THE USE OF DATA AND READABILITY ANALYTICS TO ASSIST INSTRUCTOR AND ADMINISTRATOR DECISIONS IN SUPPORT OF HIGHER EDUCATION STUDENT WRITING SKILLS

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In 2016 employers hiring four-year college graduates indicate that 27.8% have deficiencies in written communication. Postsecondary learning objectives should focus on improving specific writing skills like grammar, sentence structure, and vocabulary usage for individual students and monitoring text readability as an overall score to measure learning outcomes. Web-based applications and the tools integrated into them have the potential to serve as a diagnostic solution for analyzing the text readability and writing skills of students. Organization and structuring of Canvas data was required before adding text readability and other writing skills analytics as part of the process to develop diagnostic learning analytics that interprets student writing skills in the learning management system. Decision modeling was used to capture and describe the specifics of literacy improvement decisions for instructors and administrators in a graphical notation and structured format.

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INTRODUCTION

The importance of developing effective writing skills is one of the most important job skills articulated by employers. Four participating organizations including The Conference Board, Corporate Voices for Working Families, Partnership for 21st Century Skills, and The Society for Human Resource Management jointly surveyed over 400 employers across the United States. These employers outlined the skill sets that recently hired graduates from four-year colleges need to succeed in the workplace. Among the most important skills identified were professionalism, oral and written communications, collaboration, and critical thinking. The deficiency of four-year college graduates was written communications (27.8%), writing in English (26.2%), and leadership (23.8%) (Casner-Lotto & Barrington, 2006).

Research consistently indicates that even with a college degree, students are graduating with a deficiency in skills critical to their success in the workplace, including writing abilities. A recent Society for Human Resource Management's report stated that 68% of human resource professionals and executives hold four-year universities responsible for workforce preparation (Wessels, Esen, Di Nicola, & Schramm, 2016). A team from a peer-to-peer learning vendor StudySoup used the Hemingway application to analyze hundreds of written documents to gauge students' writing skills (Ascoine, 2017). Two unique scores were used to evaluate the writing samples for clarity and readability. The first score assigns a content grade level using a readability algorithm that determines the lowest education level needed to understand the writing. The study found that the writing samples students submitted scored an average of 12.35 or a 12th-grade level. This score suggests that writing skills of students at these universities are not improving past the high school level. Cumulative scores for 55% of the universities fell below this average. The second score is a rating scale of “good,” “ok,” or “poor” to identify sentences that are difficult to read and judge the writing coherence of the document. Only one university received a score of “good” on more than half of the submitted documents. 60% of the universities received a “poor” rating on 50% or more their documents (Ascoine, 2017).

Poor writing skills are not a new concern. In 1874, more than half of the first-year students at Harvard failed an entrance writing exam. Students continue to arrive on college campuses needing remediation in basic writing skills (Goldstein, 2017). According to Kate Walsh, president of the National Council on Teacher Quality, the widespread or systematic teaching of writing is not covered, based on reviews of course syllabi from 2,400 education preparation programs. Educators agree that most instructors have no formal training in how to teach writing skills and are often weak writers themselves (Troia et al., 2016).

Writing instruction first emerged in the US in the late nineteenth century after the formation of discrete academic disciplines when there was a push for mass education because of industrialization and urbanization (Russell, 1991). Writing instruction was necessary to teach the emerging discourses attached to the new disciplines. Professionals and academics communicated with one another primarily through writing, and began to write for specialized communities rather than general audiences and writing “was no longer a single, generalizable skill learned once and for all at an early age; rather it was a complex and continuously developing response to specialized text-based discourse communities” (Russell, 1991, p. 5).

Research became the emphasis as universities expanded becoming compartmentalized by specialization. Undergraduate teaching was no longer the central focus for faculty. Testing replaced a portion of student writing for assessment, freeing up time for faculty to conduct research (Russell, 1991). Admissions continued to open to a wider cross-section of the population, so to become fluent in the discourse the students needed explicit writing instruction.

Russell traces the emergence of what eventually became known as Freshman Composition back to this period. In 1900, Harvard made the “English A” subject a university-wide requirement. The idea spread rapidly to other institutions (Russell, 1991, pp. 50-51). The intentions at Harvard were for English A to be the initial component of a degree-long course in writing development. However, adoption of the plan did not transpire. Most institutions implemented first-year writing courses without follow through across the degree. After 1970, universities adopted multiple choice exams as an automated assessment option. The result was a decrease in long-form writing, and once again concerns about student writing abilities were raised.

Today these first-year writing courses vary in length, aiming to familiarize students with academic conventions at the start of the studies. They may cover critical thinking, rhetoric, academic integrity, research skills, and genres of academic writing. The best offer discipline-based options so students can align the requirement with their preferences. However, compartmentalization of writing outside of disciplinary practices in an entry-level writing subject was insufficient (Anson, 2002, p. ix). In this context, the practices include writing across the curriculum (WAC) and writing in the disciplines (WID) are complementary strategies used to develop student communication in higher education, particularly in the US. WAC and WID developed from a recognition that communication practices are different between discipline areas and writing, as one aspect of communication, is fundamental to intellectual development within a discipline.

Students need to learn and understand sentence structure, because this is necessary to form written sentences that sound correct and proper grammar is essential to learning to write sentences that can be understood and sound natural (Harmer, 2004). Students should continue to build on and maintain skills like grammar, spelling, speech, voice, tense, and writing style throughout their academic career (McMurray, 2006). College students should be able to employ argumentative skills, expressing themselves clearly, using logic, and following proper formats. Good writers need to learn to balance description, dialogue, detail, and information, but careful word choice takes time to learn as well as a great deal of practice (Vickers & Ene, 2006). Instructors need to teach these writing skills and provide feedback to students by building their confidence and encouraging them to take risks (Sugita, 2006).

Giving written feedback to students is an important part of writing skills instruction; however, few studies have been conducted to investigate current trends of written corrective feedback in secondary and university contexts. Sia and Cheung (2017) conducted a qualitative synthesis of published research that examined corrective feedback. Four claims emerged in their analysis of 68 empirical studies published in journals from 2006-2016:

1. Individual differences play a part in the effectiveness of written corrective feedback.
2. Student and teacher perceptions affect the effectiveness of written corrective feedback.
3. Giving corrective feedback through technology is beneficial to students.
4. Written corrective feedback is more effective when done concurrently with collaborative tasks.

One technology available to consider in more detail is learning analytics (LA). LA is the process of data collection, analysis, and reporting to improve the teaching and learning process and environment. Businesses have long used business intelligence (BI) to collect data and analyze the processes, methods, measurements, and systems to view, interpret and understand information relevant to the history, current performance, and future projections of organizational effectiveness. Institutions of higher education have more recently started to put these principles into practice by collecting LA data about students, courses, enrollments, and engagement (Siemens & Long, 2011).

There are two main categories in the field of LA research. The first is how to capture, process, and present data to educational stakeholders in useful ways. The second focus is how to take up and use LA in practice to inform choices or prompt action (Wise, Vytasek, Hausknecht, & Zhao, 2016). Most recent research has concentrated on creating useful information from existing warehouses of collected data (Dawson, Gašević, Siemens, & Joksimovic, 2014). Additional research should be conducted on how to use collected data analysis outcomes to inform improvements to traditional course design and to achieve related institutional performance objectives in higher education institutions (Ferguson, Clow, Macfadyen, Essa, Dawson, & Alexander, 2014; Lockyer, Heathcote, & Dawson, 2013; West, Heath, & Huijser, 2016; Wise, 2014; Wise, Vytasek, Hausknecht, & Zhao, 2016).

LA holds potential applications for a range of stakeholders in higher education including instructors, researchers, curriculum developers, learning environment designers and university policymakers. LA is increasingly being integrated into institutional learning management systems (LMS) and can be used to analyze data at the course level for instructors and students (Dziuban, Moskal, Cavanagh, & Watts, 2012). An LMS is a web-based application that allows instructors to put class materials on the Internet. Basic LMS courses include a syllabus, learning materials (documents, videos, etc.), discussions, calendar, email and notifications, announcements, grades, quizzes, assignments, and learning analytics (LA). Monitoring student progress, predicting student success or failure, and informing instructional design can be tracked and analyzed using student activity data.

Instructors can teach writing skills to guide, encourage, and support students once text readability scores are made available through LA to academically support students (Agnihotri & Ott, 2014; Harrison, Villano, Lynch, & Chen, 2016; Jayaprakash & Lauria, 2014; Dunbar, Dingel, & Prat-Resina, 2014). Diagnostic uses of LA at the course-level is an important area of research that may improve learning outcomes in online and blended courses. Instructors use the diagnostic information to modify how the frequency and format of feedback, changes to instructions, and other pedagogical revisions can affect a student's writing skills and impact the overall readability score. Instructors must be able to easily understand and react to the information presented (McKee, 2017). Data from across multiple courses can be collected for administrators to review traditional course and curriculum design. The overall student readability scores for a selected group of courses establish a benchmark of student writing skills in a program. Writing skills instruction can be reviewed and pedagogical changes incorporated into a defined set of courses. Continuous review of the LA by administrators can detect changes in student writing skills to verify readability outcomes, without directly interfering with students (Dunbar, Dingel, & Prat-Resina, 2014).

Purpose of the Study

Linguists refer to language as the art of communication. According to Oakland and Lane (2004), "Language refers to all forms of communication through which thoughts and feelings are symbolized in ways that convey meaning to others, transmits culture, [and] impacts all other cognitive abilities" (p. 240). DuBay (2004) claims there are two substantive issues, the reading skills of the audience and the readability of the text. Oakland and Lane (2004) claimed that, "Communication requires both the producer and recipient of a language-based message to share a common understanding of language symbols" (p. 240). These definitions of communication are critical when it comes to audiences being able to comprehend the language (writing) that the author is sharing. A second substantive communication issue is the readability of produced texts.

This study focuses on the use of communication data and LA available at Texas Woman's University (TWU). TWU is a co-educational university in Denton, Texas with 15,000 undergraduate, graduate and professional students enrolled and approximately 1,000-employed instructors. TWU currently provides instructors with two LA tool options. TWU instructors have access to either Canvas Analytics as part of the Canvas LMS or Blackboard Course Reports as part of the Blackboard LMS. Instructors use both tools and are encouraged to use the available LA; however, their use of these LA tools depends on individual motivation or interest.

For this study, the focus is on communication data available in Canvas. Canvas Analytics includes a collection of reports that provide information regarding course activity, submissions, and grades as presented in the following (Figure 1). Course activity displays both page views and participation for users by month; submissions are presented as on time, missing, or late; and grades present the total range of grades, the grades in the top 25% and the bottom 25% are highlighted, and the median graded is noted.

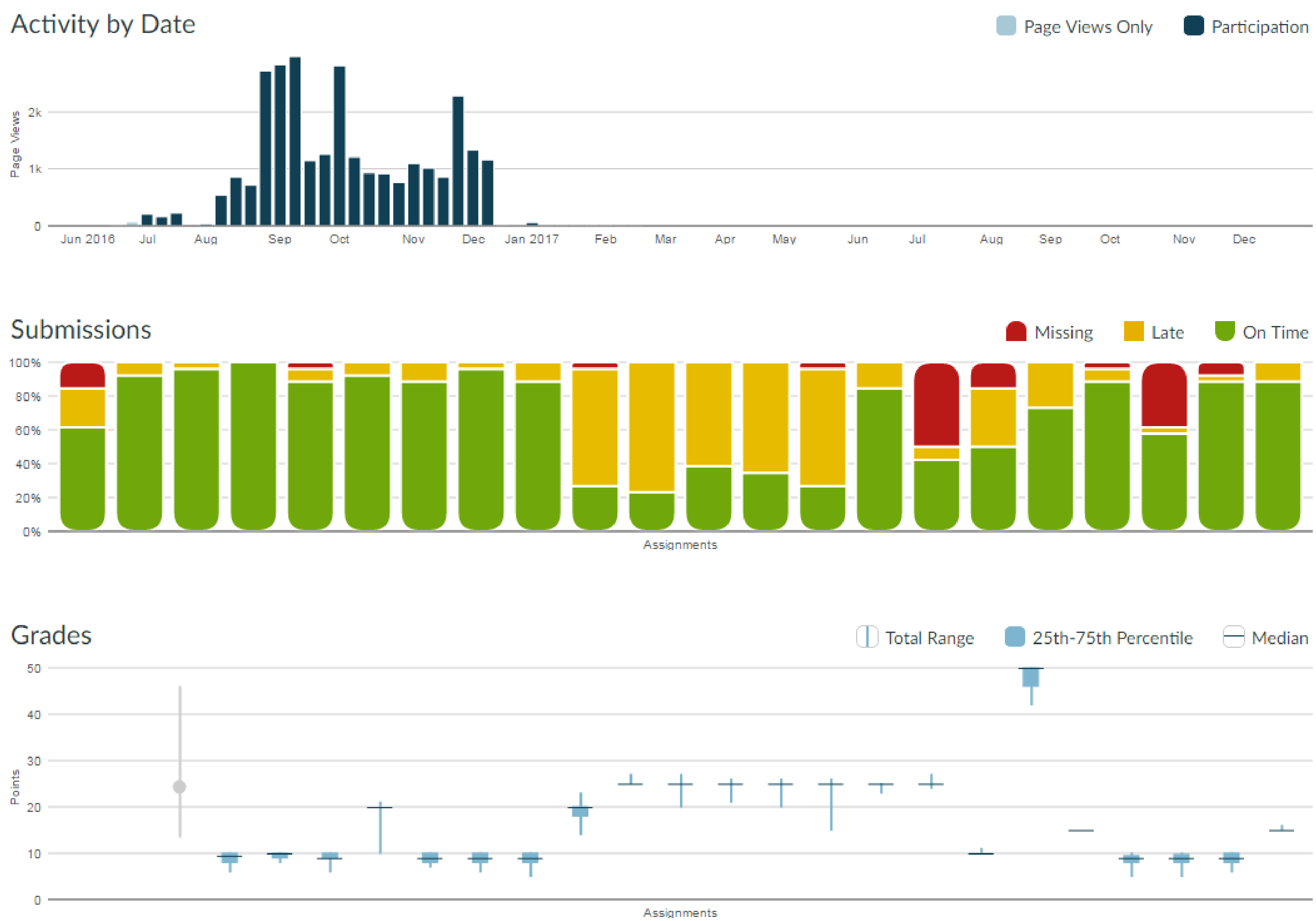


Figure 1. Canvas course analytics report.

During a semester, page views and student activity are tracked and visually presented to instructors and administrators. The submissions section shows each assignment with *on time*, *late*, and *missing* percentages. The *grades* section displays lowest and highest scores as well as percentiles for each assignment. Student analytics provide a separate report for each student in the course. This report shows individual student activity, communication, submissions and grades throughout the semester. Student analytics reports provide information regarding individual student activity, communication, submissions, and grades. Course analytic reports provide a broader view of what is happening in the course as shown in Figure 2. However, individual instructors are responsible for the interpretation of these reports and determining what actions to take. When analyzing data in educational systems, there are specific requirements to consider that are not present when analyzing other domains. Pedagogical aspects of the learner and the system are the primary focuses that need to be considered by LA.

The LA available in Canvas to TWU instructors is not sufficient to provide feedback on the readability of student writing, so a readability measure is needed. Flesch-Kincaid grade level (FKGL) scores are used extensively in the field of education as a readability scoring formula. The score on the text will interpret what level of education someone will need to be able to read a piece of text easily. The FKGL formula generates a score between 1 and 100 and a conversion table is used to interpret this score. For example, a score between 70 and 80 is equivalent to a U.S. 7th grade level. The score reflects the number of years of education required to understand the text. The following formula is used to calculate the grade-level:

$$0.39\left(\frac{\text{total words}}{\text{total sentences}}\right)+11.8\left(\frac{\text{total syllables}}{\text{total words}}\right)-15.59$$

The Flesch Reading Ease (FRE) calculates readability by the average sentence length and the average number of syllables per word.

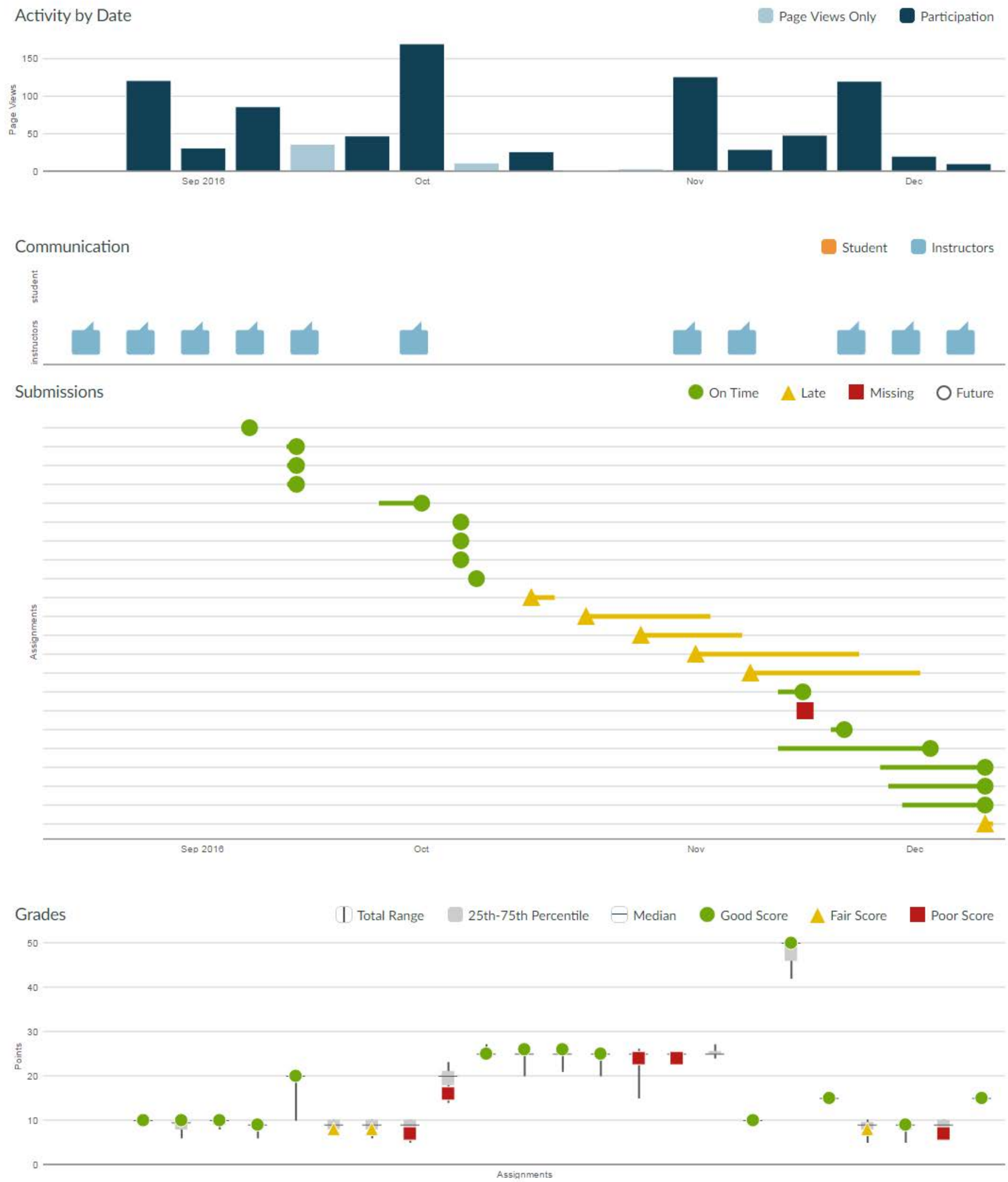


Figure 2. Canvas student analytics report.

The text is rated on a scale from one to one-hundred; the lower the score, the harder the text is to read. The score is 65 for Plain English with the average word containing two syllables, and the average sentence contains 15 to 20 words. The following formula is used to calculate the readability score:

$$206.835 - 1.015\left(\frac{\text{total words}}{\text{total sentences}}\right) - 84.6\left(\frac{\text{total syllables}}{\text{total words}}\right).$$

The automated readability index (ARI) formula grades text based on a combination of word and sentence structure. Computers have difficulty analyzing syllables, so the ARI uses a formula based on the number of characters per word. The following formula is used to calculate the grade-level:

$$4.71\left(\frac{\text{characters}}{\text{words}}\right) + 0.5\left(\frac{\text{words}}{\text{sentences}}\right) - 21.43$$

An email message was sent to Canvas instructors at TWU for approval to use discussion content (Appendix A). Student writing samples from fall 2016 and spring 2017 Canvas courses were extracted, cleansed, and additional calculations applied for use in this study. These calculations and scores include grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentence starts, vocabulary, and text readability. There is a total of twelve discussion forums and 422 student writing submissions included in the study. These include:

- Four English discussions and 93 student writing submissions from fall 2016
- Four business discussions and 250 student writing submissions from spring 2017
- Four kinesiology discussions, two discussions and 39 writing submissions from fall 2016, and two discussions and 40 writing submissions from spring 2017

In a similar study, e-learning recommendation agents (Lu, 2004) visualize what a student is doing and recommend actions determined to be beneficial to the student. Recommender agents can be used to incorporate material found on the Internet and integrated into the system (Tang & McCalla, 2005). Also, recommender agents can be infused with domain knowledge and ontologies to create semantic web mining at every stage of the knowledge discovery process for students (Vanzin, Becker, & Ruiz, 2005). Adaptive and intelligent web-based education systems like LMSs currently apply the organization and structuring of data for analysis using several techniques: statistics and visualization; clustering, classification and outlier detection; association rule mining and pattern mining; and text mining (Romero & Ventura, 2007).

Learning analytics (LA) designs frequently rely on data associated with student interaction associated with information and communication technologies (ICT) that include the LMS, student information systems (SIS), and digital platforms (Dunbar, Dingel, & Prat-Resina, 2014). Organization and structuring of the data techniques are applied to identify patterns in the content for analysis (Baker & Yacef, 2009). The interpretation of these patterns can be used to improve our understanding of learning and teaching processes, predict the achievement of learning outcomes, inform support intervention rules, and aid decisions on resource allocation (Siemens & Gasevic, 2012; Vivolo, 2014).

Problem Statement

The research problem is that there is a gap in the literature regarding instructor and administrator diagnostic use of student performance and text readability data to support writing skills improvement. As such, there is a need to identify data from the LMS to support the instructor-specific use of LA that contribute to the understanding and knowledge concerning readability of student writing samples. Currently, it is a manual process for an instructor to analyze each student writing sample and most instructors do not provide feedback at the level of metric readability outcomes. Grading written assignments requires thoughtful consideration and is a time-consuming, laborious task. Using algorithms built into LA as part of the LMS can improve the speed of analysis and provide diagnostics with specific direction and visualization. This may allow the instructor to target their pedagogical instructions to individual students based on their specific writing issues. The instructor can also use the LA provided to submit a general message to all students if certain negative writing skills patterns are recognized that all students should correct or be aware of in their future writing. The instructor can also consider the diagnostic LA provided to send an additional clarification to students on writing assignments or modify assignment instructions.

By pulling a broader set of data and applying the same readability and writing skills diagnostics, administrators can produce a department level dashboard to visualize the readability score of students in their program. WAC and WID curriculum development could be modified to incorporate objectives and pedagogy to improve student writing skills. Course learning analytics would continue to be monitored to provide diagnostics and determine if program modifications are generating positive changes to the readability score and individual writing skills of student's in their program.

There are recent studies on how various learners, instructors, and administrators can effectively use LA tools in practice to support the student learning process as well as institutional effectiveness-focused metrics. For example, West, Heath, and Huijser (2016) presented a framework for institutional implementation of LA to support student retention efforts, a general measure of institutional effectiveness. Another study addressed this issue in part by focusing on using LA to provide data on student participation in discussions (van Leeuwen, Janssen, Erkens, & Brekelmans, 2014). Other studies included instructors using analytics to support students working in groups (van Leeuwen, Janssen, Erkens, & Brekelmans, 2015) or how an LA dashboard can provide an aggregated view of student engagement and grades for a course (Ginda, Suri, Bueckle, & Borner, 2017).

There is a need for a decision model to support both instructor-specific and administrator-specific use of diagnostic learning analytics outcomes to monitor readability scores and related student writing skills. The decision model will document the identification, extraction, and calculations for readability and writing skills scores applied to the data. Specific presentation and visualization are applied to generate the diagnostic LA. Instructors can use the information to determine needed

- Student feedback
- Frequency of student feedback
- Teaching style adjustments
- Change to instructions for future assignments, and other pedagogical decisions

Administrators can use the information to

- Create broad readability and writing skills goals for the department that impact all students
- Include writing skills objectives in course curriculum
- Monitor the change in readability and writing skills scores and calculations
- Attend to performance indicators without directly interfering with students

Significance of the Study

LA research commonly uses the term “intervention” to describe the act of taking up and using analytics in practice (Lockyer, Heathcote, & Dawson, 2013; Wise, 2014; Zacharis, 2015). Interventions often present the instructor with information generated by the analytics. For example, Ginda, Suri, Bueckle, and Borner (2017) developed an analytics dashboard that would summarize student engagement and scores in real time for instructors. However, interventions alone do not necessarily improve the instructor's reflection and course refinement but afford the instructor with an opportunity to reflect and respond to achieve the desired outcome (Roll & Winne, 2015). Wise, Vytasek, Hausknecht, and Zhao (2016) pointed out that the term intervention can be useful but can also include the undesired connotation that LA use is an interruption in the regular teaching and learning process. Instead, they chose to use the term "LA implementation" to describe the use of learning analytics as an ongoing part of the regular monitoring and response adjustment to teaching and learning practices. This study also used the term "LA implementation" to describe the process of taking up and using analytics in practice.

The study attempted to investigate the direct relationship between readability scores and specific writing skills. Because prior research has reported evidence supporting written feedback instruction (Sia & Cheung, 2017), the proper instruction and practice is expected to improve college students' writing skills. Improved student writing skills should also partially mediate the relationship to their readability score. The current study should contribute to the existing literature on college writing skills by expanding the research and technology used to support decision-making regarding literacy instruction in the United States higher education settings. Few studies have investigated factors that may influence achievement in college readability scores (Elliot, 1999), especially those that employ digital tools used to produce data that lends itself to rapid analysis for learning diagnostic purposes. Results from this study should provide insight into writing skills that impede college students' writing success. Additional research on this topic is needed, but this study should provide an initial foundation for future investigations as well as decision-making criteria and metrics for instructors and administrators regarding how to address student literacy in practice.

Topics of Inquiry

The following topics of inquiry guided the study:

1. What Canvas data should be used to identify the effectiveness of student writing skills to create a diagnostic tool for instructors and administrators?

2. What effect does grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentences, and vocabulary have on the readability score of student writing samples?

3. What is the readability score of sample student text and how can it be used as an input for instructor decision-making to quickly assess student writing skills and administrator decision-making to create broad readability and writing skills goals?

Data Collection and Analysis Approach Plan

A quantitative research approach was determined best to confirm the correlation between readability scores and individual writing skills. The analysis is completed by documenting the data in the form of numbers and statistical results using database queries and other software tools in a highly structured format. Quantifiable answers can be used to answer the first two topics of inquiry, and the results are documented using objective language. For the third topic of inquiry, decision models are used to identify decisions and sub-decisions, define the input data, map the decision logic, and illustrate diagnostic services to improve student literacy. This study will implement the following data collection and analysis approach plan:

1. Identify and extract student graded writing samples from English, business, and kinesiology courses in Canvas.
2. Calculate the text readability scores for individual student writing samples and determine the correlation of grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentences, and vocabulary.

3. Create decision models to illustrate how the readability score can be used to make student literacy objectives less complex, easier to manage, and more robust.

This study used a fixed approach, quantitative, non-experimental design that includes an analysis of college student writing samples collected using an LMS open data warehouse to examine the relationships between the readability score and writing skills. Specifically, this study investigated, during a specific period, whether college students wrote at grade-level and seeks to understand potential mediating relationships among the readability score and grammar, poor sentence phrasing, use of transitional words, sentence length, passive voice use, simple sentence constructions, and level of vocabulary used in text produced by students.

These writing samples were chosen based on instructor and internal review board (IRB) approval. The population and sample are from Texas Woman's University. The collection of sample graded discussion posts will come from undergraduate and graduate students enrolled in English, business, and kinesiology courses at the university in the fall 2016 and spring 2017 semesters. The text is extracted from the Canvas data warehouse and cleansed to remove the names of all instructors and students. Using grammar and writing assessment tools the scores and calculations for readability, grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentence starts, and vocabulary are appended to the data collection.

Analysis of the Canvas data consists of a two-part process. First, a bivariate correlation is run to investigate the relationships between the readability score and individual writing skills. Second, structural equation techniques were used to test the relationships among the projected mediating items. This step involves the use of confirmatory factor analysis to establish measurement models of each writing skill. Once measurement models are established, structural equation modeling is used to illustrate the structural relationships detected within each model.

Relevance and Significance

Much LA literature has focused on how to create, process and present data to educational stakeholders. There is limited research on how instructors utilize LA tools in practice. Instructors and administrators must make real-world decisions and implement changes or feedback for LA information to provide practical utility. It is important that higher education institutions, not only provide LA to instructors but take a systemic organization-wide approach to their implementation (Dawson, Gašević, Siemens, & Joksimovic, 2014). Instructors and administrators require a meaningful and systematic implementation strategy using diagnostic data to improve writing skills and increase student learning, improve course performance, and track program key performance indicators.

There is a need for more data construction and validation research to guide and inform the use of LA by students, instructors, administrators, and various educational stakeholders (Dahlstrom, Brooks, & Bichsel, 2014). There is a specific need for writing skills research and addressing it can help provide meaningful guidance to instructors on the effective use of feedback and allow administrators to track readability scores and integrate writing skills into the curriculum. This study is an initial, exploratory step towards identifying a collection of scores and calculations that guide instructors and administrators to improve student writing skills and, ultimately, readability scores in an LMS. This study also contributes to the field by identifying a deficit of college writing skills by providing a validation study utilizing several relevant quantitative research methods.

Barriers and Assumptions

The University of North Texas (UNT) and TWU have approved the study, and both are supportive of the study’s goals and methods. While the data collection algorithms use specific LMS and LA digital tools, the aim is not to develop readability and writing skills scores and calculations to support only the use of a specific LA tool. Rather, it is to establish the correlation between readability and writing skills, so that providing diagnostic information to facilitate feedback to improve writing skills can be integrated into an LMS. The diagnostic tool would be similar to how LA tools are designed to help instructors manage and facilitate originality or plagiarism reports with tools like Turnitin.

The decision model can be used to demonstrate how individual and department level intervention and pedagogical choices are best applied using diagnostic LA, with the ability to test outcomes in practice coming in future studies. Decisions based on scientifically obtained data are expected to allow informed choices, reducing the chances of errors, distortions, assumptions, guesswork, subjectivity, and all major causes for poor or inequitable judgments. This knowledge-based approach (Grant, 1996) should promote consistent and high-quality decisions and reduces the risk and uncertainties associated with decisions, in keeping with concepts from the field of decision sciences. Any decision-making process can require careful consideration and deliberation of data; however, the benefits may only accrue when taken at specific times. As such, a limitation could be that the decision model is most effective when making long-term and policy decisions rather than short-term or rapid decisions.

In the past, expected participating instructors at TWU have reported utilizing the available LA tools from Canvas Analytics, and their motivation or interest in LA drives use. A diagnostic tool can effectively demonstrate how improving targeted writing skills can directly impact readability scores that are transferable to many LMS environments. The instructor and department convenience sample using specific writing samples and LA tools are a limitation.

Participation will only include TWU instructors creating a delimitation. The discussion posts that are used for writing samples are culled from TWU Canvas data warehouse for the fall 2016 and spring 2017 semesters from English, business, and kinesiology courses. Extended data collection would not be beneficial until the correlation between readability scores and writing skills is understood.

Definitions of Terms

- Discussions – The action or process of talking (in speech or writing) about something, typically to reach a decision or to exchange ideas.
- Flesch-Kincaid grade level – A readability score based on a formula used extensively in the field of education. The score of the text will interpret what level of education someone will need to be able to read a piece of text easily.
- Knowledge – Information is often viewed as a kind of preliminary stage to knowledge where knowledge is often seen as information with specific properties (Lueg, 2001). When information is integrated with experience, intuition and judgment, information becomes knowledge. This is because the piece of information is now endowed with a context.
- Learning analytics – "The measurement, collection, analysis, and reporting of data about learners and their contexts, for understanding and optimizing learning and the environments in which it occurs" (Siemens & Long, 2011, p. 34).
- Writing skills – Writing is a form of communication that documents knowledge, ideas, and other facts on paper, to organize their research, opinions, and beliefs into convincing arguments that convey meaning through well-constructed text. Writing evolves from simple

sentences to paragraphs and essays. Spelling, vocabulary, grammar, and organization work together to demonstrate advanced skills.

List of Acronyms

- ARI – Automated readability index
- BI – Business intelligence
- FKGL – Flesch-Kincaid grade level
- FRE – Flesch reading ease
- ICT – Information and communication technologies
- LA – Learning Analytics
- LMS – Learning management system
- SIS – Student Information System
- TWU – Texas Woman's University
- UNT – University of North Texas
- WAC – Writing across the curriculum
- WID – Writing in the disciplines

Summary

The research problem is that there is a gap in the literature regarding instructor and administrator diagnostic use of learning management system data and text readability scores to support student writing skills improvement. A quantitative research approach was determined best to confirm the correlation between text readability scores and individual writing skills. The analysis is completed by documenting the data in the form of numbers and statistical results using database queries and other software tools in a highly structured format. Quantifiable answers can be used to answer the first two topics of inquiry, and the results are documented using objective language. For the third topic of inquiry, decision models are used to identify decisions and sub-decisions, define the input data, map the decision logic, and illustrate diagnostic services to improve student literacy.

CHAPTER 2

REVIEW OF THE LITERATURE

Researchers remain inconsistent in defining the term “basic writers,” and basic writing skills, Shaughnessy (1977) defined basic writers by the errors appearing in their writings. Basic writers produce a small number of words with large numbers of errors (roughly 15 to 35 errors per 300 words). These errors are regular features of Standard English. Also, she claimed:

> [Basic writers] seem to be restricted as writers, but not necessarily as speakers, to a very narrow range of syntactic, semantic, and rhetorical options, which forces them into a rudimentary style of discourse or a dense and tangled prose. (137)

Ternes (2008) completed a study at Ivy Tech Community College in Indiana, regarding the persistence and success patterns of students enrolled in remedial courses. In the summer of 2005, the success rate for higher-level remedial writing courses was 65.6% and 66.1% in the fall of 2005. The survey of 23,764 students revealed that basic writers do well in the degree required writing courses only after completing remedial writing courses.

Friedberg, Howard, Nguyen, and Cochran (2007) pointed out that students in developmental writing courses were traditionally not passing the class, and therefore, not able to pursue a college degree. Their case study was conducted utilizing qualitative research on the students who placed in the lowest level of creative writing during their first semester at the Community College of Philadelphia. To give these students creative writing opportunities, they completed two additional courses where they wrote articles and became the editorial staff to publish their own literary magazine. Despite students’ unsatisfactory success with remedial writing courses, research has shown these courses can be significant in providing writing skills for college-level composition courses.

Troyka (2000) stated that the identification and implementation of more effective teaching strategies are needed to prevent students from failing basic writing classes. Teacher effectiveness becomes a concern when students are not fully prepared to write in the course. Some instructors are reluctant to integrate writing feedback and instruction into their curricula. They often cite that teaching writing is not their jobs as opposed to teaching their course content (Hurwitz & Hurwitz, 2004). Instructors have certain expectations for students entering college (Hoy, 2010). Instructors in Hoy's study encountered issues with students being unprepared for college writing. Survey results indicated that instructor and student perceptions regarding writing skills statements were all significantly different. 75.1% of instructors disagreed to some extent with statements that students know how to use commas. In contrast, 80.8% of students somewhat agreed to strongly agreed they know how to use commas. In another example, 87.6% of instructors somewhat agreed to strongly agreed with statements that student use sentence fragments while 77.9% of the students agreed to strongly agreed with statements that they are aware of what a sentence fragment is and that they avoid using them. Instructors' perceptions about students influence their expectations about students' preparedness for college work. Students enter courses for various reasons, and sometimes they are not prepared or able to meet writing requirements that align with the instructors' expectations.

There is a misalignment between the metrics for determining college readiness and high school educators' and higher education instructors' expectations in Texas (College Readiness and Success, 2016). For example, the College Board set the college-ready benchmark for evidence-based reading and writing at 480 on the SAT. This industry-standard benchmark indicates that a student has a 75% likelihood of earning at least a C in their first-semester literature, writing, history, or social sciences courses. Currently under consideration for Texas "outstanding performance" graduation recognition for evidence-based reading and writing is a score of 410 (College Readiness and Success, 2016). A student achieving a 410 score in their final year of high school indicates the student is most likely behind in reading and writing and has only a 60% likelihood of earning at least a C in these courses (The College Board, 2017a). This disparity in college readiness misleads students and becomes an obstacle when they are required to enroll in developmental education courses starting their postsecondary education. These reports indicate that there is a deficiency of reading and writing skills of students entering higher education in Texas and the problem is likely to continue for several more years.

The National Commission on Writing (2004), in *The Neglected R* report that was generated after five hearings held across the United States in 2004, determined that evaluating student writing is not a concern for instructors when teaching courses other than English. On the issue of standardization, at the Austin, TX hearing, instructors felt that writing and school reform should value what teachers know and not impose scripted solutions on them. A good example of this perspective was Moore's (2009) case study where the evaluation of written correspondence and assignments took place over time. The participants were enrolled in The Online Academy based at George Mason University. The qualitative case study with four students and four instructors used interviews to establish that students taking English composition courses improved their writing, while students taking a history course did not improve. Moore's work revealed that noticeable writing issues were not a priority for instructors teaching the history course. The ideal scenario presented an opportunity for instructors to teach writing, but the history teachers only taught their course content. The study revealed that students' writing performance and communication would progress over time when they are consistently engaged in writing instruction (Moore, 2009).

Text Readability

Readable refers to text characteristics including the legibility of the content, ease of reading attributed to the interest value of the writing, and ease of understanding attributed to the style of writing (Klare, 1984). The ease of understanding is the characteristic that has received the most research. In *A Dictionary of Reading and Related Terms*, Harris and Hodges (1981) define readability as the "ease of understanding or comprehension because of the style of writing" (p. 602). They acknowledge that other text variables contribute to readability, including format, content, literary form and style, vocabulary difficulty, sentence complexity, idea or proposition density, and cohesiveness. Also, important reader variables that affect readability include motivation, ability, and interest. The interaction of the text and reader variables that determine the readability of written text for a given individual.

Readability research has two main sources, vocabulary control studies, and readability measurement studies. Research in these areas was concerned with finding objective methods for measuring the difficulty of printer materials and making textbooks more readable for students (Dale & Chall, 1948). The catalyst for most of these studies came from Thorndike's book *The Teacher's Word Book* first published in 1921. The book documented the frequency with which words occur in print along with an objective measure for estimating word difficulty. This information led to the development of the first readability formula in 1923 by Lively and Pressey (Lively & Pressey, 1923). The formula was designed to estimate vocabulary difficulty based on a sample of 1000 words selected from Thorndike's book (Klare, 1984).

From 1928 to 1939 researchers began to concentrate on other text-related factors in addition to vocabulary. Using several vocabularies and sentence factors, Vogel and Washburne (1928) developed a formula that was designed to predict inters and comprehension difficulty of children's books. Gary and Leary (1935) classified 288 factors, suggested by librarians, publishers, teachers, and directors of adult education classes, into four broad categories. These included content, style, format, and organization. Because they could not break down content, format, and organization into measurable factors, they concentrated only on style in the formulas they developed.

Formulas developed during the period from 1938 to 1952 were both efficient and easy to use. Vogel and Washburne (1928) revised their earlier formula to increase ease of application without decreasing accuracy. Lorge (1939) reduced his formula to three elements; sentence length, number of prepositional phrases, and number of difficult words and could retain predictive accuracy by using the McCall and Crabbs *Standard Test Lessons in Reading* (1926) as a criterion. The Lorge formula provided scores directly regarding grade placement allowing instructors to match reading materials to the abilities of their students. The next significant development during this period was the work of Flesch (1948) to measure the readability of adult materials. He developed the Reading Ease formula using a given number of syllables per 100 words to determine the semantic difficulty and the average number of words per sentence as an index for syntactic difficulty. Dale and Chall (1948) and Gunning (1952) developed additional formulas that were adopted and from 1953 to 1959, specialized formulas began to appear such as those by Forbes and Cottle (1953) that is used determining the readability of standardized tests.

After 1959, development continued creating new, refined, and efficient formulas. The number, variety of formulas, and purposes for use continues to increase after 80 years of reliance and popularity. However, opposition to the formulas gained national attention when the International Reading Association and the National Council for Teachers of English issued a joint statement calling on professionals to abandon the use of readability formulas for preparing and selecting school textbooks (Fry, 1989). Critics of readability formulas claim that they are inaccurate as predictors of text difficulty for two reasons. First, validation was done using inappropriate criterion passages and second, text difficulty cannot be assessed based on sentence and word difficulty alone (Dreyer, 1984; Glazer, 1974; Rubin, 1985).

The Fry readability graph was designed to provide a consensus of readability for regulatory purposes and is used in the healthcare industry today. Fry (1989) stated that readability formulas were not intended as writing guides, and researchers have found this practice to be ineffective, many writers in education and other content area use these formulas to improve the readability scores of their work (Dreyer, 1984). Many students have demonstrated that rewritten text can enhance comprehension. For example, Beck, McKeown, Omanson, and Pople (1984) revised two stories by improving coherence without altering the plot by making connections more explicit, providing additional information to fill in potential knowledge gaps, and then organizing and clarifying text events and states. Although the readability level of the scores increased by one year according to the Fry (1968) formula, their results showed that the revisions increased the comprehension scores of both skilled and unskilled readers. Research indicated that writing comprehension does not improve when text changes consist of only word difficulty and sentence length (Oakland & Lane, 2004).

As a concept of reading ease, readability has been in practice since the 1920s (Crossley, Dufty, McCarthy, & McNamara, 2007). DuBay (2004) in *The Principles of Readability*, stated the definition of readability is that "of what makes text easier to read than others" (p. 3) while Klare (1963) declared that it is the "*style of writing.*" Hargis (2000) defined it as the simple understanding of "*words and sentence,*" while McLaughline (1969) explained that text is "*comprehensible*" given the interaction between it and a group of readers knowledge, skills, and abilities. Dale and Chall (1948) believed reading ease is “the sum total” of all the characteristics of readability. Oakland and Lane (2004), said readability is the ability to process information cognitively that influences comprehension. For this study, the term readability is defined as the ease with which a reader can read and comprehend text.

Oakland and Lane (2004) contested that using readability formulas must look beyond the measure of syntax and semantic elements. Additional factors to consider include prepositions, modifiers, personal pronouns, the background of the reader, prior knowledge, and other reader characteristics. Redish and Selzer (1985) argued that readability formulas fail to include these factors because they are not measurable. Organization and coherence of text are important to influence the interest of the text and motivation of the reader. Organizational structures with expressive heading and subheading increase the readability of the text, instructions, material, paragraphs, and document (Irwin & Davis 1980, p. 126). Text layout is important to provide context and comprehension for the reader. van Rijk, Volman, de Haan, and van Oers (2017) identified the functional illiterates use the context of the text to help interpret understanding of the text. How writers position chapter and heading of text along with navigation to and from various ideas and concepts are important to comprehension.

Traditional approaches to writing focus on a writer-based approach to document writing, so the text language of the text fits the needs of the writer. For example, the technical writer audience is someone with a similar background, education, expertise or even an agency or administrator (Braun, Dunn, & Tomchek, 2017). The technical writer normally has the same interest reading level of their audience, but the words of the text are challenging for anyone that lacks the same reading prowess.

According to the literature on plain language, documents should meet the need of its readers (Flammer, 2010). When considering the reading ability of the audience, planning comes out of understanding what the written material wants to achieve, the audience requirements, the purpose of the document, and how this piece of writing fits within the plan. When planning to write a document, a writer must choose the appropriate approach or writing style. Each approach concentrates on various elements that can improve the readability of the document. Failure to effectively communicate can alienate the writer's intent and the reader's need (Flammer, 2010). There are three approaches to creating documents: the *text-based approach, reader-oriented approach,* and *collaborative approach*. Each is important and is dependent on the audience and purpose of the document.

- Text-based approach. With text-based writing, the focus is not on the audience (per se) but the syntax and so vocabulary, sentence length, and sentence structure are important. Semantics, or understanding related to a word or a word association, improve text readability for the audience.

- Reader-oriented approach. This approach tests the documents against the intended audience to gauge text readability and comprehensibility of the text. After being reviewed revisions are made to the text.

- Collaborative approach. A collaborate approach focuses on the reader by engaging the reader in the process of creating the document. Using focus groups, the readers' needs, and language are taken into consideration when rewriting the documents. Writers use the process to help create a "clear reader-friendly" document.

According to the literature on plain language and readability, the writer should first identify the audience when writing a document (DuBay, 2004; Brewer, 2018). When using various communication approaches with an audience, it is necessary to be aware of their purpose of readability and comprehension. Having knowledge of the audience's reading skills, prior knowledge, and motivation are critical when writing documents attempting to improve the text readability (Oakland & Lane, 2004). Instructors must be aware of the demographical makeup of the students when delivering information relating specifically to them. Furthermore, students in a course possess a diverse level of reading and comprehension skills that will affect their level of communication. For these reasons, the evaluation of student writing skills should be a blend of technology and human interpretation, decreasing the value of computer-based solutions alone. Readability is a complex concept that encapsulates much more than a single number or score. The learning objectives should focus on improving specific writing skills like grammar, sentence structure, and vocabulary usage for individual students while monitoring text readability as an overall score to measure learning outcomes.

Writing across the Curriculum (WAC) and Writing in the Disciplines (WID)

Writing across the curriculum (WAC) and writing in the disciplines (WID) represent the most recent movements in a 125-year history of student writing development in US higher education. They both recognize that writing practices differ considerably across disciplines and, therefore, cannot be developed as a generic, mechanical skill. Writing in academic and professional disciplines communicates the outcomes of disciplinary thinking. Gere (2011) stated that a discipline-based learning in reading and writing can improve the students' mastery towards all learning materials. Without the activities of comprehending and rewriting the materials, the student will face difficulties in comprehending the main concept. Wright and Miller (1999) conducted research in the immunology department of clinical laboratory science at Louisville University in Tennessee. They applied the programs of reading and writing across the curriculum. First the students read to learn the immunology journals. In this activity, the student wrote down key words; ambiguous words and sentences, or formulated questions regarding the immunology journals and they discussed them in groups. In the second phase the students composed a creative response considering psychological and personal aspects of the immunology journals content. The third phase consisted of the students reviewing each other's responses to further explore the topics and contribute to their own organization of ideas and information. In the fourth phase students conducted a peer-review of the contents. In the final phase students evaluated the grammar. The research conducted by Wright and Miller indicated that article analysis activities, creative writing, and review are successful strategies to improve learning. Students perceived that creative writing and article analysis are effective learning methods. Peer evaluation was determined to be a moderately effective learning method (Wright & Miller, 1999).

According to Flavell (Fahim, 2014), metacognition refers to a knowledge which emphasizes on the owned cognitive process and products or all things which are produced as the impacts from that cognitive process. Flavell also presented that metacognition refers to activities of monitoring, regulating, and process relation toward data or objectives which are thought and applied the term of metacognition in language learning identifying three types of metacognition: individual knowledge, assignment knowledge, and strategy knowledge. Individual knowledge refers to language contrived as a learner including cognitive and affective abilities. Assignment knowledge refers to the learners' comprehension of the purpose and basic objectives assigned. Strategy knowledge refers to the effective strategy used to facilitate and comprehend student learning in line with the assigned objectives. Fahim (2014) stated that teaching with metacognition is considered a pedagogy procedure which can enrich the metacognition knowledge about the students as writers, the need for writing, and the strategies to write. There are benefits for students reading and writing through metacognition in both the process and the written material produced.

A discipline's epistemology and methodology strategy for writing are the planning, monitoring, and evaluating activities (Beaufort & Williams, 2005). Writing combined with a metacognitive strategy functions as both a process and a product serving as a tool for developing critical thinking. Based on these understandings, WAC and WID work together to integrate a formative writing practice with explicit writing instruction into disciplinary curricula from degree entry to completion. WAC describes pedagogical practices and employs metacognition to strengthen students' planning, monitoring, and evaluating concepts while writing. WID describes practices that teach students how to participate in the discourse of their discipline by improving the students' ability in writing essays, exploring ideas, organizing the writing, choosing the diction, and enhancing their writing technique.

Together WAC and WID employ a variety of practices to help students learn, think about, and apply disciplinary content, while at the same time developing written communication. Although writing to learn (WAC) and learning to write (WID) is never entirely separate, WAC emphasizes expressive mode of language, using formative writing exercises and informal writing tasks to help the student think through and about content (Thaiss & Porter, 2010, p. 535). Formative writing practices include note-taking, journals, reflections on learning, summaries, definitions, minute papers, free writing, outlines, and drafting for comments by peers. These open revision activities make the discipline's discourse more explicit and the writing and thinking practices more transparent. Anson (2015) asserted that these exercises need to be practice-based, low- to medium-stakes, and easy to assess. For example, in film studies, students discuss reactions to films as a low-stakes writing to learn activity. The discussion itself is not an artifact that would stand as a formal piece of film criticism but would serve as a formative assessment or assessment for learning.

WID places more emphasis on rhetorical development and learning to write in specific ways and genres (McLeod, 1992). The focus is on mastery and often serves as summative assessment (Anson, 2015). By giving students instruction and practice in the styles, conventions, and standards of a disciple through writing tasks that are related to disciplinary and professional practices, students learn to write for their desired professions. For example, the previously described film discussion activity provides a set of notes to prepare for a high-stakes, summative assessment task like a file review or essay.

The Learning Management System (LMS)

Changes in the market for online education delivery is shifting. In 2014, a survey collected instructor and student perspectives on LMSs on higher education technology experiences and expectations (Dahlstrom, Brooks, & Bichsel, 2014). To that date, higher education institutions have consistently used LMSs to deliver courses for an average of eight years, and 15% of these institutions plan to evaluate their LMS in the next three years. In that study, instructors and students stated the LMS enhanced their teaching and learning experiences; however, most, only used a few of the features included in the application. Student satisfaction in the Dahlstrom, Brooks, and Bichsel (2014) study was highest for basic LMS features and lowest for collaboration and engagement features. Students and instructors also stated that additional skills are needed to use LMS advanced features. General digital literacy skills that students know do not readily transfer to specific technology applications and services like the LMS. Mobile devices have become ubiquitous for students, and mobile access to student-facing enterprise systems have become increasingly important (Dahlstrom, Walker, & Dziuban, 2013). In the future, an LMS should have enhanced features and operational functions, be personalized, and use analytics to enhance learning outcomes (Dahlstrom, Brooks, & Bichsel, 2014).

Web-based applications and the tools integrated into them have the potential to serve as a diagnostic solution for analyzing the text readability and writing skills of students. A more intuitive interface with individualized assessments that calibrate on-demand training and support solutions specific to the user's needs should be built into the LMS to minimize or reduce the learning curve (Bichsel, 2014). Also, a better integration of engagement and collaboration features enhances the user's experience. Making these advanced features an integral part of the course design should provide instructors with flexible, varied, and ongoing means of engagement (Flanagan, 2014). Anytime, anywhere access to online course materials and engagement using any device should be supported by a mobile optimized LMS (Dahlstrom, Walker, & Dziuban, 2013). To continue to improve the technology adoption requirements, the LMS will need to solve the technical, procedural and process challenges through meaningful interactions among users. The ability to personalize the system settings and interface will add value to both the instructor and student experience. Instructors will continue to need these enhancements and predictive modeling suggestions to promote success strategies within their courses (Brooks, 2014).

There are several studies on the positive impacts of the LMS on learning (Dahlstrom, Brooks, & Bichsel, 2014; Dahlstrom, Walker, & Dziuban, 2013; Bichsel, 2014; Brooks, 2014; Flanagan, 2014) find that use should enhance instructors and students teaching and learning experiences. They have been found useful for storing content in ways that only enrolled students can access (Al-Busaidi & Al-Shihi, 2012) while also offering assessments, facilitated discussions, published grades and different ways to integrate communication in a central web-based application. Also, an LMS can be compliant with the Family Educational Rights and Privacy Act (FERPA), copyright compliance, and archival. The system has evolved by increasing the functionality of these capabilities over the past 20 years.

Institutions increasingly relying on the use of LMSs need to understand student use when designing learning pedagogy (Sivo & Pan, 2005). This study included 460 students in both psychology (n = 230) and engineering (n = 230) classes using the WebCT LMS to deliver the courses. There were two questionnaires, with one administered at the beginning and the second at the end of the semester. A comparison of the perceived usefulness, the perceived ease of use, and the attitude toward the system use was studied to determine the actual system use. A multi-sample analysis was conducted using LISREL to measure these latent variables. The results revealed that the influence of peer pressure and instructor expectations were stronger for engineering students (r = .45) than for psychology students (r = .16). Conversely, psychology student perceptions of ease of use (r = .58) had a stronger effect regarding the usefulness of the LMS for completing coursework than for engineering students (r = .30). Regardless of whether students were studying engineering (r = .18) or psychology (r = .16) their attitude toward the LMS played only a minor role in their final grade.

There are studies on the negative impacts of the LMS on learning. Al-Busaidi and Al-Shihi (2012) conducted a survey completed by 82 instructors that had used an LMS for classes. Using partial least square to measure latent variables, data analysis found that instructor computer anxiety (r = .91) was the key factor negatively impacting LMS satisfaction and adoption. Computer anxiety is “the fear or apprehension felt by individuals when they used computers, or when the considered the possibility of computer utilization” (Simonson et al., 1987, p. 238). The user's acceptance of the LMS and their perceived satisfaction may negatively be affected by their fear of computers (Piccoli et al., 2001). Computer anxiety is an important factor for the acceptance of the technology and impacts the instructors' perceived satisfaction of learning (Sun et al., 2008).

Administrative support (r = .83), incentives policy (r = .96) and training (r = .83) are directly related to instructor satisfaction of LMSs (Al-Busaidi & Al-Shihi, 2012). Teo (2009) found that administrative support indirectly affects instructor acceptance of technology in education. Consequently, a lack of administrative support of the LMS initiative and encouragement to use the system can negatively impact the adoption of LMS use. Effective use of the LMS for teaching and learning required sufficient training to instructors. Training programs can be in the form of workshops, online manuals, and seminars (Sumner & Hostetler, 1999). An LMS is used to support both traditional classroom education and distance education for learning and teaching practices (Ashrafzadeh & Sayadian, 2015). The LMS of the future should function as a digital learning environment for students and as an administrative system for instructors to manage their courses and interact with students (Bichsel, 2014). There should be an underlying data warehouse that institutions can integrate into the administrative information technology (IT) landscape to leverage analytic applications (Dahlstrom, Brooks, & Bichsel, 2014). LA are being used from predicting student retention and graduation (Asif, Merceron, Ali, & Haider, 2017) to using patterns to predict the effect of alcohol on higher education student performance (Pal & Chaurasia, 2017). The institution will need to establish their own boundaries regarding decision-making. For example, tacit knowledge about the student should be executed within the course if decisions are made by the instructor and uploaded into an institutional data warehouse for decisions made by administrators. Decision models can be used to document the use of data and LA in an LMS.

Higher education institutions are using established and emerging technologies for learning. Involvement by students, instructors and administration are important to LMS success. A study was completed to investigate the roles of student and instructor involvement in LMS success (Klobas & McGill, 2010). Using the DeLone and McLean (2003) model of information systems success as a framework, data was collected using an online questionnaire completed by students enrolled in an Australian university. The findings revealed that student involvement effected perceived learning and improvements in the process of study by students using the LMS even though perceptions of improved learning were not matched by expectations of improved grades. Instructor involvement was found to guide appropriate use, both regarding the nature of use, and the extent of use. Also, instructor involvement contributed to student benefits by affecting information quality.

Learning Analytics (LA)

The following examination is a brief overview of the current state of the body of knowledge in the learning analytics (LA) field regarding data capture, processing, and display or visualization of analytics data outcomes. The review includes studies utilizing a design and development research strategy combined with aspects of organizing and structuring data for diagnostic solutions. The use of LA is a growing field of study and LA evolved from online learning research to use LMS data to examine learning success. However, there are challenges to be overcome to enhance learning and teaching practices using analytics. For example, there is a strong dependence on complex statistical methods and numbers, rather than learning theory and processes in approaches to organize and structure the data for analysis. Several researchers have argued that a students' perspective is required to interpret the data (Ferguson, 2012) and the results should provide actionable recommendations (Gasevic, Dawson, & Siemens, 2015). A theoretical learning framework aligns the practice and interpretation of LA and the associated implementation of LA tools and functions should be easy for educators to understand and use. Instructors should be aware of their students' progress and level of understanding. Simple and intuitive presentations of students' performances are required to convince instructors to accept and use LA (Gasevic, Dawson, & Siemens, 2015). The leading factors of students' learning behaviors about performance should be identified and validated in various contexts to build effective prediction models and suggest practical solutions.

A learning management system (LMS) accumulates information valuable for analyzing student behavior, but there are specific requirements to consider when applying techniques to organize and structure data in educational systems that are not present when analyzing other domains. Pedagogical aspects of the learner and the system are the primary focus that should be considered by LA. E-learning recommendation agents (Lu, 2004) see what a student is doing and recommend actions determined to be beneficial to the student. Recommender agents can integrate material found on the Internet into the system (Tang & McCalla, 2005). Also, recommender agents can also be integrated with domain knowledge and ontologies to create semantic web mining at every stage of the knowledge discovery process for students (Vanzin, Becker, & Ruiz, 2005). Several techniques are used to apply data organization and structuring to the LMS and adaptive and intelligent web-based educational systems (Romero & Ventura, 2007).

LA designs frequently rely on data associated with student interaction in information and communication technologies (ICT) that include the LMS, student information systems (SIS) and social media. The data recorded by LMSs includes time-stamped events about views of specific resources, attempts and completion of quizzes, or discussion posts created or viewed. Data organization and structuring techniques are applied to identify patterns in the data (Baker & Yacef, 2009). The interpretation of these patterns can be used to improve our understanding of learning and teaching processes, predict the achievement of learning outcomes, inform support intervention rules, and provide diagnostic information for student writing submissions (Siemens & Gasevic, 2012).

Mazza and Dimitrova (2007) developed and analyzed a student monitoring tool for supporting instructors in online courses. This tool monitors student activity within the LMS, but the focus was on the graphical interface. The researcher's surveyed users regarding the effectiveness, efficiency, and usefulness of their tool and found that the use of graphical representations of data was important to the user. Similarly, Ruipérez-Valiente, Muñoz-Merino, Leony, and Kloos (2015) presented a study of another LA tool that visualized data for the user. Ali, Hatala, Gašević, and Jovanović (2012) presented two evaluations of their tool, LOCO-Analyst, which also focuses on visualizing LMS data for instructors. Macfadyen and Dawson (2010) discussed the development and implementation of another dashboard-like tool that also visualizes LMS data.

While these studies included different measures of student performance or usage, they all had a common theme of visualizing data for instructors. For example, Macfadyen and Dawson (2010) found that meaningful information extracted from LMS data and tools can be developed to visualize student progress and the likelihood of their success. They all concluded that the visualization aspect is important, so instructors can readily discern outliers and points of concern and react to such circumstances quickly. Macfadyen and Dawson (2010) also stressed the importance of customizability by stating that visualization tools must be highly customizable to reflect a pedagogical intent to represent student performance.

In another study focusing on visualization of course data, Dyckhoff, Zielke, Bultmann, Chatti, and Schroeder (2012) developed, implemented, and tested the exploratory Learning Analytics Toolkit (eLAT). In contrast to the previously mentioned studies, the primary purpose of this tool was not student monitoring but monitoring of courses to support teachers in their ongoing reflection, evaluation, and improvement of their instructional design. Mor, Ferguson, and Wasson (2015) pointed out that learning design, teacher inquiry, and LA can form a continuous circle since LA can be used to inform learning design and present the results.

The distinction made by Wise, Vytasek, Hausknecht, and Zhao (2016) between LA research on data capture, processing, and presentation, as well as research on the practice of using analytics to inform decision-making and action, is a distinction made by Klein and Richey (2007). In the Klein and Richey (2007) study of the types of design and development research guiding the instructional design process, they differentiate between product and tool research and model research. Product and tool research has involved a detailed description, analysis, and evaluation of the design and development of specific products to understand conditions, which facilitate their use. In contrast, model research is the study of model development, validation, or use that results in new procedures for frameworks and conditions that facilitate their use.

Several studies are specifically relevant to the discussion of LA implementation but do not offer a model or framework as guidance. van Leeuwen, Janssen, Erkens, and Brekelmans (2014) discussed how LA could be used to support instructors in guiding student discussions and participation in an online learning environment utilizing computer-supported collaborative learning (CSCL). They presented a test group of instructors with a set of simulations of student discussion, some of which included problems that warranted some intervention. Some instructors received LA visualization tools. The control group of instructors did not receive LA visualization tools. Upon observing the instructors' interaction with students, the main findings were that when presented with LA tools and visualizations, instructors intervened more often, were better able to target those needing intervention, and presented more specific interventions to problematic students. In a related discussion of CSCL and LA, Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, and Dimitriadis (2015) made the additional point that LA can be used to support the design of CSCL situations.

In a later study, van Leeuwen, Janssen, Erkens, and Brekelmans (2015) focused not on students collaborating in discussions, but on students collaborating on group projects. The method and findings were like Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, and Dimitriadis (2015). The researchers found that when equipped with LA tools, instructors offered more support in general which indicates that LA tools increase teachers' confidence to act. van Leeuwen, Janssen, Erkens, and Brekelmans (2015) offered a useful means of measuring instructors' interventions coded according to frequency, focus, means, and specificity. This type of organization and structuring of the data for analysis could be very beneficial in research concerning instructor implementation of LA.

Learning Analytics (LA) Models

A review of the literature guided the identification of what LA tools and models that are currently available to instructors, their use, and the benefits and limitations of these tools and models. The difference is that product and tool research results in context-specific conclusions while model research promises results and conclusions that are more generalizable to the entire field. This review helped identify the data required for a diagnostic LA to assist instructors grading writing assignments to improve student writing skills and ultimately readability scores. Research in predictive analytics and knowledge discovery has a significant level of importance for higher education institutions. The ability of LA and reports to provide a diagnostic solution capable of analyzing student writing samples used to improve student readability scores is achievable. Dashboards and reporting can be used to implement learning interventions and strategies that specifically target writing skills and provide recommendations to instructors and administrators. To generate this reporting LA, research must identify the diverse ways technology is adopted and applied in course-specific contexts.

The differences in technology use related to whether and how instructors use the LMS, require consideration before the data can be merged to create a generalized model for predicting academic success (Romero, Ventura, & Garcia, 2008). One study examined the extent to which instructional conditions influenced the prediction of academic success in nine undergraduate courses offered in a blended learning model (Gasevic, Dawson, Rogers, & Gasevic, 2016). Some common themes from the literature include the need for customizability, the prevalence of visualization tools, and the need for early detection "alert" tools which flag certain students based on the level of risk. Over time a shift occurred from tool development and validation studies to research studies supporting models and frameworks. Martinez-Maldonado, Pardo, Mirriahi, Yacef, Kay, and Clayphan (2015) recognized the need for a framework to help designers systematically develop, evaluate, and deploy effective LA tools. They pointed out that the design of effective LA tools must draw from the methodologies from multiple disciplines such as software development, human-computer interaction, and education. While each of these disciplines has their development models, there is no accepted methodology for designing LA tools that take a multidisciplinary approach. They proposed a five-stage workflow with a solid pedagogical underpinning to design, deploy and validate awareness tools in technology-enabled learning environments called LATUX. The stages of this approach include problem identification, low-fidelity prototyping, higher fidelity prototyping, pilot studies, and classroom use. Each stage includes specific steps to make sure the development process considers the learning context and integrates pedagogical requirements resulting in visual analytics tools to inform instructors' pedagogical decisions or intervention strategies. In conclusion, they stated that this work is only an initial step towards much research needed in this area.

Similarly, Greller and Drachsler (2012) presented a generic framework to guide the design of LA. The idea was to create a generic framework that would be applicable in many different contexts. The framework included the dimensions of internal limitations, external constraints, instruments, data, objectives, and stakeholders. Greller and Drachsler (2012) proposed that by considering these dimensions in the design of LA, the developer would produce a more valuable tool.

Scheffel, Drachsler, Stoyanov, and Specht (2014) further developed this area of research. The authors presented and tested an evaluation framework of quality indicators for LA tools. They recognized that, although these types of tools have become prevalent, there is no accepted measure of the quality of such tools. There is a lack of consensus on what constitutes a good, effective, efficient, and useful LA tool. The researchers sought to remedy this problem with their framework which included five criteria of objectives, learning support, learning measures and output, data aspects, and organizational aspects. They found issues with this framework during analysis but recognized that this is just an initial step to much needed research in this area.

