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Work in Progress: Evaluating Student Experiences in a Residential Learning Community: A Situated Learning Perspective

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Abstract

A residential learning community (RLC) is an integration of academic and social settings that assists learners to create meaningful learning experiences. An RLC allows students with similar interests to live and learn together. Living in an RLC improves retention by helping students develop a sense of belonging and disciplinary identity. As such, RLCs can be a solution to student attrition and low graduation rates among college students, which is negatively impacting economic growth across the United States. Developing effective RLCs involves providing authentic contexts to learners allowing them to socialize with mentors and peers while engaging in knowledge construction. In this work-in-progress (WIP) paper we evaluated student experiences in an RLC specific to data science: Data Mine Learning Community (DMLC). The DMLC is an interdisciplinary learning community that welcomes students from diverse backgrounds to live and learn data science skills. We used the situated learning perspective as our theoretical framework. The primary research question for the study was: How do students who are enrolled in the corporate partner cohort of the DMLC describe their social interactions and their learning in the context of the learning community? We used a qualitative research approach to evaluate the experiences of first-year students enrolled in the DMLC. Students enrolled in the corporate partner cohort of the DMLC were asked to voluntarily share their experiences in the form of written reflections as a part of an open-response survey at the end of each semester. To understand student experiences, we conducted a thematic analysis of student reflections after they completed their first semester. We analyzed reflections and we discussed our findings through the lens of the situated learning theory, specifically addressing its three key tenets: authentic context, social interaction, and authentic learning.

Introduction

Numerous future jobs will involve science, technology, engineering, and mathematics (STEM) knowledge. As such, it is important to attract students into STEM fields and to retain them as STEM majors. Residential Learning Communities (RLCs) can help with both aspects since they promote the development of students' sense of belonging and disciplinary identity [1], [2]. In RLCs, students who have similar interests live and learn together. These communities provide authentic educational contexts to students, which allows them to engage in knowledge construction while they socialize with mentors and peers [3]. This integration of academic and social settings allows students to create personally meaningful learning experiences, which in turn helps them develop a stronger sense of belonging and disciplinary identity. Thus, RLCs are recognized as an excellent intervention to retain, attract, and help undergraduate students to collaborate with like-minded people [4]–[6].

Since the data science profession is growing rapidly and is in great need of additional professionals for the foreseeable future [7], [8], here we focus on evaluating student experiences in an RLC specific to data science called the Data Mine Learning Community (DMLC). Our primary research question was: How do students enrolled in the corporate partner cohort of the DMLC describe their social interactions and their learning in the context of the learning community? We addressed this research question from the situated learning perspective by analyzing written student reflections.

Background

We relied on three main areas of the literature. First, we considered situated cognition, situated learning, and communities of practice as the theoretical basis for our analysis. Next, we looked at the current state of data science education and the growing need for interventions that develop data science expertise. Lastly, we looked at how RLCs have been used to help enrich the student experience.

Situated cognition, situated learning, and communities of practice

Situated cognition is a precursor to situated learning theory [9], both situated cognition and situated learning propose that knowledge is inseparable and situated within the context in which it is learned [10]. In the same way that language is learned through context and the use of the language, rather than solely from dictionary definitions, situated cognition claims that other learning domains such as data science benefit from being taught within context [10]. Situated cognition provides the structure for setting up a situated learning environment, as both are concerned with the content to be learned through authentic practice, the specific context through which the content is learned, and the social interactions that facilitate the learning process [11]–[13]. Kirk and Macdonald have argued that situated learning is an overarching theoretical framework that comprises of two sub-frameworks communities of practice and legitimate peripheral participation [14]. Furthermore, the study by Lave and Wenger [9] emphasized that learning is an informal process of acquisition of knowledge that occurs in a specific context. Their study on the Vai and Gola tailors in Liberia confirmed that it is impossible to separate context from learning as learning occurs through social interaction in a specified context [9]. Context is crucial to learning as it brings people of similar interests together and allows them to engage in communities of practice.

