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Factors Associated with Faculty Use of Student Data for Instructional Improvement

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

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

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

INTRODUCTION

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

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

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

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

In the early '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.

(2013) reported that the types of data typically gathered by learning analytics were not able yet to answer most questions that teachers had. They argued for teachers to work with analysts 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 SOTL spark interest, while others like Academic Analytics, are met with suspicion or skepticism. Macfadyen 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 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 when discussing it in 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 literature on these topics has been generated in K-12 education, 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.

First 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, understanding their position is a critical factor in expanding change based on the use of student data. Researchers had to understand faculty current beliefs about student data and learning analytics, in order to convince faculty that studying such data would be worthwhile (Dyckhoff, 2011).

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

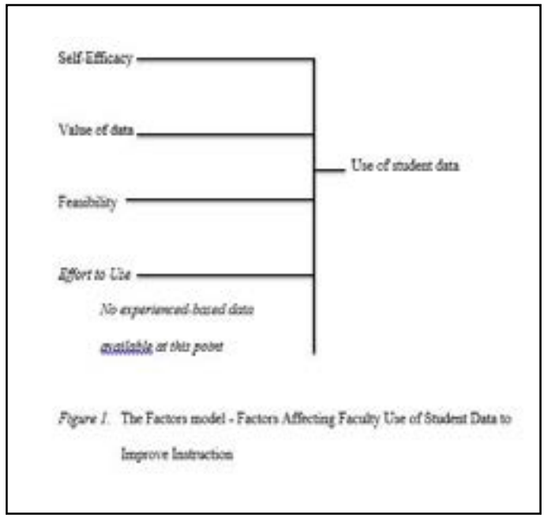

Figure 1. The Factors model - Factors Affecting Faculty Use of Student Data to Improve Instruction

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 factors 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)

These theories came from different domains and addressed special concerns within those domains, and yet have much in common, as asserted by Conner and Norman (2005a) about health behaviors. We reviewed Connor and Norman's attempt to synthesize a more integrated theory and its potential applications to faculty decisions to innovate in the discussion section of this paper. Here we highlight some of the key common factors.

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 own ability to successfully gather and interpret student data for improving instruction. Variations of this belief in one's capability to be successful at a specific behavior are found in almost every theory of innovation adoption. Bandura (1986) identified self-efficacy as a key component of social cognitive theory. Self-efficacy has been shown to be important in motivation and performance in a variety of contexts (Klassen, Tze, Betts & Gordon, 2011; Pajares, 1996; Schunk & Pajares, 2009; Van Acker, van Buuren, Kreijns, & Vermeulen, 2013; Wigfield, Tonks, & Klauda, 2009).

In a chapter about the expansion and acceptance of self-efficacy in Social Cognitive Theory, Luszczynska and Schwarzer (2005) offered the following observation on its importance.

> …self-efficacy models are no longer really distinct from other approaches because the key construct that was originally development within 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 Buuren, Kreijns, 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 (Holden & 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 (Woolfolk-Hoy, Davis & Pape, 2006).

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 internationally than in the United States. Examples of research involving postsecondary teachers include a study in Taiwan by Chang, Lin, and Song (2011), research by Norton, Richardson, Hartley, Newstead and Mayes in the UK (2005), by Prieto Navarro (2005), and Vera, Salanova and Martin-del-Rio 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 concept related to self-efficacy was proposed by Wigfield and Eccles (2000), who included expectancy for success as one of the two main bases for motivation in expectancy-value theory, the other being value of the outcome. More specifically, this theory highlighted the subjective expectancy of an individual to achieve success at a task. The effects on behavior were very similar to self-efficacy.

Need for competence. A third theory relating the impact of ability beliefs on motivation is Self-Determination Theory (SDT). Self-Determination Theory as proposed by Deci and Ryan (2000) posited that universal needs for feelings of competence, autonomy, and relatedness influence optimal functioning. Deci and Ryan stated that the extent to which these needs were satisfied was the critical element of self-determined motivation and willingness to take on new challenges.

