SENSEMAKING DURING THE USE OF LEARNING ANALYTICS IN THE CONTEXT OF A LARGE COLLEGE SYSTEM

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Robert Kenneth Morse

Sensemaking During the Use of Learning Analytics in the Context of a Large College System

This research took place as a cognitive exploration of sensemaking of learning analytics at Ivy Tech Community College of Indiana. For the courses with the largest online enrollment, quality standards in the course design are maintained by creating sections from a course design framework. This means all sections have the same starting content and the same framework for assessment. The course design framework is maintained by the curriculum committee composed of program chairs who oversee the program to which the course belongs. This research proposed to develop a learning analytics dashboard to elicit the best practices in instantiating a course design framework from the perspective of the program chair. The Instructional Design Implementation Dashboard, IDID, was designed to address the sensemaking needs of program chairs. The program chairs were asked to make sense of IDID built around the data collected from the course management system and the student information system. IDID leveraged metrics from the user activity and the learner performance from the learning management system, combined with data about the student demographics captured from the student information system. IDID was used to identify highly successful sections and examine the instructor behaviors that might be considered best practices. Data Frame Sensemaking theory was confirmed as an accurate description of the experience of program chairs when using IDID. A revised model of Data Frame Sensemaking theory was developed to explain the interaction of those using the IDID platform.

Erin Brady, Ph.D., Chair

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Chapter 1. Introduction

1.1 Introduction:

Imagine for a moment a design scenario where a course is designed according to the Quality Matters™ (QM) design standards. A major principle presented by QM literature is the concept of alignment, whereby course materials, activities, and assessments align to session level objectives, which in turn align to course-level objectives. (Shattuck, 2007) In this activity, alignment that is captured in the Session Alignment Matrix or SAM, is evaluated across two conditions: horizontal alignment and vertical alignment. Horizontal alignment is achieved when the material, activities and assessment align within a session. For example, let's state the course level learning objective as "Discuss the differences between federal and state government, including the relationship between the three branches of government." This is broken down to two session level objectives which read, "Compare and contrast the Indiana state courts and federal court systems. Include in your discussion an outline of the relation between the two courts, i.e., where do these two court structures connect or overlap?" and "Compare and contrast the functions of the executive, legislative, and judicial branches of government. Include in your discussion the concept of checks and balances and how it applies to each branch." In this scenario horizontal alignment is achieved through the alignment of the materials, a textbook chapter which compares the federal and state legal systems, the activities and assessments, a discussion board, a writing assignment, and a chapter quiz, all tie back to the stated learning objectives. Vertical alignment is achieved when there is progression in the elements of instruction from one session to the next session. For this example vertical alignment is demonstrated in the learning of a case study analysis method in one session and the practice and then later assessment using this method in future sessions.

How might we use alignment then, as a means of evaluating the overall course design quality? For instance, if the student is asked to write a culminating assignment like a presentation of a final project to classmates have they learned all the skills needed to be successful? Do students have the resources they need or know how to access the resources: in this scenario, they might need guidance on PowerPoint or where they can get help with academic presentations? In this way alignment is about filling in the instructional gaps so that students can successfully progress from one set of instructional experiences to the next set of instructional experiences.

In 2006, under a grant from the Fund for Improvement of Post-Secondary Education (FIPSE), Quality Matters became the first intra-institutional quality course improvement process (Shattuck, 2007). Appendix A describes the history of quality initiatives in online education. The internationally subscribed program does allow for some benchmarking to other institutions but only evaluates course design. Course delivery falls outside the scope of the Quality Matters rubric and therefore is best evaluated through other evaluation methods. So, within this scenario there exists the opportunity to evaluate how well the course design is implemented.

With increased focus on quality, many colleges and universities run large enrollment online courses by maintaining course masters or rather course design frameworks. A course design framework enables curriculum managers to instantiate hundreds of course sections by keeping under control the quality of common elements of instruction. By implementing the frameworks within a learning management system, data on the relative success of each section can be collected and analyzed in a learning analytics system.

Attempting to describe the decision support that a learning analytics system provides, researchers such as Siemens (2012) have applied Sensemaking Theory (Weick, 1995) to understand end-user interaction within the system. Russell, Steffik, Pirolli, and Card (1993) define sensemaking as “the process of searching for a representation and encoding data in that representation to answer task-specific questions.” (p. 1) More specifically sensemaking fits into the conceptual framework evaluating the user experience with learning analytic dashboards. In the words of Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. “Most evaluations evaluate only part of our conceptual framework and do not assess whether dashboards contribute to behavior change or new understanding, probably also because such assessment requires longitudinal studies” (2013, p.1). There is a known dependence on mental model formation to properly interpret what the analytic system represents (Greitzer, Noonan, & Franklin, 2011). Liu and Stasko (2010) are very clear about the connection of mental models to analytic reasoning. They write, “Given a problem, a mental model of an interactive visualization can be constructed and simulated in working memory for reasoning" (p. 1001). While this dependence on mental models has been shown, the knowledge sources that the user draws on to form the mental model of the interactive learning analytic are not yet fully identified. The knowledge sources which support mental model formation have not been explored fully in the conversations regarding user support for learning analytic systems. The discussion of user support for learning analytics has been limited to discussion of interface design and techniques of interaction (Keim et al., 2008). Even researchers such as Pirolli & Card (2005), Klein, Phillips, Rall, & Peluso (2007) and Attfield, Hara, & Wong (2010), who have developed models to explain sensemaking, do not mention the various sources of knowledge that a user might depend on to form his or her mental model of the interactive system. Knowing the sources of knowledge used to form a mental model of the system will assist system designers in developing support structures to promote sensemaking of the systems they design.

Curriculum managers of course design frameworks are in need of decision support systems to make sense of the activity and performance data collected by various enterprise systems.

1.2 Problem Statement:

As previously stated, curriculum managers are tasked with making sense of large amounts of data collected from every section running a particular course design framework. In this case because every section across the state has implemented the same course design framework the course is referred to as statewide. There was no central repository for both usage statistics and grade data. **Figure 1** shows the current state of course reporting at Ivy Tech Community College of Indiana.

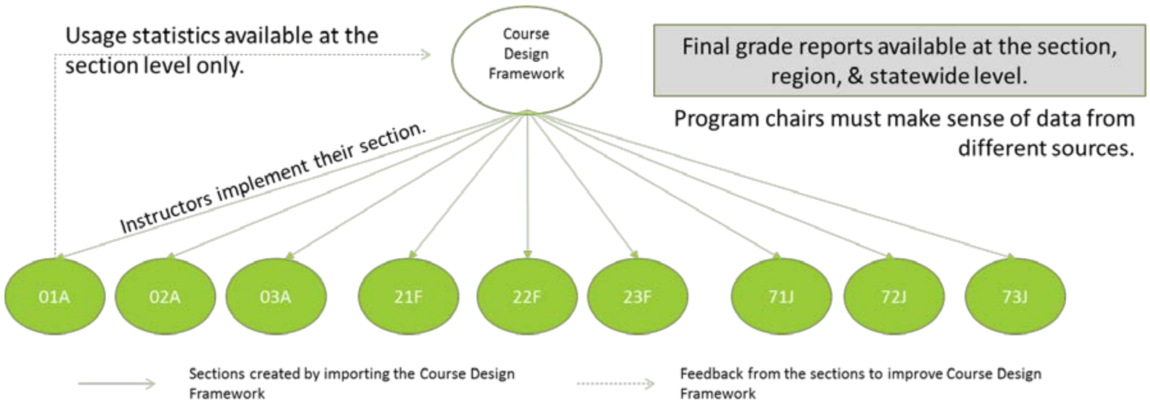


Figure 1: Previous Course Reporting Framework

In this image sections that end in the same letter are delivered in the same region. For each given region that offers a program, a program chair or designee participates in the curriculum committee for that program. Usage statistics and final grade reports are generated out of separate systems. Additionally, usage statistics are available at a section level with no aggregation of statistics from the same course design framework. Within the Ivy Tech Information Technology ecosystem there did not exist an analytic system to support the decisions that program chairs are required to make on large enrollment multiple section courses. These decisions might include determining the efficacy of optional or supplemental materials. Or the promotion of one set of materials or user behaviors over others that are not as effective. Furthermore, sense making theory lacks rich description around the knowledge that users draw from to form hypotheses about the system. **Figure 2** represents the proposed course reporting system. The new system will provide aggregate usage statistics and correlational summaries of the impact of usage on end of course performance. Instead of forcing program chairs to query multiple systems all the data from their courses will be collected in a single system. Aggregation of both usage data and grade data will be available at both the regional and statewide level.

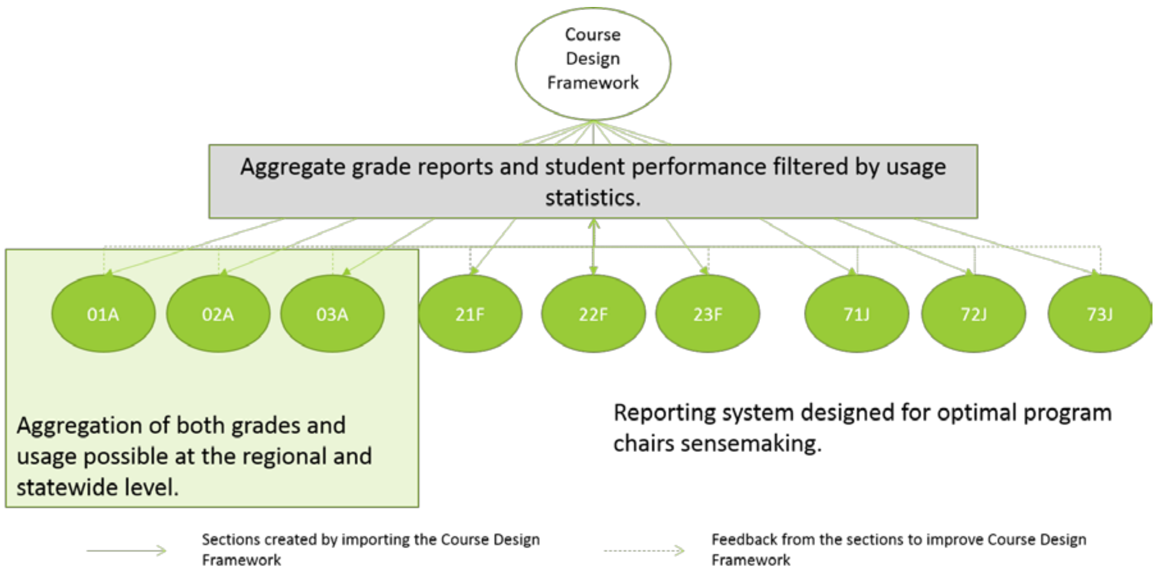


Figure 2: Proposed Course Reporting System

1.3 The Statement of Purpose:

The purpose of this research is to design a novel analytic system for the expressed purpose of supporting curriculum managers' or program chairs' efforts to improve course design frameworks. To accomplish this goal a set of system requirements from the perspective of program chairs will be captured. A further goal for this research is the exploration of the cognitive experience during use for course design decision makers using this system. A rich description of actual sensemaking is the expected outcome of this research.

1.4 Research Questions:

Main Question 1: What are the most efficient design strategies for a progam chair-centered dashboard that supports the semester to semester decision making of program chairs?

> **Sub-question 1:** What are the requirements for program chair sensemaking of learning system data?
>
> **Sub-question 2:** How well do novel analytics tools support program chair information needs?

Main Question 2: How does actual sense making by program chairs relate to sensemaking theory?

1.5 Definitions:

Key Terms:

- **Course Design Framework-** Master set of initial materials that is imported into each section.
- **Curriculum Committee-** The group of program chairs for each program. They are responsible for selecting the resources used and approving the course design framework.
- **Developers**– the person responsible for building the course design framework in the learning management system.
- **Mentors**– the shepherd of the implementation of a course design framework.
- **Program Chairs** – the key decision makers regarding curriculum. They must approve all changes in the course framework.

- **Region-** Ivy Tech has 14 regions which act as administrative units. Each region has a program chair.
- **Section-**The point of implementing a course design framework by an instructor for a class of students.
- **Statewide-** Refers to Course Design Frameworks which must be used as the starting point for every section in every region.

1.6 Limitations:

This research took place within the normal course development process at Ivy Tech Community College of Indiana. Courses are redeveloped at Ivy Tech on a three-year cycle. When a course is eligible for redevelopment the curriculum committee makes a decision if it will undergo major redevelopment or minor redevelopment. For courses in major redevelopment a brand-new session alignment matrix (SAM) is developed. For courses in minor redevelopment the existing course design is improved upon through the analysis of historical course data and instructor feedback. This research looked at actual sensemaking for courses in a minor course redevelopment.

To this end the exploration of the sensemaking phenomenon was limited to actual sensemaking from real Ivy Tech courses. In no way was the experience of decision makers influenced by an artificial manipulation of the activity and performance data being investigated. This also means that there were no preconceived notions of a right or wrong way to use the Instructional Design Implementation Dashboard (IDID). Research into the quality of decisions supported by the IDID system is still needed. It is possible that the task list provided a framework for sensemaking by end users. Users did not have a free form exploration of the learning analytics system. Instead users were guided through the analytics system with a series of questions they were asked to answer. It is possible that the task structure provided guidance to the sensemaking process. Furthermore, not only did I act as the investigator but, I was an active respondent in the consultation interviews and may have influenced the discussion through my role as Senior Instructional Designer for Quality Initiatives. Drake (2010) explores some of the challenges of insider research. She writes, “These differences offer illustrations of four aspects of the problematics of interviewing as follows: (1) personal relations and expectations position everyone in the interview; (2) the motivation for the research affects what the researcher learns; (3) the same material generates accounts that emphasize different things; and (4) things happen in people’s heads during the interviews that are not recorded.” (p. 85)

1.7 Validity and Reliability:

Following the claims of LeCompte and Preissle (1993) this research draws on the same criteria that demonstrate the high internal validity of the study. There were several practices that increased the validity and reliability of this research. First, the researcher was a part of the decision making team and had an equal stake in the proper application of the dashboard to make course improvement recommendations. As an insider research I am more familiar with the politics of institution and the cultural nuances which might be lost by someone outside the institution. The emergent categories are taken from the respondents’ own words.

Wherever possible I allowed the phrases to speak for themselves. I developed a code book for the qualitative analysis. I used my expertise in understanding the context of Ivy Tech and Human Computer Interaction to match each phrase to the most appropriate code in Nvivo. The observation occurred on the respondent's own computer not a laboratory setting. Respondents were able to interact with the IDID platform on their own computers from their own offices. This allowed for maximum comfort in demonstrating their use of IDID. Finally, the data analysis incorporated the researcher's own reflection and self-monitoring which Erickson (1973) calls disciplined subjectivity. While my own contributions to the interactions with respondents had an effect on the overall quality of the data collected, this insider researcher role was fully acknowledged and reflected on prior to and during data analysis. Here is a brief summary of my role from my own words during the pilot study. "As a senior leader of the course development process, the researcher is partly responsible for implementing course development policies. The researcher has been working with program chairs in the target program chair's committee for almost five years." It has since been another five years in completing this full research. Permission was sought at multiple levels of the institution. The Vice Chancellors of Academic Affairs who are the chief academic officers within each region were informed about the research and they forwarded my email on to their program chairs and encouraged participation in the research. This level of institutional sponsorship for the research may have had an effect on the level of participation I saw throughout this entire study.

1.8 Ethical Issues:

There are several ethical issues which needed to be considered while conducting this research. Merriam (2009) writes, “the protection of subjects from harm, the right to privacy, the notion of informed consent, and the issue of deception all need to be considered ahead of time, but once in the field issues have to be resolved as they arise. This situational nature of ethical dilemmas depends not upon a set of general pre-established guidelines but upon the investigator’s own sensitivity and values.” (p.230) Given the collaborative nature of my research I had an obligation to guide the respondents to see patterns in the data that they might have missed without my assistance. This was necessary because I was serving in a dual role of both investigator and Senior Instructional Designer. The use of the IDID platform had the side effect of identifying underperforming sections. I was very careful not to allow the tool to be used in a punitive fashion for faculty who fell into this category. Individual instructors were not identified within the tool. Sections were instead identified by section number only thus attempting to focus the review on the most successful behaviors not on the individual instructors. Likewise the tool provided the ability to drill down to the individual student record, I was careful to make sure that all interaction remained at the aggregate level and did not identify individual students or faculty. Lawson, Beer, Rossi, Moore, and Fleming (2016) cited the definition of learning analytics from the first annual Learning Analytics and Knowledge conference and state that institutional use of analytics must be perceived as serving to benefit student learning. (p. 963) Beattie, Woodley, and Souter (2014) proposed the development of learner centered learning analytics. They write, “Learner-centred learning analytics provide a clear benefit to learners, are owned and co-produced by learners and are transparently and openly used in an environment of trust where data will not be used to disadvantage or negatively stereotype anyone.”p. 423) Although, this project did fall short on fully disclosing to students how their data would be used there were some protections taken to protect student identities. All names were removed from the dataset so that individuals could only be identified by their student identification number. Each respondent was presented with an informed consent (Appendix B) which outlined the risks and benefits of the study and indicated clearly that participation at each step of the study was completely voluntary. The anonymity of the respondents was protected by using pseudonyms for each respondent. Pseudonyms were selected randomly by the researcher.

1.9 Rationale and Significance:

A tool for the identification of best practice in the instantiation of course design frameworks will be a major step forward for learning analytics. It will acknowledge that to be successful a community of practice must continue to refine and support its standards of practice. As Wenger & Snyder (2000) state, “[A community of practice is] an ideal forum for sharing and spreading best practices across a company.”(p. 141) According to Wenger (2011), “Communities of practice are groups of people who share a concern or a passion for something they do and learn how to do it better as they interact regularly.” (p.1) It is expected that the dependence on the range of knowledge sources will shift towards greater need for contextual knowledge as the unit of analysis grows in complexity, which it is expected to be demonstrated through the shift from course level to campus level to region level analysis to system level analysis. An identification of the knowledge sources for mental model formation further supports the use of visual analytics by supporting the fundamental cognitive processes associated with sensemaking. It is expected that the knowledge typology proposed may be of use with minor modifications to other domains such as medicine or government.

Both the design approach and the description of knowledge sources which support mental model formation will inform the field of visual analytics and, specifically, learning analytics. The most significant contribution is the revised model of data/frame sensemaking theory. This model describes actual sensemaking by users of IDID. Such a model would be useful to learning analytics systems designers and researchers as it describes the cognitive phases a user experiences when interacting with a learning analytics system.

1.10 Role of the Researcher:

The researcher was the main instrument of data collection and acted in a dual role of researching the phenomenon and developing tools to improve the state of data reporting from the college's learning management system. Not only did I act as the main filter for data collection and analysis but also, I was responsible for the continuous improvement of the college's course design frameworks. In this capacity I was able to apply my expertise in learning analytics to the interpretation of user experience of the IDID system.

1.11 Research Assumption:

A requirement was that the tool would address the needs of a variety of stakeholders at multiple levels of the institution. The main assumption of this research was that if the needs of the curriculum owners could be met, then the needs of the other groups, such as course developers, course mentors, and instructional designers would also be met. The curriculum owners were a much wider set of people, some of whom were also course developers or course mentors. While the design of the tool itself held to a rather positivist viewpoint regarding learner activity and performance, research of the tool remained in a rather constructivist camp, attempting to understand the ways in which users made sense of the data presented through the tool. This system works best on courses that require a lot of interaction with content from within the Learning Management System. Courses which have a lot of third party content which is managed in the third party system rather than a set of links to the same content in Learning Management System lose out on some of the insight gained by this system. Also the interaction in the course is sometimes mitigated by the content availability within Blackboard. For instance in some courses all the content is open and available to students from day one. In this case students could go in and download all their content on the first day of the semester. Subsequent interaction would occur within the local copy of the content rather than interacting with the content within Blackboard. This has the potential of skewing the activity data. Students would still be required to access each content item so use versus non-use of course resources is still recorded but, there are some limitations to how one might interpret the activity data.

1.12 Organization of Dissertation:

This dissertation is organized as follows. Following this brief introduction, the relevant literature is explored and the research project is grounded in its theoretical base of Sensemaking Theory. After the literature review, the research methods are fully articulated, followed by a chapter describing the results of the study. Following a presentation of the results, there is a brief interpretation of the results and application back to sensemaking theory. This dissertation continues with a suggestion of further opportunities for inquiry. Finally, the dissertation concludes with a summary of the contributions of this research.

Chapter 2. Review of Theoretical Background

The following is an outline of the literature that forms a theoretical base for the design of a Best Practice Finder. The Best Practice Finder or Instructional Design Implementation Dashboard (IDID) is a visual analytics dashboard which correlates the activity information, where students and faculty clicked in the learning management system, with the performance data, what the students received as a final grade. The purpose of the dashboard application is to leverage the millions of rows of data collected on students and instructors and present it in a way that allows for the easy identification of behaviors which lead to success. First, there will be a look back on the history of academic analytics and learning analytics. Second, a short overview of sensemaking theory and its application to understanding the user experience of visual analytics tools will be presented. Finally, there will be an exploration of recent trends in research of mental models of interactive systems and methods of eliciting the mental models of research respondents.

2.1 Academic and Learning Analytics:

Goldstein and Katz(2005) popularized the term “academic analytics” as part of an Educause Center for Applied Research study titled *Academic Analytics: The Uses of Management Information and Technology in Higher Education*. The report focused on how various institutions of higher education use analytic tools and to what degree. They defined five stages of application ranging from “extraction and reporting of transactional-level data” to analysis, predictive modeling, and ultimately action (triggered alerts). They found that 70 percent of the more than 300 institutions replying merely reported simple transactional data. (p.53) For education and business, analytics involves more than capturing and reporting data. The true advantage is predicting behavior and acting on that prediction. The results can then be fed back into the process, improving the predictions over time. By 2015, Educause had further refined their definition of academic analytics to encompass two main types of analytics. Institutional analytics are aimed at improving services and business practices of higher education and learning analytics are focused on improving student success. (Yanosky and Arroway, 2015)

In 2007 the Association for the Advancement of Computing in Education published a special edition of the *Journal of Interactive Learning Research* titled “Usage Analysis”. Articles in this edition were grouped into one of four categories. First, usage tracking modeling explores modeling the data flow of usage tracking systems. This parallels the modeling of the learning systems but uses language and constructs to capture the domain specialization of tracking data. Second, usage data analysis is used for descriptions of analysis systems. These may be web-based tools or separate database schema for analyzing usage data. These are in comparison to the third category, usage data visualization. Research in this area involves the development of tools to visualize the data. These tools differ from the previous category in that they provide exploration and interpretation, not necessarily summary of usage data. Fourth and finally, the usability of data explores how usage tracking data is used to improve the learning system. A major theme in these articles is the development of design patterns. (Choquet, Luengo, & Yacef, 2007)

Mazza and Botturi (2007) developed an extension to the popular open source learning system Moodle. GISMO stands for the Graphical Interactive Student Monitoring System. “[The research] illustrates how GISMO works, how it can be useful, and how it can be integrated in the day-to-day activity of online course management and delivery.” (Mazza and Botturi, 2007, p. 264) Around the same time period *Educause*, the premier organization supporting information technology in higher education, released a whitepaper on academic analytics. According to the Purdue Online Writing Lab (2017) “the purpose of a white paper is to advocate that a certain position is the best way to go or that a certain solution is best for a particular problem.” Academic analytics was coined as a term referring to the application of business intelligence methods to academic decision making. (Oblinger & Campbell,2007)

Later that year John Campbell completed his PhD program where he researched the development of an early warning system that would draw together analytics from various academic systems at Purdue University. The project later became known as *Signals*. The basic premise was to create dashboards of the most likely predictors of success for students and automate some of the student services interventions. *Signals* is currently a collaboration between Purdue, Purdue Research Foundation, and Sungard Higher Education to bring this product to market. (Arnold, 2010)

In addition to *Signals*, there have been a number of recent ventures focused around the early warning problem space. David Yaskins left Blackboard Inc. to found his own corporation. Starfish Solutions was the product of his work. When first developed “The Starfish application consists of two programs: Early Alert, which helps institutions to identify at-risk students based on their interactions in class, and Connect, which provides students with a personalized contact list of instructors, advisors, tutors, and counselors.” (Schauffhauser, 2010) In 2015 Hobsons, a leader in academic advising, retention, and student success, acquired Starfish Solutions.

Starfish is a partner of Blackboard’s Learning system. It extends Blackboard through the installation of an Application Programming Interface (API) referred to as a building block. In recent years, the functionality of learning analytics within the Blackboard frameset have been improved greatly through the development of open source building blocks. Building blocks are java-based extensions to Blackboard which take advantage of the published APIs that Blackboard has made available to the developer community for the purpose of coding these extensions to their system.

John Fritz (2010) of University of Maryland-Baltimore County has developed a building block related to the intent of this proposed research. This building block, called Check My Activity, allows students to compare their activity in the course against other students in the same class. It bins the grade book to allow students to check their activity against an anonymous set of their peers so students can self-regulate their learning behavior. However, Check My Activity does not aggregate students across sections. This functionality makes this proposal stand apart as an instructional innovation.

Fritz & Kunnen (2010) spoke about their experiences creating new tools to help monitor student behavior at the annual conference of the Educause Learning Initiative. Kunnen & Nucifora(2007) were awarded a grant through the Blackboard Greenhouse Initiative for their tool called Advanced System Tracking and Reporting (ASTRO). The ASTRO tool allows the system administrator to easily run reports on system usage across groups, schools, divisions, or other categories supported by course identifier naming conventions. From a technical perspective the tool was a massive step forward from the direct querying that was required from system administrators to get information out of the advanced system reporting (ASR) tool.

Within their grant application Kunnen & Nucifora (2007), cite the contributions of Glenn Parker from University of South Florida. Parker has made many of his Standard Query Language scripts available to the larger Blackboard community. Without his contributions, ASTRO would not be as robust as it is today. Although ASTRO makes the data of the ASR more accessible by summarizing key patterns of activity, the results are still only accessible to a system administrator role.

The inaugural conference on Learning Analytics and Knowledge was held in Banff, Canada in 2011. George Siemens (2012) cites the definition of learning analytics by the Society of Learning Analytics (SoLAR). According to SoLAR, “Learning Analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs**."** (Siemens, 2012, p. 4) This project sits between academic analytics and learning analytics as it seeks to optimize the learning design of large enrollment multiple section course design frameworks.

Looking over the contributions of previous scholars in the area of learning management system analytics and looking toward trends in the industry, this project is positioned to make meaningful improvements to an already solid foundation in this field. One important change in the Blackboard Learning System that is worthy of further mention is the Open Database project. Until recently only the ASR schema has been documented well for product developers. Starting with release 9.1 Blackboard announced an effort they are making to document the full learning system schema. This documentation significantly reduces the development time for Building Block developers who are expanding on the functionality of the core system.

Fox (2006) defines a dashboard, "A dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance." (p. 34) The predominant audience of learning analytics dashboards are individual instructors or students. (Schwendimann et al, 2017) In fact, of the fifty-five learning analytics dashboards studied only five were built for administrators. Isljamovic & Lalic (2014) describe their academic dashboard which presents student performance data with several demographic factors so that faculty and administrative staff can intervene with students who may need additional support before they result in a failing grade. Milevski, Gelova, & Zdrarev (2015) suggest several ways that data might be mined from Moodle installation to support the insight of teachers and administrators using that Learning Management System. Administrator use of learning analytics is not solely a higher education endeavor. Monroy, Rangel, & Whitaker (2013) explore their use of learning analytics within a K-12 environment through their tool STEMscopes. Orduna, Almeida, Lopez-de-Ipina, & Garcia-Zubia (2014) describe how learning analytics could be captured by a Remote Laboratory Management System. Rounding out the administrative uses of learning analytics Richards (2011) theorizes potential measures of engagement which could be collected from the learning management system. There is still plenty of room for a learning analytics dashboard which summarizes performance and activity at a course, campus, regional, and statewide level.

Yoo, Lee, Jo, & Park (2015) evaluated ten popular learning analytics dashboards. None of these tools were built specifically with the course administrator in mind. Learning Analytics dashboards have been primarily focused around micro-level interactions. (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013) At the outset of their paper on learning analytics dashboards these authors indicate that their focus is on micro-level analytics not meso or macro level. Mendez, Ochoa, Chiluiza, & de Wever (2014) explore potential methods of assessing curricular difficulty and potential drop out paths. This research proposes several techniques to feed curricular redesign. **Figure 3** shows the various levels of learning analytics. The IDID system is positioned as a Meso-level analytic system aggregating statewide usage and performance statistics. In fact, IDID stands apart from other analytic systems in its approach to aggregating data at the section, campus, region, or statewide level.