Engaging in communities of practice within a situated learning context allows students to learn from one another and move from being a novice learner to an expert learner through legitimate peripheral participation [15], [16]. It is important to note that a group of friends, neighbors, or a classroom cannot be considered as communities of practice. To attribute something as communities of practice, it is important to note that learning must be situated within context and participants must interact with one another for learning to happen [17]. Prior works have applied situated learning and communities of practice as their theoretical framework (e.g., Priest et al., [18] investigated experiences of first-year undergraduate students enrolled in a learning community). Since our study also focused on a situated residential learning community that allowed students of various disciplines to interact with mentors and instructors to learn and engage in data science practices, we used the combination of situated cognition, situated learning, and communities of practice to investigate and discuss first-year student experiences. Specifically, we characterized student experiences based on the three tenets of situated learning theory: authentic context, social interaction, and authentic learning. Furthermore, we discussed findings of our study in relation to situated cognition, learning and communities of practice.

Data Science in Education

Computation and data science continues to be one of the fastest growing and economically most needed professions [19], [20]. Data science is becoming a foundational skill that spans different fields, from business to biology [21], [22]. One pressing issue is the fact that data science does not fit well into existing K-12 and higher education settings [22]. The interdisciplinary nature of data science also makes it a complex discipline to attract and retain students, as it requires students to possess knowledge of computer science and mathematics/statistics, along with domain-specific knowledge pertaining to the data [23]. The requirement for multidisciplinary knowledge creates an added cognitive load for novice learners and can affect their retention of information [24]. Prior studies have demonstrated that learning communities are effective interventions to improve student retention and learning, as it brings students of similar interests together and allows them to learn and collaborate [25], [26]. Therefore, we hope that helping the first-year students to develop data science skills, by engaging them in a residential data science learning community, will help to retain students and create a data-driven workforce for the future. Furthermore, our study contributes to the discussion of how data science can be implemented as a foundational skill across disciplines in an effective way that meets the growing needs of the economy.

Residential Learning Communities

Residential learning communities (or living learning communities) allow students of similar interests to live and learn together [23] [28]. Living together in the residence hall on campus has proved to be an effective method of increasing socialization among students [1]. Residing on campus in residence halls and learning together with peers of similar interests is especially beneficial for first-year students [1]. The residential learning communities are known to provide an active, cooperative environment that fosters a sense of community among the students [6], [29]. Living together on-campus helps first-year students to overcome the sense of solitude and disassociation that they experience as a result of their transition from high school to undergraduate life [30] [6]. Prior studies [27], [29], [31] have revealed that a RLC has a positive impact on student success academically and socially as they bring people of common interests together with an intent to facilitate collaboration among students, instructors, and mentors. The residential learning community discussed in this study (i.e., the DMLC) is focused on providing a common context for students, instructors, and mentors who share a passion for data science. Through this study, we evaluated the impact of the DMLC through the lens of situated learning to understand experiences of first-year students.

Methods

Context

The study was conducted in an interdisciplinary residential learning community referred to as the Data Mine Learning Community, located in a large midwestern university. The DMLC was established after the success of the statistical learning community at the same university. The DMLC aims to train and develop a data-driven workforce. Since data is crucial for decision making in all disciplines, the DMLC focuses on training students from all domains (STEM and non-STEM) pertaining to data science. The DMLC began in the academic year of 2018-2019 with 100 undergraduate students, and by the 2019-2020 academic year enrollment increased to 600 undergraduate students. The DMLC does not have any recruitment criteria (i.e., any student who is passionate about data science can join the DMLC). The flexible curriculum and participation opportunities in the DMLC allow novice learners to develop data science skills. Since this is a residential learning community, it is mandatory for all first-year students who join DMLC to live in a residence hall. Living in the residence hall at DMLC provides students the opportunity to collaborate with like-minded peers. The DMLC is aimed at helping students to develop and use data science skills to solve real-world problems. All students are required to attend data science seminars to learn and develop data science skills. One credit hour seminars on data science are offered every week in the dining hall during a meal [32]. Seminars provide an opportunity for students to collaborate with instructors in an active learning environment. Topics that are discussed in seminars are inspired by Nolan and Lang [33] and comprise of topics such as data visualization, data scraping, and parsing while using programming languages like Python, SQL, and R [32]. The DMLC comprises of 20 disciplinary learning communities. For this study, we focused on the Corporate Partner (CP) cohort of the DMLC comprising of 150 students. Students in the CP cohort work in a group of 3 to 6 members on an assigned corporate data science project to develop and apply their data science knowledge. Each group of students was guided by a faculty mentor and a corporate mentor. Corporate mentors are industry professionals and act as liaisons for projects between the corporate organization and the DMLC. These corporate mentors are expected to mentor students, provide them with access to proprietary algorithms/data, and schedule industry visits for students [32]. Examples of project topics include route optimization and assessing the impact of biophysics parameters on crop yield. Overall, the DMLC aims to help students develop an identity of a data scientist by involving them in communities of practice with significant others (instructors and mentors) who are passionate about data science.

