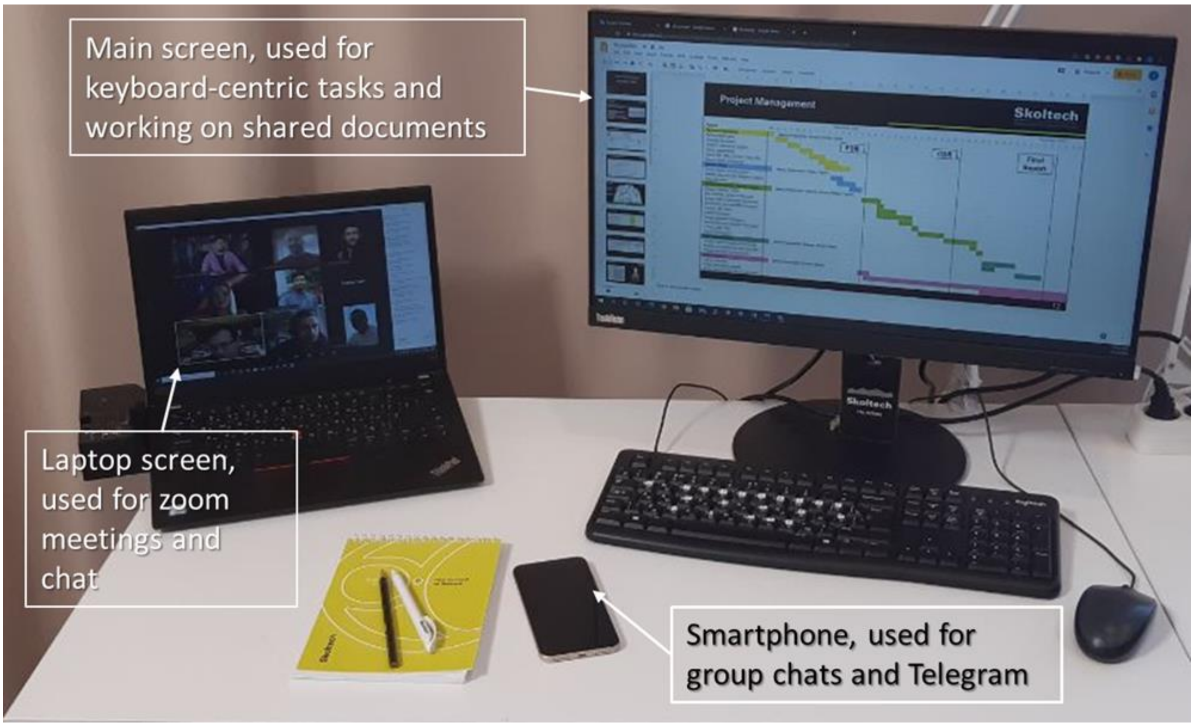


Figure 4.1.2: A sample of the horizon of observation of team members during remote work

Artefacts and Information Flow

The next two themes for analysis concentrates on the role of artefacts and information flow more precisely. The analysis focuses on the communication among the team members, their roles and the patterns of events, which define the system's mechanics (Blandford and Furniss, 2005). Table 4.1.4 presents the main virtual artefacts that played essential roles in the team collaboration in this project. In the table, the Usage

Rating column represents the team members' opinion about the level of usage of any artefact based on time and volume of information transfer (most used A and the least used E).

Table 4.1.4: The main virtual artefacts

Application/Platform	Capabilities	What the team handled with it	Usage Rating
Telegram (Durov Nikolai, 2013)	a cross-platform based on cloud, ability to instant messaging, group communication, calling, and Voice over Internet Protocol	Communicate with teammates, share information and exchange links. Also, conducting polls for appointments.	A
Google Docs (Google, 2020)	Free online documents for instant documents sharing and co-working	Sharing information, working simultaneously on documents. Usually accompanied with Zoom	B
Zoom (Zoom Video Communications Inc, 2020)	Online video services, by peer-to-peer cloud-based platform and provides teleconferencing, telecommuting.	Team meetings, negotiation sessions, networking with consultants and mentors, and in-team coordination	C
Miro (Khusid Andrey, 2020)	An online platform for visual collaboration and teamwork. Provides a whiteboard.	This virtual whiteboard provides a place to a simultaneous drawing of charts and forms	D
MagicDraw (No Magic, 1995)	A visual modelling tool for team collaboration. And the ability of analysis and design of engineering systems.	A limited volume of modelling activities performed in this environment.	E
Git (Git, 2020)	A system for distributed version control and tracking changes in documents.	Control the versions and tracking any changes.	E

Based on the DiCoT methodology, the second theme is considering the way that artefacts are designed to support cognition from the perspective of DC. From this perspective, the environment that the team (or team members) inhabit has a pivotal role in cognition, including: all artefacts, tools, representations, and environmental resources (Blandford and Furniss, 2005). Table 4.1.5 shows the DiCoT framework for information flow.

Table 4.1.5: Information flow framework, adopted from Sharp et al. (2012; 2016)

Information movement	The mechanisms used to move information around the cognitive system
Information transformation	When, how and why information is transformed as it flows through the cognitive system
Information hubs	Central focuses where information flows meet and decisions are made.
Buffers	Where information is held until it can be processed without causing disruption to ongoing activity.
Communication bandwidth	The richness of a communication channel
Behavioural trigger factors	Cause activity to happen without an overall plan

Also, Figure 4.1.3 represents how information flow happened within the dispersed team. Communication among all team members occurred completely through virtual interactions and mostly in group chats. Models in Figure 4.1.3 illustrate two different phenomena in artefacts utilities and information flow procedures; in model A, you see a collection of applications/platforms inside a circle used by the team members during collaboration, communication, and information sharing. All team members connected to the circle over a two-way line, which means they send and receive all that data through this model. The line of the team coordinator is thicker, which shows a higher volume of connections. Inside the circle, Telegram gained the largest share of usage, and MagicDraw is the smallest one with fewer usages. According to our data, if we divide artefacts into two distinct categories, communication versus technical, there is no significant difference in the summation time spent in each category (Telegram + Zoom Vs Google doc + Miro + Git + MagicDraw). Model B illustrates the team's pairing network; as shown in the drawing, most of the members had a connection with each other. While some members show more paring connections (thicker dashed lines), fewer or no connection cases were observed. The coordinator, for instance, had the maximum number of connections and collaborative activities. We also did not detect any relationship between members' backgrounds and their network strength, while members working in the same section made more connections together.

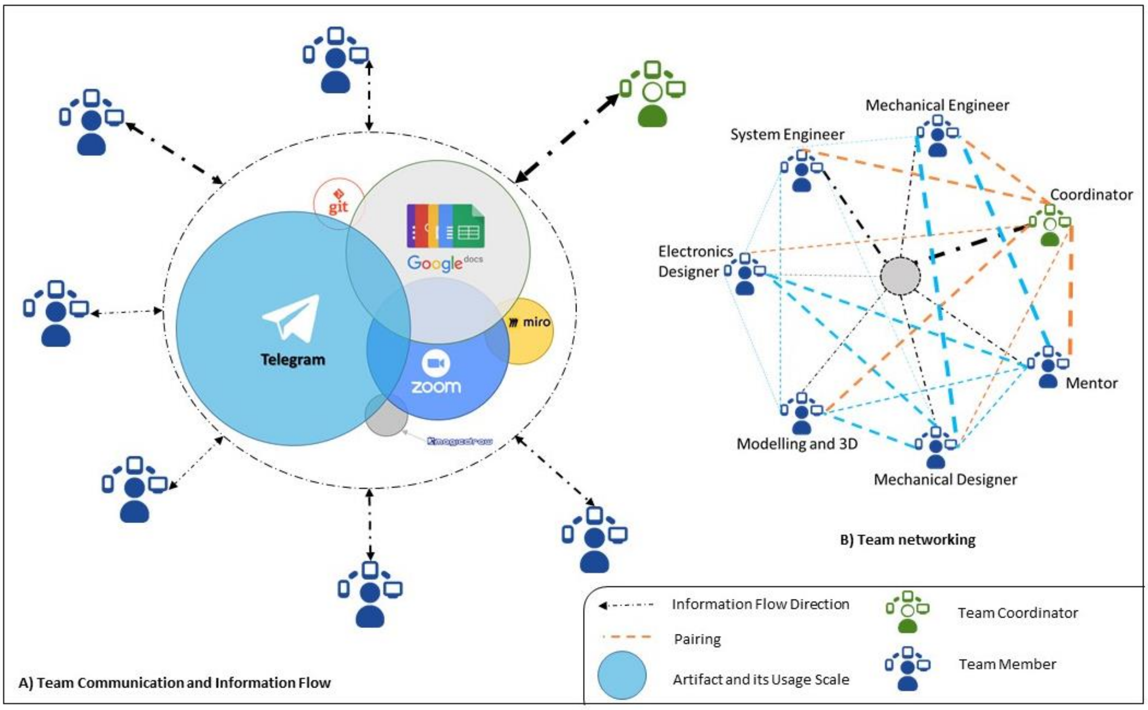


Figure 4.1.3: Team communication and sharing information layout all over artefacts, the size of the circle shows the scale of usage. B) Pairing Network, the thickness of lines indicates the strength of the connection.

Study #1 discussion

The study focused on investigating team collaboration and distributed cognition in the context of remote engineering design teaching during the COVID-19 pandemic. The project was conducted entirely online, with team members located in different countries and possessing interdisciplinary expertise. The findings align with similar studies on remote collaboration in agile software development teams, demonstrating that complex remote collaboration can be successful. The study utilized communication platforms such as Telegram and Zoom for effective communication and collaboration, while documentation and information sharing predominantly occurred through Google Docs and Telegram. The communication style was informal and primarily text-based, with members readily available for impromptu conversations. The study also employed distributed cognition analysis, revealing that information flow was enhanced through the use of various mediating artifacts, both simple and sophisticated. However, the study had limitations, including being a single case study with a short observation period. Future research could explore the long-term motivation and collaboration patterns in remote settings, as well as address the limitations of the DiCoT methodology for virtual environments. Additionally, investigations into information security, cognitive load management, and the role of artifacts in distributed cognition among engineering design teams outside academia would be valuable. Social network analysis and examining engagement levels and feedback impact are also recommended for further exploration. In conclusion, the study demonstrates the feasibility of remote engineering design teaching and provides insights into effective collaboration and information flow in distributed teams.

4.2 Case Study #2: A Dashboard to Measure, Monitor, and Visualize Active Engagement

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 web-based 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 study 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.

Introduction to study #2

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, first the background and logic of the work are presented, then, the measurement criteria and the main hypotheses of the study are described. Next section, addresses the validity of the approach by reporting the results of a case study. Then a brief discussion and concoction is provided.

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 long-term 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 4.2.1). 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 4.2.1 and 4.2.2): 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.

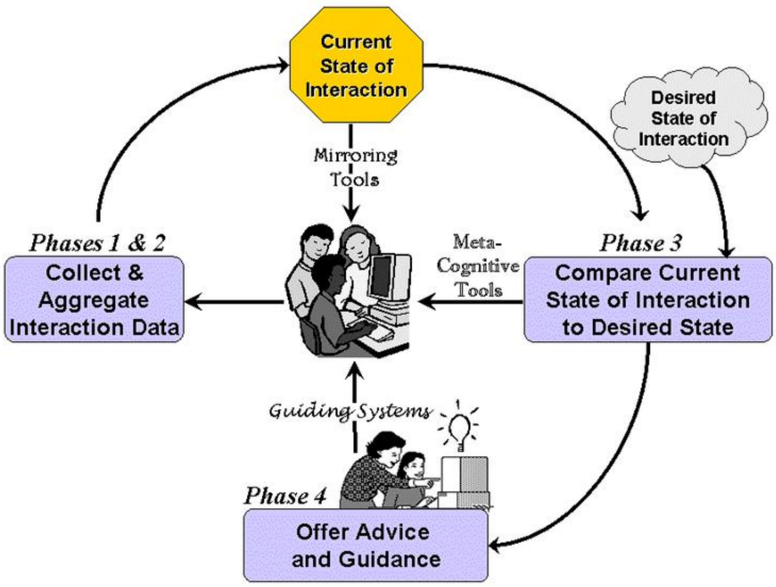


Figure 4.2.1: Mirroring, meta-cognitive and guiding systems (Figure from Soller et al., 2005)

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 4.2.2 represents the system schema; inputs are time, data, and attendance elements based on frequency and 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.

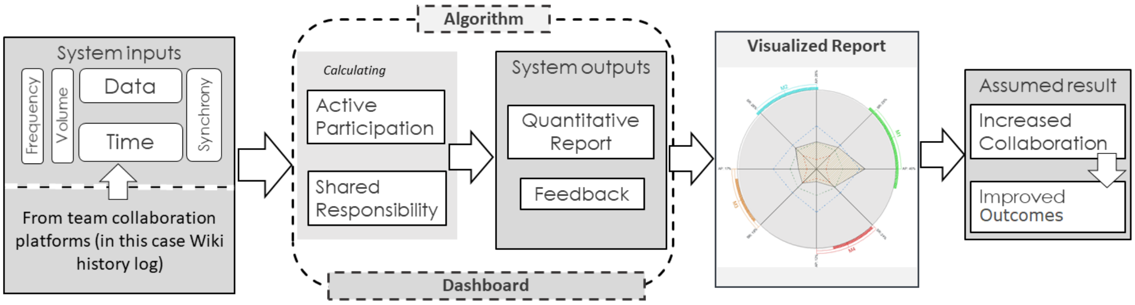


Figure 4.2.2: The system inputs and outputs

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 4.2.1 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 4.2.1, 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 4.2.1: 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)
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

In Table 4.2.1 the elements of Active Participation (AP) might be considered as a solo act. However, to explain why AP is still a part of the collaboration, we can consider a scenario where a group of individuals intends to move a carriage/car together (Figure 4.2.3). Individual efforts (pushing or pulling), such as the amount of energy (and the direction) expended, time dedicated, and the frequency of sustaining the effort, mirror solo activities within a collaborative task. Just as each person's contribution influences the overall movement of the carriage, these individual actions collectively shape the collaborative outcome. Not every solo effort would contribute to a meaningful movement. At the same time, this individual exertion represents only 50% of the collaboration measurement. The methodology also evaluates Shared Responsibility in three dimensions—on Sections (Tasks), in Time, and in Networking. This approach ensures that collaboration is evaluated not only through individual efforts but also by considering the interdependence and shared responsibilities among team members.

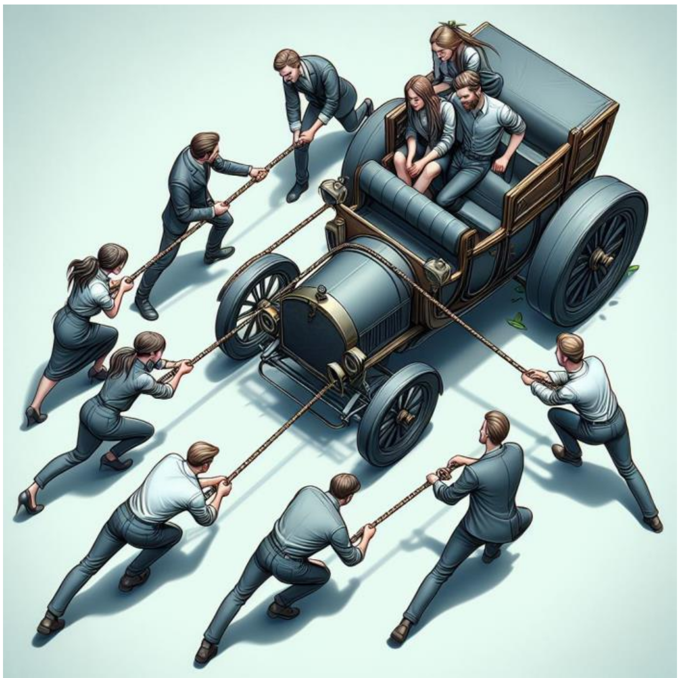


Figure 4.2.3: Synergy in Motion: Collective and Solo Contributions (The image produced through Microsoft Bing AI Image Creator)

The 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).

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 4.2.4 shows a sample report for one of the teams. Figure 4.2.5, 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 4.2.2 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 4.2.4; 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 4.2.5), participants were asked to 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 4.2.2: Projects and Teams

Team	Project Name	Members			
		Gender	Degree	Field of Study	Age
1	Automatic optical waste sorting	F	MSc	Manufacturing Engineering	
		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	23-31
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 4.2.4, 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.

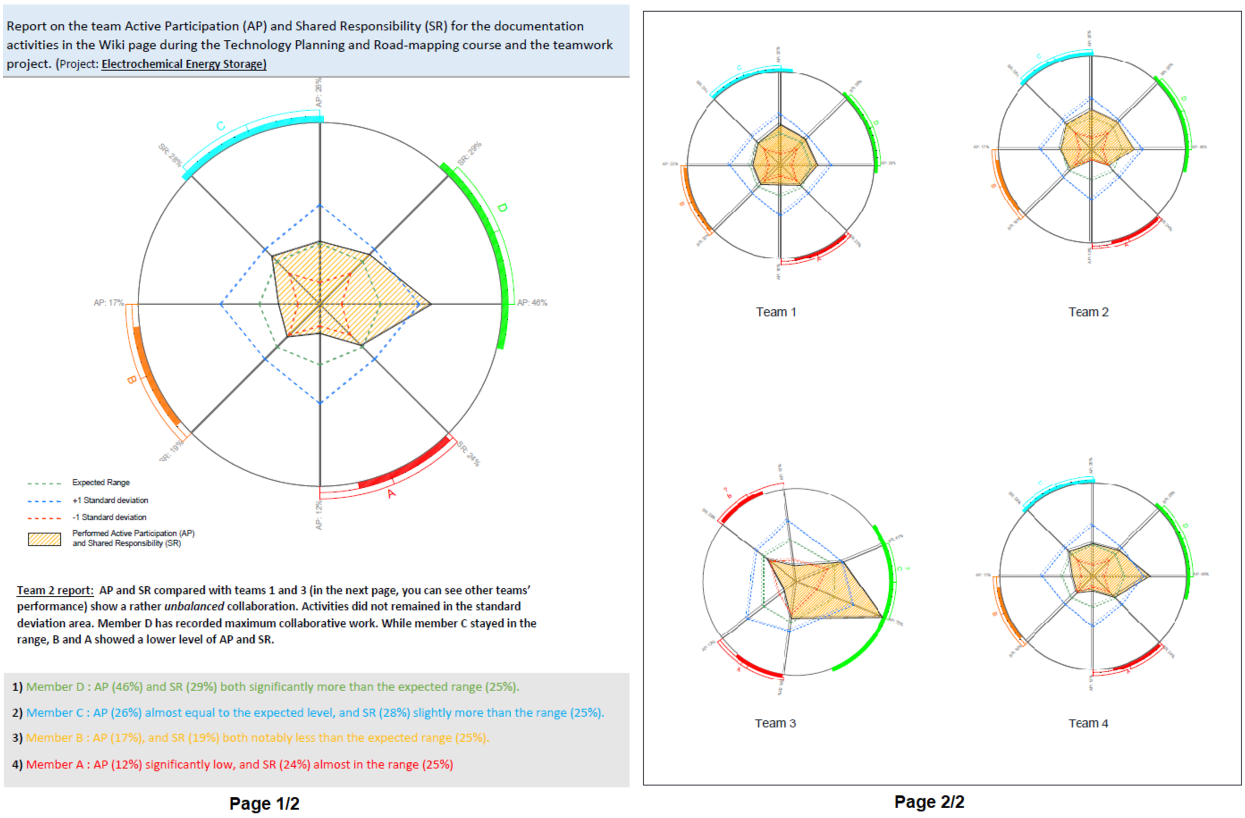


Figure 4.2.4: Page 1/2, a report of team collaboration performance. Page 2/2, all teams' graphs.