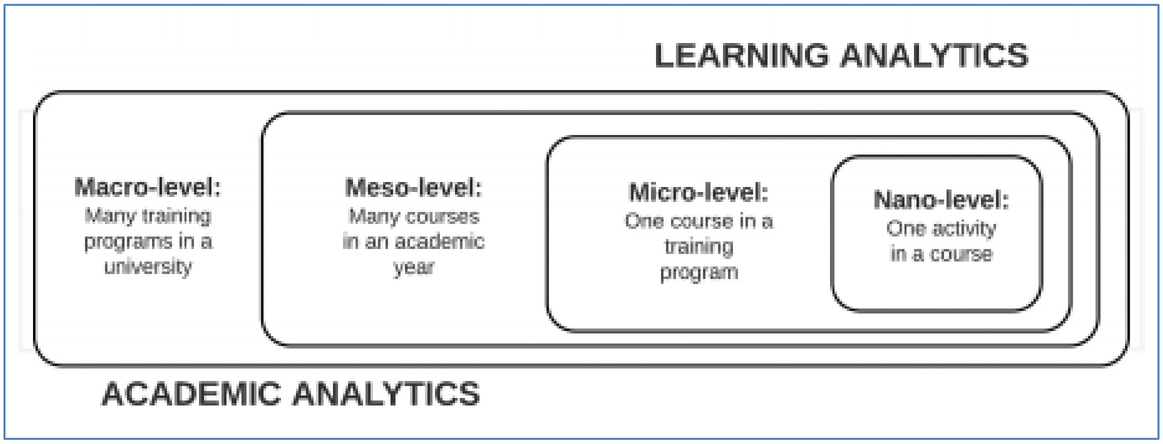


Figure 3: Categories of Analytics from Vaitsis, Hervatis, & Zary (2016)

2.2 Sensemaking Theory:

The NMC Horizon Report from 2013 defines learning analytics as the "field associated with deciphering trends and patterns from educational big data, or huge sets of student-related data, to further the advancement of a personalized, supportive system of higher education." (Johnson, 2013)

Applying Sensemaking Theory (Weick, 1995) to understand end user interaction with a learning analytic system there is a known dependence on mental model formation to properly interpret what the analytic system represents (Greitzer, Noonan, & Franklin, 2011). Liu and Stasko (2010) are very clear about the connection of mental models to analytic reasoning. They write, "Given a problem, a mental model of an interactive visualization can be constructed and simulated in working memory for reasoning" (p. 1001). While this dependence on mental models has been shown, the knowledge sources that the user draws on to form the mental model of the interactive learning analytic are not yet fully identified. The knowledge sources which support mental model formation have not been explored fully in conversations regarding user support for learning analytic systems. The discussion of user support for learning analytics has been limited to discussion of interface design and techniques of interaction (Keim et al., 2008). Even researchers such as Pirolli & Card (2005), Klein, Phillips, Rall, & Peluso (2007) and Attfield, Hara, & Wong (2010), who have developed models to explain sensemaking, do not mention the various sources of knowledge that a user might depend on to form his or her mental model of the interactive system. Knowing the sources of knowledge used to form a mental model of the system will assist system designers in developing support structures to promote sensemaking of the systems they design.

Weick, K. E.(1995) wrote a seminal work on sensemaking from the organizational development standpoint. This work is often cited as a key process to describe user interaction with an information system. Ten years later, Weick, Sutcliffe, and Obstfeld (2005) expounded on these ideas to explore the impact of sensemaking on organizational theory. They write, “Sensemaking involves turning circumstances into a situation that is comprehended explicitly in words and that serves as a springboard into action.” (p. 409) Dervin (2003) posits that sensemaking ought to be an organizing paradigm for the study of information systems. A brief evolution of the scholarship of sensemaking specific to information systems and more specifically to visual analytics (VA) systems follows. The sensemaking loop proposed by Russell, Stefik, Pirolli, and Card (1993) was originally described as the learning loop complex. The learning loop has three major stages. The generation loop is characterized by a search for representations. The analyst chooses from a set of system representations to one that best describes the problem space. The “representational shift loop” describes the process where the analyst adjusts his or her representation based on information that does not fit into his or her representation. The data coverage loop is a top-down application of the data into a representational form. It is described as the encoding of the data into visual elements that are easily understood by the analyst.

The formation of a mental model is presented by Pirolli & Card (1999) as the union of the two major loops of activity related to user activity in an information system. The overall process is organized into two major loops of activities: (1) a foraging loop that involves processes aimed at seeking information, searching and filtering it, and reading and extracting information (Pirolli & Card, 1999) possibly into some schema, and (2) a sense making loop (Russell, Stefik, Pirolli, & Card, 1993) that involves iterative development of a mental model (a conceptualization) from the schema that best fits the evidence.

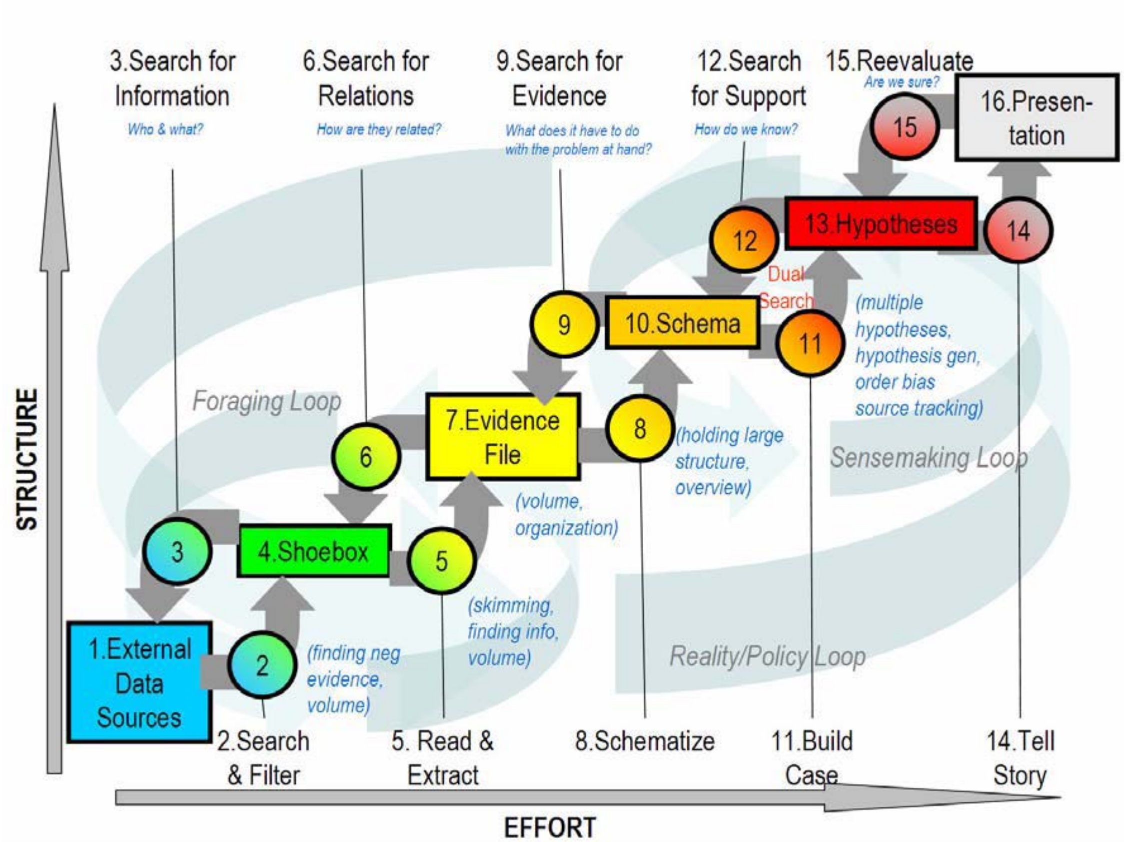


Figure 4: User Activity in Information Systems from Pirolli & Card (2005)

Two additional points that the authors consider are that (1) much day to day activity with VA systems is more about extracting information than analyzing it and (2) experts apply their mental models at all stages of the process of **figure 4**, for example in rapidly skimming and rejecting information in the early stages. The proposed research furthers the notion of mental model formation by drawing an explicit connection between steps 8 – schematize and 9- search for evidence. The placement of these steps in figure 3 indicates Pirolli & Card's notion of the schematize step as bottom up and the search for evidence step as top down.

These earlier models of sensemaking were applied to the information retrieval problem space. Keim et al. (2008) specifically apply it to the domain of visual analytics. In a summary of sensemaking, they elaborate on a model of sensemaking proposed by a computer scientist. Van Wijk (2005) proposed a means to calculate the value of a visual analytic. In addition to devising formulas to account for various costs in visualization, Van Wijk (2005) proposes a means to calculate the learning effect of a visual analytic. The main issue with this formula is that it assumes an initial state of knowledge but never accounts for the various sources of knowledge which create this initial state within the mind of the analyst.

This idea of economic visualization has become an important trend in the field. Attfield, Hara, and, Wong (2010) describe the goals of a visualization as providing insight to support a solution. They write, “Klein observed that decision-makers seldom evoke and comparatively evaluate multiple options to a problem (the normative or ‘rational’ approach). Instead, the situations they encounter evoke singular solutions in a process of ‘satisficing’; if the solution criteria are not met then another solution is sought and so on.”(p. 2) For visual analytic systems the balance between data synthesis and representation are made to produce visualizations that are “good enough” to support decision-making. It is not necessarily a quest for the best but, rather a search for a solution that simply works. They continue to further abstract the sensemaking loop. They write, “The sensemaking process is situated within a context of goals, interest and values. The significance of these is, (a) to determine the kind of model that the user is interested in generating i.e. one that can provide a basis for appropriate action in some domain or activity, and (b) that they may bias the kind of conclusion that is reached." (p. 2). All of this seems to clearly point toward an ethnographic approach to understanding user goals, interests, and values in order to shape designs that will support the knowledge needed to form a mental model of the system under analysis. Klein (2006) expounded on his data/frame theory of sensemaking. Under this theory the user goes through distinct stages, **figure 5**, of wrestling with a Data Frame otherwise known as a fragmentary mental model. The user goes from Seeking a Frame to Questioning the Frame, Comparing Frames, Preserving the Frame, Elaborating the Frame, or Re-Framing. Each of these stages is characterized by how the user defines, connects, or filters the data to make sense of it.

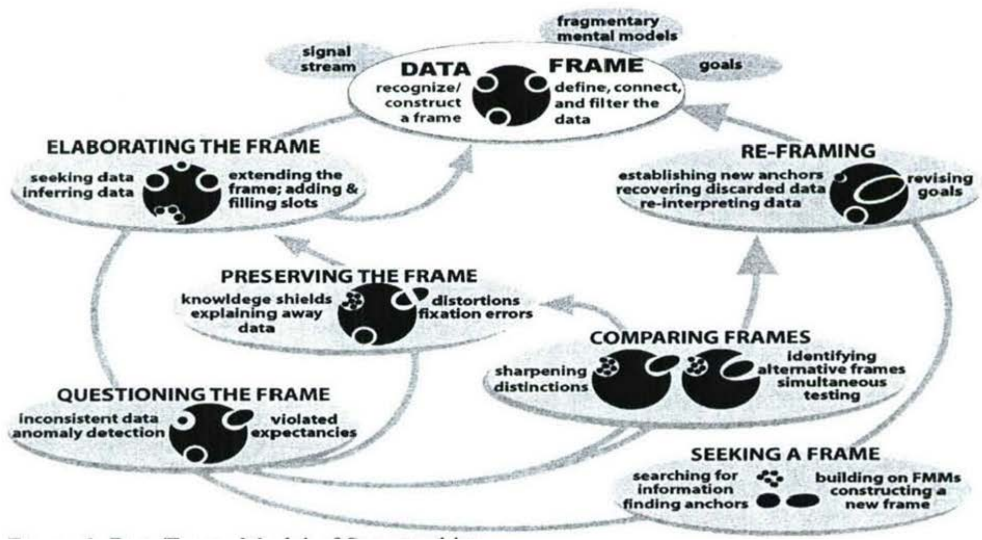


Figure 5: Data/Frame Model of Sensemaking from Klein (2006)

2.3 Measuring Mental Models:

As explained in the section on Sensemaking above, the application of mental models to the VA problem space is an important process that needs further clarification. Merrill(2009)states the main issue at hand, "When left on their own, [respondents] often activate an inappropriate mental model, thus increasing the mental effort required to acquire the integrated set of skills necessary to doing the task." (p.51) However, the challenge of researching mental models is that often these exist at the implicit level. The mental model will be made manifest as the respondents attempt to complete the task. "Building on an inappropriate mental model often results in misconceptions that show up as errors when [respondents] attempt to complete new tasks." (Merrill, 2009, p. 51)

The term "mental models" has its origins in the writing of psychologist Kenneth Craik (1943). Johnson-Laird (1983) wrote an influential work on the subject which provided a cognitive framework and theoretical base that describes mental models as psychological representations of real, hypothetical, or imaginary situations. Norman (1983) focused on a description of a mental representation of how a system operates. Senge (1990) defines mental models as one of the five disciplines that characterize a highly adaptable organization referred to as a learning organization. An important contribution for this era of thinking regarding mental models is the acknowledgement that mental models may not be explicitly known to users. They may be acting on the base of models that are seated in the implicit beliefs and attitudes.

More recently Liu & Stasko (2010) apply the following set of characteristics to mental models of visual analytics systems.

> A mental model is a functional analogue representation to an external interactive visualization system with the following characteristics:
>
> •The structural and behavioral properties of external systems are preserved in mental models.

• A mental model can preserve schematic, semantic or item specific information about the underlying data.
• Given a problem, a mental model of an interactive visualization can be constructed and simulated in working memory for reasoning (Liu and Stasko, 2010, p. 1001).

Having accepted the characteristics of mental models, this project will depend heavily on methods to measure mental models. Sasse (1991) described several methods of eliciting user mental models including think-aloud and verbal protocols, system audit trails, performance analysis for problem solving and troubleshooting tasks, information retention over time, observation of system use, user's explanation of the system, and user's prediction of system performance. In Jonassen (1995) multiple evaluation points for mental models are articulated. Each point of measurement is geared toward describing one of the characteristics of a mental model. These range from a cognitive interview to describe personal relevance to teach back or think aloud, to describe the applicability/transferability of the model. The measurement techniques described in this conference paper are put into practice to evaluate the mental models of refrigerator technicians in Jonassen & Henning (1999). They argue that mental models are evidenced in the artifacts developed by a community of practice. In this project the reports generated by an individual program chair for the purposes of support and argumentation related to course design decision making can be taken as artifacts developed by the community of practice.

Chapter 3. Methodology

3.1 Introduction:

This research uses a sequential, exploratory, mixed-methods approach. Data was collected concurrently within each phase but each phase sequentially built on the previous phase. There were three phases of research aligned with the aims of the research project. This research pursued three specific aims.

Aim I: **Eliciting Dashboard Requirements.** This aim identified the knowledge sources which support mental model formation for sensemaking of learning analytics. Seventy one program chairs of Ivy Tech who have decision making responsibilities for online course design frameworks responded to a survey in which they were asked to rank the sources of knowledge they draw on to support their sensmaking of learning analytics data. It was expected that respondents would confirm the proposed knowledge sources, which include knowledge of the statistics, knowledge of the domain, and knowledge of the system. Knowledge of the domain was further broken down into curriculum knowledge and pedagogical knowledge. Knowledge of the system was further broken down into technical knowledge and institutional knowledge. It was further expected that as analysis moves from the section level to the campus to the region to the system that the dependence on institutional knowledge will increase. It was further proposed that program chairs reporting higher levels of institutional knowledge will report that it is easier to form a mental model of the course design for the purposes of making sense of the learning analytics data than those who report lower levels of institutional knowledge. The survey

(Appendix B) asked respondents to provide written rationales for their rankings. These rationale were analyzed using the explication process outlined by Groenewald (2004).

The outcome of Aim I was the development of requirements for users at different levels of both domain knowledge and system knowledge.

Aim II**: Building the Dashboard.** Building on the requirements identified in Aim I, for each user type four design alternatives for a visual analytics tool and a knowledge support system were developed and evaluated through one-on-one user observation. The respondents were selected from the groups identified in Aim I. The respondents were from three different disciplines. One curriculum committee came from the School of Business, and two committees came from the School of Liberal Arts. Respectively, ACCT102, Managerial Accounting; MATH136, College Algebra; and PSYC201, Life Span Development were selected to participate in this phase of the research.

The outcome of this aim was a set of design elements for the support of diverse knowledge needs as well as a working prototype of a learning analytics system.

Aim III: **Evaluating the Dashboard.** The developed tool and support system was evaluated through a series of individual interviews coupled with a design confidence survey. The individuals were selected based on their participation in minor course redevelopment. Respondents were asked to indicate their reaction to the system and project its future impact on their course development. Aldag & Powers (1986) Attitudes toward Decision Process and

Solution survey was adapted to meet a learning analytics context. The specific proposition of Aim III is that committee members will react positively to the visual analytics system and their perceived level of participation will be directly proportional to the perceived impact of the visual analytics system on their course development.

The outcome of this aim was a clear evaluation plan for on-going research of this tool.

3.2 Rationale for Research Approach:

As stated earlier this research uses a cognitive exploratory approach that is a sequential exploratory mixed-methods approach. It does so because the primary research question is to understand the cognitive processes of users of the Instructional Design Implementation Dashboard (IDID). Given this aim the primary motivation of the research is the rich description of the cognitive experience of those using the dashboard. In this way, the quantitative elements of the research design supported the qualitative elements of the research design. “Unlike the sequential explanatory approach, which is better suited to explaining and interpreting relationships, the primary focus of this model is to initially explore a phenomenon.” (Creswell, 2009, 211)

3.3 Research Setting/Context:

This research took place as a case study at Ivy Tech Community College of Indiana. Ivy Tech is the largest singly accredited statewide community college system in the United States. As a community college there is a strong reliance on adjunct faculty. In fact, 75% of the faculty from spring 2016 were adjunct faculty.

(Lorton-Rowland, personal communication, 2016) This dependence on part time instructors places a greater need on supporting a wide range of experiences and backgrounds. For the courses with the largest online enrollment, quality standards in the course design are maintained by creating sections around a course design framework. This means all sections have the same initial content and the same framework for assessment. The course design framework is maintained by the curriculum committee, composed of program chairs from each region offering the curriculum, who oversee the program to which the course belongs.

This research seeks to expand the evaluation of course design by making the activity and performance data from statewide courses available for analysis and action by program chairs. Using a learning analytics tool known as the Instructional Design Implementation Dashboard (IDID), program chairs will be able to examine the impact of supplemental and ungraded resources on the actual outcomes of the courses. They will be able to compare instructional behaviors in the sections they manage to the behaviors of highly successful sections. They will be able to coach students in engaging with the course in ways that have proven to be successful for their peers. In this way the IDID platform will help program chairs identify and highlight the best practices in the implementation of their course design frameworks.

Ivy Tech is creating a large data warehouse that combines institutional data from the student information system and the learning management system. The data warehouse is built in the Amazon Web Services private cloud. In 2006 the college adopted Blackboard as its learning management system. Current aggregate reporting is available through Blackboard Analytics which is an additional service that Blackboard provides. Other Blackboard reporting options require system administrator access to run (Kunnen & Nucifora, 2007) and were not designed to meet the needs of program chairs. This research aims at designing and supporting a learning analytics front-end for the data warehouse that can be used by program chairs to make improvements to courses semester by semester. It demonstrates a potential learning analytics solution for displaying activity and performance data from large enrollment multiple section courses. Finally, it is only the first step to demonstrate and exemplify an opportunity to envision learning analytics for program chairs.

Statewide Online courses at Ivy Tech are designed according to the Quality Matters(QM)™ design standards. At Ivy Tech the course design process begins with explicit mapping of the objectives to the assessments, materials, and activities in a document called the Session Alignment Matrix (SAM). Courses are reviewed against a custom version of the QM rubric (Appendix C) which contains a set of design standards. A course review is similar to other design inspection evaluation methods. (Nielsen, 1995) This project seeks to provide a holistic evaluation of the course design by adding user activity and student performance data to the review of the course for continuous improvement.

3.4 Research Sample and Data Source:

The research sample for Aim I, the requirements phase, was the entire population of program chairs responsible for a course within the library of statewide courses. Program Chairs comprise the curriculum committee which is responsible for setting the curriculum or sequence of courses, the course outlines of record which contain the course descriptions, course objectives, and course content. They also maintain a list of acceptable textbooks which may be adopted for the course. In terms of online courses program chairs are responsible for providing feedback at each of the development milestones. This amounted to three hundred and fifty-four program chairs across the state. For Aim II, the user testing phase, the entire curriculum committees for Accounting, Behavioral Sciences, and Mathematics were invited to participate in brief one-on-one interviews with a data exploration from ACCT102 Managerial Accounting, PSYC201 Lifespan Development, and MATH136 College Algebra, respectively. For Aim III, the evaluation phase, the course developers and instructional designers responsible for making course improvement plans for the spring 2016 term were asked to participate in one-on-one interviews regarding their use of the Instructional Design Implementation Dashboard roughly one week after a brief orientation session to the tool. The course improvement process is divided into two steps. First, the course improvement plan is drafted after reviewing the course data and feedback received from other instructors teaching the course. Second, the course improvement plan is implemented after the curriculum committee has the opportunity to send additional feedback and approve each item in the plan.

3.5 Data Collection Methods:

For Aim I, the requirements phase, the data collection consisted of a brief survey developed in Zoho Creator™. The survey (Appendix B) used three static graphs, one pie chart of grade distributions, one bar graph of Activity counts, and one summary table of statistics from the Student Evaluation of Instruction. For each of these graphs respondents were asked to rank the importance of support materials that would aid them in the sensemaking process. These supporting materials included help with statistics, course content and objectives, instructional activities and course design, tools and materials, and institutional definitions or configurations. Additionally, respondents were asked to provide a rationale for their rankings, a short comment on what additional information they would like to know, and whether they would find each source of data useful.

For Aim II, the user testing phase, a prototype of the dashboard was developed. The dashboard correlated end of term grades from Banner, the Student Information System, with activity information in Blackboard. The screens that were available were

- **Student Clicks** which showed how item access related to end of term grades.
- **Internet vs. Traditional** course delivery which provided a summary of the pass/fail/withdraw rates and grade distributions for both the internet-only sections and the traditional sections.

- **Comparison of Pass** rates provided a heat map of the pass/fail/withdraw rates for all sections statewide.
- **Comparison of Final Grade** provided a heat map of the grade distribution in all sections statewide.
- **Instructor Clicks** allowed for the comparison of the instructor behavior in a single section to the statewide average.
- **Student Clicks by Grade** allowed the comparison of student behavior across any two grade groupings.
- **Student Profile** provided a summary of which majors, divisions, and degree paths students in a particular class had declared.

For Aim III, the dashboard was improved based on the user feedback from Aim II. The improved dashboard was evaluated in ten one-on-one contextual interviews. Following each interview the respondents were asked to complete a brief survey on decision confidence based on the perceptions of the degree the dashboard supported their decision making. The survey was adapted from Aldag & Powers (1986) Attitudes toward Decision Process and Solution survey.

3.6 Data Analysis Methods:

For Aim I, I analyzed the survey data by generating mean values for each of the knowledge categories. I also checked for correlations between the rankings and any of the demographic characteristics. All of the qualitative rationale were coded using Nvivo and then put into groups. The emergent requirements were then described.

For Aim II, I transcribed the dialogue from the usability interviews. The data was coded using NVivo into salient phases and grouped into clusters of meaningful recommendations. A set of design improvements thus resulted from the usability interviews. The dialogue was secondarily coded against Data Frame Sensemaking Theory (Klein, 2006) to match user experience to this theory and to refine the interpretations that would be needed in future aims.

For Aim III, I transcribed the dialogue of the evaluation study interviews. The text was coded in NVivo based on the essence of what was being communicated. The codes were grouped and further consolidated. A second round of coding was completed where phrases were matched to phases in Data Frame Sensemaking Theory (Klein, 2006).

3.7 Issues of Trustworthiness:

Guba (1981) suggests four criteria that should be considered when judging the trustworthiness of a naturalistic inquiry. The tests of trustworthiness in naturalistic inquiry are credibility, transferability, dependability, and confirmability. Credibility was achieved through sufficient exposure to the subjects, coordination of both interview and survey data, collection of referential adequacy materials (each of the interviews was recorded to capture both screen movement but audio for transcription as well), the interviews were transcribed by a third party which further separates the dialogue for analysis from personal bias. Transferability was enhanced by developing rich thick descriptions of each interview and the characteristics of each respondent. Dependability was increased through the use of a research journal to capture my maturing ideas as the research progressed.

My research advisor acted as a dependability auditor checking my processes against established norms. Finally, confirmability was achieved through the triangulation of data and the practice of reflexivity. Through a bracketing approach, I attempted to suspend my own beliefs about the interface and see the experience through the eyes of each respondent.

Chapter 4. Results and Outcomes

4.1 Introduction:

The results have been divided by the four phases of this research project. First, a small study was conducted to see how learning analytics were used by program chairs in the Computer Information Systems program. Next, the population of program chairs at Ivy Tech was surveyed about how they would require additional knowledge support to make sense of the learning analytics given them. From this survey I was able to develop a set of requirements for the next generation learning analytics tool at Ivy Tech. The requirements were quite broad and it simply was not possible to develop a tool that would address all of the requirements. Instead I focused on a subset of requirements and designed a dashboard that could serve as a baseline tool and had the capability of scaling to encompass more of the overall requirements over time. The dashboard was tested through a series of one-on-one contextual interviews. Once optimized the dashboard was evaluated against real life course design situations. Each respondent was asked to demonstrate how he or she used the tool to develop a set of recommendations for the improvement of the course design. Finally, a decision confidence survey (Appendix E) was adapted and used to measure the confidence that each decision maker had when supported by the dashboard.

4.2 Preliminary Findings:

The main lesson from the preliminary work was a confirmation that aggregate reporting was a needed area of focus. One respondent said it clearly when she answered the question “How do you or does your committee use data from statewide courses to improve the courses?" She said, "I'm not sure right now that we really do, because a lot of data is so hodge podge, it is so disconnected that is really hard to put any kind of connection to it to make it meaningful." Respondent 6.

The main outcome of the pilot study was a clarification of the tasks of program chairs in using learning analytics. Program chairs want learning analytics for statewide courses for two main reasons. First, they want to improve the design of the course and second, they want to monitor the consistency across sections. Appendix D shows that consistency was defined in three specific ways. Program chairs are concerned about ensuring that students are being evaluated consistently, that the instruction is consistent, and that the course policies are being consistently interpreted and applied across sections. The topic of grade inflation was a concern of both program chairs and students. One respondent said,

> "I don't want students to earn a grade that they feel...I don't want students to get a grade that they feel they didn't earn. And I believe that a lot of students are very conscious of that themselves and will even say well I earned an A but I'm really not comfortable with the material and I don't feel like I can do it in real life. So I do use those final grades as a possible indicator of grade inflation." Respondent 1.

This is just one example of how consistency across sections is measured and applied by program chairs. By policy program chairs are responsible for ensuring the quality of their courses. What the pilot revealed was that quality equated to consistency from the program chair perspective. This was a key takeaway from this phase of the research.

4.3 Learning Analytics Requirements:

Seventy-one responses out of three hundred fifty-four or about a 20% response rate to the survey was collected. The representation of those responding follows the same pattern as the school representation in the statewide library of courses. The main content of the survey asked respondents to rank order the importance of the five sources of knowledge already proposed to support their making sense of the data presented in the graphs. The means of the ranking was calculated as shown in **figure 6**.

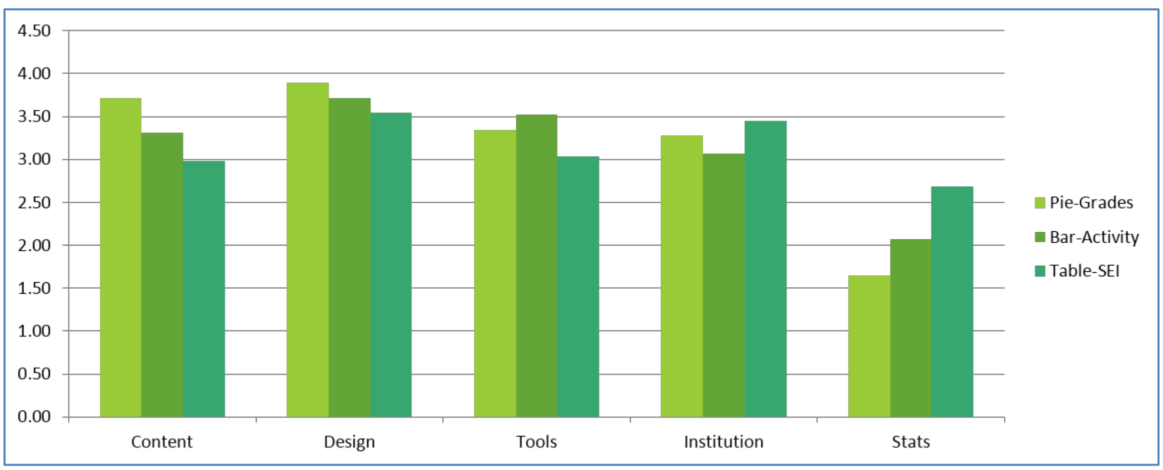


Figure 6: Means of Knowledge Rankings

For all cases additional knowledge of course design was the most important source of additional knowledge and statistical knowledge was the lowest. An interesting side note was that multiple respondents' rationales indicated that while they themselves were not in need of statistical knowledge it was important to include for their colleagues who were less data savvy. For the grade data, the second most important knowledge source was knowledge of the course content and objectives. The content category had a mean score of 3.71.

