Factors Associated with Faculty Use of Student Data for Instructional Improvement

Marilla D. Svinicki
The University of Texas at Austin, msvinicki@utexas.edu

Kyle Williams
The University of Texas at Austin, kylewilliams@utexas.edu

Kadie Rackley
The University of Texas at Austin, kadie.rackley@gmail.com

Anke J.Z. Sanders
The University of Texas at Austin

Lisa Pine
The University of Texas at Austin

See next page for additional authors

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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

Authors
Marilla D. Svinicki, Kyle Williams, Kadie Rackley, Anke J.Z. Sanders, Lisa Pine, and Julie Stewart
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Marilla D. Svinicki, Kyle Williams, Kadie Rackley, Anke J.Z. Sanders, Lisa Pine, and Julie Stewart
Department of Educational Psychology, University of Texas at Austin, Austin, TX 78712, USA
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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 ‘90’s 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, 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.
possible keys to adoption of student data use: current theories of motivation for behavior change in education. We drew on worthwhile (Dyckhoff, 2011).

understanding their position is a critical factor in expanding change. Since faculty are the ones closest to attempts to change instruction, forces operate in higher education settings. The literature on these topics has been generated in K-12 education, when discussing it in the text. The factors have been drawn from 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 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 throughout the text. 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 literatun on motivation for change in K-12 education has been 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.

In this paper, we show a composite 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.

Theoretical Perspectives on Factors Influencing Faculty Use of Student Data

Since faculty are the ones closest to attempts to change instruction, a better understanding of their behavior change is critical to 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, 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 values were drawn from the following social cognitive theories about motivation in general and for innovation and behavior change: Self-efficacy component of Social Cognitive Theory (Bandura, 1986) Expectancy-value theory of motivation (Wigfield and Eccles, 2000) Self-determination theory of motivation (Deci and Ryan, 2000) Theory of Planned Behavior (Madden, Ellen & Ajzen, 1992) Adoption or Diffusion of Innovations Theories (Rogers, 2003)

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 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 (Klaasen, Tze, Bettas & Gordon, 2011; Pajares, 1996). These theories characterize self-efficacy as the central link between a person’s perceptions of their ability to perform a skill and their performance.

In a chapter about the expansion and acceptance of self-efficacy in Social Cognitive Theory, Luszczynska and Schwarzer (2005) described the self-efficacy of faculty and other professionals in higher education:

...self-efficacy models are no longer really distinct from other approaches because the key construct that was originally distinct 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 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, Kroesjen, and Vermueun (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 (Huiden & 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 behavior.

There is not yet a similar extensive analysis of self-efficacy in postsecondary faculty, except in the area of technology use. More work has been done in K-12 education than in the area of higher education. For example, research involving postsecondary teachers include a study in Taiwan by Chang Lin, and Song (2011), research by Norton, Richardton, Hartley, Newstead and Myres in the UK (2005), by Pearson and de la Hoz in Spain (2006) and research by Gregor and Verma in Spain (2011). So far the results have 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 main bases for motivation in expectancy-value theory, the other being value of the outcome. More specifically, this theory highlighted the subjective expectancy that the individual believes he or she could meet the demands put on him or her at a future task as opposed to a pre-existing need for feeling competent. The effect of this competence need would likely be connected to an individual’s perceptions of possessing the necessary skills to perform the behavior needed to be successful at 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. However, expectations of competence can point 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

A faculty member’s value of student data 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 of the behavior would increase its likelihood and positive attitudes and greater tendency to perform the behavior.

Value of social norms. Values are also a function of social pressure in the form of positive or negative pressures (both positive and negative) toward or away from a behavior. If a 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 imagined that if a faculty member believed that CATs or SOTL programs to be mindful about how self-efficacy affects a teacher’s development and behavior.

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 any action. The second was that the choice would be made after 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 individual’s perceived control, became a factor in the model. Once the individual makes a choice, the perception of control would have an impact on the actions. The individual might make a good choice, but then believe that situational factors would work against a positive outcome. These perceptions of control are critical when individuals are in settings where high personal control was perceived. There is some question about whether perceived personal control is related more to decisions about self-efficacy or feasibility (Luszczynska & Schwarzer, 2005). These two interpretations, self-efficacy (1) Faculty Use of Student Data

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will succeed at this”) and personal control (“I have control over the situation”) have been raised in the literature (Pajares, 1996). Ryan and Deci (2000) define self-efficacy as a personal judgment, a task-specific belief that one can achieve the performance goal, i.e., benefit from using student data in innovative ways. One way to avoid this would be to support faculty autonomy by encouraging them to become involved in decision making relevant to classroom goals. Andrade and Deci (2000) pointed to these same factors when it comes to integration of technology into the classroom.