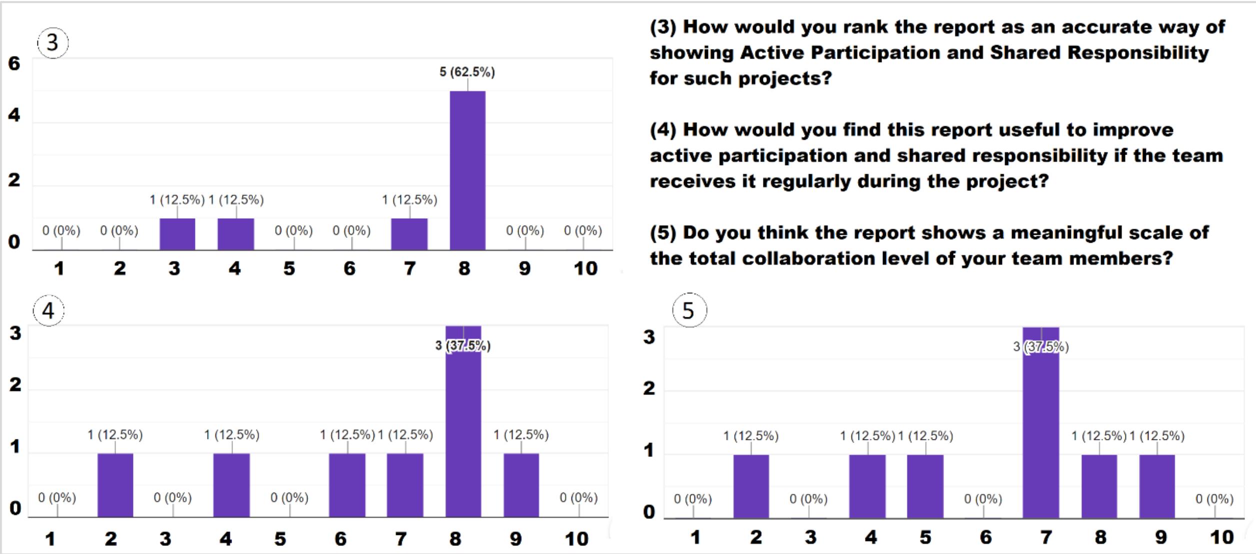


Figure 4.2.5: Questions and responses to scoring the metrics

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.

Study #2 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.

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 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 4.2.6 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.

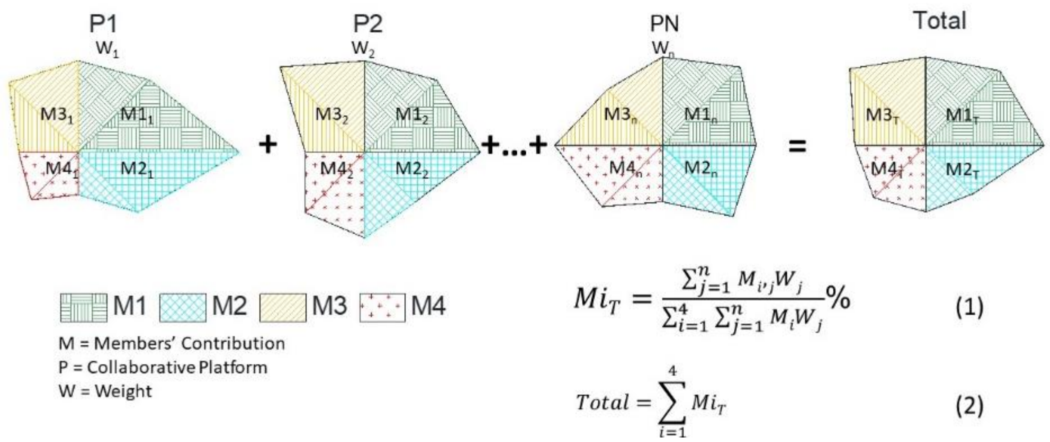


Figure 4.2.6: An example of four team members working in N number of collaborative platforms.

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.

In conclusion, 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.

4.3 Case Study #3: Feedback on Active Engagement

Introduction to study 3

This study was conducted to test the effectiveness of mirroring AE to teams as process feedback. During an eight weeks project-based Systems Engineering course, 25 students from 14 different disciplines and 8 countries were equally distributed in five teams according to their expertise, nationality, and gender (Table 4.3.2). While the structure of the teams was not set randomly and they were designed to match a normal distribution. The studied groups were determined randomly. Two teams (teams 1 and 2) were randomly assigned to the test group and the other teams were considered as the control group. Two participants dropped the course in the first week in the control group (teams 3 and 5) which made these teams continue with four members.

Case study

The projects are defined as an Urban Air Mobility development mission including five projects (Air ambulance, Parcel delivery, Mapping of territory, Air taxi, and Biological delivery). Teams optionally selected a project, and there was no limitation to selecting a duplicated topic. In order to fulfil the requirements, they had to follow the System Engineering methodology (V-Model) as outlined in INCOSE System Engineering Handbook (Haskins et al., 2006) and deliver the requirements in two stages (Table 4.3.1) including a working physical prototype.

Table 4.3.1: Project Deliverables and review stages

First Stage (Week 4) **Preliminary Design Review (PDR)**	**Second Stage (Week 8)** **Critical Design Review (CDR)**
▪ Mission Objective(s) ▪ Concept of Operation (by sketching) ▪ Stakeholder Analysis (Value network) ▪ Stakeholders Expectations ▪ System Requirements ▪ System Model (IDEF0) ▪ System Architecture ▪ Risk analysis ▪ Prototyping plan ▪ Schedule (Gantt chart)	▪ Improved PDR (according to the feedback) ▪ Assembly Integration and Test (AIT) plan ▪ Validation and Verification (V&V) plan ▪ The results of AIT and V&V ▪ A working prototype

All teams were provided with an Unmanned Aerial Vehicle (UAV) prototype that was modifiable to meet the projects' objectives. On PDR and CDR days, teams presented their project and five domain experts graded the presentations.

The main hypothesis of this study defined as follows:

1. The pattern of engagement of groups is not significantly different in the first weeks.
2. Teams who receives process feedback (test group) show significantly improved patterns of engagement (more balance and less inequality) compared with the control group.
3. Improvement in engagement leads to better results (higher grades in system design)

Table 4.3.2: Participants and teams

No.	Master Degree	Bachelor Degree	Gender	Country	Team
1	Engineering Systems	Quantum physics and nanoelectronics	F	Russia	1
2	Aerospace Engineering	Embedded systems	M	Russia	
3	Engineering Systems	Electronic Systems Engineering	M	Syria	
4	Engineering Systems	Robotics	M	Russia	
5	Engineering Systems	Applied math and physics	M	Moldova	
6	Engineering Systems	Computer Science	M	Russia	2
7	Engineering Systems	Robotics	M	Russia	
8	Aerospace Engineering	Mechanical engineering	M	Kazakhstan	
9	Engineering Systems	Nuclear physics and cosmophysics	M	Russia	
10	Engineering Systems	Aerocraft Engineering	F	Russia	
11	Engineering Systems	Radio Engineering	F	Russia	3
12	Engineering Systems	Robotics and Mechatronics	M	Uzbekistan	
13	Engineering Systems	Aerospace Engineering	F	Turkey	
14	Engineering Systems	Robotics	M	Russia	
15	Engineering Systems	Aerospace Engineering	M	Russia	4
16	Engineering Systems	Machinery Automation	M	Russia	
17	Engineering Systems	Autonomous control systems	M	Russia	
18	Aerospace Engineering	Mechanical Engineering	M	Italy	
19	Aerospace Engineering	Aerophysics and Space Research	M	Russia	
20	Engineering Systems	Aerospace Research	M	Russia	5
21	Aerospace Engineering	Aerospace Engineering	M	Turkey	
22	Engineering Systems	Industrial Automation	M	Russia	
23	Engineering Systems	Aerospace Engineering	F	USA	

As a process feedback, during the project, the experiment group (test group) received a weekly report and statistics of their engagement level (Figure 4.3.1). The control group has not received any process feedback. Both groups received the same outcome feedback in

PDR and CDR days.

Results

Table 4.3.3 shows teams, groups (Test or Control), project names and Preliminary Design Review (PDR), as well as Critical Design Review (CDR) results.

Table 4.3.3: Teams' performance over time

Team	Group	Project	PDR	CDR
1	Test	Air Taxi	10	13
2		Parcel Delivery	9.5	11.5
3	Control	Parcel Delivery	10.5	12
4		Mapping of Territory	9.5	11.5
5		Biological Delivery	11	11.5

Figure 4.3.1 represents all teams Engagement change rate during the entire time on a bi-weekly basis. Teams 1 and 2 (Test Group) received these reports as the process feedback along with feedback report on PDR and during the course, while team 3, 4, and 5 (Control Group) had not received process feedback. In the chart, 'Mn' refers to team members (M: Member, n: from 1 to 5).

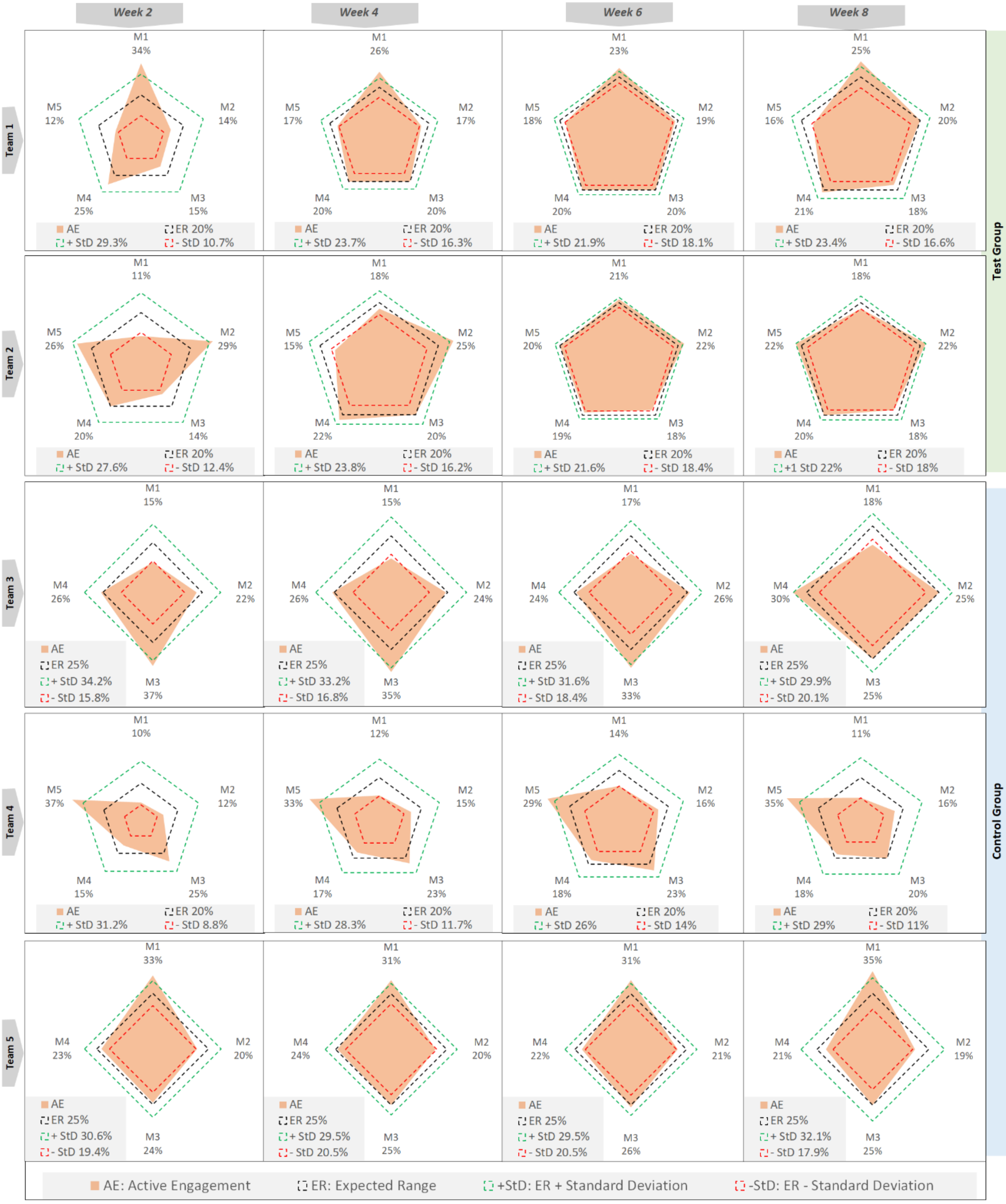


Figure 4.3.1: Radar charts of Active Engagement change over time

Data Analysis

The variable we used to compare was the distance change between the green-dashed line (+StD) and the red-dashed line (-StD) in the charts. As the samples in this study are small (only two teams in the test group represented by only two values) and this is the minimum data required to show a meaningful difference; we used the one-sample t-test (equation 3) (Student, 1908) method for statistical analysis. With this approach, the whole class is considered as the population based on the first two weeks' statistics of engagement (Five teams). Then the differences between the groups and the population were analyzed independently for each group through the t-test over time. Table 4.3.4 shows the data, and Table 4.3.5 summarized the t-test result.

$$T = (\bar{X} - \mu) / S/\sqrt{n} \tag{3}$$

In equation (3) $\bar{X}$ is the sample mean, μ represents the population mean, S is the standard deviation (equation 4) of the sample and n is the number of sample observations.

$$S = \sqrt{\frac{\sum(X-\bar{X})^2}{n-1}} \tag{4}$$

In equation (4) X is each value from the population, $\bar{X}$ is the sample mean, and n is total number of values.

Table 4.3.4: Distance between +StD and –StD over time in teams

Group	**Team**	**Week 2**	**Week 4**	**Week 6**	**Week 8**
Test	Team 1	0.186	0.073	0.037	0.068
	Team 2	0.153	0.076	0.032	0.040
Control	Team 3	0.184	0.164	0.132	0.099
	Team 4	0.224	0.166	0.121	0.181
	Team 5	0.112	0.091	0.091	0.142

Table 4.3.5: One-Sample T-Test results (T: Test Group, C: Control, Sig: Significance)

Time	**Week 2**		**Week 2 Vs. Week 4**		**Week 2 Vs. Week 6**		**Week 2 Vs. Week 8**	
Group	T	C	T	C	T	C	T	C
t-test sig	0.95	0.96	0.03	0.34	0.015	0.168	0.033	0.462

Based on the analysis; hypothesis (1) of study II is accepted; no significant differences between the test and control group were observed in the first stage of the experiment (Week 2). However, the analysis shows a significant difference between test and control group in following weeks (e.g., in week 4 t-test of Test group is 0.03 significantly lower than 0.34 t-test of Control group) with this hypothesis (2) accepted. At the same time, the control group shows no significant change in the entire process. Comparing the weeks reveals that the maximum change occurred in the sixth week, while in the eighth week the teams show a tendency to return to the starting point, both in the test and control groups.

While the average CDR grade of the test group is higher than the control group (12.75 > 11.34), the difference does not appear as significant in the statistical analysis. However, as the PDR grade was in the Pass/Fail format, we could not compare the changes. With this, we cannot completely accept hypothesis (3)

Study #3 Discussion

To improve e-collaboration we suggested a data-driven approach combined with a feedback system that is a classic method. The feasibility of the designed method, its validity, and its effectiveness have been examined in two case studies. The results of the first study show that data logs are a rich source of information to analyze and interpret collaborative activities. In addition, data logs are suitable in programming and machine language, at the same time, produced reports from logs can be on a real-time basis, fact-driven, and fast. These results are in line with previous research on online collaboration and data-driven approaches (Fan et al., 2017; Iglesias-Pradas et al., 2015). The second study illustrates two different aspects. (1) A process feedback system can be designed by relying on the log data; this finding is novel. (2) Process feedback reinforces outcome feedback and the participants reconsider their contribution and engagement. The positive effect of process feedback has been shown in previous investigations to improve group information elaboration and learning in virtual teams (Peñarroja et al., 2015). However, it is the first time that active engagement analysis trough log-data is used in a process feedback study on e-collaboration. Although more studies are needed to expand and support the results, the developers of e-collaboration need to pay more attention to the improvement of the collaboration itself in addition to the technical improvement and provide users with tools to analyze teamwork and the level of members' engagement. This point is essential to manger s to have a map of design teams' awareness, as well as in project-based learnings.

This study has some limitations; for instance, the number of participants were small, we tried to mitigate this problem through careful data collection and double-check all the analyses. The other point is the studies conducted in an educational setting. At the same time, the projects were enquiring activities and strictly followed a particular structure; these limits the generalization of the results. Clearly, collaboration and team dynamics go beyond data input and time spent at the computer in virtual teams. Accordingly, the context of work, as well as the engagement itself, are equally important. This might be a limitation that is problematic to address. However, it sheds a light on another question; how does the context work reflect in the active engagement?

While the dramatic and fast shift from co-located teamwork to e-collaboration facilitates remote work, managers consider poor collaboration as one of the main reasons for teamwork failures. Classic methods of improving collaboration do not completely cover the digitalized environment, and the current studies to address the challenge are limited. The suffering from poor collaboration along with the massive market size is an opportunity for e-collaboration developers to re-imagine improving the essence of collaboration through providing analysis tools in addition to upgrading the technology. In this study, we suggested a new data-driven approach combined with feedback systems to improve e-collaboration. The results of two case studies showed that using data logs in a visualized process feedback system is technically feasible, and positively contributes to a more balanced engagement in teams. This means that team-monitoring dashboards in e-collaboration applications can benefit from the presented method.