For the Learning Management System Activity data the second most important knowledge source was the knowledge of the tools used in the course. The tools category had a mean score of 3.52. This is not surprising since the activity data showed click counts by tool. So it follows that knowing which tools were used in the course would rank high as a knowledge need for making sense of that analytic. Additionally, in terms of sensemaking respondents felt most comfortable with knowing how to interpret the statistics presented in the pie chart. With the statistical knowledge need only increasing as the complexity of the visualization increased from pie chart to bar graph to statistical table.

Beyond the simple calculation of means, a correlation coefficient was calculated within the knowledge types showing the strength of correlation between an application of one knowledge type to another application. There were only two knowledge types that showed significant correlations, $r > .5$. For the course content and objectives knowledge type, there was a significant correlation between grades and activity data. ($r = .72$) For the institutional knowledge type, there was a significant correlation between the grades data and the activity data.

These results represent a moderate positive correlation showing that those that ranked institution data high for making sense of grade data also rated it high for the making sense of the activity data. ($r =.53$) Each of the demographic factors was examined systematically for its effect on the rankings. There were only two conditions that seem affected at all by demographic factors. *Years at Ivy Tech* appeared to affect the need for additional content knowledge. This might be due to the role that program chairs play in developing curriculum at Ivy Tech. The program chairs are responsible for writing the course objectives in a document known as the course outline of record. The other demographic factor that affects the rankings of knowledge types was a significant difference between groups with QM Training and without QM Training. Quality Matters is an internationally recognized course quality improvement program whose main instrument is a rubric of design standards for online courses. There are multiple levels of certification beginning with the Applying the Quality Matter Rubric course, a basic orientation to the program. Given the strong focus on course design it is not surprising that those who participated in training expressed a strong need for knowledge about the course design than those without training. What is surprising is that this effect seems to be concentrated around the course design knowledge for the activity data only. As far as the survey is concerned the remaining area of analysis was to explore the themes that emerged from the rationale of the rankings. The emergent themes were coded, grouped, and recoded so that a full set of requirements could be connected back to the feedback collected from actual users.

4.3.1 Emergent Requirements:

Each rationale was coded and then categorized into four areas: Knowledge Support Requirements, Data Requirements, Interface Requirements, and Functional Requirements. These requirements emerged from the qualitative data collected from the rationale of each ranking. The following presents each of the requirements areas along with a brief description of the major themes that coalesced into the requirements.

1. Support Requirements:

1.1 Support with course design for those seeking support with content and objectives.
1.2 Support with content and objectives for those seeking support with course design.
1.3 Support with institutional definitions for those seeking support with statistics.
1.4 Support with statistics for those seeking support with institutional definitions.

The strong correlation between course design and course content suggests that if a program chair starts by looking at course design information he or she will likely also wish to look at course content information, or vice versa. Likewise there was a strong correlation between knowledge about the institution and knowledge about statistics. This suggests that if a user starts looking at information in one of these areas they will likely wish to look at the other knowledge support. These pairs of support needs, course design and course content and institutional knowledge and statistical knowledge, further exemplify a key finding that there are different types of sensemakers. There are those who are course-centered and those that are institution-centered. Course-centered sensemakers tend to focus first on the course design or course content. Institution-centered sensemakers tend to focus first on the characteristics that make the institution stand out. Course-centered sensemakers are in fact the largest group. However, institution-centered sensemakers are a strong minority. The final group of sensemakers was what I termed the information-centered sensemakers. Although this sensemaking type appear much more infrequently the fact that their primary objective was to understand as much information about the course as possible makes them stand out as their own sensemaking group. This research showed that there were definite unique information needs between each of these groups.

2. Data Requirements:

- 2.1 Broad access to data
  - 2.1.1 Visibility of aggregate data to a broad audience
  - 2.1.2 Visibility of course specific data to appropriate instructors or chairs only
- 2.2 Integration with data from external tools
- 2.3 Connection to research literature for external validation
- 2.4 Availability to query historical data
- 2.5 Availability to query multiple ratings by multiple instructors

Comments about the nature of the data coalesced into three groups. First, several comments emerged about broad access to data. Respondents wanted the data on course performance to be available so that what was successful in one course could be duplicated across all courses. One respondent wrote, “If we noticed certain trends (i.e. courses with certain tools/activities doing better than others), we may find ways to improve all of our online courses.” (Respondent 42) This also speaks to the unique course design environment at Ivy Tech. By standardizing the course design and leaving the assessment structure consistent between sections it is easier to make assumptions about the effectiveness of supplemental and optional content which may vary between sections.

Broad access to data was further broken down into two specific requirements. First, the tool should make the aggregate data available to all instructors. Second, protecting the identity of individual instructors whose behavior might be called into question by this type of analytics system. Ivy Tech’s lack of a faculty governance structure made it easier to deploy such a system. However, steps were taken to identify sections by section number only. So that individual instructors were not easily identified in the tool.

Another interesting emergent theme was the need to integrate external sources of course data. External data has two requirements. First, in some courses much of the instruction occurs outside the institutional learning environment. One program chair stated the need clearly, “In some online courses 75% of the course work is completed on a platform other than Blackboard. Such courses cannot be evaluated fairly by only looking at activity on Blackboard.” (Respondent 58) There were some respondents who raised questions regarding the use of third party tools and the impact on the course design process. This issue needs further exploration but, with the increased prevalence of LTI (Learning Tool Interoperability) systems it has become possible to pass learners between learning systems seamlessly without much disruption to the learning experience thus making the need to interconnect the learning analytics much more important. This raises important questions about learner privacy and data ownership. Beattie, Woodley, & Souter (2014) call for more learner education of how their data is being used by institutions to promote student success initiatives. They specifically call for a Charter of Learner Data Rights to promote the ethical use of learning data.

The other side of the external data issue was a bit broader than simply passing learning data between systems. Curriculum managers want access to the latest learning research to validate their course designs and to support the trends they see in the learning analytics. One respondent wrote they wanted, “Research that shows which tools are most effective in helping students be successful in an online course.” (Respondent 6) This points back to a major theme of learning analytics research in that good learning analytics research is grounded in learning theory. (Wise & Shaffer, 2015).

The last set of data requirement themes emerging from survey responses were the requirements related to the breadth of the data collected and displayed. Respondents wanted the ability to query historical data. One respondent said they wanted, “historical data regarding grades over time in terms of evaluating for grade inflation.” (Respondent 24) This request poses some unique challenges since instructors are not assigned to the same section term after term. Furthermore instructors are not always assigned to the same course. Related to the issue of evaluating consistency of grading, one respondent wanted to verify that “An A from one instructor is the same as an A from another in same areas of the same course!” (Respondent 18) This could be achieved by random sampling of artifacts and secondary evaluation of the work to compare grading behavior. This requirement connects to a later requirement which calls for inter-rater reliability.

3. Interface Requirements:

3.1 Provide clear graphs
3.2 Provide clear and related descriptions
3.3 Include chart legends
3.4 Allow for a variety of support paths.
3.5 Allow for a variety of data display options.

The interface requirements highlight the comments respondents made regarding the display of data. Several requirements are standard requirements for any visual communications systems. They could have easily been pulled from a design guide on analytics systems. However, I did allow the requirements to emerge from the survey responses so these were expressed concerns by one or more of my respondents. Respondents commented on making sure the graphs and particularly the labels were easy to read and understand. They also wanted to make sure that the descriptive material presented with the data was easy to understand and clearly related to data presented. One respondent mentioned the need for clear legends on the charts that were displayed, He wrote, “Actually, I would need a legend, and I would need to know that apples are being compared to apples. What assumptions are being made when these charts are presented?” (Respondent 46) As is evident from the knowledge support rankings, decision makers do not all approach the data the same. Respondents had varying levels of experience and varying levels of knowledge about even their own courses. A clear requirement supported by the ranking data is that a new learning analytics tool built to support curriculum manager decision making needs to provide a variety of support paths. Some respondents even believed it would be necessary to critique the choice of data presentation in the static graphs of the survey. One respondent wrote, “Use another way to share data with the reader.” (Respondent 2) Rephrased into a requirement, a learning analytics tool should allow for a variety of data display options.

4. Functional Requirements:

4.1 Ability to display historical trends
4.2 Ability to calculate inter-rater reliability
4.3 Ability to conduct an item analysis of any assessment
4.4 Ability to make comparisons at multiple levels

The final grouping of requirements captures requests for specific functions that program chairs made. Already mentioned as a concern, grade inflation was mentioned several times. This respondent made the connection between showing historical trends and identifying grade inflation. “It is important to see how classes statewide compare to student success over several sessions. Grade inflation is an issue and must be considered before any data is of any value.” (Respondent 7) Beyond highlighting grade inflation through displaying historical trends, another concern raised by respondents was to somehow capture ways to judge the consistency of grading between instructors. One respondent wrote, “Some sort of data to show whether teachers are assessing students at the same level. Is it a teaching or grading issue?” (Respondent 67) Although not explicitly called by name, respondents were seeking a way to calculate interrater reliability. Stemler (2004) provides an overview of various statistical methods to arrive at interrater reliability. Another function requested is item analysis. Item analysis allows for in depth summary of responses on an assessment for the purpose of testing how well the item tests student knowledge. One program chair was able to express what the benefit of item analysis is from their perspective, “The breakdown of grades from the assessments within the class to help pinpoint areas of weakness.” (Respondent 45) The last emergent functional requirement was the use of the analytics system is best stated as an ability to make multiple comparisons on multiple levels. Respondents wish to compare section to sections, group of student to group of student, etc. One respondent stated he/she wants, “To compare my region's grade distribution with the State average, I would want to know that the course was consistently delivered throughout the state.”(Respondent 10) However, comparison will need to be supported through the tool not just in the performance summaries. For instance, one potential use is to support the comparison of course policies. All of these factors have an impact on the student success, “classroom policies on submitting/accepting any late work, extra-credit and/or make-up material.” (Respondent 5) Since all these changes are recorded in the database it technically would not be hard to include comparisons of changes in the gradecenters between sections.

The IDID is a front-end system for a larger data warehouse initiative. Both the main administrative system and the main academic system of the college are captured and transformed using Pentaho Data Integration and then loaded to a private cloud environment on Amazon Web Services. The data is uploaded into Postgres Databases for query in an analytics package of choice. For the IDID, Tableau Desktop Professional was used to create an interactive data workbook that could be used by the program chairs across the college. Future iterations of IDID would be built in the Pentaho Data Analytics platform which what the college has standardized on for an analytics solution.

4.3.2 Contextual Support:

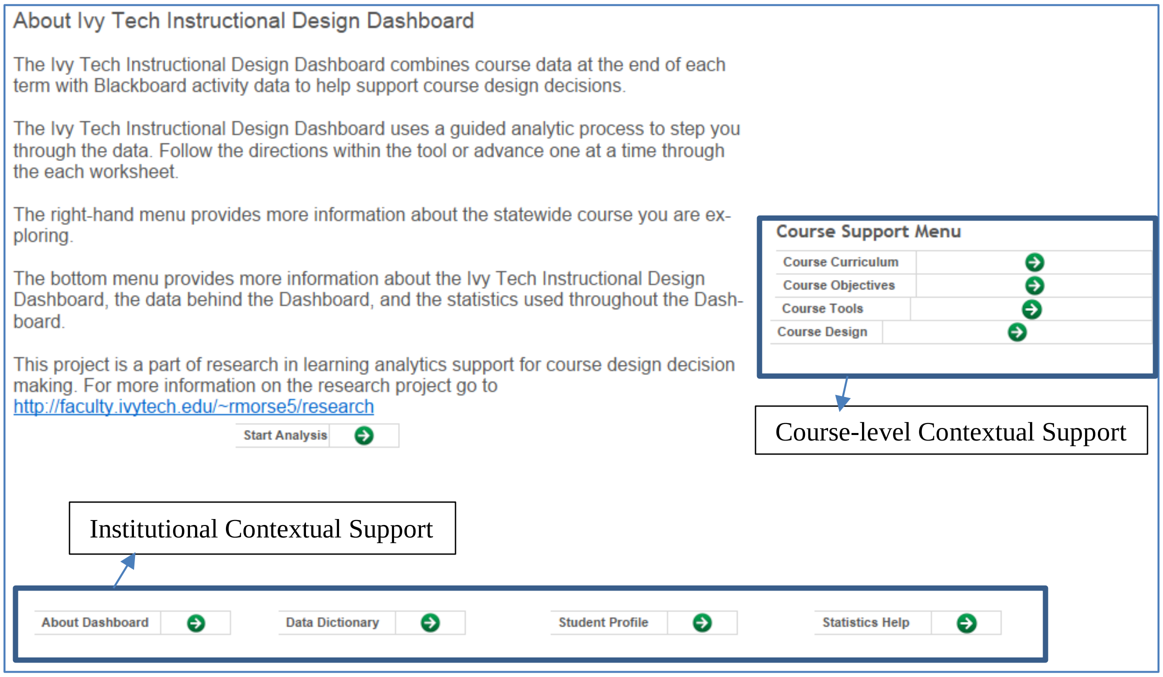


Figure 7: Two Main Avenues of Contextual Support

One of the main contributions of the IDID is the embedded contextual support. As seen in **figure 7**, there are two main levels of contextual support built into the IDID platform. First Institutional Contextual Support appears at the bottom of each workbook page. This menu includes information about the dashboard, a data dictionary, a student profile, and statistics help. The Course Support Menu appears on the right side of most screens or below the Institutional Support on screens where the visualization takes up a majority of screen real estate. The course based context includes the particulars of the course curriculum, course objectives, course design, and course tools selected. At Ivy

Tech the curriculum is outlined in a document known as the Curriculum of Record shown in **figure 8**.

For every program, the program requirements are clearly stated alongside the articulation requirements of transferring the degree to another college or university partner. The objectives and topics for each course are captured online

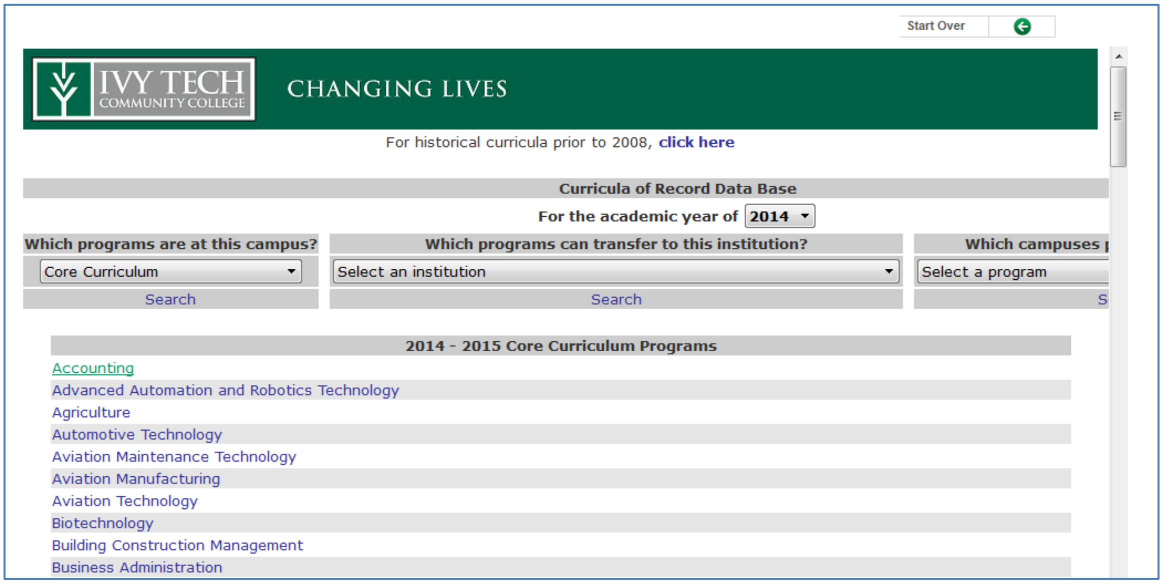


Figure 8: Curriculum of Record

in the Course Outline of Record (COR). The COR web is a web based database containing all the course objectives as illustrated in **figure 9**. It displays each set of course objectives along with the date they take effect. The first step in Ivy Tech's course development process is the production of a course design document known as the Session Alignment Matrix (SAM).

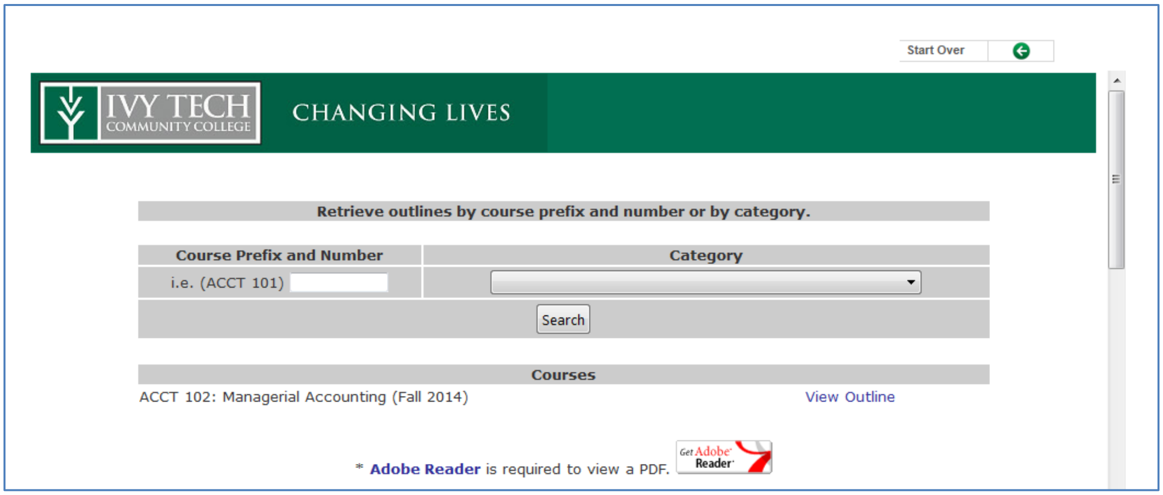


Figure 10: Course Outline of Record Web

The SAM is a table of the explicit alignment of activities, resources, and assessments to the course objectives as shown in **figure 10**. **Figure 11** shows how the contextual support links are built into the IDID interface. The links are

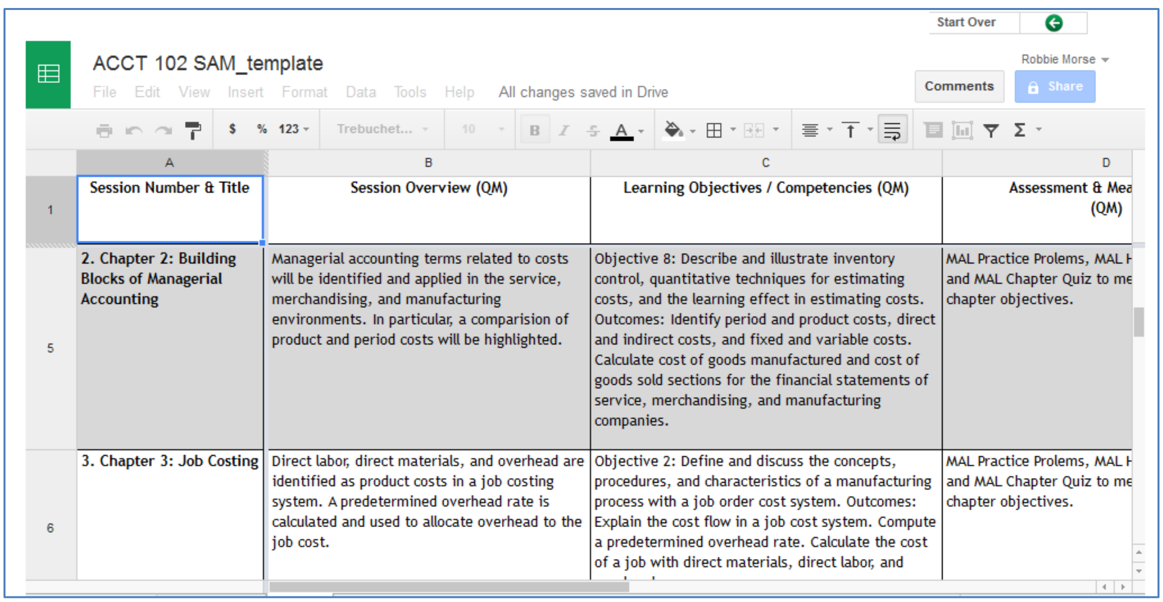


Figure 9: Example of Session Alignment Matrix

relative to the course under review. This figure shows total tool use by click in the Internet only version of the course. Clicking the tool from the list on the left changes the content title associated with that tool. Clicking on the content title changes the “grade by item” pie chart at the bottom of the page, so that the user can see the final grade distribution for students who accessed that content item.

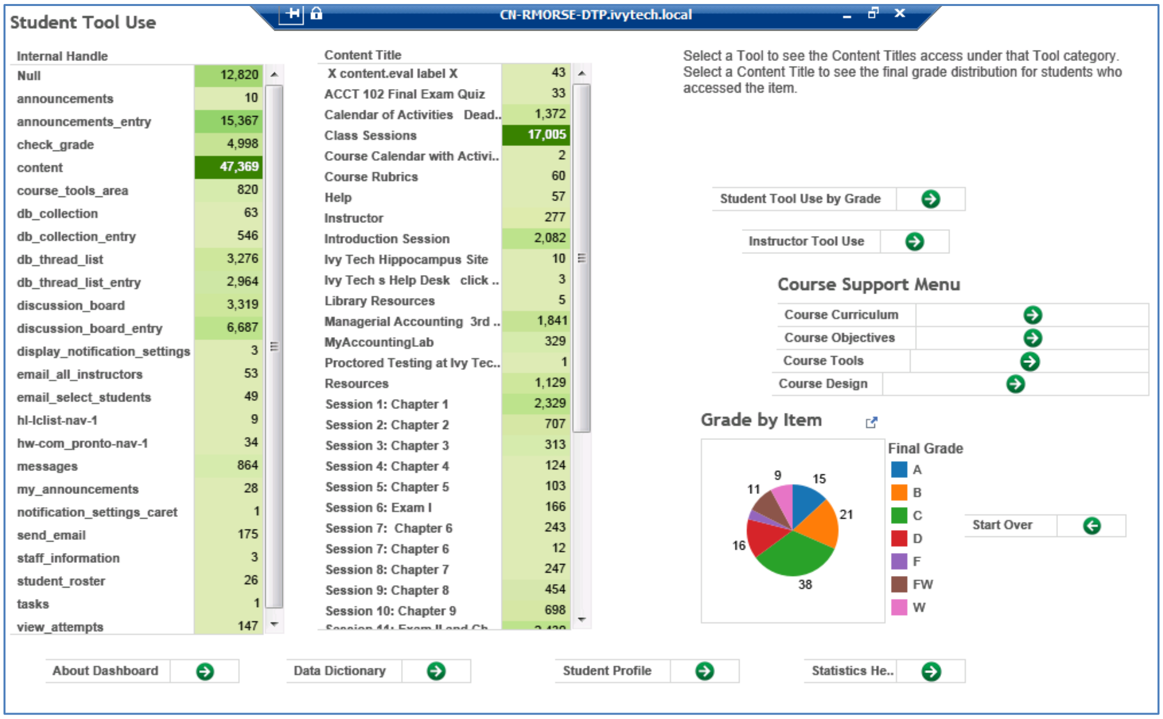


Figure 11: Early Prototype of Student Clicks Screen

An alternative support structure to the course based support is located at the bottom of the dashboard and is presented as a series of institutional support links. The support links include information about the Dashboard, the data dictionary for the institution, profile information about the students in the course and tutorials of statistics used within the IDID platform.   While the majority of the links within this group are consistent from course to course, the student profile is course and term specific, which changes based on the actual population of students under analysis.

In order to fully support the analytics provided in the IDID tool, the presentation of the data in both tabular and visual representations must have clear contexts which are both evident and decipherable without cognitive effort. It must be clear whether a graph represents data from a single section, or if it is an aggregation of data at the campus or statewide level. Although this has already been mentioned in the section of emergent requirements, the importance of context was raised by several program chairs. As a rationale for the additional context program chairs that want to make sense of learning analytics, one respondent said, “Absent this additional contextual information counting responses or assessing percentages is meaningless.” (Survey Respondent 32)

4.3.3 Multiple Comparisons between Sections:

One of the main challenges of large multi-section course data is the presentation of data for the purposes of comparison. In this regards, IDID provides an opportunity to compare the performance in one section to the performance in another. A common request from program chairs is to monitor the differences between different versions of the same course. IDID allows for comparison of final grades of Internet and traditional courses. By default, the comparison is presented at a statewide level; however, program chairs often wish to see how the courses from their regions or campuses compare. IDID provides a quick means to adjust the composition of the comparison. From a simple drop-down menu, program chairs can include all sections or grouping of sections by campus or region.

In addition to grade comparisons that are used to monitor course quality, many program chairs like to compare the instructional behavior of their faculty members against the behaviors they see other faculty members exhibit. They may wonder if their faculty members are providing timely feedback to students or interacting with students in discussion boards or through messages. The comparison tools provided within IDID allow program chairs to begin to answer these questions.

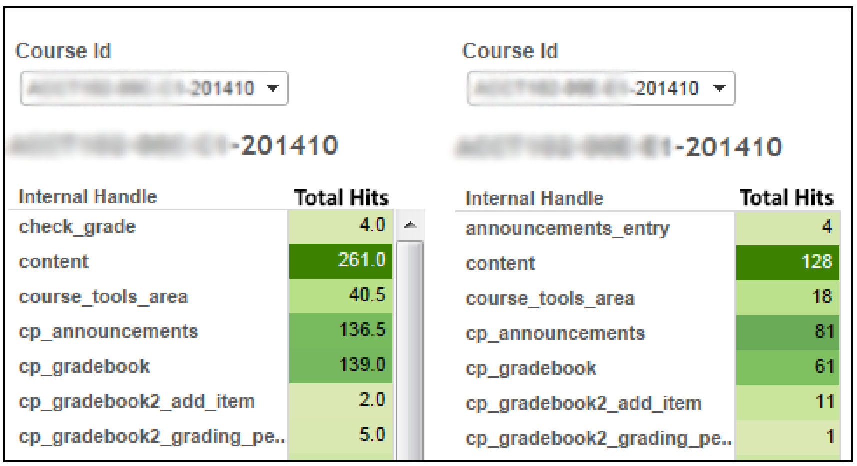


Figure 12: Comparison of Activity in Two Sections

Figure 12 shows a comparison of instructional behavior from any two sections of the course. This screen was later reconfigured to display the average on all instructor's behavior on the left and any section selected from the drop-down menu on the right. From the drop-down menu, program chairs are able to select which section's behaviors to display below each menu. This allows for flexibility in making comparisons.

In addition to the comparison of overall section performance and instructor behavior, an important analytics task is comparing the behaviors of successful students against behaviors of less successful students. IDID allows the program chair to quickly compare the behaviors of any two groups of students based on the final grades they received.

It is hoped that the ability to compare the behaviors of groups of students will allow program chairs to evaluate the success of supplemental materials. Often different sets of materials are targeted for students needing remediation and for those who would benefit from materials that enrich the learning objectives and challenge their thinking.

4.3.4 Highlighting Differences between Sections:

One of the main goals of IDID is to highlight differences in the implementation of course design between sections. One of the ways that IDID highlights differences is through the use of heatmaps for quick comparisons between sections.

