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Factors Associated with Faculty Use of Student Data for Instructional Improvement

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Factors Associated with Faculty Use of Student Data for Instructional Improvement

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 learning. 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, DeVlois & Oblinger, 2007) and used 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, Lukarow, 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.
(2013) reported that the types of data typically gathered by learning analytics were not able to answer most questions that teachers and researchers were interested in, leading them to develop methods to shape indicators and collection methods tied to teachers’ questions.

Faculty cooperation in gathering and interpreting information about learning is key to the success of all such efforts. Therefore we wonder why some approaches to data use like CATS and SOIT gained such a great spark interest, while others like Academic Analytics, are met with suspicion or skepticism. Macaldwyn and Dawson (2012) conducted a study of the use of the learning management system at one university and concluded that technical rather than teaching and learning issues were often the focus of administrative decisions about data. The authors concluded that “to have meaningful impact, learning analytics proponents must also delve into the socio-technical sphere to ensure that learning analytics data are presented to those involved in strategic institutional planning in ways that have the power to motivate organizational adoption and cultural change” (pg. 149). A first step to increasing faculty enthusiasm for student data for improvement would be to apply theories of behavior change from other fields, specifically social cognitive theories, to understand faculty beliefs about when, how, and why they already gather and use student data and how it could be even 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 will refer to this as the Factors model throughout the text. The factors have been drawn from the literature on motivation for change in various contexts and from literature on how instructors come to try innovations. Much of the theory drawn from the literature on motivation is based in social psychology: the Theory of Reasoned Action (Ajzen, 1985) and its successor the Theory of Planned Behavior (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975). We believe that the same factors in education and K-12 studies. Despite this variety of contexts, we believe that the same forces operate in higher education settings. We hypothesize that major factors influencing faculty to use student data are:

Teacher beliefs about the value of student data, Teacher beliefs about the feasibility of making changes in their personal and institutional context, Teacher beliefs about the effort required to use data for change.

We hypothesized that major factors influencing faculty to use data were their attitudes and beliefs (see Figure 1). We drew on current theories of behavior change in education, such as the use 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:

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 ability to collect and interpret student data for improving instruction. Variations of this belief in one’s ability 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 (Klaasen, Tzu, Bettis & Gordon, 2011; Pajares, 1996). There is a considerable body of literature on self-efficacy models are no longer really distinct from other approaches because the key construct that was originally developed within Bandura’s social cognitive theory has subsequently proved to be an essential component of all major models.

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 factors affecting self-efficacy, Tschannen-Moran, Woolfolk-Hoy, and Hoy (1998) found efficacy beliefs 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, Kresij, and Vermeulen (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 (Hodin & 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 and practice. There is not yet a similar extensive analysis of self-efficacy in postsecondary faculty, except in the area of technology use. More work is needed in this area in the context of online learning. Examples of research involving postsecondary teachers include a study in Taiwan by Chang Lin, and Song (2011), research by Norton, Richardson, Hartley, Newstead and Myes in the UK (2005), by Pajares and Schunk (2012) in Spain (2011). Self-efficacy is a cognitive evaluation of potential success or failure. Self-efficacy has been shown to be connected to an individual’s perceptions of possessing the skills necessary to use an innovative practice such as data-based instructional improvement. This need was not identical to self-efficacy. Self-efficacy is a cognitive evaluation of potential success at a future task as opposed to a pre-existing need for feelings of competence in the present. We hypothesized that major factors influencing faculty to use student data related to the belief in a faculty member’s ability to succeed as a source of willingness to experiment with new ways to use student data to inform instructional improvement.

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

Faculty beliefs about the value of student data for improvement refers to the faculty member’s beliefs about the ability of student data to inform instructional improvement. For example, Foley (2011) explored K-3 teachers’ instructional behaviors 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 & Ajzen, 1992). The Theory of Reasoned Action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 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 would confirm that the behavior was positive and greater tendency to perform the behavior.

Value of social norms. Values are also a function of social pressure from the social environment. Social pressure, if it is perceived as socially desirable, was very similar to self-efficacy. In expectancy-value theory, the other being value of the outcome. One could also tie this part of the theory to the value component of Expectancy Value Theory. In the current study we investigated if perceived personal control was an important factor in self-efficacy. Perceived personal control is the belief that what is to be done is within the individual’s control. This belief being achieved would lead to more efficient learning, and if other faculty were supportive of that outcome.

