Leveraging Survey and Motion Sensors Data to Promote Gender Inclusion in Makerspaces

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ABSTRACT
Over the last decade makerspaces have become more popular and prevalent in formal and informal learning environments. A finding, however, is that makerspaces are often male-dominated, and females can feel a sense of intimidation in the space. Furthermore, maker-centered learning typically adopts an open-ended structure which makes it difficult to identify students who are struggling. In this paper, we explore the use of quantitative data from survey and motion sensors to potentially assist instructors in uncovering gender differences and promoting gender inclusion. Results suggest that there are different pathways for male and female students to thrive in makerspaces. Based on survey results, male students tend to have higher self-efficacy, resulting in more self-confidence in their abilities and more positive feelings. Findings from applying network analysis on the motion sensor data show that female students persevere more consistently and use empathy to form closer ties with peers for mutual support. These findings suggest that quantitative data could help raise instructors' awareness of gender differences and use that information to cater to the unique learning needs of each group of students. Overall, this work represents preliminary steps in instrumenting makerspaces to promote gender inclusion and support maker-centered learning.

Keywords
Interaction Analysis, Learning Analytics / Educational Data Mining, Social Network Analysis, Broadening Participation, Gender, Making and Makerspaces, Technology-enhanced learning

1. INTRODUCTION
While many authors have espoused the learning benefits of makerspaces [5], other researchers have recognized the inherent difficulties of supporting student learning in makerspaces' open-ended environment [13]. First, students are expected to solve problems independently in open-ended learning environments. Such independent work may lead to feelings of isolation, and instructors may not be aware that students are struggling. Second, the iterative nature of work in the makerspaces makes it difficult for instructors to continuously monitor students' progress. Without a clear feedback system, it is challenging for instructors to differentiate when students need instructional support.

However, new sensing technology (such as motion tracking) offers an opportunity to address some of these challenges. The key benefit of using motion sensors is that they can be deployed to monitor students' learning in a continuous and unobtrusive manner. Therefore, we aim to examine how the use of quantitative data can help instructors overcome inherent challenges of assisting students in makerspaces.

For our scope, we examine how students from different genders interact in makerspaces [2;8;11], and we hope to promote gender inclusion in makerspaces. Eventually, we hope that the use of quantitative data can assist instructors in identifying the right form of support for each diverse group of students.

2. LITERATURE REVIEW
Makerspaces draw learners from a diversity of disciplines and provide multiple entry points to participation leading to "innovative combinations, juxtapositions, and uses of disciplinary knowledge and skill" [12]. However, makerspaces situated in formal learning environments are often male dominated [7]. Hence, it is an increasing priority for makerspaces to include women who are underrepresented in these communities. Central to this goal is understanding how women interact within makerspace courses. While some studies have not found gender to be a salient factor [2], other studies have shown that women often report feeling intimidated and excluded [8;11]. Most studies conducted in this area have also been qualitatively based profiles. Yet, for instructors to better support women in these spaces, more research must be conducted on gender differences in the cognitive, non-cognitive and affective domains and understand how these differences contribute to the outcomes of empowerment and community-building in maker-centered learning [5].

In this regard, the use of quantitative data from motion sensors could help provide alternative insights into gender differences. Researchers in the field of multimodal learning analytics have long explored the use of sensors to gather information on student learning because data can be collected in a sufficiently high frequency to draw rich inferences [3]. Since social interactions are an important part of makerspace projects, we focus this paper on capturing them using motion sensors. The successful utilization of motion sensors in capturing student interactions have been suggested by a couple of researchers [4;9]. One common thread in these previous works is the use of physical proximity as a rudimentary proxy for interaction. While being in close proximity is a necessary condition for interaction to occur, it is arguably not a sufficient condition. Therefore, in addition to the use of physical proximity as an indication for interactions, this study will layer on two other criteria (see Section 5.3). In essence, we hope that the use of quantitative data from motion sensors can paint a broader picture of women's experiences in makerspaces to improve instructor support and inclusivity.

3. CONTEXT OF STUDY

Quantitative data was collected from 14 female and 8 male students enrolled in a 15-week makerspace course (no students identified as non-binary). Kinect sensors were deployed 24/7 to gather skeletal joint data from students and survey tools were used weekly to assess students' learning experiences.

3.1 Course overview

The graduate-level makerspace course took place at a school of education in the northeastern part of the United States. With a focus on digital fabrication, the course aims to equip students with the necessary skills and knowledge to handle modern tools such as laser cutters. Each week, students are expected to work on a course assignment that typically involves the creation of a digital fabrication product for educational purposes. Depending on the requirements of the assignment, students could either work individually or collaborate. In addition to these weekly assignments, students also pair up to complete mid-term and final projects. While instructional support is available in the form of office hours and individual consultations, students largely work independently with minimal intervention from instructors.