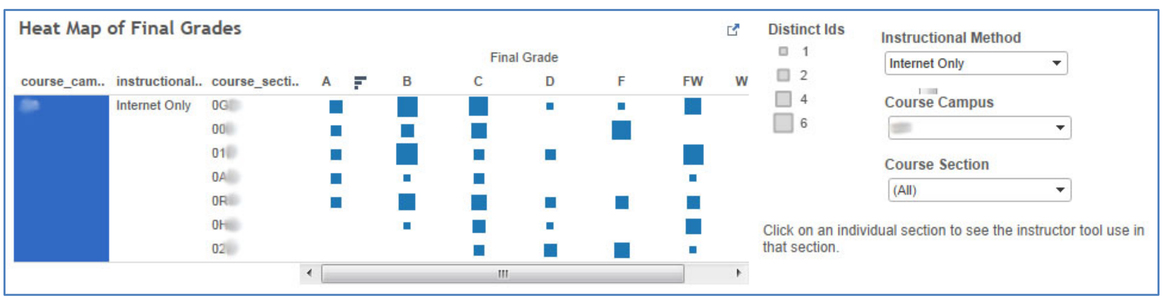


Figure 13: Heat Map of Final Grades

There are two main ways that program chairs are able to compare the performance of sections. First, the pass/fail/withdraw rate is a calculated field which groups students based on their final grades according to the definitions of passing and failing determined by Ivy Tech's participation in the Achieve the Dream Initiative. According to this national data-sharing program, passing is defined as achieving a grade of 'A','B', or 'C' and failing is defined as achieving a grade of 'D', 'F', or 'FW'. The 'FW' grade shows on the transcript as an 'F', but is used to designate those students who have failed because they no longer participate in the course but did not complete the paperwork to withdraw from the

'A' Students

Content Title	Average	Sections
Course Messages	16.45	62.00

'C' Students

Content Title	Average	Sections
Course Messages	19.76	77.00

Figure 14: Comparing Activity by Grade Groups

course.

The second comparison of section performance provided is a full categorization of final grades. Similar to **figure 13**, which represents a heat map of the pass/fail/withdraw rate, the heat map of final grades displays a table with squares of different sizes corresponding to the number of students who fit that category. It is relatively easy to compare many sections and to identify the most successful sections for further investigation.

On several sheets in IDID, the activity information is represented as a table of hit counts, **figure 14**. The background for each row is shaded based on a gradient representing the sum of the number of hits. For instance, if the Messages tool had 2,000 hits the background color of this row of data would be darker than the Check Grades tool, which only shows 1,000 hits.

4.4 User Testing Procedure:

User testing consisted of one-on-one recorded web conferences using GoToMeeting. IDID was shown on the screen and respondents first listened to a brief explanation of the interface and a brief orientation to the types of data displayed. Actual course data from the summer term 2014 was used and respondents interacted with the data from either ACCT102, Managerial Accounting, PSYC201, Life Span Development, or MATH136, College Algebra. There were a total of nine respondents. Four interacted with ACCT102, three interacted with MATH136, and two interacted with PSYC201. The respondents were asked the same set of questions.

- Using the analytics system provided, identify under-utilized resources in the course.
- Were the students who accessed these materials more or less successful than those who did not access them?
- How critical are these resources to conveying the objectives for the course?
- What recommendations could you make for improving the course design based on your review of this data?
- Is the performance between sections consistent?
- Are the instructors of your sections engaging with students in a consistent manner?

- What are your instructors of higher performing sections doing that you would want to encourage all faculty to do?

The interviews were transcribed and then coded. First, free codes were created to capture the essence of what each respondent was saying. Codes were then grouped into more meaningful themes.

4.5 User Testing Results:

The emerging themes included benefits, current limitations, improvements, new elements, potential uses, potential misuses, and positive sentiments. Benefits were further broken into increasing accountability and decreasing the amount time needed to collect data. One respondent identified the benefit of IDID as being able to help measure the efficacy of course designs. “Okay, so this design -- what is the efficacy? And we can now show them that -- exactly what you were saying. The students who utilized this resource tended to be more successful than not.”-Respondent 6. One the major benefits of IDID was that correlated grade and activity. Program chairs were able to access one system rather than several to get the information they needed to make design decisions regarding their course design framework. In addition to streamlining the data collection this tool had the potential of increasing instructor accountability by showing the program chair exactly how each of his or her courses compares to the statewide average.

Current limitations included items which still need to be more carefully considered, such as who should actually have access to the data compiled by IDID. Is the larger faculty and student community aware that their activity is being monitored and if so, what is the effect of increased monitoring on activity? In other words, could the activity be artificially increased without really being related to engagement? Merely knowing they are being monitored might alter a learner or instructor’s behavior so that he or she will look good within the statistics. Several respondents expressed the difficulty of comparing across instructional methods. An Internet-only course should be compared to another Internet-only course, not necessarily a face-to-face course. One respondent stated it rather succinctly, “There again you know you have got to make sure that we are comparing apples and apples; because you have to be comparing internet versus internet there.” Respondent 8. Perhaps this concern is related to the fact that the Internet-only classes are all built upon the same course design framework or master course. In face-to-face courses, the instructor is provided much more leeway in how he or she designs his or her course. Although all modalities must be taught from the same objectives only the internet only courses must also use the same framework of assessments. Three respondents mentioned the fact that some instructors use messaging while others use email as the main form of communication. This simple complexity of communication strategies could easily show up in the activity data as email behavior remains uncaptured by the system. Future versions of IDID may not suffer the disparity of communication tool use. In late fall 2016 the college decided to transition to the Canvas Learning Management System. As part of the migration the policies were rewritten to encourage faculty to initiate all student communication within the Canvas Conversations. This decision was made to take advantage of the Canvas

Notifications system and allow the communications to be pushed to the prefer communication channel.

One respondent mentioned the need for a team approach to decision making, “So that's how I do it because I figure I can't know -- I mean, there's no way I can know everything. So I've just decided to surround myself with people that can help me and make the decisions.” Respondent 5. This suggests that faculty beyond the program chairs may need access to the IDID system. Two additional limitations seem to fit well together. First, the need for a proper orientation became quite apparent. As a new data tool, users need to be oriented to the tool as well as how to properly interpret the data produced by the system. Second, people need time to be able to digest all the information that is being presented to them through this tool. Program chairs need time to be able to explore the data on their own. This can be a challenge for faculty who are already stretched thin. Finding time to “play” in the IDID system can be a challenge and must be a priority if data is truly going to drive design decisions.

As for improvements, the most frequent request was to translate the internal handles (Blackboards labels for the tools used) into language that is a little more understandable. As one respondent phrased it “more of a standard language rather than a Blackboard language.” Respondent 1. One example of this labelling difference is that tools that behind the control panel all begin with “cp_” as the start of the internal handle. Another indicated the need to show which sections were being referenced, “So it might be helpful. You know, I think what you've shown me here is that it's probably going to be helpful to actually list someplace on the screen what sections are actually being called for in this item." Respondent 2. While I was not able to add the specific sections to Student Clicks screen, I was able to add the total number of sections that the item appeared in. This change allowed users to more easily examine the scope of the change. They could more easily determine whether the content appeared in statewide course design framework, or if it was added to a regional course design framework, or if it was just added to a single section.

Four respondents remarked on the speed of the application. This has been addressed in future versions of IDID by running on extracts from the data warehouse instead of making a live connection to the data warehouse. This does add a file management issue to IDID deployment since there is potential for multiple extracts to be created. Currently, the IDID workbooks are extracted and placed on a community of mentors for courses that going through a course improvement plan or a minor redevelopment. Another improvement that was made based on feedback was adding a label of the sample size below the pie charts on the Student Clicks page. This was a simple change but allowed users to easily measure the impact of the content item. Additionally, an additional pie chart with the total grade distribution for the class was added to the Student Clicks page to allow for quick comparison back to the full course grade

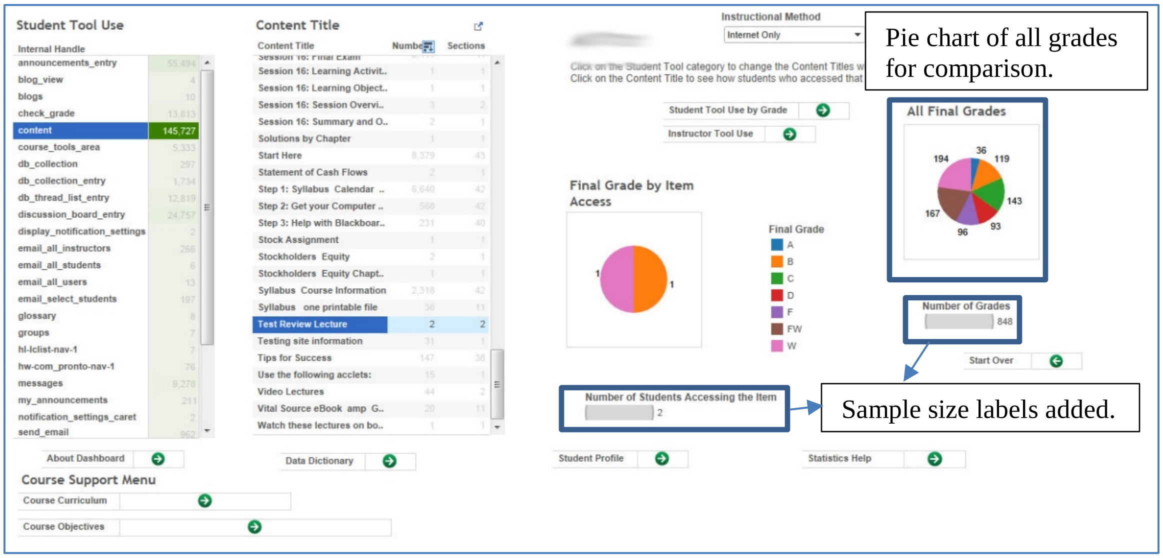


Figure 15: Later Prototype of Student Clicks Screen

distribution. **Figure 15** represents a later prototype of the system with the addition of sample size labels and an additional pie chart.

Age, gender, and GPA were all suggested as additional sorting criteria for the Student Profile page. Two additional changes were suggested. First, several respondents wanted to see the grade distribution of each item in a course. Currently IDID is configured to show grade distributions of final grades only. However, there might be a need to show midterm grades or grades on the first test or project. This has the potential of changing the IDID platform from a purely summative evaluation tool to one that could be used after a major class milestone to check progress and suggest mid-course correction. The second request was to show an historical trend for grades by instructor. The general idea behind this is to compare current grading against past grading. Although that change is technically possible, it is beyond the current scope for IDID. This change would be a bit of challenge as instructors do not allows teach the same section number semester to semester.

One of the main themes was potential use. IDID could be used to derive profiles of students and analyze their performance, making recommendations on what behaviors the more successful students are performing in the LMS. This tool was designed with the needs of program chairs but, there are self-monitoring potentials that could be achieved if the tool was redesigned to show students the effects of their behavior. IDID could be used for formative evaluations providing the right background information to tell an instructor how best to customize his or her section based on the mix of students he or she has. It could be used to establish a minimum expectation of activity for instructors and benchmarks for program chairs to be able to coach their faculty members in improved teaching methods. Annually each program chair must complete a review of his or her program which includes an extensive summary of student demographics. This could be used as a part of program review thereby reducing the time needed to prepare the documentation for this process.

Complementing potential use, respondents mentioned potential misuses of IDID. One respondent summarized her concern about other program chairs potentially misinterpreting the data. She said “And as we discussed, maybe to remind people the disclaimer about what the data is actually saying. Because, you know, there are some disciplines that when you get data like this, you do understand that it's just data and offers you more questions really than definitive answers. But there are some disciplines that don't think that way. So maybe to remind them that this is an excellent tool. It gives us the ability to ask these questions, but it shouldn't be used to do these other things.” Respondent 2.

Another potential challenge of the tool is that it makes no differentiation between 8-week versus 16-week courses. It is possible that this could confound some of the data being presented. In particular the Last Login screen would be effected by changes in the class calendar. The best way to address this issue in a more immediate manner would be to filter out the 8 week classes.

One respondent asked about whether this tool would be available to all instructors. She wondered about the need to have this data so widely distributed and questioned what would happen if it was reviewed by someone who did not know what they were looking at. It is possible that an over-zealous administrator could use this data as a way to seek out poorly performing instructors and penalize them. This makes the education about IDID and how to properly interpret the data all more important.

The last major theme that emerged from the user testing interviews was an overall positive sentiment. In particular respondents believed that the interface was intuitive and easy to understand and they commented on the ability to do quick comparisons for items and sections at a campus or regional level. This ability to perform comparisons at a campus, regional, and statewide level makes IDID stand out apart from other learning analytics dashboard applications.

4.6 Evaluation Results:

The evaluation of IDID consisted of ten one-on-one interviews conducted using GoToMeeting™. Approximately one week prior to each interview a basic orientation to the tool was conducted in a one-on-one GoToMeeting™ session. The orientation sessions were not recorded but the follow-up interviews were recorded and later transcribed for coding in NVivo™. The same set of questions was used in each interview and the basic format of the script will now serve as an organizational structure for the results. All respondents were able to use the dashboard to generate a set of recommendations for the improvement of the respective course design. The recommendations divided up into strategies to encourage student engagement and strategies to encourage instructor engagement. About half of the respondents noticed that students tend to skip the learning activities and move right into the assignments and assessments. The most successful students will complete the learning activities as intended but, the 'C' and 'D' students will navigate to the first graded assignment even though they may not be prepared to complete it. The course design template that we use at Ivy Tech calls for a separation of learning activities (ungraded material) from assignments and assessments (graded material). Since many students were jumping right to the graded materials we have since redesigned the course template so that in each module there is single path through the content and learning activities are interspersed with assessments.

One respondent mentioned that students were skipping over large portions of text as well. She said, "You know, the beginning when I asked the objectives from session, you know, your ability to do this and then at the bottom when it says, next session, I don't think that they even read any of that." Respondent 14. With the college's transition to Canvas it will be easier to see amount of time spent on each of the pages within a module. Discussion Board activity mirrored the other forms of interaction in many of the courses. There was a steady decrease in activity from the beginning to the end of the course. One respondent noticed the drop-off, “I noticed that there was a decrease in participation about mid-way through the course.” Respondent 19. This trend in participation created a reflection opportunity as the course design was evaluated. Course developers paused to consider if there was anything structurally occurring in the course to create an exodus at certain points in the semester. Discussion Board activity in some cases was affected by instructor engagement in the Discussion Board. One respondent made the connection, “If the instructor is fostering that community and making sure that students know that, number one, their posts are being taken seriously and they're being read. And then number two, that you're a real person and you're making those connections for them, you know really helping to foster a learning community.” Respondent 14. Dixson (2010) highlights that student engagement is dependent on instructors engaging through multiple communication channels.

Others identified the potential impact of the instructor, “But you have to read what they're saying. Sometimes they'll say, ‘Oh did you notice that Mary also works in healthcare’ or whatever. And so that little extra time in the beginning, I think, really helps.” Respondent 14. One respondent mentioned wanting to look more closely at the beginning sessions to see what the impact of instructor engagement was on overall retention. Salazar (2010) indicates that a key to student retention is early engagement of students and an early introduction to establish an online presence. This respondent said, “And, if you have a faculty member that's just saying, ‘Great job, great answers’, that's not helpful to the student at all and I'm kinda curious to see and I don't know if we can find this information out but if I were to review what a, what a faculty member does in their first assignments and to see what the retention rate of those students is." Respondent 12. This suggestion of content analysis to examine the nature of the feedback provided is an excellent next step for this research.

All respondents answered in the affirmative to the following two questions. "Were you able to compare performance at the section level?" and "Were you able to compare instructor behavior statewide?" So at a minimum IDID was able to support the semester to semester needs of program chairs. To the question "What additional sources of data would you want to identify your best instructors?" I received a variety of responses. One of the most common responses was an inquiry about the total amount of time for an interaction, not just the number of clicks. This speaks to one of the current limitations of the IDID system. The system currently counts click activity only so it does not account for students who will interact with the system in very different ways. Such as that student who downloads all his readings at the beginning of the semester. This student may have low activity on the system but, since he has downloaded his own copy he may in fact be highly engaged with the course content. This is especially the case in courses that lend themselves to this behavior like courses which have a lot of articles to read. When the interaction can occur offline it is not captured by such a system. One respondent phrased the question like this, "Is there any way to tell the amount of time rather than just clicks that students or instructors have?" Respondent 14. Another respondent thought that it would be helpful to look at instructional trends over multiple semesters rather than simply relying on the last semester of data. IDID is currently configured to look at the activity and performance of the previous semester only. Adding additional terms to the analysis might improve the predictive accuracy of the behaviors that are identified within IDID. Two of the respondents commented on collecting and leveraging more qualitative data along with the quantitative data. One respondent remarked, “What I would say is, what I would need in order to get a full picture of the instructor performance, is I would need qualitative data, as well as quantitative.” Respondent 18. Content analysis or sentiment analysis could be applied to investigate what kind of interaction the most successful instructors are conducting. However, another respondent indicated that she would want to know more about the nature of the announcements being posted. How many are content related? How many are purely administrative? How many are leaving qualitative comments for students in the grade center? Finally, one respondent requested deeper analysis of instructor behavior by session of the course rather than overall tool count. Her argument was that by paying attention to what instructors do in the first two weeks of the course one would be able to tell who remains engaged with his or her students and who is able to keep the students engaged. One of the outstanding questions raised by this research is that of those instructors who showed higher than average gradebook activity are they grading at several times during the semester or are they grading in smaller batches throughout the semester.

In response to the question “What features of the tool did you like?”, all the respondents were positive about the tool and its potential impact. All respondents were happy that this research was being conducted and that someone was invested in creating data tools to help them be more successful. One respondent said “But, I mean, I think it's very good data. It would take some time to really get used to how to use it but there's really good data there.” Respondent 10. There is much training needed to educate program chairs about what data is possible to report on and how to interpret the data. Other respondents commented on how simple the interface is to understand. Another respondent stated, “And that it consolidates it all into one pretty little package is nice. That's what I like the best. Instead of having to try to decipher it yourself based on comparing side by side something in blackboard or something like that.” As compared to previous behavior piecing together data from disparate systems, IDID made a huge step forward in assembling the data in a single location. Another respondent noted the visual appeal of IDID. “Well, I really liked the graphs on the individual persons, I like when those pie charts come up and I can visually kind of see the breakdown along with the layer.” IDID attempted to make the comparison predominantly visual in nature. Another respondent stated it a little differently, “So, not only do you have the numbers but you also have the visuals like those pie charts, the graphs, the bar graphs and it helps you to visualize the data rather than just looking at the numbers and having to make inferences from that.” Respondent 18. The power of a visualization is that it sometimes allows the data patterns to be more evident than if the data was presented in another manner.

The predominant response to the question, “What features of the tool caused the most frustration?” was a resounding belief that nothing was frustrating. One respondent seemed to summarize the views of the majority, “There was really no frustration with any of the tools.” Respondent 19. There were some minor issues that are worthy of mention. Two respondents remarked about losing track of which filters had been applied. IDID tried to address this issue by placing all the filters applied to dataset are visible on the screen. One respondent requested additional granularity to the Student Clicks and Student Clicks by Grade pages. I was quickly able to add the course identification number as an additional filter on these pages, which gave her the level of detail she was wanting. Finally, there was one respondent who had some technical difficulty in that Information Technology installed the previous version of Tableau Reader on his desktop and he was unable to open the dashboard on his own. Working with local IT to insure the proper versions of software are installed if your learning analytics solution depends on this approach is the best solution to this problem.

In Aim I, I identified three potential sensemaking groups. Those were course-centered, institution-centered, and information-centered sensemakers. When posed with a real course design scenario all sensemaking appeared to be course-centered. However, what did emerge from the data was that within this type of sensemaking there were several subgroups. Seven of the ten focused their sensemaking on the Student Clicks screen. Five of these seven were focused on the Student Clicks within the content and the other two focused on Student Clicks by Grade. It is worthy of mention that both respondents were recommending improvements to the same course. One was the course mentor, while the other was the instructional designer. Two respondents focused early attention on the differences they were seeing between the Internet vs Traditional students. The last respondent jumped immediately to the Last Login screen to determine where within the course design we were losing students. It was hard to tell how much the interface design effected the sensemaking process. More research is needed with different designs to examine the potential impact of the dashboard layout on the sensemaking process.

Nine out of ten respondents responded to the survey. Respondents were asked to rate their level of agreement with statements related to their confidence making decisions after using the system. The statements were presented with a five point Likert scales ranging from strongly agree to strongly disagree. Some of the statements were negatively worded to prevent simply marking each statement with strong agreement.

Table 1: Results from the Decision Confidence Survey

Field	Min.	Max.	Mean	Std. Deviation	Variance
The approach taken to make design decisions was very well structured.	4.00	5.00	4.44	.50	.25
My decisions for this course were good ones.	4.00	5.00	4.22	.42	.17
People in the course who would be affected by my decisions would probably be satisfied with them.	3.00	5.00	3.89	.57	.32
It took too much time to make decisions.	1.00	2.00	1.78	.42	.17
I’m pleased with the approach used to analyze the course data.	4.00	5.00	4.44	.50	.25

Analyzing the course data improved my problem-solving skills.	4.00	5.00	4.33	.47	.22
I wish I had approached the course data differently.	2.00	3.00	2.22	.42	.17
I'm not sure my decisions were appropriate.	2.00	3.00	2.22	.42	.17
Analyzing the course data frustrated me.	1.00	3.00	1.56	.68	.47
I really felt lost in trying to tackle the course data.	1.00	2.00	1.44	.50	.25
I might find it hard to get my decisions implemented.	1.00	3.00	2.00	.47	.22
The time and effort used to analyze the course data were well spent.	4.00	5.00	4.78	.42	.17
My analysis of the course data was systematic.	3.00	4.00	3.89	.31	.10
Analyzing the course data was a useful learning experience.	4.00	5.00	4.56	.50	.25
I may have missed important things in the course data.	2.00	4.00	3.11	.87	.77
I could easily justify my design decisions.	4.00	5.00	4.44	.50	.22
Analyzing the course data was interesting.	4.00	5.00	4.67	.47	.22
The approach used to analyze the course data wasn't worth the effort.	1.00	2.00	1.33	.47	.22
I'll be able to handle future course design decisions better because of the approach I used to analyze the course.	4.00	5.00	4.33	.47	.22
I'm not confident about my decisions.	1.00	4.00	1.78	.92	.84
I analyzed the course data in a step-by-step manner.	2.00	5.00	3.89	.74	.54

The two statements that had the greatest variance were "I'm not confident about my decisions", which had a variance of .84, and, "I may have missed important things in the course data", which had a variance of .77. This illustrates that these two statements had the largest range of responses. Furthermore, this two statements had the highest standard deviation at .92 and .87 respectively.

Showing that these statements had the greatest average distance from the average. This shows that these two responses were the least concentrated around the mean for each statement.

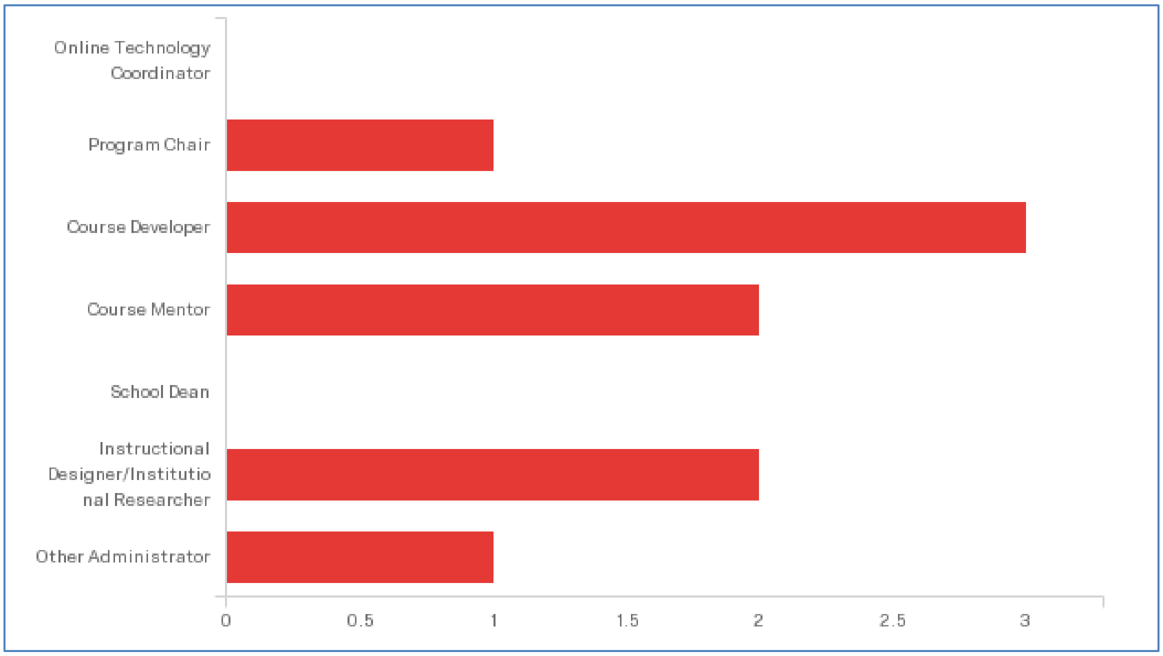


Figure 16: Breakdown of Respondent's Main Role at Ivy Tech

Figure 16 shows the breakdown of respondent's main role at Ivy Tech. There were three respondents whose main role was course developer and two whose main role was course mentor. Two respondents were instructional designers. This shows that the course redesign responsibilities do not fall to program chairs. Full time faculty and adjuncts as well as program chairs serve as course developers or course mentors and are primarily responsible for reviewing the course data and making recommendations for improvement.

Figure 17 represents the graph of the number of years respondents have been teaching online. Four respondents indicated that they have been teaching online 6-10 years. Three respondents indicated that they have been teaching online for 2-5 years. And only two respondents indicated they have been teaching online for 11-20 years.

Figure 18 represents the number of years that respondent have been Ivy Tech. There were three respondents who indicated they had been at Ivy Tech 2-5 years. There were three respondents who indicated they had been at Ivy Tech 6-10 years. Two responded they had been at Ivy Tech 11-20 years. One responded that he or she had been at Ivy Tech for over 20 years.

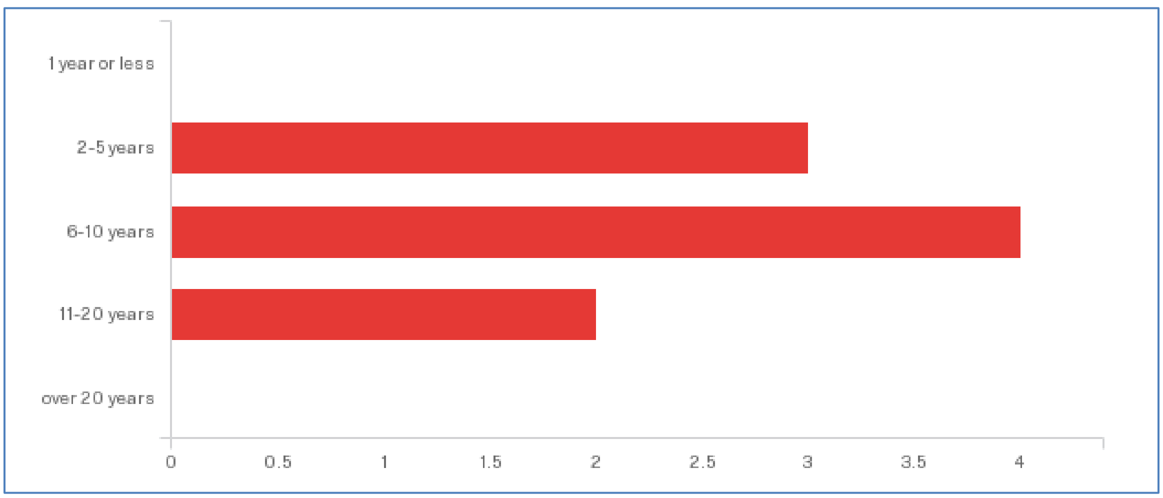


Figure 17: Number of Years Respondents Have Been Teaching Online

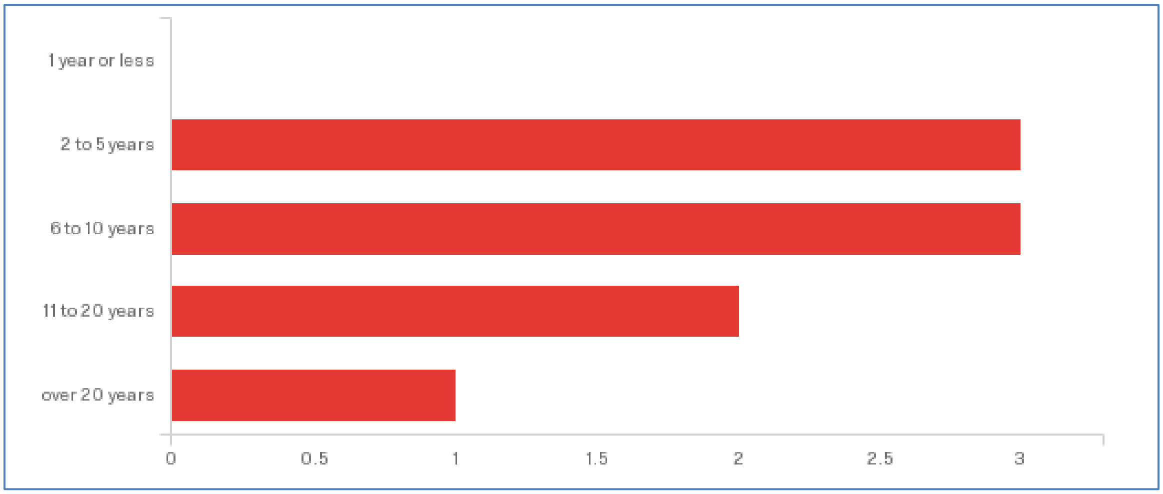


Figure 18: Number of Years Respondents Have Been at Ivy Tech

4.6.1 Summaries of User Experience with IDID:

The following vignettes are actual user experiences of the IDID platform. All names have been changed to protect the identity of the user. Refer to Appendix H for a full system walkthrough.

