# Analyzing Team Cognition and Combined Efficacy In Makerspaces Using Multimodal Data

Nisumba Soodhani K
Indian Institute of Technology Bombay
nisumba@gmail.com

## ABSTRACT

Makerspace has been growing as a major phenomenon since 2005. Learners' participation in makerspaces has proved useful in terms of their cognitive, affective and psychomotor outcomes. Many studies have reported on improved outcomes because of makerspaces, but how the learning process actually occurs is not clearly known. One reason for this is the makerspace setting itself which poses challenges for data collection, as makerspaces generally involve teams coming together and creating something. Capturing team dynamics in a real-time setting where mobility is hugely a part of it poses difficulty in multimodal data collection. To overcome the above-mentioned challenges and to understand the learning process in a makerspace, this thesis proposes multimodal data collection in a makerspace using a camera and eye tracker. Data will also be collected through surveys and interviews to understand team cognition, combined efficacy, and interests. Patterns will be identified and triangulated will inform us of the learner model and the learning process occurring in the makerspaces

## Keywords

Makerspaces, multimodal data, team cognition, combined efficacy, self-efficacy, interest

## 1. INTRODUCTION

An increasing number of individuals are participating in the making of items in their daily lives and seeking ways to share their methods and artifacts with others through both physical and digital platforms [10]. The various learning theories associated with the maker movement are Seymour Papert's "constructionism", Jean Piaget's "constructivism", and John Dewey's idea of "learning by doing". Understanding these theories helps in designing and analyzing opportunities for learners to participate in makerspaces, create personalized projects and products that are meant to connect to students' own lived experiences demonstrate authenticity, and structure activities for enhancing teamwork and collaboration [4]. Literature signals strong links between interdisciplinary STEM (Science, Technology, Engineering, and Mathematics) and making, particularly the skills and capabilities utilized in projects, and opportunities to develop and apply STEM knowledge [9]. The National Research Council of the USA has recently identified makerspaces as learning environments with the potential for helping students to learn science and engineering concepts through investigation and design [5].

The relatively recent rise of the Maker Movement is a direct result of the widespread availability of low-cost digital fabrication technologies, the development of the Internet as a tool for sharing information, and an increase in media (e.g., Make magazine) and events (e.g., Maker Faires—community gatherings celebrating the Maker Movement) related to making [14]. In makerspaces collaboration is evident and the complexity of design problems requires that makers from different fields come together also a variety of scaffolds should be available to them to solve the problem. Organizations turn to teams in today's complicated and dynamic work environment to solve issues quickly and effectively. Teams-based organizational structures promote productivity, innovation, and other crucial organizational outcomes across industries [12].

The findings of the research also support the notion that makerspaces can aid in the development of a wide range of twenty-first-century skills [8]. Twenty-first-century skills (for example, collaboration, problem-solving, and digital citizenship) are a broad set of competencies that, when combined, indicate that individuals are prepared to be productive members of the workforce [13]. Research has been done to establish that there is some cognitive, affective and psychomotor gain, but limited research has examined how these skills and knowledge are developed. Even in those studies, qualitative methods such as observation, interviews, and self-reported surveys are heavily used. This thesis aims to address this gap by using multimodal data collection to understand the process of team cognition and also the role of self-efficacy and interest in it.

## 2. BACKGROUND

The recent developments in physiological sensing techniques technologies such as eye-tracker, EEG, wrist bands, etc., open ways to collect data in other modalities rather than focusing only on self-reports or questionnaires to understand the process of learning. They also have advantages such as

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less labour-intensive data collection over longer periods, allowing for the measurement of team cognition in real-world task contexts as opposed to simulated ones. Data can also be collected and analyzed in real-time which is also scalable. Data from one channel may not be enough to capture knowledge sharing, especially in a group setting where the focus is on team cognition and the combined efficacy of the team. Hence, there is a need to use data from multiple sensors. Multimodal analytics in makerspaces refers to the use of multiple types of data, or modalities, to gain a more comprehensive understanding of learners' activities and behaviours. This might include data from video cameras, sensor logs, and other forms of digital tracking, as well as more qualitative data such as interviews, surveys, and observations. By using multiple types of data, multimodal analytics can provide a more holistic view of the learners' experience in the makerspace and can help to identify patterns and trends that may not be visible when using only one type of data [2].

For example, sensor logs can provide data on the frequency and duration of use of different tools and resources, while video cameras can capture more detailed information on how learners are using those tools and resources. Interviews and observations can provide insight into learners' motivations, goals, and perceptions of their experiences in the makerspace [6]. By integrating these different types of data, multimodal analytics can help to identify patterns and trends that may not be visible when using only one type of data. It is important to note that multimodal analytics also involves a combination of quantitative and qualitative data [2]. This allows researchers to gain a deeper understanding of the learners' experiences in the makerspace and to identify patterns that may not be visible when using only quantitative data. For a better understanding of how knowledge is shared among team members and applied to solve problems, more research is required in the areas of team cognition, combined efficacy, and interest. Multimodal data analytics also has its own challenges, such as difficulty in temporally aligning data sources with different sampling rates and determining the amount of data to be sampled. Other challenges include the fusion of features from one modality to another for classification tasks, co-learning between modalities, and the generation of new features from one modality to another. Addressing these challenges is crucial for the effective analysis of multimodal data.