### Adoption and Diffusion of Innovation

The characteristics of the innovation that facilitate its adoption included its relative advantages over the existing system; its compatibility with the beliefs and values of the potential users; 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 personal communication among peers 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, Froyd, & 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 in engineering education; they found that norms of the context and the perceived control by the individual influence implementation, and Self Determination Theory (Deci & Ryan, 2000), which points to these same factors when it comes to integration of technology into the classroom.

### Research Question 1

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

A recent attempt to use the diffusion model to understand problems in innovations in engineering education (Borrego, Froyd, & 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 in engineering education; they found that norms of the context and the perceived control by the individual influence implementation, and Self Determination Theory (Deci & Ryan, 2000), which points to these same factors when it comes to integration of technology into the classroom.

### Research Question 2

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

A. How high did the faculty in the sample rate their self-efficacy for collecting and using student data? B. What was the correlation between faculty reported self-efficacy for collecting and using student data and their reported use of the reflective student data-based instructional improvement process? C. How much did the faculty in the sample rate their self-efficacy for collecting and using student data? D. What was the correlation between faculty reported value of student data and their reported use of the reflective student data-based instructional improvement process? E. 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?
with a follow-up interview as well.

Institutional Information
The institution at which the study was conducted is classified by the Carnegie Classification 2015 version as a Doctoral University: Highest Research Activity. There are approximately 64,000 students and 3090 faculty at the institution. This data collection was a part of a campus wide initiative to improve the instruction in large undergraduate courses.

Measures
The data gathered by the online surveys consisted of the following quantitative sources.

Data relative to past use of student data. The following two variables were benchmarks representing patterns of data use by faculty before the start of the project.

Outcome measure 1: Prior use of student data. The prior use survey asked faculty to check any of six types of student data they had used in the past, including an option to indicate that the individual did not use student data to modify instruction, and an option to suggest other types. The purpose of these indicators was to create a sense of types of data used by these faculty. The types of student data were selected as the most commonly used (See Table 3). They were compiled from suggestions of two experienced faculty developers, each with at least 30 years of working with faculty, and focused on the institutional improvement goals. Items were worded generally and an example of each was given in order to be recognizable to the widest range of disciplines.

Outcome measure of engaging in the reflective student data-based improvement process (adapted from College Teacher Sense of Self-efficacy (CTSES), Prieto Nevarro, 2005). The survey on use of the reflective process asked how often the respondent engaged in nine reflective activities used for gathering and interpreting student data (e.g. “In your teaching, how often do you design data collection strategies for monitoring what is happening in class?”) and making instructional improvements based on data in the reflective student data-based improvement process (e.g. “In your teaching, how often do you reflect on your teaching practices with the aim of making appropriate improvements?”). The survey used a six-point scale from 1 - never to 6 - always. Items representing components of the reflective process can be found in Table 5. Cronbach’s alpha on this scale was 0.83. Slightly reworded items from the pretest were also used for Factor 1 – Self-efficacy for gathering and using data (see below).

Data related to the current model. The data focused on aspects of our proposed theoretical model including (1) self-efficacy of participants in using student data, (2) value of student data for changing instructional practice, (3) feasibility of gathering student data, and (4) effort needed to gather and analyze data relative to other teaching responsibilities.

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 link to the survey, a consent document outlining the purpose 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 and if 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 of the model that were not directly part of the study 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 notified that they would be in touch to provide more in-depth information to their survey responses.