The need in 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 (Pajares, 1996). Nevertheless both perspectives pointed to the belief in a faculty member's own 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

Utility value of data. Utility value 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 lead to positive attitudes and greater tendency to perform the behavior.

Value of social norms. Values are also a function of social pressures of the individual's social network. If the behavior was socially desirable, the individual was more likely to engage in it. One could also tie this part of the theory to the value component of Expectancy Value Theory. In the current study we imagined that instructors might adopt innovative uses of student data if they believed doing so 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 each action and make a rational choice. Second, once 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, perception of personal control, became a factor in determining actions. The individual might make a good choice, but then believe that situational factors would work against a positive outcome (Fishbein & Ajzen, 2010). Behavior would be executed only 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 (Luszcrynska & Schwarzer, 2005). These two interpretations, self-efficacy ("I

will succeed at this") and personal control ("I have control over the situation") have been raised in the literature (Pajares, 1996). When the idea of being able to succeed at a task (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 AcceptanceTheory. Calls for use of technology in education resulted in several more focused theories about diffusion of technology specifically. One theory, created by Hubona and Kennick (1996), was 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. These echo the initial factors of self-efficacy and value used in the current study.

Van Acker, 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 class situation was present. Use would also be affected by colleagues' opinions about whether they would use it in their own teaching.

Factor 3: 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 the probability that a given task will be possible to complete, given the situation in which is carried out. In this study we broke this construct into more discrete units as described next.

Personal control (Agency). Ryan and Deci (2000) proposed that feelings of autonomy were necessary for intrinsic motivation. In addition to believing student data were useful, an instructor must also believe that he or she had control over the decisions about environment and resources (personal control - has agency) or the conditions made it possible to engage in the task (context control). These ideas are related to two theories described earlier - the Theory of Planned Behavior (Madden, Ellen & Ajzen, 1992), which asserts that norms of the context and the perceived control by the individual influence implementation, and Self Determination Theory (Deci & Ryan, 2000), which points to feelings of autonomy (another way to characterize personal control) as key to motivation. Autonomy paired with perceived personal knowledge and capabilities produce greater intrinsic motivation (Ryan & Deci, 2000) and willingness to act.

Context control. Contextual factors such as opportunities for choice and self-direction increase feelings of autonomy but also affect perceptions of do-ability. This meant that a belief that the environment made it possible to enact the intentions to innovate would influence a behavior choice.

Interestingly, Andrade (2011) discussed how pressures to use data for institutional purposes in accreditation could actually decrease faculty's perceived autonomy for using student data in innovative ways. One way to avoid this would be to support faculty autonomy by encouraging them to become involved in designing assessment relevant to classroom goals. Andrade suggested administrative strategies such as increasing perceptions of administrative support through actions, and access to resources, could boost faculty feelings of autonomy and increase their motivation to use innovative practices. On the other hand, if policies or practices for collecting and using data run counter to a faculty member's feelings of autonomy, he or she may balk at becoming involved in institutional level analytics, which would defeat the purpose of creating the analytics. Faculty input into the process must be solicited in a way to increase feelings of autonomy.

Similar theories focusing on feasibility issues are found in the literature on technology acceptance. Mumtaz (2000) conducted a literature review of innovation acceptance and concluded that opinions of the teacher were critical to adoption. Mumtaz listed teacher beliefs about access to resources, quality of support, as well 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.

Adoption and Diffusion of Innovation. Perhaps the most well known theories that discuss contexts for innovation came from the business, healthcare sectors, and technological fields, for example, Rogers (2003) adoption and diffusion of innovation theory. In an early version, Rogers (2001) listed four main elements of diffusion of innovations. An innovation would diffuse due to 1) characteristics of the innovation itself; 2) the communication channels available to make others aware of the innovation; 3) time; and 4) the social system into which it was diffusing.

