Factors Associated with Faculty Use of Student Data for Instructional Improvement

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Abstract
Much is being said in education about the value of adopting data-based or analytics approaches to instructional improvement. One important group of stakeholders in this effort is the faculty. "In many cases, the key constituency group is faculty, whose powerful voice and genuine participation often determine the success or failure of educational innovations, especially those that involve pedagogical and academic change” (Furco & Moely, 2012, pg. 129). This paper reports the results of an exploration of factors that influence faculty to consider or reject using analysis of student data to improve instruction based on social cognitive theory. Self-efficacy, value of the outcome, and feasibility of using a student data-based reflection process were found to be related to the actual use of components of the reflection process by faculty.

Keywords
Scholarship of Teaching and Learning, Faculty classroom research, use of student data for instructional improvement

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Much is being said in education about the value of adopting data-based or analytics approaches to instructional improvement. One important group of stakeholders in this effort is the faculty. “In many cases, the key constituency group is faculty, whose powerful voice and genuine participation often determine the success or failure of educational innovations, especially those that involve pedagogical and academic change” (Furco & Moely, 2012, pg. 129). This paper reports the results of an exploration of factors that influence faculty to consider or reject using analysis of student data to improve instruction based on social cognitive theory. Self-efficacy, value of the outcome, and feasibility of using a student data-based reflection process were found to be related to the actual use of components of the reflection process by faculty.

INTRODUCTION

Much is being said in education about the value of adopting data-based or analytics approaches to instructional improvement. Writing about the rise of analytics as the vanguard of this approach, Campbell, DuBois and Oblinger (2007) said, “Whether the catalyst for adoption is a call for accountability from outside of higher education or the need for scorecards or decision-making models from within, analytics is in higher education’s future” (pg. 41).

One important group of stakeholders in this effort is the faculty. “In many cases, the key constituency group is faculty, whose powerful voice and genuine participation often determine the success or failure of educational innovations, especially those that involve pedagogical and academic change” (Furco & Moely, 2012, pg. 129). This paper reports the results of an exploration of factors that influence faculty to consider or reject analysis of student data to improve instruction.

To what degree are faculty willing to base the success or failure of their teaching on student data? In a survey of faculty trust in the accuracy of learning analytics (Drachsler & Greller, 2012), responses fell halfway between no confidence and total confidence. The authors attributed their findings to faculty having “a slight skepticism toward ‘calculating’ education and learning.” (pg. 7). In this paper, we discuss how interest in student data-centered models for instructional improvement has surfaced under different names and different theories of instructional improvement and the role of faculty in its progress.

Early Efforts to Adopt a Student Data-based Model for Instructional Improvement

In the early ’90s the idea that instructional improvement should be based on verifiable data was adopted by leaders in the faculty development. Individuals like K. Patricia Cross, Thomas Angelo, Wilbert McKeachie, Art Chickering, Zelda Gamson, and many others looked for ways of encouraging faculty to be more systematic in their teaching. The Classroom Assessment Techniques and Classroom Research movement Cross and Angelo championed was a turning point in this direction at the university level.

Classroom Assessment Techniques. Attempts to adopt instructional improvement based on student data were encouraged by the work of Angelo and Cross (1993). These authors inspired faculty to gather data about learning by offering classroom assessment techniques (CATs) that could be used easily in classes. The techniques included activities such as the Minute Paper, the Muddiest Point in the day’s class, and concept mapping to determine how well students understood class that day. The CATs were very popular with faculty and still are widely used to monitor student learning.

Classroom Research/Scholarship of Teaching and Learning. Cross subsequently introduced the idea of engaging in Classroom Research, a more teacher driven version of action research that was common in education (Cross and Steadman, 1996; Angelo, 1998). Classroom Research was an early version of the Scholarship of Teaching and Learning (SOTL) movement (Huber & Hutchings, 2005; Kreber, 2007). The biggest difference between the two strategies was that Classroom Research was focused more on understanding a particular class situation and not on creating a literature base for teaching and learning in higher education. SOTL and various instantiations were focused on applying practical research strategies to find more effective teaching. SOTL aimed also to create a field of research and a body of literature to support instructional improvement.

Classroom Research and SOTL both inspired faculty by these activities. While Classroom Research has continued to be done by individual faculty in their classes, SOTL has founded scholarly journals, and inspired communities of inquiry as faculty find others with similar questions about teaching. The Carnegie Foundation for the Advancement of Teaching has been especially instrumental in nurturing this format of communities across disciplines for investigating student learning in real classrooms.

Learning Analytics. The enthusiasm faculty exhibited for CATs and SOTL has not yet generalized to using the kind of “big” data that many administrators and accreditors prefer (Andrade, 2011; Siemens & Long, 2011). These data, called “academic analytics” (Campbell, DeBlois & Oblinger, 2007) and done on databases of information available through technology, are viewed with some skepticism by faculty (Parry, 2012). This technology-based data usage has made more inroads with faculty when the focus is on “learning analytics”, directed more at student learning in a context (Siemens & Long, 2011). These analyses are more systematic than Classroom Research studies, but not based on large numbers of students like the “academic analytics.” They are closer to action research, although their questions differ. According to Dyckhoff, Lukarov, Muslim, Chatti, and Schroeder (2013), action research derives from teacher questions, whereas learning analytics come more from close analysis of data already collected. Dyckhoff, et al.