Ali, Asadi, Gašević, Jovanović, and Hatala (2013) took yet another perspective on this topic in their study on factors influencing adoption of LA tools. They sought to identify what specific factors would lead instructors to use or not use LA tools. They found that factors such as ease-of-use, perceived usefulness, and information design skills could influence whether instructors choose to adopt LA tools and another interesting area of research which could inform the adoption and use of such tools.

Verbert, Manouselis, Drachsler, and Duval (2012) presented another framework relevant to LA research. The purpose of this framework was to aid researchers in the field by offering guidance on the analysis of available datasets used for exploratory research on LA. Swenson (2014) presented a unique perspective on LA model development by suggesting a framework to establish an ethical literacy regarding LA. Swenson (2014) discussed the ethics of specific LA "artifacts" (dashboards, visualizations, etc.), the ethical effects of LA, and the establishment of an ethical literacy. The ethical effects of LA included: consequences of classification, identifying power moves, and considering voice. Swenson (2014) pointed out some concerns researchers in the field should consider. Perhaps the categorizing or labeling of students though LA could have some negative or even harmful consequences. Perhaps some of these tools could lead to forms of segregation leaving some students feeling marginalized. It is important that institutions keep these possibilities in mind when adopting these tools so as not to lead to unintended negative consequences for students. Swenson (2014) offered a useful framework to guide the adoption of LA tools but lacks validation.

Macfadyen and Dawson (2012) pointed out that the institutional strategic planning process should consult and integrate LA. Ferguson, Clow, Macfadyen, Essa, Dawson, and Alexander (2014) presented a framework to support the implementation of LA at the institutional level. The RAPID (research and policy in development) outcome mapping approach (ROMA) Framework was adapted for the context to offer guidance on institutional implementation of LA. The steps of the approach include: define a clear set of overarching policy objectives; map the context, identify the key stakeholders, identify LA purposes, develop a strategy, analyze capacity and develop human resources, and develop a monitoring and learning system. Additionally, they provided several case studies to discuss the implementation of this framework at different institutions. This study shows how such a general framework can be adaptable to apply to different situations or LA tools.

Dringus (2012) described many principles, without a specific framework or model, for the adoption of LA tools while expressing an attitude of caution when considering LA as being potentially “harmful.” Five principles were stated as “musts” for LA in online courses:

- LA must develop from the stance of getting the right data and the data right
- LA must have transparency
- LA must yield from good algorithms
- LA must lead to responsible assessment and effective use of the data trail
- LA must inform process and practice

Wise (2014) presented a discussion of designing interventions based on the output of LA tools pointing out that this part of the process is often ignored and is a relatively unexplored area of research. There are three specific aspects of the application of LA. These include capturing traces of learning, how to present these traces to learners, and how to frame the inclusion of analytics as part of the course activity to guide their use in productive decision-making by students and instructors (Wise, Zhao, & Hausknecht, 2014).

The Wise, Vytasek, Hausknecht, and Zhao (2016) framework consisting of integration, diversity, agency, reflection, and dialogue was used to design embedded and extracted LA interventions to monitor activity in online discussions. In this framework, the use of the LA intervention is an integral part of the learning activity. This study showed how such a framework could guide the use of LA and empower students to take responsibility for regulating their learning process. While this framework is a good starting point, the research problem remains that there is a lack of evidence-based guidance on how instructors can effectively implement LA to support students.

Lockyer, Heathcote, and Dawson (2013) addressed this issue in part by presenting the idea that a conceptual framework for typical LA patterns expected from learning designs would help teachers interpret the information that analytics provides. The idea is that the LA measures should be mapped back to the course learning design for the analytics to reflect pedagogical intent. This mapping creates a practice where instructors will document their pedagogical intent in their learning design which then serves as a means of querying the analytics and making sense of the information provided. Without being developed or validated, the authors presented an example of Lockyer's model by suggesting a practice of identifying in the learning design what activity patterns to expect for a student to be successful using analytics as a checkpoint to identify personal progress during the learning activity. Lockyer's model has a narrow focus on how learning design can inform the use of LA and is difficult to generalize to a variety of learning situations.

Decision Models for Diagnostic Learning Analytics (LA)

Knight, Shum, and Littleton (2014) introduced the idea that the design of LA tools should incorporate epistemology, assessment, and pedagogy. They made the point that it is not the tool itself, but the wielding of the tool, which determines the value. This idea leads to the discussion of decision models to guide the implementation and use of LA tools. Instructors and administrators set learning objectives for individual courses and entire programs. Improving readability scores and writing skills is possible if institutions of higher education decide to implement to act differently regarding student readability. Strategic and tactical decisions matter, however, the operational decisions that impact individual assignments, individual students, courses, and programs are central to increase readability scores. A useful definition of a decision model for diagnostic LA is:

> a determination requiring pedagogical expertise; the resolving of a gap in student writing skills by identifying some correct or optimal choice.

Identifying and manipulating the data available to evaluate student writing skills and presenting the results visually to instructors and administrators through diagnostic LA allows them to make decisions. Making single decisions may require the presence of several diagnostic LA. When issues identified in student writing samples trigger a decision, the instructor needs to take some action or provide an appropriate response. Without diagnostic LA instructors and administrators are not focused on student writing skills and corrective action is less likely to occur.

Decisions to impact readability scores and correct writing skills should be addressed in the short-term, whether that action is made in person or by the system. For instance, administrators can identify readability score goals and implement learning objectives for writing skills in a series of Canvas courses. Midterm essays or another internal trigger in Canvas will update the diagnostic LA dashboard or visualizations allowing instructors and administrators to monitor student writing skills in targeted courses. In some situations, the LA is used as a benchmark to review progress. Other times a decision or additional action requires research to determine the best course of action.

Experience shows that many of the decisions made as a response to LA (an instructor provides a vocabulary score to a student) are also part of a larger decision (tracking the readability score for students in the MBA program). Decomposing student writing skills activities by individual instructors are independent activities responding to diagnostic LA. However, the collection of these decisions creates a network demonstrating the importance of the reuse of decisions. Decision modeling is about capturing and describing the specifics of decisions in a graphical notation and structured format. There is an increasing amount of research about how to develop decision models (Pourshahid, Mussbacher, Amyot, & Weiss, 2013) and the decision model and notation (DMN) standard (Rucker, 2015).

Some of the key elements of a decision model include:

1. The information required by the decision – a decision model that shows the individuals and data required for each decision

2. The knowledge required to make the decision – the analytic knowledge sources that show how to improve decisions

3. The description of the decision – each decision is decomposed into a set of elements enabling a precise definition of the decision-making while allowing high-level models to serve as a roadmap

4. The management of automation boundaries – each decision needs to be described in appropriate detail, include the identification and documentation of automated and manual parts of the decision

The solution is to identify each decision as a task within diagnostic LA. Managing decisions separately reduces the complexity of the solution, and a simpler process is easier to understand and change, increasing the university's decision-making agility to improve readability scores. This approach results in smarter processes and allows for greater automation. Decision models identify where diagnostic LA fit into improving decision-making (Johari Shirazi, 2012).

A decision model allows for a structured decomposition of decision-making and data mapping. Also, incrementally develop the decision model. Each decision included as part of the model can be expanded on and developed independently. While the decision model evolves, the benefits are incurred by the deployed decisions (Horkoff et al., 2014). Decisions are driven by an analytic prediction to help students improve their grammar skills require actions driven by knowledge of the student, the frequency of grammar errors, and other considerations. Decision modeling works best when considering decisions first and data second (Pourshahid, Mussbacher, Amyot, & Weiss, 2013).

Data Visualization and Dashboards

Administrators and instructors are required to distill information into actionable intelligence. Fact-based decisions require the right data to be easily accessed and in a logical format using communication-based and information-based instruments (Lascoumes & Le Galès, 2007). The typical form is a data visualization or dashboard adopted from the automobile or aircraft dashboard as a snapshot of separate measures. The automobile dashboard is limited to the status of situation data like speed and miles traveled, decision makers require data in context to manage performance over time (Beer, 2013). Administrators will need a comparison of current values to past performance and future objectives. Strategic goals require a high-level view across campuses, colleges, disciplines, and curriculum that covers months or years. Instructors tasked with meeting daily or weekly goals, require a narrower timeframe and a targeted set of data to investigate the cause of variance. For example, the number of students that have not started working on an assignment that is due in the next week. Department administrators must approach performance data with a set of unformed questions. For example, with an understanding of WAC objectives, department administrators might research the need to expand the number of writing intensive courses and assessment criteria for those assignments from one semester to the next.

In addition to time and purpose requirements, data visualizations must leverage human perception capabilities to facilitate understanding of status and intuitive guided analysis (Rose, Degen, & Melhuish, 2014). Factors such as placement, attention cues, cognitive load, and interactivity contribute greatly to the effectiveness of a dashboard and the value it provides (Pappas & Whitman, 2011). To make dashboard visuals effective the purpose and audience must be known to derive the data type as either quantitative or qualitative; and scope as either institutional or departmental (Beer, 2013). To provide guidance for a useful taxonomy three categories of data visualization are considered: strategic, analytic, and operational.

- Strategic**.** The strategic dashboard is designed to communicate the institution's performance relative to strategic objectives. It contains comparative data, contrasting current with past performance or current to target levels. Strategic dashboards should have an uncluttered interface to quickly guide administrators to answer whether the institution is on track. The strategic dashboard is shared to a wide audience providing insight on performance across the institution to promote alignment across the institution.

- Analytic**.** The analytic dashboard shares extended timeframes with the strategic dashboard. However, drill-down and visual exploration are essential for discovering patterns and trends in the data. Administrators are looking for variances in writing skills among writing assignments, courses, and disciplines. In addition to looking back to examine root cause, the analytic dashboard can be forward looking to forecast outcomes. By examining current trends, department administrators can model outcomes by adjusting variables to recommend actions to optimize results.

- Operational**.** Monitoring operations requires timely data, tracing changing activities that could require immediate attention. Effective operational dashboards require an uncomplicated view to easily identify measures that are off-target and require intervention. The operational data visualization must be meaningful in the situation and the appropriate response easy to identify or mistakes can be made.

Data visualization in a dashboard is meant to be viewed all at once without having to scroll or navigate to multiple pages so the device used by administrators and instructors is important. Tablets might require a different format for the visualization to be effective. Information is integrated, risk is quickly noticed, and decisions are formulated using visuals arranged together so they can be seen simultaneously. This allows for processing the information with minimal effort (Gitelman & Jackson, 2013). Additional interactivity within the dashboard should be outlined in the requirements. For example, selection criteria to define a period or discipline, drill-down capabilities to obtain details, hyperlinks to additional or relevant information, and communication features like commenting. The resulting dashboard is based on user requirements and system capabilities (Rose, Degen, & Melhuish, 2014). Any visualization produced using software and digital data is created through networks of actors and technologies with the capability to shape engagement and interaction and depict the truth (Gitelman & Jackson, 2013).

For the strategic dashboard use visuals that combine multiple indicators in one space and provide some interactivity (Pappas & Whitman, 2011). For example, data brushing is a feature that allows the administrator to select data values in one visualization and the corresponding data values in other visualizations will update to match the new data selection. Department administrators require ways to provide optional views of the data. For example, viewing a scatterplot with a cluster of points might require the ability to zoom into the cluster and view only the selected range in a table or bullet chart for alternative comparisons. Instructors who focus on individual student writing skills require a near real-time currency of the data with a persistent connection to the data. A notification capability can be accommodated by small mobile devices. Taking cues from human perception and learning, decisions models should be used to design data visualizations that are easily accessed as a valuable source of information.

Summary

This review of literature presented a definition of basic writers and the gaps in their writing skills. In 2016 employers hiring four-year College graduates indicate that 27.8% have deficiencies in written communication. Postsecondary learning objectives should focus on improving specific writing skills like grammar, sentence structure, and vocabulary usage for individual students and monitoring text readability as an overall score to measure learning outcomes. Web-based applications and the tools integrated into them have the potential to serve as a diagnostic solution for analyzing the text readability and writing skills of students. Organization and structuring of the extracted Canvas data was required to add text readability and other writing skills analytics as part of the process to develop diagnostic LA that interprets student writing skills in the LMS. Building decision-making models based on the knowledge retrieved from these datasets is an important area for exploration (Han, Wang, & El-Kishky, 2014). Decision modeling are used to capture and describe the specifics of literacy improvement decisions for instructors and administrators in a graphical notation and structured format.

CHAPTER 3

METHODS

To further explore the data available in the Canvas warehouse and the effect of writing skills on text readability scores as an illuminative example of how such data can be used for instructor decision making to support student success, the following topics of inquiry guided the study:

1. What Canvas data should be used to identify the effectiveness of student writing skills to create a diagnostic tool for instructors and administrators?
2. What effect does grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentences, and vocabulary have on the readability score of student writing samples?
3. What is the readability score of sample student text and how can it be used as an input for instructor decision-making to quickly assess student writing skills and administrator decision-making to create broad readability and writing skills goals?

The strategy of inquiry to complete this study will adopt the quantitative approach to research. Creswell (2013) suggested that a quantitative approach seeks to identify variables associated with the purpose of the study. Empirical observations, measures and statistical techniques, and procedures are used in this study answered the topics of inquiry. The readability scores of a sample of student writing submissions are analyzed using the Flesch Kincaid grade level (FKGL) formula, the Flesch Reading Ease (FRE) readability score, and the automated readability index (ARI) readability score. The student readability scores are compared to the expected (or targeted) education attainment level of college students in the business, English, and kinesiology departments at TWU.

Descriptive and associational statistical methods were chosen to conduct the research and answer the research question. Teddlie and Tashakkori (2009), describe methods as, "[p]rocedures for summarizing data, with the intention of discovering trends and patterns, and summarizing results for ease of understanding and communication" (p. 257). The outcome helps connect the existing knowledge of readability of student writings to current writing and designing practices.

Readability Scores and Instruments

Readability, as defined by Klare (1963) is "the ease of understanding or comprehension due to the style of writing." The definition focuses on the student's writing style as separate from issues such as content, coherence, and organization. Calculations included three readability scores to assess a student's writing sample readability. The first two text readability formulas used were the Flesch-Kincaid grade level (FKGL) and the Flesch reading ease (FRE) formulas because of their frequent use in Education. The third text readability formula used was the automated readability index (ALI). Computers have difficulty analyzing syllables, and the ARI readability formula uses the number of characters. Because all the text readability scores were generated using a computer, this formula is appropriate. Trochim and Donnelly (2008) wrote that a good assessment is reliable in its findings and produces consistent results.

The FKGL method of assessing text has been utilized by the Department of Defense, for academic, social research, and implemented in Microsoft software packages. The FRE formula takes personal references, such as pronouns and names, into an account that makes it unique from other formulas. There is an interpretation table that includes a reading ease score and grade level score that account for the curvilinear of the equation. The FRE formula measure has a range from 0 to 100, zero being very difficult to read and 100 is very easy to read (Dubay, 2004;

Flesch, 1948). A FRE score between 60 and 70 is considered a normal readability level. Using both the FKGL and FRE, the reading ease score compares with the grade-level of the text. Microsoft Excel and programming languages can be used to assess the readability scores of text programmatically.

The FKGL produces a grade-level score instead of a readability score. The Flesch Kincaid scale signifies a reading grade level between 0 and 19, the lower the number, the easier the written text is to read. For example, a text that generates a score of 10 indicates that the sample text has a reading level of 10th grade. The FRE score has demonstrated a high correlation with the ARI score. The ALI and FRE formulas can be modified by recalculating regression algorithms. As a result, these two text readability formulas will grade a given narrative passage nearly the same and can be used interchangeably. Both formulas are designed to measure the intelligibility of a text (Kincaid, Fishburne, Rogers, & Chissom, 1975). Flesh (1948) found the FRE is more easily understood when the measurement of word length is indirectly a measurement of word complexity (r = .87) and the word complexity is indirectly a measurement of affixes and abstract words (r = .78). There are additional correlations found between the sentence length (r = .78) (Gary & Leary, 1935) and sentence complexity (r = .72) (Sanford, 1941).

Sample and Data Collection

One objective of this study was to examine the grade-level readability of business, English, and kinesiology students writing samples, specifically discussion posts. Written permission was granted from instructors at TWU to use student writing samples in their Canvas courses from fall 2016 and spring 2017. The data sample will only include graded discussions with some expectation that students would submit quality writing samples. There were twelve discussions pulled from Canvas and included in this study. The data extraction generated a total of 422 writing submissions.

Grammarly Writing Tool

The first software application applied to the extracted Canvas discussions is Grammarly, an English language proofreading, grammar checker, and contextual spell checker application. Grammarly is used for proofreading discussion posts incorporated grammar rules, punctuation, and sentence structure. One calculation will include the percentage of passive voice sentences in the writing sample. In grammar, the voice is about the relationship of the subject to its verb; every verb has a voice; it is either active or passive. In the active voice, the subject of a verb acts and in the passive voice, the subject is acted upon. Many instructors feel that passive voice represents poor writing form.

Paper Rater Writing Instruction

Paper Rater is the second application used to provide feedback and writing instruction. One module provided is the evaluation of bad phrase usage. The “bad phrase” score measures the quality and quantity of trite or inappropriate words, phrases, egregious misspellings, and clichés found in the discussion posts. The usage of transitional phrases is contained in the second module. This score measures the quality of transitional phrases used within writing samples. Transitional words and phrases contribute to the cohesiveness of a text and allow the sentences to flow smoothly. Without transitional phrases, a text will seem disorganized and is more likely to be difficult to understand. The third module provided by Paper Rater is the usage of academic vocabulary. This score measures the quantity and quality of scholarly vocabulary words found in the text. A vocabulary score and simple sentence starts are the final calculations provided by Paper Rater. Simple sentence starts are a percentage of total sentences in the post. Sentences should start with a variety of prepositions, adjectives, adverbs, articles conjunctions, pronouns, nouns, and verbs.

Sentence length information includes the total number of sentences, the average length of sentences, and sentence variation. Short sentences have less than 17 words, and long sentences have more than 35 words. Sentence variation is the standard deviation in sentence length. Sentence length conveys a specific rhythm and matches the actions described. Shorter sentences provide succinct information and emphasize one or two points. Long sentences provide more detail and information and are used to investigate in-depth ideas. There is no correct sentence length but analyzing the amount of short and long sentences will identify variations in the discussion posts.

FKGL, FRE, and ALI Text Readability Scores

Microsoft Excel is the third application applied to the extracted Canvas discussions to calculate the FKGL, FRE, and ALI scores. In general, to assess the text readability score the student writing sample needs to contain at least 100 characters. The definition of a writing sample is any valid student writing submission substantial enough to generate at least one text readability score for FKGL, FRE, or ALI. The calculated scores are appended to the extracted Canvas data.

Automatic Grading of Writing Skills

Discussions are one type of graded writing assignment that instructor's frequently created. Open Diary was an early Internet site that brought together online diary writers into one community. Originating in 1979, Truscott and Ellis from Duke University created the Usenet, a worldwide discussion system that allowed Internet users to post public messages (Kaplan & Haenlein, 2010). Kaplan and Haenlein, (2010) describe discussion forums as a format that allows a group of individuals to share and discuss their opinions, experiences, and knowledge on a topic (Bickart & Schindler, 2001). Discussion forums remain relevant to this day and contribute a significant portion of user-generated content (Wang et al., 2008). Due to their user-centric nature, it was realized over time that valuable deposits of information could be extracted from these discussion forums and used for the benefit of instructors (Guo et al., 2006).

Grading written assignments require the instructor to complete a series of steps to teach the revision process to students and provide feedback to improve specific writing skills. Automated grading tools provide immediate feedback and help the instructor provide targeted suggestions to the student (McCrea, 2013). Auto-grading has been used successfully for the past decade in the U.S. and has a role in pre-assessing writing, but it is not likely to replace hand-grading anytime soon. TWU instructors handle the time-consuming process of grading writing assignments on their own with the help of the university's LMS, Canvas. Instructors can annotate writing assignments that have been submitted by students. Common types of feedback include adding commentary, highlighting passages, and suggesting grammar, sentence structure, punctuation, and vocabulary improvements. Instructors may consider handing over some of the grading work to a machine, but several elements are often missing or inserted in written assignments (Shum, Sándor, Goldsmith, Wang, Bass, & McWilliams, 2016). For example, incorrect use of commas and semicolons within citations is a common problem. If a checklist of these elements were turned over to a diagnostic tool then the grading process could be facilitated, grading would be consistent, and the time spent grading reduced.

Statistical Analysis and Procedures

The Canvas dataset is created using Canvas data and the ALI, FRE, and FKGL readability scores generated. Writing skills scores and calculations are added to the dataset. The IBM Statistical Package for Social Sciences (SPSS 25) is used to run the statistical analysis. Descriptive statistics will summarize the ALI, FRE, and FKGL readability scores. Also, descriptive statistics are used to summarize writing skills measurements.

Descriptive statistics are the foundation of the quantitative analysis that was needed to establish the combined text readability scores for English, business, and kinesiology student writing samples. A paired sample t-test will compare the FKGL readability score to the individual writing skills. The correlation will be determined for grammar errors, grammar errors as a percent of total words, “bad phrases”, transitional words, total sentences, average sentence length, short sentences count (<17 words), long sentences count (>35 words), sentence length variation, passive voice as a percent of total sentences, simple sentence starts as a percent of total sentences, vocabulary, vocabulary word count, and vocabulary words as a percent of total words.

A one-sample t-test is used to compare the disciplines mean FKGL to the overall FKGL to determine whether the sample of writing samples comes from a population with a specific mean. An assumption is the t-test has a sample size less than 50. Babbie (2012) stated it is useful to use a statistical method that will account for the sample size; however, as (n) approaches infinity, T=A=F, it does not matter. The difference between the FKGL score mean difference among disciplines (business, English, and kinesiology) is determined using one-way ANOVA statistics. A one-way ANOVA statistic is employed to see if there is a difference between the FKGL score mean difference among courses.

Diagnostic Learning Analytics (LA) Decision Model

This study develops decision models which help in the design of the diagnostic LA to improve student writing skills. Several decisions included as part of the models are expanded on and developed independently (Horkoff et al., 2014). As the decision models evolve, the independent decisions being made by administrators and instructors become a collection of benefits. The diagnostic LA decision models account for the various types of decisions that need to be made by administrators and instructors. There are four decision models generated. The first decision model is an overview of the processes and types of decisions needed to measure student writing skills in higher education. To address specific challenges measuring writing skills performance and targeting writing skills to improve, a WAC decision model is designed with a dashboard to monitor actual student writing skills performance against targeted objectives. For department administrators to review a summary of student writing skills at a course level, a WID decision model with a dashboard is created. The fourth decision model is the diagnostic LA for instructors to review an individual student’s writing sample. There are recommendations provided to the instructor on whether individual writing skills are being performed satisfactorily based on results from applications like Grammarly and Paper Rater. Using the results presented in diagnostic LA instructors can provide grammar, vocabulary and other recommendations to students to improve their writing skills. The decision models will show what grading and report information is automatically generated and the points in the processes that instructors and administrators need to make decisions and take some action outside of the diagnostic LA tool.

In practice, the availability of information with diagnostic LA would affect the outcome of decisions made by instructors when grading student writing submissions. The diagnostic LA will quickly show whether grammar, bad phrases, transactional words, or other writing skills are above or below targeted scores. For example, the information available about vocabulary from diagnostic LA influences the instructor to provide feedback or an additional writing task to improve the student's vocabulary skills. The recommendation is broken into several components by the diagnostic LA allowing different aspects of writing skills to be selected by the instructor and taught to the student. The decision models allow for single decision recommendations. The choice is to do something at that moment or not respond to the student. The network of decisions made by instructors using diagnostic LA is summarized within the individual courses to monitor WID objectives. These administrators can offer suggestions to instructors on different writing skills to focus on with students to have the greatest impact improving the FKGL score for the department. In turn, these become a network of decisions made by department administrators to be summarized within different disciplines to monitor WAC objectives. These administrators can spend time working with the disciplines that need the most improvement in student writing skills and constantly review and monitor progress.

Summary

The strategy of inquiry to complete this study will adopt the quantitative approach to research. Creswell (2013) suggested that a quantitative approach seeks to identify variables associated with the purpose of the study. The first software application that is applied to the extracted Canvas discussions is Grammarly. Paper Rater is the second application applied to provide feedback and writing instruction. Finally, the data collection will incorporate the calculations for FKGL, FRE, and ALI scores. A one-sample t-test is used to compare the disciplines mean FKGL to the overall FKGL. The difference between the FKGL score mean difference among disciplines (business, English, and kinesiology) is determined using one-way ANOVA statistics. A paired sample t-test will compare the FKGL readability score to projected mediating items. There are four decision models generated. The decision models will illustrate what grading and report information should automatically be generated and the points in the processes that instructors and administrators should make decisions and take some action outside of the diagnostic LA tool.

CHAPTER 4

RESULTS

A series of descriptive statistics such as measurements of central tendency, dispersion, and range were run to produce data that described the student writing samples (Appendix B). The first research question “What Canvas data should be used to identify the effectiveness of student writing skills to create a diagnostic tool for instructors and administrators?” was addressed using results from the data’s descriptive statistics. A total of 422 writing samples were selected from the pool of Canvas writing samples from Canvas courses at TWU. The 422 writing samples were in 12 different courses approved for use by instructors at TWU. The writing skills evaluated were grammar errors, grammar errors as a percent of total words, poor sentence prhasing or a “bad phrases” score, transitional words score, total sentences, average sentence length, short sentences count (<17 words), long sentences count (>35 words), sentence length variation, passive voice as a percent of total sentences, simple sentence starts as a percent of total sentences, vocabulary score, vocabulary word count, and vocabulary words as a percent of total words. The writing samples had to be submitted by students and be substantial enough to generate readability scores. Based on this criterion, the sample returned a new population of 277 writing submissions (Table 1 and Appendix C). Having a larger sample size ensured the study would have less sampling error while controlling for threats of internal and external validity (Babbie, 2001, 2012; Bryman, 2008; Trochim & Donnelly, 2008). A larger sampling size can reduce sampling error and ensure greater statistical results.

Table 1

Descriptive Statistics of Writing Skills

Writing Skills	Minimum Statistic	Maximum Statistic	Mean Statistic	Standard Deviation Statistic
Grammar Errors	0	125	9.21	9.86
Grammar Errors Percent	0.86%	22.45%	6.55%	3.33%
Bad Phrases Score	0.00	10.71	3.29	1.99
Transitional Words Score	0.00	190.00	55.47	27.92
Total Sentences	3	60	13.32	9.69
Average Sentence Length	9.00	37.50	18.85	5.46
Short Sentences	0	28	6.63	6.00
Long Sentences	0	10	.82	1.42
Sentence Length Variation	2.20	34.30	9.56	3.91
Passive Voice	0.00%	83.30%	14.40%	12.69%
Simple Sentence Starts	0.00%	67.00%	19.25%	15.07%
Vocabulary Score	0.00	838.45	295.90	156.36
Vocabulary Word Count	0	96	13.71	14.29
Vocabulary Word Percent	0.00%	20.10%	7.69%	3.98%

The skewness of the FKGL readability score was reviewed to determine that the data distribution was considered normal. The formula to determine the acceptable amount of data skewness is to compare the skewness numerical value to twice the standard error of skewness and include the range from minus twice the standard error of skewness. If the value of skewness falls within this range, then the data distribution is acceptable. The distribution in the Canvas data set falls within an acceptable distribution. As seen in Figure 3, the sample population was normally distributed (skewness = .40; standard deviation x 2 = 2.45 x 2 = 4.9; skewness falls between 4.9 and -4.9).

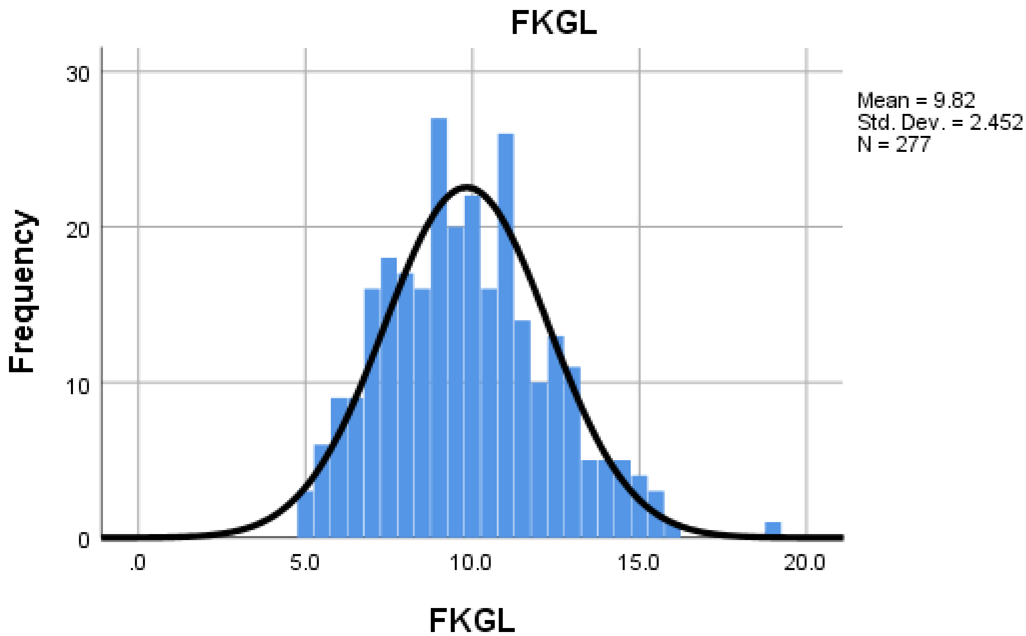


Figure 3. Distribution of FKGL readability scores.

For the second research question, “What effect does grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentences, and vocabulary have on the readability score of student writing samples?” a paired samples t-test was conducted to test for differences between the mean FKGL and the student writing skills scores and calculations. The paired writing skills statistics resulted in a statistically significant difference for grammar errors as a percent of total words, bad phrases score, transitional words score, total sentences, average sentence length, short sentences count (<17 words), long sentences count (>35 words), passive voice as a percent of total sentences, simple sentence starts as a percent of total sentences, vocabulary score, vocabulary word count, and vocabulary words as a percent of total words. The paired writing skills statistics that resulted in no statistically significant difference were grammar errors and sentence length variation (see Table 2).

Table 2

Paired Samples t-*Test between FKGL and Student Writing Skills*

Paired Samples Test		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper	*t*	*df*	Sig. (2-tailed)
Pair 1	FKGL – Grammar Errors	.62	9.93	.60	-.56	1.79	1.04	276	.301
Pair 2	FKGL – Grammar Errors Percent	3.27	4.63	.28	2.73	3.82	11.78	276	.000
Pair 3	FKGL – Bad Phrases Score	6.54	3.67	.22	6.10	6.97	29.63	276	.000
Pair 4	FKGL – Transitional Words Score	-45.64	27.59	1.66	-48.90	-42.38	-27.54	276	.000
Pair 5	FKGL – Total Sentences	-3.50	9.69	.58	-4.65	-2.34	-6.01	276	.000
Pair 6	FKGL – Average Sentence Length	-9.03	4.53	.27	-9.56	-8.49	-33.14	276	.000
Pair 7	FKGL – Short Sentences	3.19	6.74	.40	2.40	3.99	7.91	276	.000
Pair 8	FKGL – Long Sentences	9.01	2.19	.13	8.75	9.26	68.42	276	.000
Pair 9	FKGL – Sentence Length Variation	.27	3.70	.22	-.17	.71	1.21	276	.226
Pair 10	FKGL – Passive Voice	-4.58	12.69	.76	-6.08	-3.08	-6.00	276	.000
Pair 11	FKGL – Simple Sentence Starts	-9.43	15.81	.95	-11.30	-7.56	-9.92	276	.000
Pair 12	FKGL – Vocabulary Score	-286.07	155.36	9.33	-304.45	-267.70	-30.65	276	.000
Pair 13	FKGL – Vocabulary Word Count	-3.88	13.26	.80	-5.45	-2.31	-4.87	276	.000
Pair 14	FKGL – Vocabulary Word Percent	2.13	3.74	.22	1.69	2.58	9.50	276	.000

Descriptive statistics frequencies were conducted to learn more about the characteristics of the readability scores. As previously described, the writing samples were those that the instructor graded and deemed that writing skills were important. The third research question begins "What is the readability score of sample student text?" and was addressed using results from the selected text readability scores. The sample writing samples had a mean ARI of 10.43 (a 10^{th}-grade reading level), a median of 10.10, and a mode of 10.9 (standard deviation = 3.09). The writing samples had a mean FKGL of 9.83 (a 9^{th}-grade reading level), a median of 9.60, and mode of 9.9 (standard deviation = 2.45) (see Table 3).

Table 3

Descriptive Statistics Frequencies of Text Readability Scores

		ARI	FKGL	FRE
N	Valid	277	277	277
	Missing	0	0	0
Mean		10.43	9.83	53.62
Median		10.10	9.60	55.90
Mode		10.9	9.9	48.5
Standard Deviation		3.09	2.45	15.55
Range		20.8	13.9	90.1
Minimum		4.8	5.0	-7.3
Maximum		25.6	18.9	82.8
Skewness		.95	.40	-.84
Standard Error of Skewness		.15	.15	.15

A one-sample *t*-test was executed to determine the difference of mean FLGL readability scores between business, English, and kinesiology students. The *t*-test statistic shows that the FKGL mean difference was 9.74 for business students writing samples, slightly lower than the FKGL mean difference of 9.83 for all business, English, and kinesiology student writing samples. The FKGL of the business student writing samples is statistically significant, $t = 55.09$, $p < .000$ (see Table 4).

Table 4

One-Sample t-*Test between FKGL and Business Student Writing Samples*

One-Sample Statistics	n	Mean	Standard Deviation	Standard Error Mean
FKGL	162	9.74	2.25	.18

One-Sample Test Discipline = Business, Test Value = 0					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
FKGL	55.09	161	.000	9.74	9.39	10.09

For English student writing samples, the t-test statistic shows that the FKGL mean difference was 10.50, higher than the FKGL mean difference of 9.83 for all student writing samples. The FKGL of the English student writing samples is statistically significant, $t = 29.04$, $p < .000$ (see Table 5).

Table 5

One-Sample t-*Test between FKGL and English Student Writing Samples*

One-Sample Statistics	n	Mean	Standard Deviation	Standard Error Mean
FKGL	62	10.50	2.85	.36

One-Sample Test Discipline = English, Test Value = 0					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
FKGL	29.04	61	.000	10.50	9.78	11.22

The *t*-test statistic for kinesiology student writing samples show that the FKGL mean difference was 9.30, lower than the 9.83 for all business, English, and kinesiology student writing samples. The FKGL of the kinesiology student writing samples is statistically significant, $t = 27.93$, $p < .000$ (see Table 6).

Table 6

One-Sample t-*Test between FKGL and Kinesiology Student Writing Samples*

One-Sample Statistics	n	Mean	Standard Deviation	Standard Error Mean
FKGL	53	9.30	2.42	.33

One-Sample Test Discipline = Kinesiology, Test Value = 0					95% Confidence Interval of the Difference	
	t	*df*	Sig. (2-tailed)	Mean Difference	Lower	Upper
FKGL	27.93	52	.000	9.30	8.63	9.97

The difference between the FKGL score mean difference among disciplines (business, English, and kinesiology) was determined using one-way ANOVA statistics. The difference between the three disciplines is statistically significant ($F = 3.73$; $p = .025$), see Table 7. English student writing samples have the highest FKGL readability score of 10.50, followed by business students with an FKGL readability score of 9.74, and finally, kinesiology student writing samples with an FKGL readability score of 9.30.

Table 7

One-Way ANOVA between FKGL and Discipline (Business, English, Kinesiology)

Discipline	Mean	N	Std. Deviation
Business	9.74	162	2.25
English	10.50	62	2.85
Kinesiology	9.30	53	2.42
Total	9.83	277	2.45

FKGL * Discipline	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	43.94	2	21.97	3.728	.025
Within Groups	1614.79	274	5.89		
Total	1658.73	276			

The difference between the FKGL mean score and the difference among courses were determined using one-way ANOVA statistics. The difference between the twelve courses is statistically significant ($F = 5.68$; $p < .000$), see Table 8. Ranking the FKGL mean score difference of courses shows the 16FAENG03 course with an 11.89 FKGL readability score followed by two business courses, the 17SPBUS02 course with an 11.03 FKGL readability score and the 17SPBUS01 course with an 11.00 FKGL readability score.

Table 8

One-Way ANOVA between FKGL and Course ID

Course ID	Mean	*n*	Std. Deviation
16 FA ENG 01	10.12	19	4.03
16 FA ENG 02	9.47	7	2.70
16 FA ENG 03	11.89	12	2.10
16 FA ENG 04	10.40	24	1.82
16 FA KINS 01	9.00	16	3.13
16 FA KINS 02	8.09	10	1.49
17 SP BUS 01	11.00	36	1.85
17 SP BUS 02	11.03	33	1.56
17 SP BUS 03	9.17	50	2.17
17 SP BUS 04	8.35	43	2.04
17 SP KINS 03	10.03	19	1.68
17 SP KINS 04	9.68	8	2.94
Total	9.83	277	2.45

(table continues)

FKGL * Course ID	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	316.63	11	28.79	5.68	.000
Within Groups	1342.10	265	5.07		
Total	1658.73	276			

Decision Models

The third research question concludes "How can (the text readability score) be used as an input for instructor decision-making to quickly assess student writing skills and administrator decision-making to create broad readability and writing skills goals?" and was addressed as a series of decision models. Based on the literature review and the quantitative analysis of the Canvas data, the researcher developed a diagnostic LA decision model to support improving student writing skills. The model is meant to fill the research gap discussed in Chapter 1 by offering guidance to instructors want to implement diagnostic LA in their courses. These decision models were developed based on research conducted at TWU. The decision models are meant to be generalizable to most LMS environments and LA tools. The themes identified as the decision echoed research found in the literature. It includes practical as well as conceptual guidelines for administrators and instructors wanting to implement diagnostic LA in their courses and should offer guidance and support.

Institutions make decisions of different types (Table 9). Strategic decisions are infrequently made but have a large impact. They typically involve large numbers of people and large investments in time and expense. A significant amount of analysis is done to make the decision, and the implications can be significant to the institution. Analytic decisions involve administration and control. These decisions are less impactful but are required for consistency and taking the opportunity to improve the institution. Every institution makes large numbers of operational decisions around students, service, and research. These decisions are embedded into operational systems and processes and can be time sensitive.

Table 9

Types of Decisions

Decision Types	Decision Description	Decision Maker
Strategic Decisions	Infrequent, large impact	College Administrators
Analytic Decisions	Management and control, moderate impact	Department Administrators
Operational Decisions	Day-to-day decisions that affect students, service, and research	Instructors

Any decision can be documented using decision models. The essence of decision-making is to select from an array of possible actions, pick one, and then perform the action (Taylor, 2011). Decisions can be action-oriented or about getting information. There need to be some criteria to include a decision in a decision model. Decisions that improve consistency, define shared work processes, and share best practices are good decisions to include (Taylor, 2011). For the diagnostic LA tool, decisions considered to be rules to manage and control the application are important. However, there can be one-off decisions or exceptions that are complex, decision-making approaches that are contentious, and decisions that need to be transparent and to add to the decision model. Almost any decision that involves an assessment of student writing, risk, student opportunity or similar through the analysis of historical data is a candidate for decision modeling.

Another approach taken in this study is to consider key performance indicators (KPI), and metrics to combine with Canvas data. Any KPI or metric is valuable only if it helps motivate suitable behavior, implying that someone's actions can change the value of the KPI (Debevoise

& Taylor, 2014). The point that decisions are made in processes can be identified by investigating KPIs and finding out when and where administrators and instructors make choices that move KPIs up or down. Each opportunity for choice-making, for selecting an action from a possible set of actions is a decision (Debevoise & Taylor, 2014).

Using the data collected for this study a standard business process model and notation (BPMN) is developed to provide an institution with an understanding of their WAC and WID internal procedures in a graphical notation. These diagrams give the institution the ability to communicate these procedures in an industry accepted standard format (Object Management Group, 2011). The graphical notation will facilitate the understating of the collaborations and the transactions between administrators, instructors, and Canvas data. The visualization helps ensure that the institution understands their roles and individual participation in the program and will enable users to adjust the new writing objectives and practices quickly. The elements used in the diagrams include pool objects, event objects, activity objects, gateway objects, and connection objects (Figure 4).

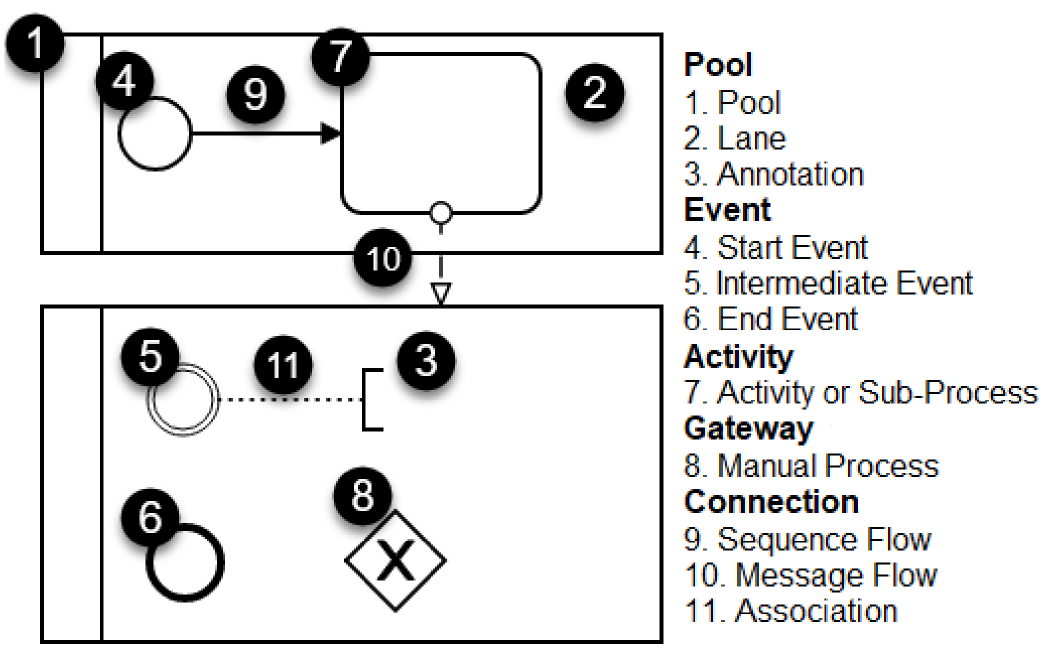


Figure 4. Business process model and notation (BPMN) objects.

- Pool. The *pool* represents the major participants in a process, typically separating different roles in the institution. A pool contains one or more *lanes* (like a swimming pool with swim lanes). A pool is depicted as a large rectangle show one or more lanes. A lane is used to organize and categorize activities within a pool by role. An *annotation* is used to provide additional notes or understanding. A lane will contain annotations, events, activities, gateways, and connections.

- Event. An event is represented by a circle and denotes something that happens. The *start event* acts as a process trigger; indicated by a single narrow border. The *intermediate event* represents something that happens between the start and end events and is indicated by a double border. For example, a task could flow to an event that only happens once in a repeated process; like what an instructor does at the end of a semester. The *end event* represents the result of a process and is indicated by a single thick border.

- Activity. An *activity* is represented by a rounded corner rectangle and describes the task. The rectangles in the diagnostic LA decision models are a form of sub-process in which all the tasks associated with the activity would need to be completed in entirety to meet the objective.

- Gateway. A *gateway* is represented with a diamond shape and determines forking and merging of paths. The diamond containing an X is an exclusive event that appears before a manual activity or sub-process that requires a decision to be made by an administrator or instructor.

- Connections. Events and activities are connected to each other using connection objects. A solid line and arrowhead represent a *sequence flow* and shows in which order the activities are performed. A *message flow* is represented by a dashed line, an open circle at the start, and an open arrowhead at the end and indicates what messages flow across institutional boundaries. A message flow can never be used to connect activities within the same pool. A dotted line represents an *association*. It is used to associate an annotation with an event.

Diagnostic Learning Analytics (LA) Decision Model

Institutions of higher education are implementing WAC and WID programs in response to on-going concerns regarding undergraduate student writing proficiency and the need for a comprehensive strategy to improve student writing outcomes (Thaiss & Porter, 2010). There are several considerations to define WAC and WID programs (Figure 5). First, at a college level shown in row one, the institution fosters a writing culture that values, support and enriches the communication practices of both instructors and students. Second, at a department level shown in row two, undergraduate students must meet benchmarks for undergraduate writing competencies identified in a set of program-specific student writing outcomes objectives. Third, instructors employ a range of writing activities shown in row three in a variety of learning situations and demonstrate leadership in the development of writing pedagogy in their courses. Fourth, the diagnostic LA presents the Canvas data and program logic to meet the WAC and WID program requirements shown in row four. Each row of the decision model shows the specific needs of each group. The requirements from each row above are used by the row below to align their requirements and objectives with the group above.

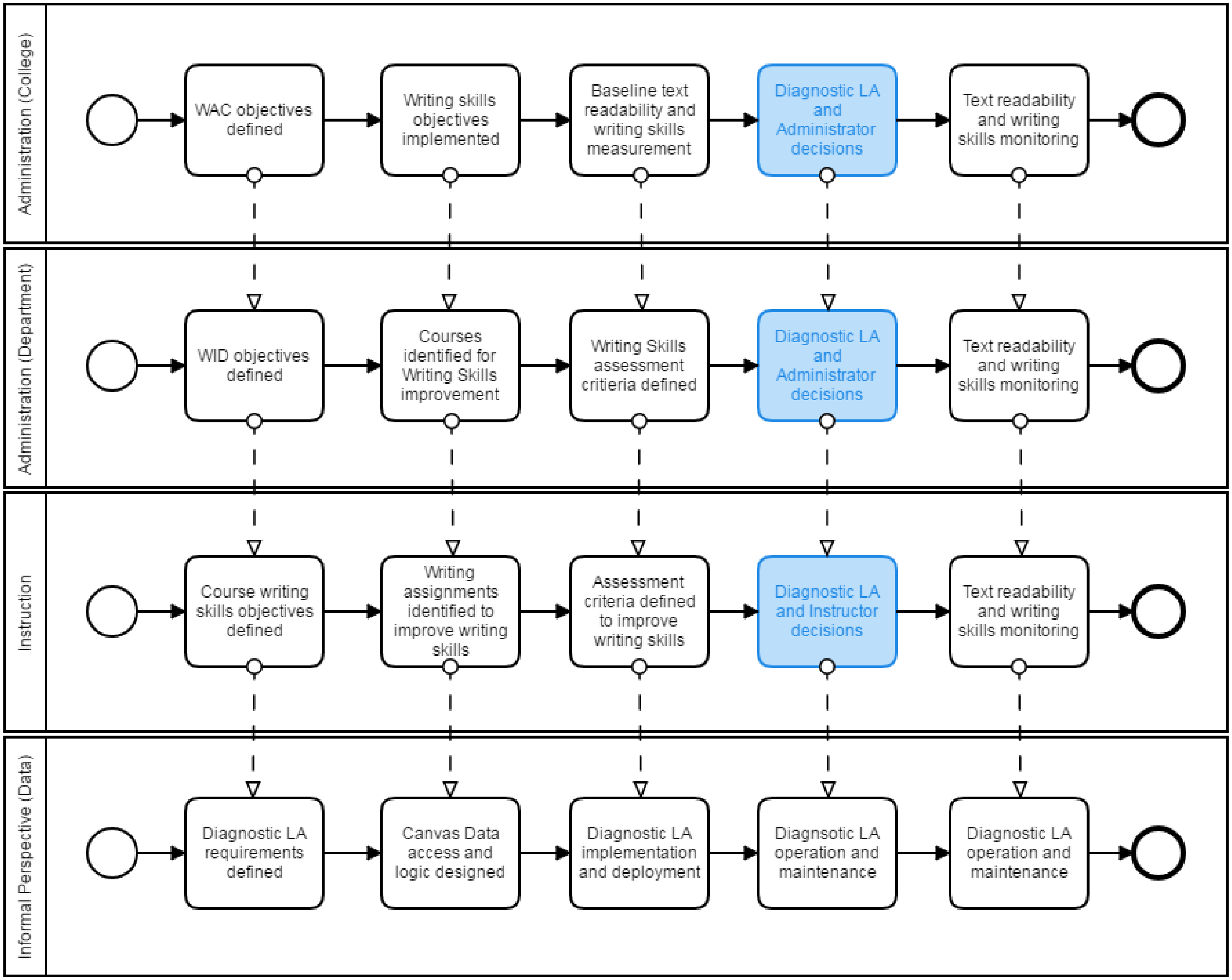


Figure 5. The diagnostic learning analytics (LA) decision model.

Figure 5 does not include the processes embedded within the individual activities in the diagram. These details outline a systematic approach for creating a unified writing curriculum. For example, the creation of a WID stream of courses in each program builds on the discipline-specific writing that students are required to complete, emphasizing the need for consistency and transparency in the development and communication of writing-specific learning outcomes and assessments. The WID courses assessment criteria levels or limits map to the requirements of the diagnostic LA. WID course development in each program will then progress from year to year following the cohort; in all identified first-year courses across the curriculum through all identified second-year courses, and so on.

Diagnostic LA College Administrator Decision Model

There is considerable writing already embedded across the curriculum. However, there is frequently a lack of transparency and coordination between administrators, instructors, and students concerning undergraduate writing expectations and requirements (Beaufort, 2008). The first activity, WAC objectives defined, is the development of a more systematic approach to undergraduate writing and outline a strategy for creating a unified writing curriculum. The design phase named *writing skills objectives implemented* is the identification and targeted improvement of the disciplines, and professional writing needs prioritized in academic, strategic, and institutional planning processes. The next subprocess is to establish a baseline text readability and writing skills measurement for a student cohort. The diagnostic LA tool will assist in the cyclical program review of student writing skills progress. Figure 6 expands the diagnostic LA and college administrator decisions in detail.

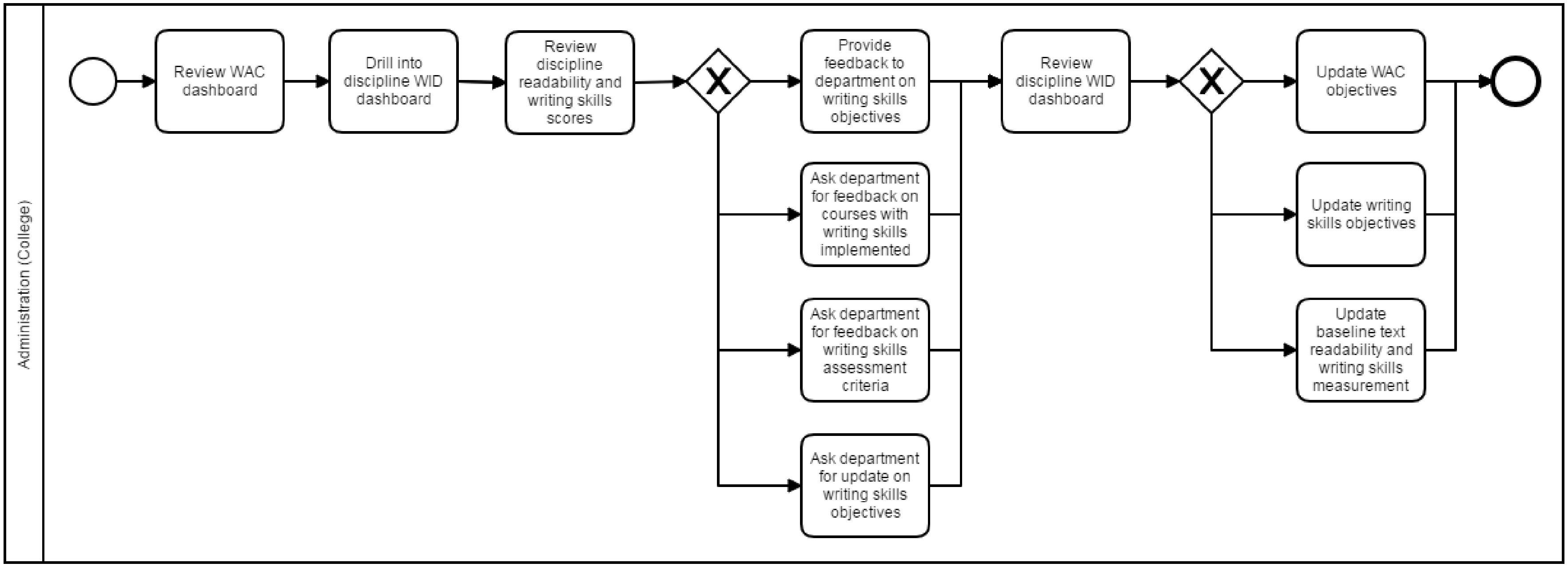
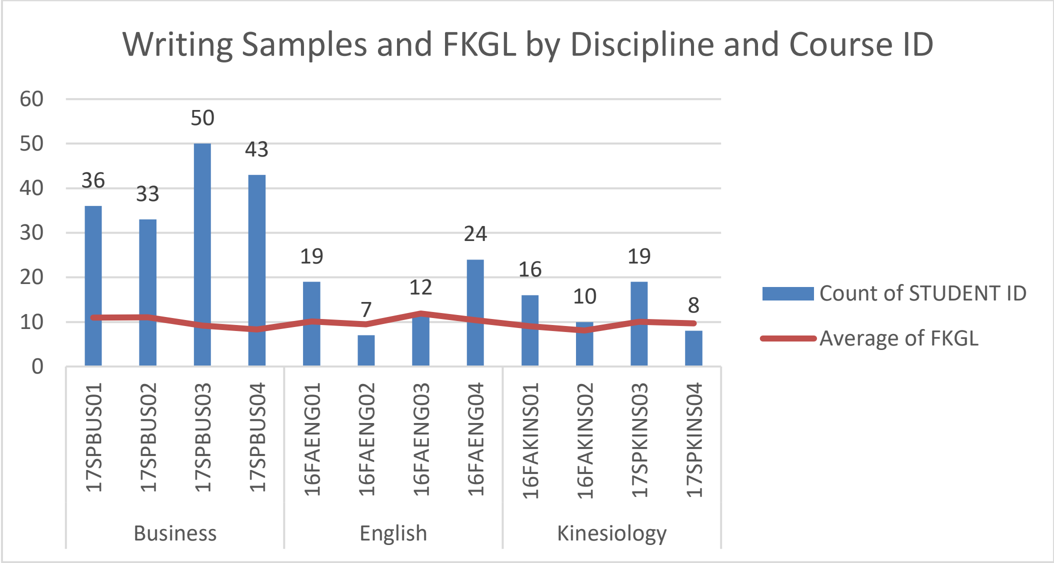
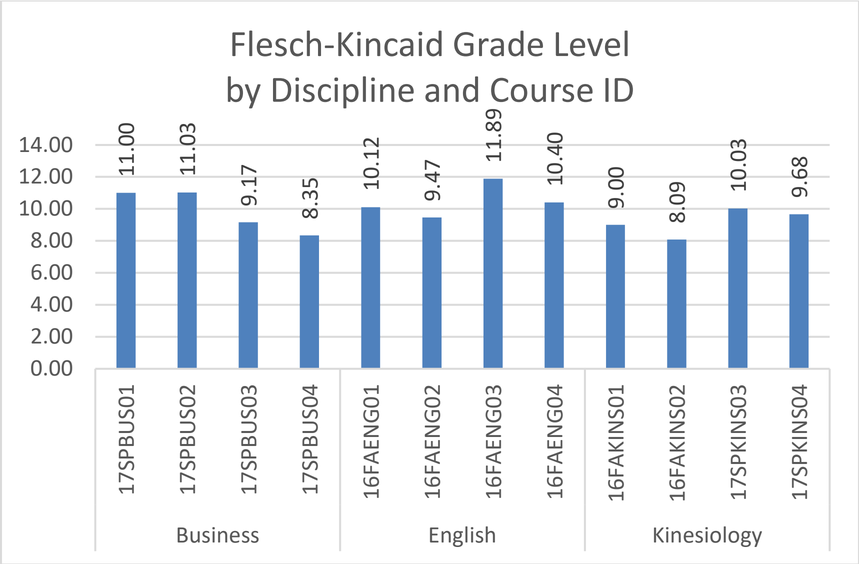


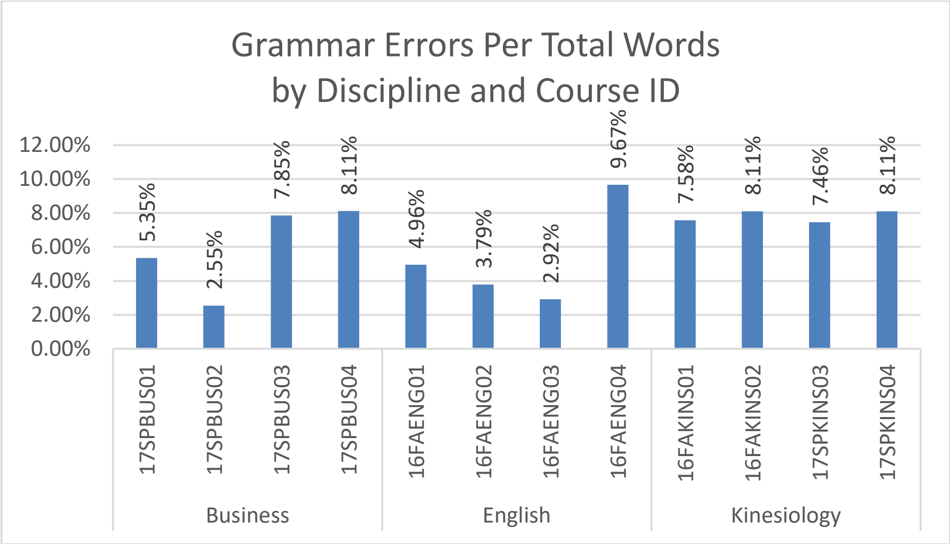
Figure 6. Diagnostic LA and college administrator decisions.

The FKGL text readability score is used as the key performance indicator that provides a high-level measurement of the current student writing skills. Administrators can review the WAC dashboard (Figure 7) to determine the effect of the WAC program-level learning outcomes at any time. A sample WAC dashboard would be a single web page that includes a collection of graphs providing a visualization of the WAC program performance against targeted objectives. For example, using the TWU Canvas data, this WAC program has identified English, business and kinesiology disciplines to improve student writing performance. The first visualizations show the number of writing samples submitted and the average FKGL mean score for these submissions by discipline and courses within the discipline. The second graph presents the FKGL mean score by discipline and courses within the discipline. The remaining visualizations provide the grammar errors per total words and vocabulary scores by discipline and courses within the discipline. As time passes, a series by semester would be added to the graphs to compare student FKGL mean scores for the cohort through the years.

Writing Across the Curriculum – Diagnostics	
Period:	Fall 2106, Spring 2017
Disciplines:	Business, English, Kinesiology




Flesch-Kincaid Grade Level
by Discipline and Course ID
14.00
12.00
10.00
8.00
6.00
4.00
2.00
0.00
11.00
11.03
9.17
8.35
10.12
9.47
11.89
10.40
9.00
8.09
10.03
9.68
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology


Grammar Errors Per Total Words
by Discipline and Course ID
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
5.35%
2.55%
7.85%
8.11%
4.96%
3.79%
2.92%
9.67%
7.58%
8.11%
7.46%
8.11%
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
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Business
English
Kinesiology

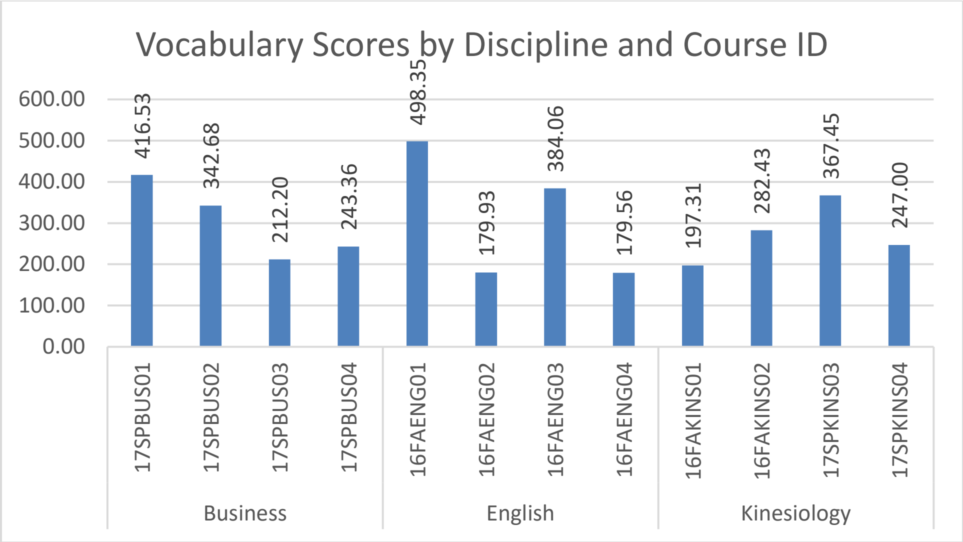


Figure 7. Writing across the curriculum (WAC) dashboard.

The college administrator can analyze additional details in the data to look for insights. The WAC dashboard is a summary of student writing sample data by discipline, course, time-period, FKGL, writing skills, and other targeted dimensions. Each visualization presented in the dashboard holds some measure of the WAC objectives stored in the Canvas data warehouse. Conceiving data in hierarchical dimensions leads to conceptually straightforward operations to facilitate analysis (Ehmke, Großhans, Mattfeld, & Smith, 2011). The college administrator can drill into the WID dashboard by navigating among levels of data ranging from the most summarized (up) to the most detailed (down), aligning the data content with a familiar visualization to enhance administrator learning and productivity. For example, the WAC and WID dashboards can be used to review discipline readability and writing skills scores. This information can be used as information by the college administrator to complete a variety of manual activities. Some of these include:

- Provide feedback to the department on writing skills objectives
- Ask department for feedback on course with writing skills implemented
- Ask department for feedback on writing skills assessment criteria
- Ask department for updates on writing skills objectives

The college administrator will continue to review the discipline WID dashboard while communicating with the department administrators. At a designated time, college administrators will need to complete the manual review of the WAC program. Some of the decisions and activities include update WAC objectives, update writing skills objectives, and update baseline text readability and writing skills measurement.

Diagnostic LA Department Administrator Decision Model

The sub-processes in this pool are to develop a systematic approach to discipline-specific writing in the curriculum. The first activity, WID objectives defined, is the identification of disciplinary and professional writing needs for the department. The design phase named courses identified for writing skills improvement is to identify a WID stream of courses in each undergraduate program such that all students will take one WID course at each year level. The next subprocess is the writing skills assessment criteria defined to align WID courses with professional writing needs. These criteria allow students to progress through benchmarks to meet degree-level learning outcomes for writing and will gain practice in writing specifically for their programs. The diagnostic LA tool will assist in the cyclical program review of student writing skills progress. Figure 8 expands the diagnostic LA and department administrator decisions in detail.

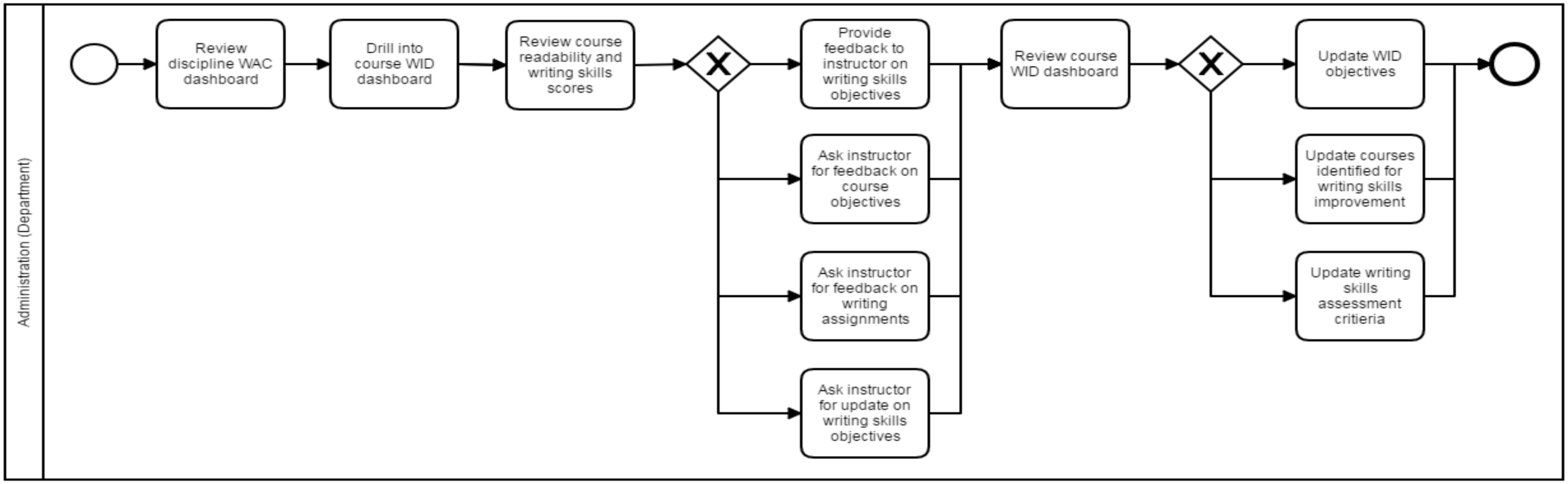


Figure 8. Diagnostic LA and department administrator decisions.

