Using Motion Sensors to Understand Collaborative Interactions in Digital Fabrication Labs

Edwin Chng[✉], Mohamed Raouf Seyam, William Yao, and Bertrand Schneider

Harvard University, Cambridge, MA 02138, USA
chng_weimingedwin@g.harvard.edu, mohamedseyam@gse.harvard.com,
william_yao@college.harvard.edu,
bertrand_schneider@gse.harvard.edu

Abstract. Open-ended learning environments such as makerspaces present a unique challenge for instructors. While it is expected that students are given free rein to work on their projects, facilitators have to strike a difficult balance between micromanaging them and letting the community support itself. In this paper, we explore how Kinect sensors can continuously monitor students' collaborative interactions so that instructors can gain a more comprehensive view of the social dynamics of the space. We employ heatmaps to examine the diversity of student collaborative interactions and Markov transition probabilities to explore the transitions between instances of collaborative interactions. Findings indicate that letting students work on their own promotes the development of technical skills, while working together encourages students to spend more time in the makerspace. This confirms the intuition that successful projects in makerspaces necessitate both individual and group efforts. Furthermore, such aggregation and display of information can aid instructors in uncovering the state of student learning in makerspaces. Identifying the instances and diversity of collaborative interactions affords instructors an early opportunity to identify struggling students and having these data in a near real-time manner opens new doors in terms of making (un)productive behaviors salient, both for teachers and students. We discuss how this work represents a first step toward using intelligent systems to support student learning in makerspaces.

Keywords: Motion sensors · Social interactions · Makerspaces

1 Introduction

Makerspaces are open-ended learning environments that offer students unique learning opportunities for developing a maker's mindset [1] as well as critical 21st century competencies [2]. The nature of makerspace projects allows students with diverse prior knowledge and experiences to come together in pursuit of personally meaningful projects. Such learning opportunities effectively model the demands of a professional workspace and cultivates students with the proper skills and mindset to meet the challenges of the 21st century. As such, makerspaces have become increasingly popular over the last decade.

Open-ended learning environments, however, make it challenging for instructors to continuously monitor students' progress. While there may be pockets of instructional time when instructors explicitly teach students, students are often left to their own devices when it comes to project work. In fact, the many benefits of makerspaces cannot be divorced from the need to leave students to productively struggle on their own. As a result, instructors have to strike a difficult balance between micromanaging students and simply leaving them without any form of support.

The use of minimally invasive sensors such as Kinect can provide instructors with a dual advantage: to unobtrusively monitor student progress without affecting their natural workflow, and to intervene whenever necessary to help struggling students [3]. In particular, the study of students' collaborative interactions within makerspaces can bring a unique insight into students' learning. As proposed by Lave [4], 'learning is a process of becoming a member of a sustained community of practice' (p. 65). By examining how students socially interact within makerspaces, we hope to identify indicators that will inform instructors of students' needs. Thus, the goal of this paper is to examine the instances and diversity of student collaborative interactions within makerspaces using Kinect sensors.

2 Literature Review

Makerspaces embody learning under the long tradition of constructionism [5]. Within makerspaces, students are encouraged to address open-ended problems and figure things out for themselves with minimal aid from instructors. In such learning environments, instructors play the role of facilitators while students are given free rein to explore the space as they construct knowledge for themselves [2, 6].

However, since students are still novices, they may encounter barriers to learning. If struggling students are not promptly identified by instructors, repeated failures may result in them developing a sense of learned helplessness [7]. On the other hand, instructors may not want to intervene too early so that they can fail productively [8]. This creates an inherent tension between instruction and construction in makerspaces [9]. Instructors need to strike a balance between giving direct instruction to help struggling students and leaving students to productively fail and construct knowledge for themselves. This balance in instruction has been discussed by scholars such as Star [10], who pointed out that despite the many benefits of productive failures [8], there are instances when instructors should step in to prevent students from giving up entirely.