Value of Personal Control. Madden, Ellen, and Ajzen (1992) refined the Reasoned Action Theory by adding perception of individual control as a factor that influences choices. This theory was called the Theory of Planned Behavior. The difference between these two versions was 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 together the positives and negatives of a behavior and make a rational decision. 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 perceived personal control, was added. Perceived personal control was perceived to be a rational element of self-determined motivation and willingness to take on new challenges. It was hypothesized that if the SDT closest to self-efficacy was the need for feeling competent. The effect of this competence need would be connected to an individual’s perceptions of possessing the skills necessary to use an innovative practice such as data-based instructional improvement. This need was not identical to self-efficacy. Self-efficacy is a cognitive evaluation of potential success at a future task as opposed to a pre-existing need for feelings of competence in the present. We hypothesized that major factors influencing faculty to use student data related to the belief in a faculty member’s ability to succeed as a source of willingness to experiment with new ways to use student data to inform instructional improvement.
will succeed at this”) and personal control (“I have control over the situation”) have been raised in the literature (Pajares, 1996). In the present study, faculty self-efficacy was measured as a task-specific belief that one can handle the situation. A high level of self-efficacy is contrasted with being in a situation over which one has control over completing a task (personal control), it is a fine line that separates self-efficacy and feasibility.

### Technology acceptance theory

Calls for use of technology in education resulted in several more focused theories about diffusion of technology specifically. One theory, created by Everett Rogers, is the Technology Acceptance Model. This model proposed that for acceptance a technological innovation had to be consistent with teacher values and beliefs about learning, be both useful and easy to use, and it had to inspire teacher confidence in the teacher’s ability to use the innovation. The initial factors of self-efficacy and value used in the current study.

Van Ackerv, van Buuren, Kreijns, and Vermeulen (2013) used the integrative model of behavior prediction from Fishbein (2000) to determine what variables influenced teacher adoption of digital instructional materials. Research based on this model indicated that attitudes and self-efficacy were the best predictors of teacher use of a new digital resource.

In the present study, the Theory of Planned Behavior (Madden, Ellen, and Ajzen, 1992) would predict that an instructor’s intentions to collect and use student data would be influenced both by whether resources needed to accomplish the goal were available and if personal control over the situation was present. Use would also be affected by colleagues’ opinions about whether they would use it in their own teaching.

### Faculty: Beliefs about Feasibility of Collecting and Using Student Data to Improve Instruction

The foregoing influential theories of social psychology also fit well with the next component of the Factors model in the present study – the factor of feasibility of implementation. We define this as ease of use as important to a teacher’s decision to innovate. In fact most of the literature on the spread of technology in education points to these same factors when it comes to integration of technology into the classroom. A number of these theories include: Rogers’ Technology Acceptance Model, Social Cognitive Theory, and Self Determination Theory (Deci & Ryan, 2000). Rogers (1995) listed four main elements of diffusion of innovations. An innovation would diffuse due to: 1) characteristics of the innovation itself; 2) the communication process; 3) time; and 4) the social system into which it was diffusing.

### Adoption and Diffusion of Innovation

The characteristics of the innovation that facilitate its adoption included its relative advantages over the existing system; its compatibility and values that the potential users have; how difficult it was to understand; “trialability” or the opportunity to try it out first; and observability – the degree to which others can see it work. In terms of communication channels, Rogers concluded that it was the personal communication channel between peers that seemed to have the biggest effect on adoption and diffusion. A recent attempt to use the diffusion model to understand problems in innovations in engineering education (Borrego, Fryedt, & Hall, 2010) allowed us to see how contextual factors seemed to overwhelm those trying educational innovations. The authors were tracking the acceptance of seven different instructional innovations across the past five semesters. They found that the department chairs were aware of the innovations, only 47% reported having adopted the innovations to some extent in their departments. Over half of the comments about barriers cited resources (time, number of types of data used, self-efficacy, value and skepticism regarding evidence of improved student learning). (pg. 199) All of these can be seen in the discussions of context factors that influence a behavior choice. When teachers’ motivation and factors that can keep faculty from experimenting with student data and innovations in instruction. In another insightful research on diffusion, Macfadyen and Dawson (2012) found that those making recommendations for changes were “assessing the degree to which any change suggested advanced their colleagues and their need to learn how to use complex new tools, and/or the need to redesign their own teaching and practices without offering any compensation.” (pg. 160) The feasibility-factor can make things much easier, and often a low effort appear in many ways to affect innovation.