Anna Brown has been an adjunct faculty member for several years. She has experience as a professional accountant. She is both a course developer and a mentor. She is comfortable with analytics software and even exported some of the data provided into Excel for further analysis. The main recommendation that she had was to reorganize the course in a way that forces students to complete the learning activities before moving on to the assignments and assessments. She also suggested redesigning some of the Discussion Boards into blog assignments to encourage more interactivity as well as finding new resources to bring the subject matter alive and increase student engagement. Overall, she was happy with IDID remarking that it brought a lot of good data together in one place. She expressed a little frustration with setting the filters and forgetting that the filters were in place.

Isabella Veracruz has been at Ivy Tech for eight years. She has been an adjunct faculty member for that time completing the Ivy Tech Online Instructor and Online Mentor certifications as well as the peer reviewer certification with Quality Matters (QM). She has served as course developer and course mentor for Spanish I, II, III, and IV. She interacted with data from SPAN 201, Spanish III, as the course developer for this course and in preparing for a course redesign. She determined that students accessed the first session, read the instructions for the corresponding third-party application and had little need to access the remaining sessions in Blackboard other than to complete the Discussion Board. Additionally, instructors who had lower levels of engagement in Blackboard tended to have lower pass rates with one exception. There was one instructor who only accessed the gradecenter 76 times for 26 students or roughly 3 times per student who had extremely high pass rates. The rigor of this instructor's grading was drawn into question. The recommendations for improvement included slight revision to the instructional materials of each class session within Blackboard as a means to increase student engagement. Additionally, the instructor guide should be revised to encourage increased instructor engagement with the content. The one improvement to IDID that was recommended was the inclusion of some summary statistics showing merely total access time in Blackboard. It was difficult to determine the nature of the clicks through a simple count of clicks. Length of stay might help determine whether the click was a mistake in navigation or was more intentional.

Julie Klein has been a program chair since 2012. She has completed the IVYC101 and IVYC251 courses, the Ivy Tech Online Instructor and Online Mentor certifications. She has been a mentor and a developer. She did not have much time to explore the data set before the meeting. She did notice that students were skipping over the learning activities and jumping straight into the assignments and assessments. She wanted a way to look into instructor behaviors by session, particularly the first session. There was quite a bit of discussion about the differences between the motivation and intention of F and FW students. She was rather concerned about the number of students who were "gaming the system." Specifically, the concern came in two ways: students who play at completing the assessments through trial and error rather than study and review and students who remain enrolled long enough to get their financial aid money, then do not participate in any class activities.

Jeff Rawlings has been a program chair for seven years but for the last three years he has been a Department Chair. He has served as a course developer and a course mentor. He holds certifications as an online instructor and a course mentor as well as the Applying the Quality Matters Rubric certification (QM). His biggest frustration was that IT installed the wrong version of the Tableau reader and he was unable to fully review the data set prior to the meeting. In fact, he required me to share my screen and navigate through the data. The biggest issue that was discovered in the data was that there are many students who are skipping the learning activities folder and jumping right into the assignments and assessments folder. He suggested adaptive release, a feature in Blackboard of conditional releasing content, forcing students to complete something in the learning activities before the assignment and assessments would be available to them.

Lucy Crawley is a course developer and mentor who also acts as an online technology coordinator for her region. She has regional administrator access to Blackboard which has been beneficial in the past, allowing her and her co-developer to inspect specific sections for instructor announcements and qualitative grading comments. She described her approach to analyzing the data as very systematic at the section level. Her data package was slightly modified to allow filtering of a Blackboard course identification on both the Student Clicks page and the Student's Activity by Grade page. She was conducting A/B testing of two distinct course designs and evaluating the relative impact of the designs on student interaction at different grade ranges.

Samantha Peters has been an instructional designer for the past three years at Ivy Tech. She did not explore the data in depth before the interview because her developer was very comfortable working with the data set. She indicated that she would start her analysis on the Internet Versus Traditional screen. She mentioned that the development process is condensed so she does not have a great deal of time to analyze what is occurring in the various sections. If she had more time, she would be interested in looking at what specific activities were occurring in the traditional course that might translate well to the internet only modality.

Trisha James has been on faculty at Ivy Tech for twenty-eight years. She started as an adjunct faculty and moved into full-time status. She seemed to approach this project in a very methodical step-by-step manner. She followed the instructions quite closely and arranged her comments on her use in that order as well. One of the most interesting things she mentioned was that she moves back and forth between screens very fluidly. She might see something on one screen which will cause her to look for the same data from a slightly different perspective on another screen. Additionally, she was asked about the embedded contextual support and she confirmed what another respondent observed, which was that the data dictionary was not used.

Kelly Hudson is a full-time faculty member. She started with an exploration of the Last Log In page. She indicated that her analysis showed that in the first few days, students discover that the course is much more work than they had expected. However, past the first week, there did not seem to be a point in the semester that was resulting in significant withdrawals. When she looked at the Internet Versus Traditional screen, she saw that a lot more students take this course online as compared to those who take it in the traditional format. Further, it was noted that there was a fairly even distribution of As, Bs, and Cs in the online courses, whereas in the traditional courses there we very few Cs. She did note that the traditional course uses a completely different textbook and a different course design so it is difficult to compare the Internet and traditional formats. She described the importance of building community to influence the failure and withdrawal rates. She discussed the benefit of including a syllabus quiz to get students to read the syllabus and become comfortable with how the course is organized. The course maybe mistitled and should be called Business Communications instead of Technical Writing. This course is hugely popular with guest students; especially, juniors or seniors at Indiana University and Purdue University who need a second English course. Students are bypassing the learning activities and navigating directly to the assignments and assessments. She suggested that we could put a “carrot” in the learning activities, like examples of successful student work.

Michael Phillips is an instructional designer. He has worked in this role for one and half years. Prior to becoming an instructional designer he served as an online technology coordinator. He has completed multiple QM certifications including the Applying the Quality Matters Rubric Certification, the Peer Reviewer Certification, and the Online Facilitator Certification. He immediately noted that he and the developer focused heavily on the Student Clicks by Grade screen. They compared the behavior of A and B students against the behavior of C and D students. They found that the A and B students were accessing the practice activities, whereas the C and D students tended to skip the optional learning activities and jump right into the graded assignments and assessments. They decided to change the optional activities into required activities and reexamine the course data in a future semester to see if that change made a difference. He also mentioned that some of the questions raised by the data are more easily handled by the subject matter expert, who is much more familiar with the course content, than by the instructional designer. He went on to explain his role as an instructional designer. That role is to make sure the developer has access to the data, to review the findings with the developer, and to help the developer implement the changes suggested by his or her interpretation of the data. He mentioned that he did not need to direct the developer to any of the embedded contextual support because the supporting documents like the Session Alignment Matrix (SAM) are provided to the developer in advance to their exploration of this data. "I was able to get who I would consider a pretty non-technical person to be able to use it without too much of a problem. I think that speaks volumes to being pretty usable."

Chapter 5. Discussion and Conclusion

The first major outcome of this project was the design requirements for a learning analytics dashboard designed specifically for program chairs. These requirements could be useful for any college or university seeking to develop such tools for their program chairs. While these requirements were written with Ivy Tech specifically in mind, it is expected that others who use curriculum owners to manage course design frameworks would find the requirements useful. The requirements took into account not only the sensemaking support needs, but also the data requirements, interface requirements, and functional requirements for a learning analytics tool built to address the needs of program chairs. Although the requirements were not all addressed in the prototype design of the Instructional Design Implementation Dashboard (IDID), the design was intended to provide embedded contextual support at both a course and institutional level, multiple comparisons between sections, and highlighting differences between sections. The prototype is built as a front end to a larger data warehouse project. The data warehouse combines data from the Student Information System (in the case of Ivy Tech, we use Banner) and data from the learning management system (in the case of Ivy Tech, we use Blackboard). The queries used in Tableau combine the three different tables from the data warehouse. The Blackboard activity table, which contains one row per student per activity record from Blackboard, is joined to the instructor role table to indicate whether the activity is from an instructor or a student and it is joined to the unit record table, which is the student’s final grade and midterm grade as well as a number of demographic variables for each student. **Figure 19**, represents the architecture of the NewT data warehouse. The custom SQL for the IDID in Tableau are

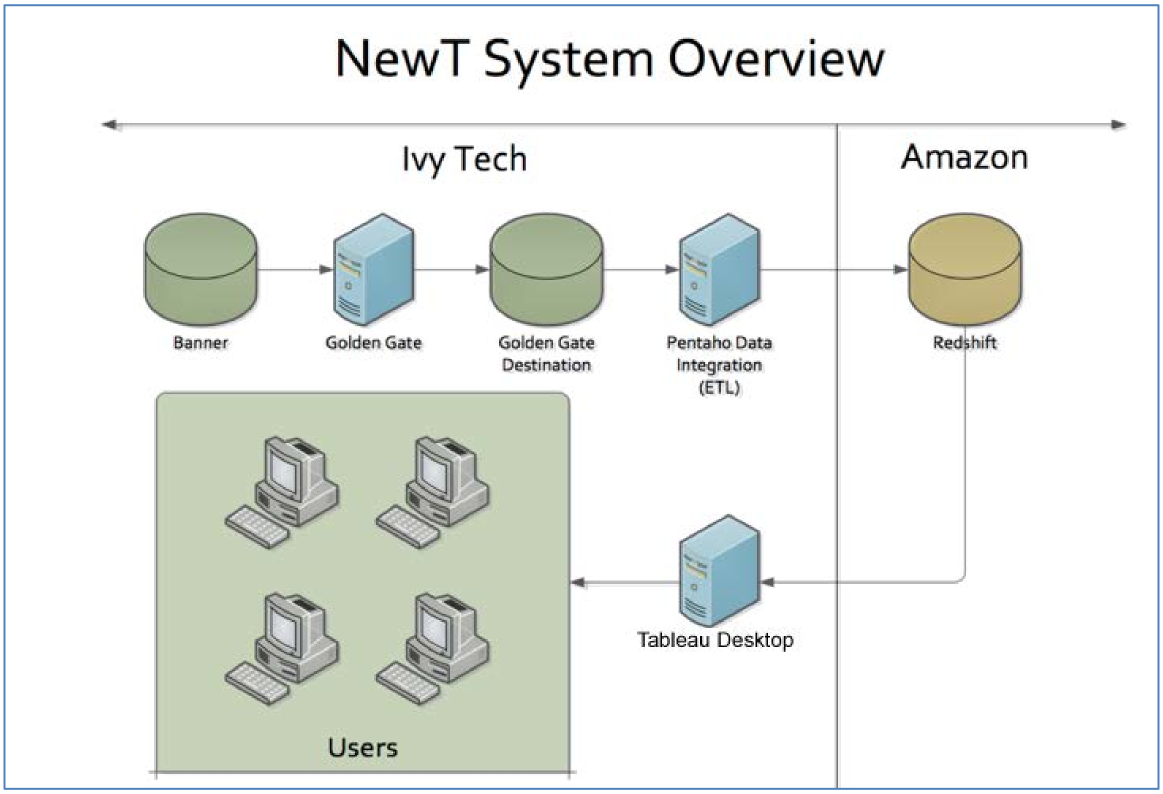


Figure 19: NewT Data Warehouse Architecture

provided in Appendix F.

The student information system is replicated in Golden Gate then transformed in Pentaho Data Integration. Pentaho Data Integration also queries the Blackboard Open Database and pulls all activity and grade data off of this system on a daily basis. All of this data is pushed into Postgres Databases on Amazon Redshift. The Redshift instances are queried using Tableau Desktop to create extracted workbooks. The extracted workbooks are shared with course mentors and course developers through the course mentors organization. Thereby, limiting access of the workbooks to users who have a legitimate need to review the workbooks.

As an additional layer of analysis, the observations of the user testing sessions and later the evaluation phase were coded against Data/Frame Theory of Sensemaking. Klein(2006) describes the connection between data inputs and mental representations (frames). The Data/Frame Theory describes six processes on frames during sensemaking: seeking a frame, elaborating the frame, questioning the frame, comparing frames, preserving the frame, and reframing. Appendix G contains a full elaboration of these sensemaking stages and examples of how some of these stages were experienced by users of the IDID platform.

The dominant feature of Seeking a Frame is the user's search for a mental representation that matches what they are seeing in the data. The two sub-steps that were most frequently expressed were finding Anchors and Searching for Information. The observations that were coded as Finding Anchors were those that drew attention to a particular aspect in the data. It varied from Searching for Information in the depth of attention drawn to the data. While Finding Anchors scans the data to find a frame to hold onto, Searching for Information is a broad look at data that fits the chosen frame.

Elaborating a Frame occurs when the user begins to fill in the pieces of his or her frame either through Adding and Filling Slots or through drawing on previous knowledge. Klein(2006) defines this as Internal Knowledge. Out of the four interviews that were coded as Internal Knowledge, one respondent in particular drew much of her insights from internal knowledge, that is, knowledge about the course that was not evident through the data being investigated. The most prevalent sub-step in Elaborating a Frame was Adding and Filling Slots. This was characterized by users filling in a richer picture of what was occurring in the courses. Seeking Data occurred when users began to investigate the data more deeply.

Questioning the Frame occurs when one of three things appears in the data. First, anomaly detection happens when something strange occurs in the data. Second, inconsistent data occurs when something in the data does not make sense. From the evaluation study, one respondent said “That means three times during the semester for each student.” Respondent 11. She was trying to reason why the gradecenter was only accessed 76 times. The final stage of Questioning the Frame is from violated expectancies. This occurred in the user testing when the user expected to see age, gender, and GPA in the student profile, but instead that area shows major, division, and degree aspirations.

Comparing Frames was experienced very little in the user testing and evaluation of IDID. Seeking Distinguishing Evidence was supported by the IDID application. Here is what one respondent said, “I used this data to look at student activity within the course. I looked at it from the standpoint of specific sections compared to designs that ran concurrently during the fall term. I was looking to see in the students click page. I specifically brought up the 2 different designs to see how whether or not one design had a great participation from students than another. I also appreciated the fact that I could separate out which course sections that I was looking at.” Respondent 15.

Preserving the Frame occurs when the user adjusts the data to make it fit with his or her perception of reality. Only two sub-steps were experienced by users and each of these was only experienced one time. These were Explaining the Data Away and Knowledge Shields. The unaccounted for sub-steps were Distortions and Fixation Errors. Under Explaining the Data Away, the user tries to rationalize why the data is shaped the way it is. This can be seen in this exchange were the user tries to reason why the F and D students showed higher average clicks than A, B, and C students. The user says, “I would look at that too to make sure, did they really prepare for these quizzes, which it appears to be me, yes they did, because it shows that up is 1.7 versus 2.8, so even though there are more on the average for the failures or the D's, than the passes, so there is probably some other way that those who got the A, B, C's prepared for their performance result that was seen.” Respondent 17. Knowledge Shields occurs when the user holds onto their frame in the face of contradictory data.

Reframing occurs when the user decides to revisit data based on a new mental model. Reframing involves Establishing New Anchors, which are new areas of evidence found in the data to support the formation of a new frame. In order to reframe, the user may revisit previously discarded data, thus Recovering Discarded Data or Re-Interpreting Data. In this example of Revising Goals, the user has modified his or her suggested improvement, “There's something that needs to be done to encourage the instructor to have more interaction or give more updated feedback to the students.” Respondent 11.

The two most prevalent phases based on the user testing were Seeking a Frame and Elaborating a Frame. This should not be surprising, given the context of the user testing and evaluation scenarios. Making sense of activity data at this level was a new skill that the respondents were asked to perform. The user testing confirmed the need for a proper orientation to the data as well as to give the respondents sufficient time to explore the data on their own. It is not surprising that the predominant sensemaking activities were Seeking a Frame and Elaborating a Frame. For the user testing from within Seeking a Frame the most prevalent task was Constructing a New Frame. For the evaluation phase the most prevalent tasks were Finding an Anchor and Searching for Information. For the user testing the most prevalent task from within Elaborating a Frame was the application of internal knowledge. This shifted a little in the evaluation phase to Adding and Filling Slots. However, Internal Knowledge had the highest number of references. Again, this was not surprising, because all respondents had a large body of experience from past courses to apply.

Turning attention to those processes of sensemaking that were not evident within the user testing session and evaluation, Preserving the Frame and Reframing were two processes that seemed to be ignored by the user testing and evaluation sessions. It could be that in order to perform these functions, one has to commit to a particular frame of reference. Perhaps these were not seen because they require assumptions of what the data should look like and being a new analytics tool, many respondents were unsure about these assumptions. For the user testing, under Questioning the Frame there were two instances of violated expectancies. There were only three such instances during the evaluation. It is likely that respondents had not established any expectancies for this data. There was one instance in which the respondent did expect to find a certain type of information and what was actually shown was not expected. The respondent said, “Okay, okay. All right. So like on the Student Profile, it's going to tell me if they're male, female, single, their age...” During the evaluation a respondent questioned the data stating that “where the pass rate is 100 percent, that is really unbelievable for me.” Respondent 11.

There are several implications of the IDID system that are worthy of discussion. First, one the main goals IDID was to improve the evaluation of our courses by adding usage statistics to the overall analysis of the course for the redevelopment process. This immediately raises questions about data privacy and ownership. This is further compounded as we try to bring more and more of the data from the learning ecosystem into our data warehouse. As we begin to make data sharing agreements with third party content providers, ownership of the learning data is drawn into question. More education is needed with end users regarding their data rights and how to protect their data. The challenge is that by offering an opt-out for students we run the risk of no longer maintaining a usable data set. So there is a rub between working to improve student performance and at what cost to the student does this insight bring. I would argue that a solid awareness campaign for students would encourage rather than discourage participation. It would at the minimum raise awareness of data which is being collected on their learning. Third parties like Pearson, McGrawHill, and

Cengage use learning data to improve their products. Students are signing over their data rights when they sign the user agreement to set up an account on these systems.

In addition to training students on the use of their data, we have a ways to go to better educate faculty about the use of their data. As Ellis (2011) states it, “The concern that some may have at being ‘surveilled’ through an analytics strategy may raise concerns about privacy and academic freedom and may raise the spectre of a ‘big brother’ institution.” (p.11) The challenge is to demonstrate the effect on student performance and to develop an attitude of continuous improvement within the faculty. The data should be used for positive professional development opportunities rather than a means to discipline under performing faculty. There must be a commitment to this approach to the data from all levels of leadership.

Not only should faculty be trained on an awareness of what data is being collected and how it is being analyzed but, they should receive training on how to ask good questions of the learning data. Undoubtedly this tool will make new data available that has previously not been presented in a format that is easy to consume. As the faculty become more familiar with working with learning data there may be new questions that they raise that could trigger development of other learning analytics systems.

The expected outcome of the IDID system is increased student success. Primarily it seeks to do this through improved course design. This would lead to an improved instructional experience for both students and instructors. Through the identification and promotion of behavior that has proven to be successful IDID seeks to identify best practice from both the student and instructor perspective. The tool allows for the articulation of profiles of proven behavior. This would provide students and instructional support staff to obtain knowledge of what success looks like from an activity standpoint. It would pinpoint precisely where the most successful students are spending their time thus improving student advising. Students would have more information to use to decide what materials to spend their time on within the course.

Chapter 6. Opportunities for Future Research

This research was the first foray into the application of big data and learning analytics at Ivy Tech Community College. Since starting this project, the college has started an initiative called Project Early Success, PES for short. (Schneider, 2016). PES seeks to identify at-risk students by using a machine learning algorithm to predict student success based on a number of factors. A strong predictor of success is access to Blackboard. PES uses the same query of the Blackboard Open Database that is used to populate the IDID project. PES is a statewide initiative and the college is measuring its impact.

Machine learning and task automation provide an exciting area of potential improvement for the IDID system. Training systems to identify patterns in the interaction data can be used to improve the predictive nature of systems such as PES. IDID could be reconfigured to look at midterm or final exam or some other key assessment. Or, performance on one of these milestone assessments could be factored into the predictive model for the end of term grade. Semantic analysis could be coupled with machine learning to discover the content posted by highly successful students or the content posted by the most highly successful instructors. Automated identification of high performing behaviors would allow for computer generated reporting of tasks which are today manual processes within the IDID system. Specifically, automated identification of content that does not receive a specified threshold of activity would allow the course design decision maker to rely on the technology to presort the items that would warrant further investigation. This could potentially improve the overall decision confidence by reducing the likelihood of overlooking something of significance within the data.

In addition to the Blackboard activity data we are seeking to enhance the data warehouse with some additional data not currently available to us. For example we have engaged with each of the major publishing partners to establish a regular data feed of student activity data from their systems into our data warehouse. The main issue is that typically 75% to 90% of all student learning activity is taking place in systems outside of Ivy Tech owned platforms. Pearson My Math Lab or McGraw Hill Connect serve as examples of these third party systems. The desire is to bring the activity stream from these systems into the data warehouse so that we have reporting capability over the entire learning cycle. Without that data major activities related to student learning remain invisible to Ivy Tech. Having this data would allow us to extend IDID to include insight in the instructional design of these third party systems.

There are a number of ways to expand the functionality of the IDID platform. An easy win would be to incorporate Quality Matters review data into the dashboard as well. This would expand the role of the QM review to incorporate usage data. Even if a learning object is well designed and aligned to the objectives, if it is not receiving any attention, it should either be removed or the message around the object needs to be changed.

Another area of potential future investigation is the exploration of grade data on the analysis of instructional design efficacy. Currently IDID is configured to look at correlation of final grade and activity information. It would be helpful to allow for the configuration of which grade to correlate. The same questions about the efficacy of item access on final grade could easily be applied to the midterm grade or any other major assessment in the course. For example, we could see the impact of item access on the final exam or the final research project.

There is a potential for research on grade analysis in and of itself. We could perform a regression analysis on the major assessments in the course and verify that they statistically contribute to the overall success in the course. This type of analysis further validates the course design by insuring that the major assessment are in fact contributing to success in the course.

There is also Learning Management System data that we are not capturing today, which would provide intriguing channels of additional inquiry. For example, we could capture Discussion Boards or class announcements and perform semantic analysis on the content to categorize the types of engagement that highly successful instructors are performing. For instance, are the announcements generally related to the content or are they administrative in nature? If they are content related, are there certain themes that are receiving more attention than others? This would be an exciting research opportunity that merits further investigation.

Beyond the potential avenues of learning analytics research that is now opened up by this research there is a whole range of additional user research opportunities. We could test multiple dashboards to identify the characteristics of highly usable designs. There is much more about the sensemaking process that we have yet to uncover. How exactly does a frame become established? What are the precise patterns in the data that cause fixation or consideration of alternative frames? Are there ways to present the visualization that contribute to either fixation or consideration of alternative frames?

Although I captured the screencast, it would be informative to collect additional data such as eye movement during the “think aloud session” of sensemaking. In fact, it would be fascinating to compare initial sensemaking with the summarized sensemaking activity which was captured in this study. In such future research one could compare actual sensemaking with perceived sensemaking.

In December 2016, the college announced its intention to migrate to the Canvas learning management system effective summer 2017. IDID will need to be reconfigured to use data from the Canvas Data Portal. Besides page views the system will show student and instructor activity in conversations, discussion boards, assignments, and quizzes. I am working with the team for Decision Support to create a Canvas Data cube in our data warehouse environment. It is likely that the IDID tool will be rebuilt in Pentaho which is the underlying Business Intelligence suite that the college has adopted.

The implications of dashboard design are enormous and the potential research of instructional design evaluation is equally as large an opportunity for future researchers. This research barely scratches the surface of what we know about the sensemaking process. Much more investigation of this phenomenon in other contexts is needed to more richly describe the process.

Chapter 7. Summary of Contributions

There are three main areas of contribution to this study. These correspond to the phases or aims of the research. The study first sought to capture the user requirements of a new learning analytics system from the perspective of program chairs. These requirements needed to account for the sensemaking needs of the user. Second, a novel learning analytics tool was developed which aggregates learner activity information and correlates it to end of course performance. IDID in itself is a contribution of this research. Finally, the user experience was related back to theoretical sensemaking and Klein's(2006) Data / Frame Theory of Sensemaking was confirmed with actual sensemaking experiences. This further refines the model and provides actual user experiences from which to design future learning analytics tools.

7.1 Requirements:

The first major contribution of this study was the comprehensive set of requirements derived from the survey of sensemaking needs of program chairs. These requirements were divided into the knowledge support requirements, data requirements, interface requirements, and functional requirements. These requirements could be applied to learning analytics for curriculum owners in large college systems. The knowledge support typology, **figure 20**, could be useful in a number of similar contexts. It provides a framework around which to consider providing knowledge support to help make academic decisions.

Statistical Knowledge	Domain Knowledge		System Knowledge		Person Knowledge
	Curriculum Knowledge	*Pedagogical Knowledge*	*Technical Knowledge*	*Institutional Knowledge*	
Assumptions of Methods	Course Objectives	Teaching Methods	System Definition of a Click	Data Refresh Rate	Demographics about Instructors
Meaning of Statistics Vocabulary	Course Content	Point Distribution	Categories of Tools,	Default Tools	Demographics about Students
Meaning of Graphs		Instructional Modality	ie. Content Files,	Schools/Departments	
			Communication Tools,	Term Structure	
			Assessments	Class Size	
Examples:	*Examples:*	*Examples:*	*Examples:*	*Examples:*	*Examples*
Statistics Tutorials	Curriculum of Record	Session Alignment Matrix	Course At-A-Glance	Data Dictionary	Demographics Pulled from Data Warehouse
	Course Outline of Record		Known Issues by Tool	Articulation Agreements	

Figure 20: Typology of Knowledge Support Needs

Originally, I had proposed the need for statistical knowledge, domain knowledge, and system knowledge. However, the survey responses uncovered the need to answer the questions about who was involved in the learning activity. Participants indicated the need to know who was teaching and who was learning. Figure 18 shows the revised typology of support needs along with specific types of support and examples of support resources. The typology could be applied to any learning analytics situation to describe the knowledge support needed to make sense of the analytics.

In addition to the requirements three main design themes emerged out of the rationale for sensemaking rankings. These were embedded contextual support at both course and institutional levels, multiple comparisons between sections, and highlighting differences between sections. Taken together these requirements called for a data warehouse solution. It was fortunate that Ivy Tech was launching a large data warehouse project at the same time I began to develop solutions to meet the stated requirements. It is expected that other learning analytics applications would find similar differences in the types of sensemakers using their systems. At a minimum learning analytics designers should consider the support needs of institution centered, course centered, and information centered sensemakers.

7.2 Instructional Design Implementation Dashboard:

The Instructional Design Implementation Dashboard was another major contribution to the field. The SQL queries that were developed could be used by future researcher or learning analytics dashboard developers to correlate grade data with learner activity data coming from the Blackboard learning management system. Appendix F outlines the custom SQL that was developed for this project. This project confirmed the importance of user testing, because several users reacted to the design in unexpected ways. For instance, user testing uncovered small design enhancements that made a big difference for users. One example of this was the inclusion of sample sizes below each of the charts and graphs. Another design enhancement was the inclusion of a static graph which represented the grade distribution of all students so that the user could compare the impact of content items on the grade distribution. The design and development of the IDID platform is well documented so that it could easily be replicated at other institutions.

7.3 Revised Sensemaking Model:

Perhaps the biggest contribution to the field was the confirmation of Data/Frame Sensemaking Theory. The revised model is presented here.