Recognizing the need to balance instruction and free exploration presents instructors with a new challenge. Using traditional methods, it is difficult for instructors to monitor students' progress without disrupting their natural workflow. Constructionist researchers like Berland et al. [11] have proposed the use of technology-enabled learning analytics to derive rich inference about learners whilst preserving minimum instructor interference. For the purpose of providing instructional support, several related works have been conducted. For instance, orchestration graphs were created by Prieto et al. [12] to suit teaching needs using data and Behoora and Tucker [13] have examined how body language can expose the emotional states of students, which is suitable for identifying frustration. Such work goes beyond just the simple extraction and assimilation of data

for presentation as algorithms used value-added by showing teachers information that is pedagogically meaningful.

A reasonable question is what data our sensors should be collecting within makerspaces. A potential answer comes from Lave's call for situating learning in communities of practice [4]. In his seminal paper, Lave [4] states that 'learning is recognized as a social phenomenon … the process of changing knowledgeable skill is subsumed in processes of changing identity in and through membership in a community of practitioners; and mastery is an organizational, relational characteristic of communities of practice' (p. 64). When viewed through this lens, makerspaces can be seen as natural grounds for the formation of a community of practice, and students' collaborative interactions become natural targets for data collection. As such, this paper aims to provide instructional support in makerspaces through the examination of the instances and diversity of student collaborative interactions using motion sensors.

3   Context of the Study

This section outlines the curriculum of the makerspace course the students were enrolled in, the infrastructure of the multi-sensor data collection system and the primary research questions for this study.

3.1   Course Overview

Over the course of 15 weeks, the research team collected motion sensor data and survey responses of 16 graduate students enrolled in a hands-on digital fabrication course. The goal of the course was to teach students the usage of modern fabrication technologies such as 3D printers and laser cutters, and their application in educational contexts. Throughout the semester, students were responsible for prototyping educational toolkits using digital fabrication tools, all of which were provided in the makerspace. Students were given access to use the space any time they wanted and collaborate across teams at their discretion, without presence of an instructor required.

The 15-week makerspace course can be divided into four discrete units of 3–4 weeks: 1) Introductory unit where students complete individual tasks, learn about makerspace tools and build up basic technical knowhow. 2) Making focused unit covering microprocessor programming using block-based code, fabrication and robotics 3) Programming focused unit involving the use of more advanced computer applications and techniques such as fiducial marker tracking, MMLA sensing and object-oriented programing basics 4) Final project unit during which students work on their group capstone projects for the class relying on the techniques and principles they learned during the first 3 units. For units 2, 3 and 4, students work in groups of 2–3 and their group members were assigned to them.

3.2   Makerspace Setup

The makerspace was equipped with two Kinect v2 sensors to capture human motion within the space. The sensors were placed on opposing ends of the makerspace lab, collecting data streams independently as shown in Fig. 1.
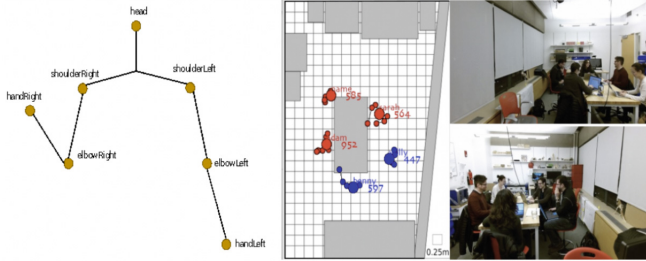
Fig. 1. Skeletal joint data collected by the Kinect (left). Sample frame from the video generation script showing a few students working together after course hours (right).

3.3   Research Questions (RQs)

– **RQ1**: Do the *instances* of collaborative interactions (as detected by Kinect sensors) provide meaningful and accurate information about students' performance in the makerspace?
– **RQ2**: Do the *diversity* of collaborative interactions (as detected by Kinect sensors) provide meaningful and accurate information about students' performance in the makerspace?
– **RQ3**: What can the *transitions between instances of interactions* inform instructors about student learning experiences in the makerspace?