### Integrating the Factors to Encourage Faculty Use of Data

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 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 (personal and conditional) 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

1A. How high did the faculty in the sample rate their self-efficacy for collecting and using student data? 1B. 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?

### Research Question 2

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 value of student data and their reported use of the reflective student data-based improvement process?

### Research Question 3

3A. How strongly did the faculty in the sample believe that it was feasible for them to collect and use student data for instructional decisions? 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?

### Research Question 4

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?

### The Present Study

We have drawn on the above theories to inform our investigation of faculty use of student data. For the quantitative portion of our study, we hypothesized that participants who had high scores on measures of self-efficacy, value, and feasibility of collection and use would also show a higher level of use of student data in the past and more use 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

Fifty-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 asked to participate in a larger scale participatory action research project (n=20). They completed the above questions in terms of rank, gender, and college (n=20) and agreed to respond to the survey component.

### 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>Rank</td>
<td>Lecturer</td>
<td>Assistant Prof</td>
<td>Associate Prof</td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>12</td>
<td>8</td>
</tr>
<tr>
<td>Years Teaching</td>
<td>1-5</td>
<td>6-10</td>
<td>11-20</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>5</td>
<td>13</td>
</tr>
</tbody>
</table>

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3
Factor 1: Instructor self-efficacy for using student data to reflect on and improve instruction.

Question 1A – Level of self-efficacy. To answer research question 1A, we adopted the adapted CTSES to examine reported self-efficacy for using student data. Figure 2 shows the percent of participants reporting self-efficacy in either gathering data or using it for improvement. Eighty-seven percent responded that they expected their colleagues to be 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 collection and use was 4.67 (SD 0.61) with higher means associated with higher self-efficacy.

Factor 2: Instructor beliefs about the feasibility of using student data.

Question 1B – Relation to use of the reflective process. Exploration of feasibility of student use of the reflective process for student data collection and use and the actual use of the reflective student data-based improvement process was 0.75 (p < 0.001). Those who were confident in their ability to use student data were also likely to report engaging in the reflective process for data use. We will see later that while the correlation with actual use is high, the percent of faculty reporting that they actually used the process was lower. Seventy-three percent for gathering data but also 73.7% for using the data to improve instruction (Figure 3).

Factor 3: Instructor beliefs about the feasibility of gathering and using student data.

Question 3A - Feasibility of collecting and using data. To address research question 3A, we asked participants to rate the feasibility of student data gathering and use. As was shown in Table 4, neighborhood data gathering could have been a belief that such data are not useful. To address research question 3A, we examined instructor ratings of the value of student data. The overall mean of the scale value was 4.77 (SD 0.52). Of instructors who had labeled this factor “feasibility” and identified four factors: authority to make a change, flexibility to change, resources to support the change, and peer and administrative support for implementation of the change. Each bar represents a potential contribution of data use (e.g., increasing the effectiveness of instruction). Over 80% of participants agreed with the usefulness of data in most areas. The one area with the lowest (75%) was the possibility of student data use in raising student course evaluations. From these results it appeared that faculty believe student data could be useful in many ways.

A relation 2B – relation to use of the reflective process. The correlation between believing in the value of student data and the actual use of the reflective student data-based improvement process was 0.63 (p < 0.001). Those who saw value of student data also reported engaging in the reflective process for data use.

Factor 3: Instructor beliefs about the feasibility of gathering and using student data.