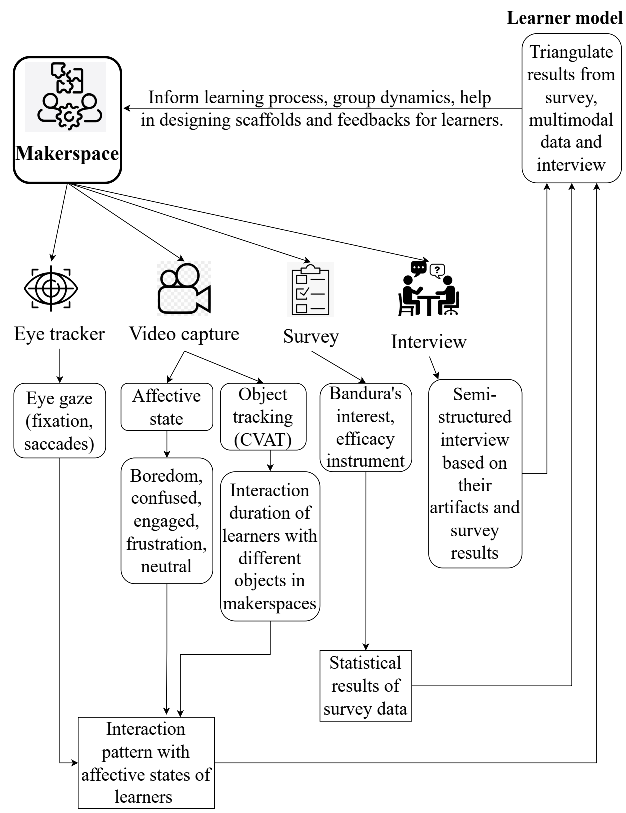


**Figure 1: Overview of the proposed method.**

## 3. THEORETICAL FRAMEWORK

The suitable theoretical framework for understanding interests, beliefs, attitudes, and self-efficacy in makerspaces is the Self Determination Theory (SDT) developed by [7]. SDT is a framework that explains how individuals engage in activities and how that engagement is related to well-being and motivation. SDT suggests that individuals have innate psychological needs for autonomy, competence, and relatedness and that when these needs are met, individuals are more likely to engage in activities that are self-determined, intrinsically motivated, and lead to well-being. In the context of makerspaces, individuals who feel autonomous in their decision-making and have a sense of competence in their abilities to create and innovate will be more likely to engage in making activities.

Interest, belief, and attitudes are also important factors in SDT. Interest is an intrinsic motivation for engaging in an activity, and beliefs and attitudes can influence an individual's perception of competence and autonomy in the activity. For example, if an individual holds a belief that they are not creative or do not have the necessary skills to participate in making activities, they may be less likely to engage in these activities [15]. Self-efficacy, or an individual's belief in their ability to perform a specific task, is also important in SDT. In makerspaces, individuals who have a high level of self-efficacy in their making abilities will be more likely to engage in making activities and persist in the face of challenges [15]. Overall, SDT provides a theoretical framework for understanding the factors that influence individuals' engagement in making activities in makerspaces, and how these factors are related to well-being and motivation [11].

## 4. RESEARCH OBJECTIVES

From the previous sections, we established that there is a need to investigate the interplay between various factors that influence students' interest, identity, and self-efficacy (beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments) when they work together to solve problems collaboratively. Additionally, it is necessary to examine how each of these influences team cognition. To do this, I intend to take advantage of the

Table 1: Data Sources

| Data type | Data source | Data |
|---|---|---|
| Qualitative data | Interviews and observation | They can provide valuable information about the resources and support provided in the makerspace, as well as the ways in which students are using the space and the impact it is having on their learning. |
| Quantitative data | Bandura's self-efficacy, interest survey | Self-report on individual self-efficacy, combined efficacy, and interest. |
| | Camera | Detect facial expressions. The video can also be used for object tracking and analyzing the amount the time spent by a learner interacting with different materials in the makerspaces. |
| | Eye tracker | Track the student's gaze and infer their level of engagement or interest in the task. |

introduction of new technical tools like wearables and other covert measurement methods, which will provide us with the chance to advance our understanding of the science behind team cognition. Because of these technical developments, it is now possible for academics to evaluate data streams that are far larger than they have ever been. Additionally, when combined with conventional metrics, these tools can give additional context for comprehending the level of cognition among teams. Collectively, these efforts will