4   Methods

This section describes the data and analysis methods used in this study. Kinect data were collected 24/7 for the duration of the semester, and we obtained information about the collaborative interactions of students using the data collected. Instructors also rated the students based on their perceived levels of collaborative interactions and technical competence. Information was also gathered through surveys given to the students on a weekly basis, asking about the amount of time spent in the space and on solving the weekly assignment, and 5-point Likert items on personal evaluation of levels of challenge, frustration, and engagement.

4.1   Kinect Data

Two Kinect sensors were used to collect motion and posture data in the makerspace. Motion detection and tracking was possible by the embedded IR sensor within each Kinect sensor. Before data were processed, the multi-sensor system collected approximately 1.04 million observations. From those observations, 800,513 were labeled with identity numbers, and after removing non-participants (the teaching team) and performing further preprocessing (as described below), 352,943 observations were used to perform our analysis.

  Kinect Data - Cleaning and Labeling: To detect episodes of collaboration, students and instructors needed to be identified. OpenFace, an open-source facial recognition

algorithm was used to label the individuals in each data collection instance. When applied to each week's facial image dataset, the algorithm achieved an accuracy of approximately 88%, which was determined by manually validating 100 face images per week.

Kinect Data - Standardizing and Deduplicating: This study involved the simultaneous use of two Kinect sensors, so the first step in preprocessing was to translate the data into one reference coordinate system. Data cleaning was facilitated via the use of a custom video generation script, which allowed manual checking for further detection of erroneous data. In many cases, the two Kinect sensors would pick up the same person within the makerspace, due to an overlap in the field of view of the sensors. Duplicates were identified by calculating the Euclidean and cosine distances between the head joints of two skeletons and comparing the value to a lower threshold. Upon the identification of a duplicate, a decision tree was used to determine whether to average the data collected between the two sensors or choose one and discard the other.

Kinect Data - Instances of collaborative interactions: A student is said to have collaboratively interacted with another student or instructor if he/she is within one meter to another student or instructor. Even though the choice of using physical proximity is admittedly a necessary but not sufficient condition for collaborative interaction, prior work has demonstrated the reliability and efficacy of using proximity as a proxy for collaborative interactions [14–17]. Furthermore, based on the theory of proxemics, individuals normally interact at an optimal distance of one meter [18]. If the distance is too far, individuals will tend to move closer to facilitate a quality interaction, and if the distance is too near, individuals will tend to move apart to avoid unease in encroaching into each other's personal space. We classify the different instances of collaborative interactions as students working individually, working in a group of students and interacting with an instructor.

4.2 Instructor Rating Data

To gain a complementary perspective of the students' collaborative interactions and learning progress, we invited two senior instructors of the teaching team to assess students on two dimensions at the end of the course: social and technical. For the social dimension, instructors rated each student based on their observed ability to collaborate with others. For the technical dimension, instructors rated each student based on their perceived mastery of makerspace tools and skills. The rating for each student was completed separately by each instructor before they came together to review the given ratings. A rating of 1 on any dimension indicates weak, 2 indicates average, and 3 indicates strong. If any of the ratings differed, the instructors had to negotiate to settle on an agreed score. In this manner, the ratings assigned to the students were the result of deliberations from senior members of the teaching team.

5 Results

RQ 1: Do the *instances* of collaborative interactions (as detected by Kinect sensors) provide meaningful and accurate information about students' performance in the makerspace?

We correlated the time spent by students in each interaction category ("individual": working alone; "instructor": working with an instructor; and "student": working with peers) with the scores assigned by the instructors on each of the performance dimensions. As shown in Table 1, we found that receiving a higher technical score was significantly correlated with spending more time working individually ($r = 0.54$, $p < 0.05$) and spending more time working with other students ($r = 0.64$, $p < 0.01$) – but only in the 4th unit. On the other hand, no significant results were uncovered in the first three units. One interpretation is that the nature of the final projects (which is only executed in the 4th unit) necessitates both individual and group efforts to produce an outcome that meets instructor expectations on the technical dimension.

