Experiential Learning & Teaching in Higher Education

Volume 3
Number 3 *NSEE 2020 Conference Proceedings*

Article 13

5-15-2021

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Introduction

Experiential learning, or learning from doing, stems from Dewey's proposition that "there is an intimate and necessary relation between the processes of actual experience and education" (Dewey, 1938, p. 19 – 20). The concept was further developed by Kolb (1984) and studied in educational practice and research (Allison & Wurdinger, 2005; Beard & Wilson, 2006; Breunig, 2008; Ewert & Sibthorp, 2009). Experiential learning has also been used for career exploration (Mendel, 2018), transfer of theory and technical skills to a work environment (James et al., 2020), and the development of 21st-century skills (Council, 2018; Dieu et al., 2018; Fischer, 2018; James et al., 2018; Servant-Miklos, 2018).

"... it is possible that learners' interactions with the technology could be indicative of a learner's mindset, approach to learning, and learning history."

Traditional experiential learning interventions like co-op experiences and internships, where students work full-time in a work environment, lead to meaningful learning outcomes (Ambrose & Poklop, 2015). However, they are less accessible to non-traditional students, like working adult learners, international students and some underrepresented minority students (URM's), particularly rural and first-generation university students (Tiessen et al., 2018). The lack of experiential learning access overall is attributed to experiential learning programs being complex, labor-intensive, and difficult to design and deliver (Henderson, 2018). However, the lack of access is magnified for learners whose life commitments outside of their education are not amenable to undertaking a full-time internship in traditional working hours, covering additional costs of travel, relocating to access an internship in their field of study, or leveraging their personal connections to secure an internship opportunity.

The emergence of learning analytics and machine learning paired with their use in innovative instructional technology holds promise when developing alternative experiential learning models like virtual internships and capstone projects, that are more accessible. Moreover, their use could help address the labor intensity of facilitating experiential learning opportunities overall (James et al., 2018). For example, the effective use of real-time learning analytics could augment management and facilitation tasks in technology enabled learning environments (Hernandez-Lara et al., 2019; Alblawi & Alhamed, 2017). Specifically, displaying a real-time learning analytics dashboard that identifies potential issues students or industry partners are having could decrease the time facilitators need to invest to find out what is going on, and allow them to instead re-invest that time supporting additional students. This augmentation could responsibly address the equity gap in accessibility to experiential learning by reducing the complexity and labor intensity for teachers and faculty, if underpinned by learning theory (Gašević et al., 2017; Reimann, 2016).

Research Objective

This research project aims to examine how the aggregation of learning analytics and learning theory could augment the facilitation of experiential learning to increase accessibility without compromising the quality of the learning experience for individual students. This objective is achieved by addressing these two research questions in the following sequence:

- Which data captured by an experiential learning technology can be used to provide actionable insights for facilitators?

- How can data captured by an experiential learning technology be used by facilitators to support their practice in experiential learning?

Learning Context

This research project uses de-identified and retrospective data from a technology-enabled experiential learning program designed specifically to open access to experiential learning for international students in Australia. Practera, the learning technology used to enable the Experiential Business Project program (EBP), is explicitly designed to support the design and facilitation of learning programs underpinned by Kolb's experiential learning cycle (Kolb, 1984). While completing the EBP, students use the technology to complete a business project with a team, receive feedback on the project from an industry partner, and receive support from the program coordinators who monitor a real-time learning analytics dashboard to identify when support is required.

Throughout the EBP, learners complete two learning theory-based surveys. The surveys are embedded in the program to help develop their metacognitive ability and reflexivity. These surveys identify each student's self-perception on their tendency towards a fixed mindset, a growth mindset (Dweck, 2017), a deep approach to learning, and a surface approach to learning (Marton & Saljo, 1976). Additionally, students complete a demographic survey that enables the identification of their learning history (Kwak, 2016).

Research Design

The research design stems from a realist, anti-positivist idiographic perspective (Cohen et al., 2007) that perceives agency (Bandura, 2001) as the driver of an individual's choice between determinism and voluntarism (Burrell & Morgan, 2005) at each point of actuality (Sachs, 2005). This perspective suggests that humans are irrational and unpredictable, implying that students' interactions with technology enabling the EBP would lack a pattern or logic. However, neurological research finds that although humans are unique and irrational, our learned behavior can be predicted (Wood & Rünger, 2016). Therefore, it is possible that learners' interactions with the technology could be indicative of a learner's mindset, approach to learning, and learning history. Unearthing these patterns could provide experiential learning facilitators with insights that enable them to provide personalized support to learners.

Data Collection

The data collected for use in this study include the course design for the EBP program, de-identified, and retrospective data for over six hundred students participating in the EBP program. The student data includes all the interactions and time spent on learning content, project submissions, skill development reflections, and feedback.

Data Analysis

The data analysis process is completed in three steps:

- The classification of each element of the course design into content categories (Table 1)

Table 1. Categorization of program tasks

Category	Number of Tasks
Operational Tasks	**30**
Orientation	25
Other	5
Project Tasks	**39**
Skill_ Plan	10
Assessment_ Plan	2
Skills_Research	4
Skill_Aggregate Findings	5
Project_Draft	5
Assessment_Draft	2
Skill_Presentation	4
Project_Report	5
Assessment_ProjectReport	2
Skill Development Tasks	**45**
Skill_Collaboration	6
Self-Assessment	7
Skill_Teamwork	20
Self_Peer_Assessment	2
Skill_Reflection	5
Skill_Networking	5

- The scoring of the three surveys used to identify students' mindsets, approaches to learning, and learning history.