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Innovation and health promotion grounded in the educational and worthwhile (Dyckhoff, 2011). Based on the use of student data. Researchers had to understand understanding their position is a critical factor in expanding change in technology-based education, and especially in health behavior literature on how instructors come to try innovations. Much of the literature on motivation for change in many contexts and from investigate in this study. We will refer to this as the Factors model. In Figure 1 we provide a model of what factors we chose to be more useful. This was the focus of the current study.

A Model Emphasizing Factors Affecting Faculty Use of Student Data

In Figure 1 we provide a model of what factors we chose to investigate in this study. We refer to this as the Factors model when discussing data collection and use. The factors have been drawn from the literature on motivation for change in many contexts and from literature on how instructors come to try innovations. Much of the literature on motivation for change in education, and especially in technology-based education, and especially in health behavior studies. Despite this variety of contexts, we believe that the same forces operate in higher education settings.

The first factor included in the Factors model was Teacher beliefs about the value of student data. Teacher beliefs about the effort required to use data for change. Favorable values for all these beliefs could lead to positive attitudes about using data for instructional improvement. These beliefs were drawn from the existing literature on the social cognitive theories, to understand faculty beliefs about when, how and why they already gather and use student data and how it could be more useful. This was the focus of the current study.

Theoretical Perspectives on Factors Influencing Faculty Use of Student Data

Since faculty are the ones closest to attempts to change instruction, understanding their behavior change is a critical factor in expanding change in education. Understanding faculty beliefs about student data while based on the use of student data. Researchers had to understand faculty current beliefs about student data and learning analytics, in order to convince faculty that studying such data would be worthwhile (Dyckhoff, 2011). We hypothesized that major factors influencing faculty use of data were their attitudes and beliefs (see Figure 1). We drew on research on behavior change in education. There are three related areas of innovation and health promotion grounded in the educational and social psychology literature. We selected the following factors as possible keys to adoption of student data use:

- Teacher self-efficacy for student data gathering and use.
- Teacher beliefs about the value of student data.
- Teacher beliefs about the feasibility of making changes in their personal and institutional context.

We refer to this as the Factors model (the Factors model in Figure 1) that illustrates some of the factors that the literature leads us to believe will affect the acceptance of innovations in student data collection and use. We highlight theories on individual choice and provide brief overviews on each theory and its relevance to faculty decisions to innovate. We then summarize and relate our findings to research on faculty use of student data.

**Factor 1: Faculty Self-efficacy for Collecting and Using Student Data**

Self-efficacy. The first factor included in the Factors model was a teacher’s self-efficacy for the collection and use of student data. Self-efficacy in this context is defined as instructors’ belief in their current and future ability to successfully gather and interpret student data for improving instruction. Variations of this belief in one’s capability to be successful at a specific behavior are found in almost every theory of innovation adoption. Bandura (1986) identified self-efficacy as a key component of social cognitive theory. Self-efficacy has been shown to be important in motivation and performance in a variety of contexts (Klassen, Tze, Betts & Gordon, 2011; Jajera, 1996). The Aiken, Green, and Quinn model (2012) suggests that combining measures of self-efficacy and self-esteem is critical to understanding behavior change. Based on this, we hypothesized that self-efficacy models are no longer really distinct from other approaches because the key construct that was originally developed in Bandura’s social cognitive theory has subsequently proved to be an essential component of all major models. (pg. 144)

The role of self-efficacy in teaching has been explored most widely in the K-12 system using the Teachers’ Sense of Efficacy scale developed by Tschannen-Moran, Hoy, and Woolfolk-Hoy (2001). In research on the scale’s model, Tschannen-Moran, Woolfolk-Hoy, and Hoy (1998) found efficacy models predicted teachers’ goal selection, effort expended, and persistence. In another study of the role of self-efficacy in teacher behavior at the K-12 level, Van Acker, Van Baaren, Krosjin, and Vermue (2013) found that teacher attitudes toward technology and self-efficacy for technology use were the top influences on their use of digital learning materials in teaching. The spread of such studies increased with the growing acceptance of technology for teaching (Haiden & Rada, 2011). Reviews of self-efficacy research in K-12 teachers have been increasingly instrumental in encouraging teacher education programs to be mindful about how self-efficacy affects a teacher’s development. There is not yet a similar extensive analysis of self-efficacy in postsecondary faculty, except in the area of technology use. More work in the literature on motivation for change in technology-based education includes exploring the self-efficacy models for faculty use of student data. Examples of research involving postsecondary teachers include a study in Taiwan by Chang Lin, and Song (2011), research by Norton, Richardson, Hartley, Newstead and Myers in the UK (2005), by Prieto Navarro in the Netherlands (2006) and Vera, Salanova and Martin-del-Rio in Spain (2011). So far the paralleled those of K-12 teachers in the US in terms of faculty adoption of new procedures.

**Expectancy for success.** A third theory related to self-efficacy was proposed by Wigfield and Eccles (2000), who included expectancy for success as one of the two main bases for motivation in expectancy-value theory, the other being value of the outcome. More specifically, this theory highlighted the subjective expectations of an individual of achieving success at a task. The effects on behavior were very similar to self-efficacy.

**Need for competence.** A third theory relating to the individual concerns is the Self-Determination Theory (Ryan & Deci, 2002). The Self-Determination Theory as proposed by Deci and Ryan (2000) postulated that universal needs for feelings of competence, autonomy, and relatedness influence optimal functioning. Deci and Ryan stated that the basic needs of people are satisfied when the environment provides the necessary context for the three needs: autonomy, relatedness, and competence as a third variable. The need for competence is defined as the need for meaningfulness of the task at hand. This need is fulfilled when teachers report that they are competent in their tasks. Teachers who feel competent are more likely to engage in tasks that they perceive as meaningful.