Similarly, both spending more time interacting with instructors and spending more time interacting with other students were found to significantly positively correlate to social score ($r = 0.60$, $p < 0.05$ and $r = 0.56$, $p < 0.05$ respectively) in the 4th unit. This might suggest that actively seeking help and interacting with others - whether students or instructors - is related to getting assigned a higher score on the social dimension. This finding could also reflect the collaborative and open-ended nature of the final deliverable. As such, it appears that a certain balance of the three interaction types - provided sufficient overall time has been spent by the student - is required to maximize student performance during this course.

Table 1. Correlations between collaborative interaction and performance (* $p < 0.05$; ** $p < 0.01$)

Unit	Interaction type	Performance	Pearson's correlation
4	Individual	Technical	$r = 0.54$*
4	Instructor	Social	$r = 0.60$*
4	Student	Technical	$r = 0.64$**
4	Student	Social	$r = 0.56$*

To further investigate and visualize the instances of collaborative interactions, bar plots (Fig. 2) and line plots (Fig. 3) were created to show the differences in interaction profile. For each dimension of instructor rating, two separate bar plots were generated. Within each bar plot, the students were grouped according to the scores that they received from the instructors. The x-axis reflects instructor-rated scores while the y-axis indicates fluctuations (from class average at $y = 0$) in time spent for each instance of collaborative interaction. Fluctuations were studied because we treated the class average as the baseline amount of time spent and we are interested in the deviations from this baseline.

Examining the social dimension bar plot (Fig. 2), we see that social scores received by the students is proportional to the amount of interaction time with instructors and other students. For instance, students with lower social scores (below 2.0) spent notably less time with instructors and other students. This demonstrates that the Kinect sensor data can indeed reflect students' collaborative interactions within makerspaces. Based on

the technical dimension bar plot, students who received an instructor-assigned score of 1.0 spend less time (about 30 min lesser per week) working individually than their peers; and spent nearly the same average time (fluctuation $= 0$) interacting with an instructor or with other students across the semester. In contrast, students with high technical skills spent a lot of time working individually. Thus, it seems important that students spend sufficient time working alone to hone their technical skills.
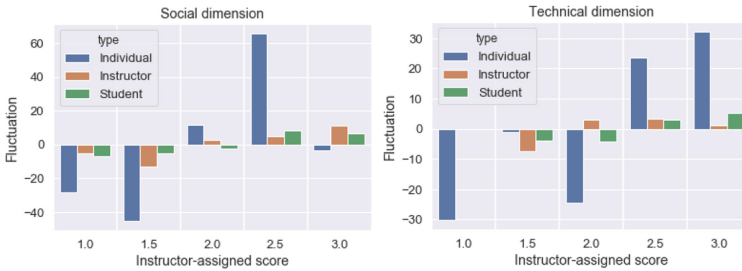

Fig. 2. Bar plots indicating fluctuations (from class average) in time spent (minutes) for students grouped according to instructor ratings. Box colors indicate interaction type. (Color figure online)

Line graphs in Fig. 3 show the weekly time spent for different interaction instances averaged for the whole class and for a student with a low technical score (whose anonymized name is *Pat*). Comparing the general shape of the two-line graphs, it is clear that the interaction profile for *Pat* is distinct from the entire class. In particular, the amount of time committed by *Pat* decreases as the weeks go by, with a relatively low period from week 7 to week 10. The amount of time spent by *Pat* only increased towards the end of the course, presumably because of the final project that he/she has to undertake. In contrast, the interaction profile for the entire class exhibits an ebb and flow that is in line with the demands of the course. For instance, the class' weekly time spent peaks in week 6 and 10 when the midterm and final term projects are ongoing. Overall, these data can aid instructors by providing a clear visualization to indicate which students have interaction instances that are inconsistent with class averages.
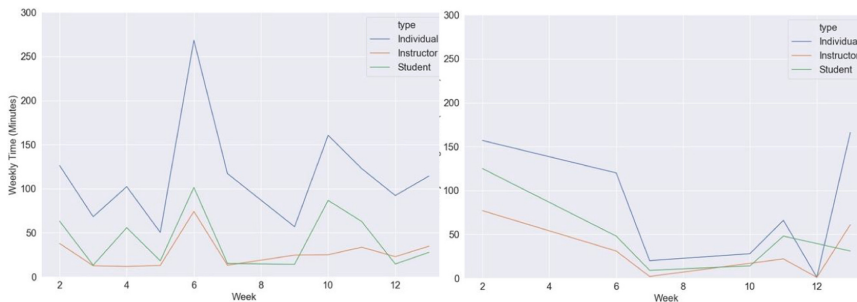