- A multiple regression analysis using R package glmulti to identify to what extent a learner's behavior engaging with the EBP could be predictive of their mindset, approaches to learning, and learning history.

Ethical Considerations

The use of a learner's data in educational decision making is discussed and critiqued in literature. Considerations include how data is capture, used, and stored (Slade & Prinsloo, 2013). Each of these considerations is looked at through both the lens of privacy (Rubel & Jones, 2016) and efficacy (Sclater, 2016). Taking these concerns into consideration, the following parameters were used:

- The data was de-identified by the technology provider before being passed to the researcher.

- The technology provider obtained consent from participants.

- Program coordinators were unaware of the consent status of participants.

- A data privacy impact assessment was conducted to ensure every effort was taken to prevent unauthorized access to the dataset.

Results

The multiple regression analysis results indicate that a learner's behavior engaging with the EBP could have some predictive power in identifying a learner's learning history, approach to learning, and mindset. Two crucial factors when evaluating the fit of a multiple regression model is the symmetry of the model, indicated by the residuals (Table 2), and the percentage of the variance in the dependent variable that can be explained by the independent variables, indicated by adjusted r.squared (Table 3). In this analysis, the fit is determined by the percentage of the students' variance in the learning theory surveys that can be explained by the student's behavior engaging with particular sub-categories of tasks in the EBP.

The Symmetry of the Models

The residuals (Table 2) show that the learning history, surface approaches to learning, fixed mindset, and growth mindset models appear to be symmetrical, indicated by a median being close to zero and a consistent symmetry throughout the model. The deep approaches to learning model is asymmetrical. Howev-

Table 2. Regression model residuals

Regression	Min	1Q	Median	3Q	Max
Learning History	-12.2785	-2.8880	0.5876	1.2311	14.2311
Deep Approach	-33.797	-2.039	1.5	1.5	20.101
Surface Approach	-22.6993	-2.6993	0.8362	0.8362	22.3007
Fixed Mindset	-7.9919	-0.9919	0.2937	0.2937	9.0081
Growth Mindset	-15.5038	-0.7297	0.2802	1.3140	6.4962

er, the median and 3Q value are 1.5, indicating that over 25% of the students' actual scores were exactly 1.5 points higher than their predictive score. This model is also unbalanced at the extremities, which could indicate an outlier score that impacts the symmetry of the model.

Predictive Power of the Models

Table 3 presents the adjusted r.squared for the five regression models developed. Adjusted r.squared indicates how well the model fits the data, identifying the percentage of variance in a learner's score of the learning theory survey that can be explained by the time a learner spent on each of the sub-categories of learning tasks in the EBP. The learning history model indicates a predictive power of 49%. The result needs to be considered, understanding that the data set is skewed towards one side of the learning history continuum. A more balanced dataset may impact the result. The surface approaches to learning and deep approaches to learning models have a 40% and 51% predictive power, respectively. The surface approaches to learning model has the lowest predictive power and lowest overall significance value for each sub-category of tasks that have a relationship with a learner score on the survey used to identify approaches to learning. Finally, the fixed mindset and growth mindset models both have a 49.6% predictive power.

Discussion

The regression analysis results indicate that capturing the time spent on different types of learning tasks can be used to provide facilitators insights on a learner engaging with the EBP program. Importantly, the analysis provides insight into additional data that could further develop these regression models and, subsequently, the accuracy of the insights provided to experiential learning facilitators.

The analysis found that time spent on learning content consumption, submission of project tasks, reflective tasks, peer feedback, and administrative tasks can provide insights about a learner as they engage in the EBP program. Interestingly, no one type of task had a direct correlation to a particular learning theory category. The context of the task in relation to the project is relevant when it comes to identifying the learning history, mindset, and approaches to the learning of learners in the EBP. For example, research on mindset by Dweck (2017), indicates a fundamental difference in a human's behavior based on whether they believe their intelligence, skills, and performance can be developed or not. This analysis found that learners who indicated a self-perception of a fixed mindset on the survey spent more time on tasks that others could see. For example, project task submissions or learning tasks helped them present their

Table 3. Adjusted r.squared for the five regression models

Category	Learning History	Deep Approach	Surface Approach	Fixed Mindset	Growth Mindset
Adjusted r.squared	0.495	0.513	0.401	0.496	0.496

work to others, whereas learners who indicated a self-perception of a growth mindset on the survey spent more time on learning tasks that indirectly impacted the project, like the 21st century skill self-assessments and development plans.

Implications for Practice

The results of the analysis indicate that data captured by instructional technology could provide actionable insights for experiential learning facilitators and instructional designers. Before discussing the implications of this analysis on the design and facilitation of experiential learning in higher education, it is essential to note the analysis' limitations. The analysis provides a proof of concept for how the effective integration of technology into experiential learning programs could augment the facilitator and provide insights that would help improve the instructional design. The regression models developed in the research project are specific to the EBP program and require further testing on larger data sets before being used in practice.

However, as a proof of concept, the results of this analysis suggest that it is possible to use data from instructional technology to gain insight about learners. The analysis could be built into an instructional technology analytics dashboard and visualized for learning facilitators alongside insights from the learning theories themselves. Facilitators can use these insights to tailor their support and feedback to specific students. This implementation of real-time learning analytics into technology supported experiential learning programs could increase the volume of students an experienced facilitator can support. Moreover, it could provide the "training wheels" for faculty interested in implementing experiential learning opportunities into their courses but do not have experience facilitating experiential learning. ■

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