Question 3A - Feasibility of collecting and using data. To address research question 3A, we asked participants to rate the feasibility of student data gathering and use. As was shown in Table 4, neighborhood data gathering could have been a belief that such data are not useful. To address research question 3A, we examined instructor ratings of the value of student data. The overall mean of the scale value was 4.77 (SD 0.52). Of instructors who had labeled this factor “feasibility” and identified four factors: authority to make a change, flexibility to change, resources to support the change, and peer and administrative support for implementation of the change. Each bar represents a potential contribution of data use (e.g., increasing the effectiveness of instruction). Over 80% of participants agreed with the usefulness of data in most areas. The one area with the lowest (75%) was the possibility of student data use in raising student course evaluations. From these results it appeared that faculty believe student data could be useful in many ways.
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 6.67, but its lowest rate was comprised, representing 39% of the respondents. Table 5. Overall Use of Student Data for Reflecting on and Changing Instruction

<table>
<thead>
<tr>
<th>Question</th>
<th>Mean (sd)</th>
<th>1 = not at all confident to 6 = always confident</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reflect on teaching practices with the aim of making appropriate improvements</td>
<td>4.83 (1.05)</td>
<td></td>
</tr>
<tr>
<td>2. Design data collection methods for monitoring what is happening in class</td>
<td>3.07 (1.03)</td>
<td></td>
</tr>
<tr>
<td>3. Use different evaluation methods to assess student learning</td>
<td>3.71 (1.10)</td>
<td></td>
</tr>
<tr>
<td>4. Interpret student learning data in a way to plan instruction</td>
<td>3.78 (1.11)</td>
<td></td>
</tr>
<tr>
<td>5. Adapt teaching practices in response to your students’ evaluations of your teaching</td>
<td>3.95 (1.26)</td>
<td></td>
</tr>
<tr>
<td>6. Decide on the most appropriate evaluation method for a particular course</td>
<td>3.71 (1.21)</td>
<td></td>
</tr>
<tr>
<td>7. Employ systematic methods that permit you to assess your own teaching</td>
<td>3.89 (1.30)</td>
<td></td>
</tr>
<tr>
<td>8. Adapt to the needs of your students when planning class sessions and assignments</td>
<td>4.22 (1.19)</td>
<td></td>
</tr>
<tr>
<td>9. Be flexible in your teaching strategies even if you must alter your plans</td>
<td>4.32 (1.19)</td>
<td></td>
</tr>
<tr>
<td>Overall Mean</td>
<td>3.86 (0.82)</td>
<td></td>
</tr>
</tbody>
</table>

**Summary of Quantitative Data**

The survey data showed that 50% or more of the faculty in this sample did use 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 processes. 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 they would need to make it happen.

**Qualitative Component of the Study**

To complement our quantitative data and create a better understanding of faculty perceive and use student data for reflective practice, 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

Interviews 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.

**Coding process**

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, Milawi, & 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 (“Would I be allowed?”), and effort (“If I personally 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**

The following section, findings from the qualitative data are described. Here, frequency of codes are discussed and excerpts are provided to support our interpretations.
A student data statement, “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 I’m noticing that a lot of learning outcome I-1 was missed, then I can say, ‘OK, 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 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, especially 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 in the model, was created during the coding process due to its frequent occurrence. Intended use referred specifically to plans faculty mentioned about future data use.

“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 know when 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’s 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. Despite the effort required, several faculty 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.”

“Value of the data was evident in survey comments during interviews. 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.”

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 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 need 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 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 three: Feasibility
Quantitative results. Overall results of the survey items assessing feasibility had a relatively high mean of 4.67 (77) in Table 2. This would indicate that faculty believed it was feasible to collect and use student data for improvement. In addition, the overall feasibility score was positively correlated with use of the reflective data-based student data for improvement process (r = .55, p < .001). Of the four subcomponents of feasibility, availability of resources was the lowest, indicating that if there was something amiss with feasibility, it was whether the faculty had the resources to go forward.

Qualitative results. Feasibility was not a factor mentioned by faculty spontaneously, but when it was, the responses tended to highlight the lack of resources and observation supported the qualitative results with regard to perceptions of the lack of resources noted in that item of the survey.
Our purpose for this study was to evaluate the proposed model for the 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, and to mediate 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.

Social cognitive 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 to determine what would influence 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 benefit of a Model of Factors that Affect Faculty Use of Student Data. We argue that social cognitive theory provides a specific 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. For example, if faculty self-efficacy is a key factor, then programs should incorporate components that increase or support self-efficacy of faculty. One approach is the use of other faculty who were successful at data use acting as mentors to show outsiders 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 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 various contexts. Some self-report that are easy to 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 constructs will fail. 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


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