Fig. 3. Class overall (left) compared to *Pat* - student with low technical score (right)

RQ 2: Do the *diversity* of collaborative interactions (as detected by Kinect sensors) provide meaningful and accurate information about students' performance in the makerspace?

To visualize the diversity of student collaborative interactions, we generated heatmaps based on the time that each student spent with each other in the makerspace. A single cell within the heatmap indicates the amount of time (in hours) that student A (on the x-axis) spend with student B (on the y-axis). The longer the amount of time spent, the brighter the color of the cell. Additionally, the students are grouped according to the level of technical ratings that they receive from the instructors on the x-axis and according to the level of social ratings on the y-axis.

Figure 4 shows the generated heatmaps of all students for the duration of the course. The heatmap on the left includes student interactions with their assigned partners while the heatmap on the right leaves out all student interactions with their assigned partners. By comparing the two heatmaps, we see a stark difference between the time spent among partners compared to non-partners: not surprisingly, a lot more time is spent with assigned partners compared to the rest of the student population.

Furthermore, it can be observed from the heatmaps that students with higher social ratings have more diverse collaborative interactions (which is expected), and students with higher technical ratings have less diverse collaborative interactions (which corroborates with the findings in RQ1). The heatmaps allow instructors to directly identify pairs of students who worked closely together. For instance, we see that *Ben* and *Pat* share a close working relationship. *Pat* has been identified previously as someone who might be struggling in the space. On the other hand, *Ben* received a high technical rating. In this case, it is likely that *Pat* has reached out to *Ben* to address his learning challenges.
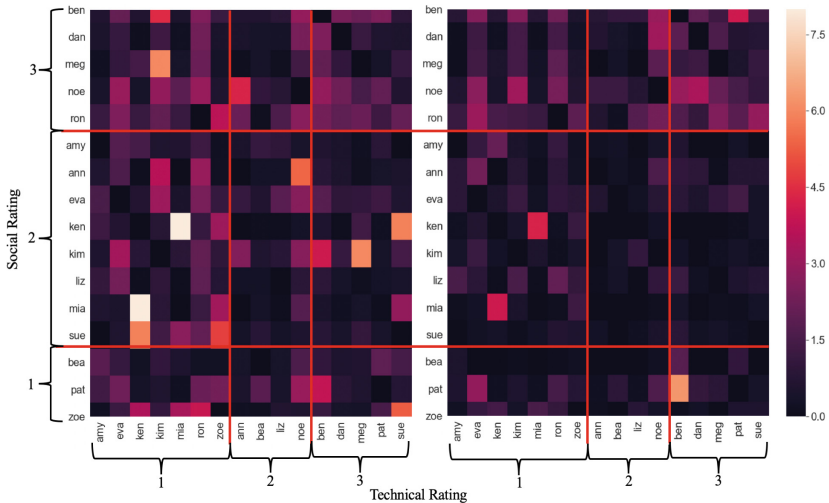

Fig. 4. Heatmaps indicating diversity of interactions. Students are arranged according to the instructor technical ratings on the x-axis and according to the instructor social ratings on the y-axis.

RQ 3: What can the *transitions between instances of interactions* inform instructors about student learning experiences in the makerspace?

