Practices and Beliefs about Educational Data Usage

Ajay Sivanand and Dr. Brian Frank

Queen's University

a.sivanand@queensu.ca and brain.frank@queensu.ca

Abstract – As programs drive to innovate in educational delivery they are increasingly seeking to apply and connect diverse data sets, including student performance data arising from learning outcomes assessment, student activity data in learning management systems, and survey data. This research study is aimed at developing a model to support visualization of educational data to support a range of data needs from individual reflection to program improvement and change management. A literature review around assessment data usage indicated that there is currently a gap in the assessment cycle between collecting the educational data and putting it to use towards educational data needs. Facilitating ways to close this gap served as the motivation for the study. The first phase of this study, as approved by the instructional research ethics board, was to find out how instructors, faculty administration, and educational developers use data and the role it has in improving the student experience.

We conducted semi-structured interviews of twelve faculty and educational staff who collect, analyze, and reflect on educational data. Interviews were created according to McCracken and analyzed using Charmaz's abductive approach to grounded theory. The emerging data presents a number of emergent themes around the affective aspects of how stakeholders feel about how data is and is not being used.

This paper will describe the method to approach to the qualitative data gathering and analysis procedure, and the ideas that emerged from the interviews that we think are of interest to readers.

Keywords: educational data, educational data mining, assessment data, qualitative research

1. INTRODUCTION

In recent years, post-secondary faculties across a variety of disciplines have spent considerable effort building systems to collect assessment data with the goal of helping improve the student experience [1]. However, using this data to guide program improvement decisions at any level has been inhibited by a lack of familiarity among instructors, administrators and support staff to extract

actionable information effectively [2], [3]. The goal of our project is to create a support tool that will aid assessment practitioners in their pursuit to make evidence based improvements to their institutions and programs. Specifically, to build a model and support toolkit for information visualization of educational data so educators and educational developers can readily take advantage of the field of information visualization to help with the hurdles they are facing in their pursuit for data-driven improvement.

Information visualization is a promising approach to tackling this hurdle of data interpretation due to its ability to take advantage of the knowledge and insight of the people viewing it [4]. Unlike other methods for data interpretation, information visualization does not require that the users have a background in statistics or be adept at a particular software to gain insights into their programs or classrooms. To be useful however, the visualizations need to be purpose built for the field it is being applied toward [5]. In this case, that purpose is using educational data toward improving the student learning experience, both directly and indirectly. Unfortunately, someone looking to try making visualizations for that purpose has no direction or supports as to how to go about that, and would have to start from scratch.

The project is a qualitative study, looking at how assessment practitioners are using and hope to use the educational data available to them, as well as their views and beliefs on the assessment practice, data usage, and visualizations. The project goal is to build a support toolkit that can direct a struggling educator to appropriate visualizations, given their assessment needs. To build an effective design of such a toolkit that would support real hurdles and current practices, we had to first build a conceptual model of how educational data was being used in departments currently and the beliefs that surrounded its usage.

Data was drawn from interviews and focus groups participated primarily by faculty and support staff at universities involved with teaching and learning, specifically around assessment data gathering, analysis, and support. The study is planned to be conducted in three phases, of which we are currently still in the first. Briefly, the three phases are an exploratory interview phase where we are trying to identify the major concepts from which the

model will be built; a feedback phase in which it is built with the help of a focus group of experts; and finally an evaluative phase in which a version of the toolkit is built and tested by prospective users in various roles. The project is in the second of its three phases. The findings from the first section are what are discussed in this paper. The research questions that have been guiding the research are:

- (i) What are the most common motivations to use educational and learning outcomes data?
- (ii) What kinds of data are currently available to and/or collected by faculties?
- (iii) What barriers have been the biggest hindrance to an efficacious use of the data?
- (iv) Are there supports that have helped in illuminating information from large sets of data?
- (v) **What are the attitudes and beliefs from faculty surrounding data collection and usage?**
- (vi) What key characteristics of visualizations maximize the provided insight pertinent to each of the common motivations for data usage?

Specifically, this paper focuses on the fifth research question. The rest of the paper is structured as follows. We will discuss our methodology and process for qualitative research, followed by the analyzed findings and finally, we sum up with the future work in the project and conclusions.

