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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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Factors Associated with Faculty 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, “whose powerful voice and genuine participation often determine the success or failure of educational innovations, especially those that involve pedagogical and academic change” (Furco & Moely, 2012, pg. 129). This paper reports the results of an exploration of factors that influence faculty to consider or reject using analysis of student data to improve instruction based on social cognitive theory. Self-efficacy, value of the outcome, and feasibility of using a student data-based reflection process were found to be related to the actual use of components of the reflection process by faculty.

INTRODUCTION

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

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

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

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

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

Classroom Assessment Techniques. Attempts to adopt instructional improvement based on student data were encouraged by the work of Angelo and Cross (1993). These authors inspired faculty to gather data about learning by offering classroom assessment techniques (CATs) that could be used easily in classes.
(2013) reported that the types of data typically gathered by learning analytics were not able to answer most questions that teachers have. The review of several studies led us to hypothesize that student data analysis can help students to shape their learning and improve their outcomes.
will succeed at this”) and personal control (“I have control over the situation”) have been raised in the literature (Pajares, 1996). When perceived control (i.e., self-efficacy) is contrasted with being in a situation over which one has control over completing a task (personal control), it is a fine line that separates self-efficacy and feasibility.

### Technology Acceptance Theory

Calls for use of technology in education resulted in several more focused theories about diffusion of technology specifically. One theory, created by Deci and Ryan (2000), is the Self-Determination Theory. This model proposed that for acceptance a technological innovation had to be consistent with teacher values and beliefs about learning, be both useful and easy to use, and it had to inspire teacher confidence in their ability to use 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, & Azjen, 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 made 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, & Azjen, 1992) and Self Determination Theory (Deci & Ryan, 2000), which points to feelings of autonomy (another way to characterize personal control) as key to motivation and the degree of internal perception of control by the individual influencing implementation, and Self Determination Theory (Deci & Ryan, 2000), which points to the faculty element of innovation (personal control—feeling that the innovation is appropriate for you). Over half of the comments about barriers cited institutional policies or practices for collecting and using data within the department that were perceived as barriers. The second largest category was faculty concerns. Borrego, Frydt, and Hall noted that “department chairs were aware that the innovations, only 47% reported having adopted the innovations to some extent in their departments. Over half of the comments about barriers cited institutional policies or practices for collecting and using data within the department that were perceived as barriers. The second largest category was faculty concerns. Borrego, Frydt, and Hall noted that “department chairs were aware that the innovations, only 47% reported having adopted the innovations to some extent in their departments. Over half of the comments about barriers cited institutional policies or practices for collecting and using data within the department that were perceived as barriers. 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### Research Question 1

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

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

2. 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 improvement process?

### Research Question 2

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

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

2. What was the relationship 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**

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

2. 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 employed at the institution. This data collection was 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. For the purposes of this study, we considered their use to be a form 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 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 respondents engaged in nine reflective activities 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 3. Cronbach's alpha for this scale was acceptable at .73. The Four items were rated on a six-point scale ranging from 1 – strongly disagree to 6 – strongly agree. For example, faculty self-efficacy for gathering and using data in the reflective student data-based improvement process was 0.63 (p =.001). Those who saw value of student data were more likely to report engaging in the reflective process for data use. The correlation between seeing the value of student data and the correlation between the value placed on data by the instructor’s use of any of 9 strategies of careful gathering and analysis of the data shown in Table 3. (scale 1 - 6).

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 instructions on how to access the online survey. The participation of faculty members was voluntary. The data were compiled from participants who had consented to participate in the study and whose feedback was used. The consent to participate document was made available online for participants (see Table 5). The Cronbach’s alpha for this scale was acceptable at .73. The Four items were rated on a six-point scale ranging from 1 – strongly disagree to 6 – strongly agree. For example, faculty self-efficacy for gathering and using data in the reflective student data-based improvement process was 0.63 (p =.001). Those who saw value of student data were more likely to report engaging in the reflective process for data use. The correlation between seeing the value of student data and the correlation between the value placed on data by the instructor’s use of any of 9 strategies of careful gathering and analysis of the data shown in Table 3. (scale 1 - 6).