Figure 5 displays Markov chains for a well performing student (*Meg*) and for a struggling student (*Pat*). The Markov chains demonstrate the transitions between states over the entire duration of the course. For example, *Meg*'s chain in Fig. 5 indicates that at any given minute of working individually in the makerspace (Individual state), *Meg* has a 81% chance of continuing to work alone, an 13% chance of transitioning to working with others (Student state), and a 6% chance of transition to working with instructors (Instructor state). We notate a state transition probability value by the initial state and the next state. For example, Instructor-Individual corresponds to 0.41 in *Meg*'s diagram. For each state transition, we computed 16 transition probabilities for each student, which were then correlated against the survey and technical skill measures gathered. The significant correlations are reported in Table 2.
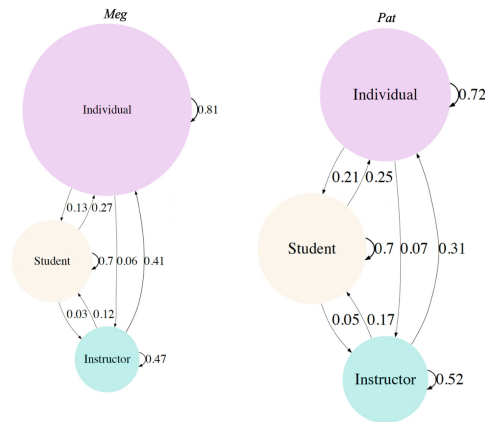

Fig. 5. Examples of Markov chains representing state changes within the makerspace. Individual: working individually state, Student: working with other student(s) state, Instructor: working with instructor(s).

Table 2. Transition probabilities correlations. Technical rating refers to the instructor rating on the technical aspect. Time spent refers to the students' self-reported amount of time spent in the makerspace. Frustration level refers to the students' self-reported level of frustration from the weekly survey.

	State transition	Measure	Correlation	p-value
1.	Individual – Individual	Technical rating	0.59	0.017
2.	Student – Student	Time spent in makerspace	0.50	0.050
3.	Instructor – Individual	Frustration level	−0.52	0.038

1. This correlation indicates a positive relationship between the Individual-Individual transition probability and the technical skills of the student. In other words, students who are more likely to stay in an individual working state, gain greater technical competence. This is an expected finding which corroborates the findings in RQ1, indicating that mastering the tools of the makerspace requires individual practice.
2. This correlation indicates a positive relationship between the Student-Student transition probability and the time spent within the makerspace by the student. In an open-ended learning environment, it is motivating to work in a group, and this correlation aligns with this idea.
3. This correlation indicates a negative relationship between the Instructor-Individual transition probability and the frustration levels of students. It is likely that when an instructor effectively addresses a student's challenges, the student transitions from working with the instructor to working alone once again. This correlation could indicate that the instructors are effective in helping students get unstuck, which is demonstrated by the lower levels of reported frustration.

6 Discussion

The results of our analyses suggest the possibility that letting students work on their own promotes the development of technical skills, while working together encourages students to spend more time in the makerspace. Heatmaps and line charts generated from these data allow instructors to visualize student behavior, and how far each student is from the right balance of collaborative interactions. This is a task that is challenging for an instructor to accomplish based solely on personal observations or interactions with students. Limitations of our study include using a relatively small sample size (16 students over 15 weeks). Additionally, the Kinect sensor data are inherently noisy owing to such aspects as overlapping student bodies, obscured joints, and other errors in skeleton tracking. Lastly, in future analysis we are planning to use a finer grain proxy for collaborative interactions that includes joint visual attention (from head orientation), body gestures and speech data to replace the current coarse proxy for collaborative interaction by physical proximity. Nonetheless, the information and data made available by the Kinect sensor system, paired with analysis techniques and methodologies to understand and interpret the data, opens new doors for both teachers, as classroom facilitators, and students for making (un)productive behaviors salient. For example, teachers will be afforded a greater awareness of how much support each student is receiving and can make informed pedagogical decisions accordingly.

7 Conclusion

While makerspaces hold much promise in providing training grounds for students to emulate the practices of a professional working environment and develop 21st century skills, instructors face the constant tension in deciding when and how to intervene in the pedagogical process. In this respect, we explored the use of Kinect sensors in identifying the instances and diversity of student collaborative interactions to help instructors gain a comprehensive view of student progress and to intervene when necessary. These findings

suggest that multimodal sensors have a role to play in aiding instructors in harnessing the full potential of makerspaces and represent initial steps towards the development of a semi-automated teacher dashboard to provide instructional support for makerspaces.