Because of the open-ended nature of makerspaces, the course is designed with several scaffolds. Every week, the same cycle of design-prototype-create is adopted for each course assignment. In this manner, students continually receive opportunities to refine their skills. The presence of these weekly cycles also provides the research team with a natural unit of analysis and all quantitative data collected is aggregated at the week level.

3.2 Kinect Setup

Six Kinect v2 sensors were deployed in the makerspace to collect skeletal joint data. The sensors were positioned to achieve maximum coverage of the space (see Figure 1). When an individual's presence is detected in the Kinect's field of vision, the Kinect starts to record the x,y,z coordinates of the individual's head joint, left and right shoulder joints, left and right elbow joints, and left and right-hand joints. When there are multiple individuals present in the space, each Kinect sensor has the capability of recording up to 6 individuals at 30 Hz (i.e., 30 observations per second).

4. RESEARCH QUESTIONS

RQ1: What gender differences can be extracted from quantitative data collected from a makerspace?

RQ2: Which quantitative factors can account for students' development of a sense of empowerment and community spirit?

We examined students' sense of empowerment and community spirit in the second research question because these are key attributes of a maker mindset [5].

5. METHODS

In order to investigate how different genders work and interact in the makerspace, we constructed social networks from Kinect observations and derived network measures for each student (described in section 5.2 and 5.3). Additionally, we conducted weekly surveys of students to better understand their learning experiences (section 5.1). These surveys not only served as a triangulation measure for the Kinect observations, but also complemented the data by providing a more holistic description.

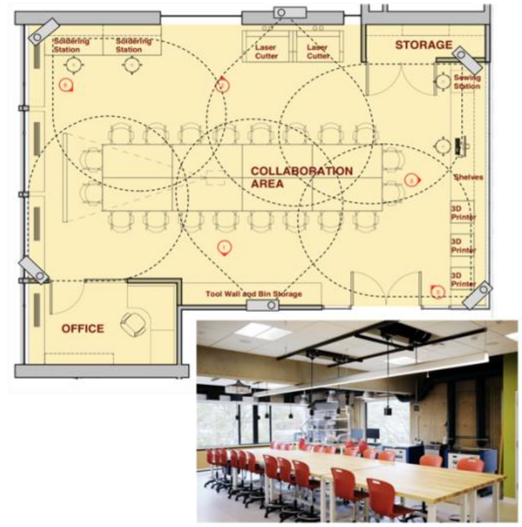

Figure 1. Layout of makerspace with positions and fields of vision of the Kinect sensors (top). Picture of the makerspace (bottom)

5.1 Survey Data

Surveys were administered to students after class each week. These surveys were crafted based on a literature review of surveys and to validate the questions, we conducted a validation study with students from a previous iteration of the course.

Table 1. Details of the surveys administered

Dimensions	Survey item	Scale	Source
Cognitive	- Tool Use - Time Committed	Likert 1-7 Numerical	General questions
Non-cognitive	- Perceived Competence - Self-Regulation - Motivation	Likert 1-5	[10; 15]
Affective	- Frustrated - Nervous - Interested - Inspired	Likert 1-5	[14]
Maker's attribute	- Sense of empowerment - Community spirit	Likert 1-5	[5]
Maker's mindset	- Can-do attitude - Empathy - Curiosity - Perseverance - Resourceful - Collaborative	Likert 1-7	[5]

Referencing Table 1, students' learning experiences were captured based on three dimensions: cognitive, non-cognitive, and affective. The two dimensions of maker's attribute and maker's mindset act as proxies for student outcomes. To determine gender differences, we conducted t-tests on these survey scores.

5.2 Kinect Data

Kinect observations were used for this study to infer the social interactions amongst students. Examining student interactions is key because communities represent an indispensable resource for students working in an open-ended environment. The following steps were taken to clean and process the Kinect data.

1) Student identification: Even though the Kinect sensors have no ability in establishing the identities of students, they capture video images from their fields of vision. These images were fed into OpenFace [1] to identify students.

2) Data homography: The coordinate system that the sensors operate in is relative to the actual positions of the sensors in the space. Hence, there is a need to convert the data into a coordinate system that better represents the 3D positions of the skeletal joints. Data homography was used to achieve this. A research team member stood in front of each sensor at nine different locations, forming a grid. Using the marked-out grid locations on the floorplan of the space and the measured positions of the skeletal joints, the coordinate system of sensors was translated into a coordinate system that is based on the floor plan (Figure 1).