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 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, 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 for engineering education. They reported that although 82% of 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 resource limitations as the biggest cause of failure to innovate. The second largest category was faculty issues. Borrego, Froyd and Hall said "department chairs stressed that adoption of educational innovations is heavily reliant on participation of faculty members." (pg. 199) They continued by citing "Faculty time for preparation and management of labor intensive innovations,… the culture of engineering higher education,… faculty resistance to change, marginalization of teaching in promotion and tenure, and skepticism regarding evidence of improved student learning." (pg. 199) All of these can be seen in the discussions of context factors that impede diffusion of innovation 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 will burden themselves and their colleagues with the need to learn how to use complex new tools, and/or the need to redesign change their teaching habits and practices, without offering any appreciable advantage or reward."(pg. 160) The feasibility factor can take many shapes, but convenience and low effort appear in many guises 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 their agency and the feasibility for being able to use student data were related to their actual data collection and use. Data collected from the faculty in the current study followed the Factors model shown in Figure 1. Here self-efficacy, value, and feasibility (personal and conditions) were proposed as the major factors in faculty decisions to collect and use student data to improve instruction. The following research questions were addressed:

Research Question 1
Factor 1: Faculty Self-efficacy for Collecting and Using Student Data
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
Factor 2: Faculty Beliefs about the Value of Student Data for Instructional Improvement
2A. How much did the faculty in the sample value student data in terms of its usefulness for instructional decisions?
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
Factor 3: Faculty Beliefs about Feasibility of Collecting and Using Student Data to Improve Instruction
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
Development of measurable outcomes of student data use
4A. To what extent did the faculty in the sample report the collection and use of student data in the past? Were some kinds of data collected more frequently than others?
4B. To what extent did the faculty use the reflective processes involved in the reflective student data-based improvement process?

Research Question 5
Relationships between model factors and outcome variables
5A. What did regression of data types used on self-efficacy, value, and feasibility show about the strength of any effect of any of the studied variables?
5B. What did regression of the reflection processes on number of types of data used, self-efficacy, value and feasibility show about the relative strength in affecting the target variable?

The Present Study

We have drawn on the above theories to inform our investigation of faculty use of student data. For the quantitative investigation of our hypotheses we predicted that participants who had high scores on measures of self-efficacy, data 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

Forty-one faculty participated in this study. (Because not everyone participated in both quantitative and qualitative parts of the study, occasional discrepancies in total responses occur.) Demographics of the participants are shown in Table 1. Procedures for protection of the participants and confidentiality of their information were guided by IRB human subject requirements of the University. Faculty who participated in this initial data collection were instructors in large undergraduate classes that were targeted for redesign (n=21) plus faculty who were matched to the instructors in terms of rank, gender, and college (n=20) and agreed to respond to the survey component

TABLE 1. Sample Demographics

College	Liberal Arts	Natural Science	Professional	
	21	12	8	
Rank	Lecturer	Assistant Prof	Associate Prof	Full Prof
	19	5	13	3
Years Teaching	1-5	6-10	11-20	>20
	5	7	15	13

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 in 18 school and colleges. 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 related 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 items was to establish a baseline 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 worded to focus on the instructional improvement goals of assessment. Items were worded generally and an example of each was given in order to be recognizable to the widest range of disciplines.

Outcome measure 2: Frequency 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 item stems from this measure were also used for Factor 1 – Self-efficacy for gathering and using data (see below).

Data related to the current model. The following data focused on aspects of our proposed theoretical model including (1) self-efficacy for the gathering and analyzing 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.

Factor 1: Self-efficacy for gathering and interpreting data and making improvement based on the data (adapted from CTSES, Prieto Navarro, 2005). This self-efficacy survey consisted of nine statements in two sets – five representing self-efficacy for gathering and interpreting data (e.g. "I am confident that I can use student data to design data collection strategies for monitoring what is happening in class?") and four representing self-efficacy for making improvements to teaching based on data (e.g. "I am confident that I can use student data to interpret student learning in a way to plan instruction."). Participants rated statements from 1 – strongly disagree to 6 – strongly agree. Items are shown in Table 4. Note that the statements parallel those from outcome measure 2 described earlier. The Cronbach alpha for the overall self-efficacy scale was acceptable at .83.