1. Inform researchers about how knowledge is shared in team cognition, interest, and combined efficacy's role in it.

2. Understand and model participants' learning processes.

3. Inform designers and developers to provide scaffolding and feedback.

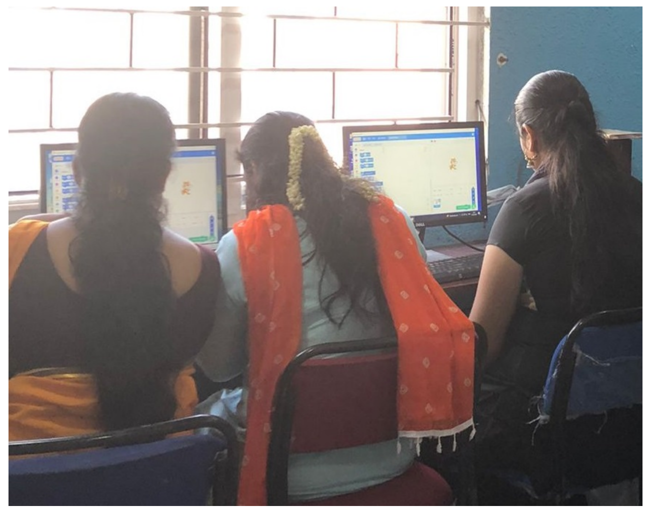

Figure 2: Participants working on Scratch.

# 5. RESEARCH METHODOLOGY

## 5.1 Preliminary study

The preliminary study was conducted with fourteen participants who were introduced to digital making – TinkerCAD and Scratch. All participants identified themselves as female. Participants discussed the socio-environmental and economic issues with their peers and came up with a critical making design plan to tackle the identified problem. The plan or ideas submitted by them were the artifacts and their responses to the survey questionnaire focusing on self-efficacy, beliefs, and attitudes were the primary data sources. This questionnaire was adapted from Bandura's self-efficacy scale [3]. This survey was administered after the workshop. Their artifacts were analyzed using content analysis and the survey results were mapped to the artifacts. This pilot study helped in understanding the self-efficacy and interest of first-time makers. The quality of artifacts and the statistical results of surveys had a correlation. Participants who reported high efficacy had better artifacts in terms of their actionable plan.

## 5.2 Participants and Data Collection

The future study will be conducted primarily amongst undergraduate program students as individuals at this level are young adults and usually are at the starting point of shaping their lives based on their interests and have certain autonomy to do so. The data that will be collected and the data sources are mentioned in Table 1. Data collected from self-reported surveys and interviews will be mapped with the patterns and findings from multimodal data analytics. In order to understand the learner's behaviour a quantitative approach will be used which will employ machine learning.

## 5.3 Data Analysis

The video can be used for object tracking with CVAT, which can record the duration of interaction with a specific object [1]. This information, combined with eye gaze data, can provide insight into a task's level of engagement and interest. The combined efficacy and interest questionnaire survey results can be statistically analyzed to provide additional data. To identify patterns and understand the meaning of these patterns in the context of the data, the interview data can be coded and analyzed using grounded theory. The patterns that emerge from the multimodal data can be used to triangulate the qualitative analysis findings, providing a more comprehensive understanding of the learning process in the makerspaces. Using this method of study and analysis will help in coming up with a more detailed and nuanced understanding of the process. The triangulation with survey results and interview data will help us in explaining the role of self-efficacy and combined efficacy in social learning environments like makerspaces.

# 6. ONGOING AND FUTURE WORK

The pilot study is completed and the next step in the research process is to conduct data collection and analysis of the primary study. The data collection should involve gathering qualitative and multi-modal data from the makerspaces, such as observations, interviews, and documents. This data should then be analyzed in order to address the research question and answer the study's objectives. One potential challenge when analyzing multimodal data is finding a way to effectively combine and analyze data from multiple modalities, such as eye gaze, and video. This may involve using specialized software or techniques and may require consulting with experts in the field of multimodal data analysis.

# 7. CONCLUSION

Makerspaces are defined by groups of people getting together to create something in real-time, which requires a lot of movement, making data collecting challenging. This thesis proposes the use of multimodal data gathering to better understand the learning process in makerspaces. While the advantages of makerspaces for learners have been well acknowledged, the specifics of how learning takes place in this context have remained unknown due to data-gathering issues. In addition to questionnaires and interviews, the suggested use of a camera and eye tracker attempts to overcome these limitations and give a more thorough knowledge of the cognitive, emotional, and psychomotor effects of involvement in makerspaces. The identified patterns will be triangulated to inform a learner model and shed light on the learning process occurring in makerspaces. This will provide insight into group dynamics, learning processes, and help designers in scaffolding and providing feedback for learners.

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