Participants

Participants of this study were 150 first-semester students enrolled in the CP cohort of the DMLC for the Fall 2019 semester. At the end of the semester, students were asked to voluntarily share their opinions on authentic context, social interaction, and authentic learning through an open-ended reflection survey. There were 25 students who responded to the reflection survey. In this pilot study, we analyzed perceptions of 13 students. We obtained IRB approval before conducting the study.

Data collection

Students were given reflection questions as part of the open response survey to understand their perceptions of the DMLC. Questions were categorized into the three core constructs associated with the situated learning theory: context in which learning occurred, social interactions that facilitated learning, and authentic learning experienced within the context. Table 1 lists the three tenets along with the corresponding reflective questions.

Table 1. Survey questions corresponding to the three tenets of situated learning

Tenets	***Questions***
Authentic Context	How would you explain what the Data Mine Learning Community is to someone who was unfamiliar with the program?

Social Interaction	Tell me about a time in which you had to manage conflict within your team. Tell me about a time when you had to work with someone completely different from you.
Authentic Learning	What sort of transferable skills or knowledge did you gain as a result of your participation in the data science project?

Thematic analysis

Since the intent of the research question was to understand student experiences within the DMLC with respect to social interaction and learning, we chose an inductive process of thematic analysis to search for rich themes [34] that described student experiences within the DMLC in terms of context, socialization, and learning. The inductive process allowed us to investigate the data deeper and not get restricted by the theory [34], [35]. The inductive analysis theory acted as a supportive framework to evaluate and discuss reported themes [34], [36]. Prior studies [16], [37] used inductive thematic analysis while investigating the impact of engaging in communities of practice in the higher education settings. We followed the six steps of Braun and Clarke [34]: (1) becoming familiar with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing a report. While our codes and themes are inductively emergent from the data, the initial categories of context, social interaction, and authentic learning are deductive because the categories are derived from the situated learning literature [38]. We present our initial results below from Step 3 (i.e., searching for themes).

Preliminary Results and Discussion

Our results are divided into three theme-based sections: context, social interaction, and authentic learning. Definitions and example quote for each theme are given below.

Themes of Authentic Context

Results of the thematic analysis for authentic context led to three main themes: collaborative learning, developed data science skills, and interdisciplinary nature. Definitions and example quotes are given for each theme in Table 2 below. The themes demonstrate the impact of context on the DMLC students. From the perspective of situated learning, the learning community that served as the context played a crucial role in allowing students of similar interests to collaborate and work towards developing and applying data science skills. The opportunity to live in a residence hall and interact with like-minded people from various disciplines helped novice learners to immerse in social learning [9] and that resulted in development of their data science skills.

Table 2. Themes of authentic context with definitions and quotes

Themes	***Definition***	***Student Quote***
Collaborative learning	Students of similar interests live and learn together	"It is a learning community which means that all of the students that we live with are also interested in data science and working on similar projects."
Developed data science skills	Students develop and apply data science skills within the context	"We attend weekly seminars in our own dining court where we learn new skills in a very laid back and friendly environment and we get to attend talks, frequently in the [Learning Community] lobby, that expose us to current and groundbreaking efforts in the world of data science."
Interdisciplinary nature	Students from any discipline can join DMLC	"The Data Mine is a program at Purdue that allows students from all majors to learn data science through coding courses and a year long project."