The department administrators will map WID writing-specific course learning outcomes with learning activities and assessments. Administrators can review the discipline WAC dashboard (Figure 7) to review the FKGL text readability score set as the key performance indicator. The administrator can drill into the course WID dashboard, a single web page that includes a collection of graphs providing a visualization of the course performance against learning outcomes with learning activities and assessments (Figure 9). The WID dashboard would be used to review course readability and writing skills scores. The first visualizations show the number of writing samples submitted by students in the course. The second graph presents the FKGL mean score by the student within the discipline. The third graph includes the total number of sentences submitted by the students in the course. The remaining visualizations provide the grammar errors per total words, vocabulary scores, bad phrase score, and transitional word score by student. The first writing activity of the semester is used as a benchmark. After that, a series comparing past writing samples to current writing samples would be added to the graphs to compare student writing progress throughout the semester.

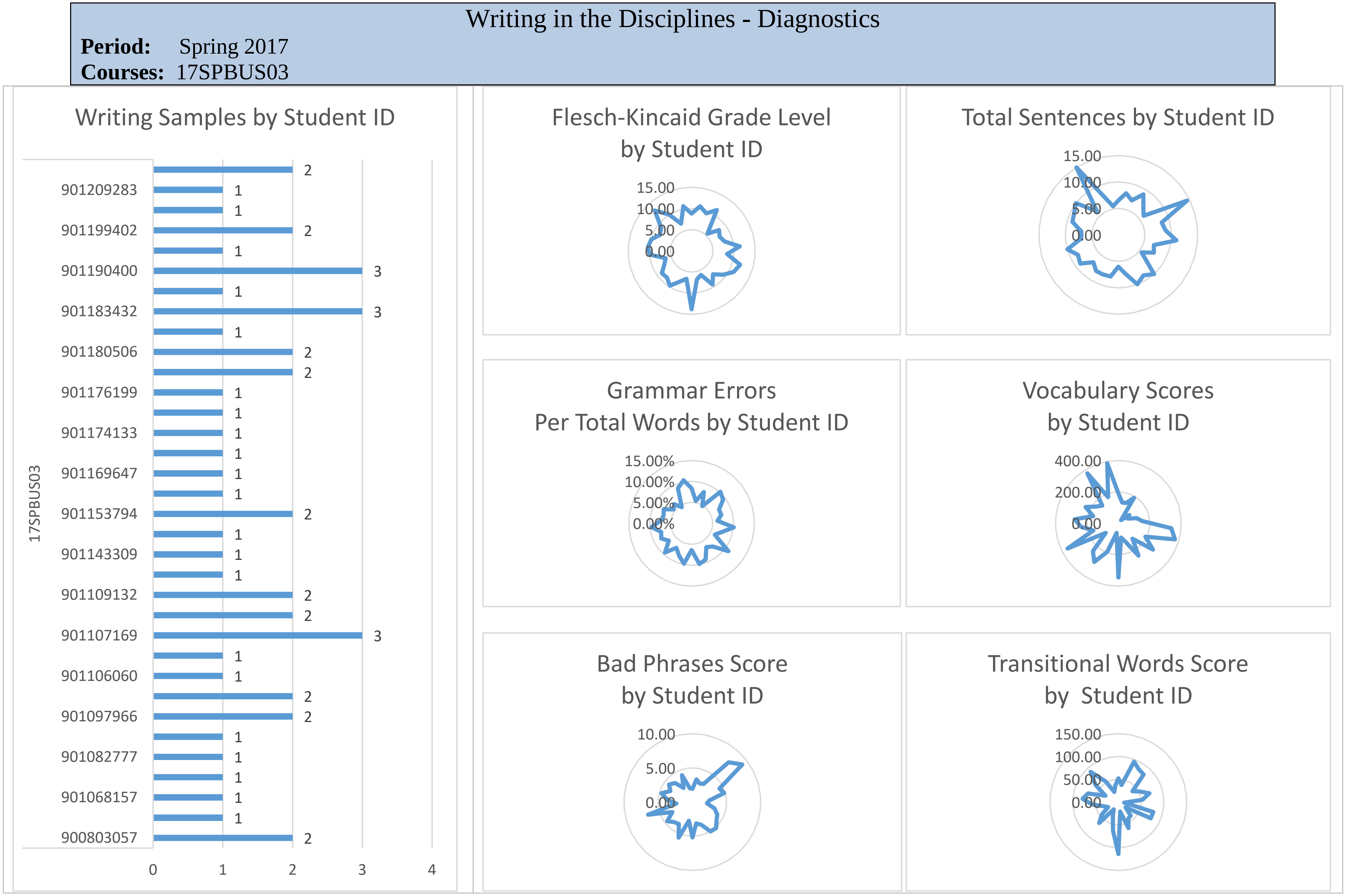


Figure 9. Writing in the disciplines (WID) dashboard.

The department administrator can analyze additional details in the data to look for insights. The WID dashboard is a summary of student writing sample data by course, time-period, FKGL, and other targeted writing skills dimensions. The department administrator can review course readability and writing skills scores. This information can be used as information to complete a variety of manual activities. Some of these include:

- Provide feedback to the instructor on writing skills objectives.
- Ask the instructor for feedback on course objectives.
- Ask department for feedback on writing assignments.
- Ask the instructor for updates on writing skills objectives.

The department administrator will continue to review the course WID dashboard while communicating with the instructors. At a designated time, department administrators will need to complete the manual review of the WID courses. Some of the decisions and activities include update WID objectives, update courses identified for writing skills improvement, and update writing skills assessment criteria.

Diagnostic LA Instructor Decision Model

The sub-processes in this pool are for instructors to review and advance best practices in the teaching and assessment of writing assignments. The first activity, course writing skills objectives defined, is the alignment of the course learning outcomes and assessment criteria with WID objectives. The design phase named writing assignments identified to improve writing skills is to employ identified writing assignments with criterion-referenced and equity-based assessment strategies. The next subprocess is assessment criteria defined to improve writing skills using templates and models of assessment criteria and rubrics made available to instructors through communication and workshops. These criteria allow instructors to help students progress through benchmarks to meet degree-level learning outcomes for writing. The diagnostic LA tool will assist in the cyclical assignment review of student writing skills progress. Figure 10 expands the diagnostic LA and instructor decisions in detail.

The instructor will grade a student writing submission. To review a writing skills analysis, the instructor can run diagnostic learning analytics for the student submission. The analysis is developed as a Canvas learning tools interoperability (LTI) tool. The title has the word "Diagnostics" followed by the name of the assignment, the FKGL score for the writing submission, and the Grammarly review (Figure 11). The tabs are either red or green. The red tabs indicate that the student's writing submission falls below the recommended level and additional teaching opportunities are available for consideration. The tabs include grammar, bad phrase score, transitional words score, sentence length, passive voice, simple sentence starts, and vocabulary score. Each of the tabs provides details evaluating the writing submission to other undergraduate college students.

- Grammar. This score is based on the number of critical issues identified by Grammarly. When this score is above the recommended level, the instructor can focus on determiners, prepositions, subject-verb agreement, verb form, verb tense shifts, spelling, and other common grammar errors (Figure 11).

- Bad phrase score. This score is based on the quality and quantity of inappropriate words, phrases, misspellings, and clichés found in the writing submission. When this score is above the recommended level, the instructor can encourage the use of a thesaurus to replace or reduce the usage of words and phrases that are used excessively (Figure 12).

- Transitional words score. This score evaluates the use of transitional phrases (e.g., therefore, consequently, furthermore). Transitional words and phrases contribute to the cohesiveness of a text. Without transitional phrases, a text will seem disorganized and likely be difficult to understand. When students need to improve the use of transitional words the instructor will want to teach the use of conjunctions, prepositional phrases, and adverbs (Figure 13).

- Sentence length. The use of sentence length conveys a rhythm and matches the described actions. Short sentences are useful for conveying small bits of information. They emphasize one or two points. Long sentences provide more detail and information and are used to present in-depth ideas. By teaching students to analyze the number of short and long sentences in writing in addition to their variation in use helps a student use both in their writing (Figure 14).

- Passive voice. The use of passive voice sentences can be considered poor writing form. These sentences allow the object of an action to be the subject of a sentence. The diagnostic LA tools will list the passive voice sentences detected in the text. The goal is for student writing to be clear. If reducing passive voice sentences would improve the student's writing skills teach writing active voice sentences that emphasize the person or object performing the action (Figure 15).

- Simple sentence starts. Creatively arranging sentence beginnings breaks up the simple noun phrase followed by a verb. Students could benefit from paying attention to sentence starts. The diagnostic LA will list sentences that start with a simple noun followed by a verb. Instructors can use this as an opportunity to teach writing sentences that start with different parts of speech (e.g., adjectives, adverbs, articles, conjunctions, nouns, prepositions, pronouns, verbs) (Figure 16).

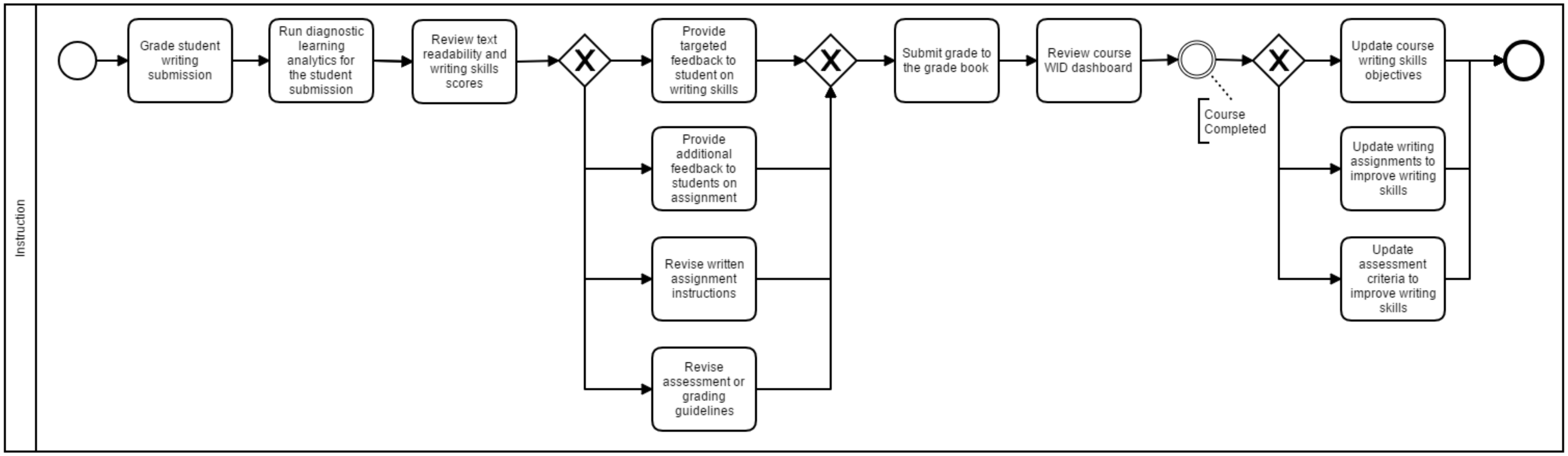


Figure 10. Diagnostic LA and instructor decisions.

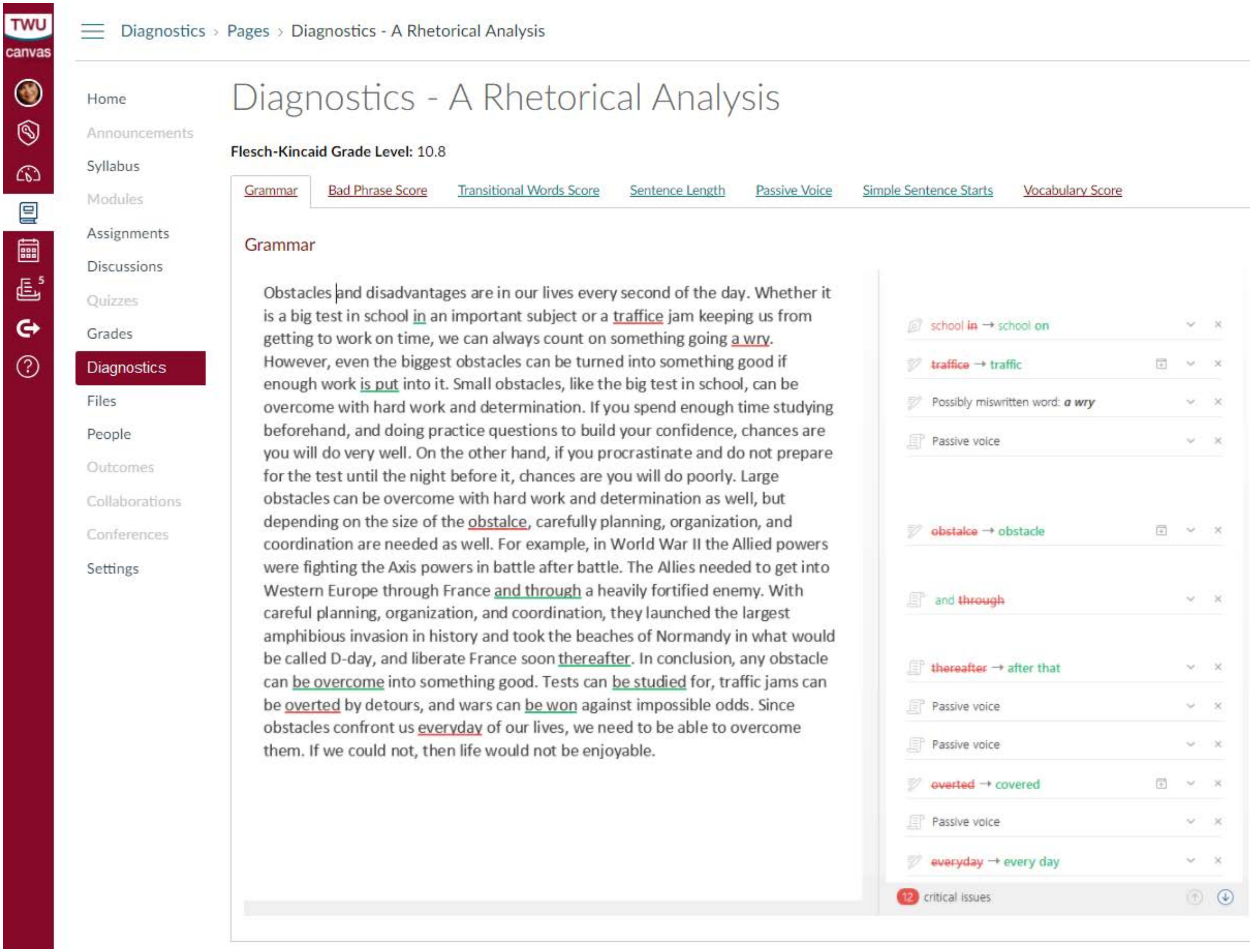


Figure 11. Diagnostic LA for instructor – grammar tab.

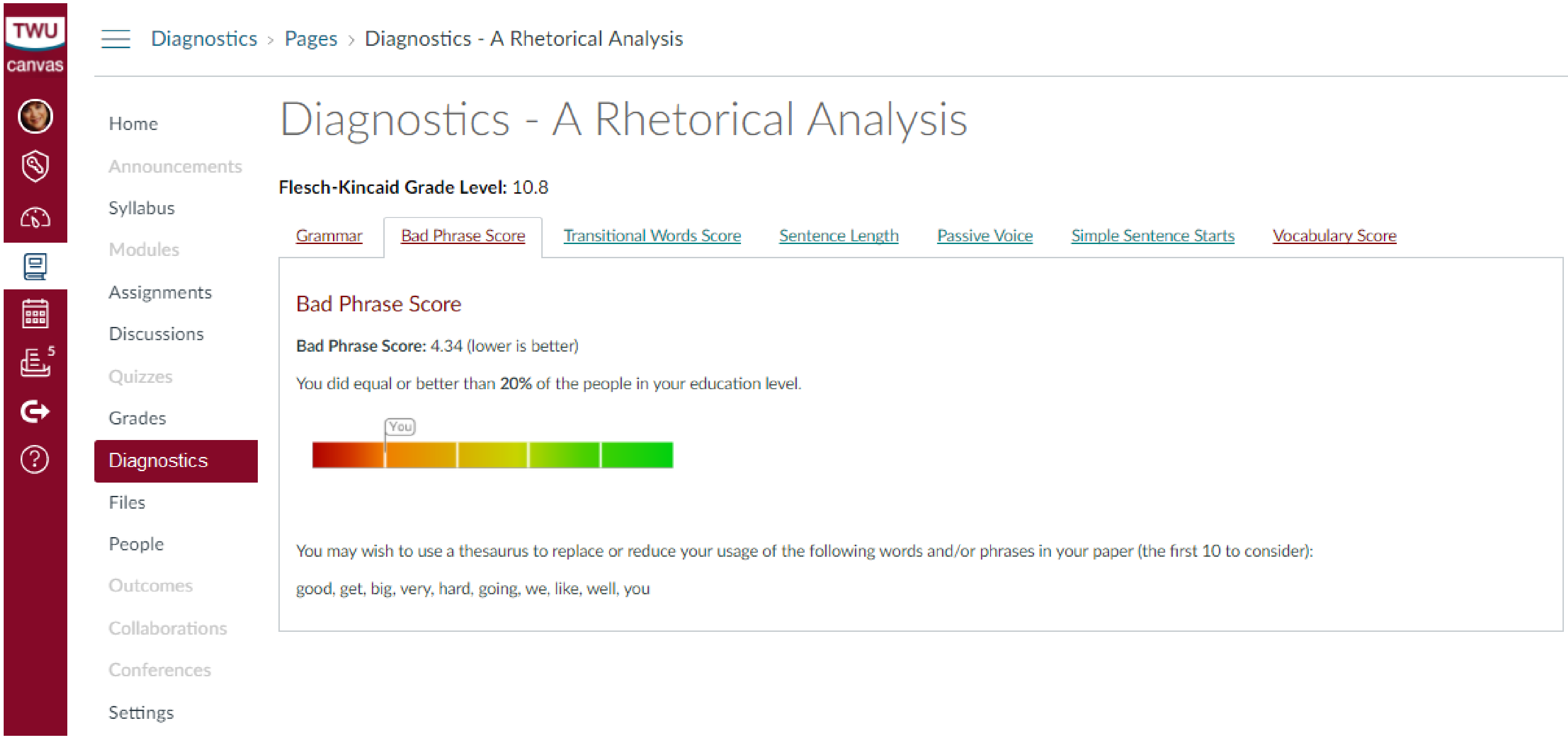


Figure 12. Diagnostic LA for instructor – bad phrase score tab.

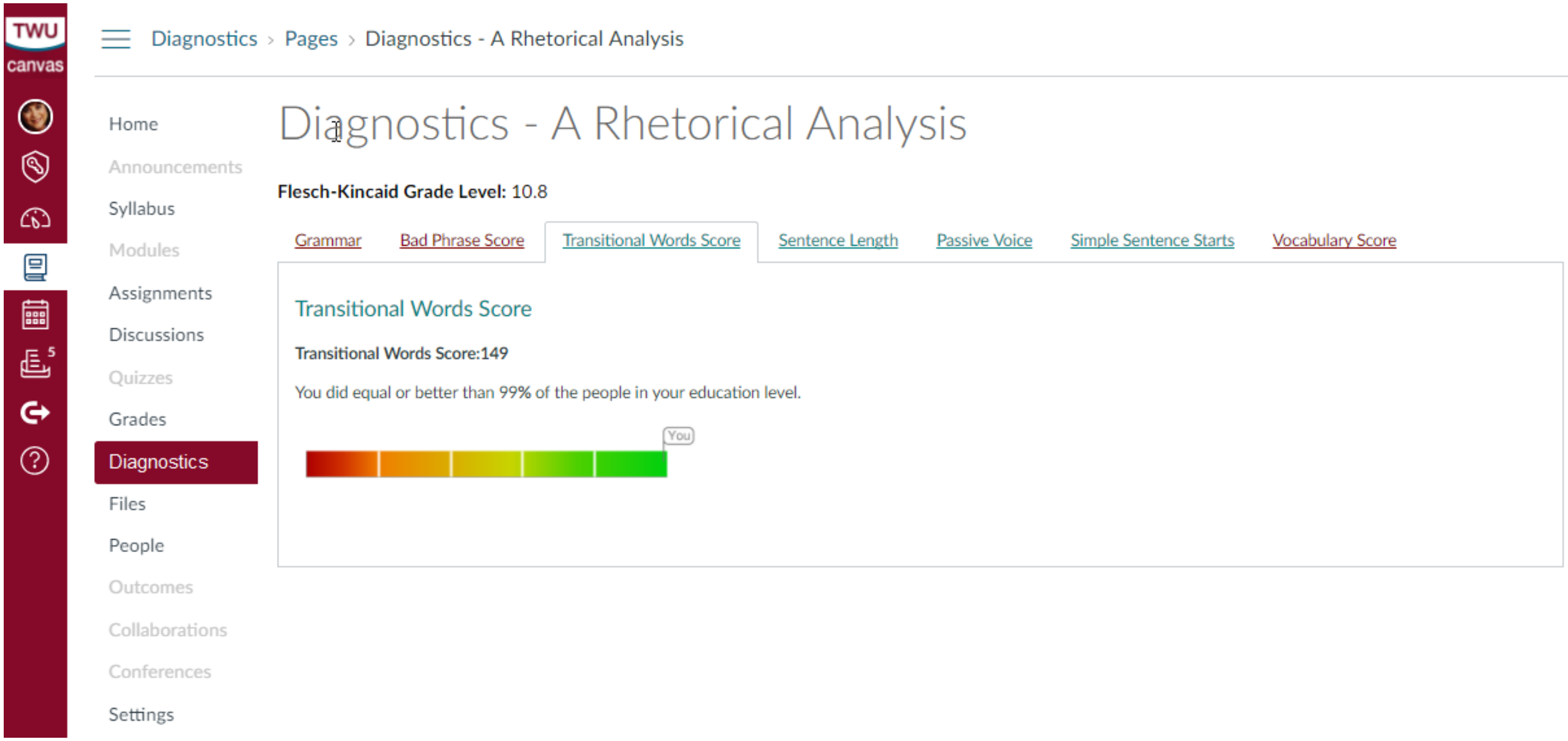


Figure 13. Diagnostic LA for instructor – transitional words score tab.

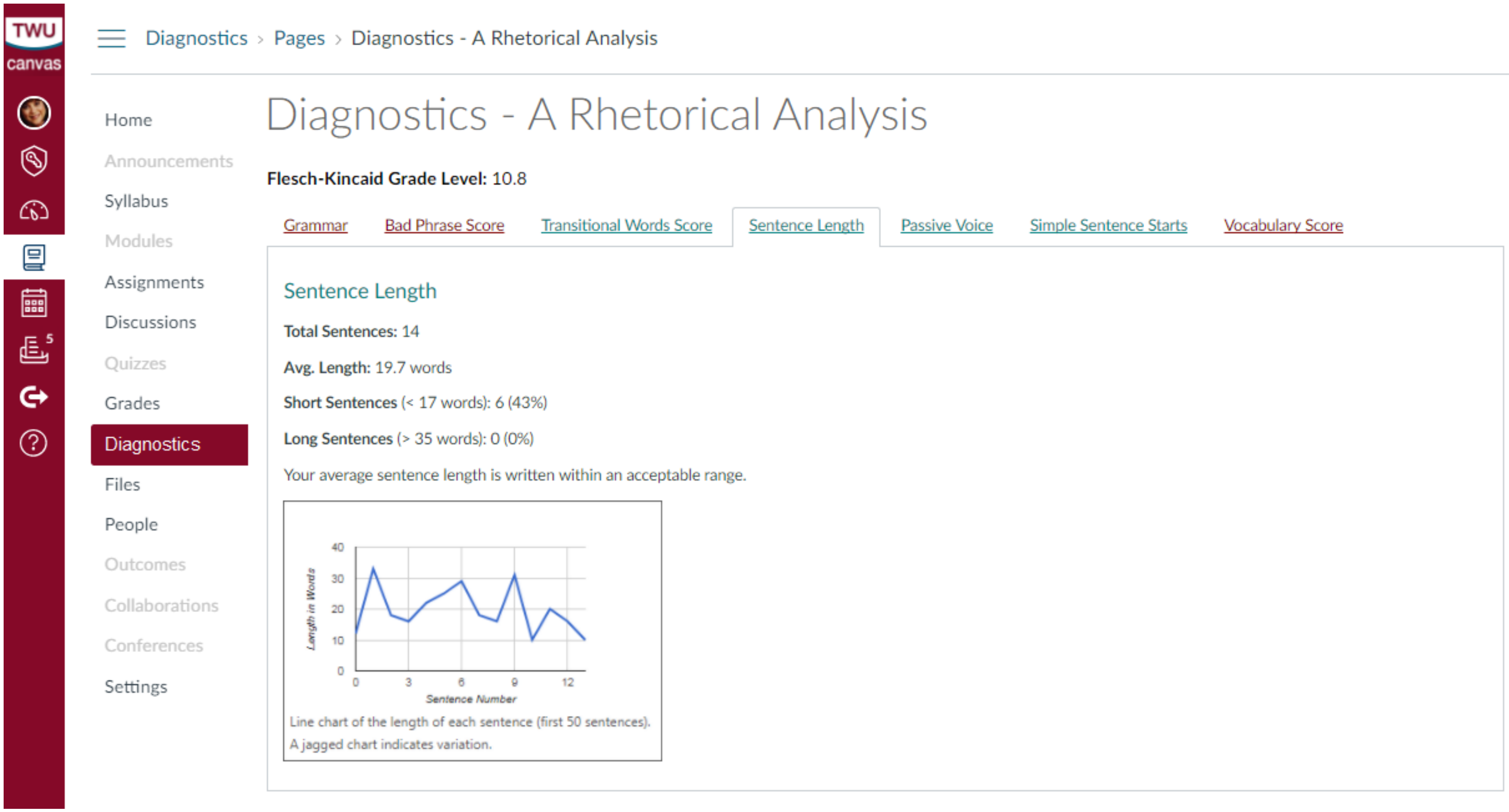


Figure 14. Diagnostic LA for instructor – sentence length tab.

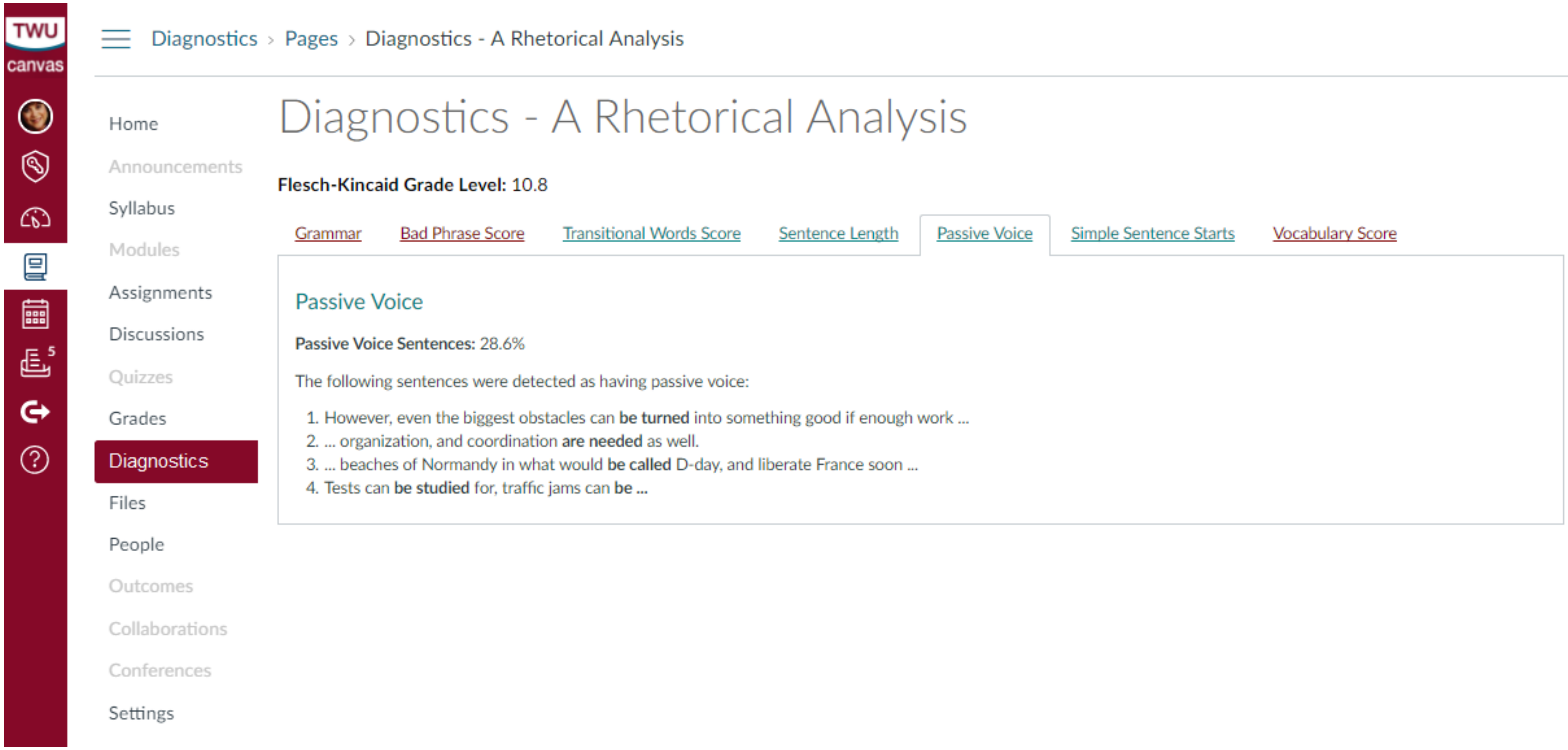


Figure 15. Diagnostic LA for instructor – passive voice tab.

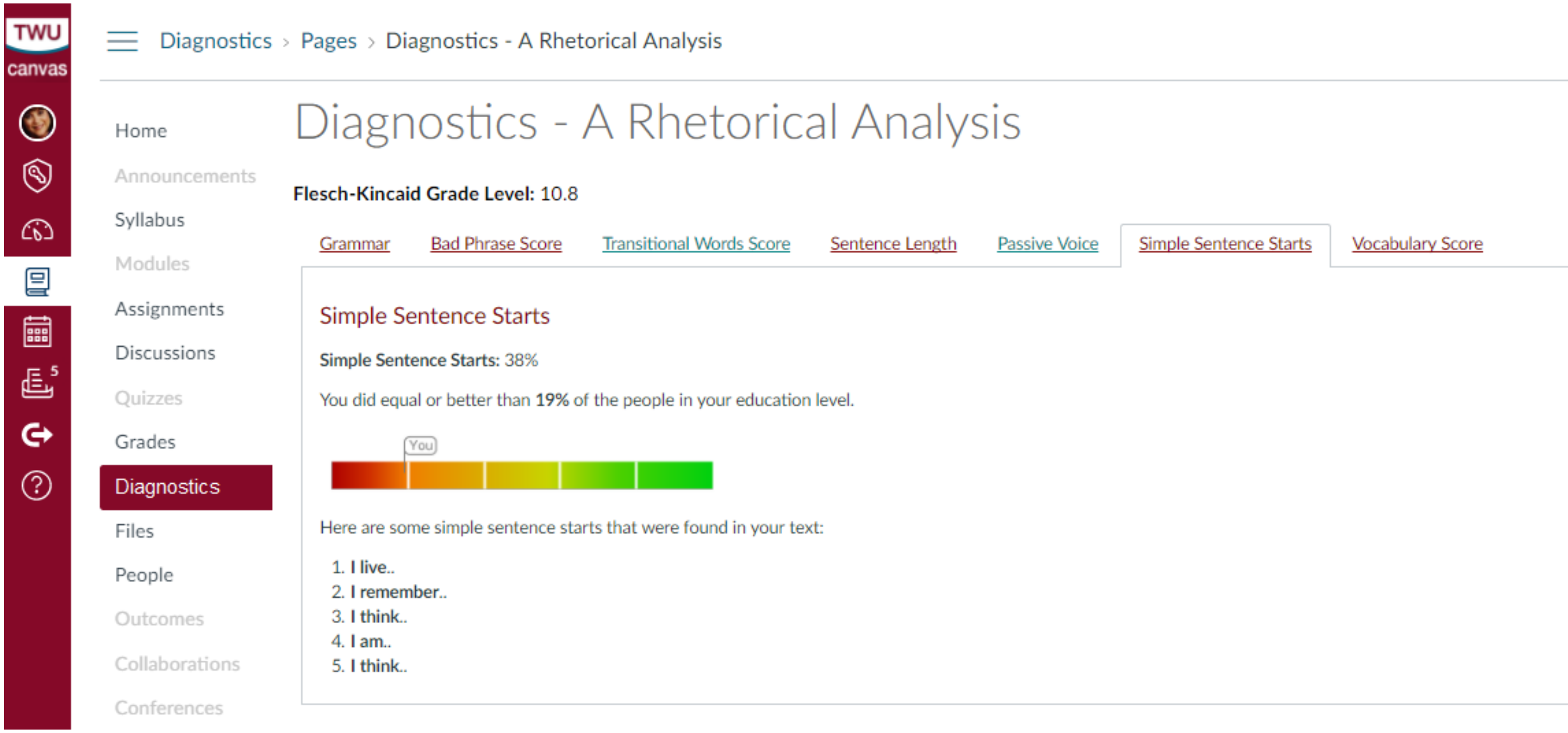


Figure 16. Diagnostic LA for instructor – simple sentence starts tab.

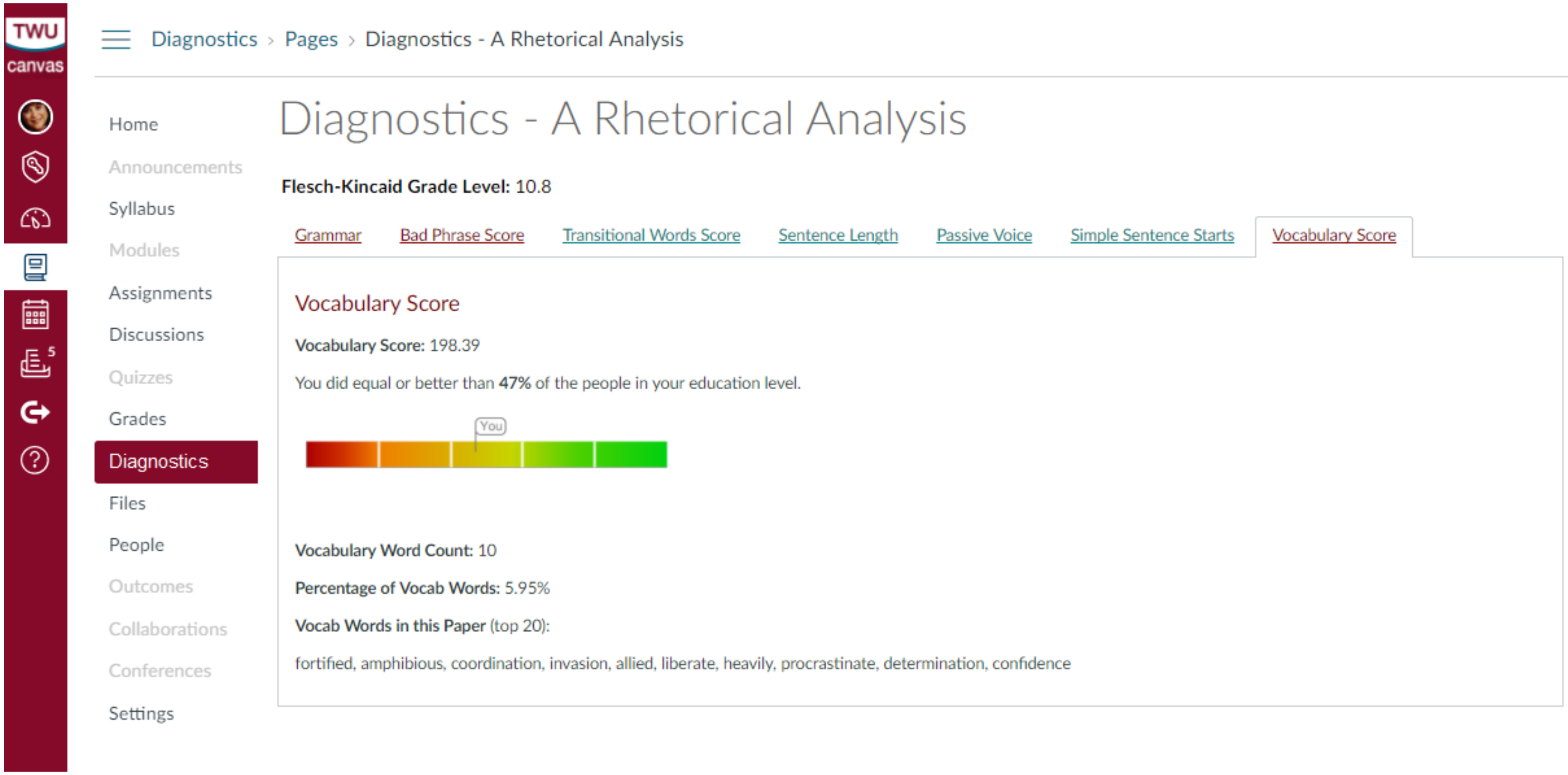


Figure 17. Diagnostic LA for instructor – vocabulary score tab.

- Vocabulary score. This score is based on the quantity and quality of scholarly vocabulary words found in the text. The diagnostic LA will display the vocabulary word count, the percentage of the text that are vocabulary words, and provide a list of the top 20 vocabulary words included in the writing submission. There are several vocabulary building tools that instructors can recommend to students to teach the understanding and knowledge of words (Figure 17).

Knowing that writing activities must support student learning to improve writing skills, the instructor can review text readability and writing skills scores to analyze additional details in the text to look for insights that advance writing pedagogy. The diagnostic LA can be used as information to complete a variety of manual activities. Some of these include:

- Provide targeted feedback to the student on writing skills.
- Provide additional feedback to students on assignments.
- Revise written assignment instructions.
- Revise assessment or grading guidelines.

After the text has been evaluated, and any interaction with the student is complete the instructor will submit the grade to the grade book. The instructor will continue to review the course WID dashboard and completing the WAC assignments and activities. After the semester concludes, instructors will need to complete the manual review of their courses. Some of the decisions and activities are to update the course writing skills objectives, update writing assignments to improve writing skills and update assessment criteria to improve writing skills.

Summary

The first research question "What Canvas data should be used to identify the effectiveness of student writing skills to create a diagnostic tool for instructors and administrators?" was addressed using results from the data's descriptive statistics. A total of 277 writing samples were selected from the pool of samples from Canvas courses at TWU. For the second research question, "What effect does grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentences, and vocabulary have on the readability score of student writing samples?" a paired samples t-test was conducted to test for differences between the mean FKGL and the student writing skills scores and calculations. The paired writing skills statistics resulted in a statistically significant difference for 12 of the 14 variables. The third research question begins "What is the readability score of sample student text?" and was addressed using results from the selected text readability scores. The writing samples had a mean FKGL of 9.83 (a 9^{th}-grade reading level). The third research question concludes "How can (the text readability score) be used as an input for instructor decision-making to quickly assess student writing skills and administrator decision-making to create broad readability and writing skills goals?" and was addressed as a series of decision models meant to be generalizable to most LMS environments and LA tools. The themes identified in this study echoed research found in the literature.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

In 2014, 34% of Texas students who took the SAT did well enough to demonstrate readiness for college work without remediation (The College Board, 2017b). A SAT score of 1550 out of 2400 is associated a 65% probability of obtaining a first-year college grade point average (GPA) of B- or higher. 60% of Texas high school graduates to take the ACT scored well enough to show readiness for college English (College Readiness and Success, 2016). Another indicator of postsecondary readiness is the State of Texas Assessment of Academic Readiness (STAAR) with scores that suggest 60% of students will do well in college English. Based on these reports, in 2014, about 40% of recent high school graduates in Texas public universities and colleges need at least one remedial class. The students that took a first college-level course in fall 2015, 39% passed with a C or better in reading and 61% passed with a C or better in writing (College Readiness and Success, 2016).

Limitations

This study revealed that the writing samples of students at TWU completing graded writing assignments in English, business, and kinesiology had a mean FKGL score of 9.83 (a 9^{th}-grade reading level), a median of 9.60, and mode of 9.9 (standard deviation = 2.45). Therefore, using data warehouses like Canvas data as a resource to research the current reading and writing skills of students would benefit the institution in several ways. These writing samples are available for local pattern analysis allowing the organization and structuring of the data to be performed without moving the data to a central repository (Witten, Frank, Hall, & Pal, 2016). The limitation would be that the scope of the diagnostic LA tool is limited to the courses with writing assignments in Canvas. If the institution uses multiple LMSs or there is no presumption that instructors use Canvas features for student writing submissions and grading, then any WAC or WID objectives and reporting across the institution would not be possible directly from the LMS.

This study pivoted on there being a strong correlation between the FKGL readability score and individual writing skills. A paired samples t-test was conducted to test for differences between the mean FKGL and the student writing skills scores and calculations. The paired writing skills statistics resulted in a statistically significant difference in grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentences, and vocabulary. The LA diagnostic tool presents information to the instructor grouped into writing skills categories to help the instructor focus on what to help the student improve their writing. However, if the instructors or department administrators are not making decisions or taking action to improve student writing, then there would be no significant improvement in student written communication while students are in college.

Decision models illustrate what is central to the institution, and various roles that contribute in decision-making do matter. For repeatable decisions, the role is not an individual but a team or department (Buede & Miller, 2016). Multiple roles can own, make or care about specific decisions. Often one part or level of the institution owns a decision, but a different level makes daily decisions. College administrators might own the WAC program and objectives, but student writing submissions are evaluated by instructors every day. If decisions are automated or partly automated, then the institution that passes on the decision to a student could be considered the decision-maker too. While many decisions have only owners and makers, sometimes there are other parts of the institution that might take an interest and expect consideration of their opinions. The diagnostic LA tool will require settings to be defined and configured. However, not knowing how decisions are made or by what role, minimizes the use of dashboards to summarize the effect of decisions being made.

Decisions also have an application context. There are places and times where they are applied. Decisions show up in processes, systems, and events (Debevoise & Taylor, 2014). Very few processes can execute all the way through without making decisions. These decisions might be automated or manual, but they are essential to the process. Understanding which tasks require a decision helps identify where in the process decisions are used. Existing systems are often fixed points in an institution's information technology landscape that provide input and are hard to change but are essential to daily operations (Debevoise & Taylor, 2014). Understanding that data from other systems must be delivered into or supported by another application helps identify implementation constraints on the diagnostic LA tool and approach used for decision-making. Reporting, the use of the dashboard, writing skills statistics and other technical components might be managed by other systems making part or all the diagnostic LA tool redundant.

The use of the Flesch-Kincaid grading level formula as a KPI has the potential to be a limitation. A limitation of the FKGL measurement has been the lack of validity that is inherent in its construct of selected variables that correlate with specific writing skills (Dubay, 2004; Oakland & Lane, 2004). The formula does not consider the background of the reader, the interest of the reader, or the conceptual load of the text. Quantitative machine-driven formulas look for anomalies like the same sentence repeated multiple times but can yield readability scores when the passage is not written in a formal order of comprehension (Redish, 2000). Formulas like ALI and FKGL cannot measure comprehension, account for the organization, design, or layout of the text and interpret difficulty of ideas. Klare (1976) suggested that a good score to be derived from a formula will depend on the passage selected (p. 134).

WAC and WID programs select student writing assignments for review that are designed for both assessing and fostering learning. These programs refer to creating and using writing assignments to help students analyze, synthesize, and apply course content information as students develop as writers in college and their chosen professions (Townsend, 2001). WAC would focus on assignments such as journals, discussion boards, and other short pieces. Writing to learn assignments give students practice in writing and helps them improve writing skills. WID assignments use different conventions and styles and include reports, article reviews, and research papers which provide examples of disciplinary thinking and writing. WAC and WID assignments can be combined. For the WAC and WID objectives to use the FKGL measurement as a KPI, a decision regarding the number and type of written assignments that would be aggregated into the WAC and WID dashboards would need to be identified as part of implementing the diagnostic LA tool. Without a thoughtful selection of writing assignments, the FKGL readability score would need to be considered more of an FKGL measurement range rather than an FKGL readability KPI. The same degradation of the FKGL readability score could happen when combining multiple cohorts or disciplines. The writing skills of new students could be measurably different than students that have been in the program for a length of time, so reporting by semester would raise awareness to the difference in overall FKGL readability scores and the impact of different writing skills within the cohort. The writing skills of students in different disciplines could also be unique and should be reported separately.

Implications

Canvas data provides a feasible way to generate patterns of writing skills. The individuality of every student's writing samples or the individuality of the student writing samples for a specific course is available to find writing patterns specific to the smallest populations. Integrating this data into multiple database might lose these patterns. The Canvas data warehouse is considered low-complexity because it only targets relevant individual data sources (Wu, Zhu, Wu, & Ding, 2014). Canvas data offers a strategy for synthesizing forwarded patterns at multiple levels of abstraction in databases. For example, text readability scores by discipline provide global patterns, text readability scores by course provide sub-global patterns, and writing samples by student provide local patterns.

This study indicated that there is a significant correlation between the FKGL score and grammar errors as a percent of total words, poor sentence prhasing or a "bad phrases" score, transitional words score, total sentences, average sentence length, short sentences count (<17 words), long sentences count (>35 words), passive voice as a percent of total sentences, simple sentence starts as a percent of total sentences, vocabulary score, vocabulary word count, and vocabulary words as a percent of total words. Using these writing skills, instructors can draw attention to several writing concerns that include:

- Correct spelling, grammar, punctuation, and syntax
- Consistency in spelling, hyphenation, numeral, fonts, and capitalization
- Sentence structure, transactional words, and voice
- Run-on sentences
- Changes that can be made to improve the rhythm of the text
- Sections of writing where the action is confusing or the student's meaning is unclear due to bad transitions

- Tonal shifts and unnatural phrasing
- Passages that do not read well due to bad word choice or use of the language
- Words or phrases that may clarify or enhance the meaning of the text

Canvas data provides a means for two-level decisions mapped out using decision models. Global decisions for programs like WAC and WID based on the synthesized patterns and branch decisions found in student writing samples. For example, department administrators make decisions based on the patterns seen in courses and instructors make decisions based on patterns seen in individual student writing samples. The main objective in knowledge discovery from databases is to capture interesting patterns concerning a defined point of view (Freitas, 2013). The instructors and administrators may not be data analysis experts, but they are experts in the writing samples reviewed from the local database. The importance of any pattern depends on the interest of the user. By using local pattern analysis strategy, department administrators can use different interesting measures for evaluating local patterns of student writing samples in Canvas (Freitas, 2013). These may not be the same measure used by the college administrator in global pattern synthesizing using only text readability scores. For example, the vocabulary score measure is used by department administrators, and college administrators use the text readability score in their corresponding reports or dashboards. Once synthesized, the rule building vocabulary scores in student-written submissions improves overall FKGL text readability scores in the WAC dashboard. It shows that the strategy of local pattern analysis enabled by the department administrators and instructors were able to adopt different metrics for evaluating patterns (Taylor, 2014).

Decision models outline improving processes, framing predictive analytics efforts, and ensuring learning analytics dashboards are action-oriented. Defining decisions as part of the requirements process offers several benefits. Identifying and modeling decisions separately from the process ensures that the process is less complex and easier to make changes (Buede & Miller, 2016). By modeling the decisions, the solution is a clear and concise definition of decision-making requirements. Most process models are developed using the business process model and notation (BPMN) standard (Object Management Group, 2011). When getting started with requirements, identifying decisions is the focus of the process. Consider decisions that are repeatable and non-trivial decisions where understanding how making the decision in advance is worthwhile (Taylor, 2011).

The focus of the diagnostic LA tool to evaluate student text is to help instructors evaluate student writing skills rather than using the solution as an automated process (Verbert et al., 2014). It is inspired by a modest computing approach (Dillenbourg et al., 2011) where the organization and structuring of the data and technology is used to support student’s becoming better writers by helping instructors make educated decisions on the best way to provide meaningful feedback and training. The diagnostics are provided by organizing and structuring the Canvas data for analysis to complete repetitive, rule-based tasks. The need for student writing skills to improve (College Readiness and Success, 2016) was the impetus defining the data to extract from Canvas. Several recent studies are looking for a consensus on what data in the LMS is relevant (Fritz, 2016; Ruipérez-Valiente, Muñoz-Merino, Leony, & Kloos, 2015; Dawson, Gašević, Siemens, & Joksimovic, 2014; Verbert, Govaerts, Duval, Santos, Van Assche, Parra, & Klerkx, 2014). Rather than looking for characteristics or data that can be measured, look at strategic programs within the institution and use those requirements to design and develop LA tools and dashboards to provide the needed measurements (Little, 2004).

The decisions involved in a diagnostic LA tool are those identified explicitly as being involved and the decisions required, directly or indirectly. From this, it is possible to determine which text readability and writing skills objectives to include in the diagnostic LA tool. The diagnostic LA will have settings to identify the data in Canvas included in any dashboards; the reports, KPIs, and links on the dashboard layouts; the courses that will have the diagnostic LA tool enabled; and the writing skills included in the diagnostic LA tool for instructors to review. The decision models provide the requirements. For example, a college administrator would decide the target FKGL score for students in a specific cohort in the next year. This information is entered as a setting and becomes a rule in the diagnostic LA tool. From the WAC dashboard, the college administrator could "click into" or "down" the hierarchy to see the courses those students are enrolled in for the semester. Department administrator and instructor decisions that are extracted from the decision models as rules provide the view "up" the decision hierarchy. An example is the courses in the kinesiology discipline that will include writing skills objectives for the next semester. Each decision from the decision models is a rule that provides the context of those decisions and dictates how those decisions fit in the broader decision-making. The limitation is that without these decisions, a generic set of rules would apply to the diagnostic LA tool, and there is a danger of presenting meaningless data that is confusing rather than helpful.

Recommendations

There are a growing number of applications and LTI integrations that are mining large sets of data from the LMS. The challenge is determining what is meaningful. The problem exists when considering learning where there is less consensus on what is relevant data and the criteria for who and when to present the data (Plaisant, 2004). This study is consistent with the view that the focus should be on the design, development, and deployment of data and artifacts to study the effects that these have in real learning contexts (Shneiderman & Plaisant, 2006). By collecting data that students leave behind, data sets can be built that turn learning research into an empirical science (Verbert et al., 2011). The result of supporting LA continues to be more effective, and the result is empowering (Purpura, Schwanda, Williams, Stubler, & Sengers, 2011). Providing grammar, punctuation, spelling, vocabulary, sentence structure, and other writing skills to instructors using the data available in Canvas is considered by this study to be empowering, and decision models should provide a map to evaluate the best use of this information to improve student writing skills.

Using decision models to define decision requirements as part of the overall requirements gathering will provide the needed structure for the implementation of a diagnostic LA tool, supporting iteration, and software configuration. Decision models should make the WAC and WID processes less complex, more robust in the face of change, and easier to manage. Framing the organization and structuring of data and diagnostic analytic projects with decision models', links LA to institutional results and helps ensure a successful deployment. Understanding the decisions relevant to a dashboard structures knowledge and puts a premium on action. Decision models are becoming a common language across institutions and information technology (IT) improving collaboration, increasing reuse, and easing implementation. Decision modeling has five steps performed iteratively that include decompose and refine the decision model; identify decisions; describe decisions; specify decision requirements; and embed the requirements into diagnostic LA.

Step 1 - Decompose and Refine the Decision Model

Continue drilling into the decision models, identifying additional decisions that need to be described and specified. These decision models can be used to generate requirements documents as part of a formal requirements process for diagnostic LA. Each decision is used as a map to describe the information needed to make a manual decision or an analytic with associated rules (Figure 18).

When completing the task WAC objectives defined and identifying decisions in this activity look for program goals that are written in broad enough terms to encompass roles and activities undertaken by the institution to increase the breadth and depth of writing within undergraduate programs. The areas to identify or define are curriculum, instructor development, and student learning.

The WID objectives defined are found within the curriculum goals. These goals are articulated by two different approaches. The first is to increase the commitment of individual department administrators and instructors to the teaching of writing in their courses. The second is for the institution to approach the solution structurally by changing graduation requirements and requiring students to complete some number of writing intensive courses to receive a degree (Townsend, 2001). The inclusion of these types of requirements in the curriculum would be defined by departments that offer the writing intensive courses students need for graduation. Over time, there has been a convergence of these approaches with institutions undertaking both strategies to meet their objectives (Townsend, 2001). An extensive list of disciplines and courses that roll up into the WAC program are identified as an output from this activity in the decision model.

Instructor goals, expressed in many ways, stress the need to provide instructors with professional development opportunities related to the teaching of writing so more occasions for student to write are incorporated into their courses. Institutions have also taken different approaches to professional development.

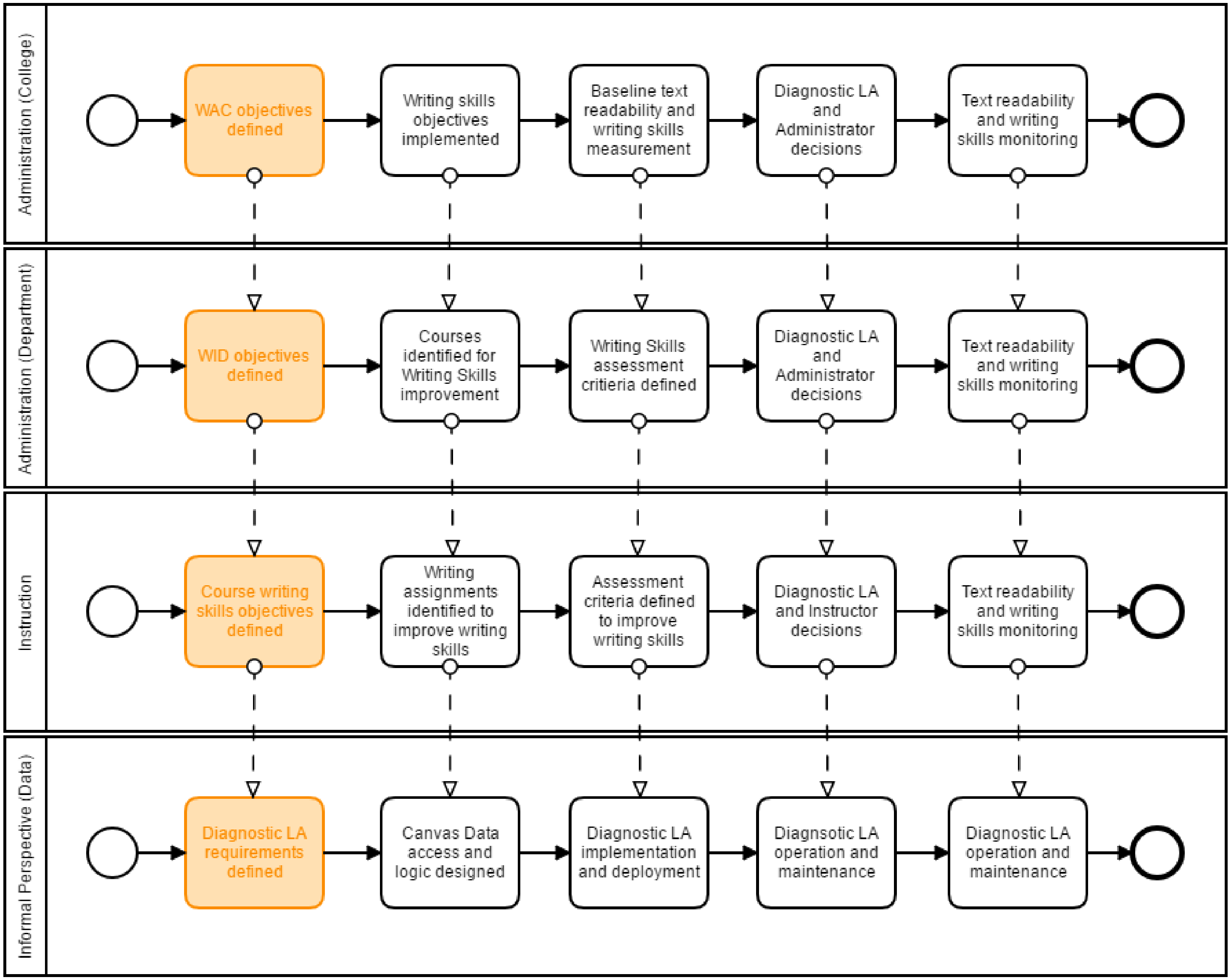


Figure 18. Step 1 - Decompose and refine the decision model.

One option is to require instructors who teach writing intensive courses to be certified as writing instructors. When no certification is required, instructors have opportunities to learn about good writing pedagogy. These professional development opportunities will outline the course writing skills objectives as an output from this activity in the decision model and should produce a list of writing skills that need to be improved.

The focus on students is secondary in the development and implementation of the WAC program. The decision models assert that improved instructor practices will result in improved student writing outcomes. The diagnostic LA requirements defined at this point in the decision model are a complete list of the disciplines, courses in those disciplines, instructors teaching those courses, and students who are provided more direct instruction on the reading and writing practices that are specific to a discipline.

Step 2 - Identify Decisions

Identifying the program structure of decisions for the WAC program is the focus of the next selected activities in the decision model. The location and reporting structure of the WAC program provide the roles and activities for the decisions identified in Figure 19. There are several reporting structures for WAC programs although they ultimately report through the provost's office. However, there is a lot of disparity regarding the centrality and reach of the reporting relations. In a 2010 study of 19 institutions, four WAC programs reported directly to the provost's office, seven to senior administrators in the provost's office, four to an associate provost, three to a dean with college-wide responsibility, and one to the English department (Thaiss & Porter, 2010).

The reporting structure is relevant because the functional responsibility for undergraduate education programs provides an indication of the scope of the diagnostic LA tool. Also, the coordination of the WAC program is a shared responsibility. There can be issues evaluating the impact of WAC and WID programs on writing outcomes of students that can be difficult to measure because of these indirect relationships. There are two fundamental assumptions. The first is that writing pedagogy is integrated into courses, and second that instructors would assess course curriculum to see whether there were adequate opportunities for students to be exposed to the learning of writing. Most institutions monitor the number of writing intensive courses as part of the program. The writing skills objectives implemented will likely be found as an output in a closer examination of these writing intensive courses. If the institution has a proficiency exam to demonstrate student readiness for graduate courses, look there for an output of this activity.

Look at the list of courses identified as the output of the WID objectives defined activity. Take the time to compare this list to the courses identified as the input data for the writing skills objectives implemented activity. Following up with the department administrator decision maker to confirm the courses identified for writing skills improvement as the output of this activity. Look at the list of writing assignments identified as the output of the course writing skills objectives defined activity. Take the time to confirm this list with the department administrator decision maker or instructors teaching these courses to confirm the writing assignments identified to improve writing skills as the output of this activity.

The list of courses and writing assignments confirmed from previous decision model activities become the input for the Canvas data access and logic designed activity. The Canvas LMS administrator will configure the diagnostic LA tool in these courses. The instructors of these courses can “enable” the diagnostic LA tool as a setting for writing assignments in the course. The information presented by diagnostic LA will assist making operational decisions for improving student writing skills.

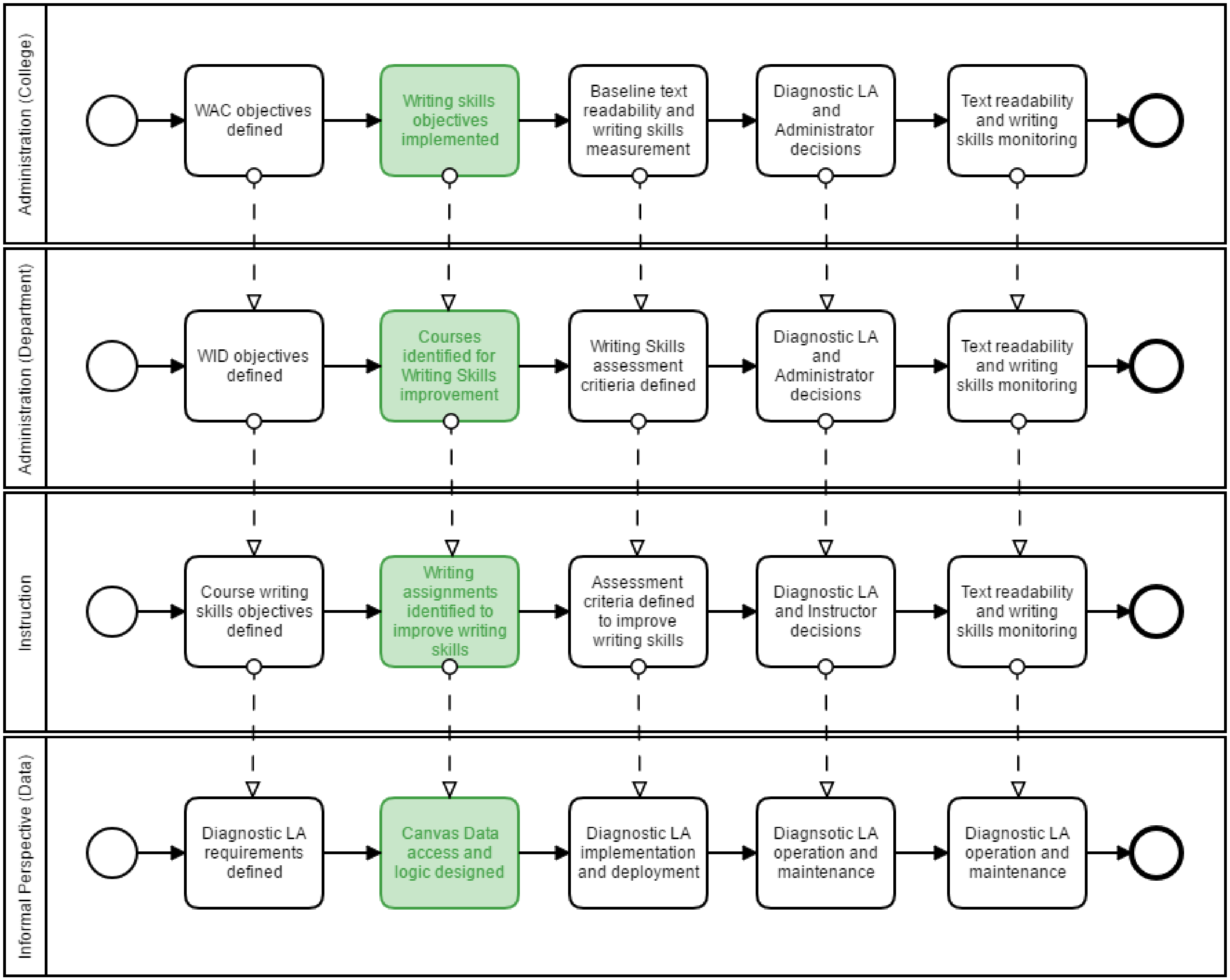


Figure 19. Step 2 - Identify decisions.

Step 3 - Describe Decisions

Describe the decisions and document how the WAC and WID program is assessed and metrics documented for the institution (Figure 20). The quality of student writing will have to be measured to assess the quality of student writing and the effectiveness of the program. One model for measuring WAC and WID programs are before and after studies of writing samples from writing intensive courses. The evaluation enables the institution to consider how much progress students made in their writing skills over a semester. The second model considers a sample of student work independent of a course. The project reviews the quality of writing against the number of writing intensive courses taken by the students. These can be multi-year projects. The third model uses student e-portfolio writing assignments as the data source to evaluate WAC and WID program effectiveness.

The most common form of assessment is a review of writing intensive course syllabi to monitor how writing is being taught and whether the courses meet the criteria established by the WAC and WID program objectives. Using text readability scores and identifying specific writing skills for improvement to impact the score should transform how WAC and WID programs are measured. Using the results of previous studies or the writing samples used in these studies as the input a baseline text readability and writing skills measurement can be set as an output of this activity.

Look at the syllabi of the writing intensive courses or the professional development material as the input for the assessment criteria to improve writing skills activity. The output is a list of writing skills learning objectives. These objectives can be mapped to individual writing skills that are linked to the FKGL text readability score. The writing skills that directly map to the learning objectives in the writing intensive courses are the output for the activity.