2. QUALITATIVE METHODOLOGY

The qualitative methodology was guided by two main resources: McCracken's guide to long qualitative interviews from *The Long Interview* [6] and Charmaz's guide to grounded theory in *Constructing Grounded Theory* [7]. Information from both were used to guide the practice and methodology of qualitative data gathering and analysis.

The initial steps for the project were guided by *The Long Interview*. Specifically, the book discusses the two major first steps being a Review of Analytical Categories followed by a Review of Cultural Categories. This former took the form of a literature review of the major works surrounding visualization [8]–[10], [5], learning outcomes assessment [2], and change management [11], [12]. While the latter was a procedure of familiarization with current assessment regulations and initiatives at the primary institution of study, Queen's University.

The next part of McCracken's process is the Discovery of Cultural Categories, which involves the creation of the interview protocol and conducting the interviews. Using the guidelines and strategies provided by the book, the research questions were expanded into questions that would best prompt the participant to recount their experiences around data usage and in a way that would not direct the participants to answer in any particular way. Elicitation tools were also used to prompt the participants.

With regards to data usage, they were provided with a list of data sources and were asked to discuss any ways those sources might relate to their practice. For questions related to visualizations, they were provided with unlabeled visualization mock-ups and asked to discuss their encounters with them. The questionnaire was piloted with members of the team and refined before being used with real participants. Once completed, we applied for and received ethics approval from the university ethics board and contacted participants for study.

With regards to the participant pool, we wanted to ensure that we were sampling from a wide range of experiences and beliefs. The major criteria for sampling diversity included whether they were at Queen's or not; whether they were faculty or staff; instructor or administrative role; whether they had a formal or informal role relating to assessment data or visualization; and whether they were from a professional program, a science program, or a liberal arts program. Support staff in this case refers to roles in university units that function to support teaching and learning in indirect ways. This includes offices of research and planning and centers for teaching and learning. To find participants, we used Snowball Sampling where the initial set of participants were based on a pool suggested by the research team. From there, additional participants were selected from suggestions from the participants. The aim is to make sure at least one participant from each criteria was being sampled to ensure that no major aspects happening in specific roles or departments that might be crucial to the framework were missing.

Since the project team was largely from an engineering background, the initial set of participants and their subsequent suggested participants had close ties to engineering. Due to logistical constraints, the participants are largely sampled from Ontario. Since education policy is driven at the provincial level, this might be an important constraint on the scope of the support as other provinces might have different concerns and beliefs about assessment data. A summary of the participant pool criteria can be found in Table 1.

Table 1: Participant distribution

	Number of Participants	
Faculty vs. Staff	5	7
Instructor vs. Administrator	5	7
Queen's vs. Other Org.	9	3
Engineering vs. Other discipline	6	6
Ontario vs. Other Province	11	1

Additionally as part of the Discovery of Cultural Categories step, McCracken provides guidelines for researchers about how best to run interviews. This includes

how to prompt further question effectively, elicit rich responses, and how to conduct one's self during the process. For us, interviews roughly lasted one hour which was a good amount of time for most participants to complete the questionnaire in a satisfactory way.

McCracken's final step, Discover of Analytical Categories, which deals with the analysis of the resulting interview responses was relatively sparse for such an onerous task. This is where Charmaz's approach to Grounded Theory was used as detailed in Constructing Grounded Theory [7].

Charmaz's take on grounded theory is an abductive approach that stays close to the data throughout the analysis process. This is in contrast to other forms of grounded theory which take an inductive approach, which moves further and further away from the original data as the analysis proceeds. These other approaches tend to work better when all of the information you are looking for will be found within the data. We believed that the analysis process required information and input from outside the data, especially since many of the participants were some form of researchers themselves. As such, rather than just studying them, the intent was to build this model with them. An abductive approach provided the best means to that end since it involved constantly going back to the data as new information arises.

While grounded theory is primarily geared towards building full-fledged frameworks, since there was no direct conceptual framework we could find to build off of, we used the bulk of its methodology to create and fill our model, as described in the Findings section. The difference between a framework and a model being that a framework is a perspective that guides one's thinking, while a model is usually built within such a framework and helps bring some order to the data being gathered. In our search, we were not able to find a suitable conceptual framework to work with, and picked grounded theory as a result.