Themes of Social Interaction

Results of the thematic analysis for social interaction led to two main themes: interpersonal conflicts and personal differences. Definitions and example quotes are given for each theme in Table 3. The themes of social interaction represent characteristics of situated learning as the RLC allows students to interact, experience conflict, develop the ability to resolve them, and bridge personal differences. The themes reported as the result of social interaction within the DMLC can be argued from the perspective of legitimate peripheral participation within the situated learning theory. The foundation for situated learning theory is the social interaction that takes place among the members of the community. This constant interaction also leads to negotiations and renegotiations of meanings, perspectives, and purpose among the members of the community [9], [39]. Therefore, experiencing interpersonal conflict and bridging personal differences are important skills for novice learners need to develop as they progress through the communities of practice and evolve into expert learners.

Table 3. Themes of social interaction with definitions and quotes

Theme	***Definition***	***Student Quote***
Interpersonal conflicts	Students discussing if there was conflict, reasons for conflict, and how conflicts were resolved	"One conflict my team had was towards the end of our project, in which we were compiling all of our data and conclusions into an overall presentation, was how we wanted to present our models overall."

Personal differences	Student acknowledging working with someone different from them and how they worked through their differences	"While working with my corporate partner group on the project, I found myself partnered with someone who was essentially the exact opposite of me. Whereas I consider myself flexibly but lazy with much of my work, he was very deadline oriented. Whereas I would wait a few days to start assignments once they came out, he would start them as soon as they were released and finish them before doing anything else."

Themes of Authentic Learning

Results of the thematic analysis for authentic learning led to three main themes: learning through experience, learning technical skills, and learning non-technical skills. Definitions and example quotes are given for each theme in Table 4. The RLC allows students to engage in authentic learning by allowing them to learn from their experiences and develop technical and non-technical skills required to complete the corporate project. The findings of authentic learning can be supported from the perspective of situated cognition and situated learning. Based on the two theories, it can be argued that learning is inseparable from context which supports learning and that the constant social interaction within the DMLC resulted in their learning of data science skills. Engaging with significant others and working on collaborative projects allowed students to grow from novice learners to more experienced learners.

Table 4. Themes of authentic learning with definitions and quotes

Theme	***Definition***	***Student Quote***
Learning through experience	Students discussed learning from the corporate/company environment and the open-endedness of the project. Additionally, students discussed the specific disciplinary experience gained.	"This is also the first project I have been a part of where the training wheels are removed so to speak [...] I learned how to try new methods and try to uncover things that would help for the project."
Learning technical skills	Students discussed the learning of manipulating and analyzing data, including statistical analysis. Additionally, students discussed learning logic and programming languages.	"Within the data mine program, I have learned so much about R programming, data visualization skills, and how to take large sets of data and analyze and interpret the data into a comprehensible format."

Learning non-technical skills	Students discussed various non-technical skills learned through their project such as communication, goal-setting, time management, and teamwork.	"I got to practice working on a team, which is crucial for computer science and data science majors because projects in those fields are teamwork based."

Conclusions and Future Directions

This pilot study revealed that students reported positive experiences with authentic context, social interaction, and authentic learning. By participating in the DMLC, students developed data science skills, including engaging with peers and learning to resolve personal differences and conflicts. Overall, students grew into experienced learners as a result of participating in the DMLC. The long-term goal of this research is to understand the impact of situated learning and engaging in communities of practice (e.g., the DMLC) on novice learners. We further intend to understand how these novice learners develop their identities as data scientists as they progress through the DMLC. Additionally, evaluating students for a year will help us to understand changing perceptions of students in a situated learning environment. The next steps for this study are to consider a larger sample size to extend and validate our initial coding categories. This will be done to create more connections of student experiences through situated learning and communities of practice frameworks and to develop design principles for learning communities.

Impact of RLC on Students

The three tenets of the situated learning framework served as the theoretical lens to understand experiences of novice learners within the DMLC. This pilot study revealed that students found the experience positive for all three tenets of situated learning. Social interaction among students revealed evidence of intrapersonal conflict. We need to study reasons for conflict as well as strategies students use to overcome them. Additional research is needed to evaluate students over a period of a year, so that we can understand how students' perception of context, social interaction, and authentic learning change over time. Identifying challenges along with benefits are important for the design of improved RLCs in the future. Future research intends to use a rubric to evaluate student perceptions regarding context, social interaction, and authentic learning and to cluster students into high, medium, and low categories to conduct a deeper analysis of student experiences using sentiment analysis and thematic analysis.

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