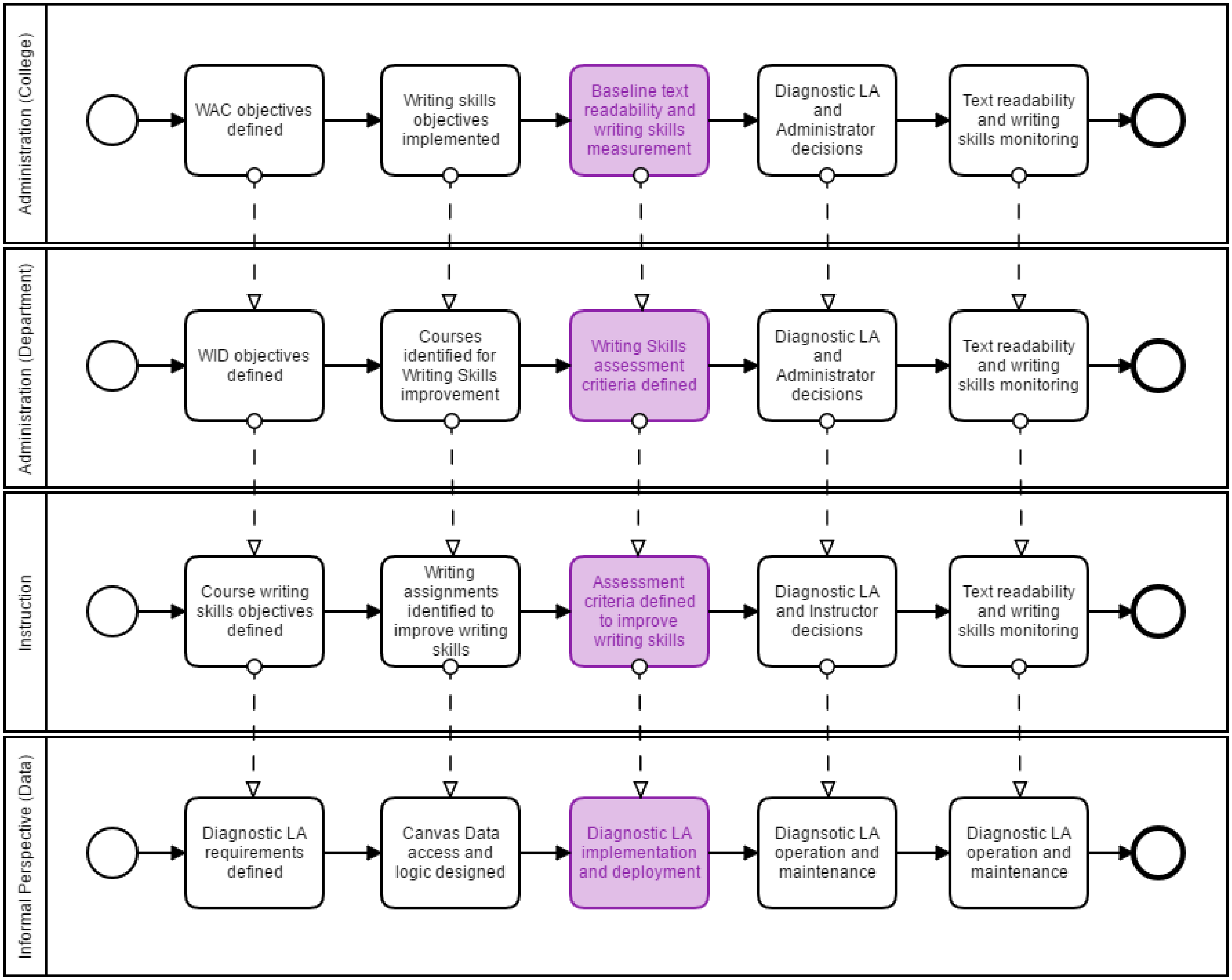


Figure 20. Step 3 - Describe decisions.

Frequently institutions have developed surveys for instructors who teach writing intensive courses about their utilization of WAC pedagogy. Many institutions also utilize student surveys to understand the impact of the writing intensive course on their writing ability. Using the diagnostic LA tool, WAC dashboard, and WID dashboard will display student writing skills scores over time as a replacement to instructor and student survey results to provide a holistic review of the WAC and WID programs that are much less intrusive. Using the assessment criteria to improve writing skills as the input the rules can be set in the diagnostic LA implementation and deployment defining the components of the user interface as the output for the activity.

Step 4 - Specify Decision Requirements

Using the outputs from the decision model detailed decision requirements are specified. The objectives, information, and knowledge required to make the decisions are the information used to configure the diagnostic LA tool settings. The diagnostic LA and college administrator decisions are presented in the WAC dashboard and the diagnostic LA and department administrator decisions are presented in the WID dashboard and outlined in Chapter 4. The diagnostic LA and instructor decisions are presented in the diagnostic LA tool integrated into Canvas and outlined in Chapter 4.

Step 5 - Embed the Requirements into Diagnostic LA

Put each decision into context. The task involves assessing the key performance indicators (KPI) and objectives that are impacted by the decision. The linkage between the KPI and the decision indicates how to differentiate between good and bad decisions. A good decision will have a positive impact on KPIs or objectives and bad decisions will not. Also, the KPIs help identify what the institution must focus on if the decision-making changes. The linkage allows a proposed change of decision-making to the possible impacts (Parmenter, 2015).

The field of information visualization and dashboards is also maturing, Usability studies and actionable evidence of measurable benefits continue to encourage the widespread adoption of dashboards (Plaisant, 2004). Dashboards require administrators and instructors to make hypotheses, look for patterns and exceptions, and then refine their hypothesis. The purpose of the dashboard is to provoke new insights, change established beliefs, and on rare occasions make an important discovery. However, for the dashboard to achieve this purpose, users must look at the same data from different perspectives and over a long period. If the right processes are in place, these users can collaborate with each other as they formulate and answer questions they did not anticipate before looking at the dashboard (Shneiderman & Plaisant, 2006). Decision-makers across the institution want well-designed tools that are synchronized with basic human perception and cognition to support the error-free performance of common tasks and provide interfaces where creative exploration is easy. These tools and dashboards should support advanced services such as search, collaboration and dissemination, as well as flexible composition, hypothesis generation, and history keeping (Shneiderman & Plaisant, 2006).

This study is a precursor to evaluating the efficacy of a dashboard for commercial product development. The strengths and weaknesses of the dashboard needs to be determined to refine the tool and warrant enough success to move forward with software development. The diagnostic LA tool must be developed and tested sufficiently with usability studies to remove obvious problems and ensure that the tool has a reasonable level of reliability and support for basic features like import-export, saving partial results, printing, and searching. There are three significant visualizations and dashboards included in the diagnostic LA tool.

The Diagnostic LA Tool for Instructors

The types of decisions made by instructors are operational for improving student writing skills. The recommendation is to document the current methods used to grade student text and determine how the diagnostic LA tool can augment these grading methods. For this study, the writing skills that directly correlated with the FKGL readability score were separated into tabs on the web page for the instructor to review in detail how well the student's writing compared to a set rule or benchmark built into the tool as a setting. The tabs are color coded in red or green. The red tabs indicate that the student could make improvements in that specific writing skill for this assignment. Under each tab additional details pointing out specific sentences, vocabulary words, or other elements in the text are highlighted demonstrating where the issues were in the text. The diagnostic LA tool should be instrumented to record the features used, the frequency of use, and datasets opened or saved by instructors. In addition to software instrumentation, focus groups and interviews should be scheduled to determine how instructors use the diagnostic LA tool, the decisions they make, how frequently they make decisions, what information they use, and what information might be missing. When appropriate, the diagnostic LA tool will have to be modified or extended to provide the functionality instructors need.

The WID Dashboard for Department Administrators

The types of decisions made by department administrators are analytic decisions for management and control. With advances in technology, department administrators should provide some direction to instructors on how to use computer-mediated written corrective feedback to students. A recent study showed that the usefulness of instructor's using technology to provide corrective feedback on student writing (Elola & Oskoz, 2016). These instructors provided feedback on the grammatical aspect of language with the help of the coding system in Microsoft Word. Also, they provided more feedback regarding content, structure, and organization. Student writing has improved with computer-mediated feedback. Department administrators must consider ways to ensure the quantity and quality of written corrective feedback by instructors under their purview. Giving written corrective feedback is a time-consuming process for instructors as they go through student's writing in detail. The diagnostic LA tool should provide input data that would reduce the time required for instructors to provide feedback to students. There are two types of information summarized into the WID dashboard for department administrators. The first is the data extracted from the students writing samples and compiled as a series of graphs described in Chapter 4 and shown in Figure 9. The second is a summary of instructor written corrective feedback to students allowing department administrators to evaluate the quantity and quality of these student interactions. One of the most significant benefits of the diagnostic LA tool is that the department administrators can directly manage and control their WID objectives without directly disrupting students with surveys, completing forms, taking assessments, and responding to email.

The WAC Dashboard for College Administrators

The type of decisions made by college administrators is strategic. For a strategic implementation of the diagnostic LA tool, specify the decision logic or rules driving the application. This approach of mapping decisions identified in the decision models to the implementation of the diagnostic LA tool has several benefits. It ensures that administrators and instructors can find and edit the implementation settings that matter to them directly, that they are familiar with, and that describe the decisions they make. For decision logic, it ensures that only one version of the rules executed by the diagnostic LA tool is managed and edited preventing duplication confusion. This implementation takes advantage of the increasingly sophisticated editors available in modern development platforms to validate, verify, test, and simulate decision-making. The solution allows the decision models to be linked to the diagnostic tool for instructors in Canvas, the WID dashboard, and the WAC dashboard. Elements in a single decision model have the potential of being implemented in all three components. For example, the diagnostic LA instructor interface developed as an LTI in Canvas and WAC and WID dashboard visualizations that are configured using a dashboard software application like Tableau look at all the available decision models to gather their requirements. Remember that each of these visualizations is designed to assist different groups of users in the manual elements of decision making like grading a student's written submission or discovering the writing skill that has the most impact on the FKGL readability score for business students.

Future Research

Several research projects could evolve from this study. A future study should look at instructor posts to determine if students model instructor text readability and writing skills after receiving feedback. There is work that could be done to understand the aspect of human problem solving and decision making, processes of technology adoption, roadblocks to strategy revision, or social processes that are necessary for institutional success with new LA tools. Continuing to focus on the diagnostic LA tool, the final stage in decision models is to decompose and refine the model, working with the institution until enough detail about the project is documented (Little, 2004). The level of detail required is subjective. The initial model is refined to decompose decisions, refine input data, define input data for analytics, and iterate. Decisions often require information that comes from other activities. Identifying additional activities that produce information needed for the decision is a critical step in further specifying the decision model. The iterative refinement can be repeated as often as necessary to flesh out a complete, coherent and useful decision model. If the diagram developed becomes cluttered or overly complex, consider developing multiple models as views of the overall decision model. Each decision model can show some of the requirements involved. In general, a high-level decision model with just the top layer of the decision and several sub-diagrams showing how that layer of decisions decomposes works well. Annotate diagrams during this documentation phase. Not everything discovered while building the decision models can necessarily be shown on the diagram formally so that notes are helpful. Keep showing the decision models to administrators and instructors that know the institution, who own the decisions, to ensure the view of decision-making remains accurate as more detail is added (Object Management Group, 2011).

Another future project is to focus on specific aspects of the diagnostic LA tool and its use. Identify a small group of instructors and administrators. Their expertise is needed to provide different perspectives. A staggered start with this team may help refine the execution of any training and processes. Expect that some of the team members might leave the project. Document any current practices that are replaced or augmented by the diagnostic LA tool and dashboards. It is important to document the current version of the tool being tested and record any changes needed to its design. Be aware of what constitutes professional success for the instructors and administrators. Levels of success might be submissions to different journals or improved writing skills of students in a discipline. Set target milestones as part of the project. Establish and stick to a schedule. Administrators, instructors, and developers need to know how much time they will need to allocate to the project.

Instrument the diagnostic LA tool to record usage data, features used, datasets accessed, and other details. Follow industry accepted project management and documentation practices to implement the solution. Consider any training requirements that are needed. Observing how hard it is to lean the diagnostic LA tool will determine what needs to be done to create expert users. Establish personal contact with the project team and rely on them to provide reflection and insight. Reflect and summarize what instructors and administrators have learned and how much progress they have made toward their goals. Continue to modify the diagnostic LA tool as needed. There is the need to modify or extend the features to provide the functionality needed by instructors and administrators. Continue to document the success and failures of the project.

There are useful studies to consider during the design, development, and implementation phases of the diagnostic LA tool and dashboard. If higher education institutions believe that writing is an essential tool for learning a discipline and helping students improve their writing skills and this is the responsibility of all faculty, then the FKGL score should provide a pulse on the continuous improvement of writing skills for a cohort of students. Using additional orgnization and structureing of data for analysis techniques, outside the scope of this study, instructors can begin to address other writing skills like:

- Words or sentences that are extraneous or overused
- Redundancies from repeating the same information in different ways
- Dialogue or paragraphs that can be more succinct
- Confusing narrative digressions

Additional research is needed to understand the complex patterns of work for administrators as they deal with difficult problems to produce insights and innovations. Assessing the creativeness of work products is difficult. The outcome may be specific suggestions for tool improvements and a better understanding of design principles. Using the FKGL score as a KPI to measure the effectiveness of writing programs and learning outcomes could be useful for several reasons. Instructor writing assignments and the student feedback provided indicate which instructors across the disciplines are consistent in their interpretation of text assessment and the required learning outcomes of written assignments. In a future study, a review of syllabi and assessment criteria for writing assignments can be pulled directly from Canvas data and evaluated for specific phrasing, topics, learning objectives, and types of assignments. This study excludes discussion posts submitted by instructors.

Conclusions

The strategy of inquiry to complete this study adopted the quantitative approach to research. Creswell (2013) suggested that a quantitative approach seeks to identify variables associated with the purpose of the study. The first software application applied to the extracted Canvas discussions was Grammarly. Paper Rater was the second application used to provide feedback and writing instruction. Finally, the data collection incorporated the calculations for FKGL, FRE, and ALI scores. A one-sample t-test was used to compare the disciplines mean FKGL to the overall FKGL. The difference between the FKGL score mean difference among disciplines (business, English, and kinesiology) was determined using one-way ANOVA statistics. A paired sample t-test compared the FKGL readability score to projected mediating items. There are four decision models generated. The decision models will show what grading and report information is automatically generated and the points in the processes that instructors and administrators need to make decisions and take some action outside of the diagnostic LA tool.

The first research question "What Canvas data should be used to identify the effectiveness of student writing skills to create a diagnostic tool for instructors and administrators?" was addressed using results from the data's descriptive statistics. A total of 277 writing samples were selected from the pool of samples from Canvas courses at TWU. For the second research question, "What effect does grammar, poor sentence phrasing, transitional words, sentence length, passive voice, simple sentences, and vocabulary have on the readability score of student writing samples?" a paired samples t-test was conducted to test for differences between the mean FKGL and the student writing skills scores and calculations. The paired writing skills statistics resulted in a statistically significant difference for 12 of the 14 variables. The third research question begins "What is the readability score of sample student text?" and was addressed using results from the selected text readability scores. The writing samples had a mean FKGL of 9.83 (a 9th-grade reading level). The third research question concludes "How can (the text readability score) be used as an input for instructor decision-making to quickly assess student writing skills and administrator decision-making to create broad readability and writing skills goals?" and was addressed as a series of decision models meant to be generalizable to most LMS environments and LA tools.

There are three significant visualizations and dashboards included in the diagnostic LA tool. They are the diagnostic LA in Canvas for instructors, the WID dashboard for department administrators, and the WAC dashboard for college administrators. Each of these visualizations is designed to assist different groups of users in the manual elements of decision making like grading a student’s written submission or discovering the writing skill that has the most impact on the FKGL readability score for business students.

The recommendation is to document the current methods used to grade student text and determine how the diagnostic LA tool can augment these grading methods. The writing skills that are directly correlated with the FKGL readability score were separated into tabs on the web page for the instructor to review in detail how well the student’s writing compared to a set rule or benchmark built into the tool as a setting. There are two types of information summarized in the WID dashboard for department administrators. The first is the data extracted from the students writing samples and compiled as a series of graphs. The second is a summary of instructor written corrective feedback to students allowing department administrators to evaluate the quantity and quality of these student interactions. One of the most significant benefits of the diagnostic LA tool is that the department administrators can directly manage and control their WID objectives without directly disrupting students with surveys, completing forms, taking assessments, and responding to email. For a strategic implementation of the diagnostic LA tool, specify the decision logic or rules driving the application. This approach of mapping decisions identified in the decision models to the implementation of the diagnostic LA tool has several benefits. It ensures that administrators and instructors can find and edit the implementation settings that matter to them directly, that they are familiar with, and that describe the decisions they make. For decision logic, it ensures that only one version of the rules executed by the diagnostic LA tool is managed and edited preventing duplication confusion. This implementation takes advantage of the increasingly sophisticated editors available in modern development platforms to validate, verify, test, and simulate decision-making. This study is consistent with the view that the focus for LA should be on the design, development, and deployment of data and artifacts to study the effects that these have in real learning contexts (Shneiderman & Plaisant, 2006). Providing grammar, punctuation, spelling, vocabulary, sentence structure, and other writing skills results to instructors using the data available in Canvas is empowering, and additional research is needed to evaluate the best use of this information to improve student writing skills.

The decision models in this study took into account software development lifecycle (SDLC) and project management concepts and do not focus on methodology but on standardizing the way decisions should be represented. The most effective way to define a decision is to specify the question that must be answered to make the decision along with the range of possible answers. Any decision requires information derived from data to be available when it is being made. This might be data about the transaction the decision relates to, reference data or other supporting information. To make a decision also requires knowledge that explains how that decision should be made. This might be based on policies, regulations, best practices, and domain expertise or data analysis. Decisions can be decomposed, broken down into their component decisions. The answers from the component decisions are information that must be available for the decision maker at the time decisions need to be made. The information and knowledge required to make these sub-decisions can likewise be specified and decomposed. This allows even very complex decisions to be broken down until they can be precisely specified. The diagnostic LA decision models apply these basic concepts to produce a network of decisions, input data or information objects, and knowledge sources or representations. As a process model is to workflow or a data model is to information, a decision model is to decision-making: A clear and unambiguous way to describe decision-making by breaking down that decision-making into a set of simple concepts.

APPENDIX A

REQUEST TO USE WRITING SAMPLES IN CANVAS

August 3, 2017

Hello,
My name is Heidi Collins and I am working with Dr. Scott Warren in the department of Learning Technologies at UNT to submit an IRB for my dissertation project. The name of the study is *The Use of Data and Readability Analytics to Assist Instructor and Administrator Decisions in Support of Higher Education Student Writing Skills*.

I need your approval to access discussion content from your fall 2016 and spring 2017 courses in Canvas. *No identifiable information (names or course numbers) are used in the study or in the subsequent dissertation.*

The discussion content I would like to access includes:

1. Instructions or directions provided for students to complete the discussion assignment.
2. Clarification or additional directions provided to students associated with the discussion assignment.
3. Comments made to students.
4. Rubrics available for students to understand how the discussion are graded.

There is additional information that is calculated from discussion content. Some of these calculations include:

1. Grammar
2. Sentence Length Information
3. Vocabulary Score
4. Overall Discussion Grade
5. Discussion Topics
6. Post Date and Time Before Due Date and Time

Please let me know if I have your permission to review and access your discussion content. Your consideration is greatly appreciated. If you approve, I will forward your response to Dr. Martin who has graciously agreed to generate the letter I need to submit with my IRB.

I look forward to hearing from you soon,
Heidi

Heidi Collins | Associate Director | Learning Systems | Texas Woman's University
940.898.3200 | hcollins@twu.edu | SH 318

APPENDIX B

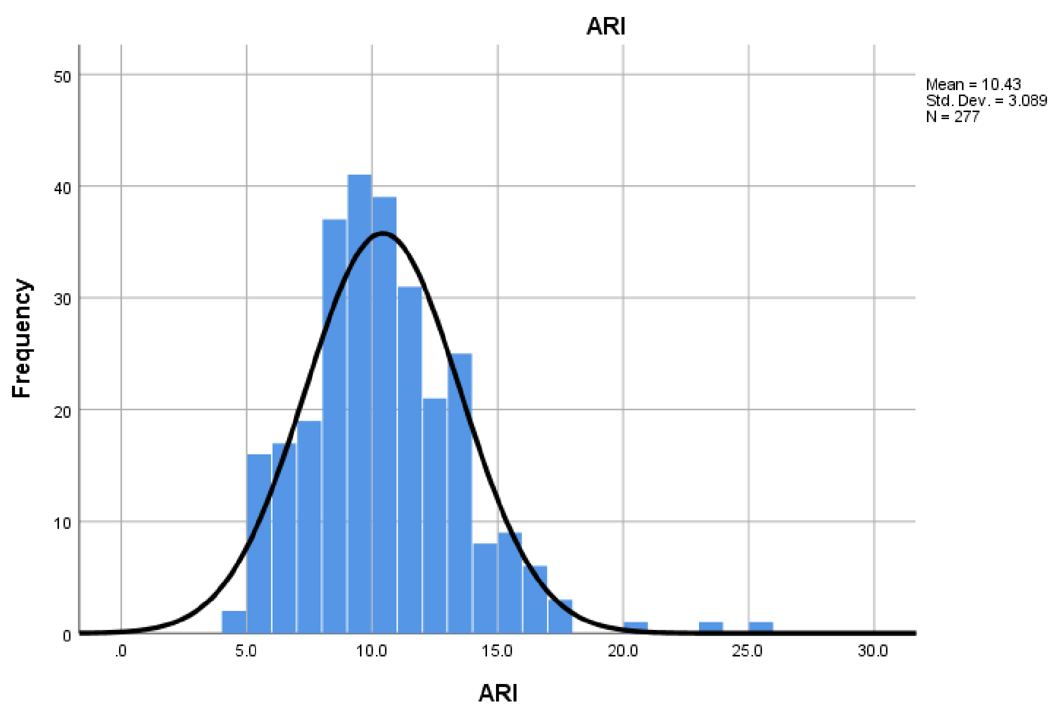
SPSS ANALYSIS

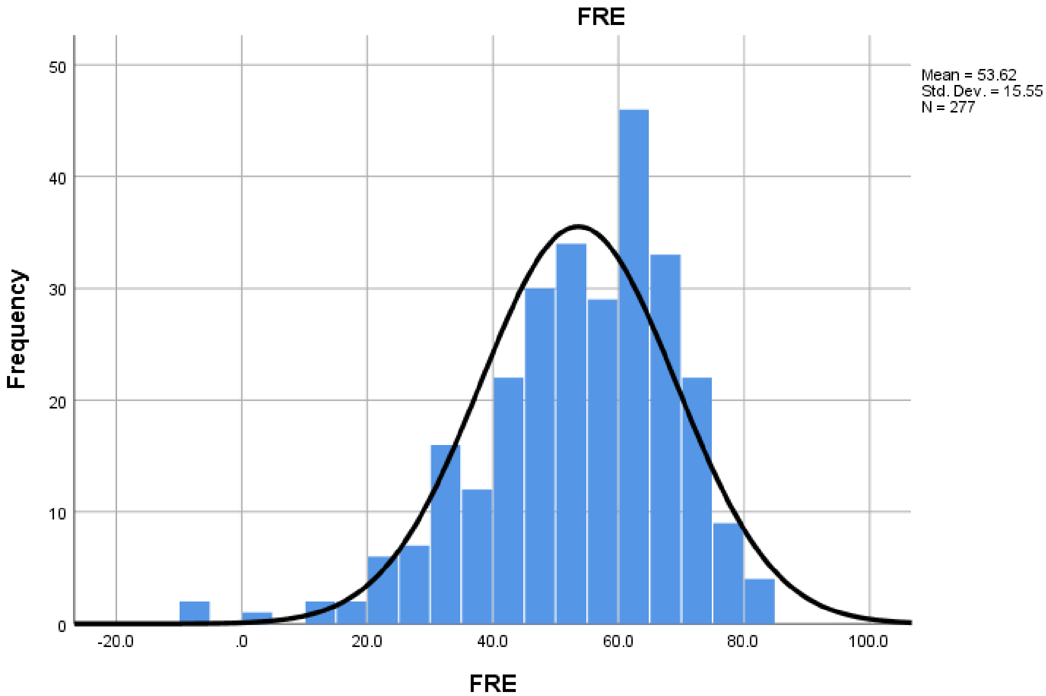
Descriptive Statistics of Writing Skills

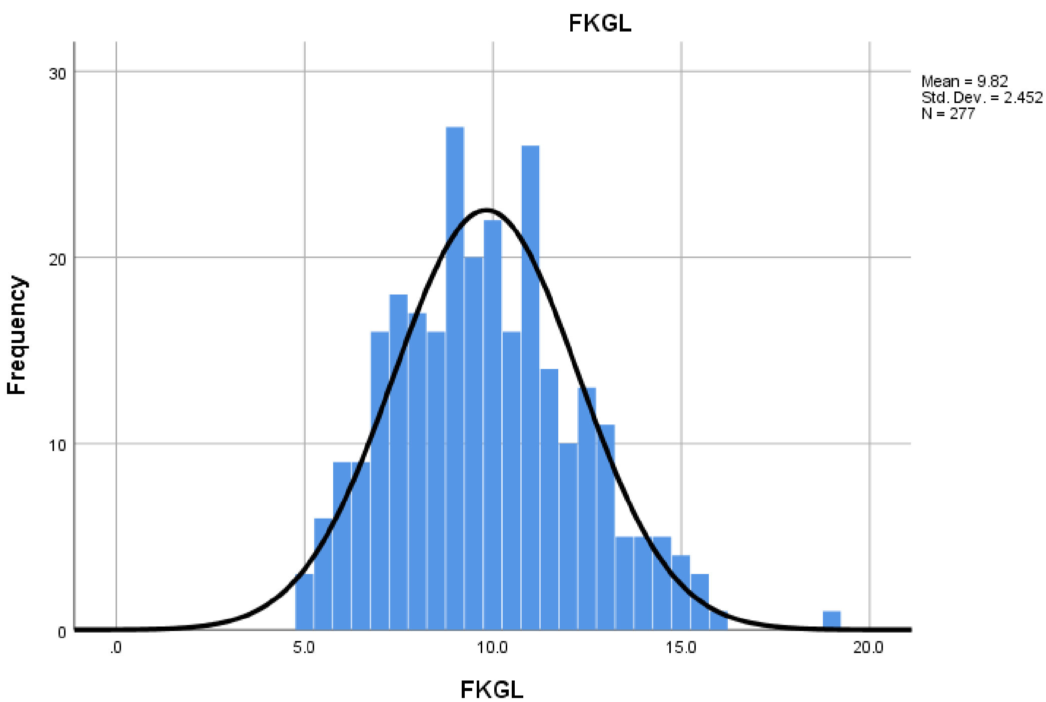
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
GRAMMAR_ERRORS	277	0	125	9.21	9.863	6.516	.146
GRAMMAR_ERRORS_PER_TOTAL_WORDS	277	0.86%	22.45%	6.5516%	3.33078%	.618	.146
BAD_PHRASE	277	.0000000000	10.71000000	3.289097473	1.993713921	.935	.146
TRANSITIONAL_WORDS	277	.0	190.0	55.465	27.9212	.855	.146
TOTAL_SENTENCES	277	3	60	13.32	9.686	1.773	.146
AVG_LENGTH	277	9.0	37.5	18.850	5.4592	.699	.146
SHORT_SENTENCES	277	0	28	6.63	5.998	1.456	.146
LONG_SENTENCES	277	0	10	.82	1.418	2.895	.146
SENTENCE_VARIATION	277	2.2	34.3	9.555	3.9056	1.939	.146
PASSIVE_VOICE	277	0.0%	83.3%	14.403%	12.6895%	1.104	.146
SIMPLE_SENTENCE_STARTS	277	0.0%	67.0%	19.253%	15.0714%	.659	.146
VOCABULARY	277	.0000000000	838.4500000	295.8962816	156.3571097	.641	.146
VOCABULARY_WORD_COUNT	277	0	96	13.71	14.290	2.312	.146
VOCABULARY_WORD_PCT	277	0.0%	20.1%	7.690%	3.9848%	.549	.146
Valid N (listwise)	277						

Distribution of Readability Scores







Paired Samples T-Test between FKGL and Grammar Errors

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	GRAMMAR_ERRORS	9.21	277	9.863	.593

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & GRAMMAR_ERRORS	277	.096	.111

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - GRAMMAR_ERRORS	.6188	9.9329	.5968	-.5561	1.7936	1.037	276	.301

Paired Samples T-Test between FKGL and Grammar Errors Per Total Words

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	GRAMMAR_ERRORS_PER_TOTAL_WORDS	6.5516%	277	3.33078%	0.20013%

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & GRAMMAR_ERRORS_PER_TOTAL_WORDS	277	-.263	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - GRAMMAR_ERRORS_PER_TOTAL_WORDS	3.27299	4.62552	.27792	2.72588	3.82011	11.777	276	.000

Paired Samples T-Test between FKGL and Bad Phrases Score

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	BAD_PHRASE	3.289097473	277	1.993713921	.1197906597

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & BAD_PHRASE	277	-.357	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - BAD_PHRASE	6.535451264	3.671221743	.2205823363	6.101213683	6.969688844	29.628	276	.000

Paired Samples T-Test between FKGL and Transitional Words Score

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	TRANSITIONAL_WORDS	55.465	277	27.9212	1.6776

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & TRANSITIONAL_WORDS	277	.179	.003

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - TRANSITIONAL_WORDS	-45.6404	27.5875	1.6576	-48.9035	-42.3773	-27.535	276	.000

Paired Samples T-Test between FKGL and Total Sentences

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	TOTAL_SENTENCES	13.32	277	9.686	.582

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & TOTAL_SENTENCES	277	.124	.039

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - TOTAL_SENTENCES	-3.5004	9.6911	.5823	-4.6466	-2.3541	-6.011	276	.000

Paired Samples T-Test between FKGL and Average Sentence Length

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	AVG_LENGTH	18.850	277	5.4592	.3280

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & AVG_LENGTH	277	.571	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - AVG_LENGTH	-9.0253	4.5321	.2723	-9.5613	-8.4892	-33.143	276	.000

Paired Samples T-Test between FKGL and Short Sentences

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	SHORT_SENTENCES	6.63	277	5.998	.360

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & SHORT_SENTENCES	277	-.105	.081

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - SHORT_SENTENCES	3.1928	6.7141	.4034	2.3986	3.9869	7.914	276	.000

Paired Samples T-Test between FKGL and Long Sentences

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	LONG_SENTENCES	.82	277	1.418	.085

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & LONG_SENTENCES	277	.464	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - LONG_SENTENCES	9.0051	2.1904	.1316	8.7460	9.2641	68.422	276	.000

Paired Samples T-Test between FKGL and Sentence Length Variation

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	SENTENCE_VARIATION	9.555	277	3.9056	.2347

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & SENTENCE_VARIATION	277	.396	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - SENTENCE_VARIATION	.2697	3.6982	.2222	-.1678	.7071	1.214	276	.226

Paired Samples T-Test between FKGL and Passive Voice Sentences

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	PASSIVE_VOICE	14.403%	277	12.6895%	0.7624%

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & PASSIVE_VOICE	277	.096	.112

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - PASSIVE_VOICE	-4.5780	12.6919	.7626	-6.0792	-3.0768	-6.003	276	.000

Paired Samples T-Test between FKGL and Simple Sentence Starts

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	SIMPLE_SENTENCE_STARTS	19.253%	277	15.0714%	0.9056%

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & SIMPLE_SENTENCE_STARTS	277	-.228	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper			
Pair 1	FKGL - SIMPLE_SENTENCE_STARTS	-9.4282	15.8121	.9501	-11.2984	-7.5579	-9.924	276	.000

Paired Samples T-Test between FKGL and Vocabulary Score

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	VOCABULARY	295.8962816	277	156.3571097	9.394588223

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & VOCABULARY	277	.414	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper			
Pair 1	FKGL - VOCABULARY	-286.071733	155.3592520	9.334632769	-304.447857	-267.695609	-30.646	276	.000

Paired Samples T-Test between FKGL and Vocabulary Word Count

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	VOCABULARY_WORD_COUNT	13.71	277	14.290	.859

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & VOCABULARY_WORD_COUNT	277	.490	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - VOCABULARY_WORD_COUNT	-3.8830	13.2627	.7969	-5.4518	-2.3143	-4.873	276	.000

Paired Samples T-Test between FKGL and Vocabulary Word Count Per Total Words

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	FKGL	9.825	277	2.4515	.1473
	VOCABULARY_WORD_COUNT	13.71	277	14.290	.859

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	FKGL & VOCABULARY_WORD_COUNT	277	.490	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	FKGL - VOCABULARY_WORD_COUNT	-3.8830	13.2627	.7969	-5.4518	-2.3143	-4.873	276	.000

Descriptive Statistics Frequencies of Text Readability Scores

Statistics

		ARI	FRE	FKGL
N	Valid	277	277	277
	Missing	0	0	0
Mean		10.426	53.617	9.825
Median		10.100	55.900	9.600
Mode		10.9	48.5[a]	9.9
Std. Deviation		3.0888	15.5502	2.4515
Variance		9.541	241.809	6.010
Skewness		.948	-.837	.395
Std. Error of Skewness		.146	.146	.146
Range		20.8	90.1	13.9
Minimum		4.8	-7.3	5.0
Maximum		25.6	82.8	18.9

a. Multiple modes exist. The smallest value is shown

One Sample T-Test between FKGL and All Student Writing Samples

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
FKGL	277	9.825	2.4515	.1473

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
FKGL	66.699	276	.000	9.8245	9.535	10.115

One Sample T-Test between FKGL and Business Student Writing Samples

One-Sample Statistics[a]

	N	Mean	Std. Deviation	Std. Error Mean
FKGL	162	9.738	2.2499	.1768

a. DISCIPLINE = B

One-Sample Test[a]

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
FKGL	55.090	161	.000	9.7383	9.389	10.087

a. DISCIPLINE = B

One Sample T-Test between FKGL and English Student Writing Samples

One-Sample Statistics[a]

	N	Mean	Std. Deviation	Std. Error Mean
FKGL	62	10.498	2.8461	.3615

a. DISCIPLINE = E

One-Sample Test[a]

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
FKGL	29.044	61	.000	10.4984	9.776	11.221

a. DISCIPLINE = E

One Sample T-Test between FKGL and Kinesiology Student Writing Samples

One-Sample Statistics[a]

	N	Mean	Std. Deviation	Std. Error Mean
FKGL	53	9.300	2.4245	.3330

a. DISCIPLINE = K

One-Sample Test[a]

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
FKGL	27.926	52	.000	9.3000	8.632	9.968

a. DISCIPLINE = K

One-Way ANOVA

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
FKGL * DISCIPLINE	277	100.0%	0	0.0%	277	100.0%
FKGL * COURSEID	277	100.0%	0	0.0%	277	100.0%

One-Way ANOVA between FKGL and Discipline

Report

FKGL

DISCIPLINE	Mean	N	Std. Deviation
B	9.738	162	2.2499
E	10.498	62	2.8461
K	9.300	53	2.4245
Total	9.825	277	2.4515

ANOVA Table

			Sum of Squares	df	Mean Square	F	Sig.
FKGL * DISCIPLINE	Between Groups	(Combined)	43.941	2	21.970	3.728	.025
	Within Groups		1614.793	274	5.893		
	Total		1658.733	276			

Measures of Association

	Eta	Eta Squared
FKGL * DISCIPLINE	.163	.026

One-Way ANOVA between FKGL and Course ID

Report

FKGL

COURSEID	Mean	N	Std. Deviation
16FAENG01	10.116	19	4.0268
16FAENG02	9.471	7	2.6980
16FAENG03	11.892	12	2.0995
16FAENG04	10.404	24	1.8229
16FAKINS01	9.000	16	3.1309
16FAKINS02	8.090	10	1.4933
17SPBUS01	11.003	36	1.8536
17SPBUS02	11.030	33	1.5625
17SPBUS03	9.168	50	2.1709
17SPBUS04	8.351	43	2.0357
17SPKINS03	10.032	19	1.6803
17SPKINS04	9.675	8	2.9363
Total	9.825	277	2.4515

ANOVA Table

			Sum of Squares	df	Mean Square	F	Sig.
FKGL * COURSEID	Between Groups	(Combined)	316.634	11	28.785	5.684	.000
	Within Groups		1342.099	265	5.065		
	Total		1658.733	276			

Measures of Association

	Eta	Eta Squared
FKGL * COURSEID	.437	.191

COURSEID	SEMESTER	DISCIPLINE	STUDENT ID	ARI	FRE	FKGL	GRAMMAR ERRORS	GRAMMAR ERRORS PER TOTAL WORDS	BAD PHRASE	TRANSITIONAL WORDS	TOTAL SENTENCES	AVG LENGTH	SHORT SENTENCES	LONG SENTENCES	SENTENCE VARIATION	PASSIVE VOICE	SIMPLE SENTENCE STARTS	VOCABULARY	VOCABULARY WORD COUNT	VOCABULARY WORD PCT
17SPBUS01	2017 Spring	Business	901096807	11.9	25.7	12.0	5	6.06%	0.96	41	11	16.5	7	1	14.5	18.2%	18.0%	638.54	24	15.8%
17SPBUS01	2017 Spring	Business	901110816	10.0	42.3	9.6	3	6.24%	1.94	77	12	14.7	7	0	6.6	8.3%	17.0%	354.76	12	9.5%
17SPBUS01	2017 Spring	Business	901209283	11.7	37.7	10.0	12	5.51%	4.31	31	15	13.3	10	0	7.8	0.0%	33.0%	412.83	17	9.8%
17SPBUS01	2017 Spring	Business	901172139	9.7	48.3	9.3	4	4.01%	0.76	40	15	18.3	4	0	8.9	20.0%	33.0%	296.73	14	7.8%
17SPBUS01	2017 Spring	Business	901107169	12.8	33.3	11.8	5	2.42%	1.04	92	19	23.9	2	3	11.0	0.0%	16.0%	575.70	49	13.1%
17SPBUS01	2017 Spring	Business	901181017	11.8	40.5	10.6	9	4.05%	1.19	65	11	24.7	4	4	18.2	27.3%	0.0%	537.62	29	14.8%
17SPBUS01	2017 Spring	Business	901169647	12.2	22.5	12.0	4	7.80%	0.81	35	10	14.1	7	0	7.2	20.0%	20.0%	443.34	14	12.4%
17SPBUS01	2017 Spring	Business	901143309	10.0	45.7	8.9	1	5.34%	1.81	37	14	14.7	7	0	7.4	7.1%	29.0%	271.19	12	7.7%
17SPBUS01	2017 Spring	Business	901068157	10.3	37.3	10.6	7	4.43%	1.23	54	17	14.6	13	0	5.4	11.8%	18.0%	363.05	17	9.9%
17SPBUS01	2017 Spring	Business	901106853	11.7	47.3	8.9	9	4.37%	1.55	54	18	14.0	10	1	11.9	0.0%	11.0%	299.41	15	7.5%
17SPBUS01	2017 Spring	Business	901188972	13.6	17.0	12.9	1	8.88%	0.39	39	7	17.7	3	0	9.7	14.3%	29.0%	657.40	18	16.5%
17SPBUS01	2017 Spring	Business	901069555	12.5	30.4	12.0	9	3.21%	1.22	67	13	26.4	2	2	12.7	23.1%	31.0%	685.28	44	17.0%
17SPBUS01	2017 Spring	Business	901153794	12.0	33.7	10.9	6	4.73%	0.74	45	13	17.9	6	1	10.8	30.8%	31.0%	322.80	16	8.9%
17SPBUS01	2017 Spring	Business	901066437	10.9	42.6	9.2	8	6.04%	1.71	44	13	14.0	8	0	8.6	15.4%	15.0%	264.33	9	6.8%
17SPBUS01	2017 Spring	Business	901243827	10.8	42.7	10.2	10	3.64%	1.54	59	14	21.6	7	2	13.1	0.0%	21.0%	439.44	25	11.6%
17SPBUS01	2017 Spring	Business	901145456	13.3	22.3	11.7	4	6.79%	1.26	35	12	13.5	8	0	6.9	0.0%	25.0%	284.43	10	6.7%
17SPBUS01	2017 Spring	Business	901199402	15.4	22.2	13.6	6	5.54%	1.93	57	8	24.8	4	1	24.1	37.5%	0.0%	584.34	25	15.0%
17SPBUS01	2017 Spring	Business	901102974	13.1	24.5	12.4	9	3.97%	1.35	38	16	17.3	6	0	7.5	25.0%	25.0%	549.47	33	14.7%
17SPBUS01	2017 Spring	Business	901180506	9.8	46.1	9.8	12	4.44%	2.61	58	14	17.7	7	1	8.6	14.3%	21.0%	198.12	10	5.0%
17SPBUS01	2017 Spring	Business	901107651	14.6	26.3	13.4	10	3.27%	1.24	75	13	25.9	2	3	13.9	15.4%	15.0%	385.48	25	8.9%
17SPBUS01	2017 Spring	Business	901174419	7.3	51.3	8.1	13	4.74%	1.29	48	16	14.5	13	1	9.6	37.5%	13.0%	294.40	12	8.3%
17SPBUS01	2017 Spring	Business	901106060	13.3	26.1	13.2	8	4.34%	0.98	84	12	21.1	6	2	12.5	33.3%	58.0%	664.73	33	15.1%
17SPBUS01	2017 Spring	Business	900803057	9.6	47.7	9.1	6	3.56%	1.64	50	21	14.7	14	0	5.7	23.8%	19.0%	357.32	20	8.7%
17SPBUS01	2017 Spring	Business	901312433	14.5	27.6	11.3	5	8.54%	0.75	21	8	16.1	5	0	6.8	12.5%	0.0%	595.44	15	16.3%
17SPBUS01	2017 Spring	Business	901087089	8.0	59.1	7.2	8	5.77%	3.11	23	12	15.9	8	1	15.7	8.3%	17.0%	176.22	6	4.3%
17SPBUS01	2017 Spring	Business	901197821	17.3	4.1	14.6	8	6.21%	2.35	20	11	16.1	5	0	8.5	9.1%	9.0%	414.22	18	10.3%
17SPBUS01	2017 Spring	Business	901300152	23.7	-5.3	15.1	3	16.87%	1.96	36	4	16.3	2	0	10.8	0.0%	0.0%	334.86	6	9.6%
17SPBUS01	2017 Spring	Business	901144306	10.1	40.7	9.5	3	7.08%	0.87	62	14	11.1	14	0	4.3	14.3%	21.0%	349.74	11	9.6%
17SPBUS01	2017 Spring	Business	901190400	12.0	30.8	11.6	7	3.09%	0.73	47	20	17.8	9	0	8.5	5.0%	20.0%	507.10	33	13.0%
17SPBUS01	2017 Spring	Business	901174133	11.0	30.2	10.9	5	4.67%	0.95	40	19	12.4	17	0	5.8	10.5%	5.0%	245.05	13	6.5%
17SPBUS01	2017 Spring	Business	901109132	13.3	25.9	11.9	4	5.26%	1.69	48	11	19.0	4	1	10.5	9.1%	36.0%	358.36	17	9.9%
17SPBUS01	2017 Spring	Business	901183432	8.1	50.4	8.5	4	4.79%	2.19	67	15	15.3	8	0	9.3	13.3%	13.0%	262.56	11	6.3%
17SPBUS01	2017 Spring	Business	901205476	11.9	37.3	12.0	13	2.96%	0.94	68	21	17.7	9	0	7.0	42.9%	24.0%	563.59	37	14.4%
17SPBUS01	2017 Spring	Business	901097966	10.2	44.1	9.5	5	3.18%	1.28	46	22	15.7	13	1	10.0	13.6%	18.0%	387.15	26	10.0%
17SPBUS01	2017 Spring	Business	901197448	11.4	41.4	10.9	4	5.12%	1.27	45	12	17.9	4	0	8.5	8.3%	0.0%	379.51	16	10.3%
17SPBUS01	2017 Spring	Business	901168982	14.2	19.5	12.9	5	5.73%	0.46	137	10	19.2	4	0	10.5	20.0%	10.0%	540.59	23	13.9%
17SPBUS02	2017 Spring	Business	901096807	15.5	32.2	14.6	17	1.76%	2.34	56	28	22.3	7	6	13.7	21.4%	11.0%	493.95	55	12.9%
17SPBUS02	2017 Spring	Business	901107651	12.7	51.4	12.4	4	11.00%	5.42	28	4	25.0	1	1	14.8	25.0%	25.0%	335.74	5	7.9%
17SPBUS02	2017 Spring	Business	901110816	9.2	52.8	9.4	15	2.45%	3.46	73	31	14.5	19	0	7.6	12.9%	6.0%	245.57	19	6.7%
17SPBUS02	2017 Spring	Business	901107651	13.5	43.0	12.7	17	1.74%	2.79	44	30	21.1	9	1	10.5	13.3%	13.0%	271.50	29	7.1%
17SPBUS02	2017 Spring	Business	901181017	11.4	44.4	11.5	28	2.05%	1.75	67	32	16.8	17	0	7.6	15.6%	13.0%	425.41	39	11.8%
17SPBUS02	2017 Spring	Business	901172139	11.6	47.9	11.1	17	2.82%	3.08	76	21	18.6	7	0	10.9	9.5%	5.0%	370.31	26	10.3%
17SPBUS02	2017 Spring	Business	901243827	13.6	37.2	13.1	7	2.79%	2.52	25	22	17.9	12	1	10.1	13.6%	14.0%	418.74	29	10.8%
17SPBUS02	2017 Spring	Business	901180506	11.0	58.3	10.7	39	1.49%	5.75	50	39	18.9	17	2	10.9	5.1%	10.0%	155.88	18	4.3%
17SPBUS02	2017 Spring	Business	901106853	9.3	52.6	9.9	14	2.84%	4.13	81	30	12.9	19	0	8.2	6.7%	13.0%	335.41	22	9.1%
17SPBUS02	2017 Spring	Business	901069555	12.9	44.9	12.3	26	1.64%	2.32	74	27	24.8	10	6	15.8	33.3%	26.0%	451.42	51	12.3%
17SPBUS02	2017 Spring	Business	901143309	11.3	50.8	10.9	24	1.64%	3.54	42	38	17.6	15	1	9.5	13.2%	16.0%	238.81	26	6.2%
17SPBUS02	2017 Spring	Business	901066437	11.2	50.4	10.8	14	2.76%	2.43	83	23	17.3	11	2	11.0	34.8%	22.0%	396.65	26	11.0%
17SPBUS02	2017 Spring	Business	901188972	10.1	51.6	9.8	30	1.74%	2.83	72	41	15.4	22	1	8.7	29.3%	29.0%	421.98	45	11.3%
17SPBUS02	2017 Spring	Business	901169647	9.8	48.5	10.1	17	1.98%	2.50	82	36	15.4	21	0	8.5	2.8%	31.0%	316.31	32	8.4%
17SPBUS02	2017 Spring	Business	901068157	11.0	47.9	11.2	21	1.83%	2.63	55	32	18.8	12	0	8.0	21.9%	28.0%	321.18	32	8.5%
17SPBUS02	2017 Spring	Business	901107169	15.9	33.0	14.6	26	1.35%	1.48	78	33	24.7	5	5	9.7	24.2%	6.0%	578.88	86	15.1%
17SPBUS02	2017 Spring	Business	901153794	9.7	53.2	9.2	16	2.08%	3.39	21	40	13.2	27	0	6.7	10.0%	40.0%	265.19	24	7.5%
17SPBUS02	2017 Spring	Business	901199402	15.5	36.3	14.0	19	3.53%	1.67	65	13	24.0	5	3	16.5	23.1%	0.0%	553.18	32	15.3%
17SPBUS02	2017 Spring	Business	901102974	12.2	43.1	11.5	32	1.49%	1.87	50	39	18.9	18	2	10.4	20.5%	8.0%	354.47	46	9.5%
17SPBUS02	2017 Spring	Business	900803057	10.7	50.6	11.0	32	1.48%	2.92	35	40	18.6	16	2	9.4	20.0%	10.0%	277.74	34	7.7%
17SPBUS02	2017 Spring	Business	901174133	9.9	42.1	10.4	12	2.66%	2.27	70	35	11.8	27	0	5.8	14.3%	37.0%	399.47	30	11.2%
17SPBUS02	2017 Spring	Business	901312433	10.0	48.8	10.0	11	2.39%	2.31	55	36	12.8	27	1	7.7	25.0%	19.0%	476.54	39	13.0%

COURSEID	SEMESTER	DISCIPLINE	STUDENT ID	ARI	FRE	FKGL	GRAMMAR ERRORS	GRAMMAR ERRORS PER TOTAL WORDS	BAD PHRASE	TRANSITIONAL WORDS	TOTAL SENTENCES	AVG LENGTH	SHORT SENTENCES	LONG SENTENCES	SENTENCE VARIATION	PASSIVE VOICE	SIMPLE SENTENCE STARTS	VOCABULARY	VOCABULARY WORD COUNT	VOCABULARY WORD PCT
17SPBUS02	2017 Spring	Business	901109132	10.3	44.8	10.6	12	2.18%	2.75	43	33	15.3	17	0	6.5	24.4%	12.0%	283.57	26	8.1%
17SPBUS02	2017 Spring	Business	901145456	10.9	50.1	11.1	30	2.35%	3.34	56	27	17.3	14	2	11.4	22.2%	11.0%	334.45	25	9.2%
17SPBUS02	2017 Spring	Business	901300152	8.7	56.1	9.1	14	5.06%	4.16	43	16	13.6	9	0	9.0	12.5%	6.0%	250.00	9	6.8%
17SPBUS02	2017 Spring	Business	901197448	10.3	54.4	9.9	30	1.53%	3.83	72	39	18.4	19	1	8.9	17.9%	33.0%	176.13	21	4.7%
17SPBUS02	2017 Spring	Business	901190400	10.7	48.5	9.8	28	1.48%	2.51	58	47	15.8	28	1	9.1	23.4%	11.0%	351.17	44	9.5%
17SPBUS02	2017 Spring	Business	901144306	8.8	52.2	9.2	10	3.61%	3.09	68	27	11.3	23	0	5.6	25.9%	33.0%	330.80	17	9.2%
17SPBUS02	2017 Spring	Business	901106060	13.5	36.9	13.1	21	2.35%	2.15	71	24	19.5	10	1	8.4	33.3%	21.0%	426.38	35	11.7%
17SPBUS02	2017 Spring	Business	901183432	11.5	50.7	11.2	19	1.94%	2.26	58	27	21.0	9	0	7.9	44.4%	7.0%	302.30	28	8.0%
17SPBUS02	2017 Spring	Business	901176199	9.5	52.5	10.1	17	2.63%	4.67	82	27	15.5	16	0	8.9	29.6%	22.0%	233.25	16	6.2%
17SPBUS02	2017 Spring	Business	901097966	9.8	54.2	9.9	19	2.19%	3.41	43	33	15.2	18	0	7.6	9.1%	18.0%	222.75	18	6.4%
17SPBUS02	2017 Spring	Business	901082777	9.4	64.9	8.8	28	3.16%	4.41	65	22	15.8	10	0	7.6	13.6%	0.0%	293.35	16	7.7%
17SPBUS03	2017 Spring	Business	901199402	13.5	47.1	12.8	10	5.59%	1.94	111	7	28.1	2	3	18.8	28.6%	29.0%	228.19	8	5.4%
17SPBUS03	2017 Spring	Business	901107169	11.1	52.9	10.8	4	6.17%	3.10	54	8	22.3	3	1	11.9	12.5%	13.0%	342.39	12	9.1%
17SPBUS03	2017 Spring	Business	901172139	7.1	69.2	7.8	6	8.28%	5.58	34	8	16.6	5	0	11.1	0.0%	38.0%	194.84	5	5.6%
17SPBUS03	2017 Spring	Business	901107169	9.6	63.1	9.0	3	12.06%	5.89	107	4	22.8	1	1	14.2	0.0%	0.0%	383.10	6	10.2%
17SPBUS03	2017 Spring	Business	901110816	6.8	67.8	7.5	9	7.48%	5.16	40	10	14.7	7	0	6.6	10.0%	10.0%	133.33	3	2.6%
17SPBUS03	2017 Spring	Business	901199402	13.9	50.6	13.0	3	6.79%	5.60	69	5	32.4	0	2	8.0	0.0%	60.0%	74.89	2	2.1%
17SPBUS03	2017 Spring	Business	901209283	6.5	72.9	6.9	5	8.99%	4.21	24	8	15.3	4	0	5.8	0.0%	0.0%	177.85	3	5.5%
17SPBUS03	2017 Spring	Business	901183432	8.8	65.0	8.7	4	10.19%	3.73	80	5	21.6	3	1	11.1	40.0%	40.0%	366.72	6	10.0%
17SPBUS03	2017 Spring	Business	901107169	16.5	31.3	15.9	1	4.35%	1.11	78	9	28.1	2	2	11.8	11.1%	0.0%	398.95	19	10.4%
17SPBUS03	2017 Spring	Business	901069555	12.5	54.6	11.3	8	4.85%	3.12	85	9	25.2	1	1	9.6	0.0%	22.0%	190.40	9	5.2%
17SPBUS03	2017 Spring	Business	901169647	5.9	69.3	6.7	11	9.82%	2.78	64	8	14.0	5	0	6.5	25.0%	0.0%	62.09	1	2.0%
17SPBUS03	2017 Spring	Business	901176199	8.4	64.1	8.8	11	6.87%	4.61	45	9	17.8	5	1	9.5	11.1%	11.0%	100.58	3	2.5%
17SPBUS03	2017 Spring	Business	900803057	9.7	66.7	9.0	3	10.87%	0.91	42	4	25.3	1	1	10.3	25.0%	25.0%	104.20	2	2.2%
17SPBUS03	2017 Spring	Business	901106060	11.3	49.3	11.4	9	6.20%	2.50	53	9	19.7	4	2	13.1	0.0%	11.0%	153.03	5	4.0%
17SPBUS03	2017 Spring	Business	901102974	7.3	71.5	7.4	7	6.83%	8.04	82	9	17.9	4	0	10.8	11.1%	22.0%	89.10	2	2.0%
17SPBUS03	2017 Spring	Business	900803057	8.7	67.3	8.6	5	5.82%	2.96	62	9	21.0	3	0	7.6	22.2%	44.0%	276.68	8	6.8%
17SPBUS03	2017 Spring	Business	901143309	9.8	60.7	9.4	9	6.68%	5.03	42	9	18.3	4	0	10.5	11.1%	22.0%	242.33	7	6.1%
17SPBUS03	2017 Spring	Business	901188972	10.1	55.9	9.9	5	6.94%	4.69	69	9	17.6	5	0	7.8	11.1%	44.0%	166.30	4	5.1%
17SPBUS03	2017 Spring	Business	901087089	8.1	72.2	8.1	6	9.40%	9.14	39	6	19.5	1	0	7.8	0.0%	17.0%	88.40	2	2.2%
17SPBUS03	2017 Spring	Business	901174419	8.0	63.3	8.6	7	9.47%	3.96	62	7	16.6	3	0	6.9	42.9%	14.0%	240.89	4	5.2%
17SPBUS03	2017 Spring	Business	901181017	10.3	53.3	9.9	7	9.64%	2.35	58	7	16.3	4	0	7.9	42.9%	14.0%	238.24	5	5.6%
17SPBUS03	2017 Spring	Business	901153794	5.4	74.9	6.4	5	10.99%	3.31	30	7	14.3	4	0	9.1	0.0%	14.0%	103.72	2	2.9%
17SPBUS03	2017 Spring	Business	901174133	9.1	61.2	9.7	13	6.91%	3.77	19	8	19.9	3	0	9.8	0.0%	38.0%	289.44	8	7.2%
17SPBUS03	2017 Spring	Business	901179573	8.7	76.6	6.6	0	8.44%	3.68	11	8	16.3	3	0	10.0	0.0%	13.0%	337.89	8	9.0%
17SPBUS03	2017 Spring	Business	901106853	7.2	59.1	8.4	5	10.10%	2.13	13	11	9.9	10	0	3.6	0.0%	27.0%	338.82	6	10.2%
17SPBUS03	2017 Spring	Business	901180506	5.4	80.1	5.7	8	10.91%	7.17	15	6	16.8	4	0	10.7	0.0%	33.0%	220.93	3	6.8%
17SPBUS03	2017 Spring	Business	901107651	10.7	58.8	9.9	10	6.25%	4.27	86	8	22.0	3	1	8.2	12.5%	25.0%	189.24	5	4.9%
17SPBUS03	2017 Spring	Business	901180506	6.8	76.5	7.0	18	4.18%	6.29	53	14	18.8	6	1	8.2	28.6%	36.0%	107.78	4	3.1%
17SPBUS03	2017 Spring	Business	901205476	10.8	52.5	10.0	8	4.50%	2.42	53	15	16.3	8	0	6.1	6.7%	13.0%	375.08	16	10.2%
17SPBUS03	2017 Spring	Business	901107651	12.3	53.6	12.3	6	6.04%	3.86	73	7	26.0	1	1	9.8	0.0%	0.0%	195.50	6	6.1%
17SPBUS03	2017 Spring	Business	901243827	9.6	57.5	9.1	6	10.60%	2.62	61	6	17.3	2	0	9.0	16.7%	17.0%	273.32	5	7.5%
17SPBUS03	2017 Spring	Business	901068157	10.9	57.9	9.5	8	8.02%	2.92	95	7	19.6	3	0	6.1	14.3%	29.0%	138.86	3	4.4%
17SPBUS03	2017 Spring	Business	901183432	11.1	58.1	10.5	4	6.44%	2.40	74	7	24.4	2	1	13.5	28.6%	29.0%	197.49	6	5.0%
17SPBUS03	2017 Spring	Business	901183432	13.9	51.9	11.8	6	5.25%	4.85	82	9	23.3	2	1	10.9	22.2%	22.0%	274.82	10	7.6%
17SPBUS03	2017 Spring	Business	901102974	9.0	59.4	8.8	1	7.90%	1.64	60	8	17.4	5	0	5.6	12.5%	38.0%	152.59	4	3.9%
17SPBUS03	2017 Spring	Business	901243827	13.9	45.5	12.3	5	10.28%	1.51	12	5	21.4	1	0	9.8	0.0%	0.0%	503.04	10	14.1%
17SPBUS03	2017 Spring	Business	901190400	10.7	60.9	8.6	2	10.38%	1.68	36	5	21.2	2	2	18.8	20.0%	0.0%	399.08	8	10.6%
17SPBUS03	2017 Spring	Business	901153794	6.7	70.7	7.3	6	8.81%	3.04	12	8	15.6	3	0	5.1	25.0%	50.0%	80.55	2	2.3%
17SPBUS03	2017 Spring	Business	901190400	8.2	66.1	7.7	8	7.50%	4.90	19	9	16.3	5	1	11.6	11.1%	33.0%	150.24	4	4.2%
17SPBUS03	2017 Spring	Business	901109132	8.0	56.3	9.1	5	12.39%	4.99	15	6	14.8	3	0	7.4	16.7%	17.0%	289.42	5	7.8%
17SPBUS03	2017 Spring	Business	901066437	11.0	63.6	10.7	13	5.43%	3.36	38	8	25.3	3	3	15.0	37.5%	13.0%	134.23	5	3.7%
17SPBUS03	2017 Spring	Business	901144306	5.5	72.7	6.1	4	9.24%	3.57	61	10	11.9	7	0	6.2	10.0%	10.0%	124.61	2	2.7%
17SPBUS03	2017 Spring	Business	901097966	8.9	67.2	7.9	6	11.58%	3.13	72	5	19.0	2	0	7.4	0.0%	0.0%	0.00	0	0.0%
17SPBUS03	2017 Spring	Business	901168982	14.8	47.5	13.8	9	6.39%	5.17	114	6	28.7	2	3	20.1	16.7%	0.0%	345.08	10	7.9%
17SPBUS03	2017 Spring	Business	901190400	9.5	60.1	8.9	18	4.57%	4.18	39	14	17.2	6	0	7.7	28.6%	14.0%	150.46	7	4.2%
17SPBUS03	2017 Spring	Business	901179573	8.6	67.5	7.8	4	7.78%	2.86	39	9	15.7	3	0	7.3	0.0%	0.0%	383.56	9	10.2%
17SPBUS03	2017 Spring	Business	901097966	7.1	71.9	6.9	10	3.08%	5.73	33	24	14.9	16	0	7.0	16.7%	17.0%	134.15	8	3.6%