**Factor 2: Faculty Beliefs about the Value of Student Data for Improvement**

Beliefs about the value of student data reflects the faculty member’s beliefs about the ability of student data to inform instructional improvement. For example, Foley (2011) explored K-12 teachers’ instructional behavioral in implementing a certain strategy. The choices they made were often tied to the usefulness the individual saw in a strategy.

**Expectations of desirable outcome.** The expectations and values of an action were also part of theories from social psychology. The Theory of Reasoned Action (Ajzen, 1985) and its successor the Theory of Planned Behavior (Madden, Ellen & Azjen, 1992). The Theory of Reasoned Action (Azjen & Fishbein, 1980; Fishbein & Azjen, 1975) proposed that behaviors were the result of intentions, which arose from beliefs about the likelihood that a behavior would result in a desired outcome. These beliefs evolved from attitudes about the behavior and subjective norms (the societal or group standards) about the value of the behavior. These attitudes were based in part on the expected outcomes of performing the behavior, much like the value component of Expectancy Value Theory discussed earlier. Positive outcomes that could be linked to a behavior and positive attitudes and greater tendency to perform the behavior.

**Value of social norms.** Values are also a function of social pressure. Values of social norms have implications for the behavior. In this context, the behavior was socially desirable, the individual was more likely to engage in it. One could also tie this part of the theory to the value component of Expectancy Value Theory. In the current study we investigated whether the behavior was seen as socially desirable, the individual was more likely to engage in it. The theory had two assumptions about direct influences: First, an individual, given sufficient information and resources, would pull the positives and negatives of an action and make a rate about their likely outcomes. Second, the individual had made the choice and intended to engage in the behavior; social pressures (both positive and negative) would affect whether or not the intention would be carried out. At this point the third variable, the actual behavior, is acted out. This third variable is the performance component of the theory. The individual might make a good choice, but then believe that the behavior would be acceptable because they perceived actions. The individual might make a good choice, but then believe that situational factors would work against a positive outcome. Faculty attitudes toward the use of student data were tied to the behaviors at the K-12 level. This research suggested that high personal control was perceived. There is some evidence that these two variables were the addition of the individual’s perceived control as a variable. The theory had two assumptions about direct influences: First, an individual, given sufficient information and resources, would pull the positives and negatives of an action and make a rate about their likely outcomes. Second, the individual had made the choice and intended to engage in the behavior; social pressures (both positive and negative) would affect whether or not the intention would be carried out. At this point the third variable, the actual behavior, is acted out. This third variable is the performance component of the theory. The individual might make a good choice, but then believe that situational factors would work against a positive outcome.
will succeed at this”) and personal control (“I have control over the situation”) have been raised in the literature (Pajares, 1996).

Skepticism regarding the extent to which self-efficacy can be increased by student data use, and if personal control over the class situation was present. Use of student data for instructional decisions about environment and resources (personal control - 2A. How much did the faculty in the sample rate their self-efficacy for collecting and using student data? 2B. What was the correlation between faculty reported self-efficacy for collecting and using student data and their use of a reflective student data-based improvement process? 3A. What did regression of data types used on self-efficacy, value, and feasibility show about the relative strength in affecting the target variable? 3B. What was the correlation between faculty beliefs about the feasibility of collecting and using student data and their reported use of the reflective student data-based improvement process? 4A. To what extent did the faculty in the sample report the collection and use of student data in the past? Were some kinds of data collected more frequently than others? 4B. To what extent did the faculty use the reflective processes involved in the reflective student data-based improvement process? Research Question 5 Relationships between model factors and outcome variables: 5A. What did regression of data types used on self-efficacy, value, and feasibility show about the strength of any effect of any of the studied variables? 5B. What did the regression of the reflection processes on number of types of data used, self-efficacy, value and feasibility show about the relative strength in affecting the target variable?

The Present Study

We have drawn on the above theories to inform our investigation of faculty data use. For the quantitative investigation, we used a survey study of the models in the present study – the factor of feasibility of implementation. We define this as the probability that a given task will be possible to complete, given the situation in which it is carried out. In this study we broke this construct into more discrete units as described below.

Personal control (Agency). Ryan and Deci (2000) proposed that feelings of autonomy were necessary for intrinsic motivation. In addition to believing student data were useful, an instructor must also believe that he or she had control over the situation. Over half of the comments about barriers cited personal control issues. Instructors felt the departmental system was not designed to fit their instructional goals.

Drawing on common elements from the literature, the current study analyzed how faculty perceptions of self-efficacy for collecting and using student data, perceived value of student data for helping to improve instruction, and their agency and the feasibility for being able to use student data were related to their actual data collection and use. Data collected from the faculty in the current study followed the Factors model shown in Figure 1. Here self-efficacy, value, and feasibility (and personal conditions) were proposed as the major factors in faculty decisions to collect and use student data to improve instruction. The following research questions were addressed:

Research Question 1 Factor 1: Faculty Self-efficacy for Collecting and Using Student Data to Improve Instruction

Research Question 2 Factor 2: Faculty Beliefs about the Value of Student Data for Instructional Improvement

Research Question 3 Factor 3: Faculty Beliefs about Feasibility of Collecting and Using Student Data to Improve Instruction

Research Question 4 Development of measurable outcomes of student data use

TABLE 1. Sample Demographics

<table>
<thead>
<tr>
<th>College</th>
<th>Liberal Arts</th>
<th>Natural Science</th>
<th>Professional</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>12</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>15</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>7</td>
<td>13</td>
<td></td>
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</tbody>
</table>

Years Teaching 1-5 6-10 11-20 >20

1.5 6-10 11-20 >20

In the present study, the Theory of Planned Behavior (Madden, Ellen, and Ajzen, 1992) was used to examine whether and how beliefs about collection and use would also show a higher level of use of student data in the past and more of the reflective processes of data use to improve instruction. Qualitative methods based on intensive interviews with the participants were used to add to and verify our predictions using their own words.