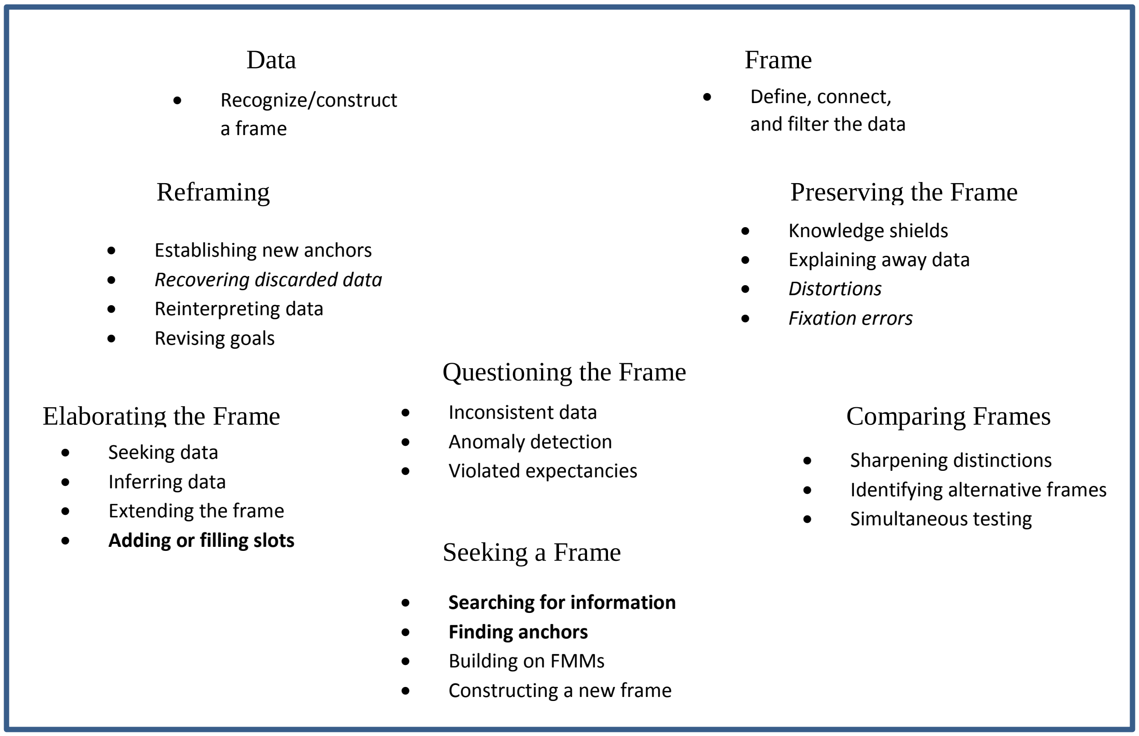


Figure 21: Revised Data/Frame Sensemaking Model

In this model, **figure 21**, the elements of theory that were not demonstrated by the recorded user experience are presented in italics. Those that appeared in five or more cases are presented in bold text. Predominantly, the sensemaking process begins with Seeking a Frame. Most often this stage of sensemaking was seen as Searching for Information or Finding Anchors. This stage is foundational to all the other stages. Following from Seeking a Frame, the sensemaking process moved into Elaborating the Frame or less frequently into Questioning the Frame and Comparing Frames. While Elaborating the Frame, the most frequent step was Adding and Filling Slots. This step was characterized by an elaboration of the user's mental model governing his or her personal understanding of the story the data represented. Sometimes the Sensemaking process would flow from Seeking a Frame to Elaborating the Frame to Questioning the Frame or Comparing Frame. If the sensemaker revised his or her goals or began searching for new anchors, then he or she entered a Reframing stage. If instead the user retains an existing frame in the face of contradictory data, he or she starts Preserving the Frame. These two stages, Reframing and Preserving the Frame, were less frequently experienced by users of the Instructional Design Implementation Dashboard. Future research of these two stages should be conducted which might involve some contrived data to highlight the inconsistencies which cause the user to either make a decision to hold onto his or her existing frame or search for a new frame. One of challenges of capturing actual sensemaking scenarios is that the data do not represent the inconsistencies that are prerequisites for the Reframing and Preserving the Frame phases of sensemaking. Much more data on real world experience of sensemaking is needed to either confirm or refute the model presented here. However, it is useful to learning analytics system designers to know the general progression of cognition while making sense of the learning analytics system. The Data Frame Model of Sensemaking aptly described the actual sensemaking experiences of real users given real world data from large online courses.

Appendix A

Overview of Quality Initiatives in Online Education

As early as 2000, the eight regional accreditation commissions agreed, “that institutions undertake the assessment and improvement of their quality, giving particular emphasis to student learning” (Higher Learning Commission, 2007, p. 1). These guidelines were titled the Best Practices in Online Certification and Degree Programs. Other quality initiatives within the last few years exist to identify best practice on an institutional level. A seminal report, Quality on the Line (IHEP, 2000), which identified 21 benchmark areas of highly successful online programs, and the Sloan-C Quality Scorecard (Sloan-C, 2011) are just two of the quality improvement programs that outline best practice recommendations for online programs.

In May 2002, reacting to the Best Practices in Online Certification and Degree Programs, a group of faculty, staff, and students at California State University Chico began to develop a rubric for determining the quality of online instruction (Sederberg, 2003). The Rubric for Online Instruction (CSU Chico, 2003) was used a means to identify within that institution examples of instructional best practice that are worthy of being recognized. In 2006 under a grant from the Fund for Improvement of Post-Secondary Education (FIPSE), Quality Matters (QM) became the first intra-institutional quality course improvement process (Shattuck, 2007). The internationally subscribed program does allow for some benchmarking to other institutions but only evaluates course design. Course delivery falls outside the scope of the Quality Matters rubric and therefore is best evaluated through other evaluation methods.

The Instructional Design Implementation Dashboard (IDID) developed here displays course design information such as a breakdown of course elements filtered by aggregate student performance data and allows for drill down to view the activity information of both instructors and students in these highly successful course sections. Such an analytic are used by program chairs on a curriculum committee to identify and promote best practices in the implementation of the course design framework at the section, or regional level. It is conceivable that program specific thresholds of activity and performance could be established to generate an early warning system to identify at-risk students or absent instructors.

If the course design framework was used in both credit and noncredit courses or in online and traditional courses there would be an expectation that the patterns of activity and performance would shift depending on the shifts in context. It is expected that the IDID will aid course curriculum committees in the preparation of an instructor guide which accompanies the course design framework.

Appendix B

INDIANA UNIVERSITY INFORMED CONSENT STATEMENT FOR

User Testing of the "Instructional Design Implementation Dashboard"

Thank you for participating in this study!
This is a study of the knowledge support for learning analytics to improve course design at Ivy Tech Community College of Indiana. This study supports doctoral research in Human-Computer Interaction (HCI). This research is being conducted by Robert Morse under the direction of Davide Bolchini, School of Informatics, Indiana University Purdue University Indianapolis (IUPUI).

This exempt study has been approved (study #14011) by the HSRB(Human Subjects Research Board) for human subjects research at Ivy Tech Community College

STUDY PURPOSE. This study tests a contextual support structure for a learning analytic system. Data presented is from a real Ivy Tech course from the Summer 2014 term.

PROCEDURES FOR THE STUDY. If you agree to be in the study you will asked to interact with the analytic system to make several instructional design decisions to improve the statewide course.

RISKS OF TAKING PART IN THE STUDY. While on the study, the risks are: By participating in the study, you may feel some fatigue from making these course design decisions, the same fatigue that you will feel when making curriculum designs as a normal part of job responsibilities.

BENEFITS OF TAKING PART IN THE STUDY. You will be exposed to an analytic system built on course data from the Summer 2014. Participating in the survey may result in thinking differently about your course and course data.

ALTERNATIVES TO TAKING PART IN THE STUDY. You may decide at any time not to participate in this study.

CONFIDENTIALITY. Respondents will be coded and responses will be preserved for triangulation should you be selected for future phases of this study. No personal data will be collected or used for research purposes. No personal information will be distributed or shared with anyone outside this research study, unless required by law.

COSTS. No costs are associated to you for taking part in this study.

CONTACTS FOR QUESTIONS OR PROBLEMS. For questions about the study you can contact Robert Morse(rkmorse@iupui.edu).

For questions about your rights as a research respondent or to discuss problems, complaints or concerns about a research study, or to obtain information, or offer input, contact the IU Human Subjects Office at (812) 856-4242 or (800) 696-2949, or by email at irb@iu.edu.

VOLUNTARY NATURE OF STUDY. Taking part in this study is voluntary. You may choose not to take part or may leave the study at any time. Your decision whether or not to participate in this study will not affect your current or future relations with Ivy Tech Community College or Indiana University-Purdue University Indianapolis.

Course Design Decision Tasks

Using the analytic system provided, identify under-utilized resources in the course?
Were the students who accessed these materials more or less successful than those who did not access them?
How critical are these resources to conveying the objectives for the course?
What recommendations could you make for improving the course design based on your review of this data?
Is the performance between sections consistent?
Are the instructors of your sections engaging with students in a consistent manner?
What are your instructors of higher performing sections doing that you would want to encourage all faculty to do?

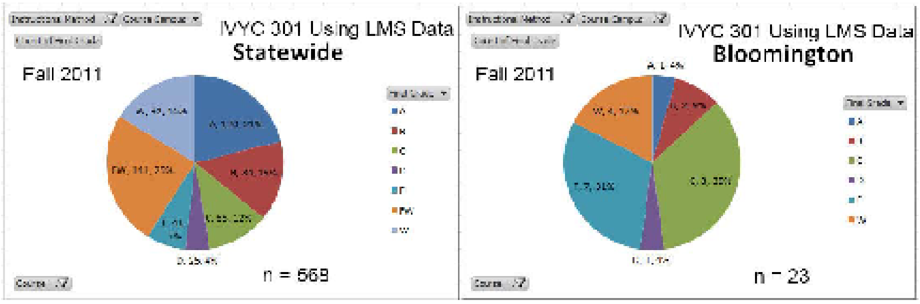
Knowledge Requirements for eLearning Analytics

This research project proposes the development of a system to collect course data about statewide online courses.
You will be asked a series of questions related to the additional knowledge support needed to properly interpret various types of course data.

Before answering the questions, please view a brief demonstration of the potential interaction for the "Best Practice Finder".
Now complete this survey as fully as possible keeping in mind that the goal is to help you use learning system course data to improve your course design.

Grade Distribution Data

Review this data pulled from Banner representing end of course grades.



If you were going to use this information to improve or take action to improve your course, what additional information do you most need?
Rank the order of importance for each of these additional sources of information. Use a 5 for the most important item and a 1 for the least important item.

More information on how to properly read a pie chart.

More information on the course content and objectives.

More information on the instructional activities and course design.

More information on which tools and materials are used in the course.

More information on institutional definitions for student success.

Provide a reason for your ranking.

What additional information do you want to know about course grades across sections of the course to improve the course?

Would this comparison be useful?

- Useful
- Not Useful

Blackboard Activity Information

Review this graph generated from the Learning Management System.

Appendix C

Ivy Tech Custom Quality MattersTM Rubric Standards
Based on the Fifth Edition, 2014, with Assigned Point Values
For more information visit https://sites.google.com/a/ivytech.edu/qm/

Course Overview and Introduction 1.8 The self-introduction by the instructor is appropriate and is available online. 1.9 Learners are asked to introduce themselves to the class. 1.10 The course uses the official Ivy Tech Online course syllabus template.	1 1 3
Learning Objectives (Competencies) 2.1 The course learning objectives, or course/program competencies, describe outcomes that are measurable. 2.2 The module/unit learning objectives or competencies describe outcomes that are measurable and consistent with the course-level objectives or competencies. 2.3 All learning objectives or competencies are stated clearly and written from the learner's perspective. 2.4 The relationship between learning objectives or competencies and course activities is clearly stated. 2.5 The learning objectives or competencies are suited to the level of the course.	3 3 3 3 3
Assessment and Measurement 3.1 The assessments measure the stated learning objectives or competencies. 3.2 The course grading policy is stated clearly. 3.3 Specific and descriptive criteria are provided for the evaluation of learners' work and are tied to the course grading policy. 3.4 The assessment instruments selected are sequenced, varied, and suited to the learner work being assessed. 3.5 The course provides learners with multiple opportunities to track their learning progress.	3 3 3 2 2
Instructional Materials 4.1 The instructional materials contribute to the achievement of the stated course and module/unit learning objectives or competencies. 4.2 Both the purpose of instructional materials and how the materials are to be used for learning activities are clearly explained. 4.3 All instructional materials used in the course are appropriately cited. 4.4 The instructional materials are current. 4.5 A variety of instructional materials is used in the course. 4.6 The distinction between required and optional materials is clearly explained.	3 3 2 2 2 1
Course Activities and Learner Interaction 5.1 The learning activities promote the achievement of the stated learning objectives or competencies.	3 3 3

5.2 Learning activities provide opportunities for interaction that support active learning. 5.3 The instructor's plan for classroom response time and feedback on assignments is clearly stated	
Course Technology 6.1 The tools used in the course support the learning objectives and competencies. 6.2 Course tools promote learner engagement and active learning. 6.3 Technologies required in the course are readily obtainable. 6.4 The course technologies are current. 6.5 Links are provided to privacy policies for all external tools required in the course.	 3 3 2 1 1
Learner Support 7.1 The course instructions articulate or link to a clear description of the technical support offered and how to obtain it. 7.2 Course instructions articulate or link to the institution's accessibility policies and services.	 3 3
Accessibility and Usability 8.1 Course navigation facilitates ease of use. 8.2 Information is provided about the accessibility of all technologies required in the course. 8.3 The course provides alternative means of access to course materials in formats that meet the needs of diverse learners. 8.4 The course design facilitates readability. 8.5 Course multimedia facilitate ease of use. 8.6 The course uses the official Ivy Tech Online course design template.	 3 3 2 2 2 3

To meet standards all 3 point (essential) standards must be met and the course must earn at least 73 points.

Appendix D

Coding Structure – Preliminary Study

Name	References	Sources
Consistency		
Consistent Evaluation	4	5
Consistent Instruction	2	3
Consistent Interpretation	1	1
Demographics		
Development Experience	4	5
Online Teaching Experience	2	2
Time at Ivy Tech	4	5
Time program chair	2	3
Data-Driven Course Design Decision Making		
Data Reporting		
Data Aggregation		
Aggregation by Region	2	2
Appropriate Levels of Aggregation	1	1
Section Level Reporting	2	3
Reporting Tools	1	1
Banner Capabilities	1	1
Assignment Reporting	1	1
Third-party Tool Adoption	1	1
Item Analysis	1	2

Pre-Test/Post-Test Comparison	1	3
Current Use of Course Data		
Don't Use Data	2	2
Disconnected Data	1	1
Anecdotal Evidence	1	1
Grades		
Grade Inflation	1	1
Student Success	1	1
Usage Statistics		
Comparing Students and Instructors	3	3
Course Component Use	2	3
Instructor Engagement	1	3
Student Engagement	1	1
Complicated Navigation	1	1
Last Date of Attendance	1	1
Student Surveys	1	2
System Expectations	1	1
Bell-Curve	1	1
Expected Presentation of Data	1	1
Face to Face versus Online Modality	1	2
Visual Appeal	1	2

Appendix E

Decision Support Confidence Survey

INDIANA UNIVERSITY INFORMED CONSENT STATEMENT FOR Evaluation of the "Instructional Design Implementation Dashboard" Thank you for participating in this study! This is a study of the knowledge support for learning analytics to improve course design at Ivy Tech Community College of Indiana. This study supports doctoral research in Human-Computer Interaction (HCI). This research is being conducted by Robert Morse under the direction of Davide Bolchini, School of Informatics, Indiana University Purdue University Indianapolis (IUPUI). This exempt study has been approved (study #15006) by the HSRB(Human Subjects Research Board) for human subjects research at Ivy Tech Community College

STUDY PURPOSE. This study tests a contextual support structure for a learning analytic system. The analytic system presents data from the spring, summer, or fall 2015 terms.

PROCEDURES FOR THE STUDY. If you agree to be in the study you will evaluate how well the system supported your decision making.

RISKS OF TAKING PART IN THE STUDY. While on the study, the risks are: By participating in the study, you may feel some fatigue from making these course design decisions, the same fatigue that you will feel when making curriculum designs as a normal part of job responsibilities.

BENEFITS OF TAKING PART IN THE STUDY. You will be exposed to an analytic system built on course data from the spring, summer, or fall 2015 terms. Participating in the survey may result in thinking differently about your course and course data.

ALTERNATIVES TO TAKING PART IN THE STUDY. You may decide at any time not to participate in this study.

CONFIDENTIALITY. Respondents will be coded and responses will be preserved for triangulation should you be selected for future phases of this study. No personal data will be collected or used for research purposes. No personal information will be distributed or shared with anyone outside this research study, unless required by law.

COSTS. No costs are associated to you for taking part in this study.

CONTACTS FOR QUESTIONS OR PROBLEMS. For questions about the study you can contact Robert Morse(rkmorse@iupui.edu). For questions about your rights as a research respondent or to discuss problems, complaints or concerns about a research study, or to obtain information, or offer input, contact the IU Human Subjects Office at (812) 856-4242 or (800) 696-2949, or by email at irb@iu.edu.

VOLUNTARY NATURE OF STUDY. Taking part in this study is voluntary. You may choose not to take part or may leave the study at any time. Your decision whether or not to participate in this study will not affect your current or future relations with Ivy Tech Community College or Indiana University-Purdue University Indianapolis.If you content to participate, choose that option below.

- ❍ Yes, I consent.
- ❍ No, no thank you.

Reflecting on your use of the Instructional Design Implementation Dashboard, select the degree of agreement with each of the statements below.	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The approach taken to make design decisions was very well structured.	❍	❍	❍	❍	❍
My decisions for this course were good ones.	❍	❍	❍	❍	❍
People in the course who would be affected by my decisions would probably be satisfied with them.	❍	❍	❍	❍	❍
It took too much time to make decisions.	❍	❍	❍	❍	❍
I'm pleased with the approach used to analyze the course data.	❍	❍	❍	❍	❍
Analyzing the course data improved my problem-solving skills.	❍	❍	❍	❍	❍

I wish I had approached the course data differently.	❍	❍	❍	❍	❍
I'm not sure my decisions were appropriate.	❍	❍	❍	❍	❍
Analyzing the course data frustrated me.	❍	❍	❍	❍	❍
I really felt lost in trying to tackle the course data.	❍	❍	❍	❍	❍
I might find it hard to get my decisions implemented.	❍	❍	❍	❍	❍
The time and effort used to analyze the course data were well spent.	❍	❍	❍	❍	❍
My analysis of the course data was systematic.	❍	❍	❍	❍	❍
Analyzing the course data was a useful learning experience.	❍	❍	❍	❍	❍
I may have missed important things in the course data.	❍	❍	❍	❍	❍
I could easily justify my design decisions.	❍	❍	❍	❍	❍

Analyzing the course data was interesting.	❍	❍	❍	❍	❍
The approach used to analyze the course data wasn't worth the effort.	❍	❍	❍	❍	❍
I'll be able to handle future course design decisions better because of the approach I used to analyze the course.	❍	❍	❍	❍	❍
I'm not confident about my decisions.	❍	❍	❍	❍	❍
I analyzed the course data in a step-by-step manner.	❍	❍	❍	❍	❍

What is your regional affiliation.
❍ Northwest
❍ Northcentral
❍ Northeast
❍ Lafayette
❍ Kokomo
❍ East Central
❍ Wabash Valley
❍ Central Indiana
❍ Richmond
❍ Columbus
❍ Southwest
❍ Sellersburg
❍ Bloomington
❍ Central Office

How would you define your main role at Ivy Tech?
❍ Online Technology Coordinator
❍ Program Chair
❍ Course Developer
❍ Course Mentor
❍ School Dean
❍ Instructional Designer/Institutional Researcher
❍ Other Administrator

How many years have been teaching online?
❍ 1 year or less
❍ 2-5 years
❍ 6-10 years
❍ 11-20 years
❍ over 20 years

How many years have you been at Ivy Tech?
❍ 1 year or less
❍ 2 to 5 years
❍ 6 to 10 years
❍ 11 to 20 years
❍ over 20 years

Which IVYC courses have you completed?
- ❑ IVYC101-Online Faculty Certification
- ❑ IVYC201-Online Developer Certification
- ❑ IVYC251-Online Mentor Certification

Which Quality Matters Training courses have you completed?
- ❑ APPQMR-Applying the Quality Matters Rubric
- ❑ PRC-Peer Reviewer Certification
- ❑ OFC-Online Facilitator Certification
- ❑ MRC-Master Reviewer Certification

Appendix F

Custom SQL for IDID

```
SELECT "Activity"."user_id" AS "user_id",
  "Activity"."student_id" AS "student_id",
  "Activity"."event_type" AS "event_type",
  "Activity"."internal_handle" AS "internal_handle",
  "Activity"."logtime" AS "logtime",
  "Activity"."bb_course_id" AS "bb_course_id",
  "Activity"."course_id" AS "course_id",
  "Activity"."content_title" AS "content_title",
  "bb_instructor"."instructor_role" AS "instructor_role",
  "dw_unit_record"."mid_term_grade" AS "mid_term_grade",
  "dw_unit_record"."final_grade" AS "final_grade",
"dw_unit_record"."instructional_method" AS "instructional_method",
"dw_unit_record"."county" AS "county",
"dw_unit_record"."course_campus" AS "course_campus",
"dw_unit_record"."course_section" AS "course_section",
"dw_unit_record"."degree" AS "degree",
"dw_unit_record"."division" AS "division",
"dw_unit_record"."major_description" AS "major_description",
"dw_unit_record"."gender" AS "gender",
"dw_unit_record"."age" AS "age"
FROM (
  SELECT DISTINCT "BB Activity"."user_id" AS "user_id",
    "BB Activity"."student_id" AS "student_id",
    "BB Activity"."event_type" AS "event_type",
    "BB Activity"."internal_handle" AS "internal_handle",
    "BB Activity"."logtime" AS "logtime",
    "BB Activity"."course_id" AS "bb_course_id",
   SUBSTRING("BB Activity"."course_id",1,7) AS "course_id",
  "BB Activity"."data" AS "content_title"
  FROM  "public"."bb_activity" "BB Activity"
  WHERE "BB Activity"."course_id" LIKE <Parameters.COURSEID>+'%'
  AND "BB Activity"."course_id" LIKE '%'+<Parameters.TERM>
) "Activity"
  LEFT JOIN "public"."bb_instructor" "bb_instructor" ON
(("Activity"."bb_course_id" = "bb_instructor"."course_id") AND ("Activity"."user_id"
= "bb_instructor"."user_id"))
  LEFT JOIN "public"."dw_unit_record" "dw_unit_record" ON
(("Activity"."course_id" = "dw_unit_record"."course_id") AND
("Activity"."student_id" = "dw_unit_record"."student_id") AND
("dw_unit_record"."academic_period"= <Parameters.TERM>) AND
("dw_unit_record"."capture_date"='MAY-13-2016'))
```

Appendix G

Stage in Sensemaking	Definition	Example
I. Elaborating the Frame		
a. Seeking Data	statement of application/data location	a. “I'm going to go over to the Content Title and look at some specific kinds of content and, let's see."
b. Inferring Data	statement indicating something that is inferred and not present in the data	b. “Well yes. It would cause me to go look at them to see exactly what they are asking to see if that is the thing that makes the difference.”
c. Extending the Frame	statements expanding the current understanding	c. “Anything that's graded is easy because there's not a grade every week, so I know the students who are doing the assignments. It's how they're preparing for the assignments is more of a mystery."
d. Adding and Filling Slots	statements providing a more complete picture	d. “But, since we're counting students, I don't expect it to be as high as it is. Okay, I get that. We got a big group of B students. Okay, so we might be seeing here a distribution pretty close to the overall distribution of the course grades?”
e. Internal Knowledge	statements applying prior knowledge about Ivy Tech or teaching in general.	e. “The results of the classroom versus online, grade comparison, are kind of, in this class, would be what I would have expected.”
II. Questioning the Frame		
a. Inconsistent Data	statement acknowledging that the data does not match the frame	a. “So it's, I don't know, I don't understand how the instructor can just access 76 times the grade book when we had at least 15, I don't

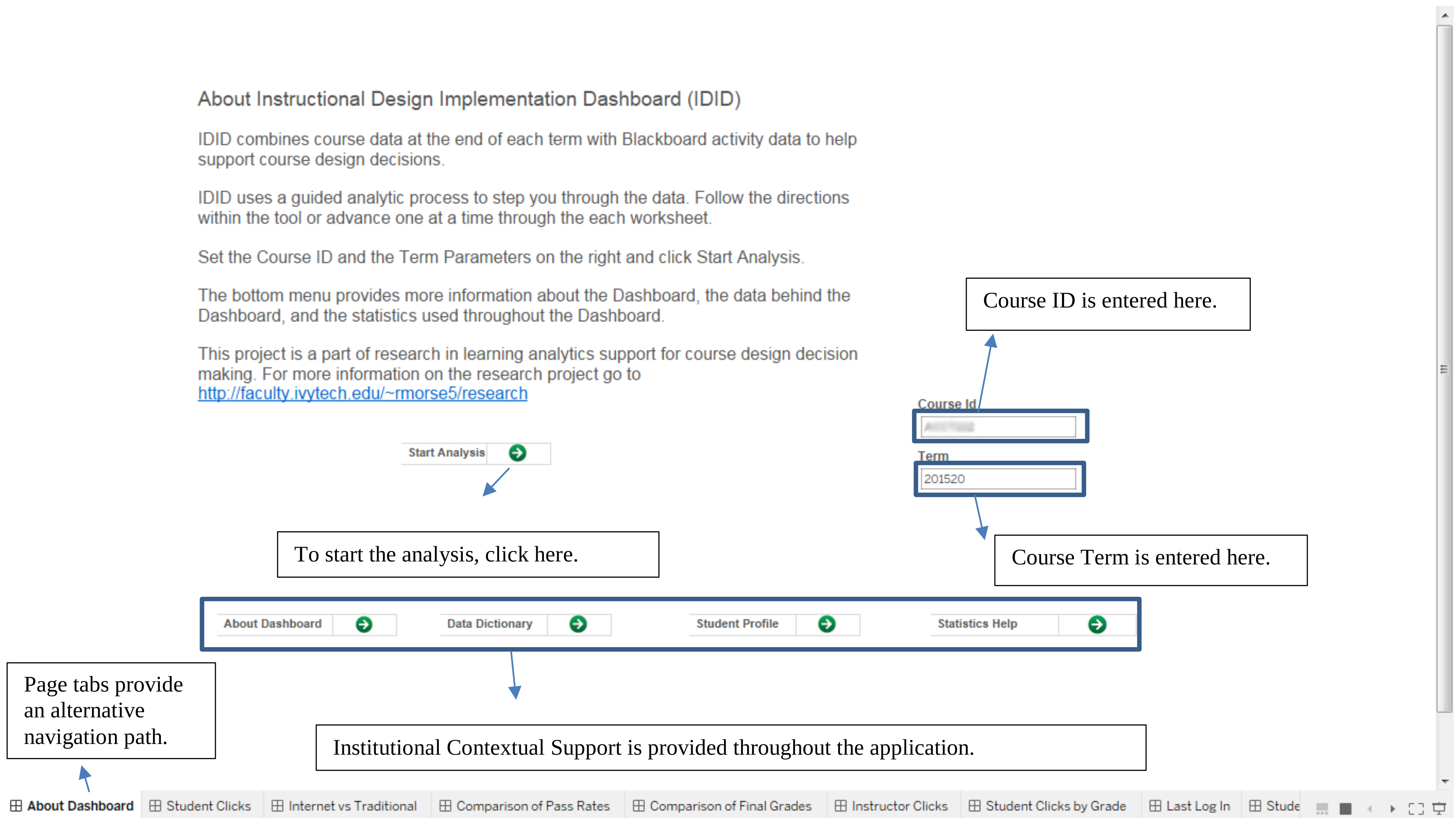
		know how many students, and the, I don't know.”
b. Anomaly Detection	detection of one piece of data that does not match the frame	b. “And while we're doing that, I'm looking at the pie chart that's showing a total of three students.”
c. Violated Expectancies	statements of when something is not as it was expected	c. “Okay, okay. All right. So like on the Student Profile, it's going to tell me if they're male, female, single, their age...”
III. Preserving the Frame		
a. Knowledge Shields	holding onto the frame in the face of contradictory data	a. “No they have a lot of interaction. If you check on the discussion board, the interests have like 6000 or something like that.”
b. Explaining the Data Away	developing justifications for why the data does not match the frame	b. “Okay, okay. So then that makes -- okay, okay. So check grade. Oh, let me see. Well these -- well, it doesn't look like there's much emailing of students going on. That's pretty low. Tab Information, Student, Tasks -- I'm not quite sure what the Tasks, what they do here. “
c. Distortions	instead of changing frames sticking with a flawed frame	
d. Fixation Errors	remaining overly focused on the frame instead of changing frames	d. “Well, I'm trying to get at the reason then that a person would want to look at this Student Profile, would it be then for me a program person to decide whether to offer a class on the internet, traditional, day, evening. I mean, is that what we're trying to get at with this information, I guess?”