Future studies can expand this investigation from several perspectives; first, using gamified process feedback instead of graphs and statistics. Second, digging into the conversation engagement through Natural Language Processing. Further, to repeat the research in the real-world environment outside of academia. Moreover, the relationship between the amounts of work that may be done beyond direct engagement in the background with engagement itself is a case to be investigated. Finally, during the process feedback, personal satisfaction with team engagement can be a measure to see how it changes with the feedback and with the level of engagements.

4.4 Case Study #4: Process Feedback using Motivational Interviewing , and AI potentials

Feedback systems are one of the solutions to improve collaboration; although teams normally receive feedback on outcomes, the collaboration process itself is neglected. In this study, 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.

Introduction to study #4

According to surveys (Boucher, 2020); 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 Systems Engineering (SE), the issue of ensuring effective team collaboration is rarely addressed even though it is widely accepted as necessary (DeFranco et al., 2011). According to INCOSE by using systems principles and concepts, along with scientific, technological, and management methods, 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 (Clark, 2009), 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 and no feedback is provided on the collaboration process of the design team. At the same time, interaction issues appear to be the most fundamental arguments concerning collaborative design, particularly when computer systems are used in the process (Kvan, 2000). One of the effective strategies to improve interaction, is Motivational Interviewing (MI), a guiding and mentoring style of communication (Rollnick & Miller, 1995), 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 Machine Learning (ML) using Natural Language Processing (NLP) techniques (Prabha & Umarani Srikanth, 2019). 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 employed MI to empower team members to facilitate the process of collaboration during an SE project. Then we compared 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 tested 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 are: (1) Using MI as a method in process feedback significantly improves collaborative design in an SE project. (2) Teams' sentiment analysis with AI through pre-trained ML and NLP techniques predicts the progress.

Case study

The Northern Sea Route (NSR) is a shipping route that crosses the seas of the Arctic Ocean (Figure 4.4.1). Annual cargo shipments on the NSR is up to 33 million tons as an energy highway for the export of hydrocarbons and other natural resources (Arcticportal, 2021). NSR has nine main ports, and each port has different levels of resources (local government, industry, population, port capacity, different weather conditions, etc.). Also, each port has its own area of responsibility for supporting NSR with different stakeholders.

Figure 4.4.1: The main Arctic Sea Routes and Exclusive Economic Zones (Source: Arcticportal.org)

With the of aim of improving the shipping process on this route, 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, checking UAV systems and loading the next route. (3) Port fuel transfer automated system in all weather conditions. (4) Ambulance system for emergency evacuation from ships based on 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. Table 4.4.1 shows the deliverables for each review stage according to “V model” of systems engineering.

Table 4.4.1: Project Deliverables and review stages

First Stage (Week 4) **Preliminary Design Review (PDR)**	**Second Stage (Week 8)** **Critical Design Review (CDR)**
▪ Mission Objective(s) ▪ Concept of Operation (by sketching) ▪ Stakeholder Analysis (Value network) ▪ Stakeholders Expectations ▪ System Requirements ▪ System Model (IDEF0) ▪ System Architecture ▪ Risk analysis ▪ Prototyping plan ▪ Schedule (Gantt chart)	▪ Improved PDR (according to the feedback) ▪ Assembly Integration and Test (AIT) plan ▪ Validation and Verification (V&V) plan ▪ The results of AIT and V&V ▪ A working prototype

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 in the test and four teams in the control group. One of the control group teams, consisting of six members, did not agreed to share the chat history and was excluded from the study. The final number of participants in each group was 20 individuals, each of which consisting of two teams of seven and one team of six.

Results and analysis

While the PDR results of the test group with a mean grade of 68% were lower than in the control group with a mean of 72%, this difference statistically is not significant (Independent T-Test with 95% confidence: 0.27>0.5). However, comparing CDR results indicate that both groups show improvement, but the difference is significant (Independent T-Test with 95% confidence: 0.017<0.5). Figure 4.2.2 shows the comparison of the two groups.

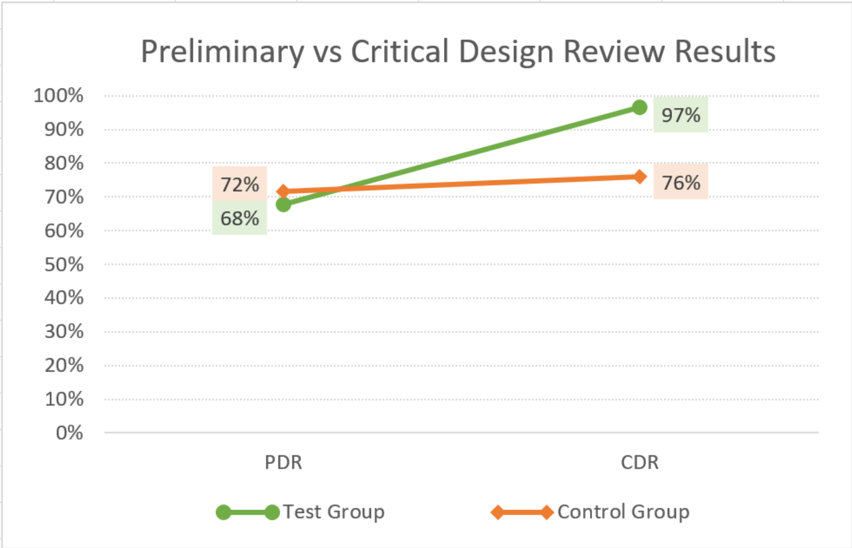


Figure 4.4.2: Test and Control groups' grades in PDR and CDR

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 4.4.3 illustrates the results.

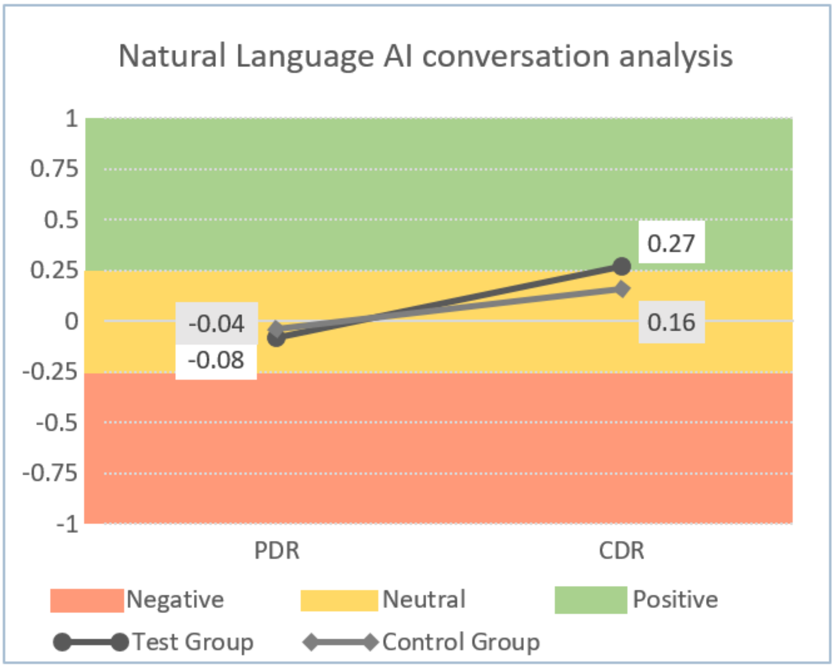


Figure 4.4.3: Sentiment Analysis with Google Cloud Natural Language

As the graph shows, the results of text-based sentiment analysis using AI and the results of changes in scores in CDR are significantly correlated.

Study #4 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 projects based on learning 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 interaction platforms. The multi- and interdisciplinary research literature review in this study indicates significant progress in the realm. However, this topic has not been studied in engineering, especially in the field of collaborative design and SE. 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 systematic analysis about MI positive influence to improve interactions (e.g., Magill et al., 2018; Schwalbe et al., 2014), however, the effect of using MI in a process feedback on collaborative design had not been studied before. This result support the first hypothesis of the study: "Using MI as a method in process feedback improves collaborative design in a SE project." In addition, the second hypothesis is also supported by the results: "Teams' sentiment analysis with AI through pre-trained ML and NLP techniques predicts the progress." This is in accordance with previous studies that investigated the application of speech analysis in predicting performance (Chowdary Attota & Dehbozorgi, 2022). 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 monitoring procedure.

In 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 showed its effectiveness in engineering work and suggested that state-of-the-art technology has the potential to help us. This paper is icebreaking from many 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 using 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 colleague.

4.5 Case Study #5: Developing a ML-NLP Model to Detect Active Engagement

This work extends the last four studies. In this study, we develop and examine a ML-NLP model for a text-based conversation in online chats with two aims. First, to study the reflection of active engagement in conversations of PBL teams through two questions; (1) how communication constructs of student group chat are good predictors of Active Engagement in PBL teams? (2) How this measure is a good predictor of team success in PBL tasks? The second aim is to test the capability of ML-NLP using text-classification techniques to perform the first objective.

Introduction to study #5

The results of the previous four case studies indicated that data-logs of cloud-based collaborative work are rich sources of information to portrait members' engagement. At the same time, some activities occur outside of the computer environment in the real world, for example in the lab or in face-to-face group discussions. Such contributions may not entirely reflect in the log data. However, we assume that engagements can be well reflected in team communications. Based on our analysis of team engagement in PBL collaborative tasks there is a significant imbalance of students' involvement. On the other hand, a study by McQuade (2020) suggests the same conclusion in conversation analysis; the analysis of engineering students' interactions indicates that students do not engage with PBL as intended, according to McQuade, we know very little about the interactional elements of PBL and how it actually works (McQuade, 2020). Recently, online chat data has been investigated as an indicator of student participation in non-engineering courses (Q. Huang, 2022). Moreover, evaluating all the student's conversations by a human agent is not easily possible due to the amount of data, nor favourable because of likely privacy and discomfort issues caused by a permanent presence of an observer in all the chats. In this case, using AI can be an alternative solution to address these issues and further expand the idea; for example, the results of the fourth study suggest that Motivational Interviewing (MI) is a significant strategy to enhance collaborative work, and evidence showed AI is capable to utilize MI as well. In recent years, machine learning approaches have achieved surpassing results in NLP to accurately classify texts in many applications to understand complex models and non-linear relationships within data (Kowsari et al., 2019). Previously, Spikol et al. (Spikol et al., 2018) used ML techniques in PBL teams for the same objective. However, the study investigated multimodal recordings of learners' group interactions including computer vision, user-generated content (physical computing components), and data from the learning objects. Results demonstrate that state-of-the-art computational techniques can provide insight into students' PBL. The aforementioned reasoning and conclusions provide a reasonable case to explore and compare the analysis of log-data and work procedure on one side, and the conversation analysis on the other side. If the experiment supports the idea that the collaboration is reflected in the conversation, then the feasibility of utilizing a single source to utilize state-of-the-art technology, e.g., ML and NLP through text classification methods is more likely (Sarker, 2021).

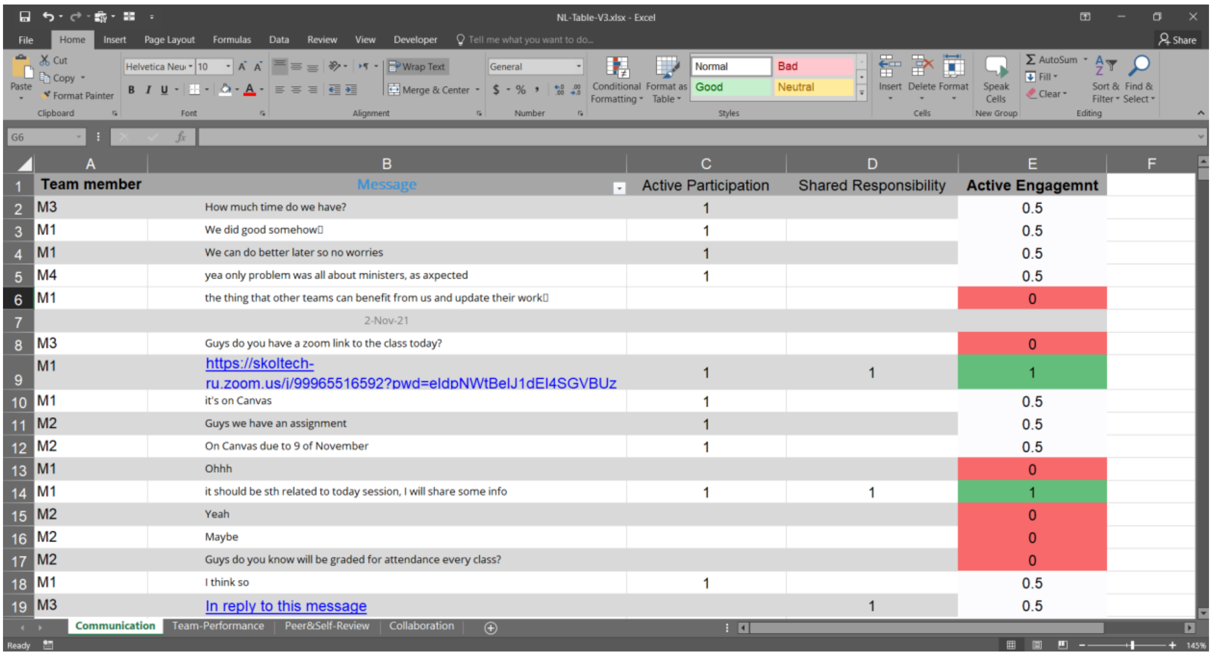
Method

Conducting this study followed three stages in a nine steps process. Stage one, literature review, compliance with previous case studies, and strategy design (steps 1-3). Stage two, selecting an ML method, and training the model (steps 4-8). Stage three, comparing the results in a test process (step 9).

The steps were: (1) Searching construct of web-based communication of teams in the literature. (2) Evaluating the compatibility of elements found in step 1 and integrating them with Active Engagement constructs. (3) Creating a communication labeling and scoring strategy based on steps 1 and 2. (4) Collecting data from existing data sets in previous study, cleaning the data and manually labeling. Step 5, defining features. (6) Developing a ML model based on NLP text-classification methods. (7) Checking accuracy. (8) Improving the model. (9) Applying the ML model in all the data sets and compare the results. Figure 4.5.1, shows stages two and three.

Table 4.5.1 shows more details on the stages one and two. We used (Marlow et al., 2017) results, which have reviewed related work and listed elements of communication in virtual teams as identified in the literature, to create a basis for futures selection (columns A). Elements of Active Engagement based on our previous work (columns B), and the way that these constructs/features have been used in the classification method and/or in the ML model (columns C). The available text-based conversations, with available data-logs and AE graphs, were used to the manual labelling. These chats originated in the team's conversations in the Telegram messaging application (including messages' meta-data).

To train the model (Figure 4.5.1, a), more than 5000 messages from two different datasets were labelled using the construct guideline in Table 4.5.1. As shown in Figure 4.5 The messages were read one by one and labelled manually by assigning a score of 1 or 0 for AP or SR to each message. In order to calculate the AE=((AP+SR)/2), in a given period, the total scores of the members were collected and normalized as a percentage. After assigning the feature and developing the ML algorithm, the accuracy was checked. If the accuracy rate is higher than 0.70 the model is accepted to go to the next testing process with other datasets (that have not been seen by the model), otherwise, the labelling and feature assigning are repeated. In the model testing (Figure 4.5.1, b), six datasets of six different teams' text-based communication in the Telegram chats were used to predict AE, and the results were mapped in a radar plot (Figure 4.5.2). To compare the ML output plots with true AE level, data logs of working platforms, self-review, and peer-review reports of participating teams were used to plot true AE in radar graphs according to the method described in case study two.



	A	B	C	D	E	F
1	Team member	Message	Active Participation	Shared Responsibility	Active Engagemnt	
2	M3	How much time do we have?	1		0.5	
3	M1	We did good somehow	1		0.5	
4	M1	We can do better later so no worries	1		0.5	
5	M4	yea only problem was all about ministers, as expected	1		0.5	
6	M1	the thing that other teams can benefit from us and update their work			0	
7		2-Nov-21				
8	M3	Guys do you have a zoom link to the class today?			0	
9	M1	https://skoltech-ru.zoom.us/j/99965516592?pwd=eldpNWtBelJ1dEl4SGVBUz	1	1	1	
10	M1	it's on Canvas	1		0.5	
11	M2	Guys we have an assignment	1		0.5	
12	M2	On Canvas due to 9 of November	1		0.5	
13	M1	Ohhh			0	
14	M1	it should be sth related to today session, I will share some info	1	1	1	
15	M2	Yeah			0	
16	M2	Maybe			0	
17	M2	Guys do you know will be graded for attendance every class?			0	
18	M1	I think so	1		0.5	
19	M3	In reply to this message		1	0.5	

Figure 4.5: Example of the labelling in an Excel file.

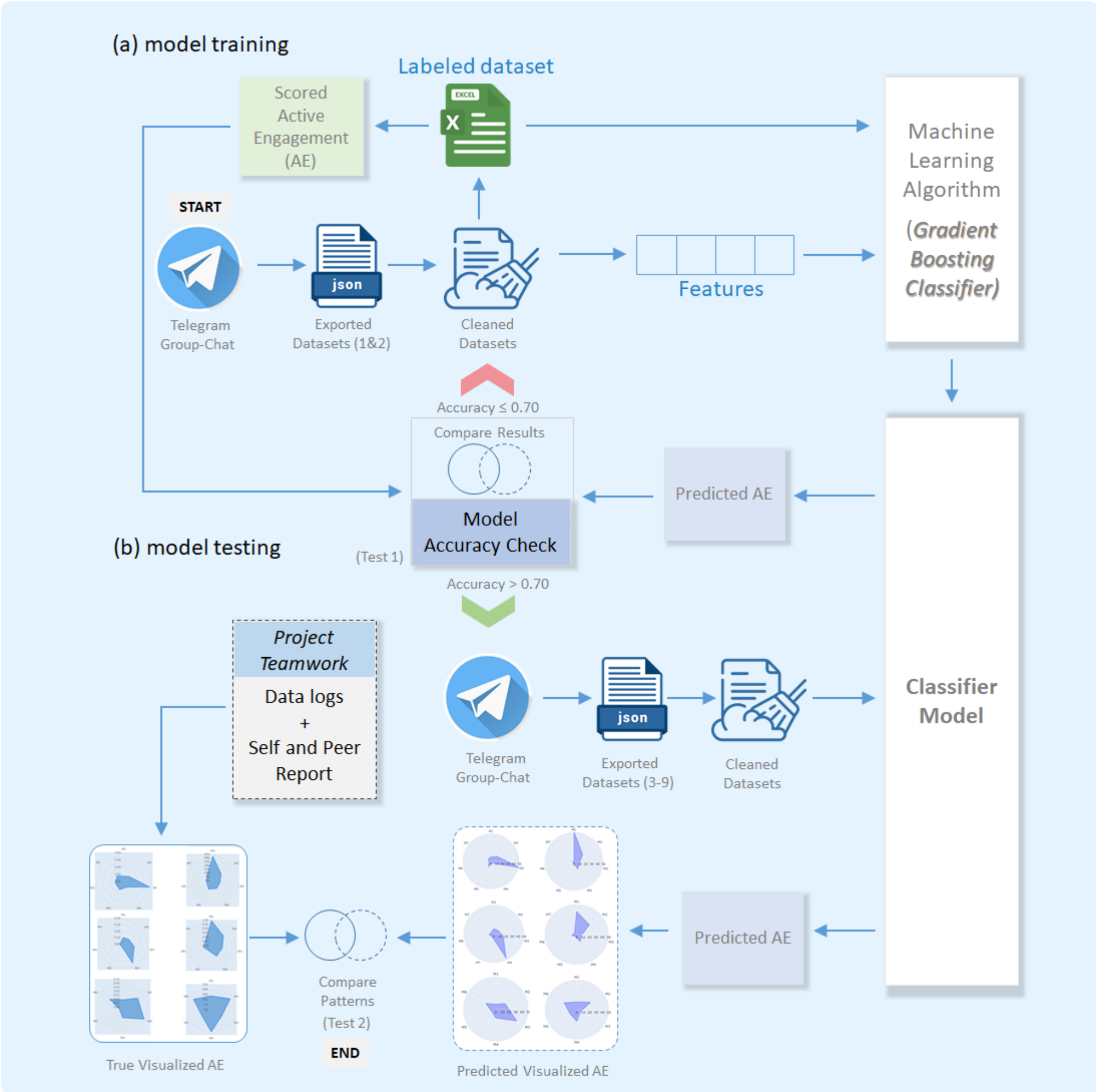


Figure 4.5.1: The procedure of model training (a) and testing (b).