Quantitative Results

Means and standard deviations for the main variables are provided in Table 2. Each variable is discussed separately 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 strongly disagreed 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 .73. Cronbach alpha for the overall self-efficacy scale was acceptable at .63.

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

Factor 3: Feasibility of using student data (developed for this study). This feasibility survey assessed participants’ confidence that they had the authority flexibility, resources, and support of others to use student data to modify instruction (see Table 6). The Four items were rated on a six-point scale ranging from 1 – strongly disagree to 6 – strongly agree. For example, faculty self-efficacy for gathering and using data in the reflective student data-based improvement process was 0.63 (p =.001). Those who saw value of student data were more likely to report engaging in the reflective process for data use. The correlation between seeing the value of student data and the correlation between the value placed on data by the instructor’s use of any of 9 strategies of careful gathering and analysis of the data shown in Table 3. (scale 1 - 6).

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 percentage of participants reporting self-efficacy in either gathering data or using it for improvement. Eighty-seven percent of instructors responded that they enough experience with student data use to make a reliable estimate of their ability to gather student data. Ninety-four percent reported that they were confident in their ability to use the data they collected to improve instruction. The average level of overall self-efficacy for data collection and use was 4.67 (SD =.61) with higher means associated with higher self-efficacy.

Factor 2: Instructor beliefs about the value of data. Question 1B – Relation to the 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 percentage of faculty reporting that they actually used the process was lower. Specifically, 39% for gathering data but also 73.75% for using data to improve instruction (Figure 3).

Factor 3: Instructor beliefs about the feasibility of using student data. Question 3A – Feasibility of collecting and using data. To address research question 3A, we asked participants to rate the feasibility of student data gathering and use. As was shown in Table 3, instructors were more likely to report using 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 it. They may be more willing to engage in the collection of student data if it is a part of a campus wide initiative to improve the instruction in large undergraduate courses.

The overall
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>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reflect on your teaching practices with the aim of making appropriate improvements</td>
<td>4.83 (.05)</td>
</tr>
<tr>
<td>2. Design data collection strategies for monitoring what is happening in class</td>
<td>3.07 (.03)</td>
</tr>
<tr>
<td>3. Use different evaluation methods to assess students learning</td>
<td>3.71 (.10)</td>
</tr>
<tr>
<td>4. Interpret student learning data in a way to plan instruction</td>
<td>3.78 (.11)</td>
</tr>
<tr>
<td>5. Adapt teaching practices in response to your students’ evaluations of your teaching</td>
<td>3.95 (.24)</td>
</tr>
<tr>
<td>6. Decide on the most appropriate evaluation method for a particular course</td>
<td>3.71 (.21)</td>
</tr>
<tr>
<td>7. Establish systematic methods that permit you to assess your own teaching</td>
<td>4.00 (.29)</td>
</tr>
<tr>
<td>8. Adjust to the needs of your students when planning class sessions and activities</td>
<td>4.96 (.95)</td>
</tr>
<tr>
<td>9. Be flexible in your teaching strategies even if you must alter your plans</td>
<td>4.32 (.19)</td>
</tr>
<tr>
<td>Overall Mean</td>
<td>3.86 (.82)</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Question</th>
<th>Mean (sd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reflect on your teaching practices with the aim of making appropriate improvements</td>
<td>4.03 (.05)</td>
</tr>
<tr>
<td>2. Design data collection strategies for monitoring what is happening in class</td>
<td>3.72 (.03)</td>
</tr>
<tr>
<td>3. Use different evaluation methods to assess students learning</td>
<td>3.71 (.10)</td>
</tr>
<tr>
<td>4. Interpret student learning data in a way to plan instruction</td>
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<tr>
<td>8. Adjust to the needs of your students when planning class sessions and activities</td>
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<tr>
<td>9. Be flexible in your teaching strategies even if you must alter your plans</td>
<td>4.32 (.19)</td>
</tr>
<tr>
<td>Overall Mean</td>
<td>3.86 (.82)</td>
</tr>
</tbody>
</table>

mean of the feasibility scale and means for each of the four items are shown in Table 6. In comparison to the other factors, overall feasibility is on a par with self-efficacy at a mean of 6.67, but its lowest rate was with respect to components ranging from 3.70 to 3.91.