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17SPBUS03	2017 Spring	Business	901197448	9.4	63.1	9.0	7	5.45%	4.26	63	10	20.2	3	0	6.4	30.0%	0.0%	176.73	6	5.0%
17SPBUS03	2017 Spring	Business	901082777	5.9	81.3	5.5	7	10.20%	7.87	82	7	15.4	3	0	6.3	0.0%	29.0%	26.27	1	1.2%
17SPBUS03	2017 Spring	Business	901109132	10.3	60.1	9.6	4	9.65%	3.87	24	5	22.8	0	0	6.4	20.0%	0.0%	264.71	5	8.4%
17SPBUS04	2017 Spring	Business	901110816	8.4	64.9	7.2	6	7.15%	2.85	117	9	17.1	4	0	9.5	11.1%	11.0%	310.64	8	7.5%
17SPBUS04	2017 Spring	Business	901069555	8.3	64.9	8.1	4	11.83%	4.97	74	6	15.5	3	0	10.9	0.0%	0.0%	168.58	3	5.9%
17SPBUS04	2017 Spring	Business	901106853	5.4	77.5	5.0	4	10.72%	3.13	41	9	11.4	7	0	5.7	0.0%	67.0%	231.17	5	7.2%
17SPBUS04	2017 Spring	Business	901199402	13.9	56.5	11.7	5	10.87%	4.29	108	4	25.3	1	0	13.3	25.0%	25.0%	58.32	1	1.0%
17SPBUS04	2017 Spring	Business	901107651	9.4	63.2	9.1	6	8.45%	7.09	88	6	21.7	3	0	9.1	0.0%	0.0%	453.41	9	11.1%
17SPBUS04	2017 Spring	Business	901069555	13.2	51.3	11.2	9	4.40%	2.71	82	9	27.8	4	2	26.9	11.1%	22.0%	364.81	17	9.1%
17SPBUS04	2017 Spring	Business	901109132	9.0	66.4	8.1	8	11.11%	4.28	28	5	19.8	2	0	8.0	20.0%	0.0%	128.34	2	2.5%
17SPBUS04	2017 Spring	Business	901106853	9.7	58.0	8.8	3	5.45%	2.18	70	10	20.2	6	0	9.9	10.0%	0.0%	265.26	9	7.7%
17SPBUS04	2017 Spring	Business	901199402	13.4	48.0	12.2	5	12.22%	4.11	73	4	22.5	1	1	12.7	25.0%	25.0%	250.94	4	7.5%
17SPBUS04	2017 Spring	Business	901199402	12.5	49.6	11.4	10	6.37%	2.24	36	6	28.8	2	3	16.8	83.3%	0.0%	385.96	12	9.5%
17SPBUS04	2017 Spring	Business	901109132	10.3	52.7	9.8	15	3.95%	3.07	52	17	16.4	9	0	5.7	11.8%	12.0%	251.18	14	7.3%
17SPBUS04	2017 Spring	Business	901169647	5.2	80.2	5.1	9	7.05%	6.38	84	10	15.6	6	0	8.8	20.0%	30.0%	287.91	7	7.4%
17SPBUS04	2017 Spring	Business	901172139	8.4	66.1	9.0	5	6.22%	4.09	59	8	22.1	2	0	8.9	12.5%	38.0%	177.99	5	4.5%
17SPBUS04	2017 Spring	Business	901188972	10.8	57.9	9.9	7	7.33%	3.54	45	6	25.0	0	0	5.6	16.7%	33.0%	295.53	7	7.9%
17SPBUS04	2017 Spring	Business	901209283	7.6	62.3	7.4	11	8.86%	1.22	52	9	13.8	8	0	4.1	11.1%	33.0%	154.05	3	3.2%
17SPBUS04	2017 Spring	Business	900803057	6.8	69.5	7.2	3	10.78%	1.09	43	6	17.0	2	0	5.1	16.7%	17.0%	145.19	2	4.9%
17SPBUS04	2017 Spring	Business	901172139	7.8	68.9	7.9	8	5.50%	5.69	87	8	25.0	0	0	4.4	12.5%	25.0%	171.11	5	4.3%
17SPBUS04	2017 Spring	Business	901117925	6.3	72.4	5.9	4	9.47%	4.13	12	7	16.6	5	0	9.3	0.0%	29.0%	275.56	5	7.3%
17SPBUS04	2017 Spring	Business	901102974	9.0	65.1	7.2	1	13.38%	3.17	45	6	13.7	3	0	7.9	16.7%	50.0%	285.15	4	7.9%
17SPBUS04	2017 Spring	Business	900803057	8.9	60.4	8.6	13	4.82%	1.94	6	12	19.0	4	0	6.3	33.3%	33.0%	185.21	7	4.9%
17SPBUS04	2017 Spring	Business	901180506	7.6	76.9	7.1	16	4.44%	6.89	36	11	22.5	3	2	11.5	9.1%	27.0%	77.65	4	2.1%
17SPBUS04	2017 Spring	Business	901243827	13.4	47.6	12.6	6	4.60%	2.43	34	8	29.9	0	1	11.1	0.0%	13.0%	294.33	11	6.7%
17SPBUS04	2017 Spring	Business	901312433	6.6	69.1	5.7	4	12.60%	0.98	27	9	9.7	8	0	3.7	11.1%	22.0%	304.52	5	7.1%
17SPBUS04	2017 Spring	Business	901143309	4.9	77.2	5.0	0	11.36%	3.14	29	8	12.1	7	0	3.9	0.0%	50.0%	220.78	4	6.5%
17SPBUS04	2017 Spring	Business	901117462	9.0	62.2	9.0	6	5.76%	2.23	44	7	27.3	1	1	9.9	14.3%	14.0%	127.68	4	3.9%
17SPBUS04	2017 Spring	Business	901066437	8.9	66.0	8.0	11	10.00%	3.93	37	5	22.0	2	1	13.0	0.0%	20.0%	59.84	1	1.9%
17SPBUS04	2017 Spring	Business	901176199	9.8	62.3	9.7	17	3.91%	2.22	112	14	20.1	6	1	12.5	14.3%	7.0%	189.35	8	4.9%
17SPBUS04	2017 Spring	Business	901145456	7.7	62.2	7.8	5	12.22%	3.08	45	6	15.0	5	1	12.1	16.7%	50.0%	344.89	6	10.8%
17SPBUS04	2017 Spring	Business	901096807	11.2	39.3	10.8	4	11.80%	1.58	37	4	23.3	1	1	11.4	0.0%	0.0%	432.22	8	11.0%
17SPBUS04	2017 Spring	Business	901107651	14.0	44.4	12.4	9	4.42%	2.53	65	11	22.6	2	0	8.5	0.0%	9.0%	190.85	8	5.2%
17SPBUS04	2017 Spring	Business	901145456	5.4	68.5	6.8	8	9.24%	4.15	48	7	17.0	4	0	7.5	28.6%	0.0%	140.22	3	3.2%
17SPBUS04	2017 Spring	Business	901174133	5.4	73.2	6.2	4	11.36%	3.11	29	8	12.1	6	0	5.1	0.0%	63.0%	317.74	5	7.6%
17SPBUS04	2017 Spring	Business	901102974	12.0	55.0	10.8	4	11.00%	0.86	65	5	20.0	1	0	8.2	0.0%	20.0%	521.37	9	14.4%
17SPBUS04	2017 Spring	Business	901097966	6.2	70.6	6.8	3	10.11%	3.42	67	8	13.6	4	0	6.4	37.5%	25.0%	64.96	1	2.1%
17SPBUS04	2017 Spring	Business	901174419	9.1	62.9	7.3	14	7.46%	2.92	34	11	13.4	7	0	4.6	36.4%	9.0%	331.88	9	9.6%
17SPBUS04	2017 Spring	Business	901174133	7.1	63.0	7.4	8	5.06%	2.19	56	15	14.5	12	0	4.3	26.7%	47.0%	346.12	13	9.2%
17SPBUS04	2017 Spring	Business	901097966	5.5	72.2	6.4	8	10.76%	7.92	14	7	14.6	4	0	8.0	28.6%	43.0%	132.84	2	4.4%
17SPBUS04	2017 Spring	Business	901097966	7.9	67.6	7.4	17	2.83%	5.99	36	24	16.2	12	0	6.5	8.3%	17.0%	84.35	6	2.6%
17SPBUS04	2017 Spring	Business	901068157	6.7	62.9	7.5	11	6.29%	4.85	63	11	15.9	7	0	8.4	27.3%	18.0%	402.38	11	11.0%
17SPBUS04	2017 Spring	Business	901179573	9.2	59.5	8.4	9	5.38%	3.21	25	11	18.6	5	0	6.8	18.2%	18.0%	346.99	12	9.6%
17SPBUS04	2017 Spring	Business	901153794	8.3	62.6	7.5	8	7.95%	3.54	37	8	17.3	5	0	7.7	37.5%	38.0%	202.61	5	6.0%
17SPBUS04	2017 Spring	Business	901168982	10.8	48.1	10.4	9	6.08%	2.54	90	8	22.6	4	2	16.3	12.5%	25.0%	340.97	12	8.7%
17SPBUS04	2017 Spring	Business	901106060	8.6	66.8	7.3	6	8.33%	1.00	59	6	22.0	1	1	10.4	33.3%	0.0%	143.76	3	3.2%
17SPKINS03	2017 Spring	Kinesiology	901225530	10.0	48.9	9.6	11	4.17%	1.08	32	20	13.2	14	1	9.4	15.0%	5.0%	326.36	15	8.1%
17SPKINS03	2017 Spring	Kinesiology	901116727	11.1	50.0	9.5	5	5.33%	1.31	85	12	17.2	5	1	8.9	16.7%	0.0%	345.73	13	9.7%
17SPKINS03	2017 Spring	Kinesiology	901250043	12.9	67.4	10.6	2	10.39%	10.66	27	3	35.3	0	2	14.2	33.3%	67.0%	60.07	1	1.6%
17SPKINS03	2017 Spring	Kinesiology	901194740	11.6	33.0	11.5	11	3.68%	0.19	102	22	13.6	18	2	12.2	4.5%	9.0%	666.50	38	18.4%
17SPKINS03	2017 Spring	Kinesiology	901225530	8.5	66.5	7.6	5	11.73%	3.26	14	7	13.4	3	0	8.5	0.0%	29.0%	356.88	6	9.8%
17SPKINS03	2017 Spring	Kinesiology	901250043	10.2	46.6	9.9	11	4.37%	1.13	34	20	12.6	15	1	9.2	10.0%	10.0%	339.60	15	8.3%
17SPKINS03	2017 Spring	Kinesiology	901025755	13.0	47.2	11.1	11	6.37%	2.68	85	9	19.2	3	0	9.9	11.1%	0.0%	413.61	13	11.3%
17SPKINS03	2017 Spring	Kinesiology	901221092	13.7	31.7	12.8	3	10.19%	1.90	63	6	18.0	4	0	4.4	0.0%	17.0%	343.28	7	7.1%
17SPKINS03	2017 Spring	Kinesiology	901163036	9.5	54.9	8.9	3	7.05%	1.39	114	7	22.3	3	1	12.3	0.0%	0.0%	385.85	10	9.7%
17SPKINS03	2017 Spring	Kinesiology	900189201	7.9	67.8	7.7	3	8.99%	3.81	69	8	15.3	4	0	7.2	37.5%	13.0%	261.00	5	5.4%
17SPKINS03	2017 Spring	Kinesiology	901075495	8.7	63.4	6.6	7	4.72%	1.09	50	21	11.1	17	1	8.8	4.8%	5.0%	465.18	20	11.4%
17SPKINS03	2017 Spring	Kinesiology	901025755	13.6	31.7	12.8	3	10.19%	1.91	63	6	18.0	4	0	4.4	0.0%	17.0%	344.22	7	7.1%

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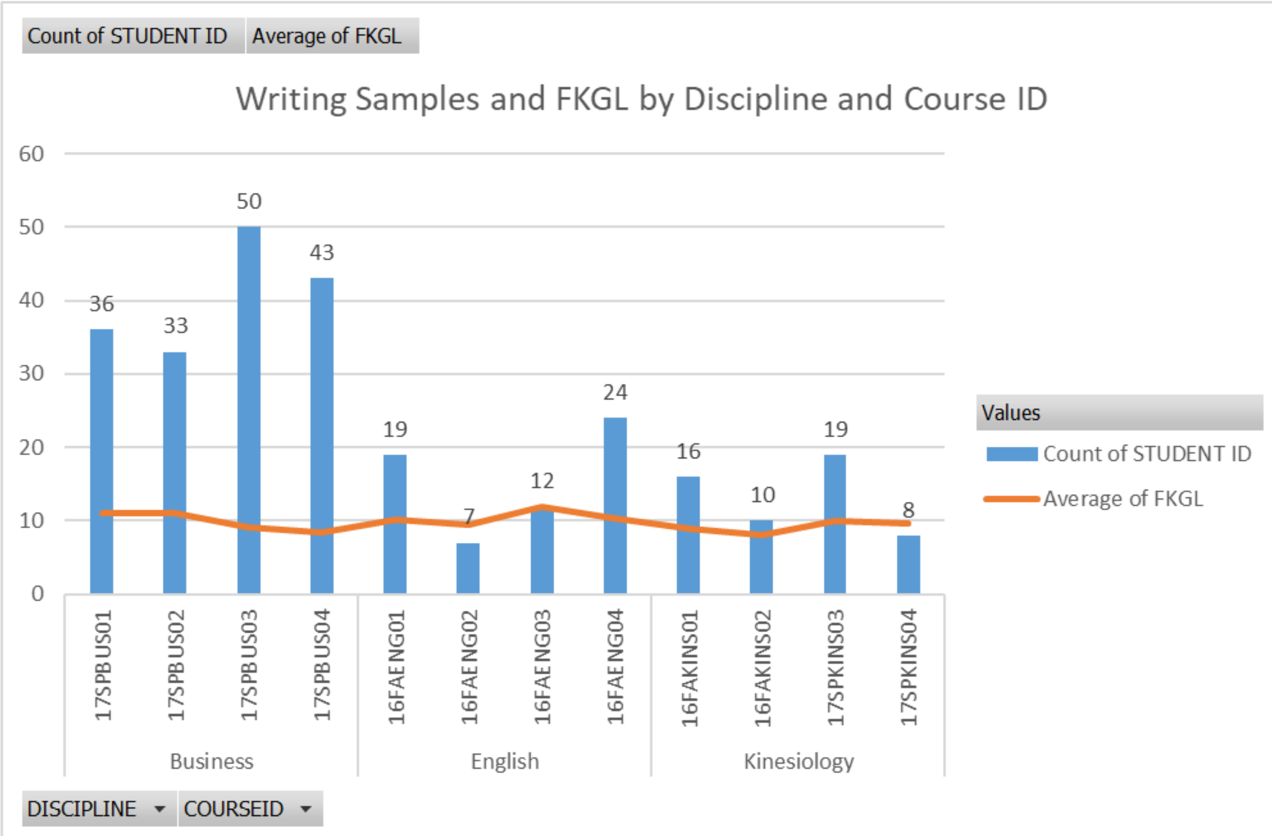
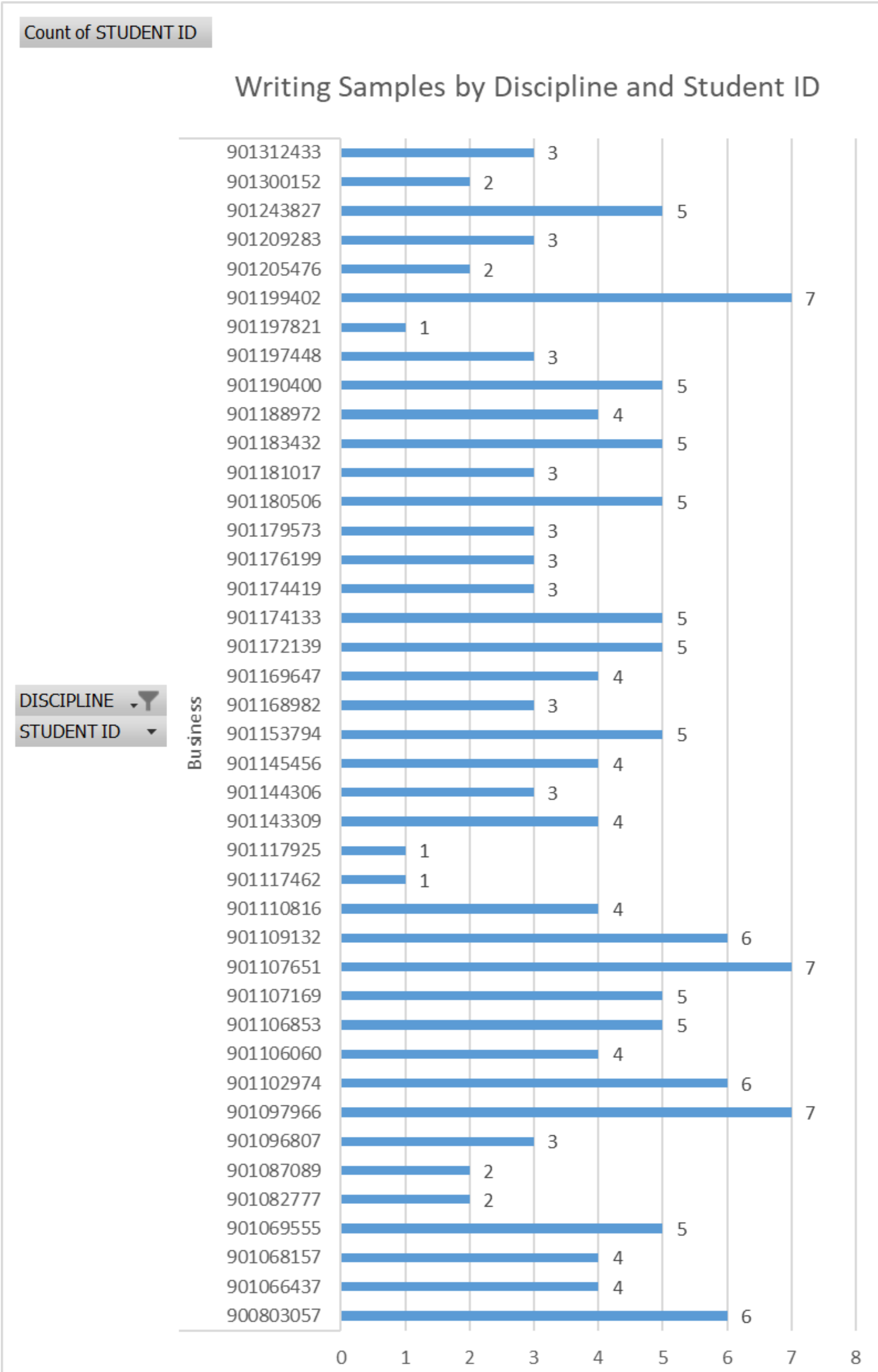
17SPKINS03	2017 Spring	Kinesiology	901297992	12.4	44.0	11.2	3	11.46%	1.77	50	6	16.0	3	1	12.2	0.0%	0.0%	554.66	10	14.8%
17SPKINS03	2017 Spring	Kinesiology	900189201	13.1	41.1	9.6	4	4.93%	0.41	44	24	9.3	21	0	6.0	12.5%	8.0%	283.71	13	8.1%
17SPKINS03	2017 Spring	Kinesiology	901197151	12.5	45.5	11.1	5	7.02%	1.81	87	7	22.4	1	1	7.1	28.6%	0.0%	336.02	9	9.1%
17SPKINS03	2017 Spring	Kinesiology	901075495	7.8	63.1	8.3	5	9.24%	6.61	83	7	17.0	5	0	7.5	14.3%	29.0%	335.34	7	9.5%
17SPKINS03	2017 Spring	Kinesiology	901183519	10.5	39.0	10.2	8	3.36%	0.39	87	29	11.3	21	0	8.1	6.9%	7.0%	466.64	30	12.3%
17SPKINS03	2017 Spring	Kinesiology	901116727	10.9	48.5	11.0	2	8.86%	3.25	32	6	20.7	1	0	4.5	16.7%	0.0%	287.65	6	7.6%
17SPKINS03	2017 Spring	Kinesiology	901183519	11.5	61.1	10.6	6	9.65%	8.74	25	4	28.5	1	1	21.3	25.0%	25.0%	409.24	8	9.9%
17SPKINS04	2017 Spring	Kinesiology	901183519	10.4	60.9	9.6	10	4.56%	3.84	28	10	24.1	2	0	9.6	0.0%	40.0%	135.49	6	3.9%
17SPKINS04	2017 Spring	Kinesiology	901183519	17.4	47.5	15.7	6	7.58%	6.32	71	4	36.3	0	1	12.4	25.0%	50.0%	112.40	3	2.7%
17SPKINS04	2017 Spring	Kinesiology	901116727	8.6	70.8	8.1	10	5.88%	4.78	8	9	20.8	5	0	7.2	22.2%	33.0%	164.34	5	4.0%
17SPKINS04	2017 Spring	Kinesiology	901221092	9.7	64.6	8.0	3	12.79%	2.53	63	4	21.5	0	0	2.9	25.0%	0.0%	73.93	1	2.1%
17SPKINS04	2017 Spring	Kinesiology	900189201	10.9	57.3	9.3	8	8.70%	4.28	190	8	15.8	4	0	7.3	37.5%	25.0%	142.49	3	3.0%
17SPKINS04	2017 Spring	Kinesiology	900789751	13.9	27.4	11.8	4	6.61%	0.24	25	15	11.1	12	0	8.6	6.7%	0.0%	569.16	20	15.5%
17SPKINS04	2017 Spring	Kinesiology	901116727	9.9	64.6	6.0	1	11.87%	0.30	35	9	10.3	8	0	7.7	0.0%	0.0%	430.30	8	9.2%
17SPKINS04	2017 Spring	Kinesiology	901271401	10.9	44.9	8.9	8	6.89%	1.79	20	12	13.3	8	0	8.7	0.0%	17.0%	347.90	12	8.3%
16FAKINS01	2016 Fall	Kinesiology	901275197	14.0	36.0	13.0	18	2.86%	1.98	61	16	24.0	6	4	11.7	31.3%	19.0%	634.60	34	17.0%
16FAKINS01	2016 Fall	Kinesiology	901275197	12.4	55.3	10.7	6	4.47%	3.69	70	12	20.5	5	2	13.9	33.3%	25.0%	230.19	10	6.2%
16FAKINS01	2016 Fall	Kinesiology	901297992	10.0	63.5	8.7	5	6.43%	4.60	55	9	19.0	5	1	8.5	0.0%	11.0%	235.71	8	6.6%
16FAKINS01	2016 Fall	Kinesiology	901163036	25.6	-7.3	15.5	0	22.45%	1.38	0	5	9.8	5	0	3.7	0.0%	0.0%	94.41	2	1.9%
16FAKINS01	2016 Fall	Kinesiology	901178494	10.1	62.8	9.2	5	5.90%	4.77	119	9	20.7	4	2	13.4	22.2%	22.0%	113.77	4	3.0%
16FAKINS01	2016 Fall	Kinesiology	901178494	8.3	74.3	6.8	5	5.99%	4.43	90	11	16.7	6	0	7.5	9.1%	18.0%	179.36	6	5.5%
16FAKINS01	2016 Fall	Kinesiology	901297992	9.5	68.3	8.0	6	7.09%	4.18	53	8	19.4	3	0	7.4	12.5%	13.0%	227.12	6	6.4%
16FAKINS01	2016 Fall	Kinesiology	901194740	6.0	82.8	5.3	5	8.67%	3.60	35	9	14.1	6	0	10.8	11.1%	33.0%	102.26	2	3.3%
16FAKINS01	2016 Fall	Kinesiology	901075495	6.3	78.0	5.4	1	9.24%	6.83	47	10	11.9	7	0	7.4	10.0%	50.0%	51.67	1	1.8%
16FAKINS01	2016 Fall	Kinesiology	901196900	9.0	69.4	8.1	9	5.61%	6.73	36	10	19.6	3	0	9.1	0.0%	10.0%	188.02	6	5.5%
16FAKINS01	2016 Fall	Kinesiology	901297992	7.6	76.7	6.5	4	7.06%	6.64	46	9	17.3	4	0	6.7	11.1%	33.0%	186.26	5	4.2%
16FAKINS01	2016 Fall	Kinesiology	901163036	12.7	61.4	11.4	7	6.83%	6.61	27	5	32.2	0	1	11.5	60.0%	40.0%	171.49	4	3.5%
16FAKINS01	2016 Fall	Kinesiology	901075495	5.9	77.2	6.0	8	6.04%	7.95	33	13	14.0	8	0	9.7	15.4%	54.0%	111.23	3	3.3%
16FAKINS01	2016 Fall	Kinesiology	901075495	16.9	23.8	11.5	0	10.48%	0.00	8	10	10.5	8	0	5.9	0.0%	10.0%	212.86	6	5.3%
16FAKINS01	2016 Fall	Kinesiology	901009274	13.4	48.1	12.5	22	3.09%	4.34	103	14	25.4	3	2	10.1	35.7%	14.0%	274.48	18	8.2%
16FAKINS01	2016 Fall	Kinesiology	901202590	6.1	73.4	5.4	11	8.99%	4.92	55	12	10.2	10	0	5.2	0.0%	42.0%	143.46	3	4.2%
16FAKINS02	2016 Fall	Kinesiology	900789751	10.9	49.6	10.8	9	10.30%	1.41	62	6	17.8	4	0	11.7	0.0%	0.0%	397.50	7	9.6%
16FAKINS02	2016 Fall	Kinesiology	901275197	11.6	60.5	10.4	14	4.14%	4.49	26	10	26.6	2	3	11.5	10.0%	10.0%	122.15	5	3.5%
16FAKINS02	2016 Fall	Kinesiology	901009274	8.1	63.5	5.9	7	9.40%	1.35	10	13	9.0	11	0	6.9	0.0%	0.0%	493.81	11	11.9%
16FAKINS02	2016 Fall	Kinesiology	901009274	7.9	66.7	7.1	5	7.43%	2.52	39	8	18.5	2	0	6.6	25.0%	25.0%	310.10	7	8.8%
16FAKINS02	2016 Fall	Kinesiology	901275197	8.7	56.9	8.3	39	2.48%	3.63	74	20	22.2	7	5	13.0	30.0%	15.0%	218.57	16	5.8%
16FAKINS02	2016 Fall	Kinesiology	901202590	8.7	68.2	7.9	7	9.75%	4.38	62	6	18.8	3	0	10.9	0.0%	50.0%	117.46	2	2.8%
16FAKINS02	2016 Fall	Kinesiology	901196900	8.9	70.3	8.3	8	8.04%	5.07	75	6	22.8	0	0	5.4	16.7%	17.0%	98.63	2	2.3%
16FAKINS02	2016 Fall	Kinesiology	900789751	9.9	61.7	7.6	6	7.91%	0.77	26	10	13.9	6	0	7.6	30.0%	10.0%	361.42	9	7.9%
16FAKINS02	2016 Fall	Kinesiology	901178494	8.0	69.1	7.3	4	9.64%	2.94	155	7	16.3	3	0	8.3	14.3%	29.0%	351.39	7	10.2%
16FAKINS02	2016 Fall	Kinesiology	901075495	7.7	67.5	7.3	4	12.00%	3.73	0	7	13.1	5	0	9.0	14.3%	43.0%	353.27	6	9.0%
16FAENG01	2016 Fall	English	900909166	20.5	12.8	18.9	12	4.01%	1.08	41	8	34.3	0	3	8.0	37.5%	13.0%	838.45	41	20.1%
16FAENG01	2016 Fall	English	900336203	6.8	64.0	7.5	6	4.24%	6.15	27	18	14.4	12	0	6.3	16.7%	44.0%	464.61	18	10.6%
16FAENG01	2016 Fall	English	900336203	12.2	45.7	11.8	6	3.70%	2.13	42	15	19.8	8	2	11.0	13.3%	27.0%	484.42	25	11.2%
16FAENG01	2016 Fall	English	901112502	6.8	71.4	7.0	12	2.67%	7.15	36	31	13.3	22	2	11.3	9.7%	19.0%	259.04	17	6.3%
16FAENG01	2016 Fall	English	901191572	6.0	72.0	6.3	7	4.67%	6.47	45	19	12.4	12	0	7.4	21.1%	32.0%	413.90	16	10.4%
16FAENG01	2016 Fall	English	901195325	16.8	31.6	15.4	6	4.65%	0.59	83	8	29.6	1	1	10.6	12.5%	25.0%	577.95	24	14.9%
16FAENG01	2016 Fall	English	900909166	6.2	60.1	7.5	10	7.69%	4.48	47	13	11.0	11	0	4.7	23.1%	23.0%	609.93	14	14.2%
16FAENG01	2016 Fall	English	900887977	9.6	64.4	8.8	6	8.81%	4.45	65	6	20.8	3	2	13.9	50.0%	33.0%	536.47	11	13.5%
16FAENG01	2016 Fall	English	901171306	16.1	26.9	15.0	13	3.51%	0.33	48	14	22.4	5	1	7.9	14.3%	21.0%	809.89	46	20.0%
16FAENG01	2016 Fall	English	900909166	5.4	70.2	6.1	10	6.10%	4.95	38	17	10.6	15	0	5.4	17.6%	12.0%	423.52	13	10.3%
16FAENG01	2016 Fall	English	901191572	11.2	56.4	10.9	13	4.47%	2.12	68	10	24.6	2	3	17.9	30.0%	10.0%	371.91	15	8.7%
16FAENG01	2016 Fall	English	900336203	5.7	71.1	6.6	5	6.22%	4.24	41	13	13.6	8	0	8.4	23.1%	23.0%	412.86	11	9.5%
16FAENG01	2016 Fall	English	901195325	5.8	65.3	6.8	9	6.19%	6.72	15	16	11.1	12	0	9.8	12.5%	6.0%	464.35	13	11.1%
16FAENG01	2016 Fall	English	901112502	15.2	33.1	13.6	8	4.82%	1.11	81	12	19.0	7	2	14.2	16.7%	17.0%	427.08	18	10.0%
16FAENG01	2016 Fall	English	901191572	6.1	64.3	6.7	10	4.78%	4.26	69	23	10.0	17	0	7.7	8.7%	22.0%	576.73	22	13.8%
16FAENG01	2016 Fall	English	900887977	15.6	35.5	13.8	13	2.34%	1.33	25	18	26.1	8	6	23.8	27.8%	0.0%	555.67	48	13.7%
16FAENG01	2016 Fall	English	901112502	17.0	41.6	15.0	11	2.62%	2.65	38	19	22.1	13	2	34.3	26.3%	11.0%	298.13	21	7.3%

COURSEID	SEMESTER	DISCIPLINE	STUDENT ID	ARI	FRE	FKGL	GRAMMAR ERRORS	GRAMMAR ERRORS PER TOTAL WORDS	BAD PHRASE	TRANSITIONAL WORDS	TOTAL SENTENCES	AVG LENGTH	SHORT SENTENCES	LONG SENTENCES	SENTENCE VARIATION	PASSIVE VOICE	SIMPLE SENTENCE STARTS	VOCABULARY	VOCABULARY WORD COUNT	VOCABULARY WORD PCT
16FAENG01	2016 Fall	English	901171306	7.8	60.1	8.4	5	6.81%	2.36	34	16	10.1	13	0	7.6	12.5%	6.0%	507.49	13	11.8%
16FAENG01	2016 Fall	English	901195325	4.8	67.8	6.1	11	5.98%	3.61	53	20	9.2	16	1	9.3	10.0%	10.0%	436.19	13	10.1%
16FAENG02	2016 Fall	English	900909166	5.4	74.4	5.9	10	3.46%	4.15	37	25	12.7	18	0	8.2	12.0%	40.0%	121.69	6	4.1%
16FAENG02	2016 Fall	English	900336203	5.5	67.9	7.1	1	4.30%	1.06	71	18	14.2	13	0	8.5	22.2%	50.0%	36.40	2	1.2%
16FAENG02	2016 Fall	English	901191572	11.2	61.5	10.4	9	3.17%	7.41	63	15	23.1	3	0	10.5	6.7%	40.0%	87.19	6	2.9%
16FAENG02	2016 Fall	English	901112502	15.3	40.2	14.4	9	3.11%	2.01	95	12	29.5	3	2	18.6	8.3%	25.0%	433.16	26	11.6%
16FAENG02	2016 Fall	English	901195325	9.1	58.9	9.3	7	4.59%	5.45	76	14	17.1	6	2	10.8	7.1%	21.0%	224.76	9	4.9%
16FAENG02	2016 Fall	English	900887977	9.6	67.6	9.4	8	3.54%	5.04	63	12	25.9	3	2	10.5	0.0%	33.0%	104.13	5	3.2%
16FAENG02	2016 Fall	English	901171306	10.2	55.1	9.8	9	4.34%	3.56	47	15	16.9	6	0	7.3	6.7%	20.0%	252.19	11	6.5%
16FAENG03	2016 Fall	English	901112502	12.9	41.0	12.5	32	0.86%	1.71	63	60	21.4	27	8	15.5	15.0%	33.0%	246.30	56	6.2%
16FAENG03	2016 Fall	English	900909166	8.7	62.5	8.2	125	2.52%	2.23	56	37	11.8	26	1	10.2	2.7%	14.0%	280.67	20	7.1%
16FAENG03	2016 Fall	English	900336203	11.5	52.1	10.4	15	2.34%	1.88	55	25	18.8	11	0	8.8	12.0%	12.0%	269.47	23	7.2%
16FAENG03	2016 Fall	English	901171306	11.3	35.9	11.5	10	2.82%	1.62	66	21	18.6	6	0	9.1	9.5%	24.0%	412.63	31	10.7%
16FAENG03	2016 Fall	English	901191572	13.7	44.7	12.4	36	0.95%	2.73	70	52	22.3	14	6	10.1	13.5%	42.0%	292.23	60	7.6%
16FAENG03	2016 Fall	English	901195325	15.0	33.7	14.2	20	1.16%	2.13	58	37	25.6	13	10	14.5	13.5%	27.0%	412.40	67	10.7%
16FAENG03	2016 Fall	English	900909166	13.4	32.7	12.3	16	2.36%	1.13	63	19	24.5	6	3	11.7	5.3%	11.0%	775.97	67	19.5%
16FAENG03	2016 Fall	English	901112502	14.6	30.8	13.5	19	1.20%	1.01	86	37	24.7	11	7	12.5	24.3%	11.0%	560.07	96	14.6%
16FAENG03	2016 Fall	English	900336203	7.8	52.6	8.3	0	6.94%	1.86	15	12	13.2	8	0	12.0	0.0%	8.0%	208.29	6	5.5%
16FAENG03	2016 Fall	English	901195325	15.6	14.5	14.0	3	6.89%	0.76	41	14	11.4	10	1	13.1	7.1%	0.0%	319.72	12	8.6%
16FAENG03	2016 Fall	English	901191572	12.0	38.5	11.1	14	3.06%	3.64	74	12	30.0	1	3	13.6	16.7%	42.0%	375.40	27	10.3%
16FAENG03	2016 Fall	English	901171306	16.0	23.4	14.3	5	3.88%	1.27	40	13	21.8	5	2	15.4	0.0%	0.0%	455.52	26	13.3%
16FAENG04	2016 Fall	English	901085280	10.1	58.0	10.3	3	11.46%	4.13	135	4	24.0	1	1	10.2	0.0%	50.0%	198.87	3	4.3%
16FAENG04	2016 Fall	English	900917984	9.0	55.0	9.0	2	12.39%	3.49	59	6	14.8	3	0	7.8	0.0%	33.0%	264.71	4	6.4%
16FAENG04	2016 Fall	English	900917984	9.2	50.0	10.1	3	8.38%	2.19	82	8	16.4	4	0	7.8	12.5%	25.0%	124.68	3	2.8%
16FAENG04	2016 Fall	English	901177665	11.7	46.9	11.7	4	11.96%	3.71	2	5	18.4	2	0	5.1	20.0%	40.0%	121.42	2	3.2%
16FAENG04	2016 Fall	English	901172593	10.8	52.3	11.0	2	11.80%	4.47	119	4	23.3	0	0	2.2	0.0%	25.0%	197.39	3	5.0%
16FAENG04	2016 Fall	English	901120004	8.9	56.5	9.2	4	6.75%	4.38	75	10	16.3	4	0	4.6	0.0%	30.0%	221.06	6	5.5%
16FAENG04	2016 Fall	English	901191844	16.6	48.5	14.8	9	4.89%	5.92	83	6	37.5	1	4	17.0	16.7%	0.0%	107.72	4	3.1%
16FAENG04	2016 Fall	English	901115194	8.1	69.4	8.7	6	7.05%	7.92	30	7	22.3	2	0	5.9	0.0%	14.0%	116.98	3	2.9%
16FAENG04	2016 Fall	English	901112764	10.9	56.8	11.2	6	7.00%	5.31	94	6	26.2	1	1	8.6	0.0%	0.0%	343.16	9	9.3%
16FAENG04	2016 Fall	English	901180464	14.3	47.7	13.6	5	10.57%	5.09	68	3	34.7	0	1	10.0	0.0%	0.0%	186.76	3	3.7%
16FAENG04	2016 Fall	English	901190633	10.7	56.2	10.3	2	9.50%	3.75	106	6	19.3	1	0	6.8	0.0%	0.0%	108.11	2	3.2%
16FAENG04	2016 Fall	English	901175869	11.8	50.5	11.1	5	12.22%	5.13	132	4	22.5	1	0	8.6	0.0%	0.0%	323.58	5	8.4%
16FAENG04	2016 Fall	English	901192186	11.1	50.7	11.2	4	9.73%	2.89	36	5	22.6	1	0	7.5	0.0%	20.0%	451.37	9	11.1%
16FAENG04	2016 Fall	English	901011338	7.6	71.7	7.1	4	9.47%	4.47	25	7	16.6	3	0	6.2	14.3%	14.0%	111.11	2	3.1%
16FAENG04	2016 Fall	English	901093076	11.2	56.6	10.9	4	8.73%	7.23	79	5	25.2	1	1	10.1	0.0%	40.0%	96.45	2	2.7%
16FAENG04	2016 Fall	English	901078069	8.9	58.5	9.4	2	11.34%	3.48	73	5	19.4	2	0	8.0	0.0%	0.0%	186.81	3	4.8%
16FAENG04	2016 Fall	English	901080620	9.1	62.2	10.0	5	10.09%	9.30	42	5	21.8	1	0	10.6	0.0%	0.0%	183.12	3	4.1%
16FAENG04	2016 Fall	English	901176159	9.1	75.6	8.4	2	8.66%	5.14	85	5	25.4	1	1	12.1	20.0%	40.0%	112.85	2	2.2%
16FAENG04	2016 Fall	English	901173099	8.8	64.2	9.4	8	7.11%	6.24	78	7	22.1	3	1	11.1	0.0%	14.0%	41.72	1	1.1%
16FAENG04	2016 Fall	English	901176159	8.5	71.6	8.2	3	10.00%	10.71	40	5	22.0	2	1	13.4	0.0%	0.0%	59.03	1	1.2%
16FAENG04	2016 Fall	English	901176159	12.3	52.1	12.5	2	11.35%	2.08	15	3	32.3	0	0	3.8	0.0%	0.0%	208.33	3	4.7%
16FAENG04	2016 Fall	English	901062832	13.3	44.4	13.1	2	12.35%	3.25	31	3	29.7	0	1	11.0	0.0%	0.0%	111.11	2	2.7%
16FAENG04	2016 Fall	English	901177665	9.5	61.3	9.0	6	9.75%	3.95	73	6	18.8	3	0	7.9	16.7%	17.0%	242.79	5	5.9%
16FAENG04	2016 Fall	English	901088019	8.4	63.7	9.5	0	9.48%	2.84	13	5	23.2	0	0	7.0	0.0%	0.0%	190.32	3	3.8%



Count of STUDENT ID
Average of FKGL
Writing Samples and FKGL by Discipline and Course ID
60
50
40
30
20
10
0
36
33
50
43
19
7
12
24
16
10
19
8
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
Values
Count of STUDENT ID
Average of FKGL
DISCIPLINE
COURSEID



Count of STUDENT ID
Writing Samples by Discipline and Student ID
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901243827 5
901209283 3
901205476 2
901199402 7
901197821 1
901197448 3
901190400 5
901188972 4
901183432 5
901181017 3
901180506 5
901179573 3
901176199 3
901174419 3
901174133 5
901172139 5
901169647 4
901168982 3
901153794 5
901145456 4
901144306 3
901143309 4
901117925 1
901117462 1
901110816 4
901109132 6
901107651 7
901107169 5
901106853 5
901106060 4
901102974 6
901097966 7
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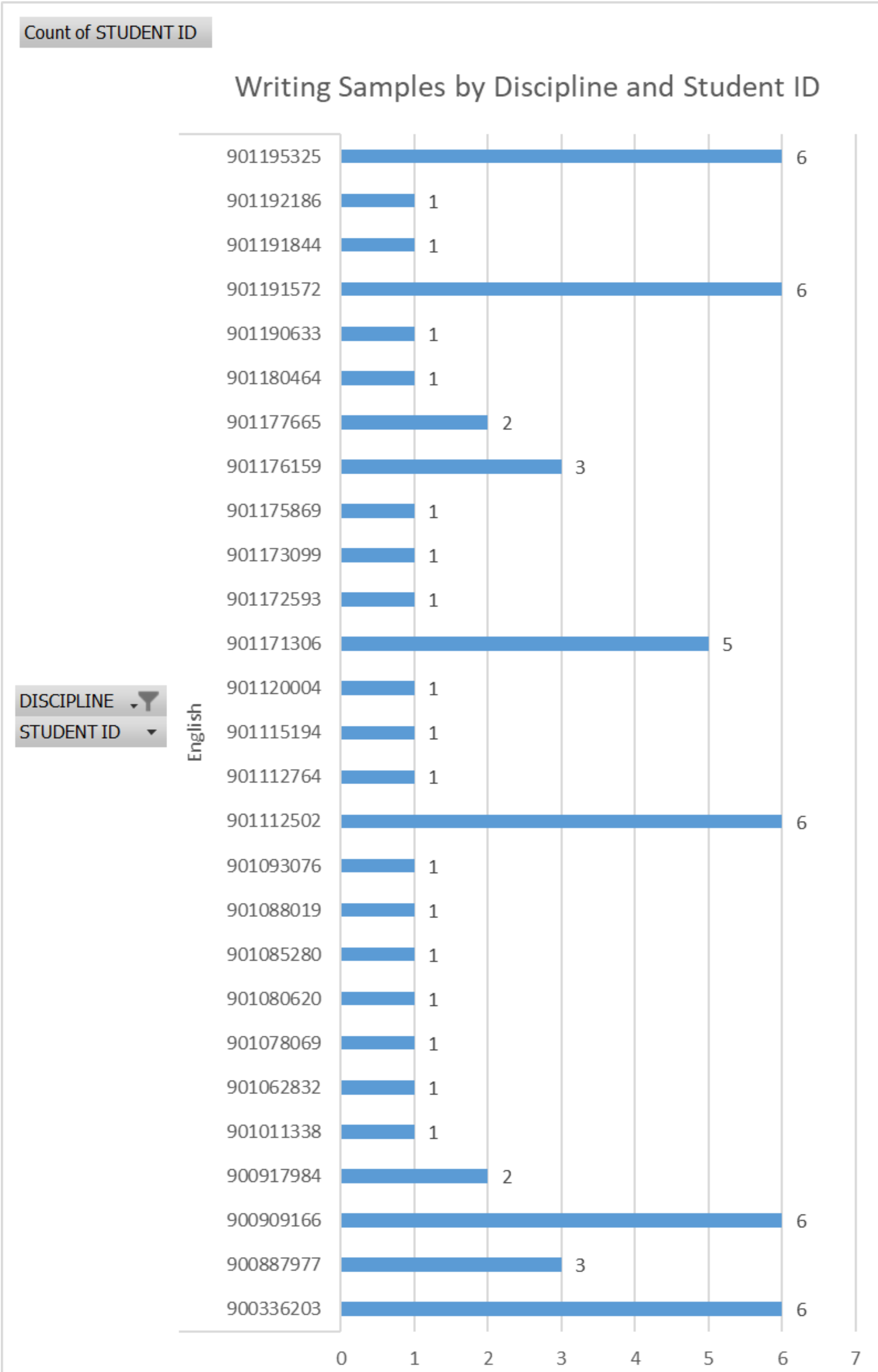
Count of STUDENT ID
Writing Samples by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901195325
901192186
901191844
901191572
901190633
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901177665
901176159
901175869
901173099
901172593
901171306
901120004
901115194
901112764
901112502
901093076
901088019
901085280
901080620
901078069
901062832
901011338
900917984
900909166
900887977
900336203
6
1
1
6
1
1
2
3
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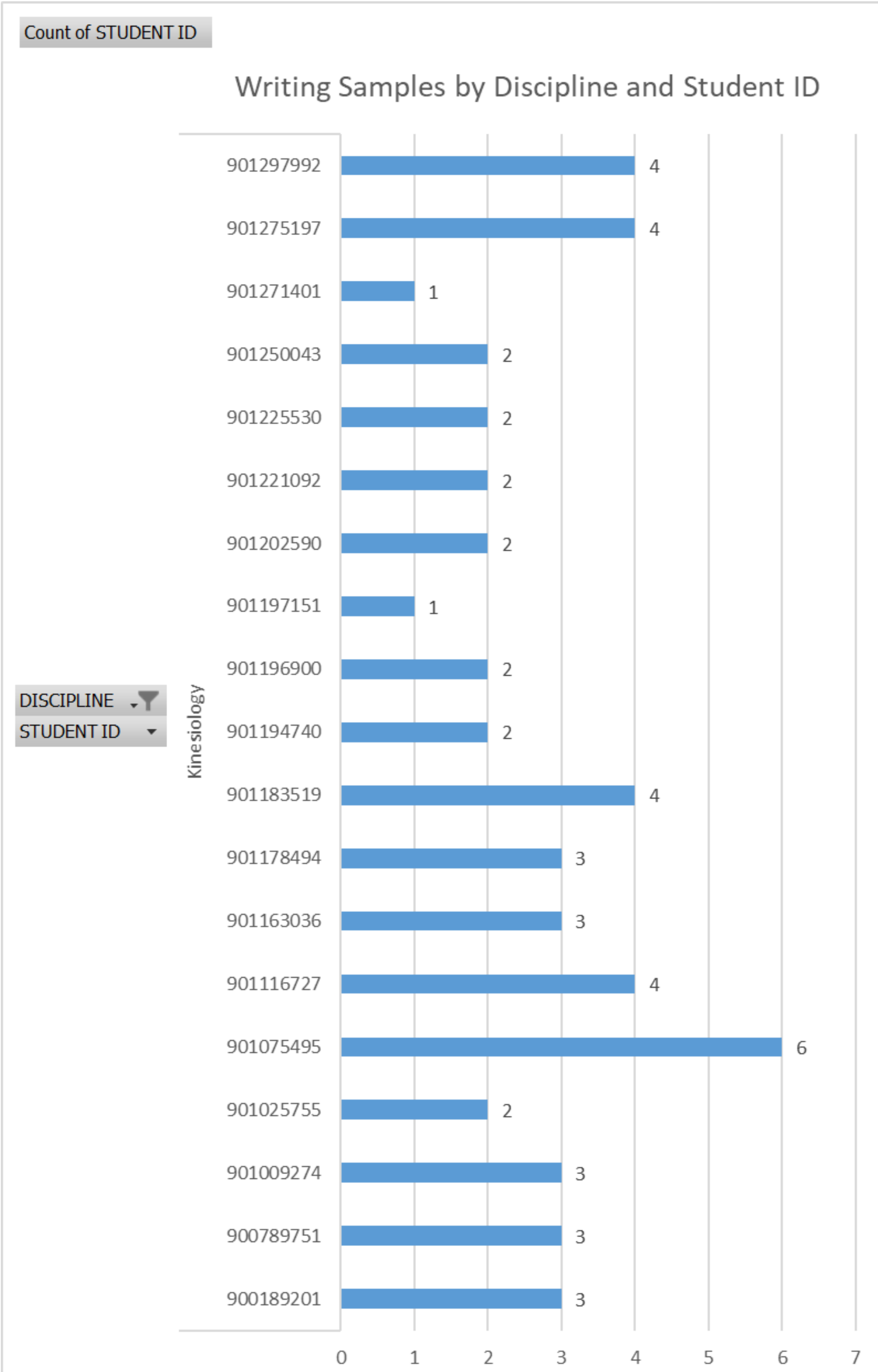

Count of STUDENT ID
Writing Samples by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
901297992
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901197151
901196900
901194740
901183519
901178494
901163036
901116727
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901009274
900789751
900189201
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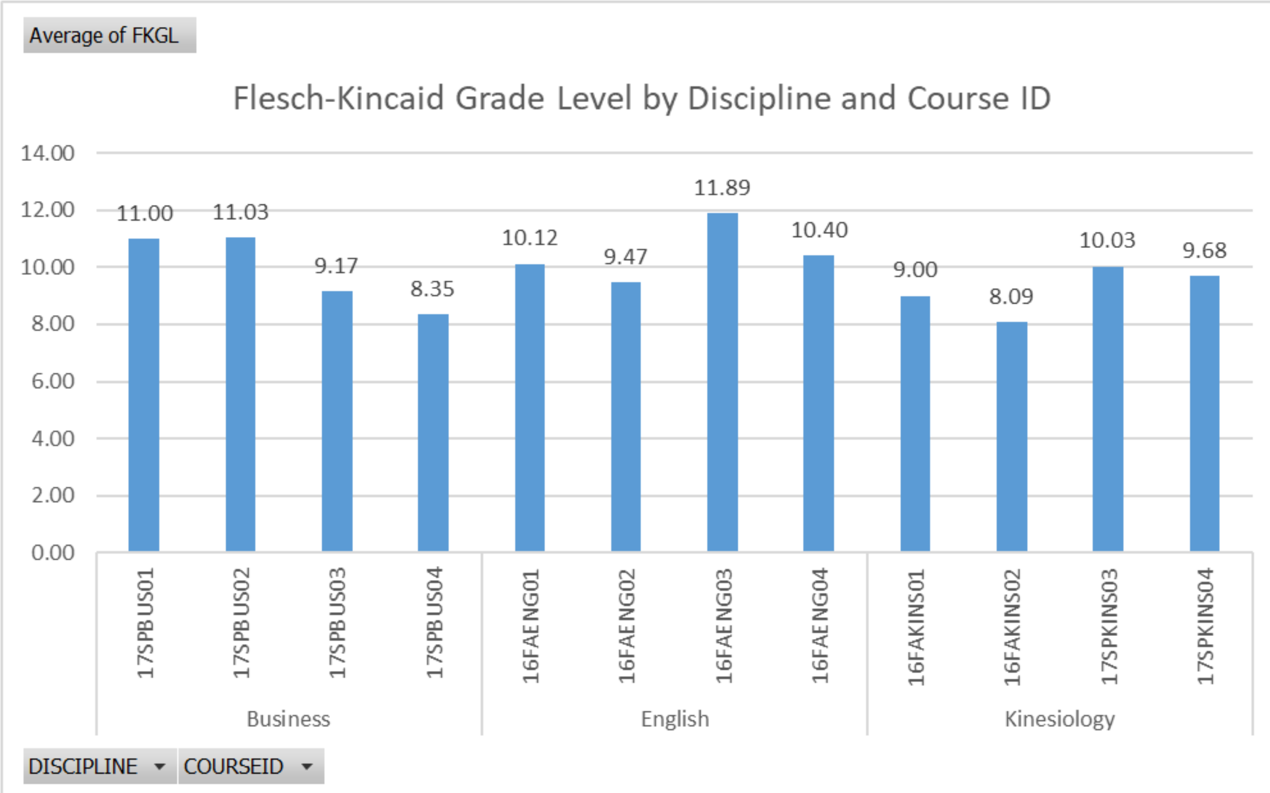

Average of FKGL
Flesch-Kincaid Grade Level by Discipline and Course ID
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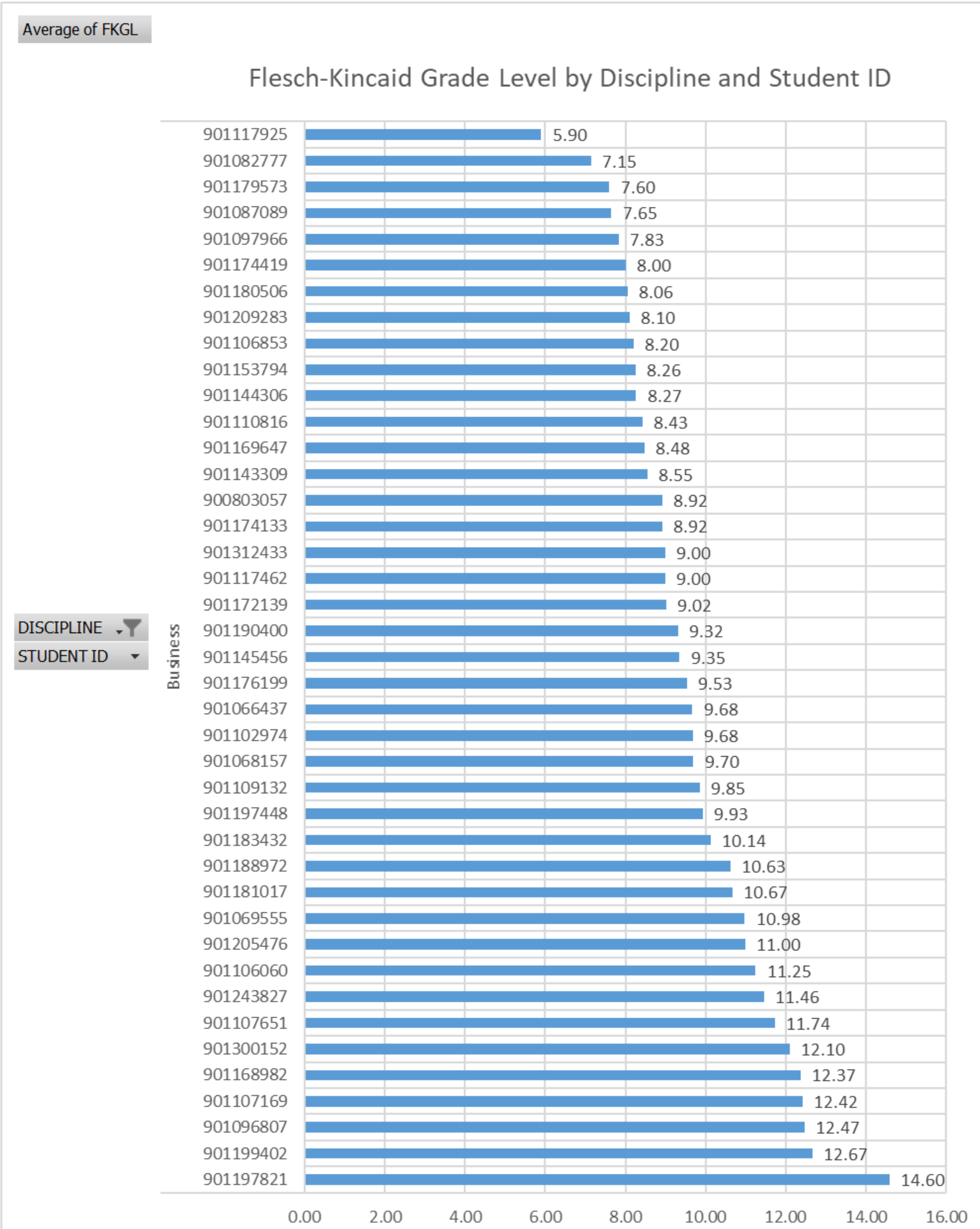
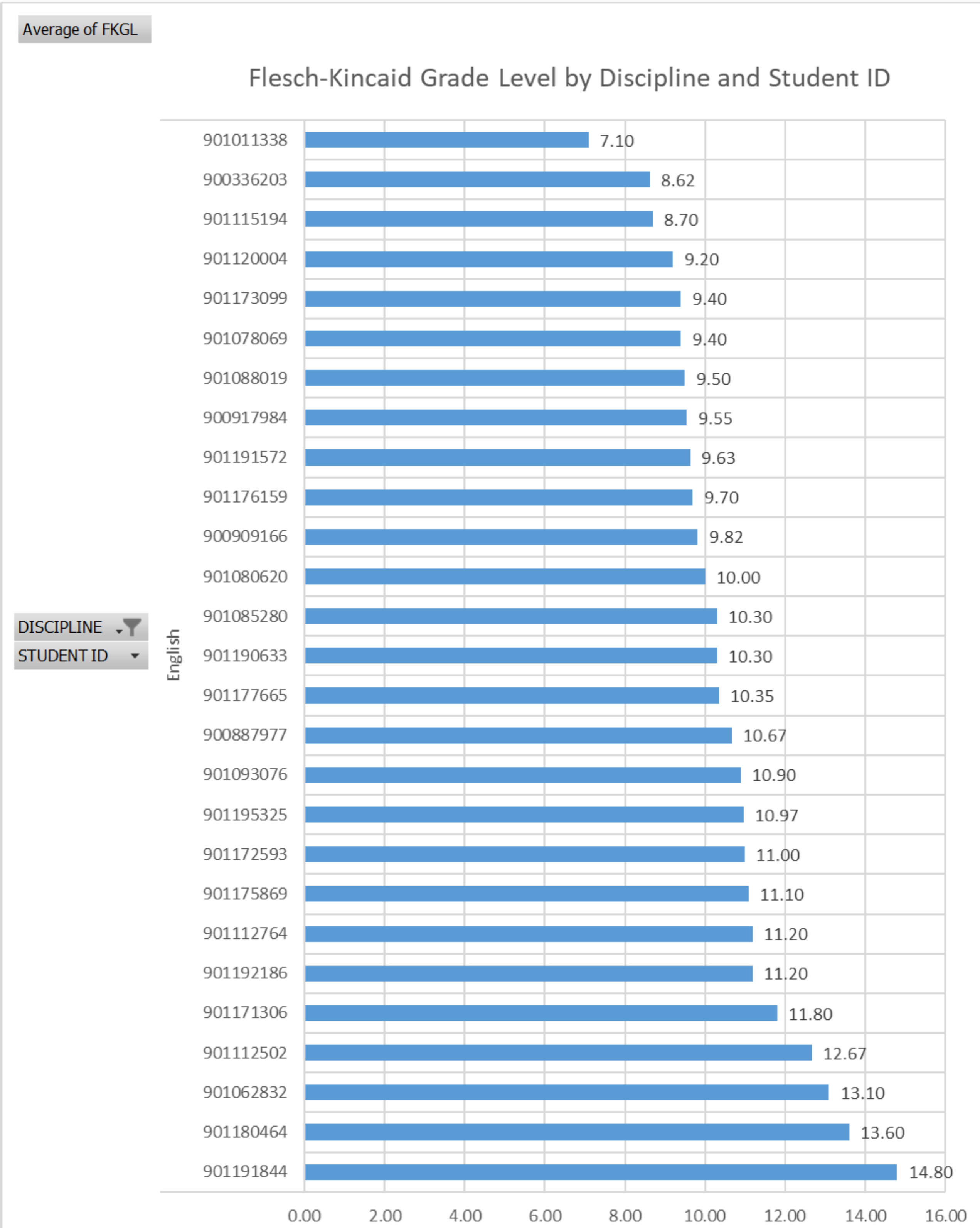
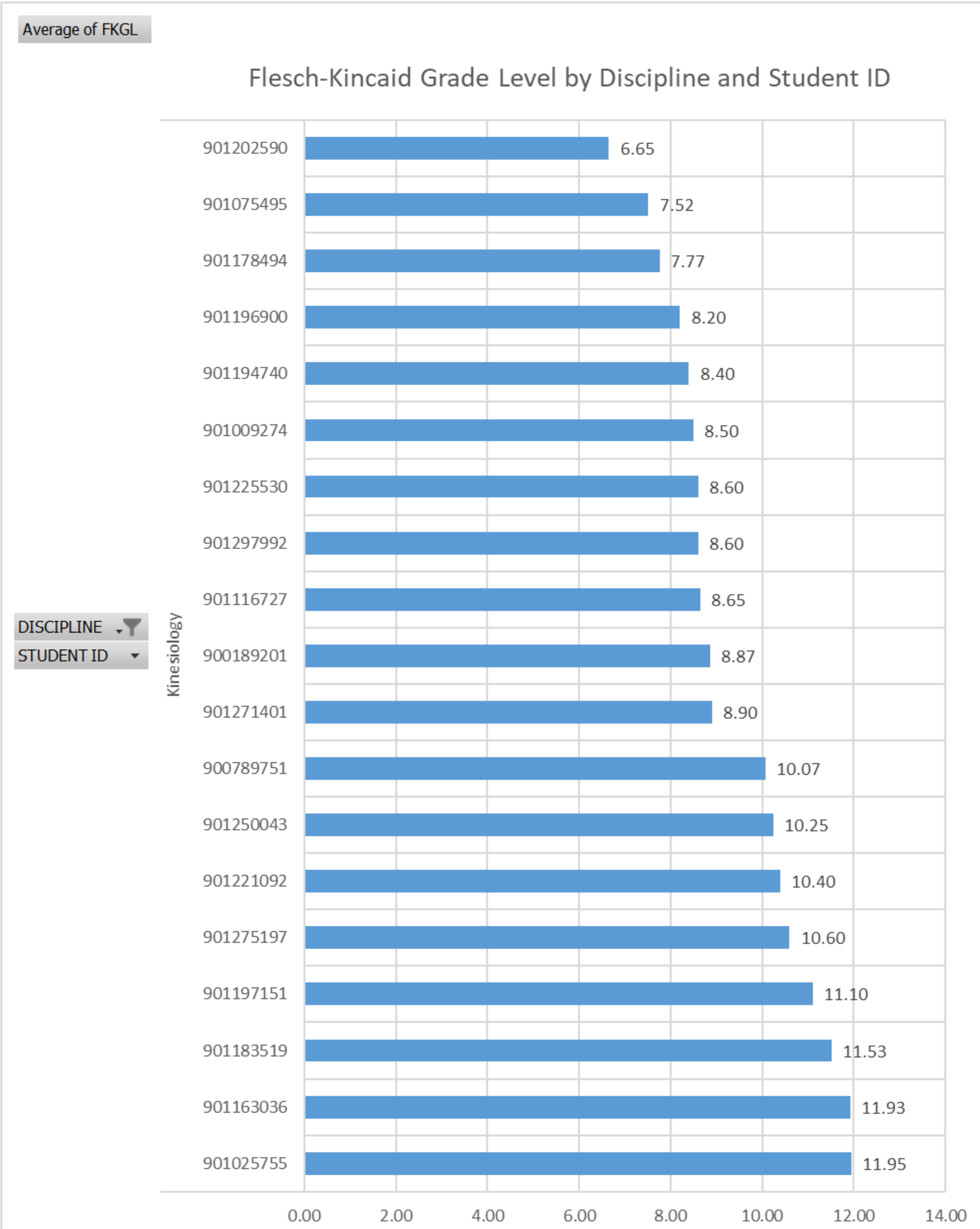
10.00
8.00
6.00
4.00
2.00
0.00
11.00
11.03
9.17
8.35
10.12
9.47
11.89
10.40
9.00
8.09
10.03
9.68
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID



Average of FKGL
Flesch-Kincaid Grade Level by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901117925 5.90
901082777 7.15
901179573 7.60
901087089 7.65
901097966 7.83
901174419 8.00
901180506 8.06
901209283 8.10
901106853 8.20
901153794 8.26
901144306 8.27
901110816 8.43
901169647 8.48
901143309 8.55
900803057 8.92
901174133 8.92
901312433 9.00
901117462 9.00
901172139 9.02
901190400 9.32
901145456 9.35
901176199 9.53
901066437 9.68
901102974 9.68
901068157 9.70
901109132 9.85
901197448 9.93
901183432 10.14
901188972 10.63
901181017 10.67
901069555 10.98
901205476 11.00
901106060 11.25
901243827 11.46
901107651 11.74
901300152 12.10
901168982 12.37
901107169 12.42
901096807 12.47
901199402 12.67
901197821 14.60
0.00 2.00 4.00 6.00 8.00 10.00 12.00 14.00 16.00


Average of FKGL
Flesch-Kincaid Grade Level by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901011338
900336203
901115194
901120004
901173099
901078069
901088019
900917984
901191572
901176159
900909166
901080620
901085280
901190633
901177665
900887977
901093076
901195325
901172593
901175869
901112764
901192186
901171306
901112502
901062832
901180464
901191844
7.10
8.62
8.70
9.20
9.40
9.40
9.50
9.55
9.63
9.70
9.82
10.00
10.30
10.30
10.35
10.67
10.90
10.97
11.00
11.10
11.20
11.20
11.80
12.67
13.10
13.60
14.80
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00