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

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

In the Factors model but not included in this phase: Effort of using student data (developed for study). Effort in this context refers to amount of time and attention that must be put forth in order to engage in a task. At this point most faculty did not have enough 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 a recruitment statement, a consent to participate document, and a model 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 model that were of interest: prior use of student 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 asked if they would consent to an interview 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 below.

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

Variable	Mean (sd) N=41
Prior use - Previous use of different types of student data (# per person)	3.46 (1.61) Number of different types used
Self-efficacy – instructors' belief in their ability to gather and interpret data and make improvement based on the data (scale 1-6)	4.66 (0.62) level of confidence – higher equals higher level
Value of student data - confidence that student data use could support various instructional tasks (scale 1-6)	4.42 (0.65) value placed on data – higher equals more value
Feasibility – instructors' belief that a given task will be possible to complete, given the situation in which it is carried out (scale 1-6)	4.67 (.77) feasibility of using data – higher equals higher feasibility
Frequency of use of the reflective student data-based improvement process. - refers to the instructor's use of any of 9 strategies of careful gathering and analysis of the data shown in Table 5. (scale 1-6)	3.84 (.82) frequency of use – higher equals more use

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 faculty responded that they felt 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 (.61) with higher means associated with higher self-efficacy.

Question 1B – Relation to use of the reflective process. Exploring further, we found that the correlation between self-efficacy for 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 but also 73.75 % for using the data to improve instruction (Figure 3).

Factor 2: Instructor beliefs about the value of data.

Question 2A – Value of data. One source of failure to engage in data gathering could have been a belief that such data are not useful. To address research question 2A, we examined instructor ratings of the value of student data. The overall mean of the value scale was 4.42 (0.65) on a six point scale with the higher end representing "very confident" in the utility of student data for instructional improvement. Figure 4 summarizes faculty confidence in value of student data for each of the listed instructional tasks. 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 lower item (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.

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

Type of data use	Percent of respondents reporting this use (N=41)
Before the semester to get an idea of who would be in the class (for example, looking at the class rosters for student levels and majors).	55%
At the beginning of the course to measure student prior knowledge (for example, doing an early baseline quiz or survey to see what the students seem to already know).	30%
At the beginning of the course to measure student motivation and interest (for example, doing a survey on the first day of class to see what goals students have in the class).	20%
During the course but outside the context of an exam to measure student understanding for the purposes of instructional changes at that moment (for example, asking questions or using clicker surveys to get immediate feedback on student understanding in the moment).	52.5%
After an exam, using the exam results to modify instruction (for example, identifying concepts that seemed to be difficult for everyone and might need review).	**75%**
At the end of the semester, using student performance or evaluation to modify future classes (for example, gathering student comments about what helped and hindered their learning overall).	**82.5%**
I do not regularly use student data to modify instruction.	12.5%

Question 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 =.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 seen in Table 3, participants reported higher use of data that were being gathered for other purposes or by other parts of the institution (enrollment information, end of course surveys, or exams). Faculty may be influenced not by how much they value data, but how difficult it is to collect and use. We have labeled this factor "feasibility" and identified four aspects: authority to make a change, flexibility to change, resources to support the change, and peer and administrative support. Over 87% of faculty felt that they had the authority, flexibility, and administrative support to improve instruction with student data. (See Figure 5.) In contrast, only 70% of faculty reported having the resources to gather data for instructional improvement. The overall