METHOD

This study consisted of both quantitative and qualitative data gathered from faculty representing a range of disciplines across a large southwestern university. Data were collected during the spring and fall semesters of 2011-12 and represent faculty perceptions and use of student data prior to the onset of a new teaching initiative at the institution.

Participants

Forty-one faculty participated in this study (Because not everyone participated in both quantitative and qualitative parts of the study, occasional discrepancies in total responses occur) Demographics of the participants are shown in Table 1. Procedures for protection of the participants and confidentiality of their information were guided by IRB human subject requirements of the University. Faculty who participated in this initial data collection were instructors in large undergraduate classes that were targeted for redesign (n=21) plus faculty who were matched to the instructors in terms of rank, gender, and college (n=20) and agreed to respond to the survey component...
making improvements to teaching based on data (e.g. “I am confident that I can use student data to interpret student learning in a way to inform instruction.”). Participants 1 – strongly disagree to 6 – strongly agree. Items are shown in Table 4. Note that the statements parallel those from outcome measure 2 described earlier. The Cronbach alpha for the overall self-efficacy scale was acceptable at .83.

Factor 2: Confidence in the value of student data. This value survey asked the participants to rate their confidence that student data could support various instructional tasks. Participants rated nine statements from 1 – strongly disagree to 6 – strongly agree. For example, an item asked faculty to rate their level of agreement with the statement “I am confident that using student data will make a difference in the effectiveness of my course.” The Cronbach’s alpha for this scale in this sample was acceptable at .88.

Factor 3: Feasibility of using student data (developed for this study). This feasibility survey assessed participants’ confidence that they had the authority, flexibility, resources, and support of others to use student data to modify instruction (see Table 6). The four items were rated on a six-point scale ranging from 1 – strongly disagree to 6 – strongly agree. For example, faculty found their ability to gather and interpret data as "I am confident that I have the authority to use student data to make decisions about instruction in the course." The Cronbach’s alpha for this scale was acceptable at .73.

In the Factors model but not included in this phase: Effort of using student data (developed for study). Effort in this context refers to amount of time and attention that must be put forth in order to engage in a task. At this point most faculty did not have experience with student data use to make a reliable estimate of the time required. Therefore, these data were not included in the analyses.

Procedures for the Quantitative Part of the Study

Data were collected during the fall and spring semesters of 2011-12. Participants received an e-mail invitation to participate, including the survey link and a consent document, and were mailed copies of the overall plan of research. If faculty chose to participate, they would click on the link to the survey to begin responding. This response also documented their consent to participate.

Because this study was part of a new teaching initiative aimed to redesign large lecture-oriented courses at the university, part of the evaluation procedures required a baseline understanding of how faculty used information about their students to inform or influence their teaching practice and course design. Participants first responded to online surveys (described above under “measures”) administered through Qualtrics regarding the components of the factors model that would later be used to construct survey data. Prior engagement in reflective instruction improvement, self-efficacy for gathering and using data, value of data, and feasibility of using data to improve instruction. Following the completion of the survey, faculty were shown how to use the findings to provide more in-depth information to their survey respondents.

QUANTITATIVE RESULTS

Descriptive Statistics of Survey Data

Means and standard deviations for the main variables are provided in Table 2 for summary purposes. Each variable is discussed separately

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency of use of the reflective student data-based improvement process</td>
<td>4.67 (0.61)</td>
<td></td>
</tr>
<tr>
<td>Frequency of use – higher equals higher self-efficacy</td>
<td>4.66 (0.62)</td>
<td></td>
</tr>
<tr>
<td>Frequency of use – higher equals more use</td>
<td>3.84 (0.82)</td>
<td></td>
</tr>
</tbody>
</table>

After an exam, an exam results to modify instruction in each of the first three months (e.g., identifying concepts that seemed to be difficult for students and might need extra work). The correlation between believing in the value of student data and the actual use of the reflective student data-based improvement process was 0.75 (p < .001). Those who were confident in their use of student data were also likely to report engaging in the reflective process for data use. We will see later in this analysis that the correlation with actual use is high, the percent of faculty reporting that they actually used the process was lower, primarily because many faculty did not use data at all. However, in this study 73.75% of faculty agreed that using student data could support various instructional tasks. 4.67 (0.61) with higher means associated with higher self-efficacy.

Factor 2: Instructor beliefs about the value of data.

Instructor beliefs about the value of data was used to examine reported self-efficacy for using data. Figure 2 shows the percent of participants reporting self-efficacy in either gathering data or using it for improvement. Eighty-seven percent of participants responded that they were confident in their ability to gather student data. Ninety-four percent reported that they were confident in their ability to use the data they collected to improve instruction. The average level of overall self-efficacy for data gathering and collection was 6.47 (6.51) with higher means associated with higher self-efficacy.

Factor 1: Instructor self-efficacy for using student data to reflect on and improve instruction.