3) Deduplication of skeletal joints: Finally, data from all six sensors were combined into a single coordinate system. However, because the sensors had overlapping fields of view, there was a possibility that multiple sets of skeletal joints were recorded for the same individual. In this case, deduplication was carried out to remove the additional skeletal joints for the same person.

5.3 Social Network Analysis

Once the Kinect data was processed, social networks were constructed. The social networks are built based on the episodes of student interaction. A student is said to have interacted with another if both students are one meter apart, have significant amounts of hand movement, and are either both sitting or both standing. The first criterion is based on the theory of proxemics [6], which states that humans maintain a comfortable distance of one meter during interactions. Admittedly, a proximity of one meter is a necessary but not sufficient criterion for establishing social interactions. Therefore, two other criteria were added to increase the probability of capturing true episodes of student interaction. The second criterion is based on the hands-on nature of the makerspace course. For two students who are in close proximity, having significant amounts of hand movement is likely an indication of collaboration. The third criterion is based on the observation that students tend to share the same eye level when working with each other. It is rare to observe two students working together with one individual standing and another sitting. While these three criteria are not perfect indicators of social interactions, observations of students working in the makerspace and crosschecks conducted by looking at screenshots from the sensors validated their use as a proxy for social interactions.

After we identified episodes of student interactions, social networks were generated based on the amount of time each student spent interacting with others. In essence, the nodes of the social network represent the individual students while the edges between nodes are weighted according to the amount of interaction time spent between students. From the weekly social networks, network measures were computed to obtain weekly network scores for each student.

Table 2. Details of network measures used

Network measures	Definition	Scale
Degree Centrality	This represents the fraction of nodes that a node is connected to.	0 to 1
Average edge weight	This is the mean of all the weights of all the edges connected to a node.	0 to inf
EI homophily index	This index is calculated by taking the difference between out-group and in-group connections and dividing by the total number of connections. For instance, in EI gender, a node for a female student would have male connections as out-group connections and female connections as in-group connections.	-1: Complete homophily (only in-group connections) 1: Complete heterophily (only out-group connections) 0: Equal number of in-group and out-group connections.

T-tests of the network measures were then conducted to extract gender differences, which addresses the first research question. For the second research question, the identified gender differences were used to build regression models for students' sense of empowerment and community spirit.

6. RESULTS

RQ1: What gender differences exist in a makerspace (from the quantitative measures)?

Table 3. Results of t-tests for gender differences

Measures	Statistical differences (t-test)
Survey: Perceived Competence	Males students (mean=5.2) reported having a higher level of perceived competence than female students (mean=4.8), t(20)=2.25, p=0.03.
Survey: Interested	Males students (mean=4.0) reported feeling more interested in the course than female students (mean=3.7), t(20)=2.21, p=0.03.
Survey: Inspired	Males students (mean=3.7) reported feeling more inspired in the course than female students (mean=3.4), t(20)=2.22, p=0.03.
Survey: Empowerment	Males students (mean=3.9) reported having a greater sense of empowerment than female students (mean=3.5), t(20)=3.11, p=0.002.
Survey: Empathy	Females students (mean=6.0) reported having more empathy than male students (mean=5.5), t(20)=2.14, p=0.04.
Survey: Perseverance	Females students (mean=5.9) reported having more perseverance than male students (mean=5.3), t(20)=2.71, p=0.008.
Network measure: EI gender	Males students (mean=0.02) have more diverse gender interactions than female students (mean=-0.16), t(20)=4.19, p<0.001.

Several items were different for males and females. First, males reported having higher perceived competence, which suggests that males are more confident individuals when it comes to assessing their abilities. Second, males recounted feeling more interested and inspired in the course. This shows that males possess more positive feelings towards the course. The lack of statistical significance for the negative affective states indicates that males and females might be struggling equally in the course. Third, males described developing a stronger sense of empowerment. This implies that males feel they have benefitted from the course and can move on to accomplish more challenging tasks.

Although males reported doing better in the course than females, the t-test results also indicate that females may possess some alternate mechanisms for thriving in the course. Females score higher on empathy, which suggests females relate better to others in the community. Additionally, females score higher on perseverance, which hints at positive struggles from females. Lastly, for the network measures, females score more negatively in the EI index for gender, which implies that females interact more with other females, possibly for more community and emotional support.

RQ2: Which quantitative factors can account for students' development of a sense of empowerment and community spirit?