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

Please select the level best reflecting your agreement with the statement. You are confident that you can:	1 = not at all confident to 6 = very confident
1. Reflect on your teaching practices with the aim of making appropriate improvements.	5.30 (.68)
2. Design data collection strategies for monitoring what is happening in class.	4.13 (.95)
3. Use different evaluation methods to assess student learning.	4.58 (1.026)
4. Interpret student learning data in a way to plan instruction.	4.50 (.81)
5. Adapt teaching practices in response to your students' evaluations of your teaching.	4.59 (1.12)
6. Decide on the most appropriate evaluation method for a particular course.	4.73 (.81)
7. Employ systematic methods that permit you to assess your own teaching.	4.20 (.99)
8. Adapt to the needs of your students when planning class sessions and activities.	4.95 (.95)
9. Be flexible in your teaching strategies even if you must alter your plans.	5.03 (1.07)
Overall Mean	4.67 (.71)

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

In the following items, please choose the responses that best fit your situation. In your teaching how often do you:	Mean (sd) 1 = Never to 6 = Always
1. Reflect on your teaching practices with the aim of making appropriate improvements?	4.83 (1.05)
2. Design data collection strategies for monitoring what is happening in class?	3.07 (1.03)
3. Use different evaluation methods to assess student learning?	3.71 (1.10)
4. Interpret student learning data in a way to plan instruction?	3.78 (1.11)
5. Adapt teaching practices in response to your students' evaluations of your teaching?	3.95 (1.26)
6. Decide on the most appropriate evaluation method for a particular course?	3.71 (1.21)
7. Employ systematic methods that permit you to assess your own teaching?	3.00 (1.30)
8. Adapt to the needs of your students when planning class sessions and activities?	4.22 (1.19)
9. Be flexible in your teaching strategies even if you must alter your plans?	4.32 (1.19)
Overall Mean	3.86 (.82)

mean of the feasibility scale and means for each of the four items are shown in Table 6. In comparison to the other factors, overall feasibility is on a par with self-efficacy at a mean of 4.67, but its lowest rated component, resources, may be holding it back.

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 gather and use student data were also likely to report engaging in the reflective process.

Outcome measures of student data use

Question 4A – Baseline measure of prior data use. To answer research question 4A, we examined past use of various types of student data. Table 3 provides the percentage of faculty reporting they had employed each of the data listed. Twelve and one half percent of the sample indicated that they did not use student data. The average number of different types of data used by the remaining faculty members was 3.46 types with a range of 0 to 6 types and a standard deviation of 1.61. Over 50% of the participants used end-of-class surveys, exam results, student demographics, and in class assessment to modify their instruction. 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 bold 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.

Question 4B - Use of reflective student data-based improvement process. As noted earlier, Figure 3 shows that a higher percentage of participants report engaging in practices to improve instruction (73.75%) than engaging in systematic data gathering (39%), despite reporting self-efficacy in Figure 2. The average overall for actual use of the reflective processes was 3.86 (.82). Means for each of the items on this scale are shown in Table 5, and are lower than the reported mean of self-efficacy for the matching design and use item in Table 4.

Predicting the use of student data

Question 5A – Predicting prior number of uses of data. We attempted to identify the factors in Figure 1 that appeared to be related significantly to levels of actual use. To address this question, the number of different data types that a faculty member reported was regressed on self-efficacy, value of the data, feasibility, and frequency of actual use of the reflective student data-based improvement process. Of these variables, both feasibility ($\beta = -.663$, $t=-2.123$) and use of reflective processes ($\beta=1.550$, $t=3.884$) were significant predictors of how many different types of data were used by faculty ($p<.05$). Note that feasibility is negatively related to the number of types of data used, suggesting that when faculty believe that there are many barriers to data use, they use fewer types.

Question 5B – Predicting use of reflective process. Additionally, when treating use of reflective processes as the outcome variable, both number of types of data used ($\beta=.191$, $t=3.884$) and self-efficacy for use ($\beta=.613$, $t=4.202$) were found to be significant predictors ($p =.001$). In other words, a faculty members' confidence that he or she can gather and analyze student data was related to engagement in reflection on data use to improve instruction and the variety of data types used.