Average of FKGL
Flesch-Kincaid Grade Level by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
901202590
6.65
901075495
7.52
901178494
7.77
901196900
8.20
901194740
8.40
901009274
8.50
901225530
8.60
901297992
8.60
901116727
8.65
900189201
8.87
901271401
8.90
900789751
10.07
901250043
10.25
901221092
10.40
901275197
10.60
901197151
11.10
901183519
11.53
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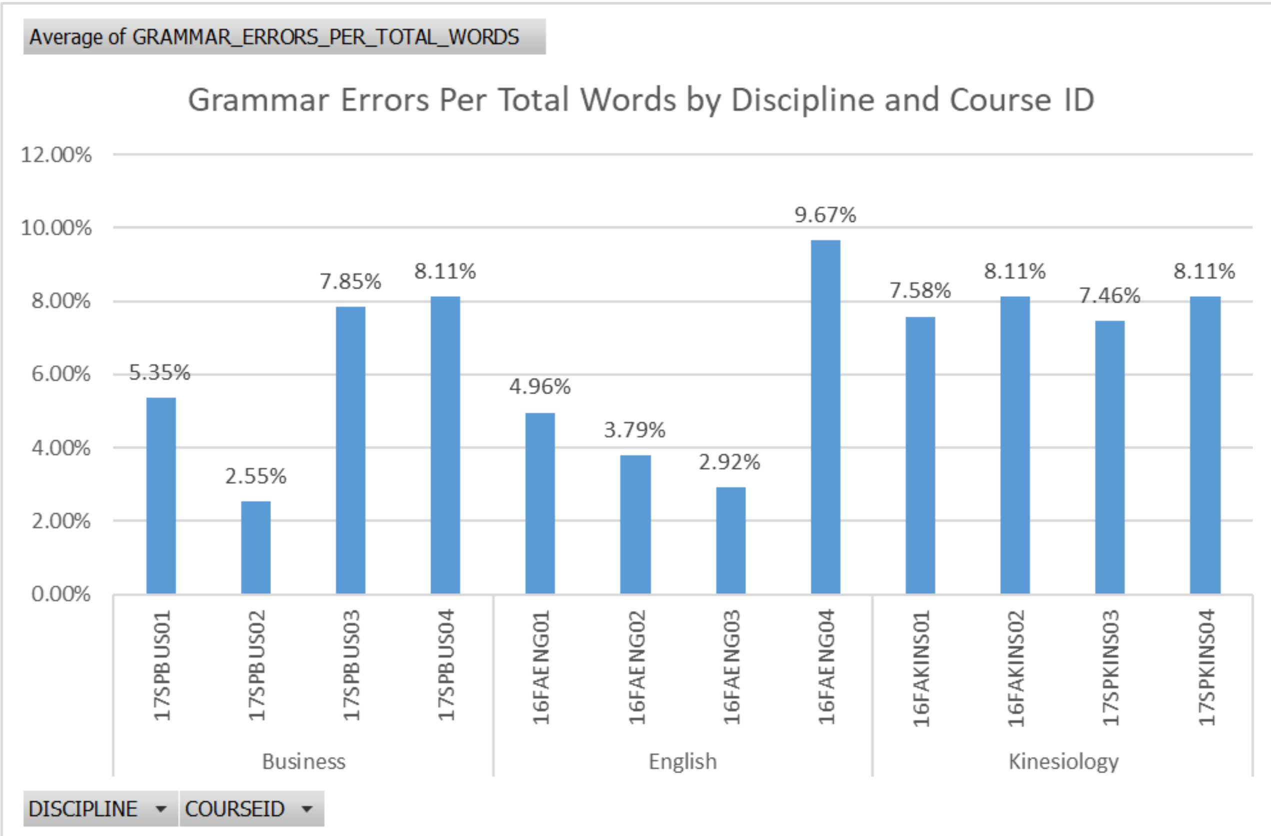
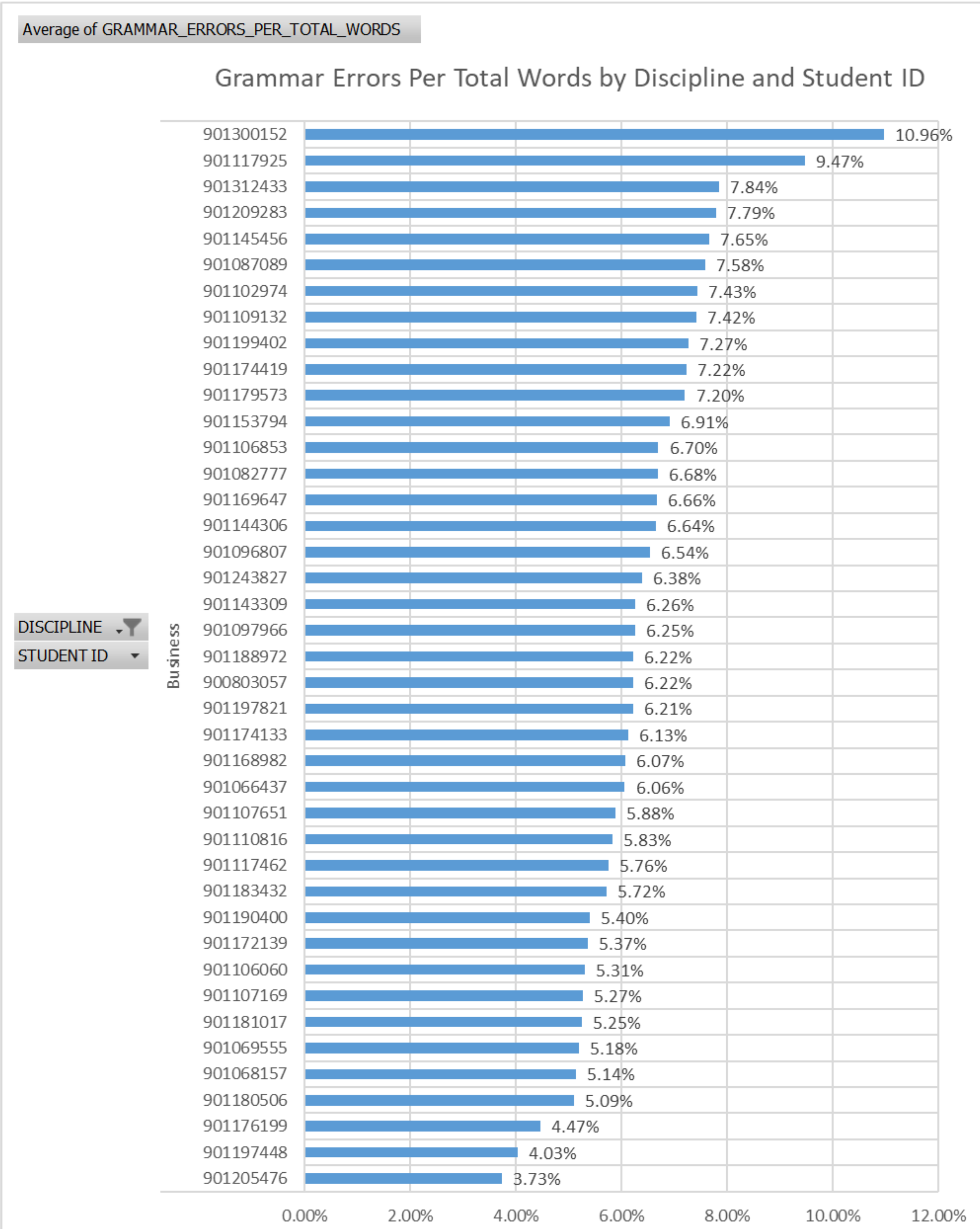
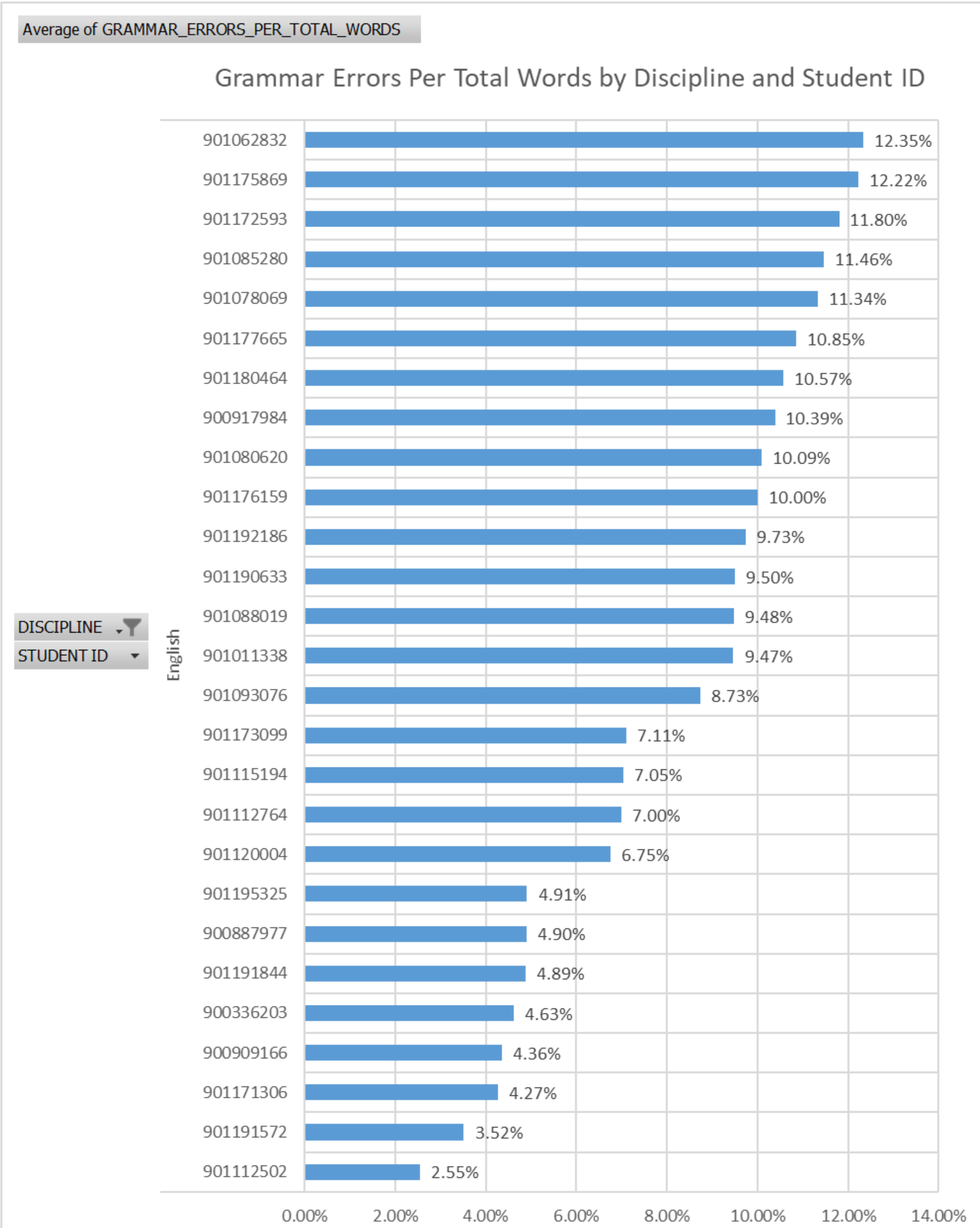
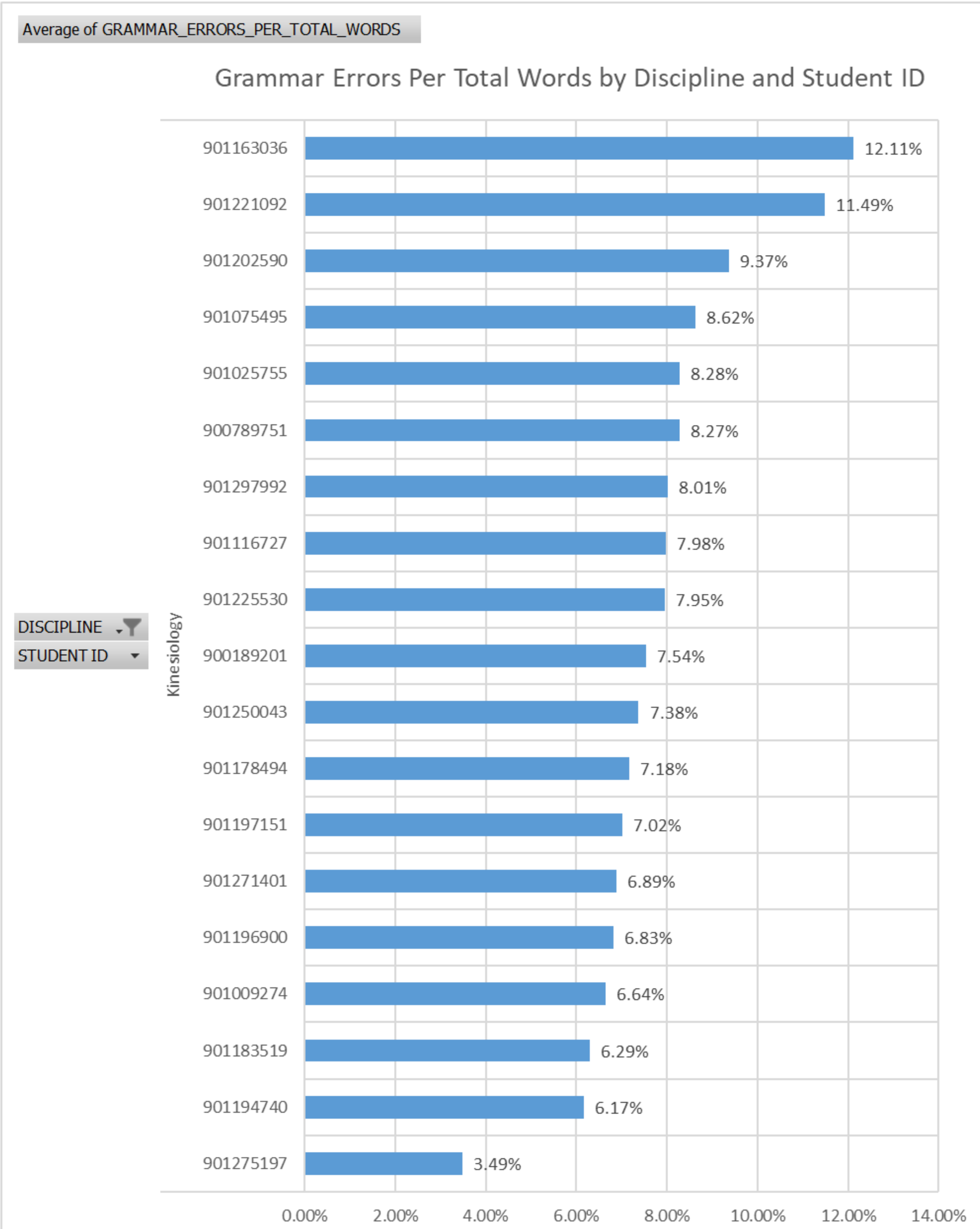
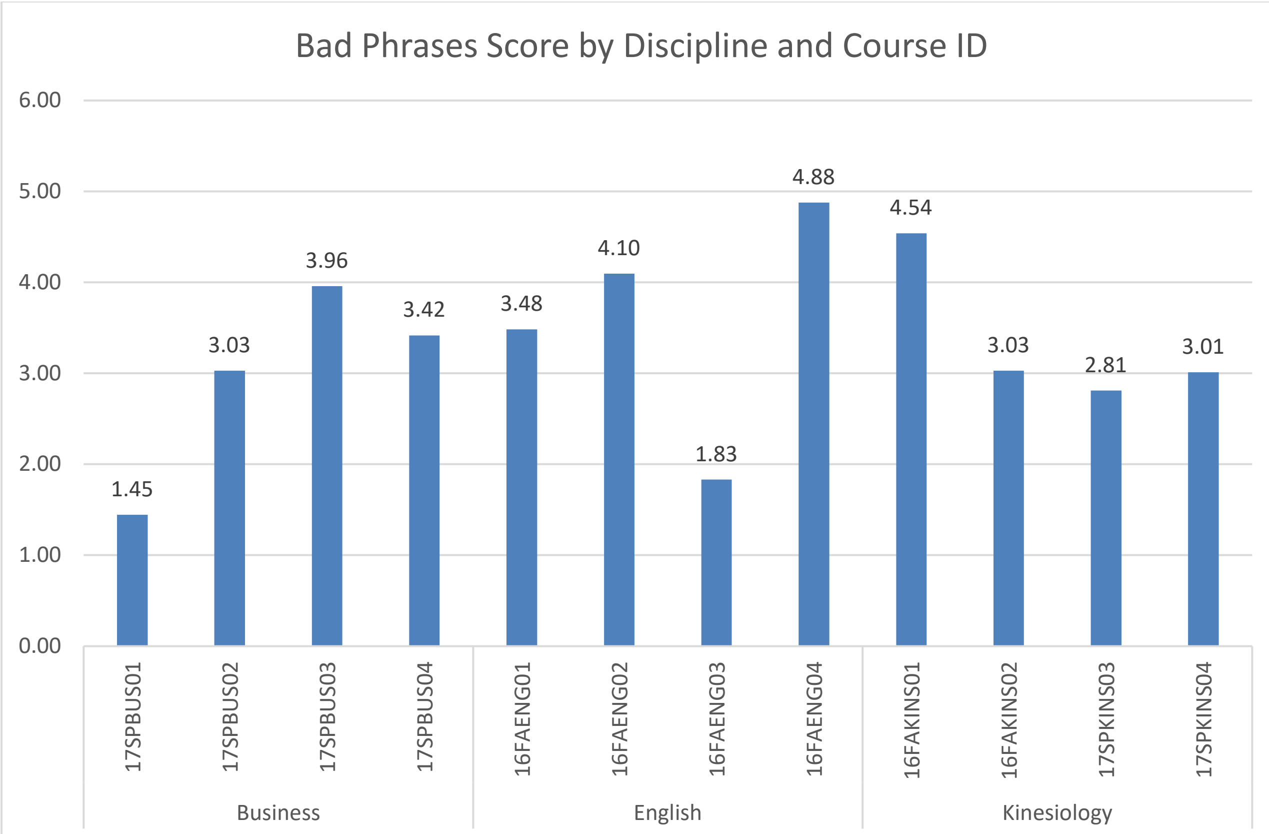
6.00
8.00
10.00
12.00
14.00


Average of GRAMMAR_ERRORS_PER_TOTAL_WORDS
Grammar Errors Per Total Words by Discipline and Course ID
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
5.35%
2.55%
7.85%
8.11%
4.96%
3.79%
2.92%
9.67%
7.58%
8.11%
7.46%
8.11%
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID


Average of GRAMMAR_ERRORS_PER_TOTAL_WORDS
Grammar Errors Per Total Words by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901300152
10.96%
901117925
9.47%
901312433
7.84%
901209283
7.79%
901145456
7.65%
901087089
7.58%
901102974
7.43%
901109132
7.42%
901199402
7.27%
901174419
7.22%
901179573
7.20%
901153794
6.91%
901106853
6.70%
901082777
6.68%
901169647
6.66%
901144306
6.64%
901096807
6.54%
901243827
6.38%
901143309
6.26%
901097966
6.25%
901188972
6.22%
900803057
6.22%
901197821
6.21%
901174133
6.13%
901168982
6.07%
901066437
6.06%
901107651
5.88%
901110816
5.83%
901117462
5.76%
901183432
5.72%
901190400
5.40%
901172139
5.37%
901106060
5.31%
901107169
5.27%
901181017
5.25%
901069555
5.18%
901068157
5.14%
901180506
5.09%
901176199
4.47%
901197448
4.03%
901205476
3.73%
0.00%
2.00%
4.00%
6.00%
8.00%
10.00%
12.00%


Average of GRAMMAR_ERRORS_PER_TOTAL_WORDS
Grammar Errors Per Total Words by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901062832
901175869
901172593
901085280
901078069
901177665
901180464
900917984
901080620
901176159
901192186
901190633
901088019
901011338
901093076
901173099
901115194
901112764
901120004
901195325
900887977
901191844
900336203
900909166
901171306
901191572
901112502
12.35%
12.22%
11.80%
11.46%
11.34%
10.85%
10.57%
10.39%
10.09%
10.00%
9.73%
9.50%
9.48%
9.47%
8.73%
7.11%
7.05%
7.00%
6.75%
4.91%
4.90%
4.89%
4.63%
4.36%
4.27%
3.52%
2.55%
0.00%
2.00%
4.00%
6.00%
8.00%
10.00%
12.00%
14.00%


Average of GRAMMAR_ERRORS_PER_TOTAL_WORDS
Grammar Errors Per Total Words by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
901163036
12.11%
901221092
11.49%
901202590
9.37%
901075495
8.62%
901025755
8.28%
900789751
8.27%
901297992
8.01%
901116727
7.98%
901225530
7.95%
900189201
7.54%
901250043
7.38%
901178494
7.18%
901197151
7.02%
901271401
6.89%
901196900
6.83%
901009274
6.64%
901183519
6.29%
901194740
6.17%
901275197
3.49%
0.00%
2.00%
4.00%
6.00%
8.00%
10.00%
12.00%
14.00%


Bad Phrases Score by Discipline and Course ID
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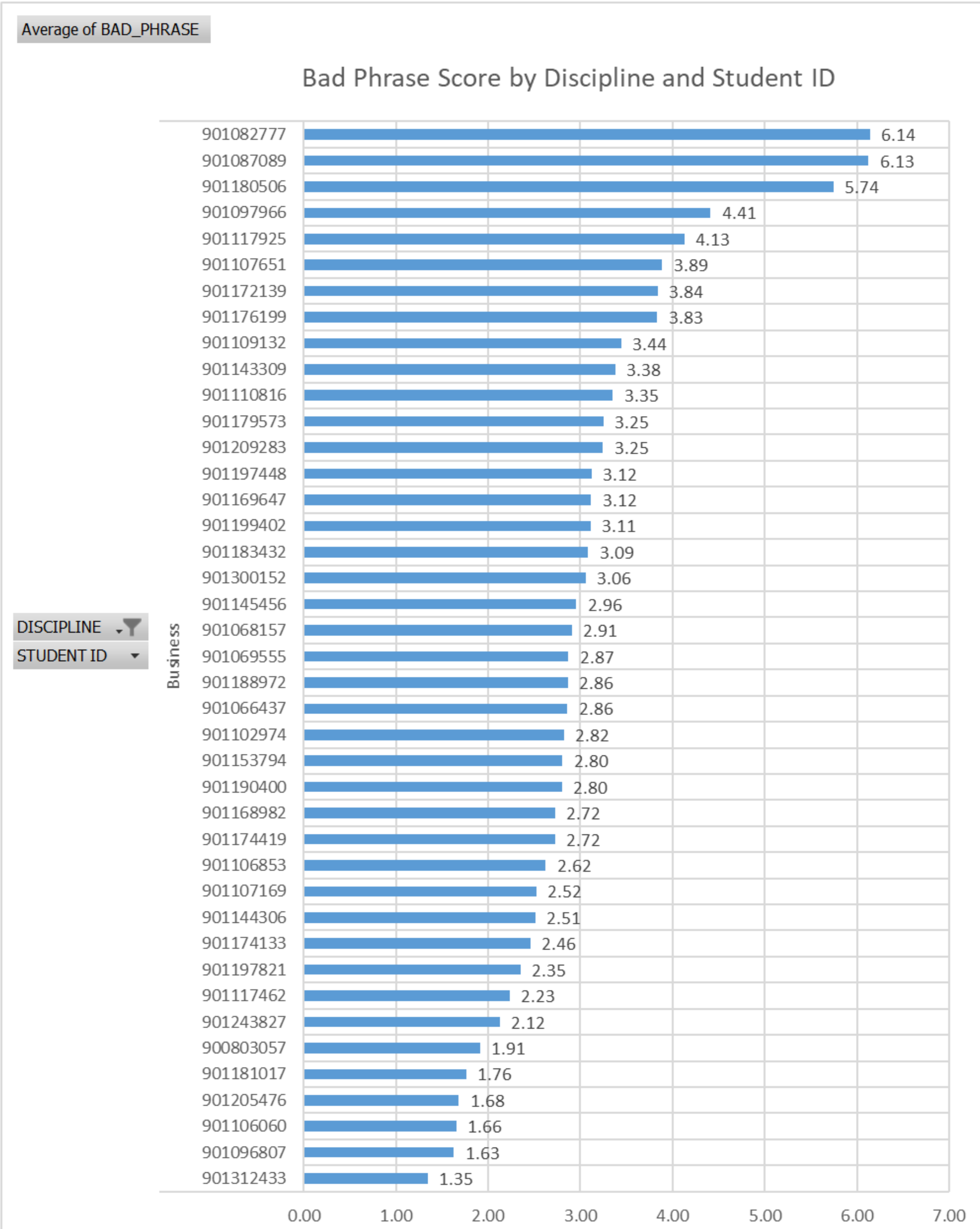
5.00
4.00
3.00
2.00
1.00
0.00
1.45
3.03
3.96
3.42
3.48
4.10
1.83
4.88
4.54
3.03
2.81
3.01
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology


Average of BAD_PHRASE
Bad Phrase Score by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901082777 6.14
901087089 6.13
901180506 5.74
901097966 4.41
901117925 4.13
901107651 3.89
901172139 3.84
901176199 3.83
901109132 3.44
901143309 3.38
901110816 3.35
901179573 3.25
901209283 3.25
901197448 3.12
901169647 3.12
901199402 3.11
901183432 3.09
901300152 3.06
901145456 2.96
901068157 2.91
901069555 2.87
901188972 2.86
901066437 2.86
901102974 2.82
901153794 2.80
901190400 2.80
901168982 2.72
901174419 2.72
901106853 2.62
901107169 2.52
901144306 2.51
901174133 2.46
901197821 2.35
901117462 2.23
901243827 2.12
900803057 1.91
901181017 1.76
901205476 1.68
901106060 1.66
901096807 1.63
901312433 1.35
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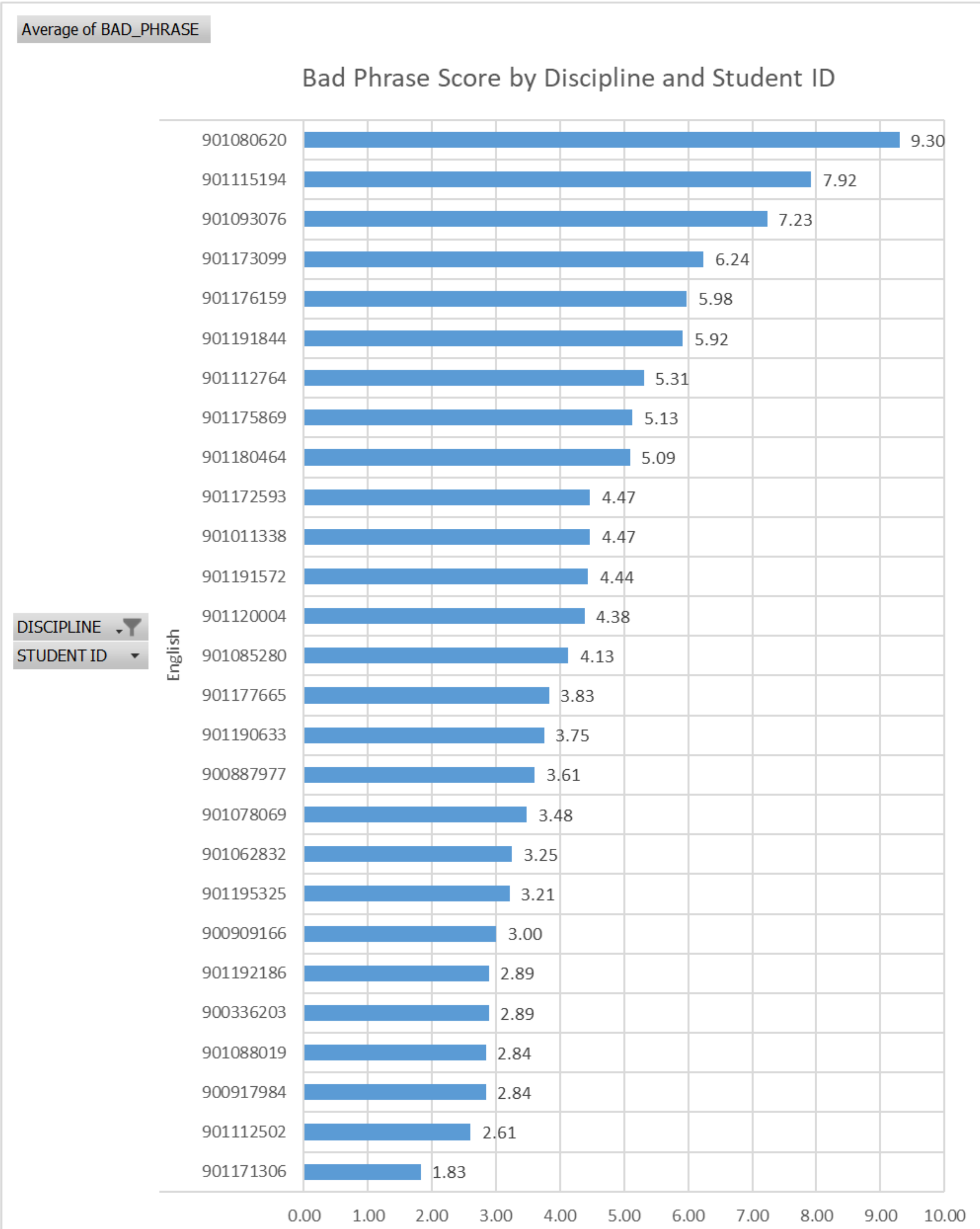
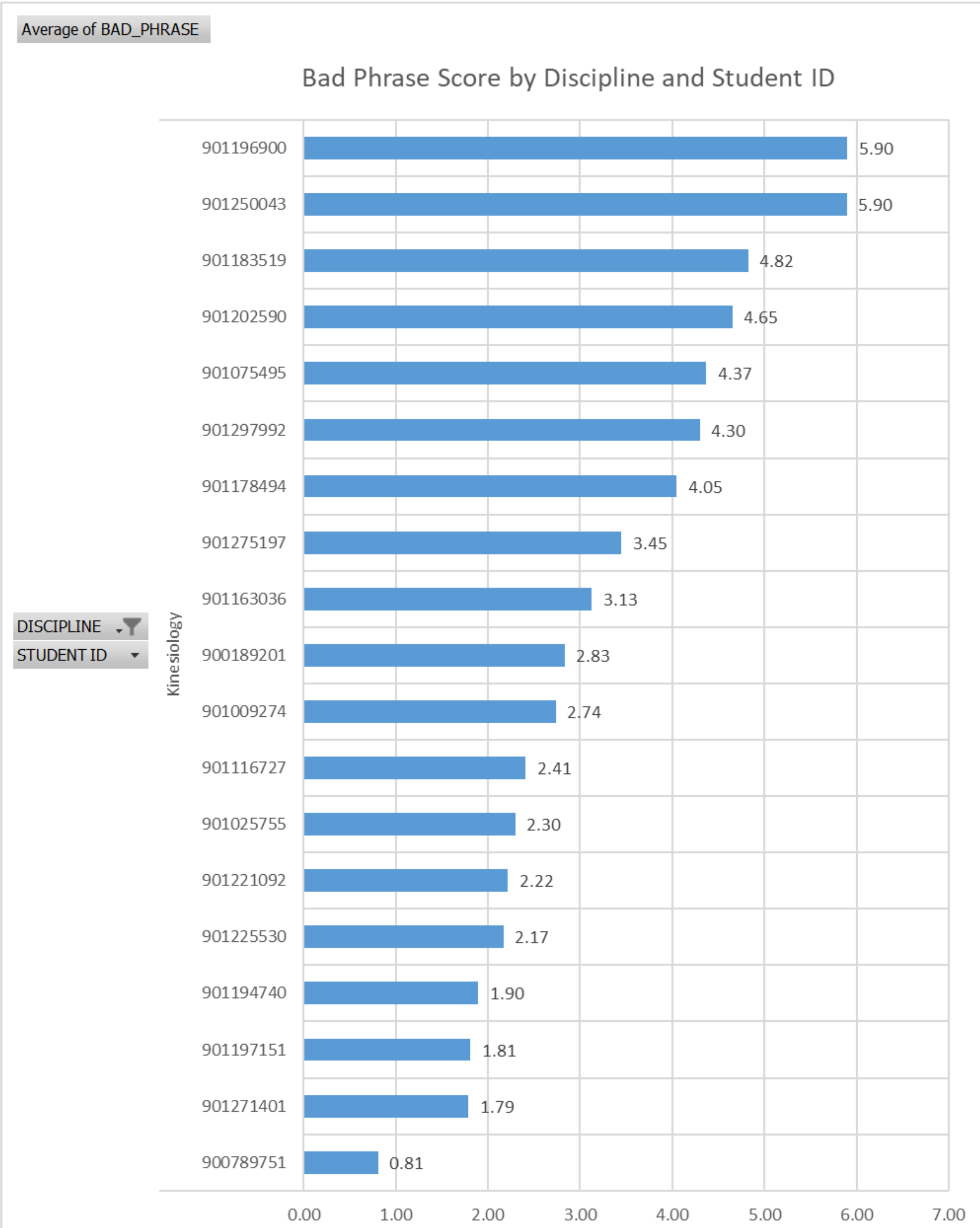
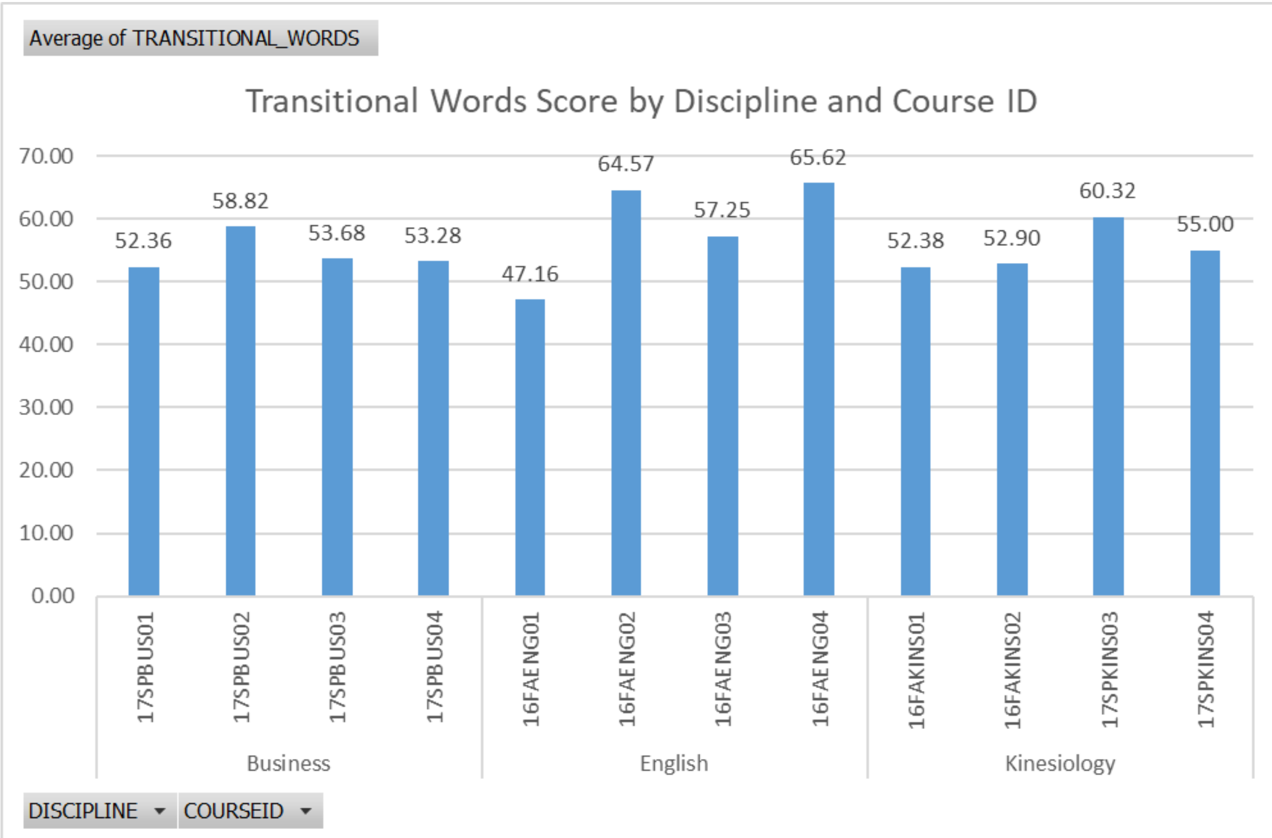
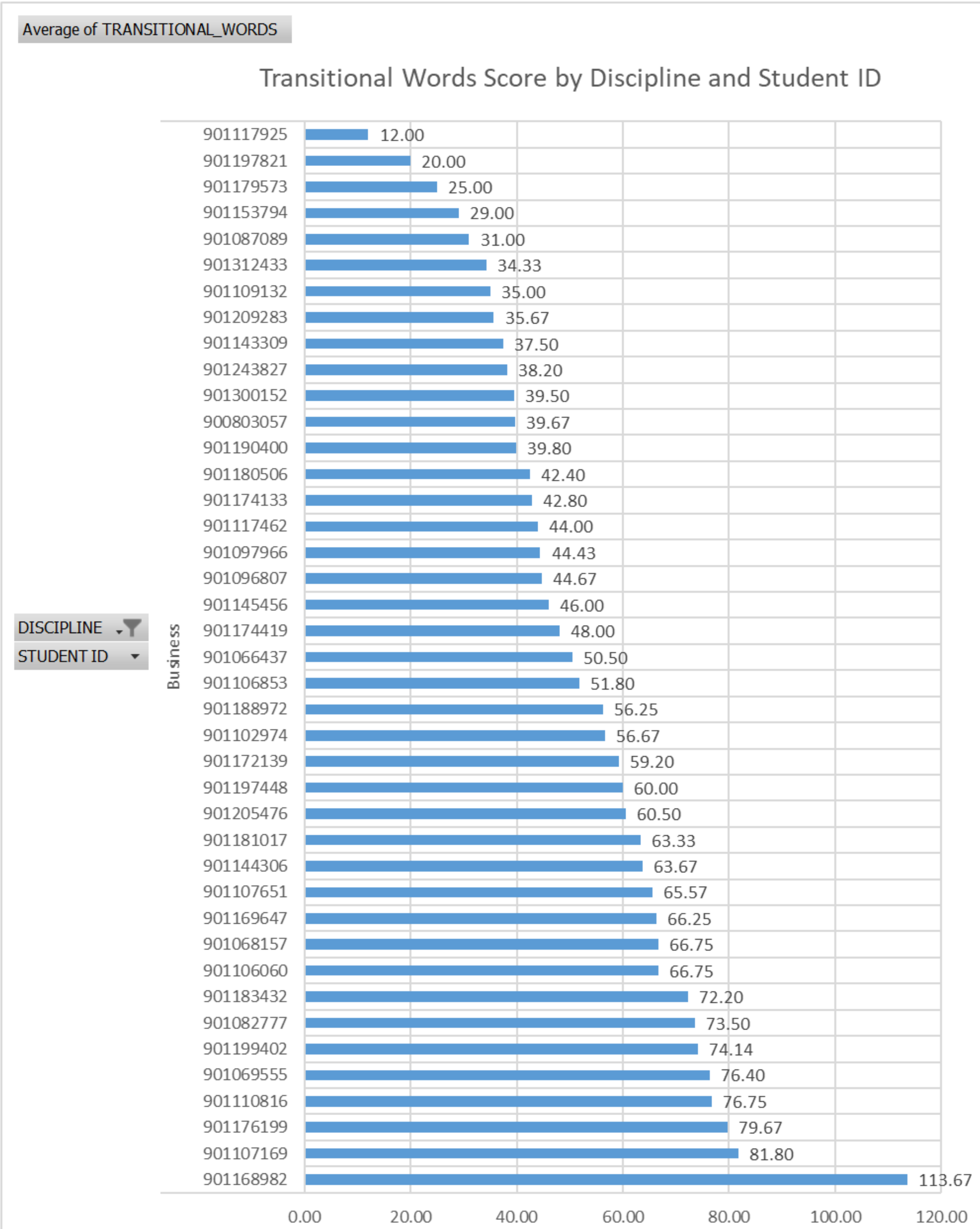

Average of BAD_PHRASE
Bad Phrase Score by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901080620 9.30
901115194 7.92
901093076 7.23
901173099 6.24
901176159 5.98
901191844 5.92
901112764 5.31
901175869 5.13
901180464 5.09
901172593 4.47
901011338 4.47
901191572 4.44
901120004 4.38
901085280 4.13
901177665 3.83
901190633 3.75
900887977 3.61
901078069 3.48
901062832 3.25
901195325 3.21
900909166 3.00
901192186 2.89
900336203 2.89
901088019 2.84
900917984 2.84
901112502 2.61
901171306 1.83
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00

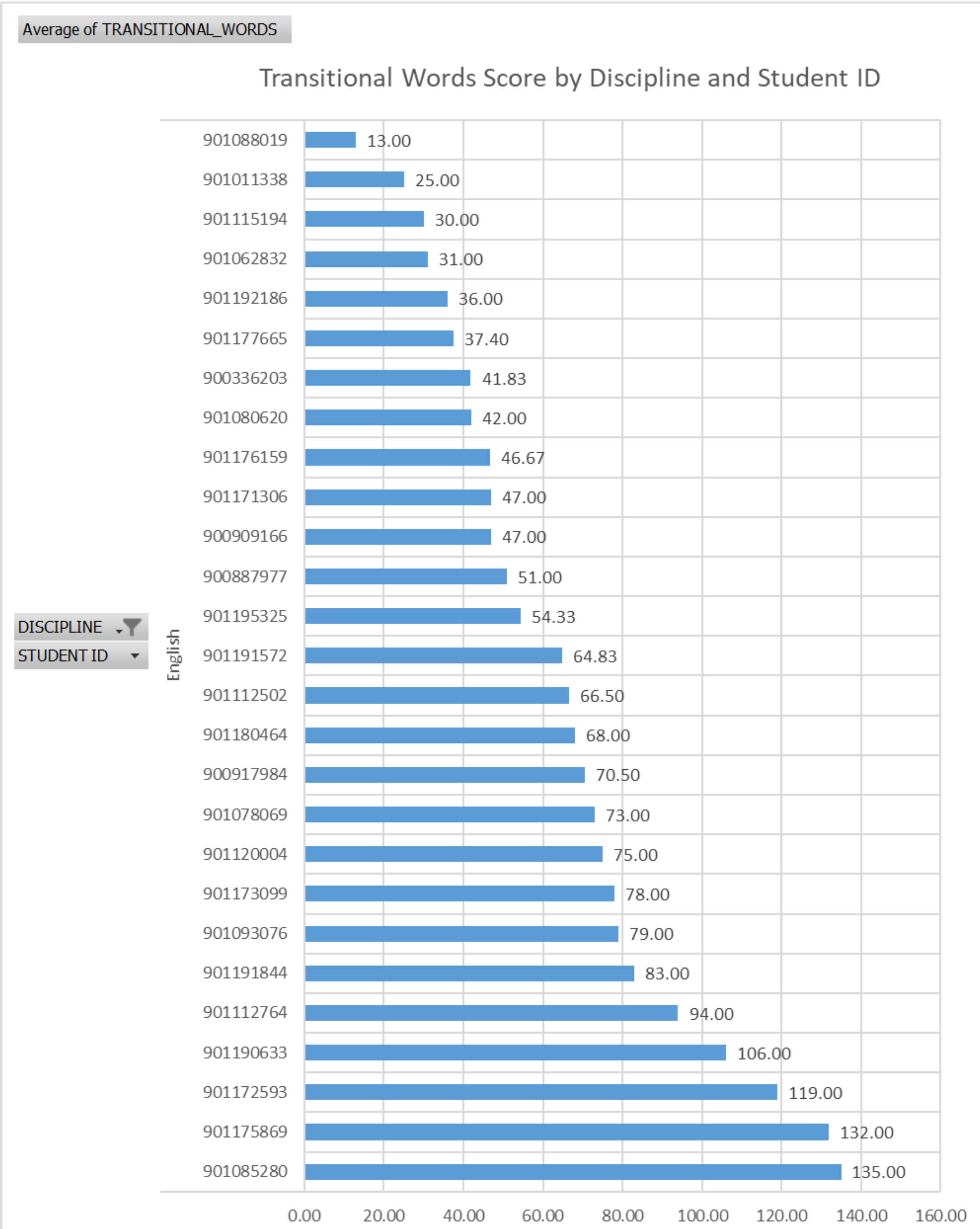


Average of BAD_PHRASE
Bad Phrase Score by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
901196900
901250043
901183519
901202590
901075495
901297992
901178494
901275197
901163036
900189201
901009274
901116727
901025755
901221092
901225530
901194740
901197151
901271401
900789751
5.90
5.90
4.82
4.65
4.37
4.30
4.05
3.45
3.13
2.83
2.74
2.41
2.30
2.22
2.17
1.90
1.81
1.79
0.81
0.00
1.00
2.00
3.00
4.00
5.00
6.00
7.00


Average of TRANSITIONAL_WORDS
Transitional Words Score by Discipline and Course ID
70.00
60.00
50.00
40.00
30.00
20.00
10.00
0.00
52.36
58.82
53.68
53.28
47.16
64.57
57.25
65.62
52.38
52.90
60.32
55.00
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID



Average of TRANSITIONAL_WORDS
Transitional Words Score by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901117925 12.00
901197821 20.00
901179573 25.00
901153794 29.00
901087089 31.00
901312433 34.33
901109132 35.00
901209283 35.67
901143309 37.50
901243827 38.20
901300152 39.50
900803057 39.67
901190400 39.80
901180506 42.40
901174133 42.80
901117462 44.00
901097966 44.43
901096807 44.67
901145456 46.00
901174419 48.00
901066437 50.50
901106853 51.80
901188972 56.25
901102974 56.67
901172139 59.20
901197448 60.00
901205476 60.50
901181017 63.33
901144306 63.67
901107651 65.57
901169647 66.25
901068157 66.75
901106060 66.75
901183432 72.20
901082777 73.50
901199402 74.14
901069555 76.40
901110816 76.75
901176199 79.67
901107169 81.80
901168982 113.67
0.00 20.00 40.00 60.00 80.00 100.00 120.00


Average of TRANSITIONAL_WORDS
Transitional Words Score by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901088019
13.00
901011338
25.00
901115194
30.00
901062832
31.00
901192186
36.00
901177665
37.40
900336203
41.83
901080620
42.00
901176159
46.67
901171306
47.00
900909166
47.00
900887977
51.00
901195325
54.33
901191572
64.83
901112502
66.50
901180464
68.00
900917984
70.50
901078069
73.00
901120004
75.00
901173099
78.00
901093076
79.00
901191844
83.00
901112764
94.00
901190633
106.00
901172593
119.00
901175869
132.00
901085280
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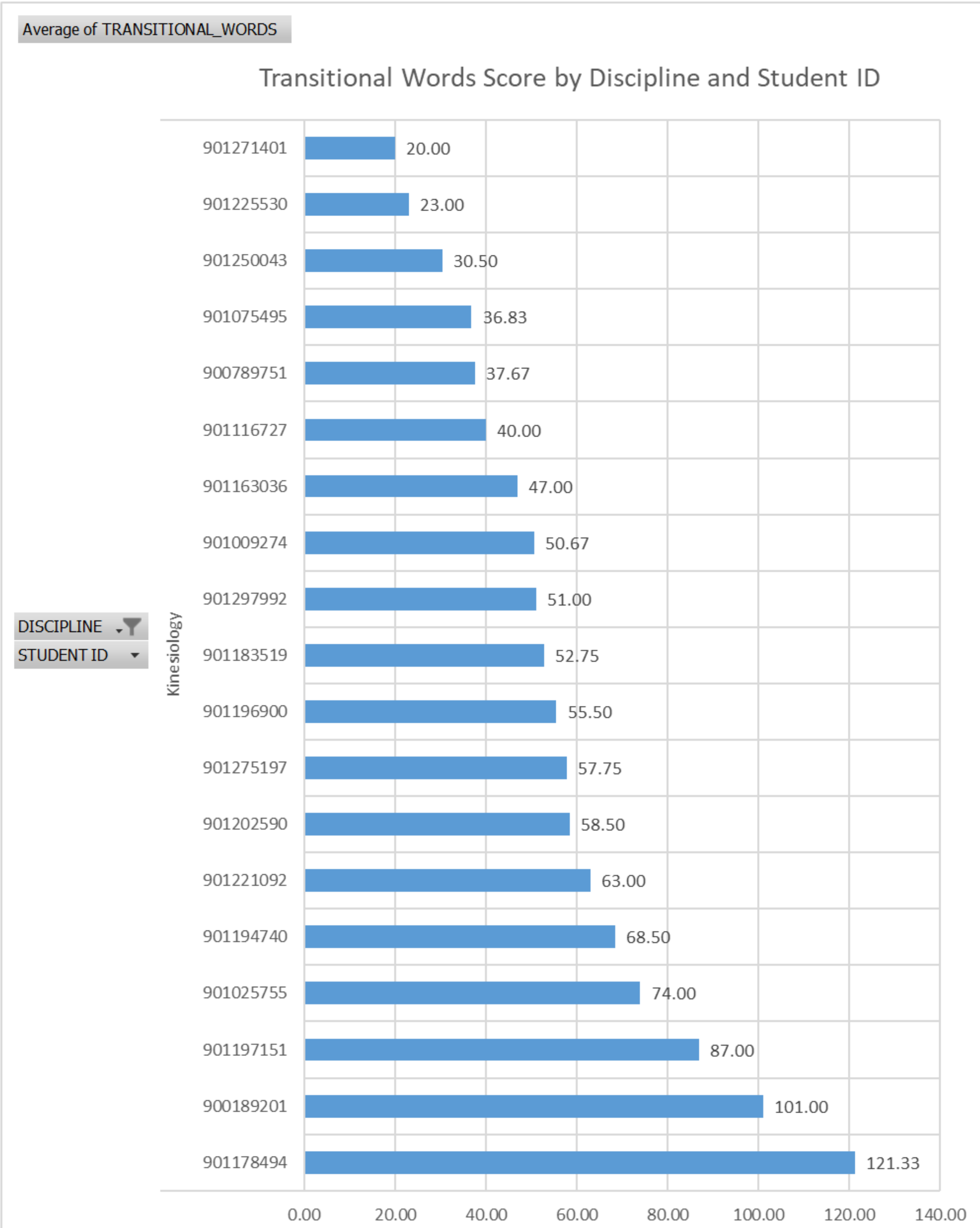
60.00
80.00
100.00
120.00
140.00
160.00



Average of TRANSITIONAL_WORDS
Transitional Words Score by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
901271401
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900789751
901116727
901163036
901009274
901297992
901183519
901196900
901275197
901202590
901221092
901194740
901025755
901197151
900189201
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23.00
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36.83
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47.00
50.67
51.00
52.75
55.50
57.75
58.50
63.00
68.50
74.00
87.00
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121.33
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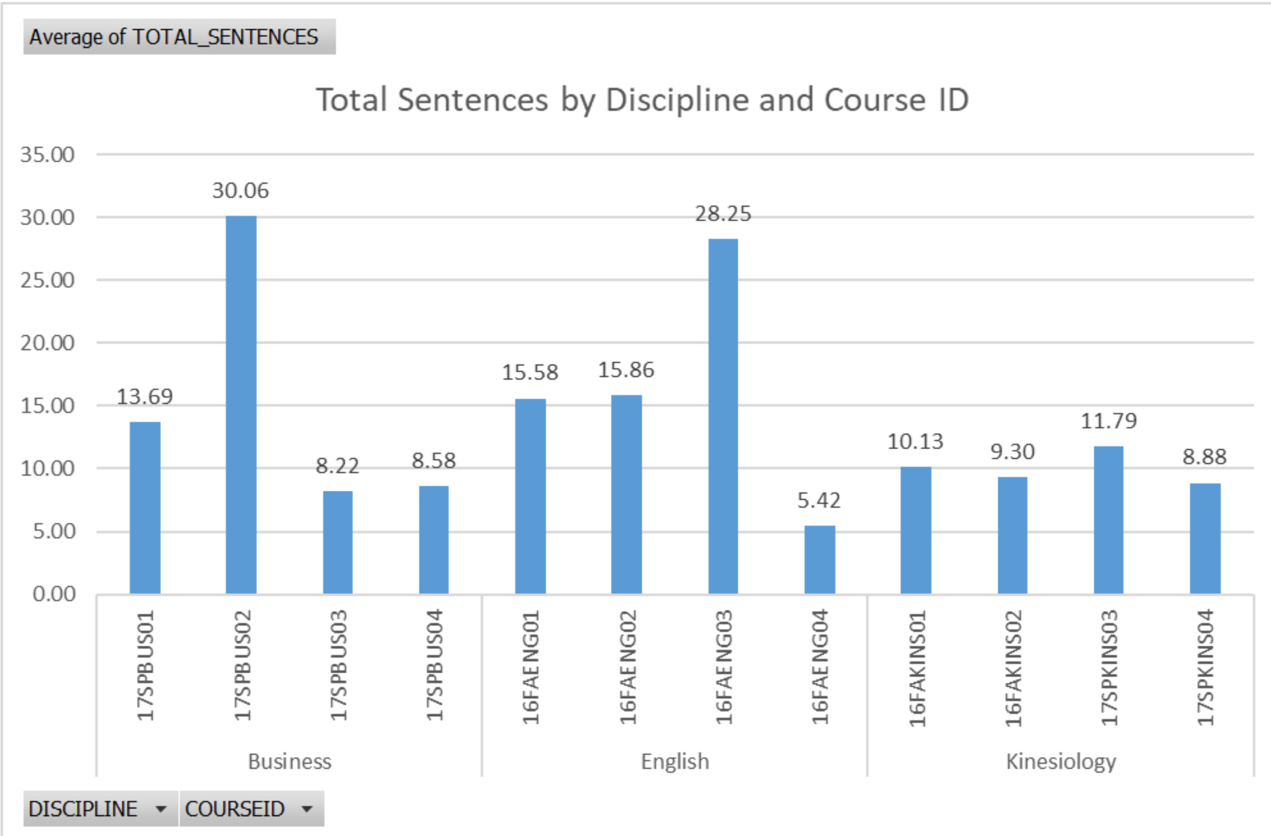
40.00
60.00
80.00
100.00
120.00
140.00


Average of TOTAL_SENTENCES
Total Sentences by Discipline and Course ID
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25.00
20.00
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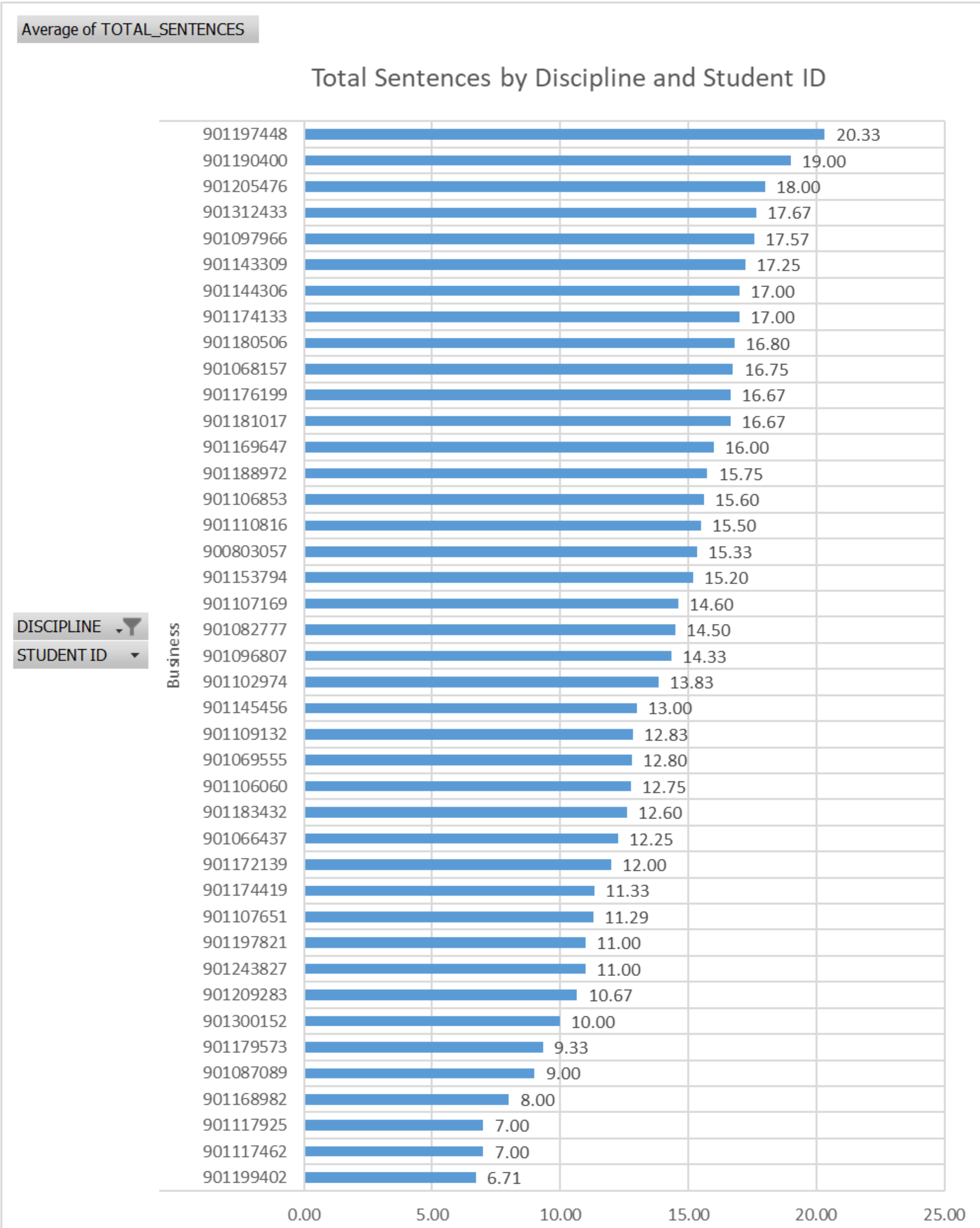
10.00
5.00
0.00
13.69
30.06
8.22
8.58
15.58
15.86
28.25
5.42
10.13
9.30
11.79
8.88
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID



Average of TOTAL_SENTENCES
Total Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
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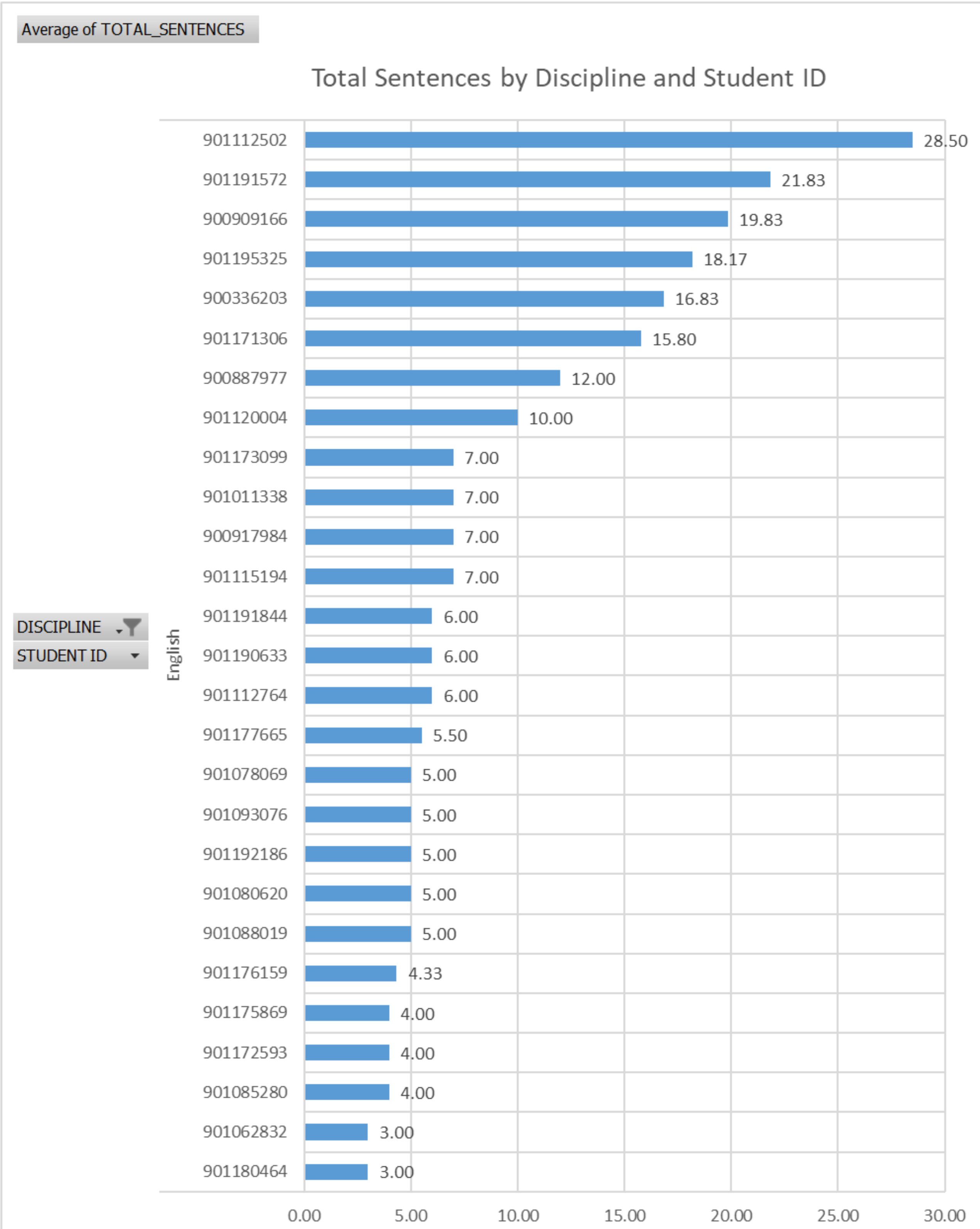
901205476
901312433
901097966
901143309
901144306
901174133
901180506
901068157
901176199
901181017
901169647
901188972
901106853
901110816
900803057
901153794
901107169
901082777
901096807
901102974
901145456
901109132
901069555
901106060
901183432
901066437
901172139
901174419
901107651
901197821
901243827
901209283
901300152
901179573
901087089
901168982
901117925
901117462
901199402
20.33
19.00
18.00
17.67
17.57
17.25
17.00
17.00
16.80
16.75
16.67
16.67
16.00
15.75
15.60
15.50
15.33
15.20
14.60
14.50
14.33
13.83
13.00
12.83
12.80
12.75
12.60
12.25
12.00
11.33
11.29
11.00
11.00
10.67
10.00
9.33
9.00
8.00
7.00
7.00
6.71
0.00
5.00
10.00
15.00
20.00
25.00


Average of TOTAL_SENTENCES
Total Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901112502 28.50
901191572 21.83
900909166 19.83
901195325 18.17
900336203 16.83
901171306 15.80
900887977 12.00
901120004 10.00
901173099 7.00
901011338 7.00
900917984 7.00
901115194 7.00
901191844 6.00
901190633 6.00
901112764 6.00
901177665 5.50
901078069 5.00
901093076 5.00
901192186 5.00
901080620 5.00
901088019 5.00
901176159 4.33
901175869 4.00
901172593 4.00
901085280 4.00
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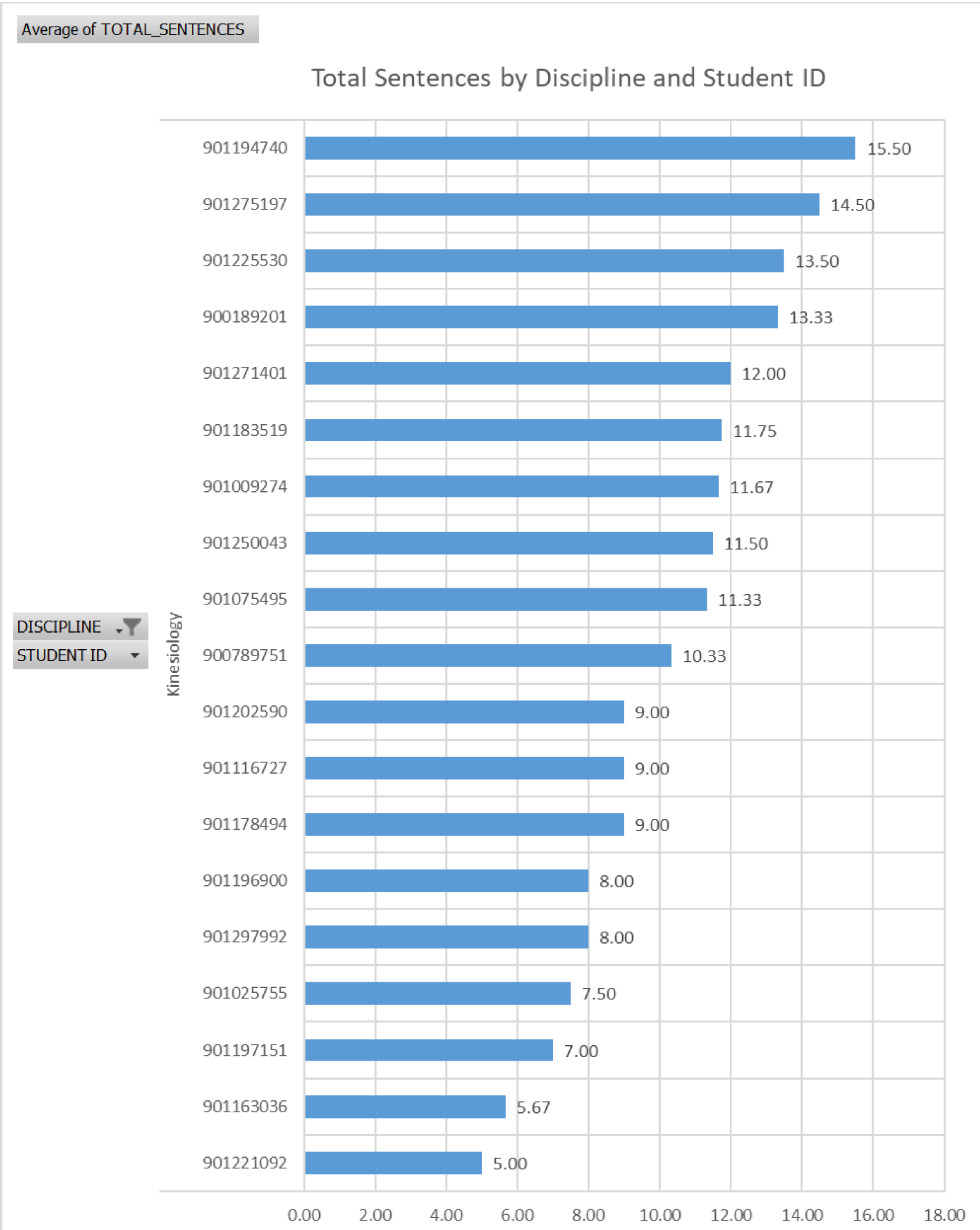
901180464 3.00
0.00 5.00 10.00 15.00 20.00 25.00 30.00