We used the adapted CTSES to examine reported self-efficacy for using data. Factor 1A was used to evaluate reported self-efficacy for using data. Figure 3 shows the percent of participants reporting self-efficacy in either gathering data or using it for improvement. Eighty-seven percent of participants responded that they were confident in their ability to gather student data. Ninety-four percent reported that they were confident in their ability to use the data they collected to improve instruction. The average level of overall self-efficacy for data gathering and collection was 6.47 (6.51) with higher means associated with higher self-efficacy.

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TABLE 3. Percentage of Faculty Reporting Use of Each Type of Data

<table>
<thead>
<tr>
<th>Type of data used</th>
<th>Percent of respondents reporting use (%N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before the semester to get an idea of what would be in the class (n = 134)</td>
<td>55.4%</td>
</tr>
<tr>
<td>At the beginning of the course to measure student prior knowledge (e.g., doing an early baseline or survey that students see already know).</td>
<td>30.1%</td>
</tr>
<tr>
<td>At the beginning of the course to measure student interest and interest (e.g., doing a survey on the first day of class to see what goals students have in the class).</td>
<td>20.5%</td>
</tr>
</tbody>
</table>

Factors 3.84 (0.82) to modify instruction (e.g., identifying concepts that seemed to be difficult for students and might need extra work). The correlation between believing in the value of student data and the actual use of the reflective student data-based improvement process was 0.75 (p < .001). Those who were confident in their use of student data were also likely to report engaging in the reflective process for data use. We will see later in this analysis that the correlation with actual use is high, the percent of faculty reporting that they actually used the process was lower, primarily because many faculty did not use data at all. However, in this study 73.75% of faculty agreed that using student data could support various instructional tasks. 4.67 (0.61) with higher means associated with higher self-efficacy.

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Factor 2: Instructor beliefs about the value of data.

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mean of the feasibility scale and means for each of the four items are shown in Table 6. In comparison to the other factors, overall feasibility is on a par with self-efficacy at a mean of 4.67, but its lowest rate of response, reporting 39% (326) reporting self-efficacy in Figure 2. The average overall for actual use of the reflective practice was 3.86 (0.82). Means for each of the items on this scale are shown in Table 5, and are lower than the mean of the feasibility scale and means for each of the four items identified in the Factors model shown in Figure 1 would be equaling more support.

Outcome measures of student data use Question 4A – Baseline measure of prior data use. To answer research question 4A, we examined past use of various types of student data. Table 3 provides the percentage of faculty reporting they had employed each of the data listed. Twelve and one half percent of the sample indicated that they did not use student data. The average of the percentages of data types used by the remaining faculty members was 3.46 types with a range of 0 to 6 types and a standard deviation of 1.61. Over 50% of the participants used end-of-class surveys, exam results, student demographics, and in-class assessment purposes, such as exams and course evaluations by students. They also reported having confidence in their own ability to gather and use data, but fewer reported actually using the reflective student data-based improvement process. The self-efficacy assessed to be an acceptable predictor of faculty use of student data. Except in the case of data improving student evaluations, the faculty did not reach significance, although it was significantly correlated with the reflective practice process. This finding is contrary to what is found in both the motivation literature and the innovation literature. The reasons for this difference need to be explored in greater depth.

Predicting the use of student data Question 5A – Predicting prior number of uses of data. We attempted to identify the factors in Figure 1 that appeared to be related significantly to levels of actual use. To address this question, the number of different types of data that a faculty member reported was regressed on self-efficacy, value of the data, feasibility, and flexibility of actual use of the reflective student data-based improvement process. Of these variables, both feasibility (β = -0.66, p =.05) and value of the data (β = 0.26, p < .05) were significant predictors. Note that feasibility is negatively related to the number of types of data used, suggesting that when faculty believe there are many barriers to data use, they will use fewer types. Question 5B – Predicting use of reflective process. Additionally, when treating use of reflective processes as the outcome variable, both number of types of data used (β = 0.22, p = .05) and self-efficacy for use (β = 0.13, p = .02) were found to be significant predictors (p = .001). In other words, a faculty members' confidence that he or she can gather and analyze student data was related to engagement in reflection on data use to improve instruction and the variety of data types used. Returning to our initial questions of whether high scores on the variables identified in the Factors model shown in Figure 1 would be associated with use of reflective processes, we found that self-efficacy and feasibility were predictors of use of the reflection process and merit further examination. In these regressions, value of the data did not reach significance, although it was significantly correlated with the reflective practice process. This finding is contrary to what is found in both the motivation literature and the innovation literature. The reasons for this difference need to be explored in greater depth.

Summary of Quantitative Data The survey data showed that 50% or more of the faculty in this sample did use some student data for improvement, particularly those data that were being gathered on a regular basis for other purposes, such as exams and course evaluations by students. They also reported having confidence in their own ability to gather and use data, but fewer reported actually using the reflective student data-based improvement process activities. The reported self-efficacy appeared to be an acceptable predictor of faculty use of student data. Except in the case of data improving student evaluations, the faculty reported valuing data for use in many phases of instruction. As to the other variables, faculty reported having the authority to modify instruction based on data, the support of administration to do so, and the flexibility to modify their course. The one area where their confidence was not as high is whether or not they had the resources necessary to help them gather and use data.

Qualitative Component of the Study To complement our quantitative data and create a better understanding of the faculty perceive and use student data, we collected qualitative data through interviews. The team interviewed faculty about their instructional use of data. The qualitative responses revealed themes supporting the quantitative findings. The following sections describe participants, coding procedures, approach for analysis, and results.