Table 4.5.1: (A) Elements of communication according to Marlow et al., (2017); (B) Elements of Active Engagement (Authors 2023); (C) The labelling basis of communication as text-classification in the ML model

	A			C	
Construct name	**Definition**	**Related citation**	**Reference**	**Function**	**Type**
Communication frequency	Volume of communication over any communication modes	Marks et al. (2000)	Text Content	Word count,	Feature
Communication quality	Clarity, effectiveness, accuracy, and completeness of communication	González-Romá and Hernández (2014)	-	Supporting AP and SR labelling	-

Communication timeliness	Extent to which communication is provided or received in a timely manner	Warkentin et al. (1997)	Meta-data	Time-stamp	Feature
Closed-loop communication	(a) A team member sends a message, (b) another team member receives the message, and (c) the original team member sent the message follows up to ensure it was received and understood	McIntyre and Salas (1995)	Text Content and Meta-data	Replies and Tags	Feature
Communication content	Either task-oriented (i.e., communication focused on task completion) or relational-oriented (i.e., communication of an interpersonal nature)	Keyton (1997)	-	Supporting AP and SR labelling	-
	B				
Active Participation (AP)	Acknowledgment, and consideration of the inputs and opinions with transparency and the free exchange of information	Arias et al. (2016)	Text Content	Variable	Label
Shared Responsibility (SR)	The member contributes his or her own abilities/experience/knowledge with a unique role in the collaborative work.	Griffiths et al., (2020)	Text Content	Variable	Label

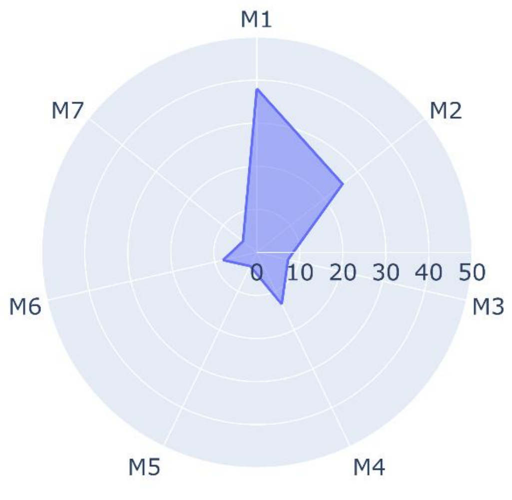


Figure 4.5.2: An example of the output radar graph of AE for a team with seven members produced by ML. In this graph, Mx represents the team members. Circles show percentage levels from zero to 50%. And the shaded area represents the AE level of all team members connected together with a line to create an irregular polygon in order to draw a visually comparable AE pattern of the team.

The ML model

We used a Supervised Machine Learning (SML) model in this study. According to Jordan and Mitchell (2015) SML is arguably the most popular field of ML; a SML model learns from a dataset that already has labels assigned to each observation, subsequently being able to predict these labels from a different input (Jordan & Mitchell, 2015). SML can read as input values from the chosen features/characteristics and learn to classify data points into one of two or more groups (Kotsiantis et al., 2006), such as semantic text classification (Sarker, 2021), or predict the value of a continuous variable (Kotsiantis et al., 2006).

One of the most popular algorithms for solving classification problems is Gradient Boosted Decision Trees (GBDT), which fits individual decision trees sequentially based on the results of the preceding trees and thus continuously improves the model performance by learning from past mistakes (Friedman, 2001, 2002). The algorithm has received wide use due to its many advantages: quick time of training and prediction, low burden on the computer memory, high accuracy, and prevention of model overfitting (Si et al., 2017). Ensemble-learning techniques, such as gradient boosting models, can be effectively applied for classification problems in the context of NLP and text analysis (Kumar et al., 2021).

To develop the ML model, we used an algorithm implementation of GBDT known as "Gradient Boosting Classifier" from a popular Python package Scikit-Learn, which contains implementations of many renowned ML algorithms in an easy-to-use interface.

The performances of the ML models were evaluated both on an internal holdout test sample dataset (data coming from the dataset used for training) and on the entire external dataset (data coming from a different population, hence not seen by the model during training). The performance metric was represented by accuracy - the most commonly-used performance measure that shows the effectiveness of the model to correctly predict the true value of the labels (Sokolova et al., 2006). This measure was used due to its ease of interpretation and calculation. The below equation returns the accuracy, where P_T is true positive, N_T - true negative, P_F - false positive, and N_F - false negative:

$$accuracy = \frac{P_T + N_T}{P_T + N_T + P_F + N_F} \tag{4}$$

Results

The results of this study can be reported in two parts. The first part compares the ML model results with manually assigned labels. These results are shown in Figure 4.5.3, which is extracted from the training data set based on weekly analysis.

Figure 4.5.3: Test 1 results, comparing the ML output with manual labelling

For estimating the variability in the performance of the ML models, we used bootstrapping for the test predictions - either from the holdout test set or the entire dataset. From the bootstrap sampling distribution, we obtained 95% confidence intervals (CI); subsequently, accuracy is reported as the mean accuracy of the bootstrap sampling distribution, with the low and high ends of the intervals given in the square brackets: accuracy = 0.75 [0.70, 0.80].

The second report is the result of comparing the output of the ML model with the true work of the team in the entire PBL period (Figure 4.5.4). The method used to generate the real work graph is described in the third study. However, the sources of analysis were the data logs of used platforms, and self and peer-report. Also, the weight of the tasks was applied using a questionnaire based on the opinion of the course instructors.

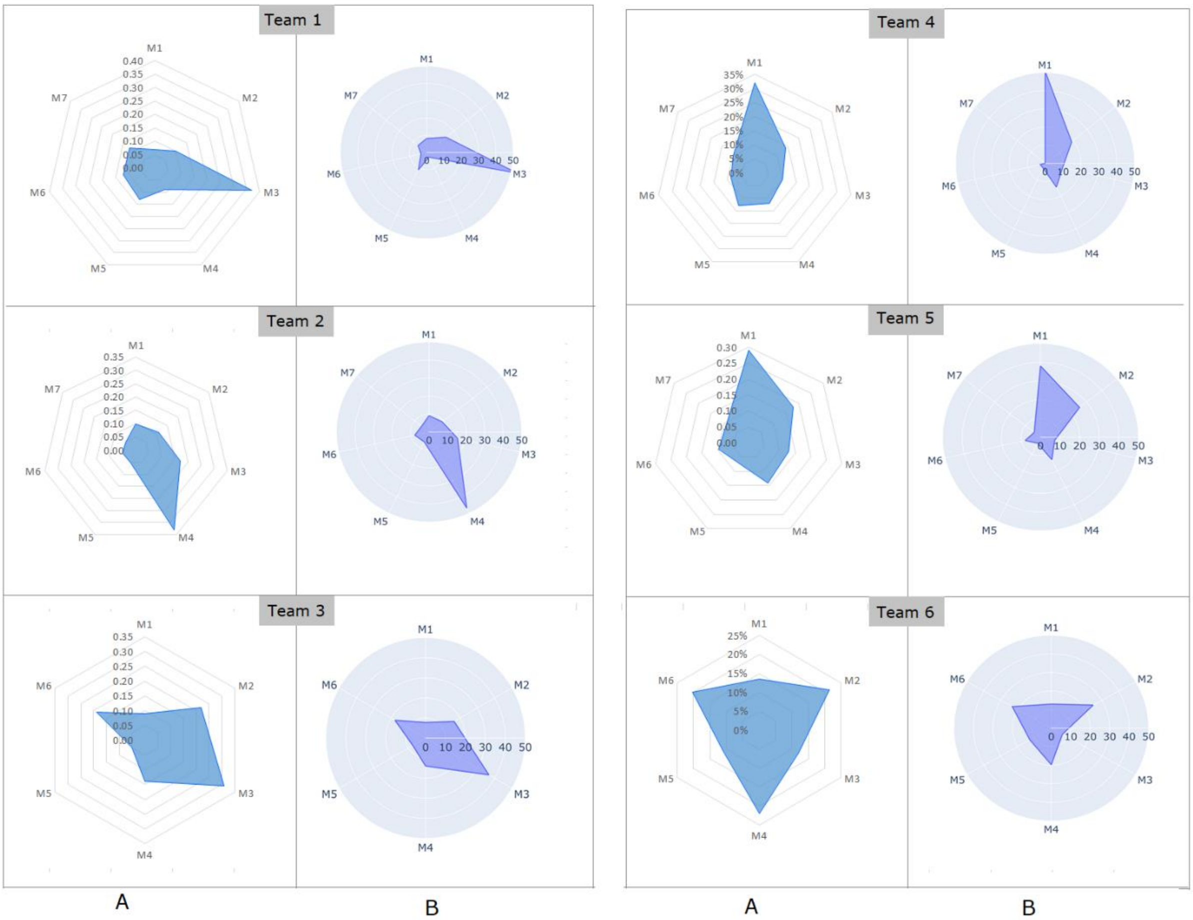


Figure 4.5.4: Test 2 results, comparing the ML output (B), with actual PBL engagement (A)

Study #5 Discussion

The results of the model test in stage one (comparing the model output with the manual output) showed accuracy levels of 0.75/1 [0.70, 0.80] and 0.81/1 [0.77, 0.85] for predicting AP and SR, respectively, for the internal holdout set (the dataset used for training). Although no universal standard for determining the acceptable accuracy threshold exists, the same performance metric are considered as meaningful in similar studies implementing ML models for classification (Maxwell et al., 2018). In addition, the visual comparison of the graphs clearly shows the remarkable overlap in test 1.

The results of implementing the model for the entire period of team conversation (the external dataset) and comparing with actual work engagement, show reduce in accuracy levels to 0.66 [0.61, 0.71] and 0.77 [0.71, 0.82], the decrease being not statistically significant as assessed by the CI overlap. However, the pattern of graphs in most of the cases is the same. For example, the most engaging person in all teams are the same members, while the percentage are not the same. For instance, in team 1, M3 in both plots shows the maximum AE, but the percentage in the actual work is 35% compared with 50% in conversation. In addition, members with less AE do not show the same records, e.g., in Team 5, M3 compared with M5 recorded lower score of AE in the conversation, but the score is higher in the actual work.

Based on the results, firstly, the conversation features of student group chat are good predictors of Active Engagement patterns in PBL teams, however they do not completely represent the same engagement level. Secondly, the AE graph of team conversation is a good predictor of team success in PBL tasks. According to the results of PBL scores, teams 6, 3, and 5 respectively received higher grades in the collaborative works. These three teams recorded more balanced AE compared with others. Furthermore, our analysis and proof-of-concept ML-NLP through text-classification techniques illustrates a significant potential of AI to analyse conversations and recognize AE in PBL.

Chapter Summary

The presented case studies collectively offer a comprehensive exploration of collaborative design in learning environments. Beginning with the investigation into the impact of the COVID-19 pandemic on remote engineering design teaching, Case Study #1 employed ethnographic methods and Distributed Cognition for Teamwork (DiCOT) analysis. The findings underscore the crucial role of online platforms in distributed cognition. The study discussed successful remote collaboration and suggested further exploring motivation and collaboration patterns and challenges.

As highlighted in Case Study #2, Active Engagement (AE) emerges as an essential element of collaboration. Moving on to the development of a data-driven method for measuring AE in web-based teamwork, the second case study introduced a novel approach utilizing data logs. Participants' positive reception and the correlation between AE and collaboration validate the measurement method. While acknowledging limitations, the study anticipates improvement in team dynamics and collaboration quality in digital environments.

Case Study #3 evaluated the effectiveness of mirroring AE as process feedback in a Systems Engineering course. The test group, received process feedback, and demonstrated positive engagement patterns, and the results revealed a significant correlation between feedback and AE improvement. The data-driven approach showed effective, and despite limitations such as a small sample size, the study calls for further research to explore the positive impact of process-oriented feedback on team engagement.

The integration of Motivational Interviewing (MI) and AI in collaborative engineering design, in Case Study #4, revealed MI's effectiveness in improving collaborative design. The study employed AI with machine learning (ML) and natural language processing (NLP) for sentiment analysis, that showed promise in predicting progress. This acknowledges the positive influence of interpersonal relationships, the study also highlighted challenges in implementing MI in large projects and the potential of AI for automated interventions.

The development and examination of an ML-NLP model for detecting active engagement in Project-Based Learning (PBL) teams (Case Study #5) advanced our understanding of collaboration in text-based conversations. The ML-NLP model demonstrated high accuracy in predicting Active Participation (AP) and Shared Responsibility (SR) in internal datasets. The study emphasized the potential of ML-NLP models to analyze and predict engagement patterns in PBL teams.

Overall, these studies emphasize a holistic approach to improve collaborative design and learning, by blending human-centered approach, data analytics, and technology. The results demonstrate the transformative potential of AI to address the challenges. The studies also shed light on the feasibility and challenges of remote collaboration, particularly in the context of engineering design and learning. The synergy between human-centric approaches like MI and technological advancements like AI is showcased as a means to achieve improved collaboration. These insights contribute significantly to the evolving landscape of collaborative learning, providing valuable guidance for educators, researchers, and practitioners seeking to enhance team dynamics and project outcomes. The call for further research highlights the need to delve deeper into the complexities and opportunities presented by technology-enabled collaborative environments.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 5

Discussion

Previous chapters provided the introduction, problem statement, methodology, objectives, and questions to the research titled **“Improving Collaborative Engineering Design and Learning through Feedback Systems in the Age of Digitalization and AI”.** Then through five different case studies, further exploration provided on examining the hypothesis, and the results, discussions and conclusions for each study reported respectively.

This work contributes to the fields of collaborative engineering design and learning. The goals were; (1) To provide a better understanding of collaborative engineering design and learning and their dynamics, key elements, and challenges. (2) To design and propose supporting technology-based tools and measurement approaches for collaboration constructs. (3) To propose human-centered approaches that enhance collaboration and lead to better outcomes. And (4), it explores the potentials of cutting-edge technology and AI advances in overcoming challenges and limitations, particularly in the realm of Human-AI collaboration.

This chapter revisits and discusses the research question that that was introduced in the beginning.

Improving understanding of collaboration

RQ1 *"How the new norms of web-based collaboration formed different patterns of information flow and distributed cognition in collaborative engineering design and learning?"*

Case study #1 conducted to address the question using ethnography and DiCOT methodologies to observe the entire process of a collaborative rocket engineering process. The results showed that digitalization transformed the forms of interaction; text-based chat and cloud based collaboration platforms plays a significant role in the design and learning process. These findings are in line with other recent studies (Brisco et al., 2020; Knoblauch, 2022). Also unequal contribution of team members was a concern raised by participants, the same issue is reported in the previous research (Viswambaran & Shafeek, 2019). Unequal contribution or engagement is one of the most serious issues of collaborative works, particularly in the learning settings, also known as the issue of free riders (James et al., 2002; Williams, 2017). The issue of free riders not only results in unfair grading (Gibbs, 2009; Sluijsmans et al., 2001) but also could lead to a frustrating and stressful environment in teamwork because of creating an extra workload for the rest of the team members (Strauss & U, 2007). A systematic review finding revels that, time, energy, and cost, on one hand, and lack of expertise, accuracy in measuring tools, design, and implementation of the measures, on the other hand, are serious issues that need to address in evaluating teamwork in engineering education (Cruz et al., 2020). In addition, while the detailed monitoring of team members' engagement and participation can be useful to evaluate the activities, a limited number of project supervisors hardly can assess a large amount of data. This poses a scalability challenge if the number of participants in a collaborative activity increases (Traverso-Ribón et al., 2016).

The answer to the first question illuminates the path to the second question; how to measure the active engagement and what support tools can be designed that are consistent with the new norms and web-based collaboration.

Proposing supporting tools for active engagement

RQ2 *"How to design a data-driven dashboard to measure, visualize, and monitor active engagement as an essential construct of collaboration?"*

To answer this question, the second study investigated the idea of measuring Active Engagement (AE) as an indicator to monitor and improve collaborative work and the feasibility of using it in a dashboard for e-collaboration platforms by designing a new data-driven model. The results of the case study showed; (i) a meaningful correlation between AE and collaboration in web-based engineering design teams on wiki platforms; this is in line with previous research (Berthoud and Gliddon, 2018). (ii) AE also is measurable through analyzing log data, with the possibility of an algorithmic run on a real-time basis. 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: firstly, 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. Secondly, the report can immediately show the real-time status. Further, it will facilitate research on e-collaboration. In addition, it makes computer-mediate feedback feasible, quick, and low-cost. Finally, such an approach paves the way for utilizing state-of-the-art technology and Artificial Intelligence (AI) systems to improve collaboration and teamwork.

After designing and validating a method for measuring and monitoring AE, the next consideration is how to effectively utilize it to enhance the current status of AE towards a desired status. Building upon the principles outlined by Jermann et al. (2001) and Streng et al. (2009) regarding feedback systems, we understand that reflecting the present situation and comparing it to the desired situation fosters a meta-cognitive state that aids in the improvement process.