The NVivo software was used to conduct the analysis due to the length of the interviews and breadth of the subject areas. Charmaz recommends that the data be coded as actions and processes: By hand, each statement from participants was coded into their own gerund, or action verb. Our approach was to find all significant statements in an interview and mark them as an open code. Once complete, each code was looked at individually and the process that it is explaining is described in a gerund. Not each open code maps to a unique process, so often the same process can be mentioned multiple times in an interview. After, in a method called focused coding, those actions and processes are grouped together based on similarities seen between them. These groups are what Charmaz refers to as 'Camps'. In subsequent interviews, the open codes are mapped to previous processes, and if there is not a process to sufficiently describe the new code, then a new one is created. Eventually, these camps start to build categories, each with properties and dimensions. One central process

code will be used as the category, while the rest of that camp will serve as its property or dimension.

In lieu of a proper conceptual framework, we used our eventual toolkit product as a goal to work back from. Since it is intended to be a software tool, we drew on software requirements engineering to help guide our model building. Specifically, we separated the system, our toolkit, from the and actors that would interface with it. We came up with three broad groups of actors which we used to link the categories that were found. These are discussed in more detail in the findings section.

During the entire analysis process, I am also keeping descriptive journals about my decision making process. This is vital for me to understand how and why I am coding the way I am. My biases and prior knowledge completely and unavoidable impact the analysis process and it important that I keep track of them so as to be aware of their influence on the findings.

Since qualitative analysis is heavily influenced by the researcher's worldview, a key part of conducting good qualitative research is member checking. It is the general process of returning to the participants after an analysis to confirm that your findings are an accurate reflection of their sentiments and responses. To do this, we recently ran a focus group with many of the interview participants as part of the second phase of the study. The protocol for the focus group was structured to give the participants a chance to reflect on our key findings, correct them and provide any further insight. Unfortunately, we have not had time to adequately analyze the responses, at the time of writing, but we do discuss major takeaways at the end of the findings section.

3. FINDINGS

As mentioned, we used the idea of actors from software requirements engineering to organize our categories into three major groupings. These are groups of actors that we found, based on the data, whose roles could be clearly defined and separated. The groups were clients, data-workers and end users. Before explaining their roles, a central idea which they are based around is what we are calling a data-need. These are tasks or goals that require data to complete or achieve. These have a wide scope and could be as small as wanting to know the distribution of students in a classroom that meet a threshold, to effectively reporting that the learning outcomes for a program are constructively aligned.

In our model, clients are the stakeholders that have initiated the data interpretation process and have data-needs for their practice. Common examples of clients would be instructors trying to improve their practice, or administrators trying to understand their program needs. Data-workers are users with experience working with large

sets of data. Their role in our model is to move the data from raw data to representations that can assist those client needs (in our case, largely through visualization). Good examples of people associated with this group might be support staff, whose role is to help with teaching and learning, or data analysis, or creation of reports. Ends users in our model are the people who the data was intended to be communicated to or analyzed by. Possible stakeholders that fall into this group might be students, or external accreditors.

Additionally, an important aspect of these model groups is that they are not mutually exclusive. A real-world user might fall one, two or all of these groups based on their practice, as with an instructor who is creating their own visualizations to explore how their class is performing. The groups were separated this way to also model when these groups are performed by distinct people in a task pipeline like in the case of an administrator (client) working with the office of research and planning (data-worker) to create a report for external quality assurance reviewers (end users). Fig. 1 displays the three groups and a sample of the camped codes that are associated with them. Notice as well, the arrows between the groups that represent the camps relating to the interaction of those groups. There were a lot of camps that were discovered from the data; too many to discuss here. For the purposes of this paper, we are only going to talk about the ones that we think might be interesting to readers.

3.1 Clients

Since it is client issues that the interview questionnaire was designed to primarily elicit, it provided the richest data. As such, to help sort information there are two further large categories that the coding camps were grouped under, practices and beliefs. Camps under practices relate to findings about how clients work with or do not work with data, while beliefs deal with findings about how data is thought about when conducting their practice.

Defining Data Needs. How data is currently being used is one of the research questions of the project. However, what was found to be equally important was how data is not being used. Specifically, how many members of faculty do not spend very much time reflecting on the collected data. One participant stated that members of their department “don’t spend a lot of time thinking about the outcome results.” However, this participant does not see it as a fault of the instructor. Instead they believe that the only activities that have enough time allocated are ones that “faculty members want to or have to get done on time. So if I’ve got an abstract deadline looming for a conference, that’s going to be ahead of reflecting on my teaching outcomes.” Also that it can be “difficult to sit down and look at the written results, particularly if they [course feedback forms] are written in a less than friendly tone of voice.” As they mentioned, “self-reflection is not part of

the teaching culture at [their institution]” and he believes that culture needs to change before instructors start taking the time to reflect with the data.