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 it was possible to gather and use student data were also more 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 reported use 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 use fewer types.

Question 3B – Predicting use of reflective process. Additionally, when treating use of reflective processes as the outcome variable, both number of types of data used (β = -.63, p = .012) and use of reflective processes (β = .55, p = .000) were significant predictors of the number of different types of data used by faculty (p = .001). 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 are less likely to use data.

Coping 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 make a change.

Qualitative Component of the Study To complement our quantitative data and create a better understanding of faculty perceptions 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

<table>
<thead>
<tr>
<th>Component of feasibility</th>
<th>Mean (sd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall component</td>
<td>4.67 (.77)</td>
</tr>
<tr>
<td>Authority to make a change based on data</td>
<td>5.07 (.88)</td>
</tr>
<tr>
<td>Flexibility to make a change based on data</td>
<td>5.02 (.88)</td>
</tr>
<tr>
<td>Resources available to support the change based on data</td>
<td>4.02 (.13)</td>
</tr>
<tr>
<td>Peer-advisory support available to use data to make a change</td>
<td>4.56 (.13)</td>
</tr>
</tbody>
</table>

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 code 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, Milauski, & Miller, 2012).

Components: Initially four factors were used, representing each factor in the Factors model. They included self-efficacy (“Can I personally do this?”), (“Is this worth doing?”), feasibility (“If I was allowed”), and effort (“Would I do this?”). Although effort was present in the model, it was not included in the quantitative analysis as noted earlier. Since it was mentioned by some of the interviewees and therefore could have provided some insight into this factor separately, effort was kept for qualitative analyses.

The team added two factors by dividing the student data component into actual use, stated as recollections of experiences with gathering 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 major challenge 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...
For other faculty, codes generally trended either high or low. An self-efficacy perceptions can be contextual. One high sometimes both categories were coded for one participant. This trend Self-efficacy referred to perceptions of competence with data mentioned about future data use. 

The concept of intended data use, not originally conceptualized encountered, such as exam scores. They also did not know what confidence. Some faculty seemed unsure of what was meant by 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 faculty placed on data use. So I say I need problems on absolute values and then they generate some and I put them in my homework problems they can pick from.”

“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 well 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 access to some of that material.”

“Sometimes I’ll do the minute thing…. And it’s hard to do because when I get that data back I write into my final exam _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 sit 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,

“Sometimes I do the minute thing…. And it’s hard to do because when I get that data back I write into my final exam _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 sit 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,
Overall Support for the Factor Model

Our purpose for this study was to evaluate the proposed model for faculty use of student data for instructional improvement. We have found that the three factors, self-efficacy, value of data, and feasibility, suggested by the literature and included in this model have a legitimate claim to being able to influence faculty use of student data. The results would not support the outcome that paying attention to these factors could not 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 member, thus the motivation and self-efficacy qualitative data helped to show that the responses were relatively consistent across measurement modes. It is a concern of research in post-secondary settings that there are not better ways to measure the key constructs. Observational data would have been a good benchmark to test the veracity of faculty self-reports. Since attitudes and beliefs will probably always include qualitative methods, for gathering data from college level faculty, much effort might need to be focused and standardized to increase the replicability (and therefore the reliability) of the data. We also suggest that research in SOTL converge on a set of more standard quantitative instruments to allow data to be compared more readily.

Small sample size.

We had a small number of participants (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 (Leventhal & Gafni, 2005). The primary premise of social cognitive theory is that in making choices, individuals cognitions act as a mediator between what is happening and the responses that the individual makes. As a result the same situation can be viewed entirely differently based on interpretations each individual makes in the moment. Choices are more a function of the individual chooser than the objective reality of the situation.

As a result the 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 (Leventhal & Gafni, 2005), 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 individuals 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 a behavior was worth doing. Among the factors, we added factors involving self-efficacy, and using 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 have the necessary skills to perform the behavior of using student data 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 outweigh 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, complexity, trialability, permanence and observability. These attributes were also used in our study.

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