Efficacy of **Feedback systems** to improve AE

RQ3 *"How a process feedback on active engagement lead to a more balanced engagement and a better design?"*

To address this inquiry, case study #3 was conducted wherein half of the teams were provided with consistent feedback regarding their engagement. By comparing the experimental group, which received the process feedback, with the control group comprising teams without such feedback, we were able to discern variations in the engagement patterns. The findings revealed a significant positive impact of the feedback in fostering a more equitable distribution of engagement; this is in accordance with other research on the impact of feedback to foster engagement. For example, a study on continuous team assessment to improve student engagement and active learning found that the introduction of continuous team assessment with ongoing feedback into tutorial classes had the desired effect of improving student attendance and engagement (Esposto & Weaver, 2011). The findings of this study also indicate that while there were observable improvements in the design within the teams that received feedback and improved engagement, the corresponding enhancements in design were not statistically significant. Consequently, the next question arises regarding how a change in the feedback or adding complementary intervention within the process can meaningfully improve the outcomes.

As described in the previous chapters, a search in the research literature for a practical approach to person-centered feedback led to the discovery of an evidence-based communication strategy that has been less studied in engineering despite significant results in teamwork in other disciplines, known as Motivational Interviewing (MI). The next question is about the effect of this method on collaborative engineering design and learning.

Human-centered approaches and the better outcomes

RQ4 *"How a communication strategy such as Motivational Interviewing contributes to a better outcome in the process feedback?"*

Case Study #4 was undertaken to address the question at hand, employing a robust double-blind methodology. In this study, the experimental group was subjected to the feedback Motivational Interviewing (MI) strategy, while the control group did not receive any feedback. By comparing the outcomes of both groups, significant improvements were observed not only in team sentiment but also in the quality of the design. However, employing such a communication strategy poses challenges when it comes to scalability, particularly in the context of large-scale projects or educational settings characterized by a substantial number of participants. For instance, engineering courses utilizing Project-Based Learning (PBL) approaches, where a multitude of students are involved.

In this study, the capability of AI in predicting the results and detecting teams sentiment were also examined. And results suggest that ML_NLP models can predict the changes. These insights and the significance of MI made us to consider the potential of cutting-edge technology and advancements in artificial intelligence (AI) as a means to address these limitations. By leveraging state-of-the-art technology and AI, we may be able to overcome the difficulties associated with the implementation of traditional feedback methods. The utilization of intelligent systems could offer scalable and efficient alternatives, facilitating streamlined communication channels and more personalized feedback. This holds particular promise in scenarios where a considerable number of individuals are engaged, such as large-scale projects or extensive educational programs.

The findings from Case Study #4 highlight the need to further exploring AI and ML in improving collaborative engineering design and learning through feedback systems.

Potentials of the cutting-edge technology to measure AE

RQ5 *"How AI and ML can measure and improving active engagement in feedback systems in collaborative engineering design and learning?"*

To answer this question, in Case Study #5, we used a retrospective approach by training and testing an ML model using the available data sets from previous case studies. Using text-calcification we succefully created a proof-of-concept to employ ML models to predicted the AE of team members in the previous case studies.

The findings from the study shed light on several important aspects. (i) It was observed that the conversation features within group chats can serve as reliable predictors of AE patterns within PBL teams. However, it is crucial to note that these features do not fully capture the entirety of the engagement level. While they provide valuable insights, there may be other factors at play that influence team dynamics and members' active participation. (ii) The AE graph derived from team conversations emerged as a strong indicator of team success in PBL tasks. This graph, which showcases the patterns of AE over time, offers valuable predictive capabilities. Teams that exhibit higher levels of engagement, as evidenced by the AE graph, tend to perform better in their collaborative endeavors. This finding underscores the significance of fostering and monitoring AE to optimize outcomes.(iii) The analysis conducted in this study, employing a proof-of-concept machine learning-natural language processing (ML-NLP) approach, highlights the substantial potential AI in analyzing conversations and recognizing AE within collaborative work environments.

These results underscore the transformative role that AI and ML-NLP techniques can play in the realm of collaborative engineering design and learning. The ability to analyze large volumes of conversation data, coupled with sophisticated algorithms, enables us to gain insights into the intricacies of collaborative work. This has significant implications for instructional design, team assessment, and the development of targeted interventions to foster and sustain AE.

It is important to note that while these findings are promising, they represent a proof-of-concept and should be further validated through continued research. Additional investigations can explore the generalizability of these results across diverse engineering design settings.

Overall view and limitations

This research contributes to improving our understanding of collaborative engineering design and learning in the digital age. Through an iterative, multi-disciplinary approach, the studies generated important insights that can inform engineering education, design practices, and policy. Fundamentally, the research underscores the growing complexity of engineering collaboration, as teams become increasingly dispersed and reliant on digital platforms. It reveals the need to re-evaluate strategies for remote collaboration, information sharing, and project management. The analysis of engagement patterns, tool usage, and communication flows provides a framework for adapting to emerging collaboration norms. The development of novel methods for measuring and visualizing engagement via data-driven dashboards demonstrates the viability of leveraging log data to monitor team dynamics unobtrusively. This opens up possibilities for scalable feedback systems to enhance collaboration. The proposed approaches can readily empower e-collaboration platforms with built-in analytics. By implementing and validating feedback interventions, the studies demonstrate the potential of process-oriented feedback, beyond just outcomes, for improving participation, balancing engagement, and nurturing team cohesion. The integration of Motivational Interviewing further highlights the value of human-centered communication strategies in strengthening interactions. Critically, the research recognizes cutting-edge AI as a transformative enabler, helping address resource limitations in providing personalized, real-time feedback for large-scale collaborations. The ML-NLP proof-of-concept represents a promising step toward conversational agents that can sense engagement levels and automate supportive interventions. On the whole, this research synthesizes cross-disciplinary knowledge spanning engineering design, systems thinking, technology, and team dynamics. It contributes frameworks, metrics, tools, and insights to enhance collaborative competencies and outcomes. The multi-pronged approach underscores the importance of understanding, measuring, and proactively improving collaboration in the digital age.

The limitations of this thesis include small sample size in some of the studies, and specific educational settings, these might constrain the generalizability of the results. Addressing these limitations in future research will enhance the validity and relevance of findings for diverse collaborative engineering design and learning contexts.

Chapter 6

Conclusion and Future Work

This work has undertaken an in-depth examination of collaborative engineering design and learning through an iterative approach and employing a Research Design Methodology (DRM) with conducting a comprehensive literature review, forming research questions, and implementing and analysis of five case studies. By investigating the effectiveness of web-based collaboration and exploring various platforms and interventions, valuable insights have been gained regarding the dynamics of teamwork, information flow, and active engagement in web-based environments, while exploring the efficacy of feedback systems and potential of cutting-edge technology. This concluding section summarizes the key findings and their implications, discusses the contributions of this research, and proposes avenues for future exploration.

Study #1 focused on investigating team collaboration and distributed cognition in the context of remote engineering design and design teaching during the COVID-19 pandemic and provides insights into effective collaboration and information flow in distributed teams. This study answered the question *"How the new norms of web-based collaboration formed different patterns of information flow and distributed cognition in collaborative engineering design and learning?"* We used Distributed Cognitive (DC) theory to observe changes happening in the cognitive processes and information flow in a different environment and complex collaborative engineering design teaching while everybody was isolated at home due to a worldwide pandemic. The obtained data aligns with the proposed hypothesis, indicating that the emergence of new norms in web-based collaboration (exacerbated by the Covid-19 pandemic) significantly shapes different patterns of information flow and distributed cognition in collaborative engineering design and learning teams.

Study #2 investigated the idea of measuring Active Engagement (AE) as an indicator to monitor and improve collaborative work in web-based engineering design teams working collaboratively on wiki platforms. To answer *"How to design a data-driven dashboard to measure, visualize, and monitor active engagement as an essential construct of collaboration?"*, the study proposed a data-driven model and found a meaningful correlation between AE and collaboration. The case study represented an initial step to implement such systems. Findings from the study are consistent with the initially formulated hypothesis, demonstrating that a data-driven dashboard can measure, visualize, and monitor active engagement by analyzing data-logs and tracking online activity records during collaborative works.

Study #3 suggested a data-driven approach combined with a feedback system to improve e-collaboration. The question was "*How a process feedback on active engagement lead to a more balanced engagement and a better design?*" During this study, the feasibility of the designed method, its validity, and its effectiveness have been examined. The study examined using data logs in a visualized process feedback system, technical feasibility, and its effectiveness in a more balanced engagement in teams. The results of the experiment substantiate the hypothesized outcome, highlighting that the implementation of a process-oriented feedback mechanism that focused on active engagement leads to a more balanced distribution of engagement levels and improves collaboration.

Study #4 focused on the significant positive influence of Motivational Interviewing (MI) as a communication strategy and mentoring style in improving collaborative engineering design in Systematic Engineering (SE) and Project-Based Learning (PBL) outcomes. The study also found that sentiment analysis is a powerful tool to recognize the team's challenges and track the changes after interventions. The question was *"How a communication strategy such as Motivational Interviewing contributes to a better outcome in the process feedback?" The evidence gathered supports the hypothesis under investigation, illustrating that using communication strategies, particularly Motivational Interviewing, during a feedback experience positively influences the outcomes and creates more effective and constructive feedback loops.*

Study #5 implemented a Machine Learning (ML) and Natural Language Processing (NLP) model to predict Active Engagement (AE) in PBL teams. The question was *"How AI and ML can measure and improving active engagement in feedback systems in collaborative engineering design and learning?"* And the results showed that the conversation features of student group chat are good predictors of AE patterns in PBL teams that can be used in an AI-powered system. The study yielded results that are in accordance with the hypothesized outcome, demonstrating that AI and ML techniques can facilitate the feedback mechanism by automatically analyzing log data and providing personalized feedbacks.

Overall, the comparison of these academic works highlights the importance of enhancing active engagement in collaborative engineering design and learning. The studies emphasize the potential of cutting-edge technology, such as data-driven models, feedback systems, Motivational Interviewing, and machine learning with natural language processing, in improving collaboration and engagement in engineering teams. The studies collectively demonstrate that remote collaboration can be successful, and various tools and techniques can be employed to monitor and improve collaboration in web-based engineering design teams. However, limitations and challenges remain, such as the accuracy of measuring AE, the need for further investigation into the impact of feedback, and the generalization of results to real-world environments.

In conclusion, the studies provide valuable insights into the role of feedback systems and the potential of cutting-edge technology in enhancing active engagement in collaborative engineering design and learning.

Moving forward, future studies should address the limitations identified in this research. Conducting multiple case studies with diverse settings and larger sample sizes will enhance the generalizability and validity of the findings. In addition, exploring the application of AI advancements, such as ML and NLP, in automating interventions and scaling up the potentials. More specifically, regarding study #1 future research should consider conducting multiple case studies over an extended period to validate and generalize the results. In accordance to study # 2, future investigations should aim to include multiple platforms to capture a more holistic view of collaboration in web-based environments. Concerning study #3 and #4, further research with larger sample sizes and diverse settings, including real-world engineering projects, is necessary to validate the effectiveness of the proposed methods. Regarding study #5, further research should explore the potential of AI advancements, including ML and NLP, in automating MI interventions through Human-AI interaction platforms to address scalability concerns.

In summary, this research aimed to improve collaborative design and learning in engineering through identifying information flow, interaction processes and issues, effective feedback systems, and opening the doors for state-of-the-art technology approaches. Based on the iterations of literature review, case study, and validation, it can be concluded that; first, relying on cloud-based technology never has been more, and this trend is increasing; in this regard, instant messaging platforms play a prominent role. Second, lack of a balanced contribution and poor engagement of learners is a serious concern is facing; while scalability and limited resources make it challenging, process feedback can significantly address this issue. Third, data-logs are rich sources of information to analyze students' active engagement and create automatic data-driven and sustainable process feedback. Results of a case study indicate that this approach meaningfully regulates team members' engagement; however, further support is required to enhance the outcomes as well. In addition, Motivational Interviewing (MI) as a communication and mentoring strategy significantly contributes to a better outcome; though the MI faces the same limitations as process feedback (i.e., limited resources and scalability issues). Furthermore, the prof-of-concept in our last case study illustrated a considerable potential of AI and NLP models to address the limitations.

Based on this conclusion, PBL instructors should consider stablishing a process feedback rather than relying only on outcome feedback. At the same time, universities might think of training instructors with a conflict resolution, and communication strategy such as MI to enhance PBL outcomes.

To better understand and enrich the implication of these results, future studies also could extend this work in different perspectives. For example, to develop a human-AI system that is able to personalize feedbacks and interact with students through a MI oriented conversation. Such a system should be able to collect data from chat rooms and/or video conferencing meetings, connect with the ML-NLP model via an API, and proved individual-based feedbacks. Moreover, using gamification in process feedback based on active engagement measures through AI systems in chatbots is another topic to investigate; for example, instead of using graphs or statistics in a feedback system, learners will probably react differently to receiving a virtual medal or badge for their active engagement.

To repeat the same study in real-world industrial engineering teams is another opportunity to further develop the generalizability of the results. Additionally, we suggest using ML algorithms to compare collaboration patterns to examine a possible correlation between the patterns and team success and/or predictability of team success based on the collaboration patterns in the early stages of a collaborative design or PBL.

Overall view

Rapid digitalization and significant advancements in AI have paved the way for assessing teamwork in engineering practice, students' engagement in PBL and providing timely process-oriented feedback at scale. The research innovation was to reimagine existing assessment and feedback systems from collaborative design and educational and information technologies perspective while considering two key factors; (1) attention to the process of collaboration instead of solely focusing on outcomes, and (2) addressing the scalability and limited recourse challenges by adapting AI capabilities.

This study contributes both methodologically, by demonstrating the potential of AI-assisted collaboration, and practically, by examining an ML-NLP approach through a PoC to assess active engagement. Our results indicate that conversational data (content, quality, and meta-data) contain valuable signals of active engagement in collaborative activities where ML-NLP techniques are able to predict the engagement patterns. This provides the possibility of automated assessment and sustained personalized feedback, or early intervention to solve the issues.

This research underscores the growing complexity of e- collaboration and the need to reimagine strategies in the digital age. By elucidating engagement patterns, proposing data-driven measurement approaches, and validating feedback interventions, the work tangibly demonstrates methods to understand and improve team dynamics. The integration of human-centered techniques and AI advances provides pathways for scalable, personalized feedback systems. On a broader level, the cross-disciplinary approach fosters competencies vital for the future of engineering education and practice. It promotes learning environments and design frameworks that nurture effective collaboration, leveraging technology as an enabler rather than just a tool. The proposed methods and tools carry real-world potential to aid educators, and engineering teams in developing impactful strategies for distributed teams. The findings will empower organizations to build cohesive, high-performing virtual teams, enhancing productivity and innovation. Moreover, the research spurs advancements in Human-AI collaboration by illuminating promising directions for AI agents to sense, analyze, and augment collaborative workflows intelligently. It contributes conceptual foundations and proof-of-concepts to shape more synergistic human-machine teaming. While this work focused on engineering design, the frameworks and technologies explored could be translated to other collaborative domains as well. Ultimately, it provides a springboard for further research and development of feedback systems, conversational agents, sentiment analysis, and other techniques to make future collaboration seamless. By fostering multi-disciplinary perspectives, this research aims to catalyze progress in remote collaboration competencies to meet the emerging landscape. The integrated knowledge culled from engineering, technology, social sciences, and management can inform the digital transformation of collaborative work and education worldwide.

Future studies should consider broader implications of machine learning and artificial intelligence application approaches in several directions; (1) to merge a text classification model with the speech-to-text system in order to cover a wider range of conversations including video conferencing and/or face-to-face conversation. (2) To integrate the system with recently emerged Large Language Model (LLMs) and validate the effectiveness of AI-powered feedback. (3) To examine gamified feedback and reward systems on active engagement. (4) To repeat the study in industrial environment.

T BLANK

THIS PAGE INTENTIONALLY LEFT BLANK

Bibliography

A. Agarwal, U. (2014), “Examining the impact of social exchange relationships on innovative work behaviour”, Team Performance Management, Vol. 20 No. 3/4, pp. 102–120.

Abedi, M., Fathi, M. S., Mirasa, A. K., & Rawai, N. M. (2016). Integrated collaborative tools for precast supply chain management. Scientia Iranica, 23, 429–448.

Abedi, M., Fathi, M. S., & Rawai, N. M. (2013). The Impact of Cloud Computing Technology to Precast Supply Chain Management. International Journal of Construction Engineering and Management, 2, 13–16.

Ahmed, V., & Opoku, A. (2022). Technology supported learning and pedagogy in times of crisis: the case of COVID-19 pandemic. Education and Information Technologies, 27(1), 365–405. https://doi.org/10.1007/s10639-021-10706-w

Akif, R., & Majeed, H. (2012). Issues and challenges in Scrum implementation. International Journal of Scientific & Engineering Research, 3(8), 1–4.

Alam, T. (2020). Cloud Computing and its role in the Information Technology. IAIC Transactions on Sustainable Digital Innovation (ITSDI), 1(2), 108-115.

Alharthi, S. A., Raptis, G. E., Katsini, C., Dolgov, I., Nacke, L. E., & Toups, Z. O. (2018). Toward Understanding the Effects of Cognitive Styles on Collaboration in Multiplayer Games. Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing, 169–172. https://doi.org/10.1145/3272973.3274047

Allen, C. (2004). Tracing the Evolution of Social Software. Life With Alacrity; A Blog on Social Software, Collaboration, Trust, Security, Privacy, and Internet Tools. http://www.lifewithalacrity.com/2004/10/tracing_the_evo.html

Almusharraf, F., Rose, J., & Selby, P. (2020). Engaging Unmotivated Smokers to Move Toward Quitting: Design of Motivational Interviewing–Based Chatbot Through Iterative Interactions. Journal of Medical Internet Research, 22(11), e20251.

Alves, A. C., Leão, C. P., Moreira, F., & Teixeira, S. (2018). Project-Based Learning and its Effects on Freshmen Social Skills in an Engineering Program. In Human Capital and Competences in Project Management. InTech. https://doi.org/10.5772/intechopen.72054

Ambler, N. P. (2015). Design in the Modern Age: Investigating the Role of Complexity in the Performance of Collaborative Engineering Design Teams.

Andreasson, R., Jansson, A. A. and Lindblom, J. (2019) “The coordination between train traffic controllers and train drivers: a distributed cognition perspective on railway,” Cognition, Technology & Work. Springer, 21(3), pp. 417–443.