Findings from the survey data suggest that male and female students in this study differ in their perceived competence, positive feelings, empathy, perseverance and diversity in gender interactions. A linear regression model was built based on these to predict the students' sense of empowerment and community spirit.

Table 4. Regression models for sense of empowerment and community spirit (*p<0.05, **p<0.01, ***p<0.001)

Outcomes (→) **Predictors (↓)**	**Sense of empowerment****	**Community spirit*****
	$F(4,17) = 6.85$ p-value = 0.0018 $R^2 = 0.6172$ RMSE = 0.7915	$F(1,20) = 16.72$ p-value = 0.0006 $R^2 = 0.4554$ RMSE = 1.0513
const	coef. = -1.034 S.E. = 1.582 p-value = 0.522	coef. = -2.672 S.E. = 1.614 p-value = 0.113
Empathy		coef. = 1.123** S.E. = 0.275 p-value = 0.001
Perceived competence	coef. = 0.770 S.E. = 0.369 p-value = 0.052	
Positive feelings	coef. = 0.232* S.E. = 0.109 p-value = 0.048	
Perseverance	coef. = 0.954** S.E. = 0.242 p-value = 0.001	
EI gender	coef. = -0.441** S.E. = 0.111 p-value = 0.001	

Based on the regression analysis, students' positive feelings, perseverance, and diversity in gender interactions are significant predictors for their sense of empowerment. Even though perceived competence is not statistically significant, its low p-value of 0.052 hints that it might be a contributing factor to students' sense of empowerment (which corroborates with RQ1's findings). Similarly, the presence of positive feelings in the model echoes previous findings of males having more positive feelings and a greater sense of empowerment. However, it is unclear if students developed a greater sense of empowerment due to their positive feelings or if students felt more positive because they experienced empowerment. Lastly, the inclusion of perseverance and diversity in gender interactions as significant predictors demonstrates that initial learning difficulties in makerspaces can be overcome if one perseveres and that reaching out to fellow members for peer support can aid in the process of learning. Since females have expressed higher levels of perseverance and more in-group preferences previously, this finding reveals a potential pathway for female students to develop a sense of empowerment.

The regression analysis of community spirit shows that empathy is the sole significant predictor. Furthermore, the regression model with only empathy included has an R^2 value of 0.4554, which means that empathy as a factor alone can explain close to half of the variability in community spirit. This is not an unexpected finding as empathy remains a much-needed ingredient for the fostering of good relationships. This result also hints at possible contributions from females in building makerspace communities since they possess higher levels of empathy.

7. DISCUSSION

The findings of this paper indicate that males in this study are more confident in their technical ability and have more positive feelings associated with the makerspace. These findings run parallel to qualitative results in the literature which show that males tend to display more initial interest in makerspaces and technically oriented making activities [8]. While males self-reported more confidence in their abilities, females in this study were more persistent. Additionally, females reported higher measures of empathy and tended to interact more with other females when in the makerspace. These results are in line with qualitative findings from [11] indicating that females tend to appreciate having other females in the space.

In terms of promoting gender inclusion, the methods used in this study can help reveal to instructors the salient differences between genders operating in their own makerspaces. When awareness of gender differences is promoted, instructors can be naturally prompted to take more active steps to cater to distinct learning needs. Additionally, these findings serve as a reminder for instructors to avoid taking on a deficit view of any gender. On the surface, it might appear that males are thriving better than females in makerspaces, but the lack of statistical significance for the negative affective states signals that males and females struggle equally. Instead, our results suggest that males and females thrive in their unique ways in makerspaces, with males using their higher individual self-efficacy, and females using their greater group empathy skills. Neither males nor females should be viewed in a deficit perspective, and the removal of any gender bias would certainly go a long way in promoting gender inclusion.

Limitations of the current study include the relatively small sample size and the fact that the survey results were based on self-reported measures. These factors call into question the generalizability of our findings, and future work should seek to corroborate these results. Additionally, any reader of these findings must be careful to not fall into gender stereotypes. These results are reported on an aggregated basis, which may or may not be applicable to any individual student. Moreover, these findings are a result of our observations conducted in this particular study. Nonetheless, the findings demonstrate the feasibility of an approach that can be used by instructors to uncover gender differences in their own makerspaces.

8. CONCLUSION

The current paper examined gender differences in makerspaces and the factors that contributed to students' development of a sense of empowerment and community spirit. T-test results indicate that there are different pathways for male and female students to thrive in makerspaces and regression analyses highlight the quantitative factors that can account for students' development of a sense of empowerment and community spirit. This work presents preliminary steps in designing an automated system for instructional use to support gender inclusion.

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