Returning to our initial questions of whether high scores on the variables identified in the Factors model shown in Figure 1 would be associated with use of reflective processes, we found that self-efficacy

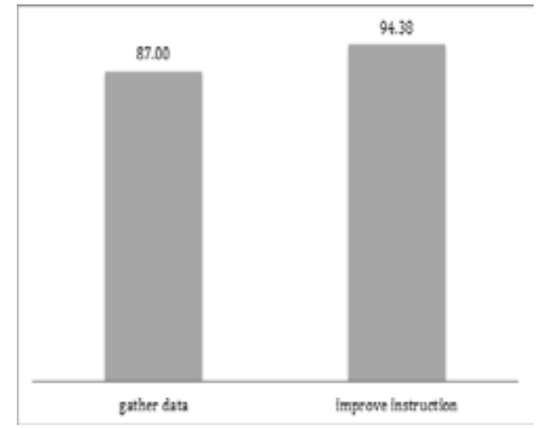

Figure 2. Percent of faculty reporting self-efficacy for gathering and using student data to improve instruction

and feasibility were predictors of use of the reflection process and merit further examination. In these regressions, value of the data did not reach significance, although it was significantly correlated with using the reflective practice process. This finding is contrary to what is found in both the motivation literature and the innovation literature. The reasons for this difference need to be explored in greater depth.

Summary of Quantitative Data

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

Qualitative Component of the Study

To complement our quantitative data and create a better understanding of how faculty perceive and use student data, the team 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.

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

Component of feasibility	Mean (sd) 6 point scale with higher values equaling more support
Overall composite	4.67 (0.77)
Authority to make a change based on data	5.07 (0.82)
Flexibility to make a change based on data	5.02 (0.88)
Resources to support the change based on data	4.02 (1.15)
Peer and administrative support for using data to make a change	4.56 (1.25)

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, 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* ("Would I be allowed?"), and *effort* ("What would it take to do this?"). Although effort was present in the model, it was not included in the quantitative analysis as noted earlier. Since it was mentioned by some of the interviewees and therefore could have provided some insight into this factor separately, effort was kept for qualitative analyses.

The team added two factors by dividing the *student data use* component into *actual use*, stated as recollections of experiences with collecting and using data, and *intended* use. The team noticed faculty expressed attitudes specifically related to data collection they *planned* to implement but had not enacted. This was not conceptualized in the Factors model, but these sentiments arose frequently enough that the team decided a distinct component was necessary.

During final coding, the team finalized and used these six components: *actual student data use, intended student data use, self-efficacy, value of data, feasibility,* and *effort*.

QUALITATIVE RESULTS

In the following section, findings from the qualitative data are described. Here, frequency of codes are discussed and excerpts are provided to support our interpretations.

Actual Data Use

Actual use referred specifically to 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

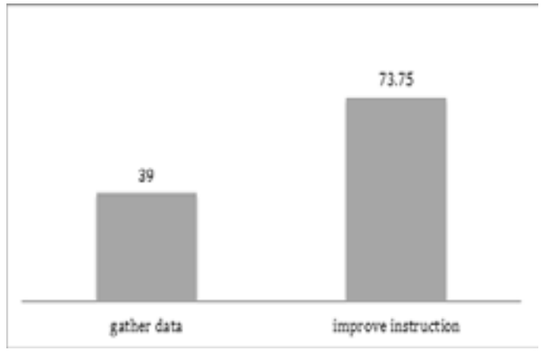

Figure 3. Percent of faculty reporting actual use of practice of gathering or using data to improve instruction

student data.

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

In general this finding supports the quantitative data finding where end-of-course evaluations and exam results were the most commonly reported data used. Clicker use was also frequently noted, but has no counterpart in the quantitative results.

Some faculty reported using data infrequently and with less confidence. Some faculty seemed unsure of what was meant by "student data" and restricted their use to the most frequently encountered, such as exam scores. They also did not know what various data types were possible, or how to interpret and use data for improvement.