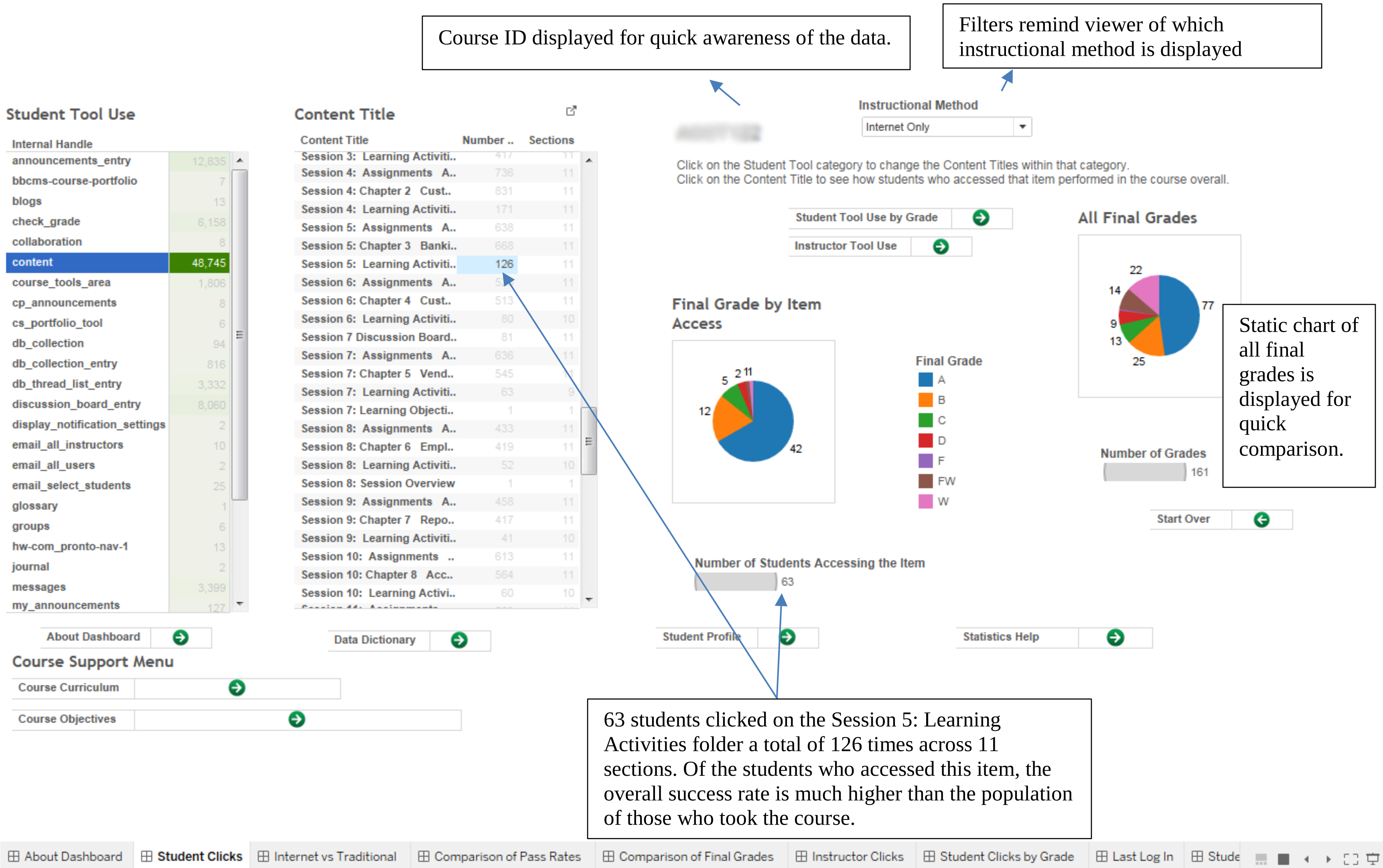
IV. Comparing the Frame		
a. Sharpening Distinctions	collecting data to support one frame	a. “So we are going to move them from optional, or mostly optional there were a few that were required, to be required across the board.”
b. Seeking Distinguishing Evidence	collecting data for an opposing frame	b.” So, will I see a sort of shift to down toward the lower end of the scale?”
c. Identifying Alternative Frames	elaborate on alternative frames	c. “Okay. So we might want to label that so that we know for sure what we're looking at because my first interpretation of that was I was looking at clicks. Because I would expect that the A students to have a huge number of clicks.”
d. Simultaneous Testing	Looking at the characterisitics of two or more frames	d. “Based on that, looking at this it allowed me to see whether one course design allowed or fostered greater student participation and I was able to determine that, to a degree. I could not reach statistical significance but they got it and I don't know if I will but I could tell that students were more active, overall, in one course from another.”
V. Seeking A Frame		
a. Searching for Information	statements of an emerging frame. The frame formation and data search go hand and hand at this stage.	a. Because if we're talking -- because I'd want to know first whether we're talking about a course that inherently has some problems with it or if it's one of those courses where we're just trying to tweak things.

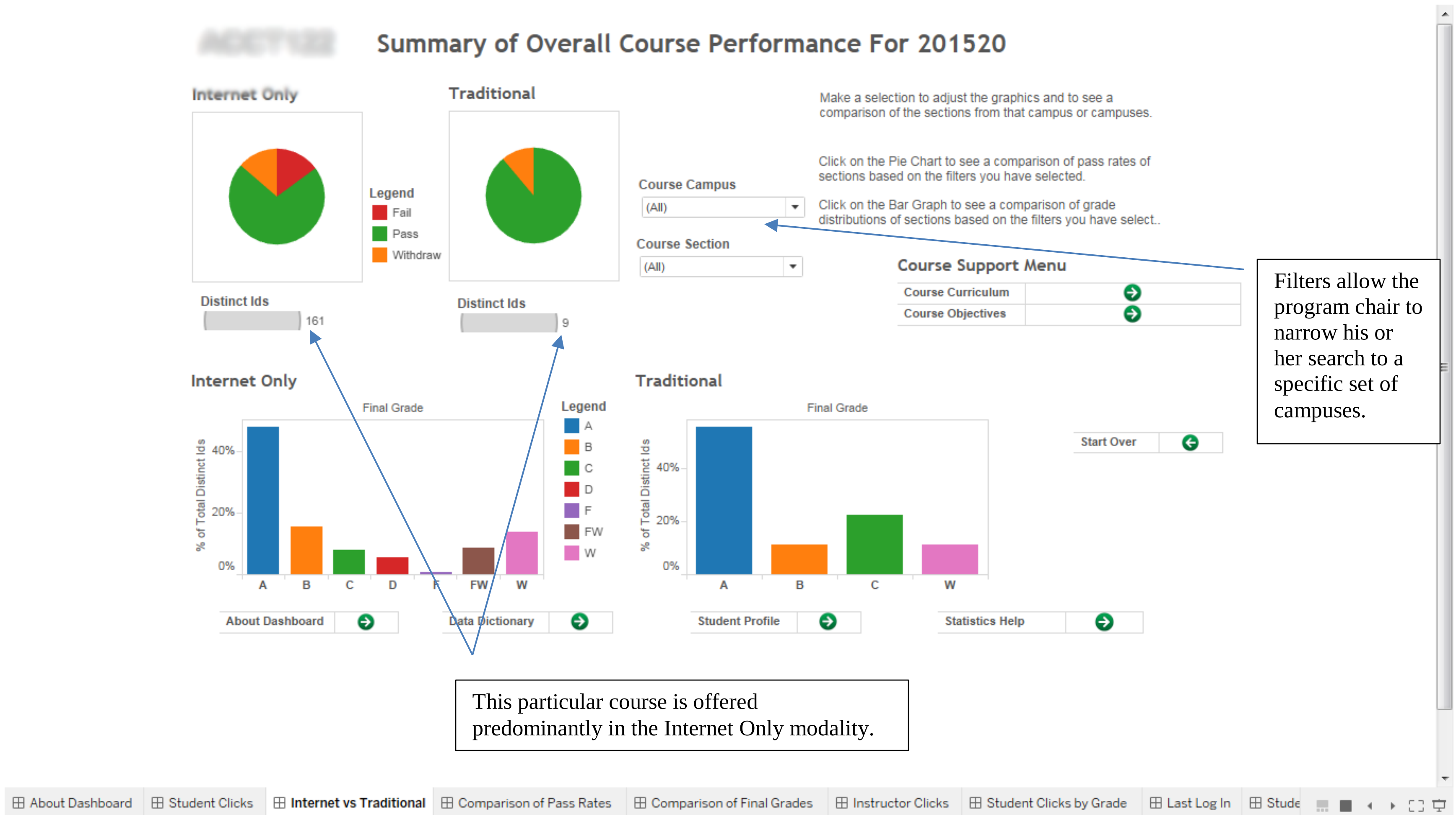
b. Finding Anchors	statements about one or two key data elements that forms the basis of an emerging frame.	b. Especially in kind of our setting because if you were doing those at maybe Lafayette, you know, probably age wouldn't be that much of a factor because everybody, most of the people would be between 18 and 22 or 23 but here at Ivy Tech, you know, I have students in their sixties, so.
c. Building on FMMs	pre-exisiting ideas about the reasons behind the data.	c. So what I'm wondering here is, will students perform more poorly; be more nervous about their grades and then clicking more frequently?
d. Constructing a New Frame	the application of data to support an alternative idea	d. So it gives us a nice -- at least in a business sense -- it gives us a benchmark that students who are successful in the class, this is what they do. So then we can bring up the behavior of the other students.
e. Schema	the application of data to solve a problem.	e."Now those are, in the pie chart, we're seeing numbers of students. Is that right?"
VI. Reframing		
a. Establishing New Anchors	statements of interpreting data as being important versus irrelevant.	a. "Mm-hm. And if you check the amounts, that's -- requiring so I don't know how representative can be that, but the entry point in the announcements has like 5000."
b. Recovering Discarded Data	reviewing data that is now relevant	
c. Re-Interpreting Data	further refining the frame based on previously discarded data.	c. "So using this instructor as an example to go backward and see what specifically this instructed did, especially the good thing in this course is that the instructor is the one that is making the revisions and so there is also a tendency to overdo it. This is what I did and we expect everybody to do the same, whether or not it was bring the same impact, is something to watch and see."

d. Revising Goals	The overall goals may need to be reexamined as the frame changes	d. “And actually, I might compare the traditional to the -- well, I guess not everybody uses the traditional class like I do so forget that."
e. Sensemaking Recovery	When the data causes the frame to be reexamined and a more complete frame emerges.	e. “R: So we can compared the two. I'm not seeing it. They're not doing it. I: Yes because if C and D students weren't doing it, then it won't show up in the list.”

Appendix H: IDID Walkthrough

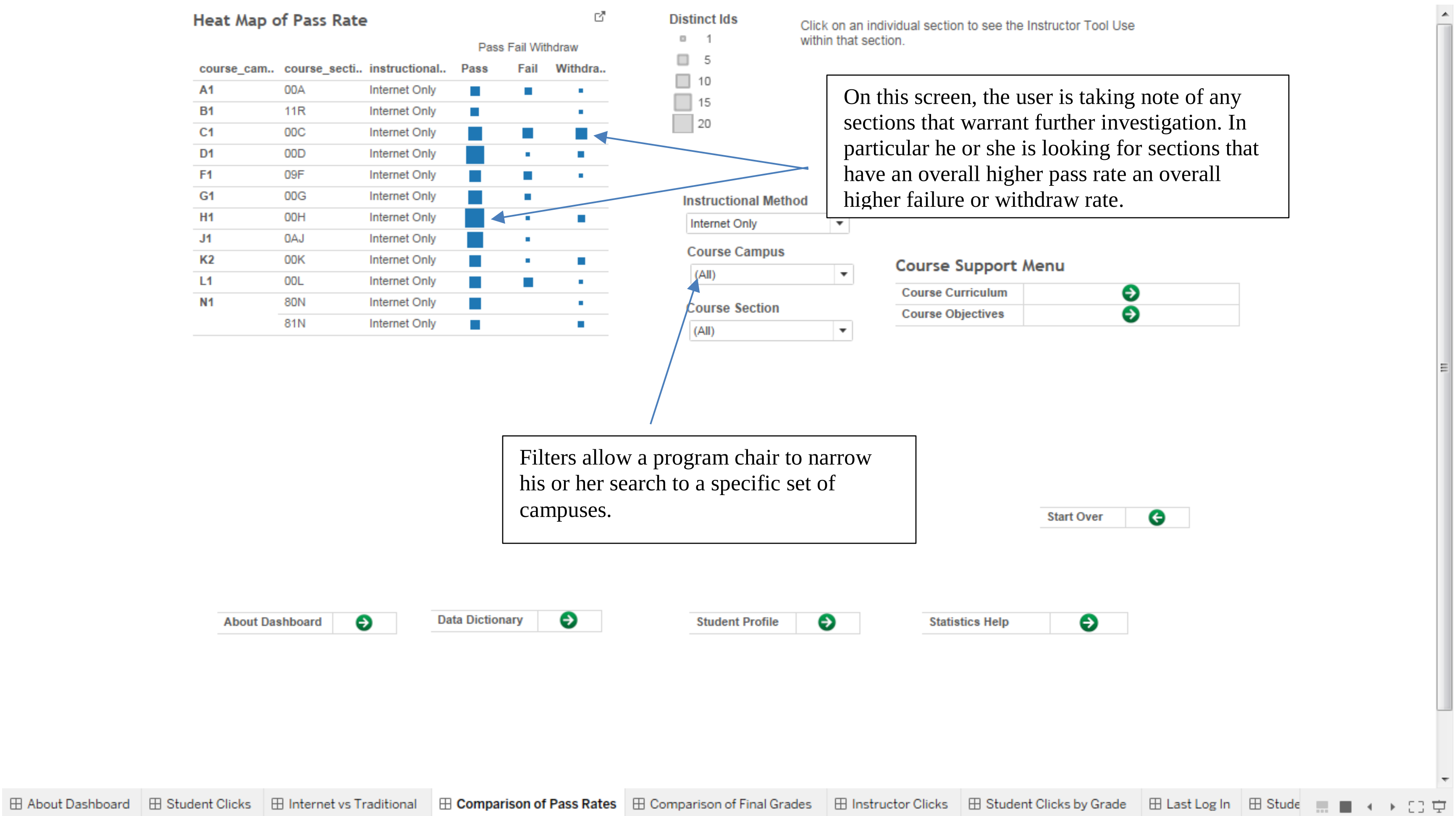



Course ID displayed for quick awareness of the data.
Filters remind viewer of which instructional method is displayed
Student Tool Use
Internal Handle
announcements_entry
bbcms-course-portfolio
blogs
check_grade
collaboration
content 48,745
course_tools_area
cp_announcements
cs_portfolio_tool
db_collection
db_collection_entry
db_thread_list_entry
discussion_board_entry
display_notification_settings
email_all_instructors
email_all_users
email_select_students
glossary
groups
hw-com_pronto-nav-1
journal
messages
my_announcements
Content Title
Content Title Number .. Sections
Session 3: Learning Activiti..
Session 4: Assignments A..
Session 4: Chapter 2 Cust..
Session 4: Learning Activiti..
Session 5: Assignments A..
Session 5: Chapter 3 Banki..
Session 5: Learning Activiti.. 126
Session 6: Assignments A..
Session 6: Chapter 4 Cust..
Session 6: Learning Activiti..
Session 7 Discussion Board..
Session 7: Assignments A..
Session 7: Chapter 5 Vend..
Session 7: Learning Activiti..
Session 7: Learning Objecti..
Session 8: Assignments A..
Session 8: Chapter 6 Empl..
Session 8: Learning Activiti..
Session 8: Session Overview
Session 9: Assignments A..
Session 9: Chapter 7 Repo..
Session 9: Learning Activiti..
Session 10: Assignments ..
Session 10: Chapter 8 Acc..
Session 10: Learning Activi..
Instructional Method
Internet Only
Click on the Student Tool category to change the Content Titles within that category.
Click on the Content Title to see how students who accessed that item performed in the course overall.
Student Tool Use by Grade
Instructor Tool Use
All Final Grades
22
14
9
13
25
77
Static chart of all final grades is displayed for quick comparison.
Final Grade by Item Access
5
2
1
1
12
42
Final Grade
A
B
C
D
F
FW
W
Number of Grades
161
Start Over
Number of Students Accessing the Item
63
About Dashboard
Data Dictionary
Student Profile
Statistics Help
Course Support Menu
Course Curriculum
Course Objectives
63 students clicked on the Session 5: Learning Activities folder a total of 126 times across 11 sections. Of the students who accessed this item, the overall success rate is much higher than the population of those who took the course.
About Dashboard
Student Clicks
Internet vs Traditional
Comparison of Pass Rates
Comparison of Final Grades
Instructor Clicks
Student Clicks by Grade
Last Log In
Stude

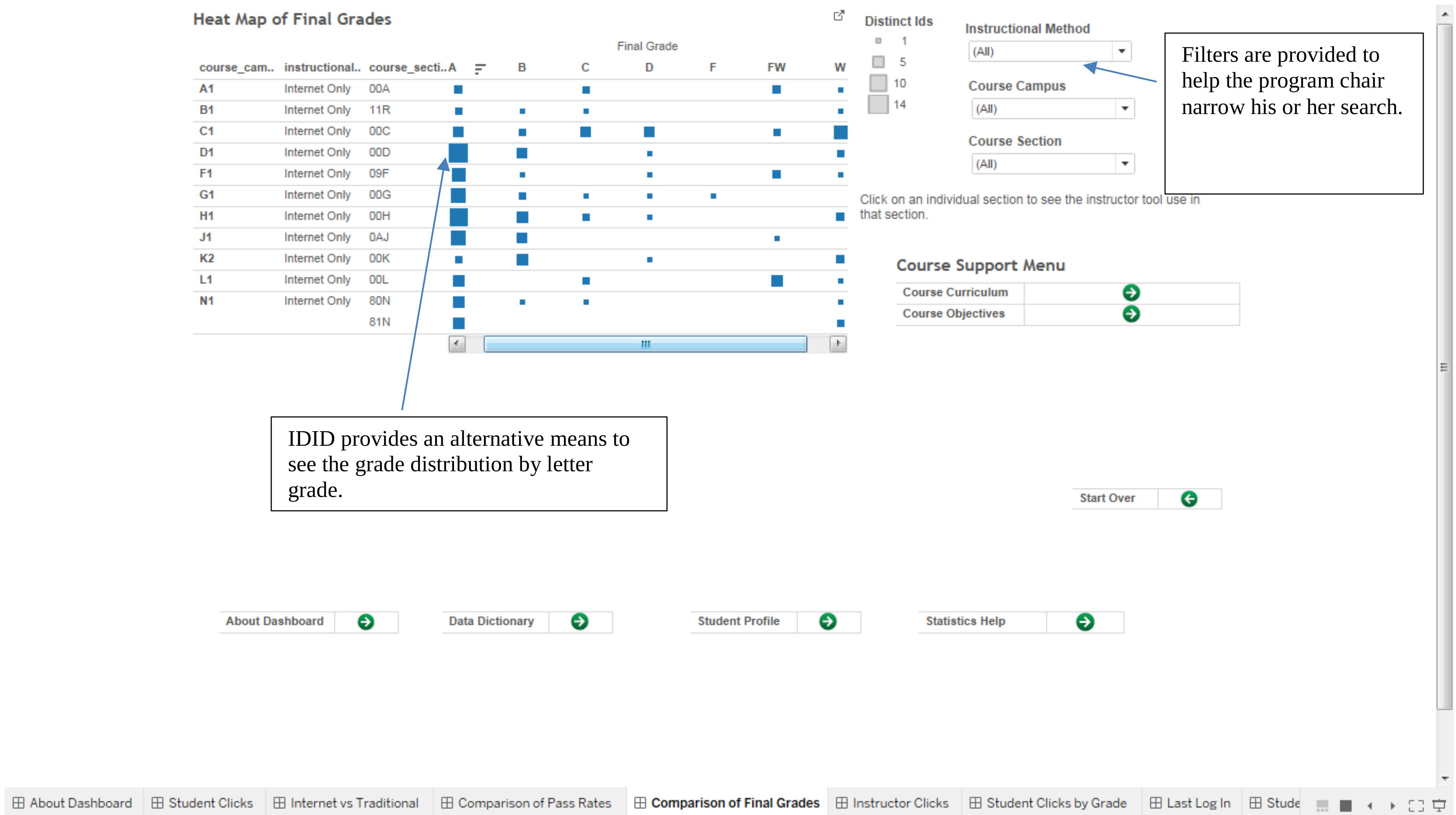


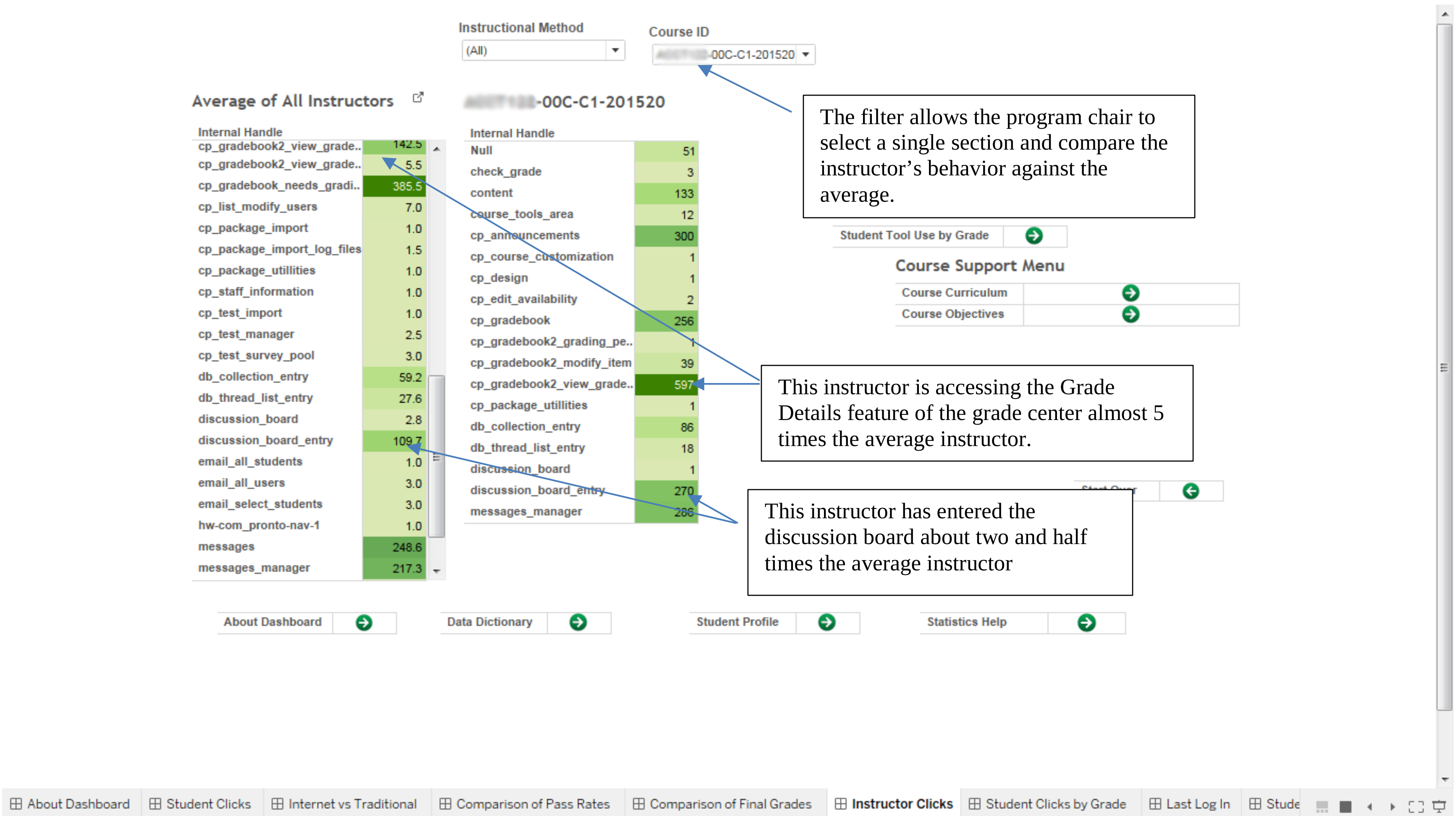
Filters allow the program chair to narrow his or her search to a specific set of campuses.

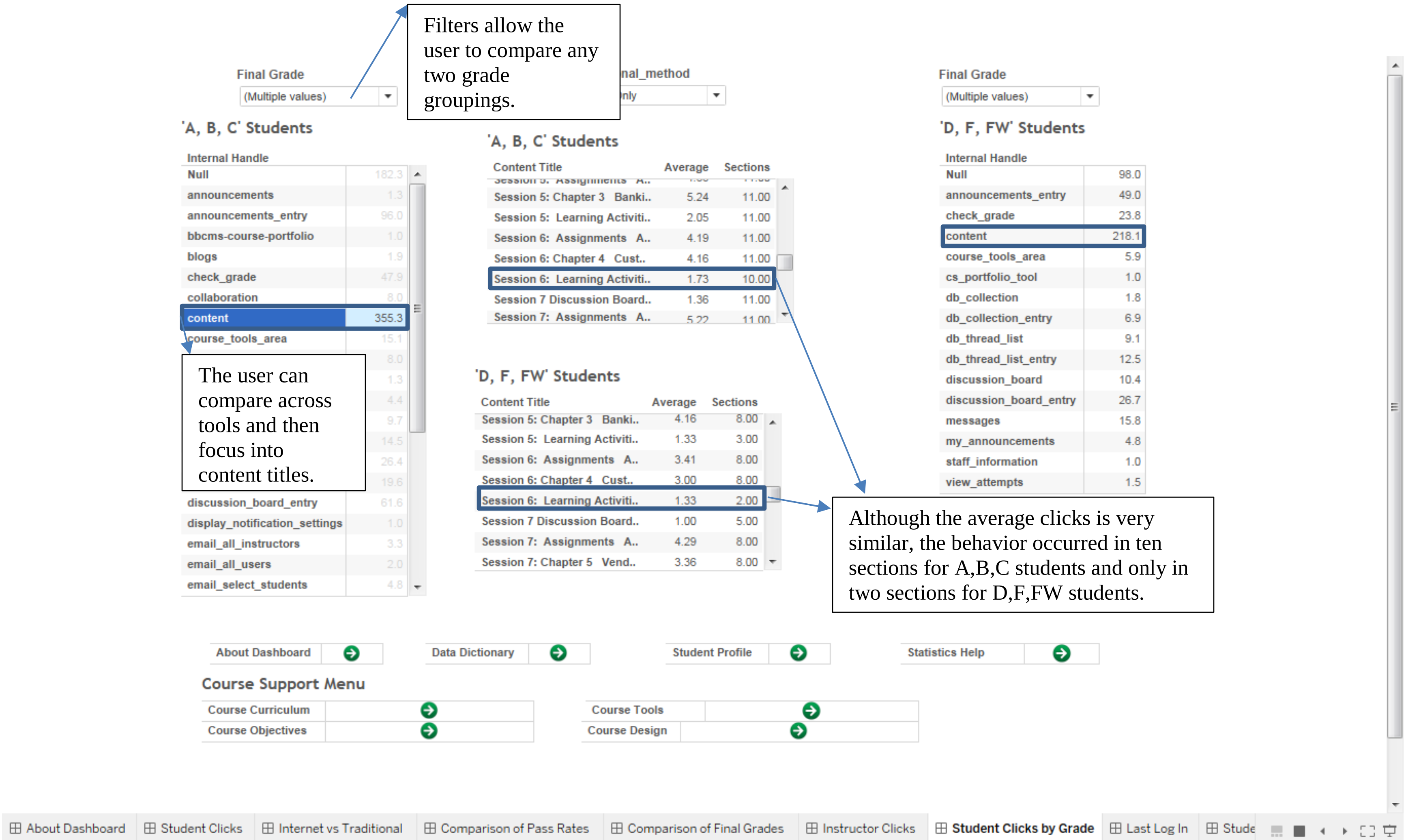
This particular course is offered predominantly in the Internet Only modality.