Participants Interventions were conducted with 29 of the participating faculty who agreed to be interviewed. The interviews were audio-recorded, and sections relevant to our research questions were transcribed and coded. The coding process is described in the following section.

TABLE 4. Efficacy for Use of Student Data for Reflecting on and Changing Instruction

<table>
<thead>
<tr>
<th>Question/Theme</th>
<th>Mean (sd)</th>
<th>Never to Always</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reflect on your teaching practices with the aim of making appropriate improvements.</td>
<td>5.30 (.68)</td>
<td>5 = Always</td>
</tr>
<tr>
<td>2. Design data collection strategies for monitoring what is happening in class.</td>
<td>4.13 (.95)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>3. Use different evaluation methods to assess student learning.</td>
<td>4.58 (1.06)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>4. Interpret student learning data in a way to plan instruction.</td>
<td>4.30 (8.1)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>5. Adapt teaching practices in response to your students’ evaluations or your classroom observations.</td>
<td>4.59 (.13)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>6. Decide on the most appropriate evaluation method for a particular course.</td>
<td>4.75 (.81)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>7. Employ systematic methods that permit you to assess your own teaching.</td>
<td>4.20 (.99)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>8. Adapt to the needs of your students when planning class sessions and assignments.</td>
<td>4.95 (.95)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>9. Be flexible in your teaching strategies even if you must alter your plans.</td>
<td>5.03 (1.07)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>Overall Mean</td>
<td>4.67 (.71)</td>
<td>6 = Very confident</td>
</tr>
</tbody>
</table>

TABLE 5. Actual Use of Student Data for Reflecting on and Changing Instruction

<table>
<thead>
<tr>
<th>In the following items, please choose the responses that best fit your situation.</th>
<th>Mean (sd)</th>
<th>Never to always</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reflect on your teaching practices with the aim of making appropriate improvements.</td>
<td>4.83 (1.05)</td>
<td>5 = Always</td>
</tr>
<tr>
<td>2. Design data collection strategies for monitoring what is happening in class.</td>
<td>3.07 (.01)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>3. Use different evaluation methods to assess student learning.</td>
<td>3.71 (.10)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>4. Interpret student learning data in a way to plan instruction.</td>
<td>3.78 (.11)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>5. Adapt teaching practices in response to your students’ evaluations or your classroom observations.</td>
<td>3.95 (.24)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>6. Decide on the most appropriate evaluation method for a particular course.</td>
<td>3.71 (.23)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>7. Employ systematic methods that permit you to assess your own teaching.</td>
<td>3.78 (.11)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>8. Adapt to the needs of your students when planning class sessions and assignments.</td>
<td>4.22 (.19)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>9. Be flexible in your teaching strategies even if you must alter your plans.</td>
<td>4.32 (.19)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>Overall Mean</td>
<td>3.86 (.62)</td>
<td>6 = Very confident</td>
</tr>
</tbody>
</table>

TABLE 6. Faculty Perceptions of Feasibility to Use Data in their Situation

<table>
<thead>
<tr>
<th>Component of feasibility</th>
<th>Mean (sd)</th>
<th>6 point scale with higher values equaling more support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall composite</td>
<td>4.67 (.72)</td>
<td>5 = Always</td>
</tr>
<tr>
<td>Authority to make a change based on data Use</td>
<td>5.07 (0.82)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>Flexibility to make a change based on data Use</td>
<td>5.02 (0.88)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>Resources to support the change based on data Use</td>
<td>4.12 (.15)</td>
<td>6 = Very confident</td>
</tr>
<tr>
<td>Peer and administrative support to use data to make a change</td>
<td>4.56 (.23)</td>
<td>6 = Very confident</td>
</tr>
</tbody>
</table>

Coping strategy The team used a thematic coding approach (Coffey & Atkinson, 1996). This approach allowed the theoretical Factors model to guide interview questions and provided opportunity to assess model accuracy in describing faculty attitudes. Additionally, the team employed the constant comparative method (Corbin & Strauss, 2008) to compare findings and develop a component chart that improved code validity and reliability. Peer-debriefing allowed the team to discuss problems and consider unpredicted findings. Standard inter-rater reliability methods were used to improve agreement through discussion. Inter-rater agreement across pairs of raters showed an average agreement level of 79.23%, acceptable for these data according to the Center for Educator Compensation Reform (Graham, Milanowski, & Miller, 2012).

Components: Initially four factors were used, representing each factor in the Factors model. They included self-efficacy (“Can I personally do this?”), value (“Is this worth doing?”), feasibility (“Is it doable?”), and confidence (“Would I do this?”). Although effort was present in the model, it was not included in the quantitative analysis as noted earlier. Since it was mentioned by some of the interviewees and therefore could have provided some insight into this factor separately, effort was kept for qualitative analyses. The team added two factors by dividing the student data use component into actual use, stated as recollections of experiences with collecting and using data, and intended use. The team noticed faculty expressed attitudes specifically related to data collection they planned to implement but had not enacted. This was not conceptualized in the Factors model, but these sentiments arose frequently enough that the team decided a distinct component was necessary. During final coding, the team finalized and used these six components: actual student data use, intended student data use, self-efficacy, value of data, feasibility, and effort.

QUALITATIVE RESULTS In the following section, findings from the qualitative data are described. Here, frequency of codes are discussed and excerpts are provided to support our interpretations.
Figure 3. Percent of faculty reporting actual use of practice of gathering or using data to improve instruction.

Figure 4. Percent of faculty reporting confidence in data to inform various aspects of teaching a course. A measure of the value of student data.