Intended Data Use

The concept of intended data use, not originally conceptualized 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,

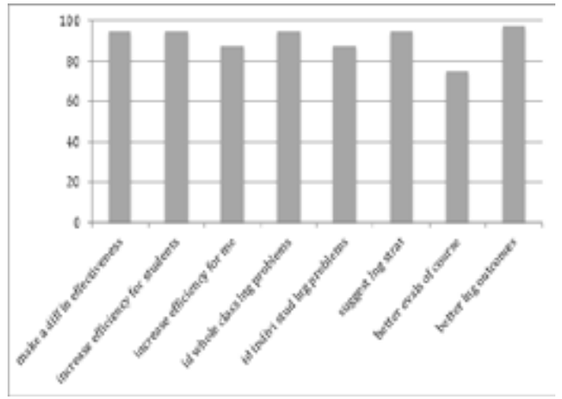

Figure 4. Percent of faculty reporting confidence in data to inform various aspects of teaching a course, a measure of the value of student data.

> "I'm not very good at it, so when I sit in meetings and they have a bunch of spreadsheets I didn't create, I don't know what it's all telling me. So I let other people tell me what it's telling me."

Value

The value component was the most frequently coded along with *actual data use.* Most of the *value* codes were positive. Faculty usually mentioned perceptions of high personal *value* for the data, but sometimes would also discuss *value* students placed on data use. Further, 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."

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

Feasibility

Feasibility was the least frequently coded. *Feasibility* referred to institutional resources and support related to data collection and use, addressing perceptions of authority to access or interpret data. When noted, it was generally in a negative context. For example:

> "The demographics and all that, I don't know if we have much access to some of that material."

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

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

Effort

Effort was also coded with moderate frequency. *Effort* referred

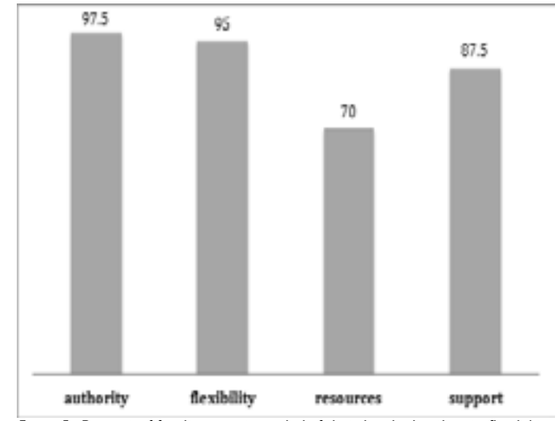

Figure 5. Percent of faculty reporting a belief that they had authority, flexibility, resources, and support to make changes in their teaching based on student data.

to perceptions of resources and expenditures required for data processes, Most codes illustrated faculty's' perceptions of high amounts of *effort* needed to collect, interpret, and use data. Typically these perceptions referred to large classes. High *effort* perceptions sometimes deterred faculty from collecting student data as shown in this excerpt.

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

Despite the effort required, some faculty collected data despite high effort perceptions, and using other resources made this easier. This excerpt shows one participant utilizing assistants to collect essay data.

> "I mean I grade probably 25 tests. The TAs do much of the grading so I get feedback from them."

These trends supported the quantitative findings because the most frequently used data involved low collection efforts since they were already collected by the university (e.g. course evaluations and exam data) or could be collected electronically (clicker questions).

GENERAL DISCUSSION

Interweaving the Quantitative and Qualitative Findings

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

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

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

Factor two: Value of student data.

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

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 comment made in the faculty interviews. This supported the quantitative findings of high value placed on student data. All the comments about student data spoke to its positive value.

Here, too, there was a more nuanced interpretation than was present in the quantitative data. Comments made by faculty also indicated a recognition that the students benefited from the collection of their data, helping them recognize their progress, successes and failures. Perhaps the multiple recipients of value (like students) need to be considered when measuring overall data value.

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 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. This observation supported the quantitative 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 factors affecting faculty use of student data for instructional improvement. We have found that the three factors, self-efficacy, value of data, and feasibility, suggested by the literature and included in this model have a legitimate claim to being able to influence faculty use of student data in making instructional improvements. The results suggest that paying attention to these factors could encourage faculty to be more systematic and productive in their use of student data.