Fig. 1. Model Diagram shows the three groups of categories and their related camps as well as the camps associated with the intersections of their roles.

Continuum of Engagement. Also in regards to that culture of data usage, there is a wide range of how departments and faculty approach the processes. At Queen’s, there is a quality assurance process that every departments must follow every seven years. This process usually involves participation from the whole department and time to reflect on how well a program is doing. This view is not always shared by the whole department. As one faculty member and department coordinator put it, “it’s approached as a box that has to be ticked ... a hoop that had to be jumped through.” And another participant in a support role that often works with departments states “There are cases where the whole process is seen strictly about accountability and departments feel that they need to defend their programs. There are other departments which take more of a continuous improvement approach- and they see the self-study as a way to get quality enhancement.”

And so there is, as the department coordinator put it, a “continuum” of engagement in the faculty. This can even be evident in reports. Upon reading one, the participant states “it’s very clear that the department tucked into this whole process and decided to make it really a great process for the department ... some departments really take in on board and they really do a great job.”

3.2 Data-Workers

When looking at data-workers, there are fewer camps and there wasn’t a need to further categorize them. The two categories that are going to be discussed here however are broken down further into the camps that are part of them.

Not Dumping Data. In many cases in a data interpretation process, it is people in the data-worker role that have access to the data and provide it to the departments. Providing this data however is not as simple as giving them access for many data-workers. As a participant in such a role described, “twenty-five years ago, offices like [theirs], put out things called Fact Books, which were thick, dense tabular data. Everything that we-everything that could be put in a table, was put in a table, undigested, unfiltered, unfriendly to the reader... Somehow, if somebody had the patience, they could probably go through and pick a number and start to learn from this data. That’s just raw data and that’s not what we do anymore...I prefer not to give raw data away...In fact, it’s not even data- raw data, it’s chaos.” So instead now, they feel that they need to add value to this process, they go on to describe the process going “from data, through to analysis, through to synthesis, through to application and interpretation. We shouldn’t be giving anyone data. Our job is to move it forward into one of those higher levels.”

Keeping Data Honest. Another aspect of this hand off of data in various stages is being careful with how one transforms the data for the client’s purpose. One participant states “the hard truth is we’ve given [the department] the data, and by [their] rethinking of it, or by repackaging it, [they’ve] missed the point. We have a responsibility to say that. So it’s not just what a user... recipient said “You know, can you twist it this way?” Because that might mask or distort the truth of the data.” Which is different from asking more honest translations, such as the client asking “Well, can you give it to us as a line chart?” ‘Okay, if it means that much to you, sure.’ Because it doesn’t distort the truth of anything.” One less active way that the data often gets distorted is through averaging data, which is used with caution. As another participant in a similar role discussing bar charts states in a scenario states, “You’re sort of only going to get one measurement or you’re going to have to do a lot of averaging to present it that way. So, I haven’t used anything like that in my reports.” And when asked further, they go on “It was important to me not to average different measurements together” but given the

often large amounts of data, “ultimately you have to, otherwise you’ve got way too much data” and so it ends up being a intricate and deliberate process “between trying to make the data accurate versus make it accessible and useful.”

3.3 Client—Data-Worker

Since in our model the role of the data-worker is to assist in achieving the client’s data needs there is some interaction that is going to be had. As part of our findings, we found some codes that relate to ideas that come into play as part of that interaction.

Understanding Data Needs. As part of the interaction, it is important that clients are able to articulate their data needs clearly and then communicate them to the data-worker accordingly so that they can assist them effectively. As a participant in a support role recounts, “how do you give an answer to the question ‘How many students does Queen’s have?’ Do you know how many different definitions there are to the number of students Queen’s has. Do you include BISC or not, what about exchange students, here and away. Do you double count those or do you just take one or the other? Is it head counts, or is it full time equivalents?” Which boils down to being able to help them, “If [the department] can’t tell us that, how the heck do we know what form they want the data in, right?” This is closely tied with adding value to the process.