Figure 5. Percent of faculty reporting a belief that they had authority, flexibility, resources, support and make changes in their teaching based on student data.

I’m interested in exam data. But then it also helps me because when I get that data back I write into my final exam key copy what percentage of students got each question right. And so if I’m noticing that a lot of learning outcome I-1 was missed, then I can say, ‘Okay, I’m not doing a very good job teaching that.’ Or if I see just a particular question that a lot of people missed I can say it is a very good question.”

In general this finding supports the quantitative data finding where end-of-course evaluations and exam results were the most commonly reported data used. Clicker use was also frequently noted, but has no counterparts in the quantitative results. Some faculty reported using data infrequently and with less confidence. Some faculty seemed unsure of what was meant by “student data” and restricted their use to the most frequently encountered, such as exam scores. They also did not know what various data types were possible, or how to interpret and use data for improvement.

Intended Data Use

The concept of intended data use, not originally conceptualized for improvement, was referred to in a number of faculty comments during interviews. “I would say the pre and post assessment, I've not done a good job with addressing any of that. We need to work and have better pre and post assessments.”

Comparatively, this intention component typically occurred in interviews with faculty already using student data.

Self-Efficacy

Self-efficacy referred to perceptions of competence with data collection and use. Self-efficacy also categorized as high or low, and sometimes both categories were coded for one participant. This trend expands our quantitative self-efficacy findings because it seems these perceptions can be contextual. One high self-efficacy excerpt reads, “That’s one thing we've done well is we want them all to nail it and we know when we want them to be confused and I think we're getting very, very good at [writing clicker questions].” For other faculty, codes generally trended either high or low. An excerpt from a participant with low data self-efficacy reads, “I’m not very good at it, so when I sit in meetings and they have a bunch of spreadsheets I didn’t create, I don’t know what it’s all telling me. So I let other people tell me what it’s telling me.”

Value

The value component was the most frequently coded along with actual data use. Most of the value codes were positive. Faculty usually mentioned perceptions of high personal value for the data, but sometimes would also discuss value students placed on data use. This was particularly true of faculty who noted the potential student data use has for positively impacting learning. The following are both positive value excerpts from two different faculty:

“Clicker questions are very, very good. And the students like it. It's a very engaged class. They're all clicking, and if everybody does well they cheer.”

“But a lot of times because of that information I will change the rest of the semester. Usually the students like that I pause, and I see they have questions and spend a lot of time doing that.”

Feasibility

Feasibility was the least frequently coded. Feasibility referred to institutional resources and support related to data collection and use, addressing perceptions of authority to access or interpret data. When noted, it was generally in a negative context. For example: “The demographics and all that, I don’t know if we have the key access to some of that material.”

In general, faculty reflections on institutional support resources showed negative perceptions or just lack of awareness. The following excerpt shows one exception.

“We have a coding team that works for CNS (College of Natural Sciences). So I say I need problems on absolute values and then they generate some and I put them in my work. So there’s a big bank in this computer system of homework problems they can pick from.”

Effort

Effort was also coded with moderate frequency. Effort referred to perceptions of the amount of effort required to collect, interpret, and use data. Typically these perceptions referred to large classes. High effort perceptions sometimes deterring faculty from collecting student data as shown in this excerpt.

“Sometimes I’ll do the minute thing... And it’s hard to do with 200 in a large class. So I don’t do that so often. I try to do that more with my smaller classes.”

Despite the effort required, some faculty collected data despite high effort perceptions, and using other resources made this easier. One less obvious phenomenon with regard to the value of student data was that the actual number of different types of data used was not very diverse. The alternatives being used were ones that didn’t require much initiative on the part of the instructor. Those data were collected for a different use, usually on a fairly regular schedule by others. While these are useful data, they do not capture the full range of student learning and therefore may not uncover real student problems causing poor performance.

Qualitative results. The value of student data was the most frequently mentioned comment made in the faculty interviews. This supported the quantitative findings of high value placed on student data. All the comments about student data spoke to its positive value. Here, too, there was a more nuanced interpretation than was present in the quantitative data. Comments made by faculty also indicated a recognition that the students benefited from the collection of their data, helping them recognize their progress, successes and failures. Perhaps the multiple recipients of value (like students) need to be considered when measuring overall data value.

Figure 6. Percent of faculty reporting a belief that they had authority, flexibility, resources, support and make changes in their teaching based on student data.

Factor one: Self-efficacy to collect and use data for improvement.

Quantitative results. Faculty in this sample rated their knowledge and ability in instructional improvement at a fairly high level overall as seen in Table 2. Comparing Table 4 (self-efficacy) with Table 5 (use of improvement) we see that self-efficacy did not translate into use of improvement practices, as shown by the lower means on the comparable use items. On the other hand, the high correlation between self-efficacy and the use of ways to reflect on improvement (r = 0.75, p = .001) indicated that those who are confident are also more likely to report use of the data process to improve. We believe self-efficacy is a circle; the more confident one is, the more one is willing to try, and the more one tries successfully, the more self-efficacy is developed.

Qualitative results. In terms of high self-efficacy being an important predictor of success, the interviewees mentioned this factor with moderate frequency in comparison to other factors. An interesting nuanced interpretation of self-efficacy that the interviews raised was that self-efficacy can be high or low and have different impacts on the individual’s behavior. Low self-efficacy might not be on a continuum with high self-efficacy, but rather orthogonal, resulting in a different set of unique beliefs, attitudes, and behavior. Although continuous levels were implied in the scales used, the possibility of orthogonal continua was more obvious by the faculty comments during interviews.