LIMITATIONS OF THIS STUDY

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

Termination of project before completion.

The biggest impact on our ability to draw causal conclusions was caused by the project being terminated before the intervention and post measures could be taken. We were able to gather most of the pre-intervention data, dealing with pre-existing faculty attitudes and beliefs about student data and past data sources they had employed. The 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. Cross-checking between the quantitative and qualitative data helped to show that the responses were relatively consistent across measurement modes.

It is a concern of research in post-secondary settings that there are not better ways to measure the key constructs. Observational data would have been a good benchmark to test the veracity of faculty self-reports. Since attitudes and beliefs will probably always include qualitative methods, strategies for gathering data from college level faculty might need to be focused and standardized to increase the replicability (and therefore the respectability) of the data. We also suggest that research in SOTL converge on a set of more standard quantitative instruments to allow data to be compared more readily.

Small sample size.

The present study 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 to understand why faculty would or would not choose to use student data in ways to improve the learning and student success.

A particularly useful discussion of the many faces of social cognitive theory was provided by Connor and Norman (2005b), from a workshop sponsored by the National Institute of Mental Health on promoting HIV-preventive behaviors. Individuals in attendance included many of the major theorists who worked within the framework of social cognitive theory. Connor and Norman reported that the experts "…identified eight variables which, they argued, should account for most of the variance in any (deliberative) behavior." (pg. 18). These were (slightly modified for length and clarity here): 1) a strong intention (or motivation) to perform a behavior; 2) the necessary skills to perform the behavior; 3) an absence of constraints on the behavior; 4) a cost benefit ratio in favor of the behavior; 5) more social pressure to perform than not to perform the behavior; 6) a behavior consistent with the individual's self-image; 7) no expectations of the outcome to be negative emotionally; and 8) high levels of self-efficacy (pg. 19-20). Connor and Norman referred to this as "the 'major theorists' model" (pg. 20).

This major theorists' model is very similar (though more inclusive) to the proposed factors used in this study. Most of the factors involved interpretation and rational decisions about whether to perform the behavior in light of its feasibility (in our case, to collect and use student data to improve instruction). We have envisioned them (in a different order from Connor and Norman) as:

1. The faculty member must have self-efficacy for data collection, interpretation and use for improvement.
2. The faculty member must value the potential contributions that student data can make to instructional improvement.
3. The faculty member must believe that collecting and using student data are feasible within the constraints of the situation, both personal and contextual.
4. *The faculty member must believe that the benefits of the gathering and use of student data out weigh the amount of effort required to follow through with the process (though effort was not yet included in this study).*

We further believe that the Factors model will apply across contexts because similar constructs have been tested on widely different outcomes. Connor and Norman (2005a) supported the notion that the many theories of behavior choice have "considerable overlap between constructs contained in the main social cognition models of health behavior" (pg. 16). We would say that these similarities exist not just in models of health behavior, but in many areas in which humans make choices. Some even span theories. For example, Rogers (2003) diffusion of innovation theory highlighted characteristics of an innovation and those who adopt it. Among those qualities of the innovation listed are relative advantage, compatibility with the adopter's beliefs, ease of use, and observability of the outcome. Bourrie, Cegielski, Jones-Farmer, & Sankar, (2014) mirrored this in their similar list of innovation features: 1) relative advantage; 2) ease to implement; 3) ease of use; and 4) adaptability. As to features of the faculty adopters, Bourrie, Jones-Farmer, and Sankar (2016) included the familiar qualities of efficacy toward change, support from principals (i.e. administrators), benefits from change, attitude toward 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 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 ones. 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; Macfayden & 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 examined over a much longer time line. Change does not come easily or quickly.

It would be helpful for the field to create some widely accepted construct definitions in order to develop instruments that can be generalized. Measurements not hampered by the disadvantages of 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; Macfayden & 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 technology, the best information, the best data, and the best innovations will die on the vine. With their support, really innovative growth in education is impossible to stop.

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