Making Data Accessible. One aspect that is closely tied to this relationship is presenting the data in a way that the client’s find value in it, “present that data in a more meaningful way and in a way that is accessible to them” and “if [another representation] makes the data more immediately apparent what it means, that would help” because “it’s quite important ... given the challenges of getting them to actually look at the data”. Again, this is closely tied with not dumping the data in a way that is honest and accounts for the client’s data needs effectively.

3.4 End Users

With the end user group, the related camps have been the least so far. This might partly be due to the interview questionnaire not focusing on their role or how we defined the group in the model. However, they are still clearly an important group to consider as well as the associated findings.

Trusting Process. An important aspect with considering many of the end-users is how they view the process of working with data. As someone in a support role states, “a lot of people are quite skeptical about it” referring to tools that “can be used to somehow assess in ninety minutes what the students have learned.” Since “it is only survey data, umm, we have to be cautious with it.” For one department head, although they have bought into the quality assurance process, they have little faith: “the data

we get, it's not really good data, and it doesn't really allow us to understand what's going on all that much better than we already did." As they state "there haven't been very many papers that actually show, "Oh, we got this outcome data and it allows us to make intelligent changes that we never would have understood to make without this outcome data." Ultimately given all that, they are "entirely convinced that the amount of effort necessary to do the process is going to show up in improvements that we couldn't have achieved through other means." As a result, this has a big impact on the engagement from the faculty.

3.5 Client—End Users

While findings related to the end users specifically has been sparse, the interaction between clients and end users has been a much richer group of coding camps.

Coming Together. One theme that came up among many of the participants was about bringing a department together for discussion. As one department head describes their current data working process, "I would probably like a more orderly system, but the relatively disordered system that we've got is working really well because we've got really good people, most of whom are going in pretty much the same direction. And if you get five of them the table, you could have lively conversation and some disagreement on just about any topic you want to pick. But if you stood back from a little more distance, you'd realize that they're all talking about the same thing with slight differences of opinion on how to approach it." As someone reading a quality assurance report can identify, the department "seemed to all work together and it has become a really cohesive group of people who can see the value of this", as part of the process the department and support personnel "can together look at some trends in the data and come up with ways of moving forward."

Not Shaming Faculty. Often, clients want to bring data back to faculty in a department to collectively reflect on how the program is doing. A big hurdle to circumvent here is presenting the data in a way that doesn't shame them. As someone in a role supporting those department explains a scenario where they ask "what program learning outcomes are really emphasized and where, and in which courses? And which ones are least emphasized and- and again, in which courses? That is not to shame those courses" because that is often their natural response. As an instructor and department head elaborates "the instructors are often worried that people are going to critique how they're grading things." As someone in a support roles states, "there is a psychology of bad data must mean, I'm being punished." Instead, it should be emphasized that "these data are provided as an improvement tool, not as a punishment." Otherwise, the unfortunate consequence is that "bad data becomes easy to ignore just because then you don't have to self-incrimination or fear of punishment, it's nonsense."

The interaction with the data-worker and end user is relatively sparse in the scenario that the data-worker and client are separate. From the interviews, there have not been many findings.

While we cannot yet provide a full analysis of the focus group, some of the major feedback was indicated that instructors and support staff alike found that there was a serious lack of resources for them to lean on when trying to work with data, in two major ways. Firstly, there were not enough personnel that could provide support. All the participants indicated that they would appreciate more roles dedicated to working with data. The other lack of resources was not having a central data storage. Many of the participants did not know of much of the data that was accessible to them, even for data about their own departments. And in many instances where they did know of other data sources, the data was in a format that would take too long to reconcile with their own data. As such, a central storage with a consistent format, for example a database, where instructors and program administrators could find and provide data based on their access privilege would be highly beneficial.

4. FUTURE WORK AND CONCLUSIONS

The findings from the interviews and focus group discussed here are going to be what shape the support toolkit. Our next steps are to analyze the focus group responses to ensure that our model has interpreted information correctly and with accurate priorities. However, much of our findings deal with hurdles outside the scope of what our project deliverable is intending to support. The support toolkit we are building is only meant to be a single piece that helps users leverage other pieces of a much bigger process.

From our findings however, we can see that educational data has intricate beliefs and practices that need to be taken into account when trying to implement data-driven change. There is a delicate interaction among a number of players, each with their own set of hurdles and practices that need to be accounted for. We are hoping that what we build can help ease some of those interactions and move data towards positive program improvement more smoothly.

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