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 2. Means and Standard Deviations for Main Variables of Total Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (sd)</th>
<th>N=41</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior use</td>
<td>4.43 (.67)</td>
<td>41</td>
</tr>
<tr>
<td>Prior use: Previous use of different types of student data (if per person)</td>
<td>4.43 (.67)</td>
<td>41</td>
</tr>
<tr>
<td>Self-efficacy: instructors belief in their ability to gather and interpret data and make improvement based on the data (scale 1-6)</td>
<td>4.67 (.63)</td>
<td>41</td>
</tr>
<tr>
<td>Value: belief that student data could support various instructional tasks (scale 1-6)</td>
<td>3.84 (0.82)</td>
<td>41</td>
</tr>
<tr>
<td>Frequency of use of the reflective student data-based improvement process – refers to the instructors’ use of any of 9 strategies of careful gathering and analysis of data shown in Table 5. (scale 1-6)</td>
<td>2.84 (0.82)</td>
<td>41</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Percentage of respondents reporting data use (N=41)</th>
<th>Type of data</th>
</tr>
</thead>
</table>
| Before the semester to get an idea of who would be in the class (83%) (see Figure 5.) In contrast, only 70% of faculty reported having the students’ current information, end of course surveys, or exams). Faculty may be influenced not by how much they value data, but how difficult it is to gather the data, and how one feels 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 (6.1) with higher mean associated with higher self-efficacy.

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 used the adapted CTSES 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 reported that they had the authority, flexibility, resources, and support of others 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 link to the survey, a consent document outlining the purpose 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.

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**TABLE 2. Means and Standard Deviations for Main Variables of Total Sample**

- **Variable**
  - Prior use: Previous use of different types of student data (if per person) (scale 1-6) with the highest score indicating most confident use.
  - Self-efficacy: instructors belief in their ability to gather and interpret data and make improvement based on the data (scale 1-6) (N=41).
  - Value: belief that student data could support various instructional tasks (scale 1-6) (N=41).
  - Frequency of use of the reflective student data-based improvement process – refers to the instructors’ use of any of 9 strategies of careful gathering and analysis of data shown in Table 5. (scale 1-6) (N=41).

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

- Before the semester to get an idea of who would be in the class (83%) (see Figure 5.) In contrast, only 70% of faculty reported having the students’ current information, end of course surveys, or exams). Faculty may be influenced not by how much they value data, but how difficult it is to gather the data, and how one feels 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 (6.1) with higher mean associated with higher self-efficacy.

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**Question 1B – Relation to use of the reflective process.** Explicitly asking faculty to rate the confidence between student data collection and use and the actual use of the reflective student data-based improvement process was 0.75 (p<.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. Specifically, 39% for gathering data and but also 73.7% for using the data to improve instruction (Figure 3).

Factor 2: 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 using. As was shown in Table 3, barriers to student data gathering and use could be a belief that such data are not useful or important. To address research question 3A, we examined instructor ratings of the value of student data. The overall mean of the value scale was 4.67 (6.23) with the higher score indicating more value placed on data – higher equals higher feasibility.

**Question 3B - 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<.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.**
TABLE 4. Self-Efficacy for Use of Student Data for Reflecting on and Changing Instruction

<table>
<thead>
<tr>
<th>Question</th>
<th>Mean (SD)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reflect on your teaching practices with the aim of making appropriate improvements.</td>
<td>5.30 (0.56)</td>
<td>-</td>
</tr>
<tr>
<td>2. Design data collection strategies for monitoring what is happening in class.</td>
<td>4.13 (0.95)</td>
<td>-</td>
</tr>
<tr>
<td>3. Use different evaluation methods to assess student learning.</td>
<td>4.58 (1.02)</td>
<td>-</td>
</tr>
<tr>
<td>4. Interpret student learning data in a way to plan instruction.</td>
<td>4.20 (0.81)</td>
<td>-</td>
</tr>
<tr>
<td>5. Adapt teaching practices in response to your students’ evaluations of your teaching.</td>
<td>4.59 (1.12)</td>
<td>-</td>
</tr>
<tr>
<td>6. Decide on the most appropriate evaluation method for a particular course.</td>
<td>4.75 (1.12)</td>
<td>-</td>
</tr>
<tr>
<td>7. Employ systematic methods that permit you to assess your own teaching.</td>
<td>4.20 (0.99)</td>
<td>-</td>
</tr>
<tr>
<td>8. Adapt to the needs of your students when planning class sessions and assignments.</td>
<td>4.96 (0.95)</td>
<td>-</td>
</tr>
<tr>
<td>9. Be flexible in your teaching strategies even if you must alter your plans.</td>
<td>5.03 (0.87)</td>
<td>-</td>
</tr>
<tr>
<td>Overall Mean</td>
<td>4.67 (0.71)</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: These are means of how many different types of data were used by the remaining faculty members, who were 3.46 types with a range of 0 to 6 types and a standard deviation of 1.6. Over 50% of the participants used end-of-class surveys, exam results, student demographics, and in-class assessments to use fewer types. Less than 30% of the participants gathered information about students’ prior knowledge or motivation and interest of students in order to guide instructional plans. Half of the participants used student information prior to the semester to understand the make-up of the class. Note that the highest levels of use, which were end-of-semester surveys to improve future classes, actual exam results used to plan remediation (both indicated in Table 3), and student information prior to the semester, are collected for other purposes or provided by other parts of the institution – that is, they are easy to collect and available without extra effort.