Average of TOTAL_SENTENCES
Total Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
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901225530
900189201
901271401
901183519
901009274
901250043
901075495
900789751
901202590
901116727
901178494
901196900
901297992
901025755
901197151
901163036
901221092
15.50
14.50
13.50
13.33
12.00
11.75
11.67
11.50
11.33
10.33
9.00
9.00
9.00
8.00
8.00
7.50
7.00
5.67
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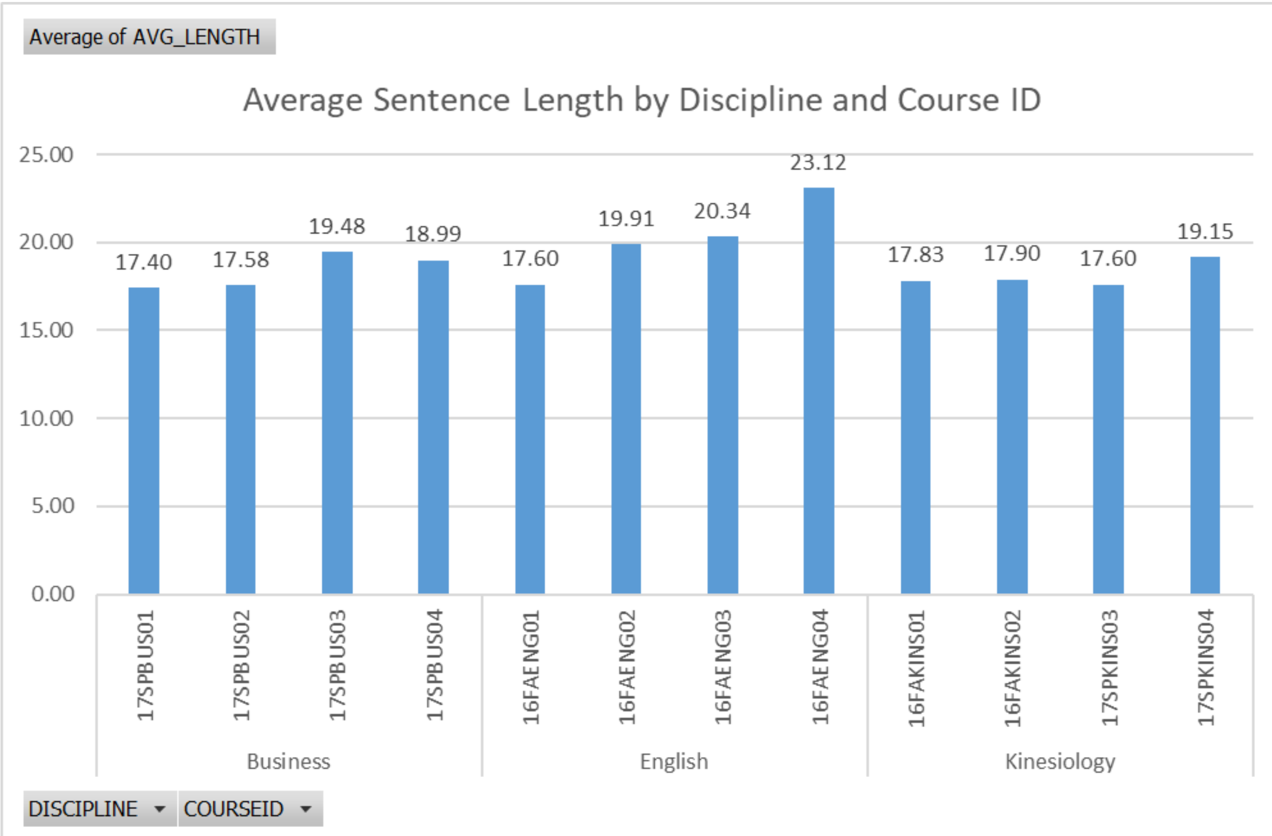
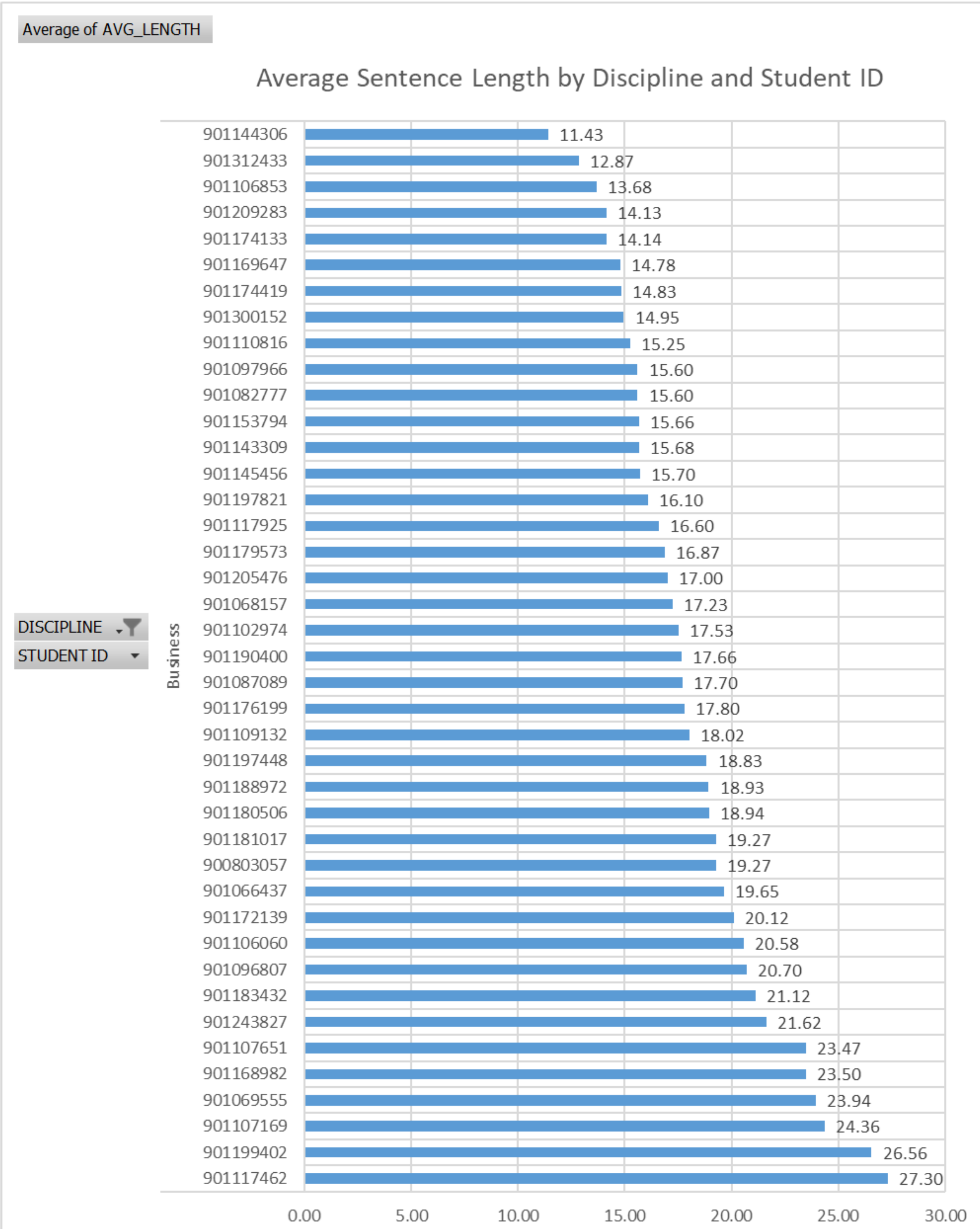
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00


Average of AVG_LENGTH
Average Sentence Length by Discipline and Course ID
25.00
20.00
15.00
10.00
5.00
0.00
17.40
17.58
19.48
18.99
17.60
19.91
20.34
23.12
17.83
17.90
17.60
19.15
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID


Average of AVG_LENGTH
Average Sentence Length by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901144306
901312433
901106853
901209283
901174133
901169647
901174419
901300152
901110816
901097966
901082777
901153794
901143309
901145456
901197821
901117925
901179573
901205476
901068157
901102974
901190400
901087089
901176199
901109132
901197448
901188972
901180506
901181017
900803057
901066437
901172139
901106060
901096807
901183432
901243827
901107651
901168982
901069555
901107169
901199402
901117462
11.43
12.87
13.68
14.13
14.14
14.78
14.83
14.95
15.25
15.60
15.60
15.66
15.68
15.70
16.10
16.60
16.87
17.00
17.23
17.53
17.66
17.70
17.80
18.02
18.83
18.93
18.94
19.27
19.27
19.65
20.12
20.58
20.70
21.12
21.62
23.47
23.50
23.94
24.36
26.56
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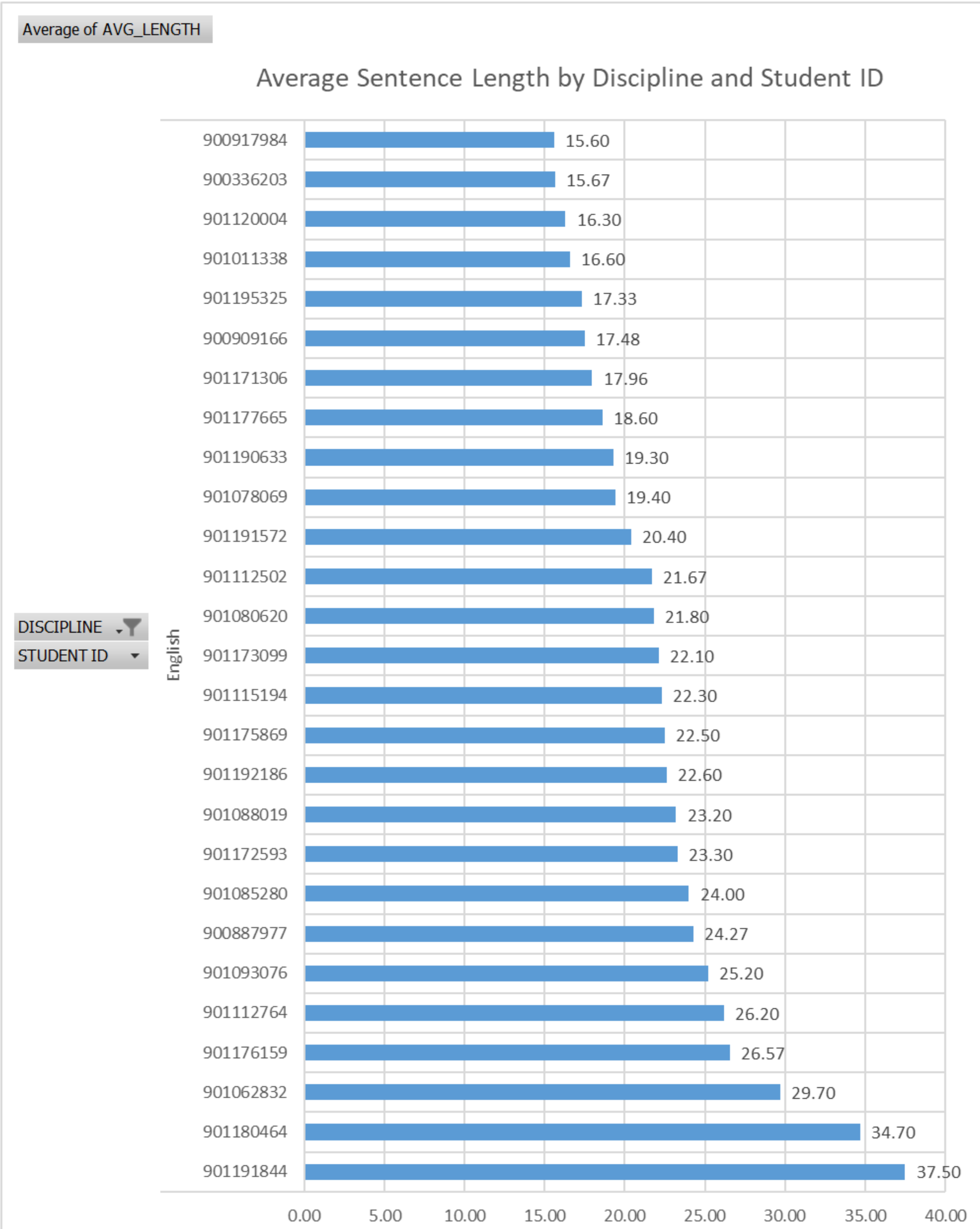
5.00
10.00
15.00
20.00
25.00
30.00



Average of AVG_LENGTH
Average Sentence Length by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
900917984
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900336203
15.67
901120004
16.30
901011338
16.60
901195325
17.33
900909166
17.48
901171306
17.96
901177665
18.60
901190633
19.30
901078069
19.40
901191572
20.40
901112502
21.67
901080620
21.80
901173099
22.10
901115194
22.30
901175869
22.50
901192186
22.60
901088019
23.20
901172593
23.30
901085280
24.00
900887977
24.27
901093076
25.20
901112764
26.20
901176159
26.57
901062832
29.70
901180464
34.70
901191844
37.50
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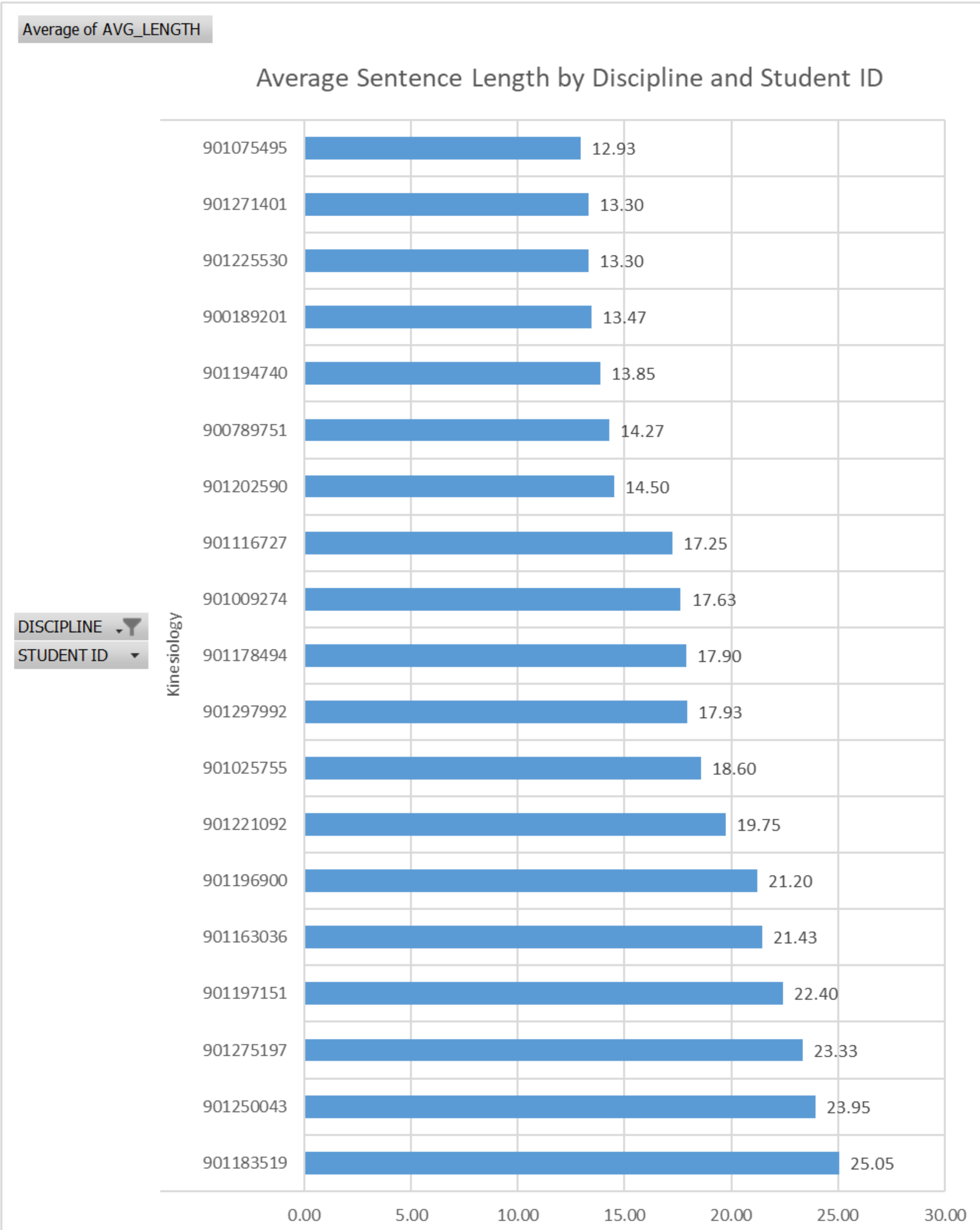
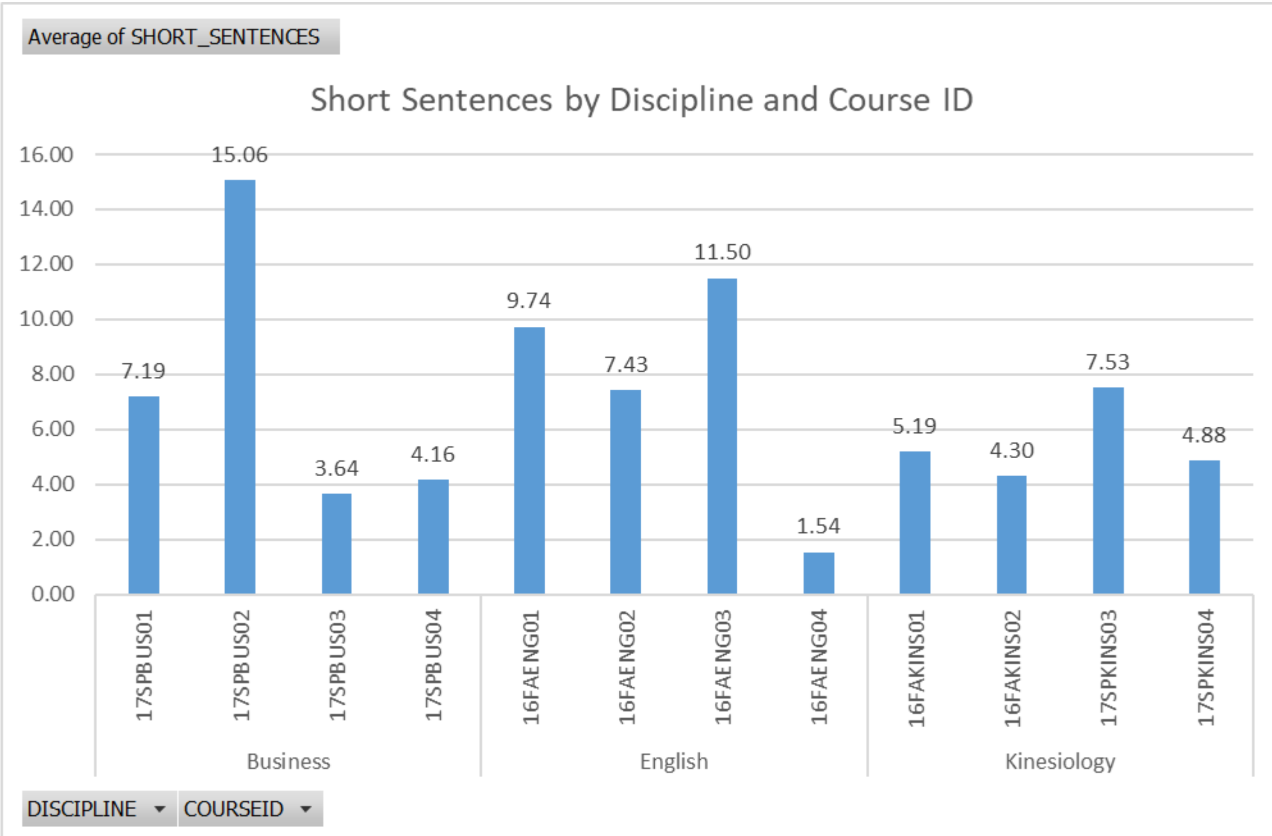
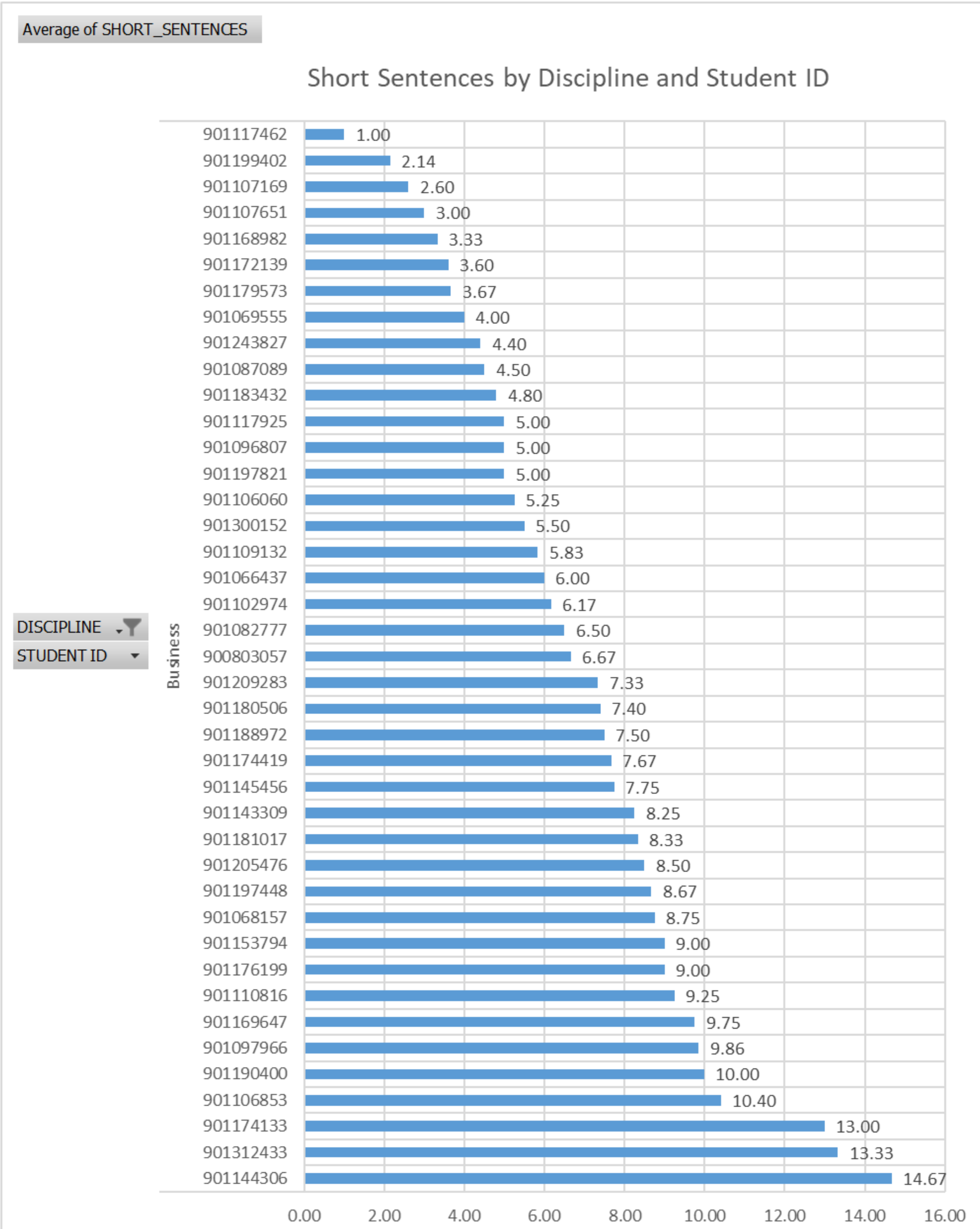
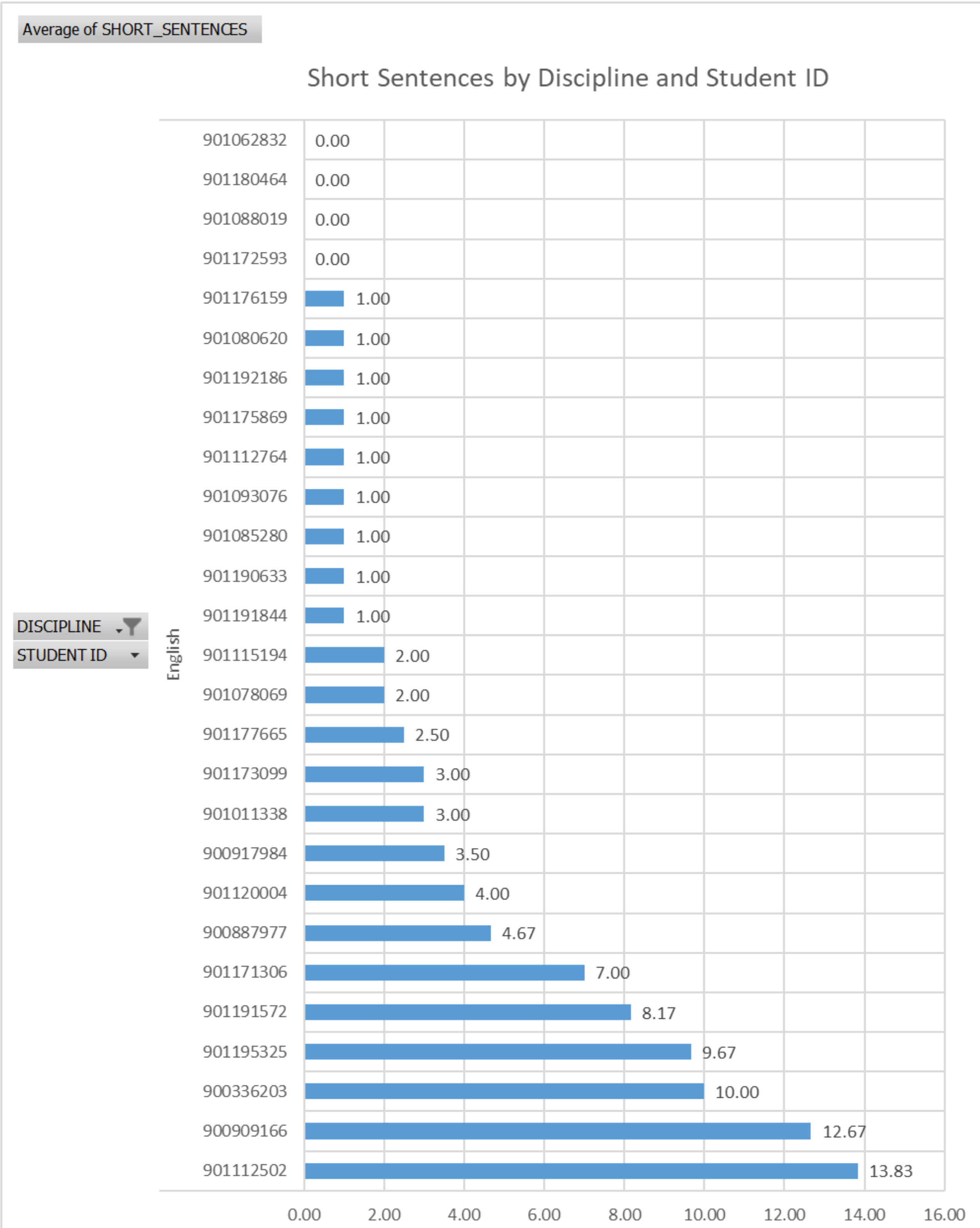
5.00
10.00
15.00
20.00
25.00
30.00
35.00
40.00



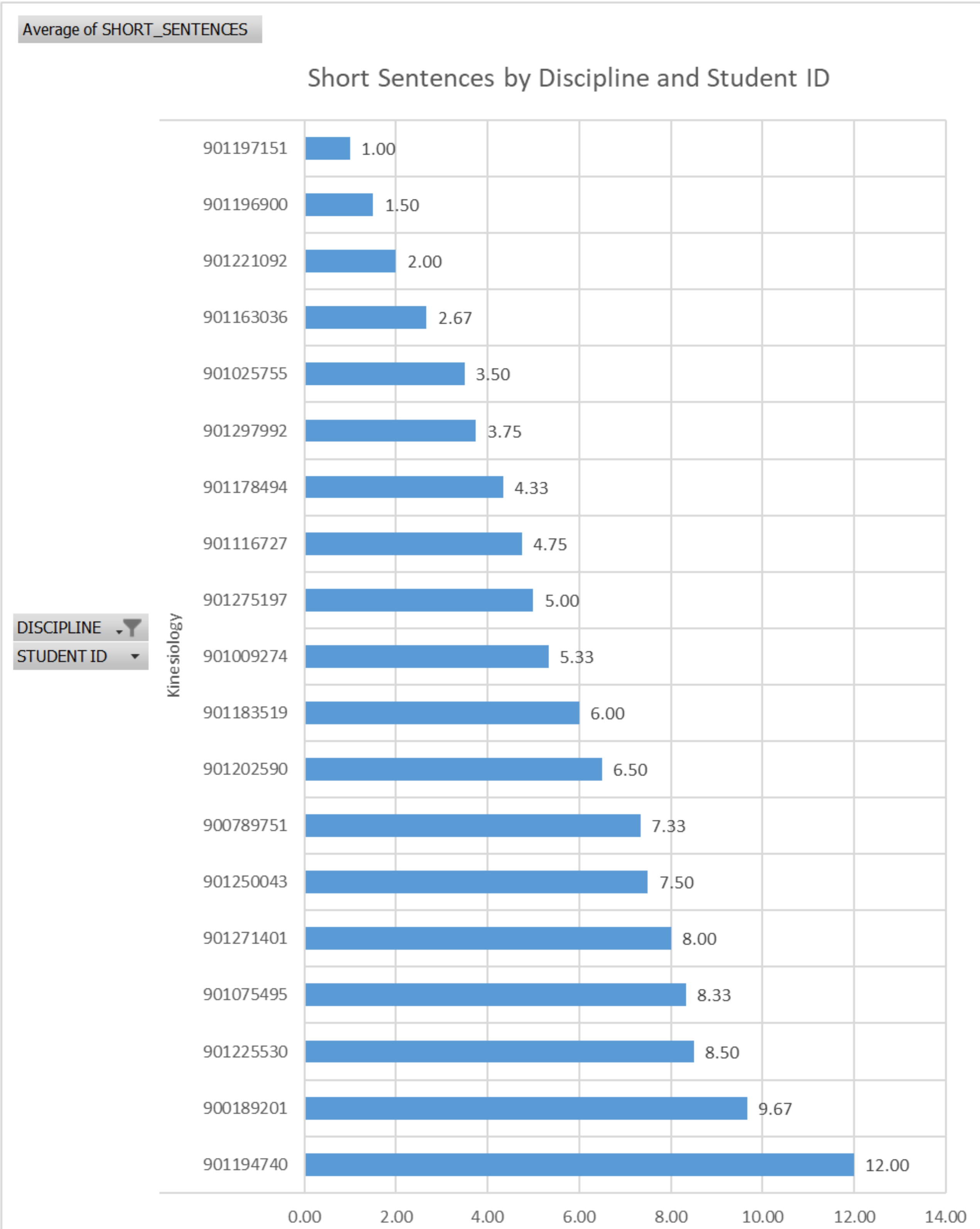
Average of AVG_LENGTH
Average Sentence Length by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
901075495
901271401
901225530
900189201
901194740
900789751
901202590
901116727
901009274
901178494
901297992
901025755
901221092
901196900
901163036
901197151
901275197
901250043
901183519
12.93
13.30
13.30
13.47
13.85
14.27
14.50
17.25
17.63
17.90
17.93
18.60
19.75
21.20
21.43
22.40
23.33
23.95
25.05
0.00
5.00
10.00
15.00
20.00
25.00
30.00

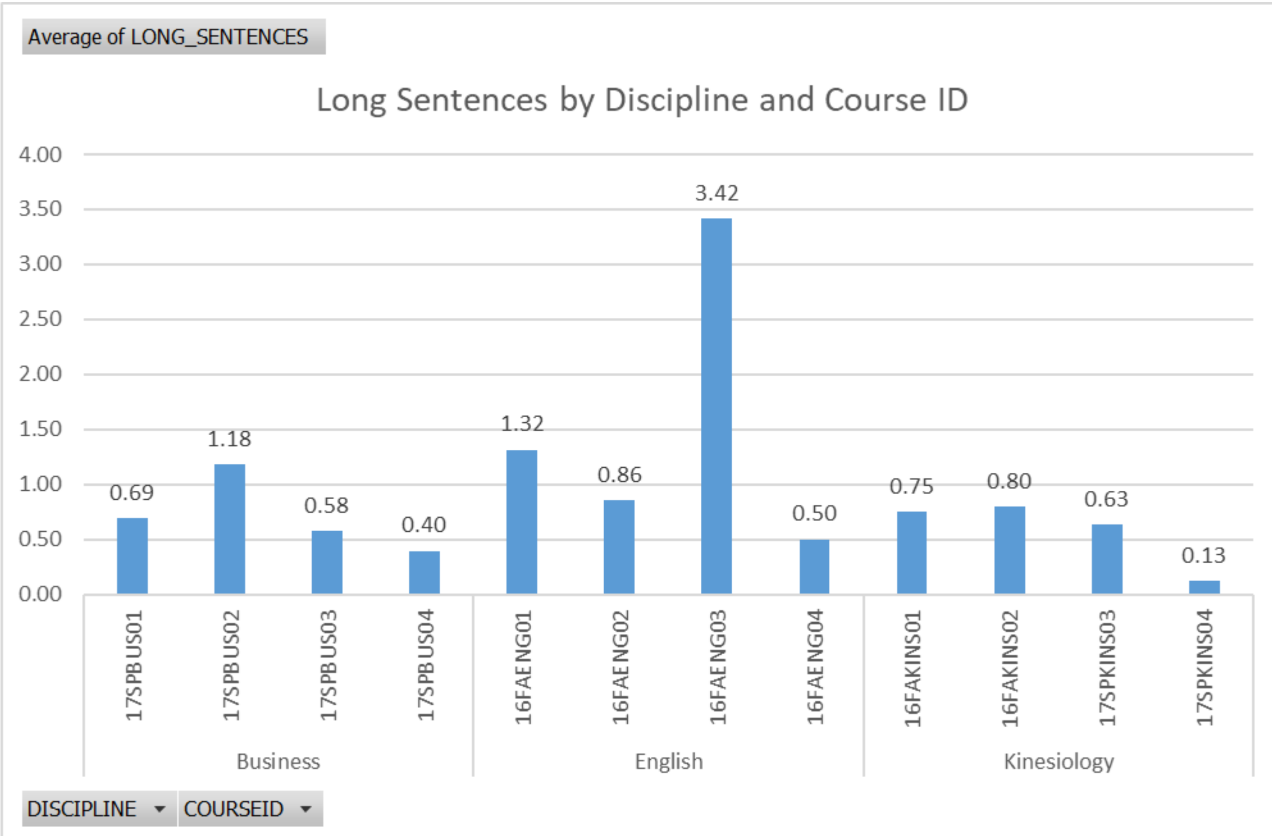

Average of SHORT_SENTENCES
Short Sentences by Discipline and Course ID
16.00
14.00
12.00
10.00
8.00
6.00
4.00
2.00
0.00
15.06
7.19
3.64
4.16
9.74
7.43
11.50
1.54
5.19
4.30
7.53
4.88
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID

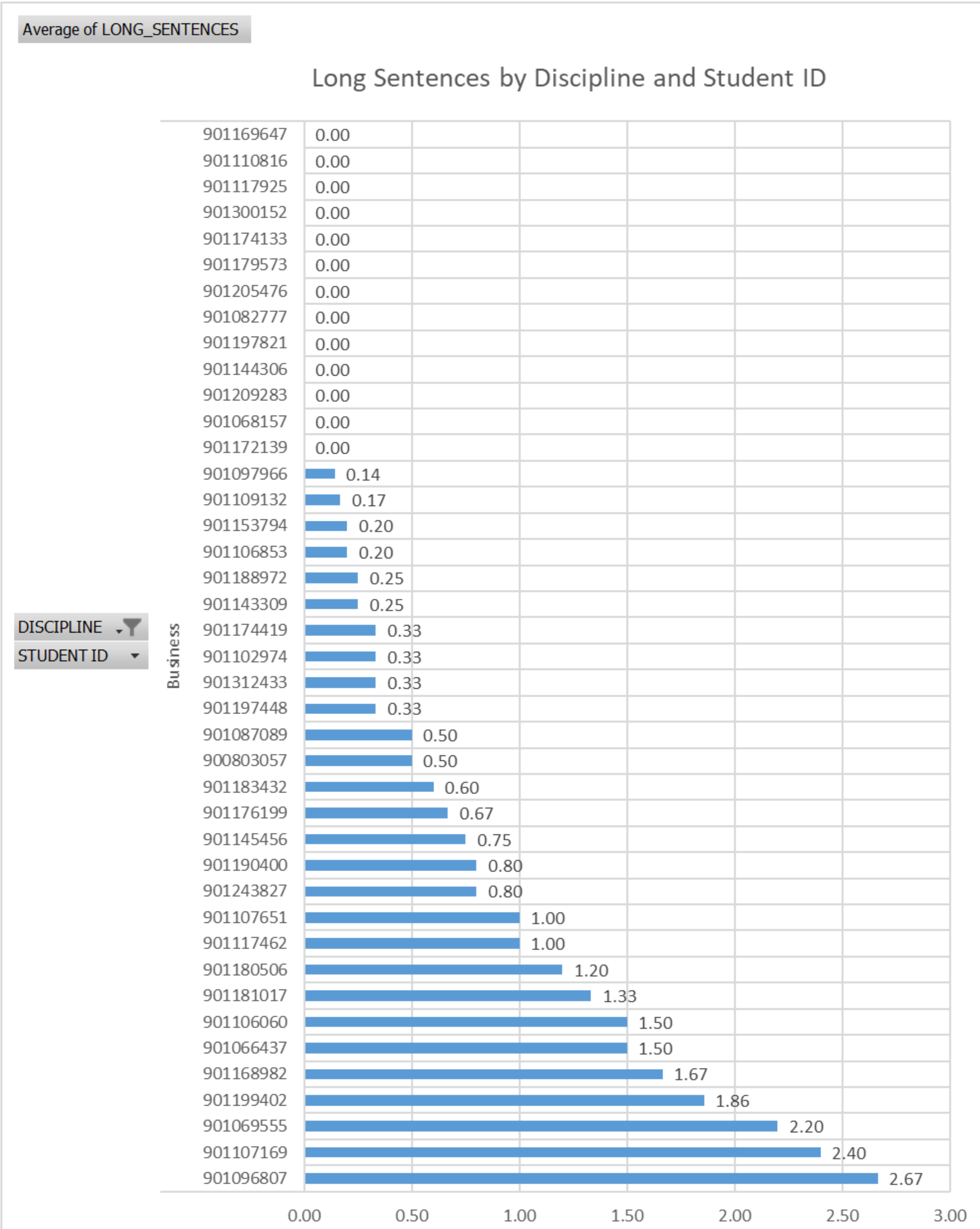

Average of SHORT_SENTENCES
Short Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901117462 1.00
901199402 2.14
901107169 2.60
901107651 3.00
901168982 3.33
901172139 3.60
901179573 3.67
901069555 4.00
901243827 4.40
901087089 4.50
901183432 4.80
901117925 5.00
901096807 5.00
901197821 5.00
901106060 5.25
901300152 5.50
901109132 5.83
901066437 6.00
901102974 6.17
901082777 6.50
900803057 6.67
901209283 7.33
901180506 7.40
901188972 7.50
901174419 7.67
901145456 7.75
901143309 8.25
901181017 8.33
901205476 8.50
901197448 8.67
901068157 8.75
901153794 9.00
901176199 9.00
901110816 9.25
901169647 9.75
901097966 9.86
901190400 10.00
901106853 10.40
901174133 13.00
901312433 13.33
901144306 14.67
0.00 2.00 4.00 6.00 8.00 10.00 12.00 14.00 16.00



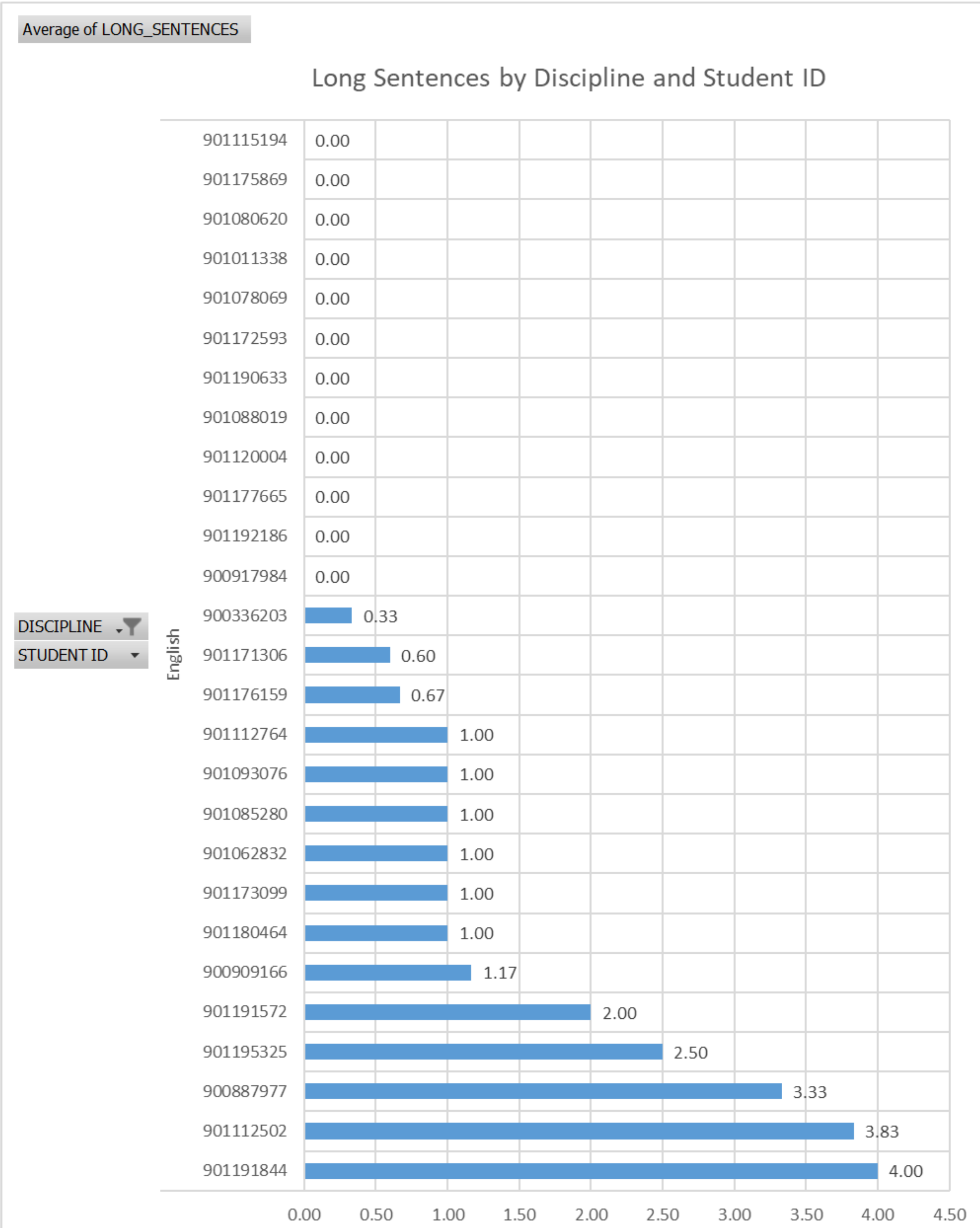
Average of SHORT_SENTENCES
Short Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901062832 0.00
901180464 0.00
901088019 0.00
901172593 0.00
901176159 1.00
901080620 1.00
901192186 1.00
901175869 1.00
901112764 1.00
901093076 1.00
901085280 1.00
901190633 1.00
901191844 1.00
901115194 2.00
901078069 2.00
901177665 2.50
901173099 3.00
901011338 3.00
900917984 3.50
901120004 4.00
900887977 4.67
901171306 7.00
901191572 8.17
901195325 9.67
900336203 10.00
900909166 12.67
901112502 13.83
0.00 2.00 4.00 6.00 8.00 10.00 12.00 14.00 16.00


Average of SHORT_SENTENCES
Short Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
901197151
901196900
901221092
901163036
901025755
901297992
901178494
901116727
901275197
901009274
901183519
901202590
900789751
901250043
901271401
901075495
901225530
900189201
901194740
1.00
1.50
2.00
2.67
3.50
3.75
4.33
4.75
5.00
5.33
6.00
6.50
7.33
7.50
8.00
8.33
8.50
9.67
12.00
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00

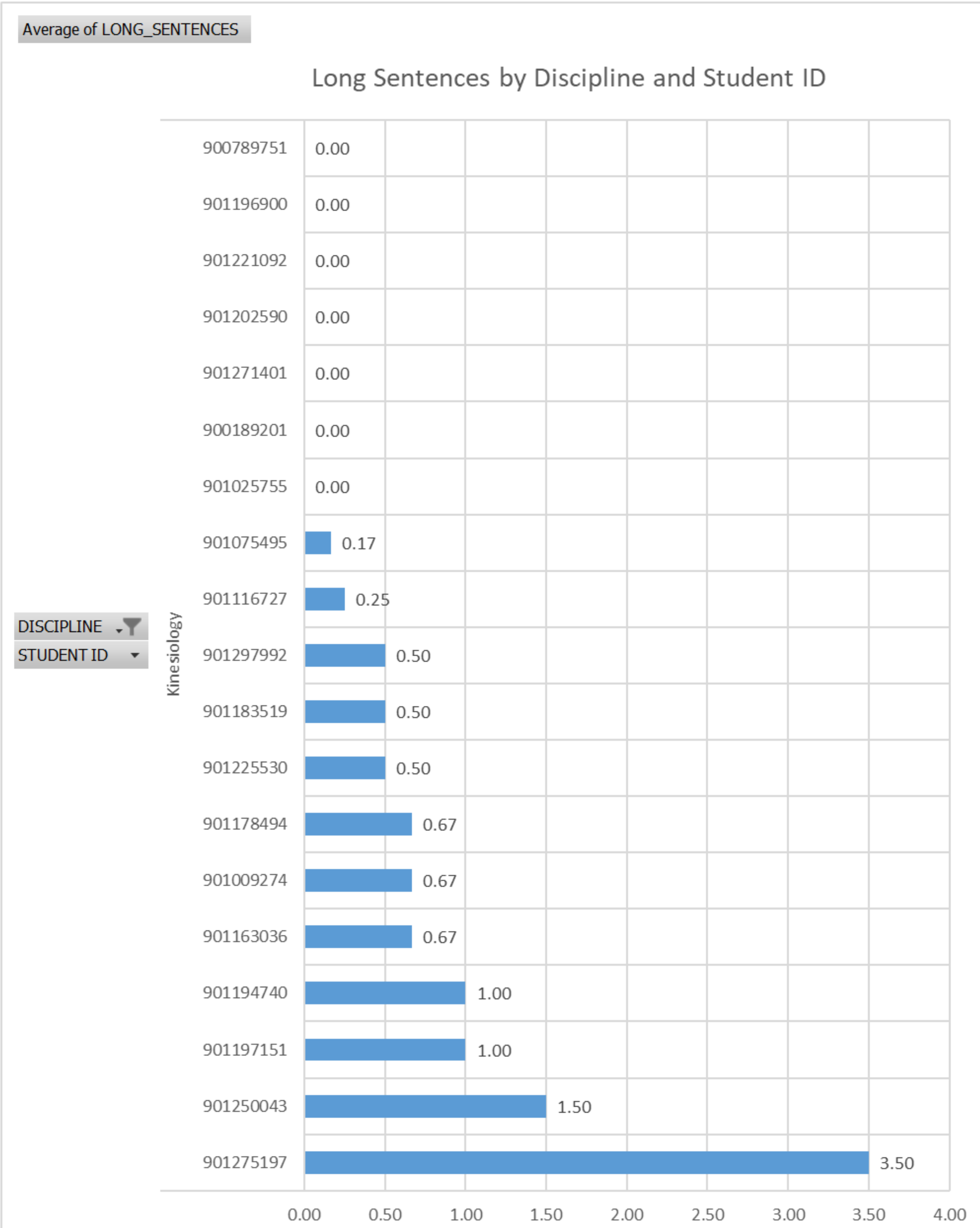

Average of LONG_SENTENCES
Long Sentences by Discipline and Course ID
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
0.69
1.18
0.58
0.40
1.32
0.86
3.42
0.50
0.75
0.80
0.63
0.13
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID



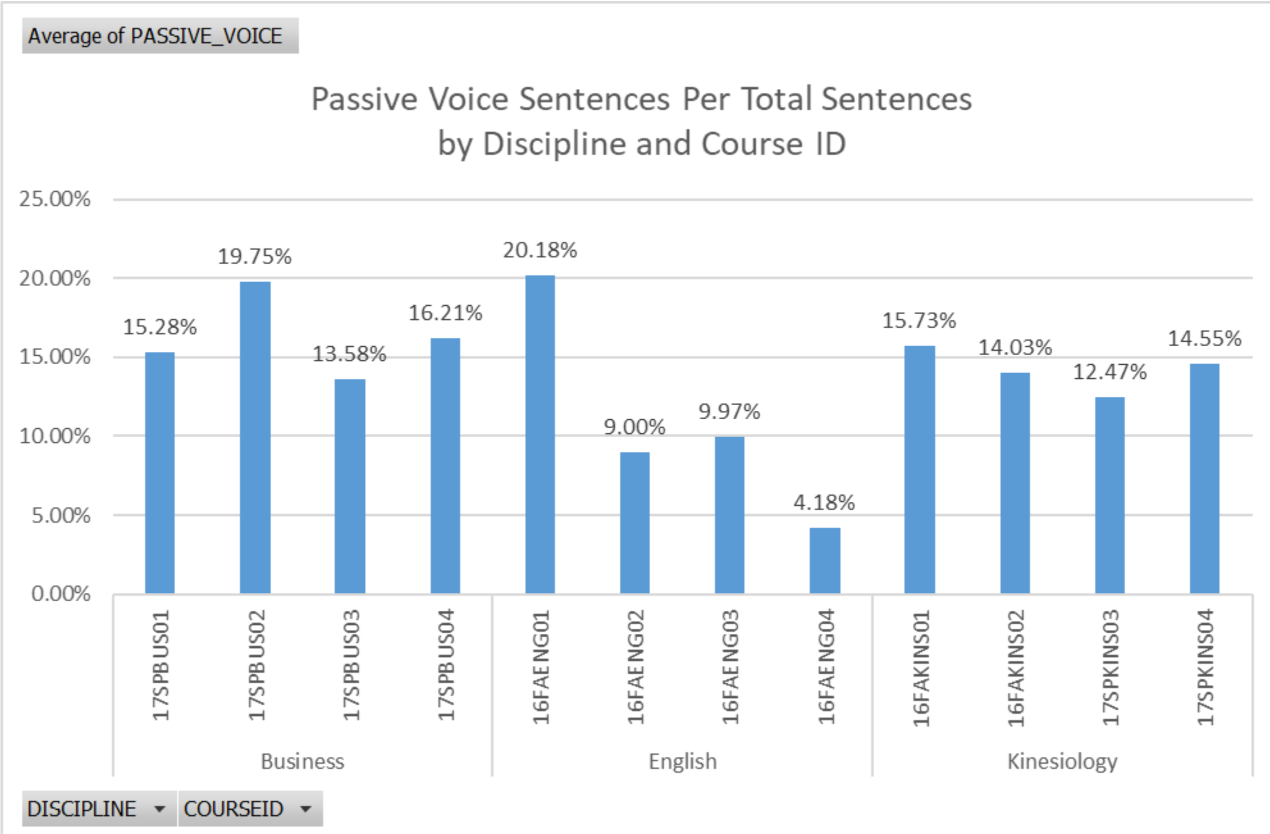
Average of LONG_SENTENCES
Long Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901169647 0.00
901110816 0.00
901117925 0.00
901300152 0.00
901174133 0.00
901179573 0.00
901205476 0.00
901082777 0.00
901197821 0.00
901144306 0.00
901209283 0.00
901068157 0.00
901172139 0.00
901097966 0.14
901109132 0.17
901153794 0.20
901106853 0.20
901188972 0.25
901143309 0.25
901174419 0.33
901102974 0.33
901312433 0.33
901197448 0.33
901087089 0.50
900803057 0.50
901183432 0.60
901176199 0.67
901145456 0.75
901190400 0.80
901243827 0.80
901107651 1.00
901117462 1.00
901180506 1.20
901181017 1.33
901106060 1.50
901066437 1.50
901168982 1.67
901199402 1.86
901069555 2.20
901107169 2.40
901096807 2.67
0.00 0.50 1.00 1.50 2.00 2.50 3.00



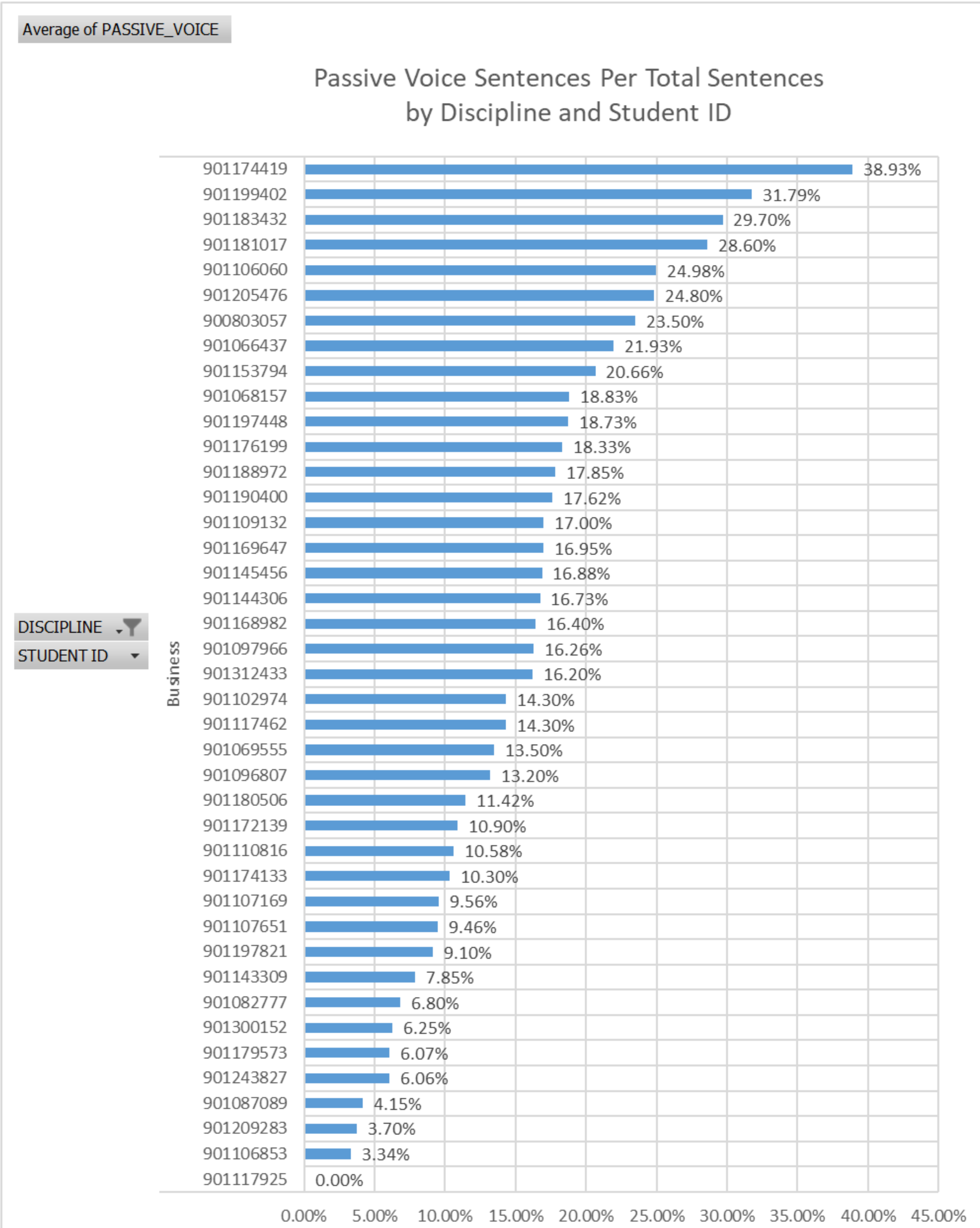
Average of LONG_SENTENCES
Long Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901115194 0.00
901175869 0.00
901080620 0.00
901011338 0.00
901078069 0.00
901172593 0.00
901190633 0.00
901088019 0.00
901120004 0.00
901177665 0.00
901192186 0.00
900917984 0.00
900336203 0.33
901171306 0.60
901176159 0.67
901112764 1.00
901093076 1.00
901085280 1.00
901062832 1.00
901173099 1.00
901180464 1.00
900909166 1.17
901191572 2.00
901195325 2.50
900887977 3.33
901112502 3.83
901191844 4.00
0.00 0.50 1.00 1.50 2.00 2.50 3.00 3.50 4.00 4.50

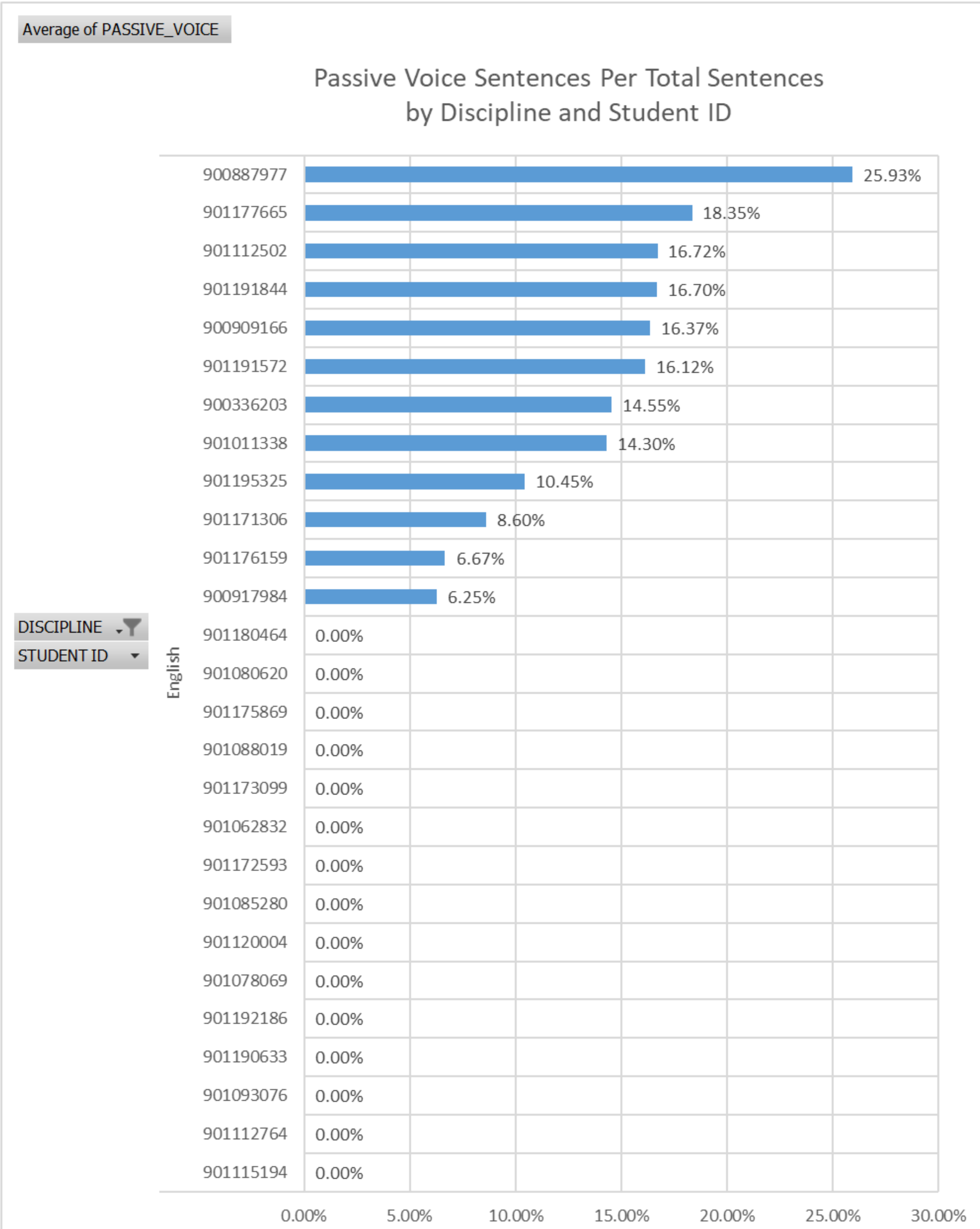


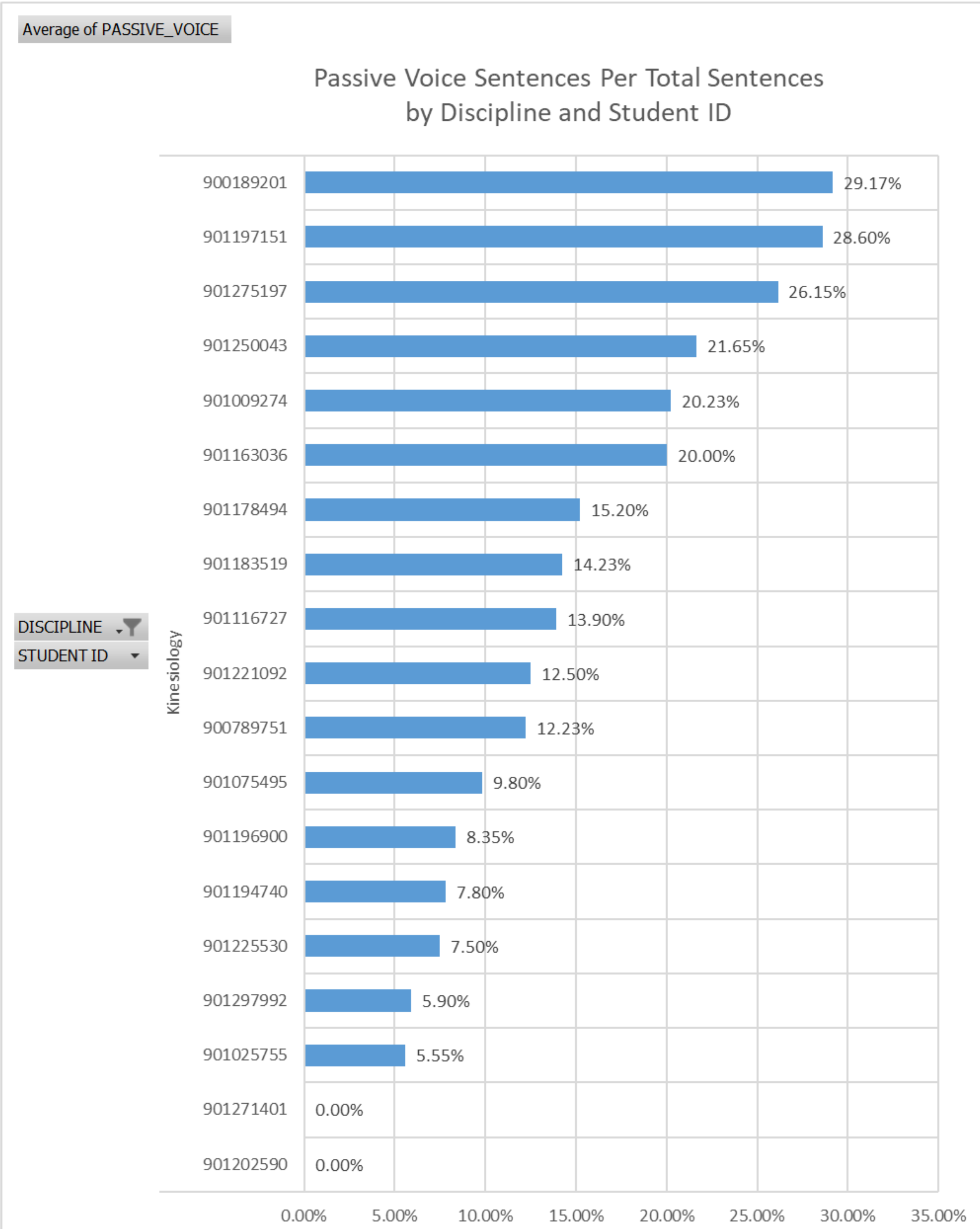
Average of LONG_SENTENCES
Long Sentences by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
900789751
0.00
901196900
0.00
901221092
0.00
901202590
0.00
901271401
0.00
900189201
0.00
901025755
0.00
901075495
0.17
901116727
0.25
901297992
0.50
901183519
0.50
901225530
0.50
901178494
0.67
901009274
0.67
901163036
0.67
901194740
1.00
901197151
1.00
901250043
1.50
901275197
3.50
0.00
0.50
1.00
1.50
2.00
2.50
3.00
3.50
4.00



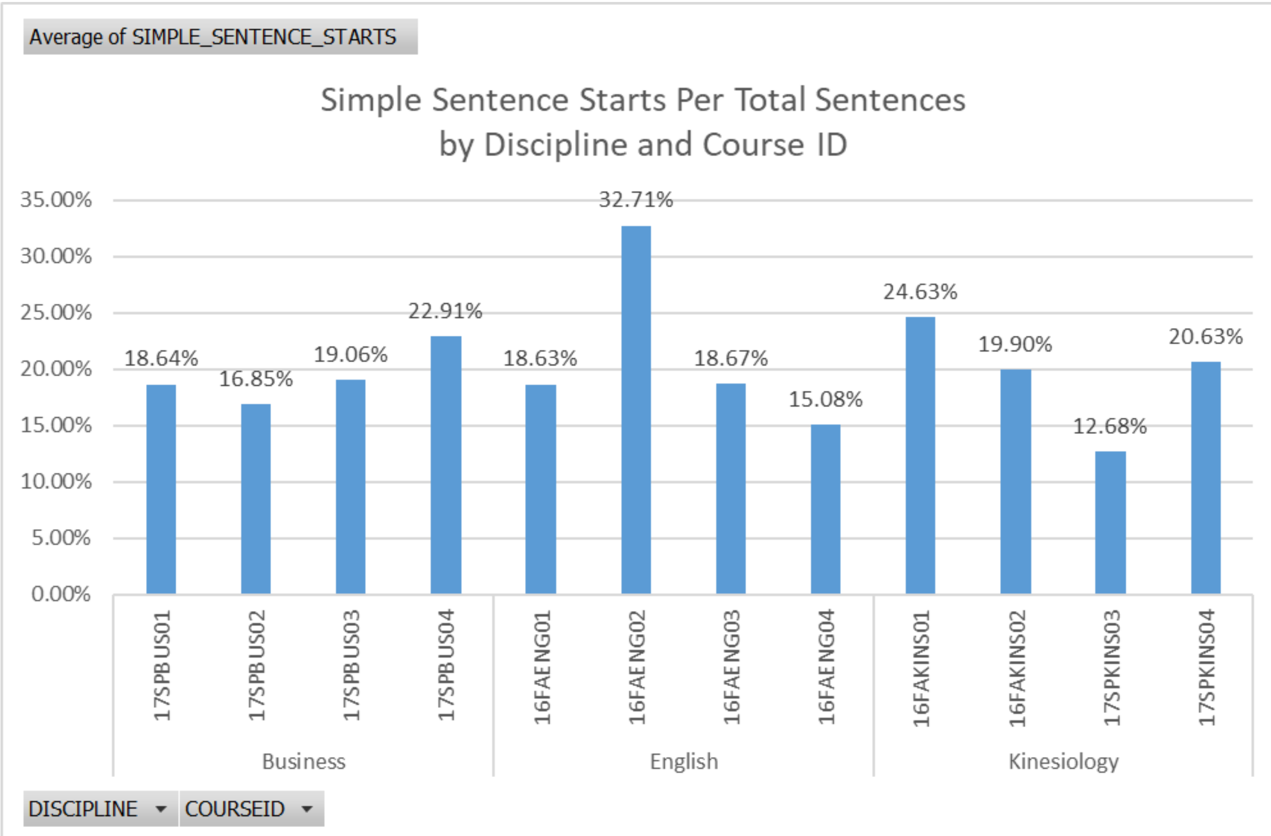
Average of PASSIVE_VOICE
Passive Voice Sentences Per Total Sentences
by Discipline and Course ID
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
15.28%
19.75%
13.58%
16.21%
20.18%
9.00%
9.97%
4.18%
15.73%
14.03%
12.47%
14.55%
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID

