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A Three-Pronged Model to Learning Analysis and Instructional Design

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Abstract: *The purpose of this article is to explore a holistic approach to organize and analyze educational data to inform the instructional design processes. Particularly, we propose a three-pronged model to conduct assessment and analysis to reflect the complexity and multi-dimensionality of leaning. We anticipate that the discussion of this study would shed light on future learning analyses and instructional design.*

Keywords: learning analysis, instructional design, learning analytic, assessment, data-driven

1. Introduction: From Assessing to Learning

Over the past thirty years, the U.S. higher education landscape has gone through dynamic changes, with technology revolution and competition from “innovative disruptions” such as MOOCs. Amidst these changes and disruptions, there have been increasing focus on assessment and accountability to demonstrate the quality and integrity of higher education. In response to these external pressures, there have been tremendous growth in assessment activities among U.S. colleges and universities. Abundant assessment resources have been developed both locally, by individual institutions, and nationally by various companies and enterprises, that examine student learning and experiences. Such a trend is encouraging. However, “an unfortunate side effect” has occurred, as Ikenberry and Kuh (2015) pointed out, in that assessment is oftentimes being viewed as “an act of compliance rather than a volitional faculty and institutional responsibility” (p. 5). As a result, assessment is conducted merely to fulfill compliance requirements but not to inform decision making. The lack of assessment-inspired actions and improvements has had faculty and administrators fatigued with and having doubts about assessment.

In more recent years, both institutional and program accreditors have shifted focus from assessing to analyzing and utilizing assessment findings to inform changes for improvement. It might be easy to simply adopt an instrument and use it to obtain data. However, turning data into actions can be quite challenging. In 2011, the National Institute of Learning Outcome Assessment published a paper by Blaich and Wise, in which the authors lamented that many institutions, in spite of the abundant data that they had obtained, had difficulty identifying and implementing changes in response to data. More and more scholars and practitioners have been paying attention to this issue and providing advice to bridge the gap between assessment and actions (e.g. Blaich & Wise, 2011; Kuh & Hutchings, 2015). For example, Blaich and Wise (2011) emphasized that assessment should be consciously designed for improvement.

Another likely cause for the lack of actions is that, amidst the heavy emphasis on learning outcomes (i.e., to what extent have students learned as a result of their education), factors such as students’ learning processes and perceptions of learning might be missing or not connected with learning outcome data. For example, how do students learn? How do they perceive learning? How do instructors perceive learning or lack of learning among students? As Kuh and Hutchings (2015) recommended, there should be a shift in focus from assessing to learning.

Across the U.S., academic institutions are beginning to embrace a big-data approach to learning analysis. In 2010, U.S. Department of Education released National Education Technology Plan (NETP) (U.S. Department of Education 2010), envisioning large amounts of data on students’ learning processes, which can be collected through online learning systems and aggregated and analyzed to provide feedback to students, instructors and administrators. The NMC Horizon Report (Johnson et al, 2015) pointed out that the emerging science of learning analytics could help detect early warning signs and create individualized learning environments to help improve student learning and success.

Higher learning institutions, in particular, seem to be ahead of the curve, in terms of using analytics for learning analysis. Dietz-Uhler and Hurn (2013) conducted an overview of learning analytics tools that different universities developed and highlighted a few of them in their article. Among them, there are University of Michigan, Purdue University, and University of Maryland Baltimore County (UMBC).

At Purdue University, educational researchers collaborated with the IT talent to launch a student success system called Course Signals (CS) to harness the power of learning analytics. CS mines large amount of data, including student grades, their behavior patterns as captured through the learning management system, their demographic characteristics and past academic history. Using the predictive modeling technique, CS predicts students' probability of falling behind his/her academic progress. This information can then be utilized by instructors to implement intervention strategies to help students stay on track and improve. Noting the positive influence that CS had on student retention, the Purdue researchers concluded that "the earlier a student encounters CS the better" (Arnold & Pistilli, 2012).

Faculty and researchers from Australia and Canada (e.g., Macfadyen & Dawson, 2012) also pointed out that for learning analytics to have meaningful impact, numbers themselves were not enough, organizational adoption and cultural change take time and leadership support is a must. It might be doable to initiate one project; but it can be tremendously challenging to change a culture. Patience and persistence will be key to success.

This article will present our effort in utilizing a holistic approach and explore multiple aspects of student learning and use the findings to improve course design and student experiences.

2. A Three-Pronged Learning Analysis Model

Educators these days are constantly faced with a lot of data from various sources: e.g., student grades, demographic information, communications, course survey, and numerous learning analytics data. The question for us is how we can use these data to inform meaningful changes. As Reeves & Herdberg (2005) argued, "decision informed by sound evaluation are better than those based on habit, ignorance, intuition, prejudice, or guesswork" (p. 4). The purpose of collecting information is to support instructional decision making. Depending on what aim to achieve, we can organize data in a more meaningful and effective way. In this study, we propose a learning analysis model which has three dimensions:

a. Analytic-Quantitative dimension: This dimension, consisting of quantitative data, aims to explore what works and testing our hypotheses (for example, in a particular course, whether face-to-face and online students perform differently). We collect data such as course grades, assignment or test scores, which indicate to what extent students are learning, and data on learning analytics, which are captured in our learning management system (LMS), such as access frequency and type of the activities.
b. Interpretive-Qualitative dimension: This dimension, consisting of qualitative data, explores phenomena related to instructions. For example, how do students react to the content, activity, and interactions designed for in a particular course? We collect this kind of data from students' course evaluation surveys, instructor interviews, and students' reflection papers.
c. Connoisseur-Appraisive dimension: Last but not least, the third dimension focuses on the unknown and creative aspects of course designs and implementations, or as Verganti suggested, the design driven innovations (2009). We aim to discover how students handle learning and how their motivation, cognition, and social interactions could and should evolve in the context. Eisner argued the critical importance to "avoid reductionistic thinking that impoverishes our view of what is possible" (Eisner, 1994, p.114). Following the