Arbuckle, M. R., Foster, F. P., Talley, R. M., Covell, N. H., & Essock, S. M. (2020). Applying Motivational Interviewing Strategies to Enhance Organizational Readiness and Facilitate Implementation Efforts. Quality Management in Health Care, 29(1), 1–6. https://doi.org/10.1097/QMH.0000000000000234

Arcticportal. (2021). The Northern Sea Route: From Strategies to Realities. Arctic Journal. https://arcticportal.org/ap-library/news/2487-arctic-journal-the-northern-sea-route-from-strategies-to-realities

Årdal, C., & Røttingen, J.-A. (2012). Open source drug discovery in practice: a case study. PLoS Neglected Tropical Diseases, 6(9), e1827. https://doi.org/10.1371/journal.pntd.0001827

Arias, J., Ramírez, M.C., Duarte, D.M., Flórez, M.P. and Sanabria, J.P. (2016), "PoCDIO: a methodological proposal for promoting active participation in social engineering projects", Systemic Practice and Action Research, Springer, Vol. 29 No. 4, pp. 379–403.

Arlington, V. (2020) Gartner HR Survey, Gartner. Available at: https://www.gartner.com/en/newsroom/press-releases/2020-03-19-gartner-hr-survey-reveals-88--of-organizations-have-e.

Baanqud, N. S., Al-Samarraie, H., Alzahrani, A. I., & Alfarraj, O. (2020). Engagement in cloud-supported collaborative learning and student knowledge construction: a modeling study. International Journal of Educational Technology in Higher Education, 17(1), 56. https://doi.org/10.1186/s41239-020-00232-z

Barron, B., & Darling-Hammond, L. (2008a). How can we teach for meaningful learning. Powerful Learning: What We Know about Teaching for Understanding, 1, 11–16.

Barron, B., & Darling-Hammond, L. (2008b). Teaching for Meaningful Learning: A Review of Research on Inquiry-Based and Cooperative Learning. Book Excerpt. George Lucas Educational Foundation.

Banihashemi, S. Y., & Liu, L. (2014). Differentiating the role of ex-ante and ex-post relational governance mechanisms in regulating client-contractor relationships. Proceedings of PICMET '14 Conference: Portland International Center for Management of Engineering and Technology; Infrastructure and Service Integration, 2467–2476.

Bavendiek, A.-K., Inkermann, D., & Vietor, T. (2016). Supporting collaborative design by digital tools – Potentials and Challenges.

Belanger, E., Moller, J., & She, J. (2022). Challenges to Engineering Design Teamwork in a Remote Learning Environment. Education Sciences, 12(11), 741. https://doi.org/10.3390/educsci12110741

Bentley, R. et al. (1992) "Ethnographically-informed systems design for air traffic control," in Proceedings of the 1992 ACM conference on Computer-supported cooperative work, pp. 123–129.

Benz, M.R., Johnson, D.K., Mikkelsen, K.S. and Lindstrom, L.E. (1995), "Improving collaboration between schools and vocational rehabilitation: Stakeholder identified barriers and strategies", Career Development for Exceptional Individuals, Sage Publications Sage CA: Thousand Oaks, CA, Vol. 18 No. 2, pp. 133–144.

Berry, P. (2021). What became of the "eyes and the ears"?: exploring the challenges to reporting poor quality of care among trainee medical staff. Postgraduate Medical Journal, 97(1153), 695–700. https://doi.org/10.1136/postgradmedj-2021-140463

Berthoud, L. and Gliddon, J. (2018), "Using wikis to investigate communication, collaboration and engagement in Capstone engineering design projects", European Journal of Engineering Education, Vol. 43 No. 2, pp. 247–263.

Besterfield-Sacre, M., Shuman, L. J., Wolfe, H., Clark, R. M., & Yildirim, P. (2007). Development of a Work Sampling Methodology for Behavioral Observations: Application to Teamwork. Journal of Engineering Education, 96(4), 347–357. https://doi.org/10.1002/j.2168-9830.2007.tb00944.x

Bikard, M., Vakili, K., & Teodoridis, F. (2023). Detrimental Collaborations: When Two Isn't Always Better Than One. INSEAD Knowledge. https://knowledge.insead.edu/leadership-organisations/detrimental-collaborations-when-two-isnt-always-better-one

Bischof, G., Bischof, A., & Rumpf, H.-J. (2021). Motivational Interviewing: An Evidence-Based Approach for Use in Medical Practice. Deutsches Ärzteblatt International. https://doi.org/10.3238/arztebl.m2021.0014

Blandford, A. and Furniss, D. (2005) "DiCoT: a methodology for applying distributed cognition to the design of teamworking systems," in International workshop on design, specification, and verification of interactive systems. Springer, pp. 26–38.

Blessing, L. T. M., & Chakrabarti, A. (2009). DRM: A design reseach methodology. Springer.

Board, M. I., & Eddington, P. R. (2013). Mars Climate Orbiter: Phase I Report.

Boucher, M. (2020). What's the Cost of Poor Collaboration? (survey results). Tech-Clarity, Inc. https://tech-clarity.com/cost-of-poor-collaboration-in-engineering/9942

Boughzala, I. and de Vreede, G.-J. (2015), "Evaluating Team Collaboration Quality: The Development and Field Application of a Collaboration Maturity Model", Journal of Management Information Systems, Vol. 32 No. 3, pp. 129–157. https://doi.org/10.1080/07421222.2015.1095042

Brace, R. P., Casani, J. R., Farquhar, R. W., Haynes, N. R., Jordan, F., Kohlhase, C., Mitchell, R. T., Polutchko, R. J., Schallenmuller, A., Slonski, J. P., & Tolson, R. H. (1999). Report on the loss of the Mars Climate Orbiter Mission : JPL special review board.

Brady, T. K. (2002). Utilization of dependency structure matrix analysis to assess implementation of NASA's complex technical projects.

Brereton, M. (2004) “Distributed cognition in engineering design: Negotiating between abstract and material representations,” in Design representation. Springer, pp. 83–103.

Briggs, R.O. and Murphy, J.D. (2011), “Discovering and Evaluating Collaboration Engineering Opportunities: An Interview Protocol Based on the Value Frequency Model”, Group Decision and Negotiation, Vol. 20 No. 3, pp. 315–346.

Brisco, R., Whitfield, R.I. and Grierson, H. (2018), “Modelling the Relationship between Design Activity and Computer-supported Collaborative Design Factors”, DS 92: Proceedings of the DESIGN 2018 15th International Design Conference, pp. 193–204.

Brisco, R., Whitfield, R. I., & Grierson, H. (2020). A novel systematic method to evaluate computer-supported collaborative design technologies. Research in Engineering Design, 31(1), 53–81. https://doi.org/10.1007/s00163-019-00323-7

Buchal, R. O., & Lu, H. (2011). Engineering Design Education and Practice as Collaborative Knowledge Building.

Boucher, M. (2020). What’s the Cost of Poor Collaboration? (survey results). Tech-Clarity, Inc. https://tech-clarity.com/cost-of-poor-collaboration-in-engineering/9942

Cappelli, P., & Tavis, A. (2016). The Performance Management Revolution: The focus is shifting from accountability to learning. Harvard Business Review. https://hbr.org/2016/10/the-performance-management-revolution

Chen, C.-H., & Yang, Y.-C. (2019). Revisiting the effects of project-based learning on students’ academic achievement: A meta-analysis investigating moderators. Educational Research Review, 26, 71–81. https://doi.org/10.1016/j.edurev.2018.11.001

Cheng, K., Davis, M. K., Zhang, X., Zhou, S., & Olechowski, A. (2023). In the Age of Collaboration, the Computer-Aided Design Ecosystem is Behind: An Interview Study of Distributed CAD Practice. Proceedings of the ACM on Human-Computer Interaction, 7(CSCW1), 1–29.

Chowdary Attota, D., & Dehbozorgi, N. (2022). Towards Application of Speech Analysis in Predicting Learners’ Performance. 2022 IEEE Frontiers in Education Conference (FIE), 1–5. https://doi.org/10.1109/FIE56618.2022.9962701

Chua, K. J., Yang, W. M., & Leo, H. L. (2014). Enhanced and conventional project-based learning in an engineering design module. International Journal of Technology and Design Education, 24(4), 437–458. https://doi.org/10.1007/s10798-013-9255-7

Clark, J. O. (2009). System of Systems Engineering and Family of Systems Engineering from a standards, V-Model, and Dual-V Model perspective. 2009 3rd Annual IEEE Systems Conference, 381–387. https://doi.org/10.1109/SYSTEMS.2009.4815831

Corel. (2023). Global Survey: 54% of Enterprise Employees Agree That Poor Collaboration Tools Result in Lost Revenue for Businesses. GlobeNewswire. https://www.globenewswire.com/news-release/2022/07/12/2478199/0/en/Global-Survey-54-of-Enterprise-Employees-Agree-That-Poor-Collaboration-Tools-Result-in-Lost-Revenue-for-Businesses.html

Cowan, R.J., Swearer Napolitano, S.M. and Sheridan, S.M. (2004), “Home-school collaboration”.

Cross, R., & Carboni, I. (2020). When Collaboration Fails and How to Fix It. MIT Sloan Management Review. https://sloanreview.mit.edu/article/when-collaboration-fails-and-how-to-fix-it/

Cruz, M. L., Saunders-Smits, G. N., & Groen, P. (2020). Evaluation of competency methods in engineering education: a systematic review. European Journal of Engineering Education, 45(5), 729–757. https://doi.org/10.1080/03043797.2019.1671810

Davis, M., McInnes, B., & Ahmed, I. (2022). Forensic investigation of instant messaging services on linux OS: Discord and Slack as case studies. Forensic Science International: Digital Investigation, 42, 301401.

DeFranco, J. F., Neill, C. J., & Clariana, R. B. (2011). A cognitive collaborative model to improve performance in engineering teams-A study of team outcomes and mental model sharing. Systems Engineering, 14(3), 267–278. https://doi.org/10.1002/sys.20178

Dehbozorgi, N. (2020). Sentiment Analysis on Verbal Data from Team Discussions as an Indicator of Individual Performance. The University of North Carolina at Charlotte.

De Hoyos Guevarra, M. L. del C. (2004). Assessment of teamwork in higher education collaborative learning teams: A validation study. The University of Texas at Austin.

Deshpande, A. et al. (2016) “Remote working and collaboration in agile teams.”

Doppelt. (2003). Implementing and Assessment of PBL in a Flexible Environment. International Journal Of Technology and Design Education, 13(2), 55–72. https://link.springer.com/article/10.1023/A:1026125427344%5Cnhttp://cedu521-k-f07.pbworks.com/f/Implementation+and+Assessment+of+Project-Based+Learning+in+a+Flexible+Environment.pdf

Dreyfus, D. (2007) “Information system architecture: Toward a distributed cognition perspective,” ICIS 2007 Proceedings, p. 131.

Driskell, J.E., Salas, E. and Hughes, S. (2010), “Collective Orientation and Team Performance: Development of an Individual Differences Measure”, Human Factors: The Journal of the Human Factors and Ergonomics Society, Vol. 52 No. 2, pp. 316–328. https://doi.org/10.1177/0018720809359522

Dubberly, H., Pangaro, P. and Haque, U. (2009), “On Modeling, What is interaction?: are there different types?”, Interactions, Vol. 16 No. 1, pp. 69–75. https://doi.org/10.1145/1456202.1456220

Duehr, K., Efremov, P., Heimicke, J., Teitz, E.M., Ort, F., Weissenberger-Eibl, M. and Albers, A. (2021), “The positive impact of agile retrospectives on the collaboration of distributed development teams–a practical approach on the example of Bosch engineering GMBH”, Proceedings of the Design Society, Cambridge University Press, Vol. 1, pp. 3071–3080.

Durov Nikolai, D. P. (2013) "Telegram." Dubai. Available at: https://telegram.org/.

Earley, P. C., Northcraft, G. B., Lee, C., & Lituchy, T. R. (1990). Impact of process and outcome feedback on the relation of goal setting to task performance. Academy of Management Journal, 33(1), 87–105.

Elsie Boskamp. (2022). 35+ Compelling Workplace Collaboration Statistics. Zippia, Inc. https://www.zippia.com/advice/workplace-collaboration-statistics/

Emmett, J., Komm, A., Moritz, S., & Schultz, F. (2021). This time it's personal: Shaping the 'new possible' through employee experience. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/this-time-its-personal-shaping-the-new-possible-through-employee-experience

Esposto, A. S., & Weaver, D. (2011). Continuous Team Assessment to Improve Student Engagement and Active Learning. Journal of University Teaching and Learning Practice, 8(1), 97–108. https://doi.org/10.53761/1.8.1.8

Fan, S., Li, X., & Zhao, J. L. (2017). Collaboration Process Pattern Approach to Improving Teamwork Performance: A Data Mining-Based Methodology. INFORMS Journal on Computing, 29(3), 438–456. https://doi.org/10.1287/ijoc.2016.0739

Farshad, S., & Fortin, C. (2021). DISTRIBUTED COGNITION TRANSFORMATION IN COMPLETE ONLINE SYSTEM ENGINEERING DESIGN TEACHING. Proceedings of the Design Society, 1, 1313–1322. https://doi.org/10.1017/pds.2021.131

Farshad, S., & Fortin, C. (2023). A Novel Method for Measuring, Visualizing, and Monitoring E-Collaboration. International Journal of E-Collaboration, 19(1), 1–21. https://doi.org/10.4018/IJeC.317223

FBI. (2022). The Global Team Collaboration Software Market Size. https://www.fortunebusinessinsights.com/industry-reports/team-collaboration-software-market-101327

Ferme, L., Zuo, J. and Rameezdeen, R. (2018), "Improving collaboration among stakeholders in green building projects: role of early contractor involvement", Journal of Legal Affairs and Dispute Resolution in Engineering and Construction, American Society of Civil Engineers, Vol. 10 No. 4, p. 4518020.

Fernandes, J., Duarte, D., Ribeiro, C., Farinha, C., Pereira, J.M. and da Silva, M.M. (2012), "iThink: A game-based approach towards improving collaboration and participation in requirement elicitation", Procedia Computer Science, Elsevier, Vol. 15, pp. 66–77.

Finger, S., Gelman, D., Fay, A., & Szczerban, M. (2006). Assessing Collaborative Learning in Engineering Design.

Fischer, G. (2004), "Social creativity", Proceedings of the Eighth Conference on Participatory Design Artful Integration: Interweaving Media, Materials and Practices - PDC 04, Vol. 1, ACM Press, New York, New York, USA, p. 152.

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. Annals of Statistics, 1189–1232.

Friedman, J. H. (2002). Stochastic gradient boosting. Computational Statistics & Data Analysis, 38(4), 367–378. https://doi.org/10.1016/S0167-9473(01)00065-2

Fu, W., Bian, J., & Xu, Y. M. (2013). A Video Conferencing System for Collaborative Engineering Design. Applied Mechanics and Materials, 344, 246–252.

Fujino, H., Matsumura, T., Saito, T., Fujimura, H., & Imura, O. (2020). Psychological Case Conference Following the Death of a Patient With Neuromuscular Disease: A Source of Emotional Support for Participating Medical Staff. In Journal of patient experience (Vol. 7, Issue 5, pp. 713–716). https://doi.org/10.1177/2374373519892413

Gabelica, C., Bossche, P. Van den, Segers, M., & Gijselaers, W. (2012). Feedback, a powerful lever in teams: A review. Educational Research Review, 7(2), 123–144. https://doi.org/10.1016/j.edurev.2011.11.003

Gabelica, C., Van den Bossche, P., De Maeyer, S., Segers, M., & Gijselaers, W. (2014). The effect of team feedback and guided reflexivity on team performance change. Learning and Instruction, 34, 86–96. https://doi.org/10.1016/j.learninstruc.2014.09.001

Geister, S., Konradt, U., & Hertel, G. (2006). Effects of Process Feedback on Motivation, Satisfaction, and Performance in Virtual Teams. Small Group Research, 37(5), 459–489. https://doi.org/10.1177/1046496406292337

Gereffi, G., Wadhwa, V., Rissing, B., & Ong, R. (2008). Getting the Numbers Right: International Engineering Education in the United States, China, and India. Journal of Engineering Education, 97(1), 13–25. https://doi.org/10.1002/j.2168-9830.2008.tb00950.x

Gibbs, G. (2009). The assessment of group work: lessons from the literature. Assessment Standards Knowledge Exchange, 1–17.

Girard, P., & Robin, V. (2006). Analysis of collaboration for project design management. Computers in Industry, 57(8–9), 817–826. https://doi.org/10.1016/j.compind.2006.04.016

Git. (2020). Git. https://git-scm.com/

Gokhale, A. (1995). Collaborative learning enhances critical thinking. Journal of Technology Education, 7(1).

Gol, O., & Nafalski, A. (2007). Collaborative learning in engineering education. Unesco, Internationa Centre for Engineering Education.

Goldman, J. (2011). The contribution of ethnographic methods to our understanding of interprofessional teamwork. Journal of Interprofessional Care, 25(3), 165–166. https://doi.org/10.3109/13561820.2011.569417

Google (2020) Google Docs. Available at: https://www.google.com/docs/.

Göttgens, I., & Oertelt-Prigione, S. (2021). The Application of Human-Centered Design

Approaches in Health Research and Innovation: A Narrative Review of Current Practices. JMIR MHealth and UHealth, 9(12), e28102. https://doi.org/10.2196/28102

Graesser, A.C., Fiore, S.M., Greiff, S., Andrews-Todd, J., Foltz, P.W. and Hesse, F.W. (2018), “Advancing the Science of Collaborative Problem Solving”, Psychological Science in the Public Interest, Vol. 19 No. 2, pp. 59–92.

Greene, M., Papalambros, P. Y., & McGowan, A.-M. (2003). Position paper: Designing complex systems to support interdisciplinary cognitive work. DS 84: Proceedings of the DESIGN 2016 14th International Design Conference, 1487–1494.

Greene, M., Papalambros, P. Y. and McGowan, A.-M. (2016) “Position paper: Designing complex systems to support interdisciplinary cognitive work,” in DS 84: Proceedings of the DESIGN 2016 14th International Design Conference, pp. 1487–1494.

Griffiths, A.-J., Alsip, J., Hart, S.R., Round, R.L. and Brady, J. (2020), “Together we can do so much: A systematic review and conceptual framework of collaboration in schools”, Canadian Journal of School Psychology, SAGE Publications Sage CA: Los Angeles, CA, p. 0829573520915368.

Griffiths, A.-J., Alsip, J., Hart, S. R., Round, R. L., & Brady, J. (2021). Together We Can Do So Much: A Systematic Review and Conceptual Framework of Collaboration in Schools. Canadian Journal of School Psychology, 36(1), 59–85. https://doi.org/10.1177/0829573520915368

Gweon, G., Jun, S., Finger, S., & Rosé, C. P. (2017). Towards effective group work assessment: even what you don’t see can bias you. International Journal of Technology and Design Education, 27(1), 165–180. https://doi.org/10.1007/s10798-015-9332-1

Hafeez, M. (2021). Systematic Review on Modern Learning Approaches, Critical Thinking Skills and Students Learning Outcomes. Indonesian Journal Of Educational Research and Review, 4(1), 167. https://doi.org/10.23887/ijerr.v4i1.33192

Hallam, P.R., Smith, H.R., Hite, J.M., Hite, S.J. and Wilcox, B.R. (2015), “Trust and collaboration in PLC teams: Teacher relationships, principal support, and collaborative benefits”, NASSP Bulletin, SAGE Publications Sage CA: Los Angeles, CA, Vol. 99 No. 3, pp. 193–216.