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

<table>
<thead>
<tr>
<th>Question</th>
<th>Mean (SD)</th>
<th>Notes</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>-</td>
</tr>
<tr>
<td>2. Design data collection strategies 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 (1.24)</td>
<td>-</td>
</tr>
<tr>
<td>6. Decide on the most appropriate evaluation method for a particular course.</td>
<td>3.71 (1.23)</td>
<td>-</td>
</tr>
<tr>
<td>7. Employ systematic methods that permit you to assess your own teaching.</td>
<td>3.78 (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>

mean of the feasibility scale and means for each of the four items is 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 of response, reporting it back to faculty, was 5.02 (SD 0.87).

Question 3B - relation to use of the reflective process. The correlation between feasibility of gathering student data and the actual use of the reflective student data-based improvement process was 0.55 (p = .001). Those who believed that it was possible to use 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 using 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 to do this. Overall composite 4.67 (0.77)

Overall composite 4.67 (0.77)

Authoritative to make a change based on data 5.07 (0.83)

Flexibility to make a change based on data 5.02 (0.88)

Resources to support the change based on data 4.02 (1.13)

Peer-administrative support for using data to make a change 4.54 (1.20)

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.

Actual Data Use

A distinction is made between student data already being used by faculty. While many data types were mentioned, the most common were end-of-semester course evaluations, grades and accuracy rates from exams, and responses to iClicker questions collected in class. The following is a good example of multiple ways a faculty uses

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>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall composite</td>
<td>4.67 (0.77)</td>
<td>-</td>
</tr>
<tr>
<td>Authoritative to make a change based on data</td>
<td>5.07 (0.83)</td>
<td>-</td>
</tr>
<tr>
<td>Flexibility to make a change based on data</td>
<td>5.02 (0.88)</td>
<td>-</td>
</tr>
<tr>
<td>Resources to support the change based on data</td>
<td>4.02 (1.13)</td>
<td>-</td>
</tr>
<tr>
<td>Peer-administrative support for using data to make a change</td>
<td>4.54 (1.20)</td>
<td>-</td>
</tr>
</tbody>
</table>

Coding process

The team used a thematic coding approach (Coiffet & Adkinson, 2004). 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 unintended 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 Educational 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 this feasible?”), and environment (“Would I be allowed?”). 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, the 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.

Actual Data Use

A distinction is made between student data already being used by faculty. While many data types were mentioned, the most common were end-of-semester course evaluations, grades and accuracy rates from exams, and responses to iClicker questions collected in class. The following is a good example of multiple ways a faculty uses
For other faculty, codes generally trended either high or low. An interesting nuance 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 behaviors. 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.

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 problems causing poor performance.

Qualitative results. The value of student data was the most frequently mentioned concern made in the faculty interviews. This supported the qualitative 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.

**Factor three: Feasibility.**

Quantitative results. Overall results of the survey items assessing feasibility had a relatively high mean of 4.67 (0.77) in Table 2. This would indicate that faculty believed it 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 methods for improvement (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; however, it was when the responses tended to highlight the lack of resources. The observation supported the qualitative results with regard to perceptions of the lack of resources noted in that item of the survey.
Overall Support for the Factor Model
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. The results of the empirical analysis would lead us to 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- and intervention data, dealing with pre-existing faculty attitudes and beliefs about student data and past data sources they had employed. The unavailability 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 members in response to the quantitative and qualitative data helped to show that the responses were relatively consistent across measurement modes.

Small sample size.
We had a small number of participants (41). 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 about behaviors, an individual’s 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.

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 as applied to choices. This is currently the most widely used model of behavior change.

We argue that having a conceptual 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 doubters 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 after 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 to other contexts. The 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 and constructed data sets, the best data, and the biggest innovations will die on the vine. With their support, really innovative growth in education is impossible to stop.

REFERENCES