Eisner model, we emphasize the creative and critical aspects of teaching and learning. This dimension is often obtained through expert reviews. For example, instructional design experts examine both the instructional alignments among objectives, instruction, and assessment and creative or lack of creative components in a course.

Table 1. A three-pronged learning analysis model

	Analysis goals	Analysis methods	Data collection techniques
Analytic-Quantitative	Determining whether the course elements work or not	Experimental Correlational using descriptive and inferential statistics	Student demographic info. Student grade, Learning analytic, etc.
Interpretive- Qualitative	Portraying how the course works or not	Interviews, survey, documents	Course evaluation Reflection paper Instructor interview
Connoisseur-Appraisive	Discovering creative or critical elements	Educational criticism and connoisseurship	Expert review Panel discussion

We believe that the three-dimensional model facilitate a holistic approach (See Table 1). The three dimensions support and are complementary to each other. Findings from the first dimensions guide the investigation of the second dimension. Analyses from the second dimension shed light on inquiries in the third dimension.

3. Case Study

In this article, we briefly illustrate our approach through one undergraduate course at a mid-sized university in the U.S.: ECON 210 Introduction to Microeconomics. As a high enrollment course, ECON 210 was placed on the review list by the university administration with an intention to improve student outcomes and retention. The three-pronged model was used to guide our analysis and evaluation as illustrated below.

In order to handle a large amount of data from a variety of sources, we first focused on the immediate questions that we needed to address. As mentioned in our model discussion earlier, our three major goals are:

- Determine whether the course elements were effective or not. These elements could be the delivery format (e.g. face-to-face vs. online), or a particular assignment.
- Portray how the course worked so that we could identify what led to learning success or what caused barriers and potential interventions.
- Explore creative or critical elements in the course, which would help us understand how students handle learning, how their motivation, cognition, and social interactions could and should evolve in the context.

First, the analytic-quantitative dimension was investigated and data associated with this dimension was compiled. The analytic-quantitative dimension focused on using grade breakdown data to determine attrition rates, the effect of delivery format, and grade distribution pattern. The grading system specified that: D: Marginal academic work; E: Unacceptable academic work; W: Withdrawal; Z: Administrative withdrawal (indicating failure). The DEWZ rate was thus defined as the failure rate of a course. During the academic year of 2014-2015, there were a total of 478 students, among which 110 were in the DEWZ category, resulting in a failing rate of 23%. Multiple chi-square tests were conducted. In terms of the overall DEWZ rates, no statistically significant differences were found between online and face-to-face sections ($p=.42$).

Second, the interpretive-qualitative dimension was investigated through comments from student surveys, instructor interviews, and environmental data from university offices such as the student learning center and the library. We aimed to portray how the course worked for students and what their course experiences were like and identify major challenges. Through comments from both students and instructors, one pattern emerged: students seemed to be overwhelmed by the fast pace and the intensive writing requirements of the course. A typical comment included: "The course was a bit of a surprise for me. I did not expect an economics class to be so writing-intensive". These comments did not necessarily mean that some writing assignments would need to be eliminated and the workload of the course should be reduced. However, it did suggest that students would need to be prepared for the right expectations at the beginning of the course or even before they registered for the course.

Third, the connoisseur-appraisive dimension was examined by using expert reviews. The expert entered the course and reviewed both the course content and interactions in the context. The expert checked various aspects such as the course alignment, course flow, course interaction, learner support, and etc. While the course review indicated that the course itself was overall well-designed, there was a lack of constructive and explanatory feedback to sustain student efforts and to improve their performances in the course. When students missed deadlines, no activities were included in the learning management system to help them catch up. There was also a lack of instructors' social presence in the course to motivate and inspire students. The online sections seemed to be lacking in meaningful "Meet" sessions (which were synchronous sessions that were generally facilitated by instructors and attended by all students).

4. Conclusion

We live in an era of big data, having access to abundant opportunities to learn not only what students are learning, but also how they are learning. This article discussed a holistic analysis framework that unveiled multiple aspects of student learning and how we used the findings for administrative and instructional decisions.

Our three-pronged approach not only integrated traditional assessment with learning analytics, but also added the creative connoisseur-appraisive dimension to capture the artistic nature of education. If the first two dimensions, i.e., analytic-quantitative and interpretive-qualitative, are considered more science-based, the connoisseur-appraisive dimension is more art-based. The latter is more dependent on whether the reviewer can imagine the learning experience holistically and dynamically and whether the reviewer can be creative and think beyond the status quo. More importantly, how can the science dimension and art dimension of learning analysis support and validate each other throughout the analysis and design processes? Further extensive studies will be required to provide insights to this question.

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