Hamalainen, R. (2008), “Designing and evaluating collaboration in a virtual game environment for vocational learning”, Computers & Education, Vol. 50 No. 1, pp. 98–109.

Handrianto, C., & Rahman, M. A. (2019). Project based learning: a review of literature on its outcomes and implementation issues. LET: Linguistics, Literature and English Teaching Journal, 8(2), 110–129.

Haskins, C., Forsberg, K., Krueger, M., Walden, D., & Hamelin, D. (2006). Systems engineering handbook. INCOSE, 9, 13–16.

Hebert, S., Bor, W., Swenson, C. C., & Boyle, C. (2014). Improving collaboration: a qualitative assessment of inter-agency collaboration between a pilot Multisystemic Therapy Child Abuse and Neglect (MST-CAN) program and a child protection team. Australasian Psychiatry, 22(4), 370–373. https://doi.org/10.1177/1039856214539572

Helle, L., Tynjälä, P., & Olkinuora, E. (2006). Project-based learning in post-secondary education–theory, practice and rubber sling shots. Higher Education, 51(2), 287–314.

Hettema, J., Steele, J., & Miller, W. R. (2005). Motivational interviewing. Annual Review of Clinical Psychology(2005), 1(1), 91–111.

Herbsleb, J. D., & Roberts, J. A. (2006). Collaboration In Software Engineering Projects: A Theory Of Coordination. International Conference on Interaction Sciences.

Hershberger, P. J., Pei, Y., Bricker, D. A., Crawford, T. N., Shivakumar, A., Vasoya, M., Medaramitta, R., Rechtin, M., Bositty, A., & Wilson, J. F. (2021). Advancing Motivational Interviewing Training with Artificial Intelligence: ReadMI. Advances in Medical Education and Practice, Volume 12, 613–618. https://doi.org/10.2147/AMEP.S312373

Hettema, J., Steele, J., & Miller, W. R. (2005). Motivational interviewing. Annual Review of Clinical Psychology(2005), 1(1), 91–111.

Hihn, J., Chattopadhyay, D., Karpati, G., McGuire, M., Borden, C., Panek, J., & Warfield, K. (2011). Aerospace concurrent engineering design teams: Current state, next steps and a vision for the future. AIAA SPACE Conference and Exposition 2011. https://doi.org/10.2514/6.2011-7238

Hine, C. (2000) Virtual ethnography. Sage.

Ho, D., Kumar, A., & Shiwakoti, N. (2019). A Literature Review of Supply Chain Collaboration Mechanisms and Their Impact on Performance. Engineering Management Journal, 31(1), 47–68. https://doi.org/10.1080/10429247.2019.1565625

Hollan, J., Hutchins, E. and Kirsh, D. (2000) “Distributed cognition: toward a new foundation for human-computer interaction research,” ACM Transactions on Computer-Human Interaction (TOCHI). ACM New York, NY, USA, 7(2), pp. 174–196.

Huang, C.-J., & Chuang, Y.-T. (2008). Supporting the development of collaborative problem-based learning environments with an intelligent diagnosis tool. Expert Systems with Applications, 35(3), 622–631. https://doi.org/10.1016/j.eswa.2007.07.028

Huang, Q. (2022). Does learning happen? A mixed study of online chat data as an indicator of student participation in an online English course. Education and Information Technologies, 27(6), 7973–7992. https://doi.org/10.1007/s10639-022-10963-3

Hussein, B. (2021). Addressing Collaboration Challenges in Project-Based Learning: The Student’s Perspective. Education Sciences, 11(8), 434. https://doi.org/10.3390/educsci11080434

Hutchins, E. (1995) Cognition in the Wild. MIT press.

Huyck, M., Ferguson, D., & Wasserman, R. (2007). Assessing Factors Contributing To Undergraduate Multidisciplinary Project Team Effectiveness. Annual Conference & Exposition Proceedings, 12.266.1-12.266.19. https://doi.org/10.18260/1-2--3016

Hwang, C., & Zhang, L. (2019). Applying Cognitive Operations in Collaborative Apparel Design Process.

IBM Corp. (2013). IBM SPSS Statistics for Windows, Version 22.0. IBM Corp.

Iglesias-Pradas, S., Ruiz-de-Azcárate, C., & Agudo-Peregrina, Á. F. (2015). Assessing the suitability of student interactions from Moodle data logs as predictors of cross-curricular competencies. Computers in Human Behavior, 47, 81–89. https://doi.org/10.1016/j.chb.2014.09.065

INCOSE. (n.d.). Systems Engineering. https://www.incose.org/about-systems-engineering/system-and-se-definition/systems-engineering-definition

IREC (2020) The Intercollegiate Rocket Engineering Competition, ESRA Spaceport America Cup page. Available at: http://www.soundingrocket.org/what-is-irec.html.

Jackson, V., van der Hoek, A., Prikladnicki, R., & Ebert, C. (2022). Collaboration tools for developers. IEEE Software, 39(2), 7-15.

Isaksson, O., Eckert, C., Panarotto, M., & Malmqvist, J. (2020). YOU NEED TO FOCUS TO VALIDATE. Proceedings of the Design Society: DESIGN Conference, 1, 31–40. https://doi.org/10.1017/dsd.2020.116

James, R., McInnis, C., & Devlin, M. (2002). Assessing learning in Australian universities: Ideas, strategies and resources for quality in student assessment. Australian, Universities Teaching Committee.

Jeffares, S. and Dickinson, H. (2016), "Evaluating collaboration: The creation of an online tool employing Q methodology", Evaluation, Vol. 22 No. 1, pp. 91–107.

Jing, N., & Lu, S. C.-Y. (2011). Modeling Co-construction Processes in a Socio-Technical Framework to Support Collaborative Engineering Design. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 41, 297–305.

Jones, M. (2012). The Evolution of Digital Technologies–from Collaboration to eCollaboration–and the Tools which assist eCollaboration. Issues in Informing Science and Information Technology, 9, 209–219.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Kapp, E. (2009). Improving Student Teamwork in a Collaborative Project-Based Course. College Teaching, 57(3), 139–143. https://doi.org/10.3200/CTCH.57.3.139-143

Khusid Andrey. (2020). Miro. https://miro.com/about/

Kihlstrom, G. (2021), "Focusing On The Most Meaningful Metrics", Forbes, available at: https://www.forbes.com/sites/forbesagencycouncil/2021/04/22/focusing-on-the-most-meaningful-metrics/?sh=1612bcb29f26.

Klonek, F. E., & Kauffeld, S. (2015). Providing engineers with OARS and EARS. Higher Education, Skills and Work-Based Learning, 5(2), 117–134. https://doi.org/10.1108/HESWBL-06-2014-0025

Knoblauch, C. (2022). Mobile Learning in Project-Based Contexts in the Higher Education Sector. New Realities, Mobile Systems and Applications: Proceedings of the 14th IMCL Conference, 1022–1031.

Kock, N. (2005). What is e-collaboration. International Journal of E-Collaboration, 1(1), 1–7.

Kokotsaki, D., Menzies, V., & Wiggins, A. (2016). Project-based learning: A review of the literature. Improving Schools, 19(3), 267–277. https://doi.org/10.1177/1365480216659733

Kolfschoten, G. L., Lukosch, S., & Mathijssen, A. (2014). Supporting Collaborative Design : Lessons from a case study at the ESA concurrent design facility.

Kolodner, J. L., Camp, P. J., Crismond, D., Fasse, B., Gray, J., Holbrook, J., Puntambekar, S., & Ryan, M. (2003). Problem-Based Learning Meets Case-Based Reasoning in the Middle-School Science Classroom: Putting Learning by Design(tm) Into Practice. Journal of the Learning Sciences, 12(4), 495–547. https://doi.org/10.1207/S15327809JLS1204_2

Kotsiantis, S. B., Zaharakis, I. D., & Pintelas, P. E. (2006). Machine learning: a review of classification and combining techniques. Artificial Intelligence Review, 26(3), 159–190. https://doi.org/10.1007/s10462-007-9052-3

Kowsari, Jafari Meimandi, Heidarysafa, Mendu, Barnes, & Brown. (2019). Text Classification Algorithms: A Survey. Information, 10(4), 150. https://doi.org/10.3390/info10040150

Krajcik, J. S., & Blumenfeld, P. C. (2006). Project-based learning.

Kropp, M., Meier, A., Mateescu, M., & Zahn, C. G. (2014). Teaching and learning agile collaboration. 2014 IEEE 27th Conference on Software Engineering Education and Training (CSEE\&T), 139–148.

Kvan, T. (2000). Collaborative design: what is it? Automation in Construction, 9(4), 409–415. https://doi.org/10.1016/S0926-5805(99)00025-4

Kumar, S., Purohit, S. D., Hiranwal, S., & Prasad, M. (Eds.). (2021). Proceedings of International Conference on Communication and Computational Technologies. Springer Singapore. https://doi.org/10.1007/978-981-16-3246-4

Lai, E. R. (2011). Collaboration: A literature review. Pearson Publisher. Retrieved November, 11, 2016.

Lang, S. Y. T., Dickinson, J., & Buchal, R. O. (2002). Cognitive factors in distributed design. Computers in Industry, 48(1), 89–98. https://doi.org/10.1016/S0166-3615(02)00012-X

Lang, V. (2021), Digital Fluency, Springer.

Larmer, J. (2018). Project-based learning in social studies. Social Education, 82(1), 20–23.

Lau, P., Kwong, T., Chong, K., & Wong, E. (2013). Developing students' teamwork skills in a cooperative learning project. International Journal for Lesson and Learning Studies, 3(1), 80–99. https://doi.org/10.1108/IJLLS-03-2013-0018

Lazareva, A. and Munkvold, B.E. (2017), "Facilitating collaboration: Potential synergies between collaboration engineering and computer-supported collaborative learning", International Journal of E-Collaboration, Vol. 13 No. 3, pp. 22–38.

Lee, D., Huh, Y., & Reigeluth, C. M. (2015). Collaboration, intragroup conflict, and social skills in project-based learning. Instructional Science, 43(5), 561–590. https://doi.org/10.1007/s11251-015-9348-7

Li, W. D., Lu, W. F., Fuh, J. Y. H., & Wong, Y. S. (2005). Collaborative computer-aided design—research and development status. Computer-Aided Design, 37(9), 931–940. https://doi.org/10.1016/j.cad.2004.09.020

Lima, M., Fontão, A., Fernandes, D., Conte, T., & Gadelha, B. (2019). How are my Students going? A Tool to Analyse Students' Interactions on Capstone Courses. Brazilian Symposium on Computers in Education (Simpósio Brasileiro de Informática Na Educação-SBIE), 30(1), 1611.

Lima, R. M., Da Silva, J. M., van Hattum-Janssen, N., Monteiro, S. B. S., & De Souza, J. C. F. (2012). Project-based learning course design: a service design approach. International Journal of Services and Operations Management, 11(3), 292–313.

Lin, C.-W., Díaz, V. G., & Morente-Molinera, J. A. (2023). Introduction to the Special Issue of Recent Advances in Computational Linguistics for Asian Languages. ACM Transactions on Asian and Low-Resource Language Information Processing, 22, 1–5.

London, J. S., Douglas, E. P., & Loui, M. C. (2022). Introduction to the special themed section on engineering education and the <scp>COVID</scp> -19 pandemic. Journal of Engineering Education, 111(2), 275–276. https://doi.org/10.1002/jee.20457

Lu, S. .-Y., Elmaraghy, W., Schuh, G., & Wilhelm, R. (2007). A SCIENTIFIC FOUNDATION OF COLLABORATIVE ENGINEERING. CIRP Annals, 56(2), 605–634. https://doi.org/10.1016/j.cirp.2007.10.010

Lubis, M., Abdulmana, S., & Ahlan, A. R. (2011). Analysis of project communication on smart card implementation in XYZ Malaysian higher education.

Lundahl, B. W., Kunz, C., Brownell, C., Tollefson, D., & Burke, B. L. (2010). A Meta-Analysis of Motivational Interviewing: Twenty-Five Years of Empirical Studies. Research on Social Work Practice, 20(2), 137–160. https://doi.org/10.1177/1049731509347850

Luwanda, M. C., & Stevens, J. B. (2015). Effects of dysfunctional stakeholder collaboration on performance of land reform initiatives: Lessons from community based rural land development project in Malawi. South African Journal of Agricultural Extension, 43, 122–134.

Magill, M., Apodaca, T. R., Borsari, B., Gaume, J., Hoadley, A., Gordon, R. E. F., Tonigan, J. S., & Moyers, T. (2018). A meta-analysis of motivational interviewing process: Technical, relational, and conditional process models of change. Journal of Consulting and Clinical Psychology, 86(2), 140–157. https://doi.org/10.1037/ccp0000250

Majid, R., & Santoso, H. A. (2021). Conversations Sentiment and Intent Categorization Using Context RNN for Emotion Recognition. 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), 46–50. https://doi.org/10.1109/ICACCS51430.2021.9441740

Malhotra, S., Dutta, R., Daminee, A. K., & Mahna, S. (2020). Paradigm Shift in Engineering Education During COVID 19: From Chalkboards to Talk Boards. 2020 12th International Conference on Computational Intelligence and Communication Networks (CICN), 287–293.

Marek, L.I., Brock, D.-J.P. and Savla, J. (2015), "Evaluating Collaboration for Effectiveness", American Journal of Evaluation, Vol. 36 No. 1, pp. 67–85.

Marker, I., & Norton, P. J. (2018). The efficacy of incorporating motivational interviewing to cognitive behavior therapy for anxiety disorders: A review and meta-analysis. Clinical Psychology Review, 62, 1–10. https://doi.org/10.1016/j.cpr.2018.04.004

Marinova, I. (2020) 28 Need-To-Know Remote Work Statistics Of 2020, Review 42. Available at: https://review42.com/remote-work-statistics/.

Marker, I., & Norton, P. J. (2018). The efficacy of incorporating motivational interviewing to cognitive behavior therapy for anxiety disorders: A review and meta-analysis. Clinical Psychology Review, 62, 1–10. https://doi.org/10.1016/j.cpr.2018.04.004

Markopoulos, P. and Mackay, W. (2009), Awareness Systems: Advances in Theory, Methodology and Design, Springer Science & Business Media.

Marlow, S. L., Lacerenza, C. N., & Salas, E. (2017). Communication in virtual teams: a conceptual framework and research agenda. Human Resource Management Review, 27(4), 575–589. https://doi.org/10.1016/j.hrmr.2016.12.005

Marshall, C., & Nielsen, A. S. (2020). Motivational interviewing for leaders in the helping professions: Facilitating change in organizations. Guilford Publications.

Martinez-maldonado, R., Ga, D., Echeverria, V., Nieto, G. F., Swiecki, Z., & Shum, S. B. (2022). What Do You Mean by Collaboration Analytics ? A Conceptual Model. 8(1), 126–153.

Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: an applied review. International Journal of Remote Sensing, 39(9), 2784–2817. https://doi.org/10.1080/01431161.2018.1433343

McAlpine, I., Reidsema, C., & Allen, B. (2006). Educational design and online support for an innovative project-based course in engineering design. Who's Learning? Whose Technology? Proceedings Ascilite Sydney 2006.

McLeod, P. L., Liker, J. K., & Lobel, S. A. (1992). Process Feedback in Task Groups: An Application of Goal Setting. The Journal of Applied Behavioral Science, 28(1), 15–41. https://doi.org/10.1177/0021886392281003

McQuade, R. M. (2020). Juggling institutional and social demands: A conversation analysis of engineering students' interactions in self-managed problem-based learning.

Miller, W. R., & Rollnick, S. (2012). Motivational interviewing: Helping people change. Guilford press.

Milojević, D., Macuzic, I., Djordjevic, A., Savković, M., & Djapan, M. (2023). COMPARATIVE ANALYSIS OF SOFTWARE TOOLS FOR AGILE PROJECT MANAGEMENT.

MINT. (2021). Understanding Motivational Interviewing. Motivational Interviewing Network of Trainers. https://motivationalinterviewing.org/understanding-motivational-interviewing

Morais, P., Ferreira, M. J., & Veloso, B. (2021). Improving Student Engagement With Project-Based Learning: A Case Study in Software Engineering. IEEE Revista Iberoamericana de Tecnologias Del Aprendizaje, 16(1), 21–28. https://doi.org/10.1109/RITA.2021.3052677

Niesen, C. R., Kraft, S. J., & Meiers, S. J. (2018). Use of Motivational Interviewing by Nurse Leaders. The Health Care Manager, 37(2), 183–192. https://doi.org/10.1097/HCM.0000000000000209

No Magic. (1995). MagicDraw. https://www.nomagic.com/products/magicdraw

Nolan, E. M. (2021). Transcending Lockdown: Fostering Student Imagination through Computer-Supported Collaborative Learning and Creativity in Engineering Design Courses. University of Toronto Quarterly.

Nolan, Edmund. (2021). Transcending Lockdown: Fostering Student Imagination through Computer-Supported Collaborative Learning and Creativity in Engineering Design Courses. University of Toronto Quarterly.

Nolan, Ej. (2021). Transcending Lockdown: Fostering Student Imagination through Computer-Supported Collaborative Learning and Creativity in Engineering Design Courses. University of Toronto Quarterly, 91, 67–87.

Numata, J. (1996). Knowledge amplification: an information system for engineering management. Sony's Innovation in Management Series, 17.

Ogles, B. M., Wood, D. S., Weidner, R. O., & Brown, S. D. (2021). Motivational interviewing in higher education: A primer for academic advisors and student affairs professionals. Charles C Thomas Publisher.

Organ, J. N. (2021). MOTIVATIONAL INTERVIEWING: A Tool for Servant-Leadership. The International Journal of Servant-Leadership, 15(1), 209–234.

Ortiz-Marcos, I., Ballesteros Sanchez, L., Prieto Remon, T., & Uruburu Colsa, A. (2015). Strengthening and Measuring Project Management Competences of Engineering Students. Inted2015: 9Th International Technology, Education and Development Conference, March, 4221–4232.

Pan, J., & Rao, Y. (2021). Research on digital collaborative management model of engineering projects based on BIM and IPD. 2021 2nd International Conference on Big Data Economy and Information Management (BDEIM), 52–58.