References

1. Clapp, E.P., Ross, J., Ryan, J.O., Tishman, S.: Maker-Centered Learning: Empowering Young People to Shape their Worlds. Jossey-Bass, San Francisco (2016)
2. Martin, L.: The promise of the maker movement for education. J. Pre-Coll. Eng. Educ. Res. (J-PEER) **5**(1), 4 (2015)
3. Blikstein, P., Worsley, M.: Multimodal learning analytics and education data mining: using computational technologies to measure complex learning tasks. J. Learn. Anal. **3**(2), 220–238 (2016)
4. Lave, J.: Situating learning in communities of practice. In: Resnick, L.B., Levine, J.M., Teasley, S. (eds.) Perspectives on Socially Shared Cognition, pp. 63–82. American Psychological Association, Washington (1991)
5. Sheridan, K., Halverson, E.R., Litts, B., Brahms, L., Jacobs-Priebe, L., Owens, T.: Learning in the making: a comparative case study of three makerspaces. Harvard Educ. Rev. **84**(4), 505–531 (2014)
6. Papert, S.: Mindstorms: Children, Computers, and Powerful Ideas, 2nd edn. Perseus Books, New York (1993)
7. Maier, S.F., Seligman, M.E.P.: Learned helplessness: theory and evidence. J. Exp. Psychol. Gen. **105**(1), 3–46 (1976)
8. Kapur, M.: Productive failure. Cogn. Instr. **26**(3), 379–424 (2008)
9. Tan, M.: When makerspaces meet school: negotiating tensions between instruction and construction. J. Sci. Educ. Technol. **28**(2), 75–89 (2018). https://doi.org/10.1007/s10956-018-9749-x
10. Star, J.: When Not to Persevere: Nuances Related to Perseverance in Mathematical Problem Solving. Spencer Foundation, Chicago (2015)
11. Berland, M., Baker, R.S., Blikstein, P.: Educational data mining and learning analytics: applications to constructionist research. Technol. Knowl. Learn. **19**(1-2), 205–220 (2014). https://doi.org/10.1007/s10758-014-9223-7
12. Prieto, L.P., Sharma, K., Kidzinski, L., Rodríguez-Triana, M.J., Dillenbourg, P.: Multimodal teaching analytics: automated extraction of orchestration graphs from wearable sensor data. J. Comput. Assist. Learn. **34**(2), 193–203 (2018)
13. Behoora, I., Tucker, C.S.: Machine learning classification of design team members' body language patterns for real time emotional state detection. Des. Stud. **39**, 100–127 (2015)
14. Echeverria, V., Martinez-Maldonado, R., Power, T., Hayes, C., Shum, S.B.: Where is the nurse? Towards automatically visualising meaningful team movement in healthcare education. In: Proceedings of International Conference on Artificial Intelligence in Education, pp. 74–78 (2018) https://doi.org/10.1007/978-3-319-93846-2_14
15. Martinez-Maldonado, R., Echeverria, V., Santos, O.C., Santos, A.D.P.D., Yacef, K.: Physical learning analytics: a multimodal perspective. In: Proceedings of the 8th International Conference on Learning Analytics and Knowledge, pp. 375–379 (2018)
16. Saquib, N., Bose, A., George, D., Kamvar, S.: Sensei: sensing educational interaction. Proc. ACM Interact. Mobile Wearable Ubiquit. Technol. **1**(4), 1–27 (2018)
17. Martinez-Maldonado, R., Echeverria, V., Schulte, J., Shibani, A., Mangaroska, K., Shum, S.B.: Moodoo: indoor positioning analytics for characterising classroom teaching. In: International Conference on Artificial Intelligence in Education. Springer, Cham (2020)
18. Hall, E.T.: The Hidden Dimension. Doubleday, Garden City (1966)