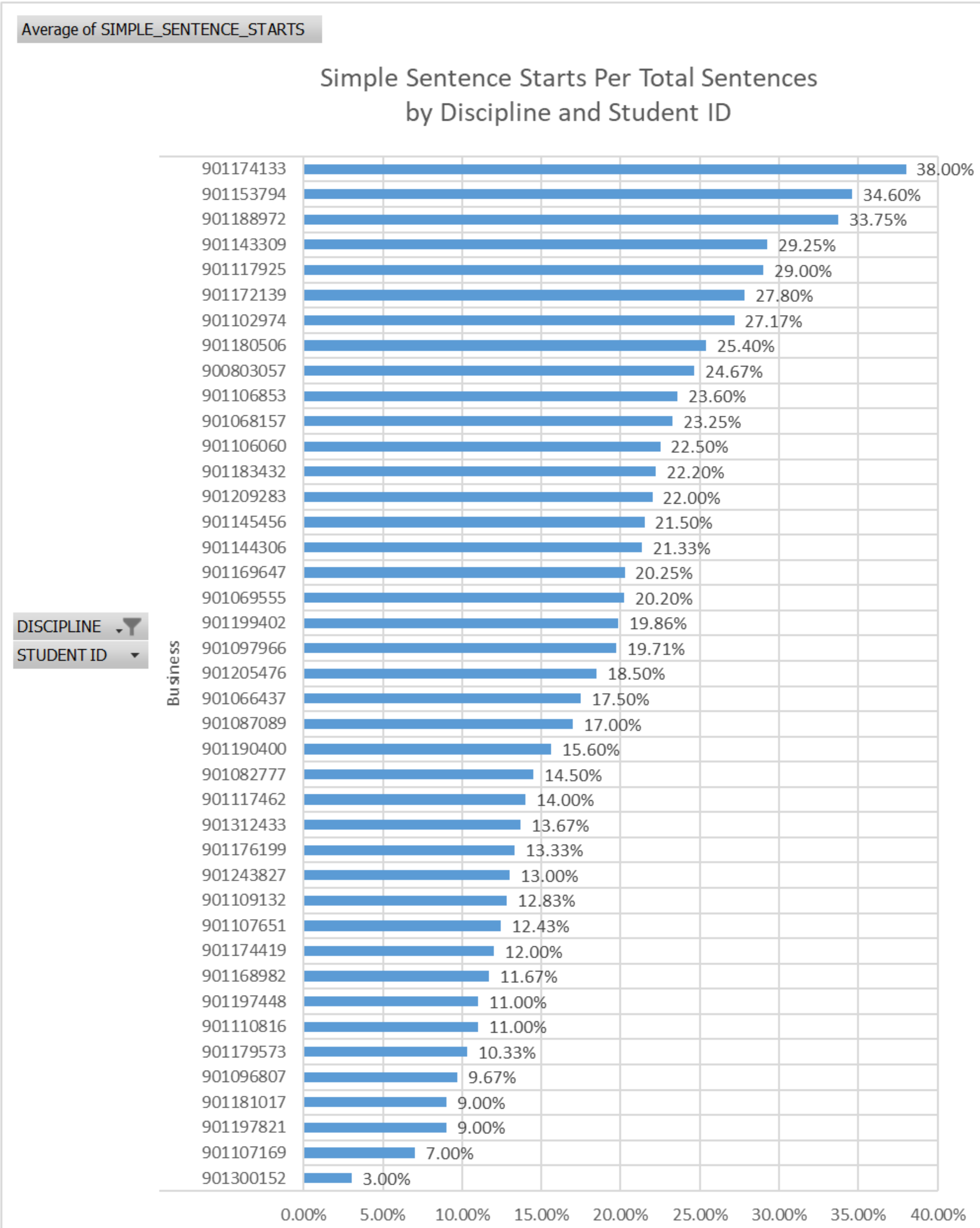

Average of PASSIVE_VOICE
Passive Voice Sentences Per Total Sentences
by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901174419 38.93%
901199402 31.79%
901183432 29.70%
901181017 28.60%
901106060 24.98%
901205476 24.80%
900803057 23.50%
901066437 21.93%
901153794 20.66%
901068157 18.83%
901197448 18.73%
901176199 18.33%
901188972 17.85%
901190400 17.62%
901109132 17.00%
901169647 16.95%
901145456 16.88%
901144306 16.73%
901168982 16.40%
901097966 16.26%
901312433 16.20%
901102974 14.30%
901117462 14.30%
901069555 13.50%
901096807 13.20%
901180506 11.42%
901172139 10.90%
901110816 10.58%
901174133 10.30%
901107169 9.56%
901107651 9.46%
901197821 9.10%
901143309 7.85%
901082777 6.80%
901300152 6.25%
901179573 6.07%
901243827 6.06%
901087089 4.15%
901209283 3.70%
901106853 3.34%
901117925 0.00%
0.00% 5.00% 10.00% 15.00% 20.00% 25.00% 30.00% 35.00% 40.00% 45.00%

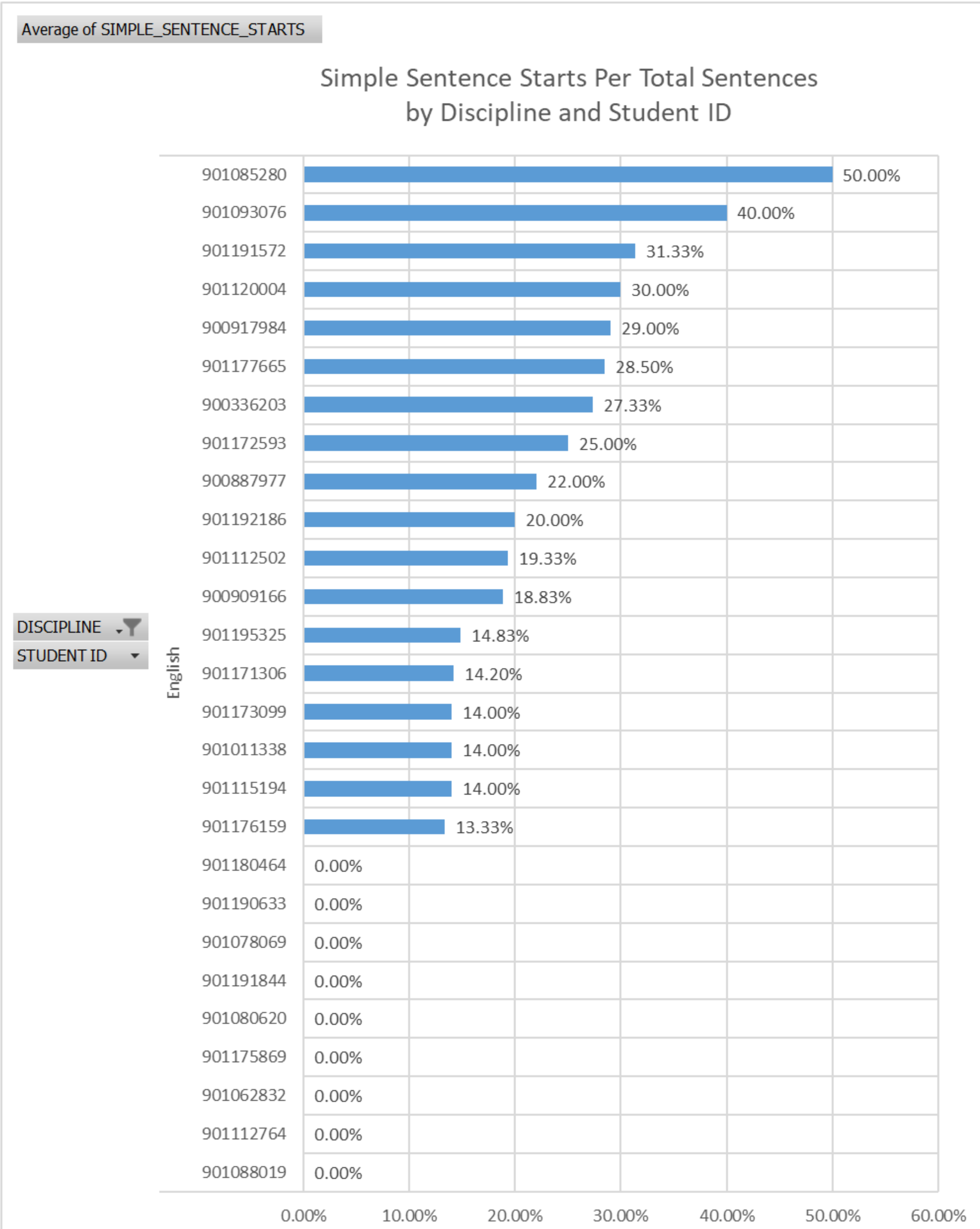

Average of PASSIVE_VOICE
Passive Voice Sentences Per Total Sentences
by Discipline and Student ID
900887977
25.93%
901177665
18.35%
901112502
16.72%
901191844
16.70%
900909166
16.37%
901191572
16.12%
900336203
14.55%
901011338
14.30%
901195325
10.45%
901171306
8.60%
901176159
6.67%
900917984
6.25%
901180464
0.00%
901080620
0.00%
901175869
0.00%
901088019
0.00%
901173099
0.00%
901062832
0.00%
901172593
0.00%
901085280
0.00%
901120004
0.00%
901078069
0.00%
901192186
0.00%
901190633
0.00%
901093076
0.00%
901112764
0.00%
901115194
0.00%
English
DISCIPLINE
STUDENT ID
0.00%
5.00%
10.00%
15.00%
20.00%
25.00%
30.00%



Average of PASSIVE_VOICE
Passive Voice Sentences Per Total Sentences
by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
900189201 29.17%
901197151 28.60%
901275197 26.15%
901250043 21.65%
901009274 20.23%
901163036 20.00%
901178494 15.20%
901183519 14.23%
901116727 13.90%
901221092 12.50%
900789751 12.23%
901075495 9.80%
901196900 8.35%
901194740 7.80%
901225530 7.50%
901297992 5.90%
901025755 5.55%
901271401 0.00%
901202590 0.00%
0.00%
5.00%
10.00%
15.00%
20.00%
25.00%
30.00%
35.00%


Average of SIMPLE_SENTENCE_STARTS
Simple Sentence Starts Per Total Sentences
by Discipline and Course ID
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
18.64%
16.85%
19.06%
22.91%
18.63%
32.71%
18.67%
15.08%
24.63%
19.90%
12.68%
20.63%
17SPBUS01
17SPBUS02
17SPBUS03
17SPBUS04
16FAENG01
16FAENG02
16FAENG03
16FAENG04
16FAKINS01
16FAKINS02
17SPKINS03
17SPKINS04
Business
English
Kinesiology
DISCIPLINE
COURSEID


Average of SIMPLE_SENTENCE_STARTS
Simple Sentence Starts Per Total Sentences
by Discipline and Student ID
DISCIPLINE
STUDENT ID
Business
901174133 38.00%
901153794 34.60%
901188972 33.75%
901143309 29.25%
901117925 29.00%
901172139 27.80%
901102974 27.17%
901180506 25.40%
900803057 24.67%
901106853 23.60%
901068157 23.25%
901106060 22.50%
901183432 22.20%
901209283 22.00%
901145456 21.50%
901144306 21.33%
901169647 20.25%
901069555 20.20%
901199402 19.86%
901097966 19.71%
901205476 18.50%
901066437 17.50%
901087089 17.00%
901190400 15.60%
901082777 14.50%
901117462 14.00%
901312433 13.67%
901176199 13.33%
901243827 13.00%
901109132 12.83%
901107651 12.43%
901174419 12.00%
901168982 11.67%
901197448 11.00%
901110816 11.00%
901179573 10.33%
901096807 9.67%
901181017 9.00%
901197821 9.00%
901107169 7.00%
901300152 3.00%
0.00% 5.00% 10.00% 15.00% 20.00% 25.00% 30.00% 35.00% 40.00%


Average of SIMPLE_SENTENCE_STARTS
Simple Sentence Starts Per Total Sentences
by Discipline and Student ID
DISCIPLINE
STUDENT ID
English
901085280 50.00%
901093076 40.00%
901191572 31.33%
901120004 30.00%
900917984 29.00%
901177665 28.50%
900336203 27.33%
901172593 25.00%
900887977 22.00%
901192186 20.00%
901112502 19.33%
900909166 18.83%
901195325 14.83%
901171306 14.20%
901173099 14.00%
901011338 14.00%
901115194 14.00%
901176159 13.33%
901180464 0.00%
901190633 0.00%
901078069 0.00%
901191844 0.00%
901080620 0.00%
901175869 0.00%
901062832 0.00%
901112764 0.00%
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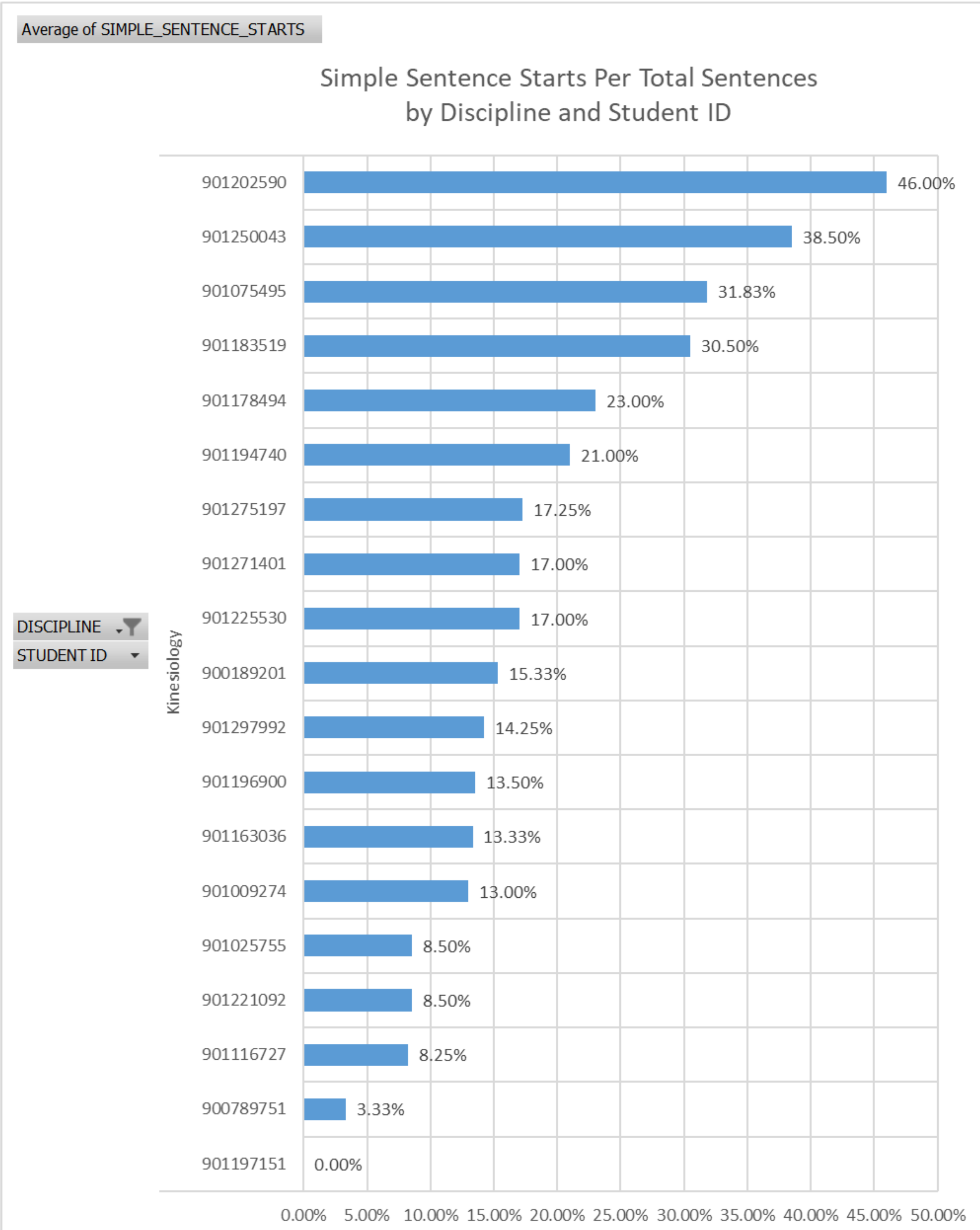
20.00%
30.00%
40.00%
50.00%
60.00%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Simple Sentence Starts Per Total Sentences
by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
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38.50%
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31.83%
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30.50%
901178494
23.00%
901194740
21.00%
901275197
17.25%
901271401
17.00%
901225530
17.00%
900189201
15.33%
901297992
14.25%
901196900
13.50%
901163036
13.33%
901009274
13.00%
901025755
8.50%
901221092
8.50%
901116727
8.25%
900789751
3.33%
901197151
0.00%
0.00%
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20.00%
25.00%
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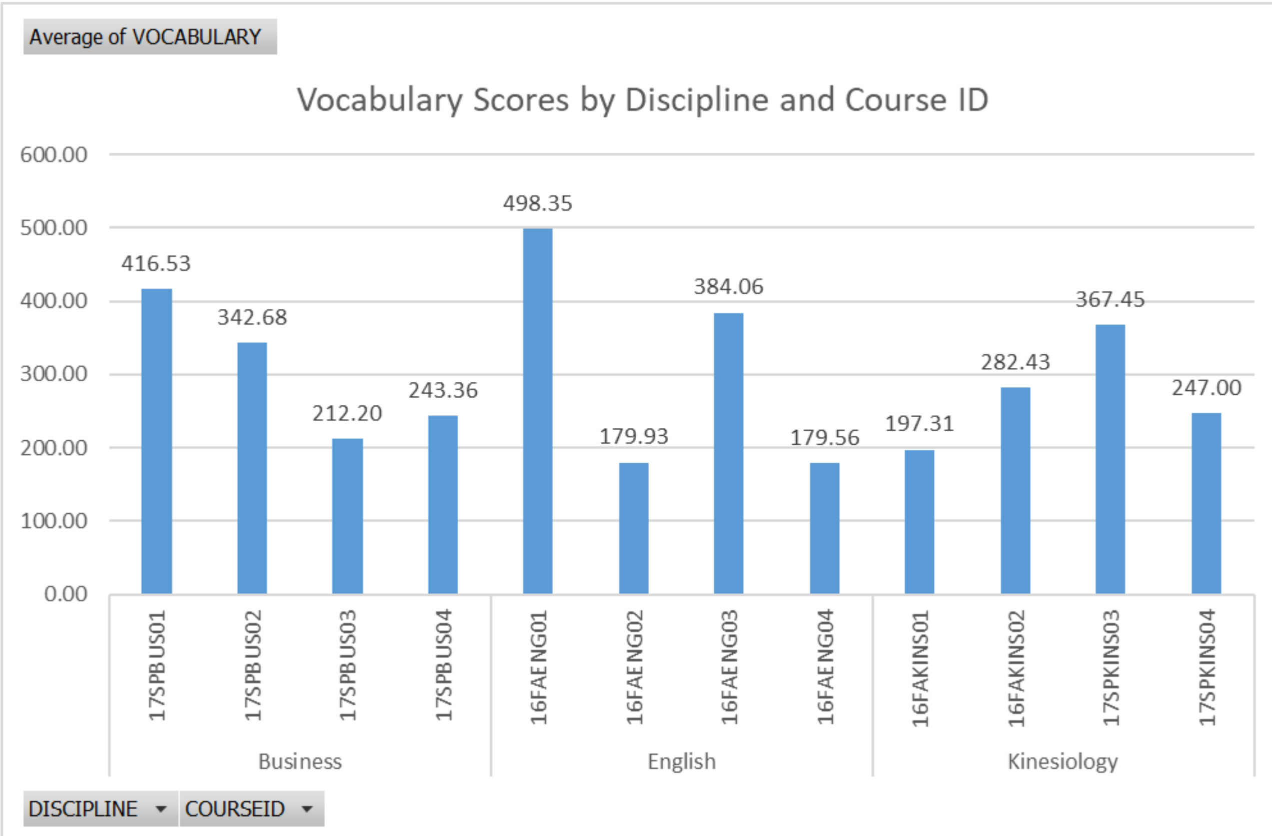
35.00%
40.00%
45.00%
50.00%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Vocabulary Scores by Discipline and Course ID
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212.20
243.36
498.35
179.93
384.06
179.56
197.31
282.43
367.45
247.00
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17SPBUS03
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16FAENG02
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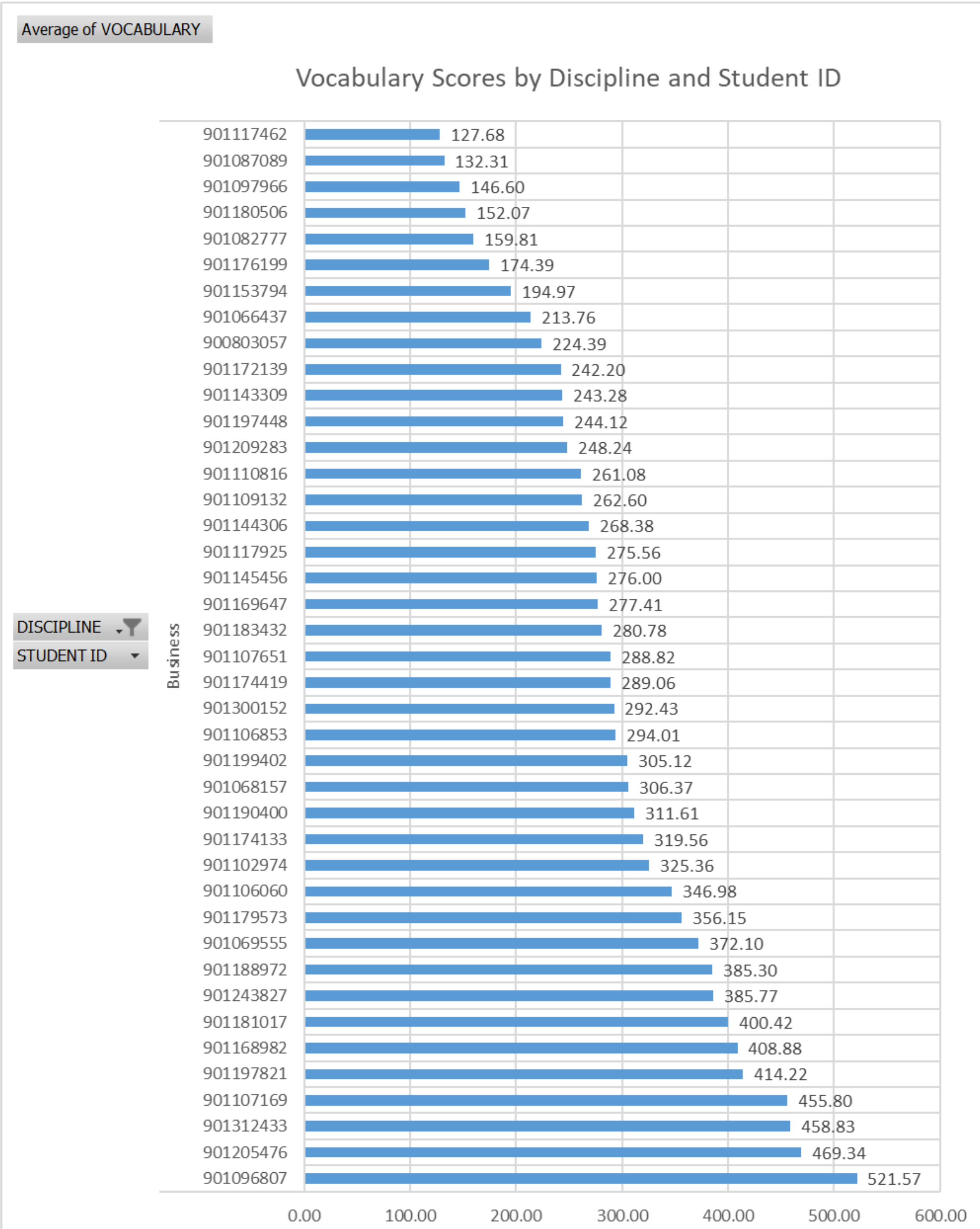
Business
English
Kinesiology
DISCIPLINE
COURSEID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Vocabulary Scores by Discipline and Student ID
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STUDENT ID
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901143309 243.28
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901199402 305.12
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901106060 346.98
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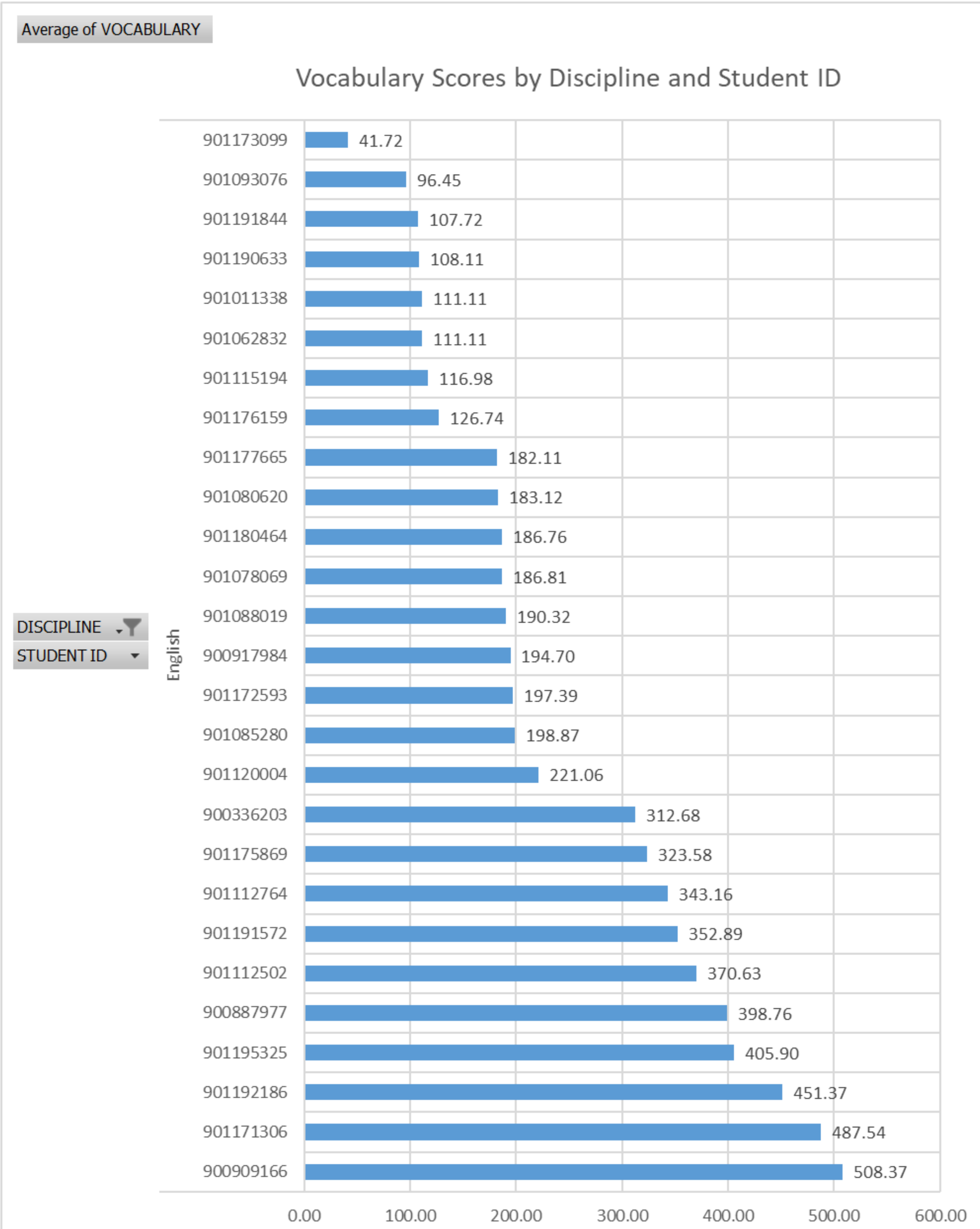
600.00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Vocabulary Scores by Discipline and Student ID
DISCIPLINE
STUDENT ID
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901180464 186.76
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901175869 323.58
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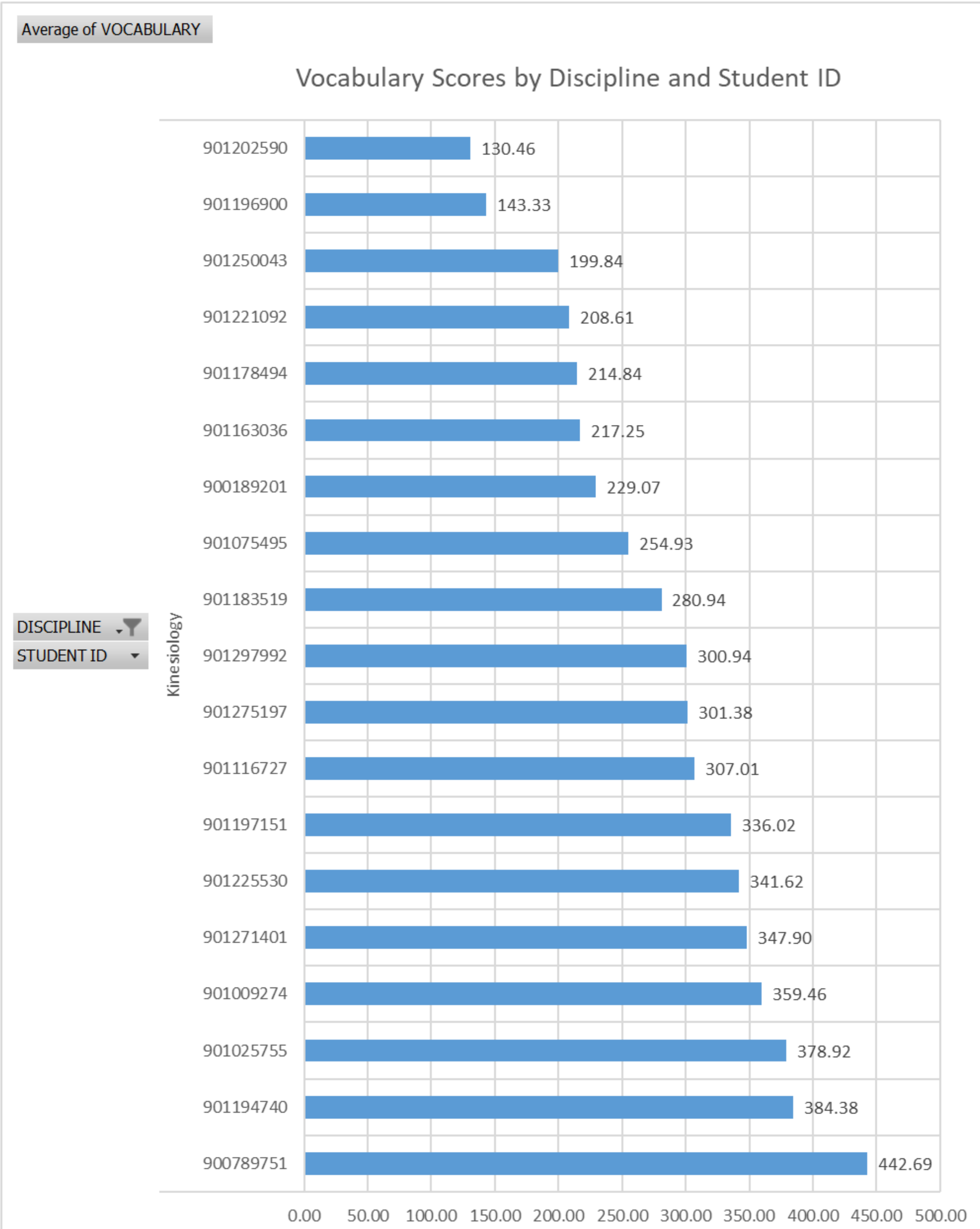
Average of VOCABULARY
Vocabulary Scores by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
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217.25
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341.62
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347.90
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359.46
901025755
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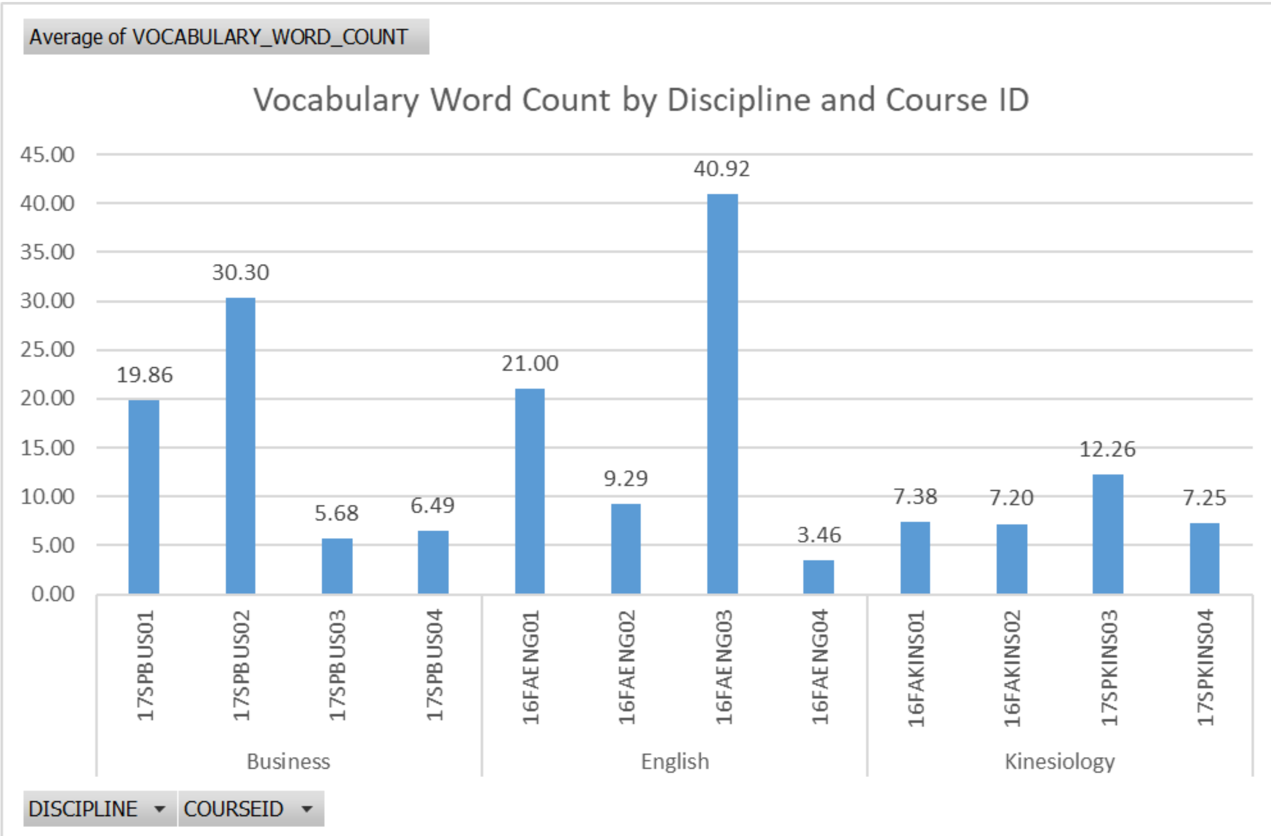

Average of VOCABULARY_WORD_COUNT
Vocabulary Word Count by Discipline and Course ID
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10.00
5.00
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30.30
5.68
6.49
21.00
9.29
40.92
3.46
7.38
7.20
12.26
7.25
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17SPBUS04
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16FAENG02
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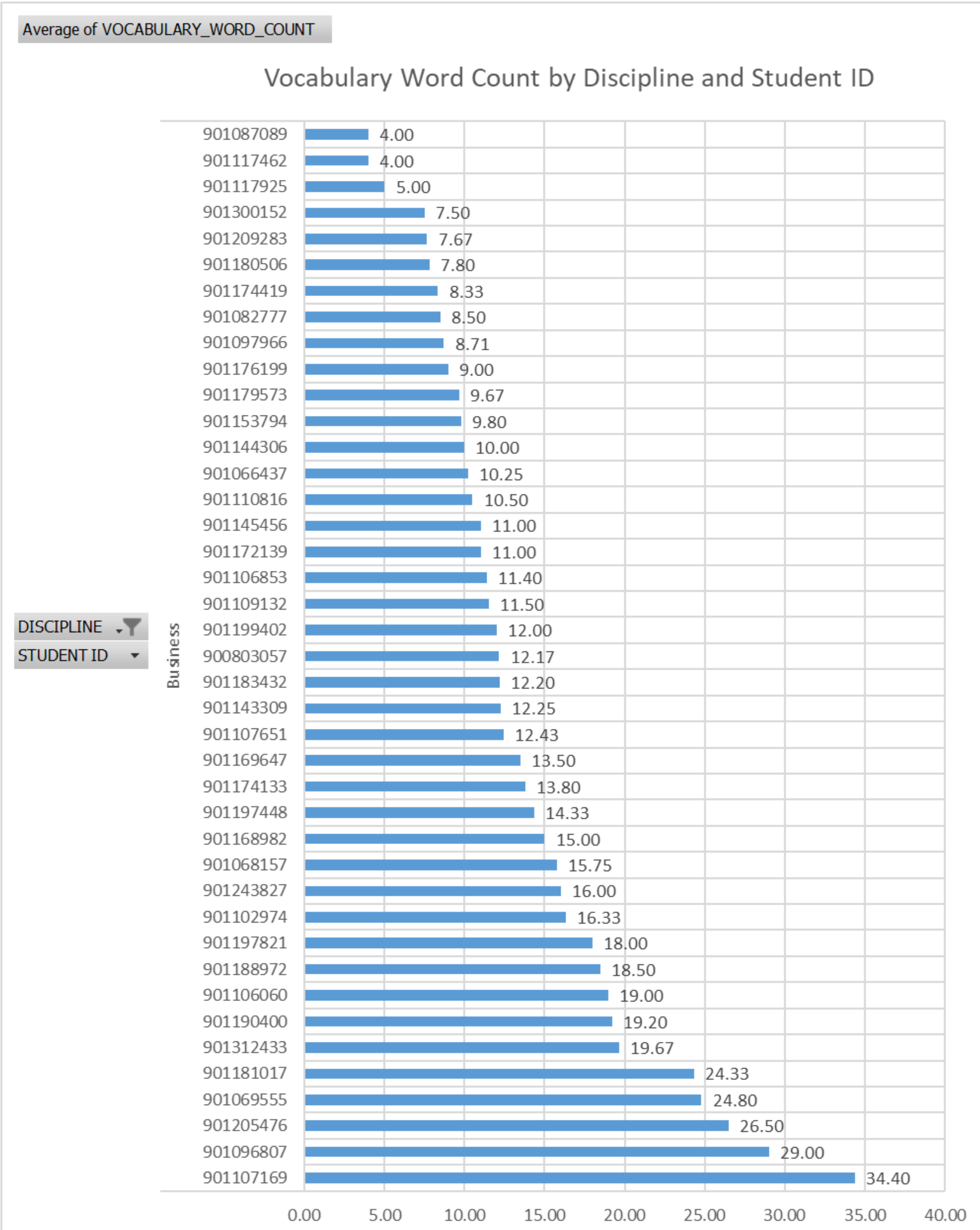
Business
English
Kinesiology
DISCIPLINE
COURSEID


Average of VOCABULARY_WORD_COUNT
Vocabulary Word Count by Discipline and Student ID
DISCIPLINE
STUDENT ID
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901179573 9.67
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901145456 11.00
901172139 11.00
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901109132 11.50
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901169647 13.50
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901197448 14.33
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901197821 18.00
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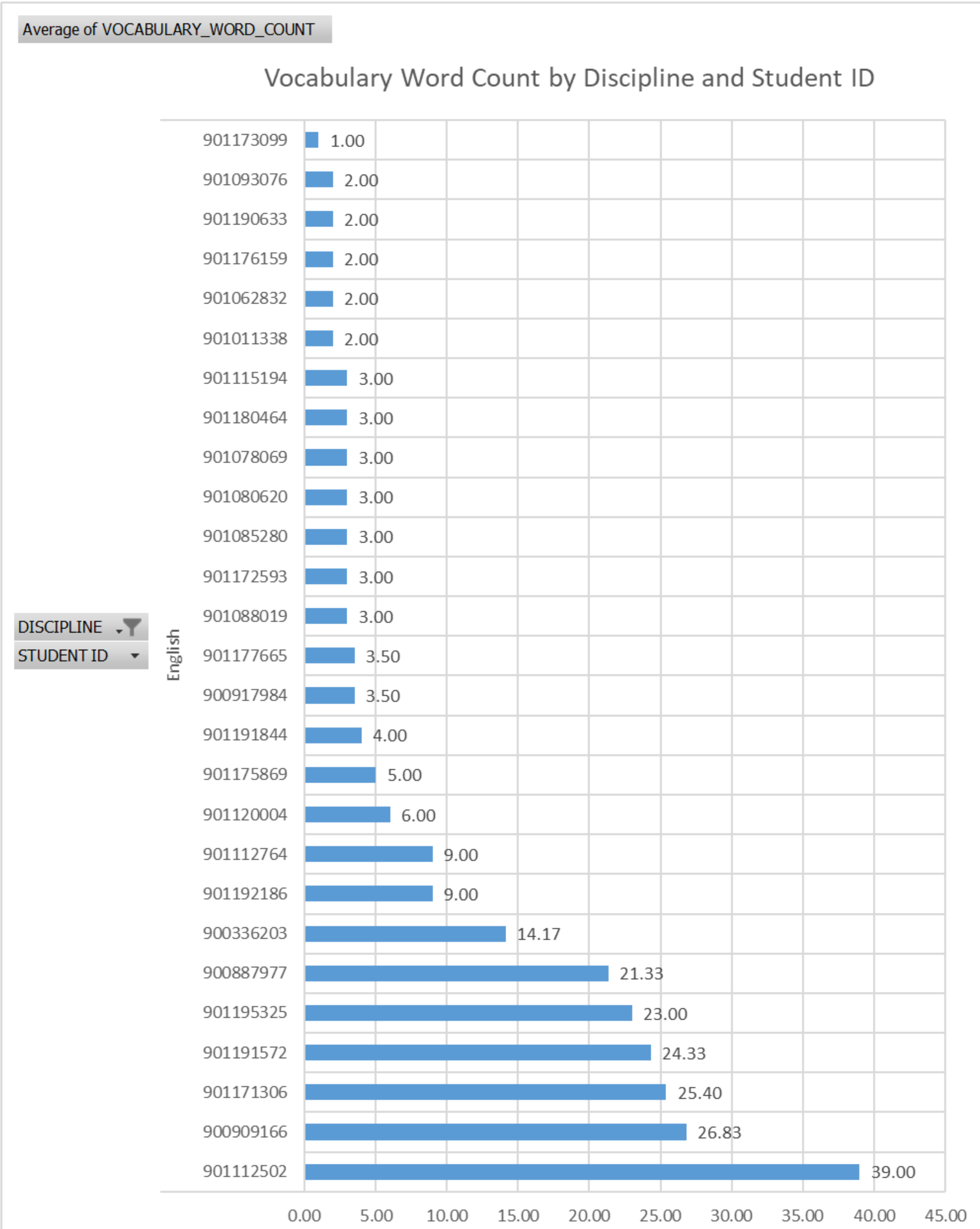
Average of VOCABULARY_WORD_COUNT
Vocabulary Word Count by Discipline and Student ID
DISCIPLINE
STUDENT ID
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901180464 3.00
901078069 3.00
901080620 3.00
901085280 3.00
901172593 3.00
901088019 3.00
901177665 3.50
900917984 3.50
901191844 4.00
901175869 5.00
901120004 6.00
901112764 9.00
901192186 9.00
900336203 14.17
900887977 21.33
901195325 23.00
901191572 24.33
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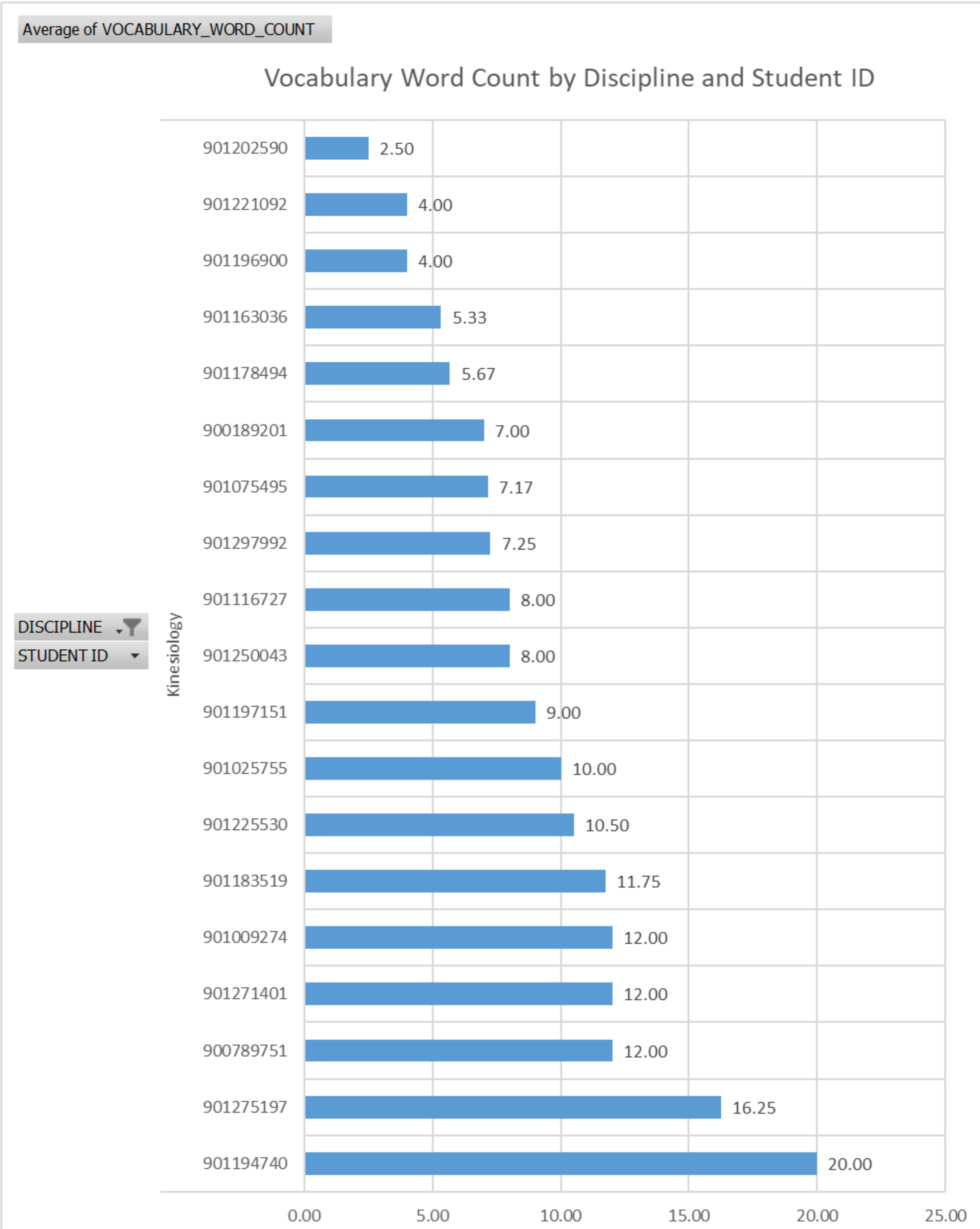

Average of VOCABULARY_WORD_COUNT
Vocabulary Word Count by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
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7.00
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7.25
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8.00
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9.00
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12.00
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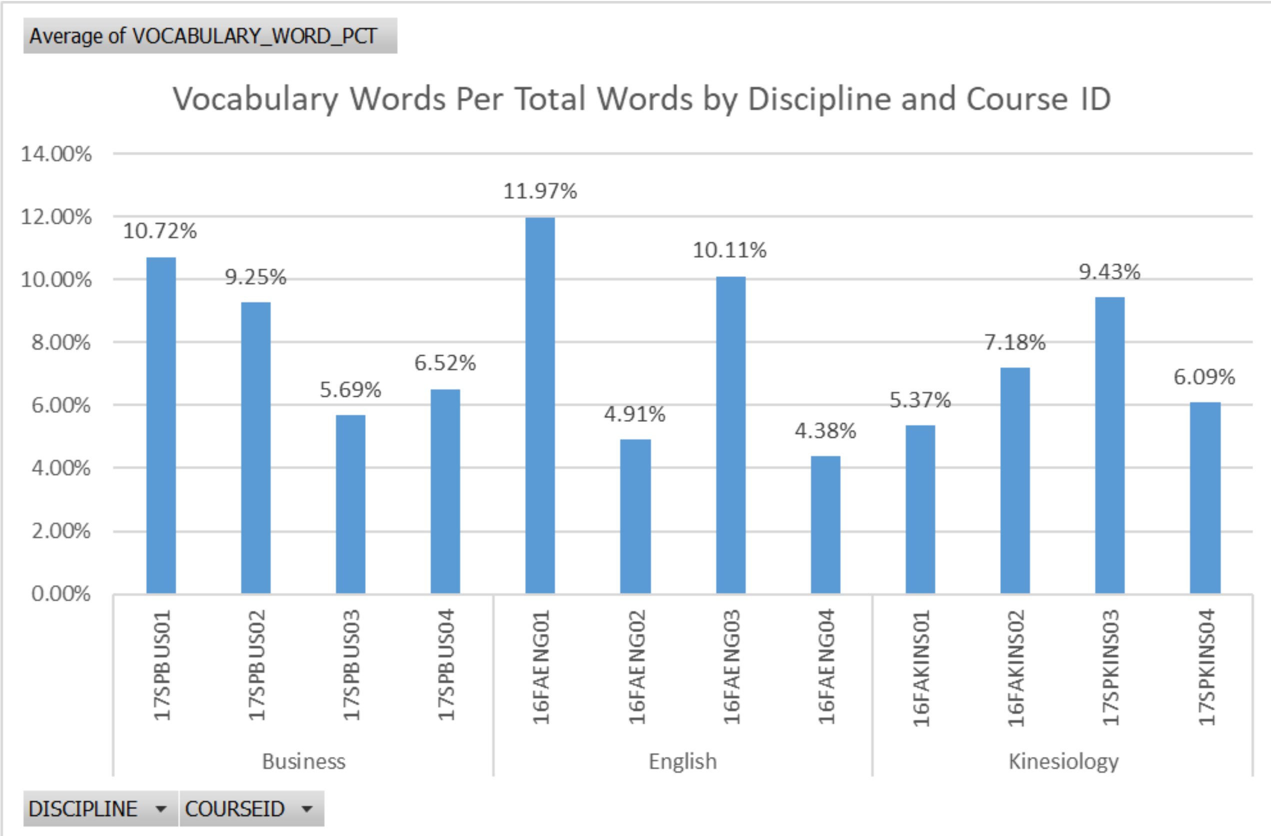
Average of VOCABULARY_WORD_PCT
Vocabulary Words Per Total Words by Discipline and Course ID
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10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
10.72%
9.25%
5.69%
6.52%
11.97%
4.91%
10.11%
4.38%
5.37%
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9.43%
6.09%
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16FAENG02
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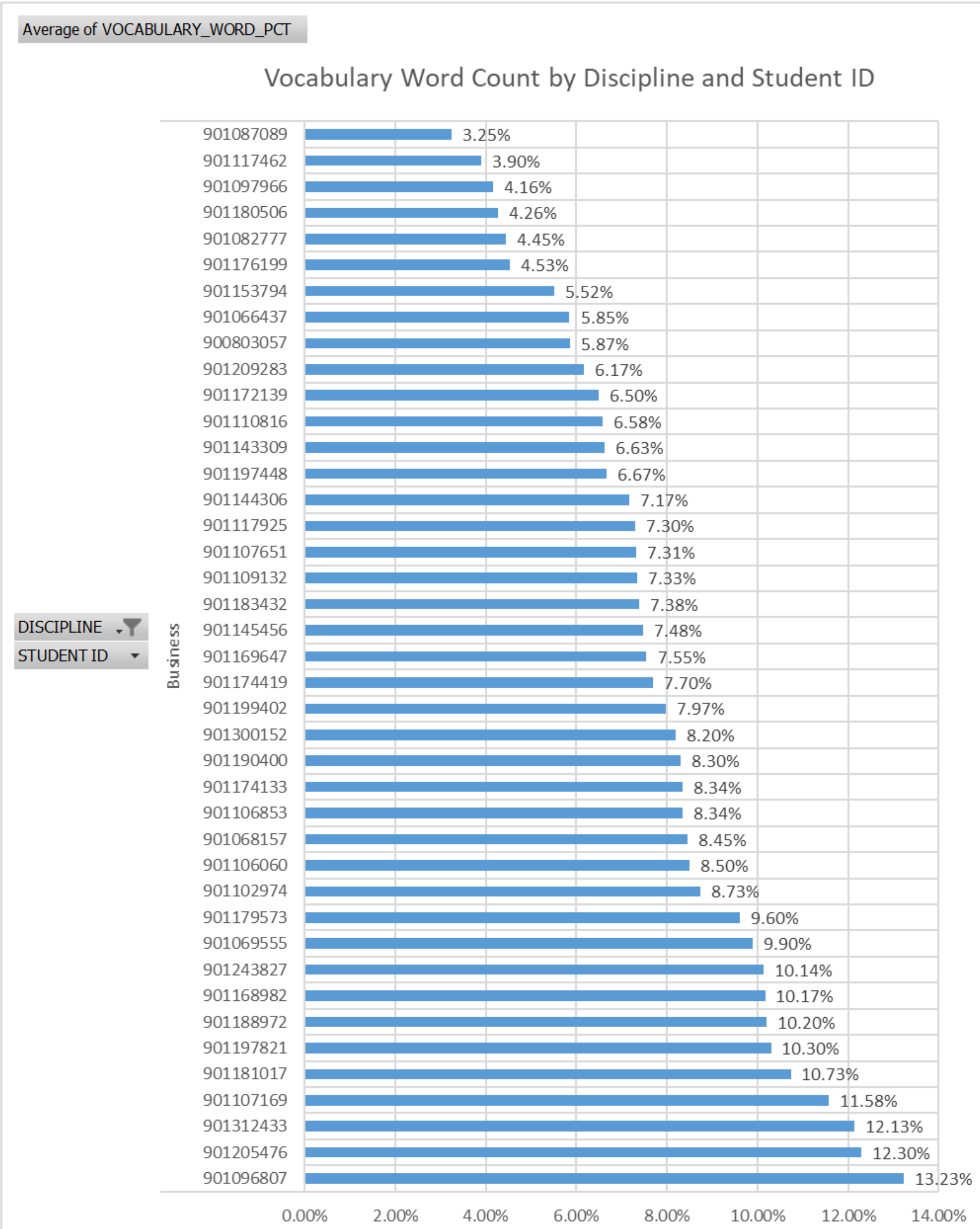
Business
English
Kinesiology
DISCIPLINE
COURSEID


Average of VOCABULARY_WORD_PCT
Vocabulary Word Count by Discipline and Student ID
DISCIPLINE
STUDENT ID
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901153794 5.52%
901066437 5.85%
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901197448 6.67%
901144306 7.17%
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901107651 7.31%
901109132 7.33%
901183432 7.38%
901145456 7.48%
901169647 7.55%
901174419 7.70%
901199402 7.97%
901300152 8.20%
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901174133 8.34%
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901102974 8.73%
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901243827 10.14%
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901188972 10.20%
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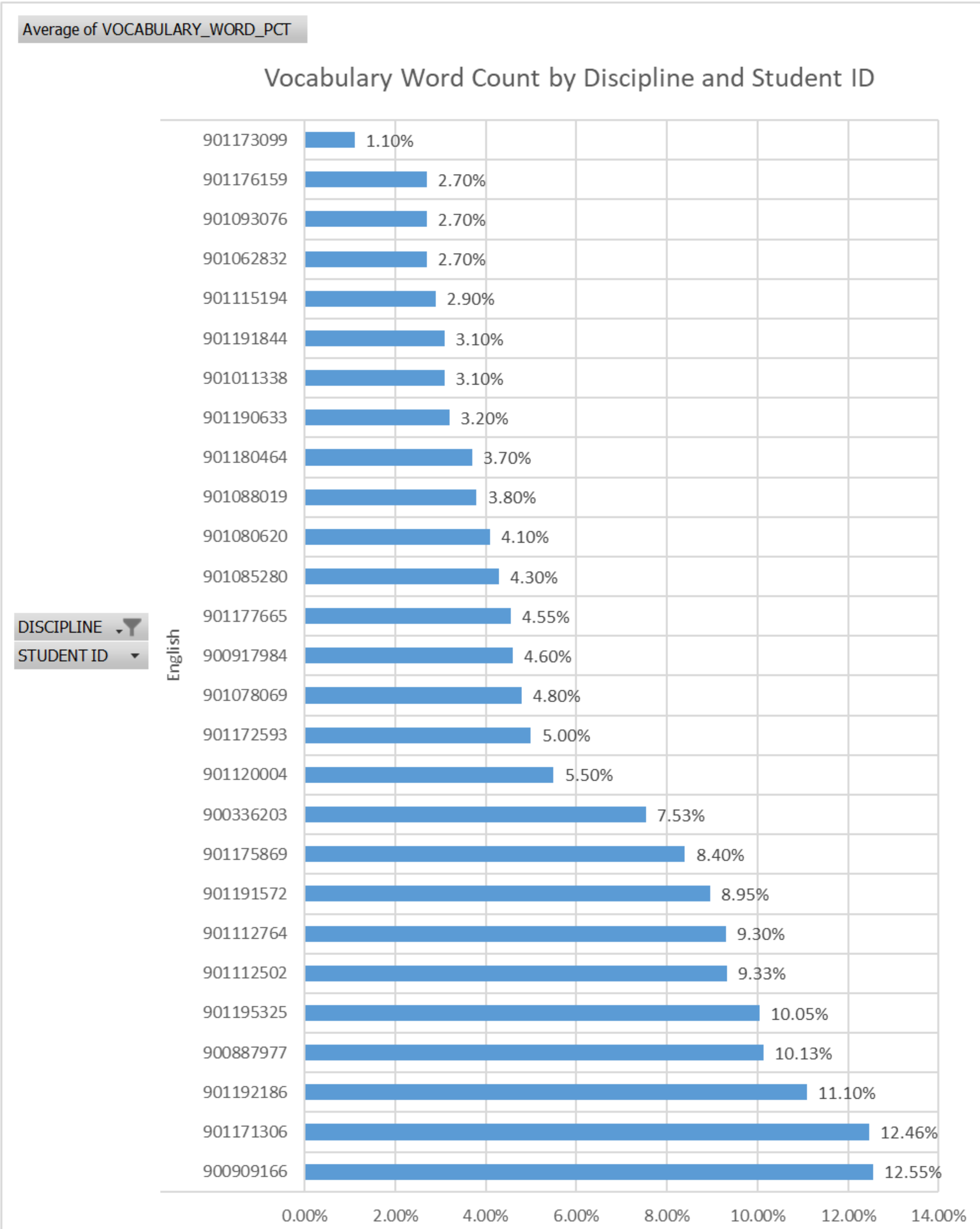

Average of VOCABULARY_WORD_PCT
Vocabulary Word Count by Discipline and Student ID
DISCIPLINE
STUDENT ID
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901191844 3.10%
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901088019 3.80%
901080620 4.10%
901085280 4.30%
901177665 4.55%
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901078069 4.80%
901172593 5.00%
901120004 5.50%
900336203 7.53%
901175869 8.40%
901191572 8.95%
901112764 9.30%
901112502 9.33%
901195325 10.05%
900887977 10.13%
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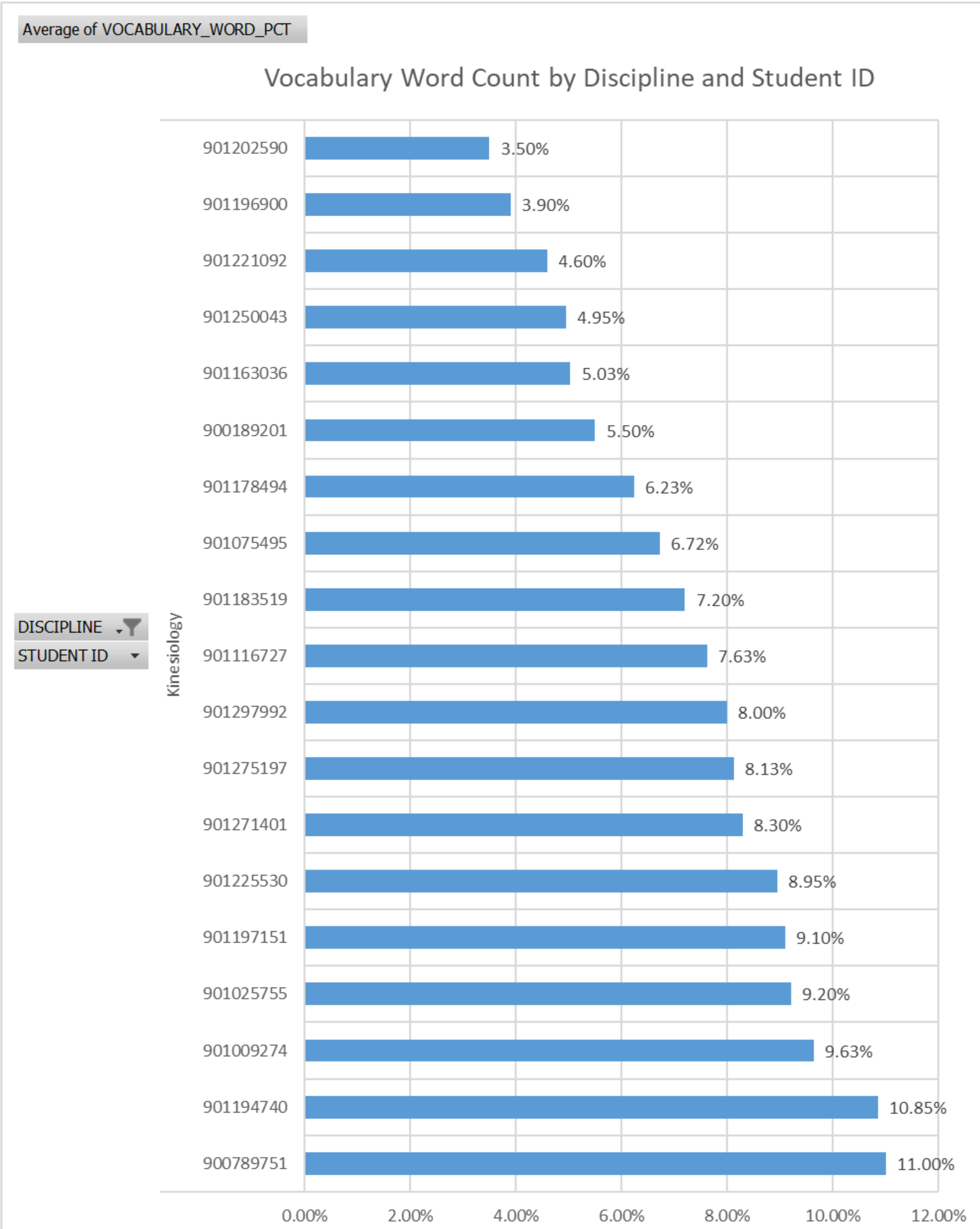
Average of VOCABULARY_WORD_PCT
Vocabulary Word Count by Discipline and Student ID
DISCIPLINE
STUDENT ID
Kinesiology
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4.60%
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9.63%
10.85%
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2.00%
4.00%
6.00%
8.00%
10.00%
12.00%

REFERENCES

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