Paulson Gjerde, K., Padgett, M. Y., & Skinner, D. (2017). The Impact of Process vs. Outcome Feedback on Student Performance and Perceptions. Journal of Learning in Higher Education, 13(1), 73–82.

Peñarroja, V., Orengo, V., Zornoza, A., Sánchez, J., & Ripoll, P. (2015). How team feedback and team trust influence information processing and learning in virtual teams: A moderated mediation model. Computers in Human Behavior, 48, 9–16. https://doi.org/10.1016/j.chb.2015.01.034

Pirkis, J., Livingston, J., Herrman, H., Schweitzer, I., Gill, L., Morley, B., Grigg, M., et al. (2004), "Improving collaboration between private psychiatrists, the public mental health sector and general practitioners: evaluation of the Partnership Project", Australian & New Zealand Journal of Psychiatry, Sage Publications Sage UK: London, England, Vol. 38 No. 3, pp. 125–134.

Plunk, A., Amat, A. Z., Tauseef, M., Peters, R. A., & Sarkar, N. (2023). Semi-Supervised Behavior Labeling Using Multimodal Data during Virtual Teamwork-Based Collaborative Activities. Sensors, 23(7), 3524. https://doi.org/10.3390/s23073524

Prabha, M. I., & Umarani Srikanth, G. (2019). Survey of Sentiment Analysis Using Deep Learning Techniques. 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT), 1–9. https://doi.org/10.1109/ICIICT1.2019.8741438

Pol, G., Merlo, C., Legardeur, J., & Jared, G. (2008). Implementation of collaborative design processes into PLM systems. International Journal of Product Lifecycle Management, 3(4), 279.

Prochaska, J.D., Croisant, S., Sommer, L.C., Treble, N., Bohn, K., Wiseman, L., Singleton, C., et al. (2021), "82003 Network Evaluation of a Community-Campus Partnership: Applying a Systems Science Lens to Evaluating Collaboration and Translation", Journal of Clinical and Translational Science, Vol. 5 No. s1, pp. 81–82.

Putnik, G. D., Putnik, Z., Shah, V., Varela, L. R., Ferreira, L., Castro, H., Catia, A., & Pinheiro, P. (2021). Collaborative Engineering definition: Distinguishing it from Concurrent Engineering through the complexity and semiotics lenses. IOP Conference Series: Materials Science and Engineering, 1174.

Qin, S. F., Harrison, R., West, A. A., Jordanov, I. N., & Wright, D. K. (2003). A framework of web-based conceptual design. Computers in Industry, 50(2), 153–164. https://doi.org/10.1016/S0166-3615(02)00117-3

Qiu, R. G. (2019). A systemic approach to leveraging student engagement in collaborative learning to improve online engineering education. International Journal of Technology Enhanced Learning, 11(1), 1–19.

Ramasamy, V., Ramamoorthy, S., Vijayalakshmi, S. K., & R., P. (2022). High Impact Practices and Collaborative Teaching to Enhance Learning and Engagement in Engineering Design Project Course. Journal of Engineering Education

Transformations.

Rashid, M., Caine, V., & Goez, H. R. (2015). The Encounters and Challenges of Ethnography as a Methodology in Health Research. International Journal of Qualitative Methods, 14.

Rodríguez Montequín, V., Mesa Fernández, J. M., Balsera, J. V., & García Nieto, A. (2013). Using MBTI for the success assessment of engineering teams in project-based learning. International Journal of Technology and Design Education, 23(4), 1127–1146. https://doi.org/10.1007/s10798-012-9229-1

Rollnick, S., & Miller, W. R. (1995). What is Motivational Interviewing? Behavioural and Cognitive Psychotherapy, 23(4), 325–334. https://doi.org/10.1017/S135246580001643X

Rometty, V. G. (2006). Expanding the innovation horizon: The global CEO study 2006. IBM Business Consulting Services.

Roy, U., Bharadwaj, B., Kodkani, S. S., & Cargian, M. (1997). Product Development in a Collaborative Design Environment. Concurrent Engineering, 5(4), 347–365. https://doi.org/10.1177/1063293X9700500407

Rubak, S., Sandbæk, A., Lauritzen, T., & Christensen, B. (2005). Motivational interviewing: a systematic review and meta-analysis. British Journal of General Practice, 55(513), 305–312.

Rutkowski, A. F., Vogel, D. R., Van Genuchten, M., Bemelmans, T. M. A., & Favier, M. (2002). e-collaboration: the reality of virtuality. IEEE Transactions on Professional Communication, 45(4), 219–230. https://doi.org/10.1109/TPC.2002.805147

Saiyed, A., Layton, J., Borsari, B., Cheng, J., Kanzaveli, T., Tsvetovat, M., & Satterfield, J. (2022). Technology-Assisted Motivational Interviewing: Developing a Scalable Framework for Promoting Engagement with Tobacco Cessation Using NLP and Machine Learning. Procedia Computer Science, 206, 121–131. https://doi.org/10.1016/j.procs.2022.09.091

Samarakou, M., Fylladitakis, E. D., Früh, W. G., Hatziapostolou, A., & Gelegenis, J. J. (2015). An Advanced eLearning Environment Developed for Engineering Learners. International Journal of Emerging Technologies in Learning (IJET), 10(3), 22. https://doi.org/10.3991/ijet.v10i3.4484

Sandahl, C., Gustafsson, H., Wallin, C., Meurling, L., Øvretveit, J., Brommels, M., & Hansson, J. (2013). Simulation team training for improved teamwork in an intensive care unit. International Journal of Health Care Quality Assurance, 26(2), 174–188. https://doi.org/10.1108/09526861311297361

Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. SN Computer Science, 2(3), 160. https://doi.org/10.1007/s42979-021-00592-x

Sasmita, F., & Mulyanti, B. (2020). Development of machine learning implementation in engineering education: A literature review. IOP Conference Series: Materials Science and Engineering, 830(3), 032061. https://doi.org/10.1088/1757-

899X/830/3/032061

Schaddelee, M., & McConnell, C. (2018). Analysing student perceptions to enhance engagement. Journal of International Education in Business, 11(2), 161–177. https://doi.org/10.1108/JIEB-09-2017-0034

Schwalbe, C. S., Oh, H. Y., & Zweben, A. (2014). Sustaining motivational interviewing: a meta-analysis of training studies. Addiction, 109(8), 1287–1294. https://doi.org/10.1111/add.12558

Schwarz, B. B., Swidan, O., Prusak, N., & Palatnik, A. (2021). Collaborative learning in mathematics classrooms: Can teachers understand progress of concurrent collaborating groups? Computers & Education, 165, 104151. https://doi.org/10.1016/j.compedu.2021.104151

Schwind, M., & Wegmann, C. (2008). SVNNAT: Measuring Collaboration in Software Development Networks. 2008 10th IEEE Conference on E-Commerce Technology and the Fifth IEEE Conference on Enterprise Computing, E-Commerce and E-Services, 97–104. https://doi.org/10.1109/CECandEEE.2008.100

Seaborn, K., Miyake, N. P., Pennefather, P. S., & Otake-Matsuura, M. (2020). Socially Embodied AI: A Framework for Recognizing the Dynamic Sociality of Artificial Agents Within and Beyond Healthcare (Preprint).

Sewell, G. (2001). What Goes Around, Comes Around. The Journal of Applied Behavioral Science, 37(1), 70–89. https://doi.org/10.1177/0021886301371005

Si, S., Zhang, H., Keerthi, S. S., Mahajan, D., Dhillon, I. S., & Hsieh, C.-J. (2017). Gradient boosted decision trees for high dimensional sparse output. International Conference on Machine Learning, 3182–3190.

Siegfriedt, R. S., Bohannon, E., Girerd, A. R., Trettel, I. A., & Roth, B. D. (2022). Making or Breaking a Rover- Systems Engineering Parameters On-Board the Mars 2020 Perseverance Rover. 2022 IEEE Aerospace Conference (AERO), 1–14.

Silungwe, C. T., Chiponde, D. B., Mutale, L. P., & Michello, N. (2015). Risk Reduction on Infrastructure Projects in the Zambian Construction Industry through Integrated Risk Management (IRM) Approach.

Simmons, L. A., & Wolever, R. Q. (2013). Integrative Health Coaching and Motivational Interviewing: Synergistic Approaches to Behavior Change in Healthcare. Global Advances in Health and Medicine, 2(4), 28–35. https://doi.org/10.7453/gahmj.2013.037

Singh, R., & Awasthi, S. (2020). Updated comparative analysis on video conferencing platforms-zoom, Google meet, Microsoft Teams, WebEx Teams and GoToMeetings. EasyChair Preprint, 4026, 1-9.

Sharp, H. et al. (2006) “The Role of Story Cards and the Wall in XP teams: a distributed cognition perspective,” in AGILE 2006 (AGILE’06). IEEE, pp. 11-pp.

Sharp, H., Giuffrida, R. and Melnik, G. (2012) “Information flow within a dispersed agile team: a distributed cognition perspective,” in International Conference on Agile

Software Development. Springer, pp. 62–76.

Shen, W., & Barthès, J. (1997). An experimental environment for exchanging engineering design knowledge by cognitive agents. Workshop on Knowledge Intensive CAD, 19–38.

Schwind, M. and Wegmann, C. (2008), “SVNNAT: Measuring Collaboration in Software Development Networks”, 2008 10th IEEE Conference on E-Commerce Technology and the Fifth IEEE Conference on Enterprise Computing, E-Commerce and E-Services, pp. 97–104.

Simmons, L. A., & Wolever, R. Q. (2013). Integrative Health Coaching and Motivational Interviewing: Synergistic Approaches to Behavior Change in Healthcare. Global Advances in Health and Medicine, 2(4), 28–35. https://doi.org/10.7453/gahmj.2013.037

Simpson, M., & Viller, S. (2004). Observing architectural design: Improving the development of collaborative design environments. International Conference on Cooperative Design, Visualization and Engineering, 12–20.

Sluijsmans, D. M. A., Moerkerke, George, Van Merrienboer, J. J. G., & Dochy, F. J. (2001). Peer assessment in problem based learning. Studies in Educational Evaluation, 27(2), 153–173.

Sokolova, M., Japkowicz, N., & Szpakowicz, S. (2006). Beyond accuracy, F-score and ROC: a family of discriminant measures for performance evaluation. AI 2006: Advances in Artificial Intelligence: 19th Australian Joint Conference on Artificial Intelligence, Hobart, Australia, December 4-8, 2006. Proceedings 19, 1015–1021.

Soller, A., Martínez, A., Jermann, P., & Muehlenbrock, M. (2005). From mirroring to guiding: A review of state of the art technology for supporting collaborative learning. International Journal of Artificial Intelligence in Education, 15(4), 261–290.

Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. Journal of Computer Assisted Learning, 34(4), 366–377. https://doi.org/10.1111/jcal.12263

Spyra, G., Buchanan, W.J., Cruickshank, P. and Ekonomou, E. (2016), “Cloud-Based Identity and Identity Meta-Data”, Psychology and Mental Health, IGI Global, pp. 1756–1773. 10.4018/978-1-5225-0159-6.ch076

Stempfle, J., & Badke-Schaub, P. (2002). Thinking in design teams - an analysis of team communication. Design Studies, 23(5), 473–496. https://doi.org/10.1016/S0142-694X(02)00004-2

Stozhko, N., Bortnik, B., Mironova, L., Tchernysheva, A., & Podshivalova, E. (2015). Interdisciplinary project-based learning: technology for improving student cognition. Research in Learning Technology, 23(1), 27577. https://doi.org/10.3402/rlt.v23.27577

Strauss, P., & U, A. (2007). Group assessments: dilemmas facing lecturers in multicultural tertiary classrooms. Higher Education Research & Development, 26(2), 147–161. https://doi.org/10.1080/07294360701310789

Student. (1908). The Probable Error of a Mean. Biometrika, 6(1), 1. https://doi.org/10.2307/2331554

Sujan, S. F., Wynford Jones, S., Kiviniemi, A., Wheatcroft, J. M., & Mwiya, B. (2020). Holistically assessing collaborative culture in the AEC industry. Journal of Information Technology in Construction, 25, 272–286. https://doi.org/10.36680/j.itcon.2020.016

Tan, L. (2020, September 10). Behaviours in design collaborations: Insights from a team learning perspective. https://doi.org/10.21606/drs.2020.330

Tausch, S. (2016). The influence of computer-mediated feedback on collaboration. lmu. https://doi.org/https://doi.org/10.5282/edoc.19975

Tausczik, Y. R., & Pennebaker, J. W. (2013). Improving teamwork using real-time language feedback. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.

Thomson, A. M., Perry, J. L., & Miller, T. K. (2007). Conceptualizing and Measuring Collaboration. Journal of Public Administration Research and Theory, 19(1), 23–56. https://doi.org/10.1093/jopart/mum036

Thomas, J. W., Mergendoller, J. R., & Michaelson, A. (1999). Project based learning: A handbook for middle and high school teachers. Buck Institute for Education.

Traverso-Ribón, I., Balderas-Alberico, A., Dodero, J.-M., Ruiz-Rube, I., & Palomo-Duarte, M. (2016). Open data framework for sustainable assessment of project-based learning experiences. Program, 50(4), 380–398. https://doi.org/10.1108/PROG-12-2015-0078

Trivate, T., Dennis, A. A., Sholl, S., & Wilkinson, T. (2019). Learning and coping through reflection: exploring patient death experiences of medical students. BMC Medical Education, 19.

Tucker, V. and Schwartz, I. (2013), "Parents' perspectives of collaboration with school professionals: Barriers and facilitators to successful partnerships in planning for students with ASD", School Mental Health, Springer, Vol. 5 No. 1, pp. 3–14.

UNESCO. (2010). Engineering: issues, challenges and opportunities for development; UNESCO report. https://unesdoc.unesco.org/ark:/48223/pf0000189753

Varela, L., Putnik, G., & Romero, F. (2022). The concept of collaborative engineering: a systematic literature review. Production & Manufacturing Research, 10(1), 784–839. https://doi.org/10.1080/21693277.2022.2133856

Vila, C., Ugarte, D., Ríos, J., & Abellán, J. V. (2017). Project-based collaborative engineering learning to develop Industry 4.0 skills within a PLM framework. Procedia Manufacturing, 13, 1269–1276. https://doi.org/10.1016/j.promfg.2017.09.050

Viswambaran, V. K., & Shafeek, S. (2019). Project Based Learning (PBL) Approach for Improving the Student Engagement in Vocational Education : An investigation on students‘ learning experiences & achievements. 2019 Advances in Science and Engineering Technology International Conferences (ASET), 1–8. https://doi.org/10.1109/ICASET.2019.8714463

Volpentesta, A. P., Ammirato, S., & Sofo, F. (2012). Collaborative design learning and thinking style awareness. International Journal of Engineering Education, 28(4), 948.

Volpentesta, A. P., Ammirato, S., & Sofo, F. (2009). Thinking style diversity and collaborative design learning. Working Conference on Virtual Enterprises, 785–796.

Vukašinović, N., & Fain, N. (2014). A decade of project based design education - Is there a future? Proceedings of International Design Conference, DESIGN, 2014-Janua, 1441–1450.

Wahl, L., & Kitchel, A. (2016). Internet Based Collaboration Tools. Int. J. e Collab., 12, 27–43.

Wang, J., Yuan, Z., He, Z., Zhou, F., & Wu, Z. (2021). Critical Factors Affecting Team Work Efficiency in BIM-Based Collaborative Design: An Empirical Study in China. Buildings, 11(10), 486. https://doi.org/10.3390/buildings11100486

Weger, K., Leder, S., Mesmer, B. L., Menon, V., & Schaub, H. (2022). How Effectively Do We Communicate? An Analysis of Team Reflexivity in Transition and Action Phases of Team Collaboration. IEEE Transactions on Professional Communication, 65, 392–410.

White, T. E., & Rege, M. (2020). Sentiment Analysis on Google Cloud Platform. Issues Inf. Syst, 21, 221–228.

Wierts, C. M., Wilson, P. M., & Mack, D. E. (2019). Awareness and use of motivational interviewing reported by Canadian university sport coaches. International Journal of Evidence Based Coaching & Mentoring, 17(1).

Willey, K., & Freeman, M. (2006). Improving teamwork and engagement: the case for self and peer assessment. Australasian Journal of Engineering Education, February 2006.

Willey, Keith, & Gardner, A. (2009). Developing team skills with self- and peer assessment. Campus-Wide Information Systems, 26(5), 365–378. https://doi.org/10.1108/10650740911004796

Williams, S. (2017). Investigating the allocation and corroboration of individual grades for project-based learning. Studies in Educational Evaluation, 53, 1–9. https://doi.org/10.1016/j.stueduc.2016.10.009

Wood, D. J., & Gray, B. (1991). Toward a Comprehensive Theory of Collaboration. The Journal of Applied Behavioral Science, 27(2), 139–162. https://doi.org/10.1177/0021886391272001

World Economic Forum. (2020). The COVID-19 pandemic has changed education forever. This is how. https://www.weforum.org/agenda/2020/04/coronavirus-education-global-covid19-online-digital-learning/

Xie, M., Meng, F., Zou, J., Feng, W., & Ma, S. (2020). Application of Artificial Intelligence in Civil Engineering Education. Journal of Physics: Conference Series, 1575(1), 012225. https://doi.org/10.1088/1742-6596/1575/1/012225

Yin, Y., Qin, S., & Holland, R. (2011). Development of a design performance measurement matrix for improving collaborative design during a design process. International Journal of Productivity and Performance Management, 60(2), 152–184. https://doi.org/10.1108/17410401111101485

Zhang, S., Shen, W., & Ghenniwa, H. (2004). A review of Internet-based product information sharing and visualization. Computers in Industry, 54(1), 1–15. https://doi.org/10.1016/j.compind.2003.09.002

Zhang, Y., Song, D., Li, X., Zhang, P., Wang, P., Rong, L., Yu, G., & Wang, B. (2020). A Quantum-Like multimodal network framework for modeling interaction dynamics in multiparty conversational sentiment analysis. Information Fusion, 62, 14–31. https://doi.org/10.1016/j.inffus.2020.04.003

Zheng, Y., Shen, H., & Sun, C. (2011). Collaborative design: Improving efficiency by concurrent execution of Boolean tasks. Expert Systems with Applications, 38(2), 1089–1098. https://doi.org/10.1016/j.eswa.2010.05.004

Zoom Video Communications Inc. (2020). Zoom. https://zoom.us/

Zumbach, J., Reimann, P. and Koch, S.C. (2006), “Monitoring Students’ Collaboration in Computer-Mediated Collaborative Problem-Solving: Applied Feedback Approaches”, Journal of Educational Computing Research, SAGE Publications Sage CA: Los Angeles, CA, Vol. 35 No. 4, pp. 399–424.

THIS PAGE INTENTIONALLY LEFT BLANK