Factor two: Value of student data.

Quantitative results. Value of the data was evident in survey responses. The overall mean on the value items was 4.42 (0.65) in Table 2. While not the highest main factor mean, it is above the middle of the scale, indicating that faculty had a positive impression of student data use for improvement. There was also a positive correlation between an instructor’s valuing of data and use of the student data-based reflection process (r = .63, p = .001). As with self-efficacy, instructors who believed student data could be useful in instructional improvement were also likely to report using the reflective data-based methods.Faculty may be ready for more sophisticated uses of data at this point.

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General Discussion

Interweaving the Quantitative and Qualitative Findings

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Overall Support for the Factor Model

Our purpose for this study was to evaluate the proposed model for faculty use of student data for instructional improvement. We have found that the three factors, self-efficacy, value of data, and feasibility, suggested by the literature and included in this model have a legitimate claim to being able to influence faculty use of student data in educational research. The results suggest that paying attention to these factors could encourage faculty to be more systematic and productive in their use of student data.

LIMITATIONS OF THIS STUDY

In any research study, there were limitations affecting our ability to make definitive statements about connections between the data collected. We list them here and their potential impact plus any solutions that we have considered.

Termination of project before completion.

The biggest impact on our ability to draw causal conclusions was caused by the project being terminated before the intervention and post measures could be taken. We were able to gather most of the pre-intervention data, dealing with pre-existing faculty attitudes and beliefs about student data and past data sources they had employed. The availability of post-intervention data limited what we could say about changes in faculty beliefs and attitudes when given additional support and resources.

Faculty self-report as sole data source.

As in most faculty development studies, the data were based on self-reports by the faculty. In light of the subjective and judgmental nature of qualitative data helped to show that the responses were relatively consistent across measurement modes. It is a concern of research in post-secondary settings that there are not better ways to measure the key constructs. Observational data would have been a good benchmark to test the veracity of faculty self-reports. Since attitudes and beliefs will probably always include qualitative methods, for gathering data from college level faculty, this might need to be focused and standardized to increase the replicability (and therefore the respectability) of the data. We also suggest that research in SOTL converge on a set of more standard quantitative instruments to allow data to be compared more readily.

Small sample size.

We had a small number of participants (#1). This limited the ability to generalize from these data to the large post-secondary population of faculty. The study should be repeated as originally planned.

Creating a More Generally Supported Model for Faculty Use of Student Data.

The overall theoretical model underlying this study was social cognitive theory as applied to choices. This is currently the most widely used model of behavior change (Luszczynska & Schwarzer, 2005). The primary premise of social cognitive theory is that in making choices individuals cognitions act as a mediator between what is happening and the responses that the individual makes. As a result the same situation can be viewed entirely differently based on interpretations each individual makes in the moment. Choices are more a function of the individual chooser than the objective reality of the situation.

A self-efficacy theory has been applied in a wide variety of circumstances where individuals are making choices, in health behaviors, in technology use, and many others. In the present study we were looking at the key factors drawn from social cognitive theory as applied to choices. This is currently the most limited the ability to generalize from these data to the large post-secondary population of faculty. The results would not lead to the conclusion that the innovation, along with openness to change, the need for change, the appropriateness of the change, awareness of the innovation, concern for student outcomes, and motivation.

The Appropriateness of a Model of Factors that Affect Faculty Use of Student Data.

We view the theory of social cognitive theory as applied to choices and cognitive theory as applied to decisions. This is currently the most closely related theory to understanding why faculty would or would not choose to use student data.

The Benefit of a Model of Factors that Affect Faculty Use of Student Data.

We suggest that a general model of factors that influence faculty use of student data has theoretical benefits as just discussed. But more important, it can highlight areas where those working with faculty can design programs that will support positive factors and minimize negative factors. For example, if faculty self-efficacy is a key factor, then programs should incorporate components that increase support or self-efficacy of faculty. One approach is the use of other faculty who were successful at data use acting as mentors to show others what can be done. This value of mentors is exemplified by the faculty learning communities approach to change. For another factor, ease of use, the importance of making complex student data such as learning analytics easy to use and interpret for faculty has been discussed by the leading thinkers in the field (Dyckhoff, Lukarov, Muslim, Chatte, & Schroeder, 2013; Macfadyen & Dawson, 2012; Siemens, 2012). Innovations that produce highly effective, yet simple implementation of change would be of great value to the faculty member who is interested in improving student learning.

FUTURE RESEARCH

There will continue to be various versions of the Factors model that will arise. Some extensions of the work reported in this paper are needed, such as a need to have the study repeated, this time to completion, to allow all the variables to be measured over a much longer time line. Change does not come easily or quickly. It would be helpful for the field to create some widely accepted construct definitions in order to develop instruments that can be generalized across contexts. Other factors are to be expected to be even more complex if they are to be used to self-report that are to be easy and deploy and easy to understand would be particularly useful. This is a caution to the learning analytics community (Dyckhoff, et al., 2013; Macfadyen & Dawson, 2012; Siemens, 2012), in which analyses and presentations of data often rely on very complex models.

Finally, faculty themselves should become more familiar with educational research. We look to programs like SOTL and the support of the Carnegie group to continue to lead the way, as they have so effectively up to this point. Faculty are key stakeholders and implementers of change in education. Without their support the best designed and best constructed models, the best data, and the best innovations will die on the vine. With their support, really innovative growth in education is impossible to stop.

REFERENCES