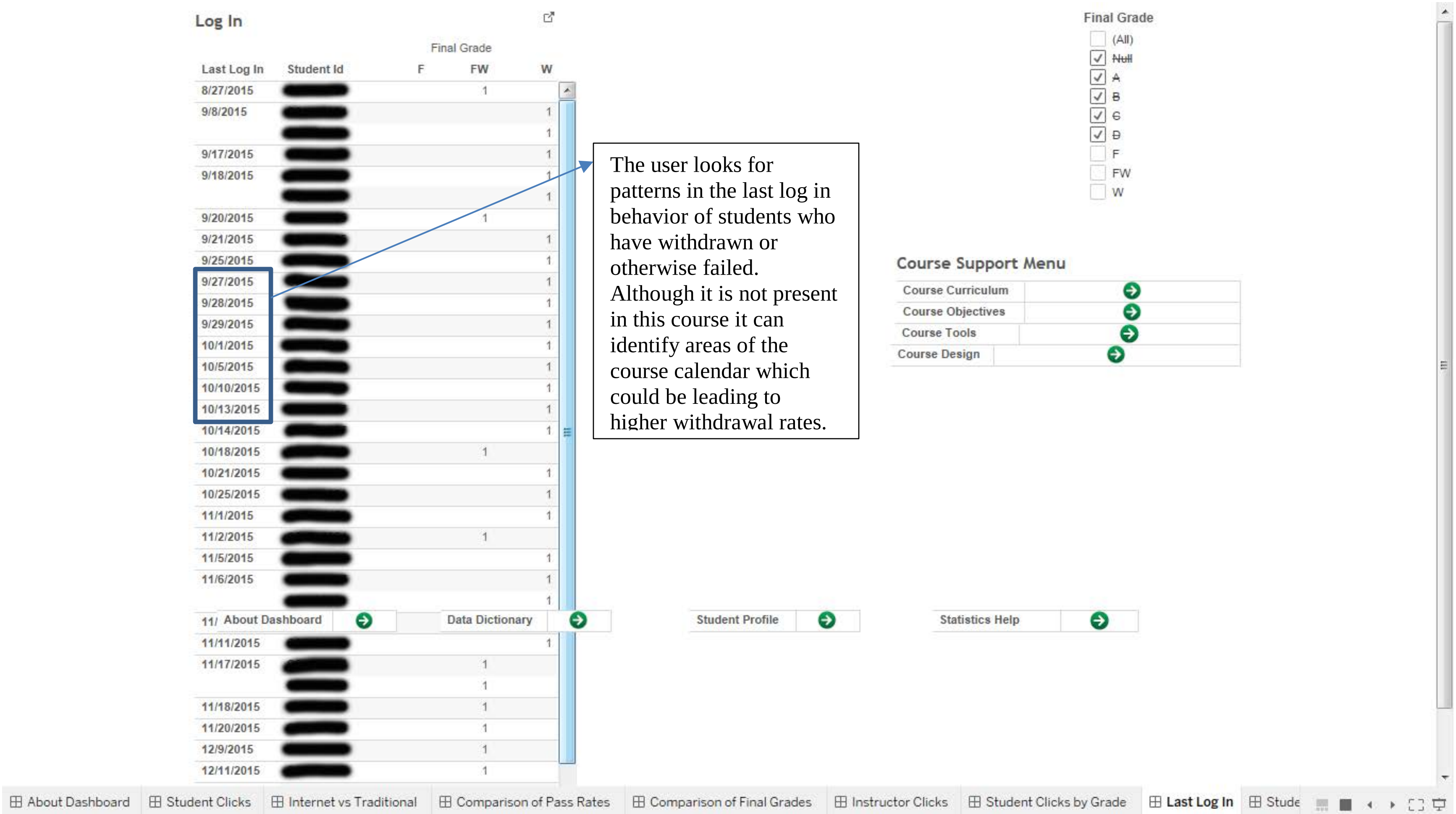


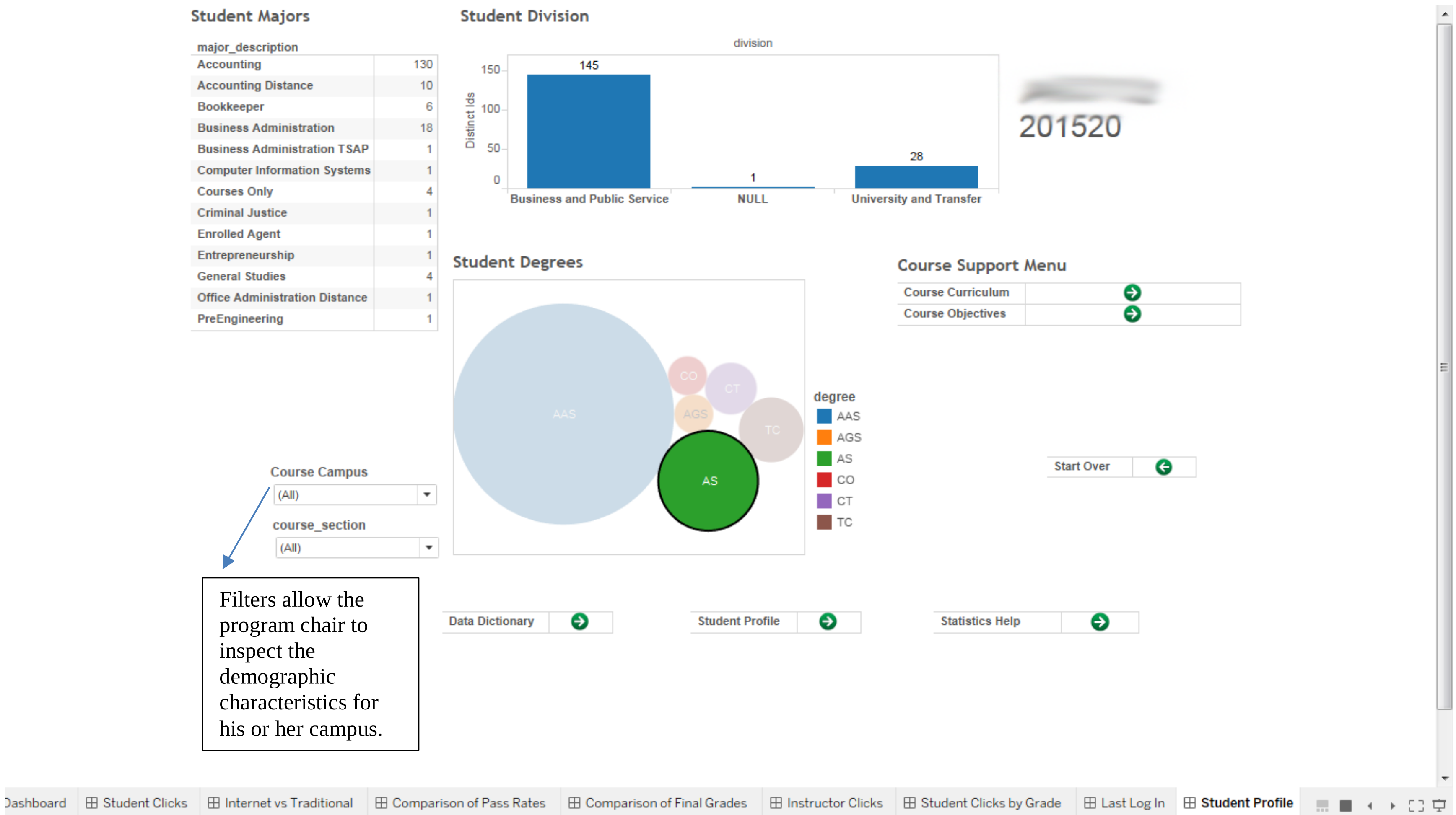
Heat Map of Pass Rate
Pass Fail Withdraw
course_cam.. course_secti.. instructional.. Pass Fail Withdra..
A1 00A Internet Only
B1 11R Internet Only
C1 00C Internet Only
D1 00D Internet Only
F1 09F Internet Only
G1 00G Internet Only
H1 00H Internet Only
J1 0AJ Internet Only
K2 00K Internet Only
L1 00L Internet Only
N1 80N Internet Only
81N Internet Only
Distinct Ids
1
5
10
15
20
Click on an individual section to see the Instructor Tool Use within that section.
On this screen, the user is taking note of any sections that warrant further investigation. In particular he or she is looking for sections that have an overall higher pass rate an overall higher failure or withdraw rate.
Instructional Method
Internet Only
Course Campus
(All)
Course Section
(All)
Course Support Menu
Course Curriculum
Course Objectives
Filters allow a program chair to narrow his or her search to a specific set of campuses.
Start Over
About Dashboard
Data Dictionary
Student Profile
Statistics Help
About Dashboard
Student Clicks
Internet vs Traditional
Comparison of Pass Rates
Comparison of Final Grades
Instructor Clicks
Student Clicks by Grade
Last Log In
Stude


Heat Map of Final Grades
Final Grade
course_cam.. instructional.. course_secti.. A B C D F FW W
A1 Internet Only 00A
B1 Internet Only 11R
C1 Internet Only 00C
D1 Internet Only 00D
F1 Internet Only 09F
G1 Internet Only 00G
H1 Internet Only 00H
J1 Internet Only 0AJ
K2 Internet Only 00K
L1 Internet Only 00L
N1 Internet Only 80N
81N
Distinct Ids
1
5
10
14
Instructional Method
(All)
Course Campus
(All)
Course Section
(All)
Filters are provided to help the program chair narrow his or her search.
Click on an individual section to see the instructor tool use in that section.
Course Support Menu
Course Curriculum
Course Objectives
IDID provides an alternative means to see the grade distribution by letter grade.
Start Over
About Dashboard
Data Dictionary
Student Profile
Statistics Help
About Dashboard
Student Clicks
Internet vs Traditional
Comparison of Pass Rates
Comparison of Final Grades
Instructor Clicks
Student Clicks by Grade
Last Log In
Stude

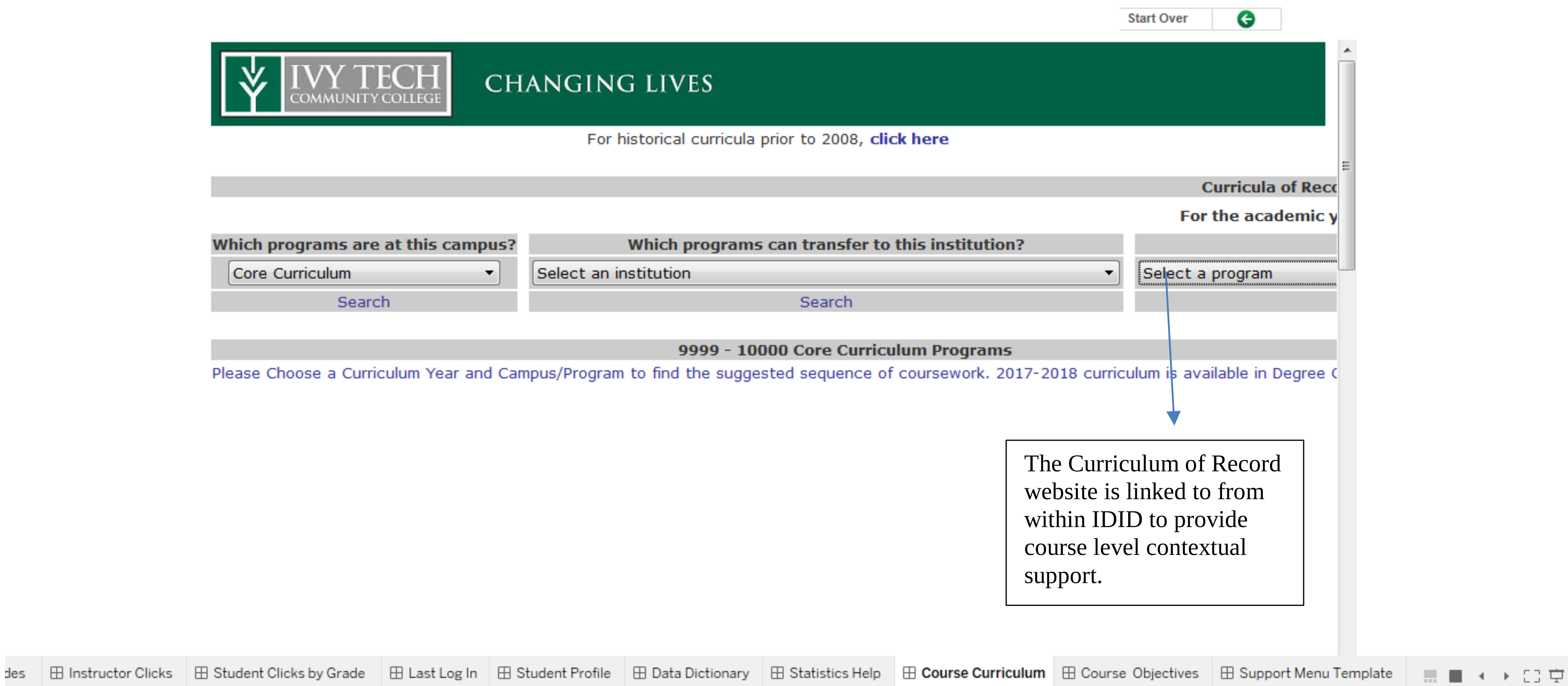

Instructional Method
(All)
Course ID
-00C-C1-201520
Average of All Instructors
-00C-C1-201520
Internal Handle
cp_gradebook2_view_grade..
cp_gradebook2_view_grade..
cp_gradebook_needs_gradi..
cp_list_modify_users
cp_package_import
cp_package_import_log_files
cp_package_utillities
cp_staff_information
cp_test_import
cp_test_manager
cp_test_survey_pool
db_collection_entry
db_thread_list_entry
discussion_board
discussion_board_entry
email_all_students
email_all_users
email_select_students
hw-com_pronto-nav-1
messages
messages_manager
142.5
5.5
385.5
7.0
1.0
1.5
1.0
1.0
1.0
2.5
3.0
59.2
27.6
2.8
109.7
1.0
3.0
3.0
1.0
248.6
217.3
Internal Handle
Null
check_grade
content
course_tools_area
cp_announcements
cp_course_customization
cp_design
cp_edit_availability
cp_gradebook
cp_gradebook2_grading_pe..
cp_gradebook2_modify_item
cp_gradebook2_view_grade..
cp_package_utillities
db_collection_entry
db_thread_list_entry
discussion_board
discussion_board_entry
messages_manager
51
3
133
12
300
1
1
2
256
1
39
597
1
86
18
1
270
286
The filter allows the program chair to select a single section and compare the instructor's behavior against the average.
Student Tool Use by Grade
Course Support Menu
Course Curriculum
Course Objectives
This instructor is accessing the Grade Details feature of the grade center almost 5 times the average instructor.
This instructor has entered the discussion board about two and half times the average instructor
About Dashboard
Data Dictionary
Student Profile
Statistics Help
About Dashboard
Student Clicks
Internet vs Traditional
Comparison of Pass Rates
Comparison of Final Grades
Instructor Clicks
Student Clicks by Grade
Last Log In
Stude


Filters allow the user to compare any two grade groupings.
Final Grade
(Multiple values)
'A, B, C' Students
Internal Handle
Null
announcements
announcements_entry
bbcms-course-portfolio
blogs
check_grade
collaboration
content 355.3
course_tools_area
discussion_board_entry
display_notification_settings
email_all_instructors
email_all_users
email_select_students
The user can compare across tools and then focus into content titles.
'A, B, C' Students
Content Title Average Sections
Session 5: Chapter 3 Banki.. 5.24 11.00
Session 5: Learning Activiti.. 2.05 11.00
Session 6: Assignments A.. 4.19 11.00
Session 6: Chapter 4 Cust.. 4.16 11.00
Session 6: Learning Activiti.. 1.73 10.00
Session 7 Discussion Board.. 1.36 11.00
Session 7: Assignments A.. 5.22 11.00
'D, F, FW' Students
Content Title Average Sections
Session 5: Chapter 3 Banki.. 4.16 8.00
Session 5: Learning Activiti.. 1.33 3.00
Session 6: Assignments A.. 3.41 8.00
Session 6: Chapter 4 Cust.. 3.00 8.00
Session 6: Learning Activiti.. 1.33 2.00
Session 7 Discussion Board.. 1.00 5.00
Session 7: Assignments A.. 4.29 8.00
Session 7: Chapter 5 Vend.. 3.36 8.00
Final Grade
(Multiple values)
'D, F, FW' Students
Internal Handle
Null 98.0
announcements_entry 49.0
check_grade 23.8
content 218.1
course_tools_area 5.9
cs_portfolio_tool 1.0
db_collection 1.8
db_collection_entry 6.9
db_thread_list 9.1
db_thread_list_entry 12.5
discussion_board 10.4
discussion_board_entry 26.7
messages 15.8
my_announcements 4.8
staff_information 1.0
view_attempts 1.5
Although the average clicks is very similar, the behavior occurred in ten sections for A,B,C students and only in two sections for D,F,FW students.
About Dashboard
Data Dictionary
Student Profile
Statistics Help
Course Support Menu
Course Curriculum
Course Objectives
Course Tools
Course Design
About Dashboard
Student Clicks
Internet vs Traditional
Comparison of Pass Rates
Comparison of Final Grades
Instructor Clicks
Student Clicks by Grade
Last Log In


Log In
Final Grade
Last Log In
Student Id
F
FW
W
8/27/2015
9/8/2015
9/17/2015
9/18/2015
9/20/2015
9/21/2015
9/25/2015
9/27/2015
9/28/2015
9/29/2015
10/1/2015
10/5/2015
10/10/2015
10/13/2015
10/14/2015
10/18/2015
10/21/2015
10/25/2015
11/1/2015
11/2/2015
11/5/2015
11/6/2015
11/11/2015
11/17/2015
11/18/2015
11/20/2015
12/9/2015
12/11/2015
The user looks for patterns in the last log in behavior of students who have withdrawn or otherwise failed. Although it is not present in this course it can identify areas of the course calendar which could be leading to higher withdrawal rates.
Final Grade
(All)
Null
A
B
C
D
F
FW
W
Course Support Menu
Course Curriculum
Course Objectives
Course Tools
Course Design
About Dashboard
Data Dictionary
Student Profile
Statistics Help
About Dashboard
Student Clicks
Internet vs Traditional
Comparison of Pass Rates
Comparison of Final Grades
Instructor Clicks
Student Clicks by Grade
Last Log In
Stude

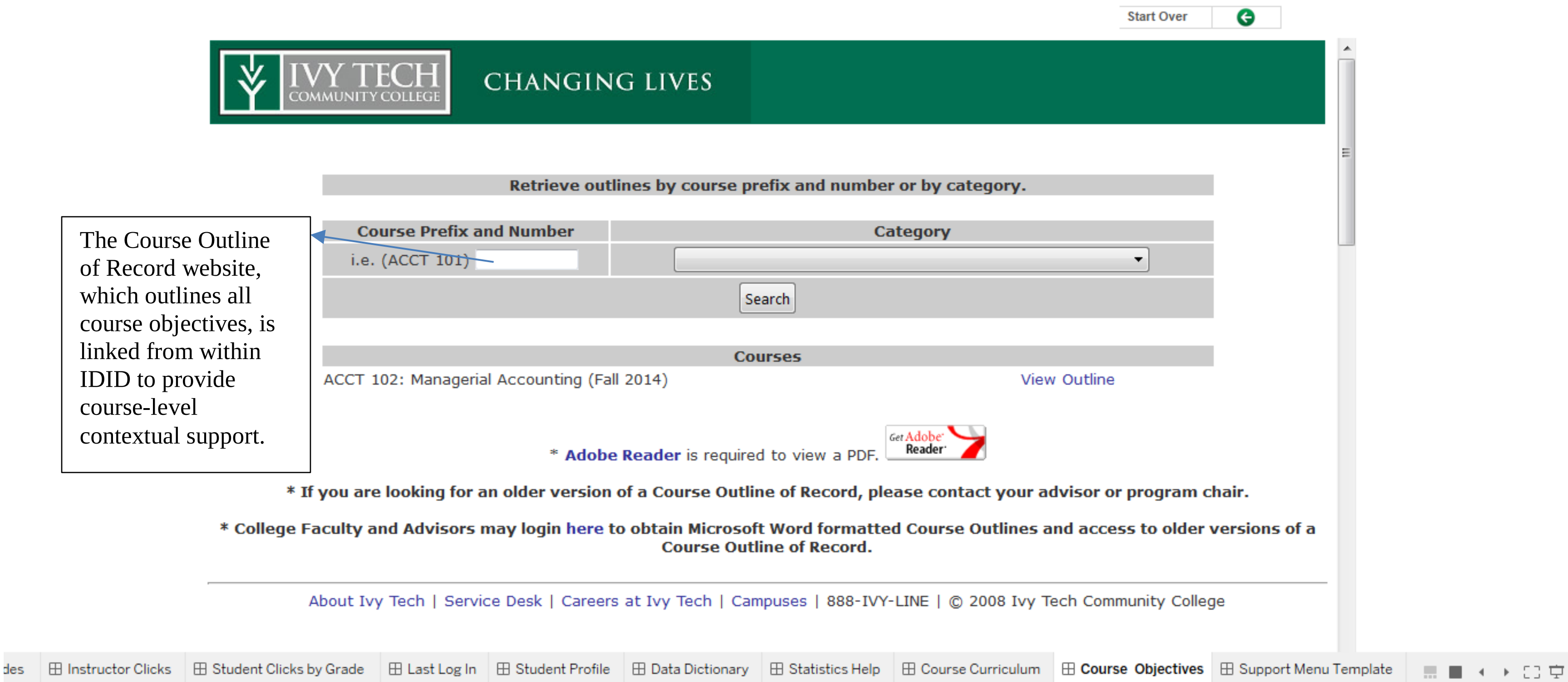


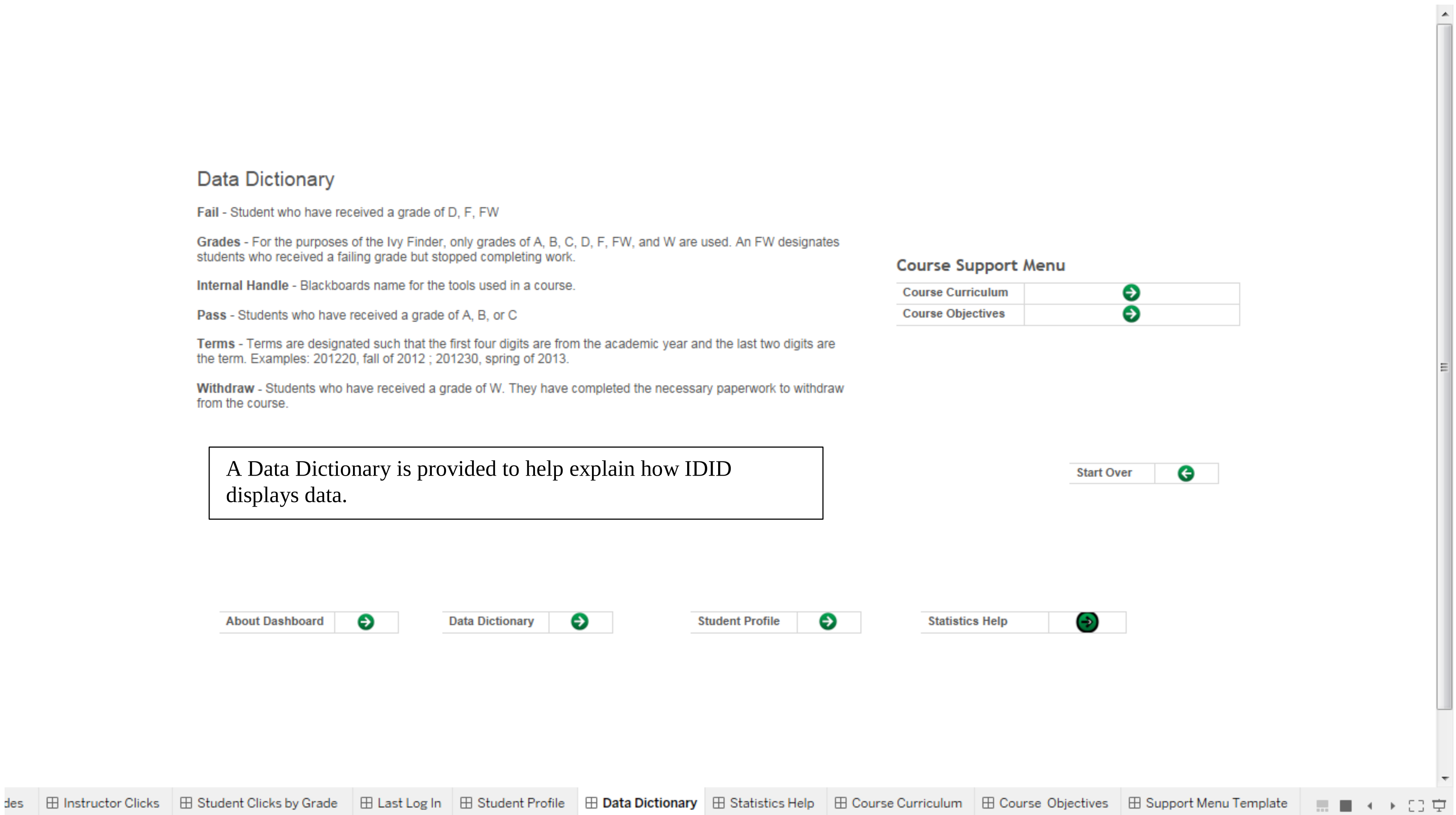
Filters allow the program chair to inspect the demographic characteristics for his or her campus.



The Curriculum of Record website is linked to from within IDID to provide course level contextual support.

The Course Outline of Record website, which outlines all course objectives, is linked from within IDID to provide course-level contextual support.





A Data Dictionary is provided to help explain how IDID displays data.

Statistics Help

This page will help explain the charts and graphs used in this workbook.

Bar graphs
Bar graphs are used to show comparisons of one category of grades to another. You will see a bar for each grade the height of the bar is determined by the number of students who earned that grade. For a nice explanation of bar graphs from the National Center of Education Statisitcs click the link below.
http://nces.ed.gov/nceskids/help/user_guide/graph/bar.asp

Heat Maps
A simple heat map provides an immediate visual summary of information. The heat maps used in this workbook clickly summarize grade information for comparison between sections. For a more information on heat maps click on the link below.
http://searchbusinessanalytics.techtarget.com/definition/heat-map

Pie Charts
Pie charts are used to show how percentages add up to a whole. Pie charts are used to show the percentage of students who have either passed, failed, or withdrawn from the class. Pie charts are also used to show how the total number of students clicking on an item ended up receiving a particular final grade.
For a nice explanation of pie charts from the National Center of Education Statistics click on the link below.
http://nces.ed.gov/nceskids/help/user_guide/graph/pie.asp

Course Support Menu

Course Curriculum
Course Objectives

This page was included to provide some statistical support for the visualizations displayed within IDID

About Dashboard | Data Dictionary | Student Profile | Statistics Help

des | Instructor Clicks | Student Clicks by Grade | Last Log In | Student Profile | Data Dictionary | **Statistics Help** | Course Curriculum | Course Objectives | Support Menu Template

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Curriculum Vitae

Robert Kenneth Morse

Education:
Ph. D. Informatics, Indiana University earned at Indiana University–Purdue University Indianapolis

Graduate Certificate in Organizational Leadership, University of Indianapolis

M.S. Ed. Instructional Systems Technology, Indiana University Bloomington

B.A. Spanish, DePauw University

Honors, Awards, Fellowships:
Blackboard Certified Instructor, 2000
Quality Matters – Peer Reviewer Certification, 2010
Quality Matters – Online Facilitator Certification, 2010

Research and Training Experience:
Fast Browsing Research Team, 2013
NVivo Workshop, 2012

Professional Experience:
Senior Instructional Designer, Ivy Tech Community College of Indiana
Instructional Designer, Ivy Tech Community College of Indiana
Instructional Designer, University of Indianapolis
Graduate Intern, Faculty Instructional Technology Support, DePauw University

Conferences Attended:
“Informing Course Improvement with Learning Analytics”Quality Matters Conference, Baltimore, MD, September 2014

“Developing QM Centered Statewide Online Course Development Policies and Procedures.” Quality Matters Conference, Baltimore, MD, September 2014”

“Supporting the Scholarship of Teaching and Learning: a case study on the development of knowledge centered learning analytics” Advancing Learning with Technology Symposium. Indiana University Purdue University Indianapolis, February 2014

"Enterprise Means Everyone: success in securing stake-holder feedback" Blackboard World Conference, Boston, MS, July 2007.

"Designing a Competency Based Technology Training Program" Independent Colleges of Indiana, August 2006

"Streamling Workshop Administration" Blackboard World Conference, San Diego, CA, March 2006

"el español viajando"(Travelling Spanish) Johnson County Public Library, February 2006

"Working the Web", SLATE, Chicago, Illinois, October 2005

"Streamlining Workshop Administration", ICI, Franklin, Indiana, August 2005

"Digital Photography 101", Johnson County Public Library, July 2005

"E-Portfolios, a Pilot Program", AACTE, Chicago, Illinois, February 2004

"E-Portfolios for Student Teachers-a pilot program", ASCUE, Myrtle Beach, South Carolina, June 2003

"The Importance of Leadership in Instructional Technology Systems: Using Planning Models in Implementation," Blackboard Users Conference, Phoenix, Arizona, March 2002

"Supporting Faculty Use of Discussion Tools," Instructional Technology Symposium, University of Indianapolis, May 2001

"Rapid ADDIE" -Instructional Systems Technology Rookie Conference, Indiana University, December 2000

"The Mission is our Future–Concept Mapping for History", April 2000, American Association of History and Computing, Baylor, Texas

Consulting Editor, "Beginning Spanish", AlphaOmega Publications Winter 2000

Technical Support — Brownstown Technical Institute, DePauw University, July 1999

Technical Support -- FITS-Mellon Faculty Summer Workshop, DePauw University, June 1999

"Student Viewpoint" Panel on the Support of Technology in the Classroom, presented June 1999, Association of Small Computer Users in Education, Myrtle Beach, South Carolina

"Teaching with Technology–views from the student perspective"–delivered April 1999, American Association of History and Computing, Philadelphia, Pennsylvania

Publications:

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