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A Study of Online Exams Procrastination Using Data Analytics Techniques

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Abstract

Procrastination appears to be an inevitable part of daily life, especially for activities that are bounded by deadlines. It has implications for performance and is known to be linked to poor personal time management. Although research related to procrastination as a general behavior has been well established, studies assessing procrastination in the context of online learning activities are scarce. In the exploratory investigative phase of this study, advanced data analytic techniques were used to gather information about online exams. The dataset included 1,629 online exam records over a period of five terms in an academic institution in the southeastern United States. The online exams were provided during a weeklong timeframe where students were asked to take them based on material they studied the previous week. Task performance time and task performance window were fixed for all records extracted. Results of this study indicate that when it comes to online exams, over half (58%) of the students tend to procrastinate, while the rest (42%) stage their work to avoid procrastination. However, those who procrastinated appeared to perform significantly lower than those who staged their work. Clear trends were also observed based on whether the students attempted exams in the morning or the evening, their academic level, and gender.

Keywords: data analytics, procrastination, online exams procrastination, online exams data analytics, data-mining techniques in online learning, business intelligence (BI) in Web-mining.

Introduction

"Procrastination is the art of keeping up with yesterday."
~Don Marquis 1878-1937 (journalist/author – New York City, NY)

The implementation and utilization of e-learning systems have substantially increased over the past two decades("U.S. Department of education," 2011). Such systems produce huge data sets when logging all tasks that users perform (Geri & Geri, 2011). The use of e-learning systems' data logs to conduct analysis has been documented in prior

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literature. For example, Hershkovitz and Nachmias (2009) reported on using data logs of 674 students to trace their learning behavior over their whole learning experience. Ben-Zadok, Leiba, and Nachmias (2010) reported on differences in behaviors of students logging from home versus logging from school, based on nearly 1,200 records collected from e-learning systems' log files. Gafni and Geri (2010) reported on a study, using 120 Master of Business Administration (MBA) students, on procrastination in submitting assignments, based on historic footprints left by the students via the data logs. While these are fruitful studies, there is limited documented research on the use of e-learning systems' data logs to investigate issues related to online exams. Data logs can provide a valuable bedrock for investigating time-based activities such as student procrastination in various e-learning systems' activities (Hershkovitz & Nachmias, 2009).Thus, it appears that an assessment of data logs in an attempt to understand valid trends, specifically procrastination in online exams, is warranted.

In the context of online exams, the main contribution of this study is the inclusion of empirical results on procrastination from a data set of tasks using data analytics techniques. The results can help support actions necessary to improve students' scores on online exams, learning strategies, academic performance indicators, and overall learning experience. Additionally, we hope that this work can spark follow-up investigations using the data analytics techniques described in detail below in the context of e-learning and Web-based systems.

This paper reviews the relevant literature related to procrastination, followed by a definition of data analytics, and a brief comparison between data analytics and traditional statistical analysis. The research goals are then outlined, followed by a description of the methodology used. Next, the results are presented, including visualization illustrations of the data. The paper closes with conclusions and discussions about the summary of the results, implications, as well as limitations and future research.

Literature

Procrastination

Procrastination is a prevalent phenomenon in modern life (Díaz-Morales, Ferrari, & Cohen, 2008; Steel, 2007). According to Gafni and Geri (2010), procrastination is defined as "the tendency to postpone an activity under one's control to the last possible minute, or even not to perform it at all" (p. 115). Various studies classified 15%-29% of the adult population as chronic procrastinators (Ferrari, 2010; Harriott & Ferrari, 1996; McCown, Johnson, & Petzel, 1989; Pychyl, 2010; Sigall, Kruglanski, & Fyock, 2000). Furthermore, according to Ferrari (2010), procrastination is prevalent at almost the same levels amongst western societies. Ancient societies viewed procrastination in positive terms, believing it helped to avoid unnecessary work and reduce impulsive behaviors. While there are acceptable pauses and delays in performing online tasks (Kalman, 2008; Kalman & Rafaeli, 2011), studies associated with procrastination found it related to personality characteristics, emotional disposition, and performance outcome (Ackerman & Gross, 2005; Van Eerde, 2003). However, procrastination may result from time pressure, rather than specific personality related characteristics (Freedman & Edwards, 1988). Moreover, Díaz-Morales et al. (2008) noted that time is the essential component of procrastination investigations. Additionally, Beaudoin, Kurtz, and Eden (2009) indicated that "time management issues emerged as far and away the most dominant issue for these [online] learners" (p. 284). While better time management appears to reduce procrastination somewhat, an increased volume of tasks among individuals in modern society still remains an unsolved challenge.

Previous research on procrastination provides mixed results on gender differences (Díaz-Morales et al., 2008; Gafni & Geri, 2010; Sarid & Peled, 2010). Procrastination may be task dependent and additional research to uncover such differences is warranted. Specifically, Díaz-Morales et al. (2008) noted that "future researchers should consider differentiating profiles of procrastinators, because distinctive profiles may lead to better diagnoses, treatments, and research on procrastination" (p. 238).

Data Analytics

Nowadays, information systems are used to facilitate or aid most daily operational tasks (Gefen, Ragowsky, Licker, & Stern, 2011). As noted previously, information systems produce significant volumes of data that result mainly from logging engines (Leventhal, 2010). Aside from the archival, retrieval, and transformation challenges associated with these logs, it is intriguing to understand what can be learned from such data sets. For example, companies are now realizing the importance of customer data, which has led to an increased interest in implementing customer relationship management (CRM) systems to better track and manage such data. Moreover, organizations are faced with the need to make knowledgeable decisions about complex situations that could have significant consequences, and CRM systems enable these decisions to be made (Grummon, 2009). In an education environment, a few examples include enrollment, schedules, learning strategies, and retention. These may be difficult to analyze, likely to be misinterpreted, and often exhibit some level of uncertainty. Consequently, universities seek to use approaches based on data analytics to enable knowledgeable decisions. Data analytics is an emerging technique that dives into a data set without a prior set of hypotheses, while letting the data derive meaningful trends or intriguing findings that were not previously seen or empirically validated (Leventhal, 2010). Data analytics in the context of businesses is known as Business Intelligence (BI), or Business Analytics (BA) (Turban, Sharda, Delen, & King, 2011). It studies the accumulation of raw data captured from various sources (i.e., discussion boards, emails, exam logs, chat logs in the context of online learning) to identify patterns, and relationships (Bose, 2009). According to Shmueli and Koppius (2011), exploratory data analytics "is used in a freeform fashion to support capturing relationships that are perhaps unknown or at least less formally formulated. This type of exploration is called exploratory visualization, as opposed to the more restricted and theory-driven confirmatory visualization" (p. 564). Thus, data analytics is distinguished from plain statistical analysis in that it does not initiate from a theoretical foundation or seek to identify a significant level to address hypotheses. Instead, data analytics uses data mining techniques to "find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner" (Leventhal, 2010, p. 138). In the context of universities, data analytics can provide decision makers with various descriptive models, forecasting, predictive models, and simulations about student behavior, level of academic performance pertaining to exams, retention, and more (Bose, 2009; Burke, 2009; Leventhal, 2010). Moreover, the majority of prior work on data analytics appear to be following the interpretive research paradigms in an effort to use the rational choice in explaining the observed phenomena. However, the positive, normative, and other types of research paradigms may also use data analytics in the future.

Research Goals

The need for this study is based on the work of Gafni and Geri (2010), who indicated that additional research is required to investigate the time element in online assignments and activities. The need for this study also stems from the work of Better, Glover, and Laguna (2007), who claimed that data analytical techniques and the discovery of resulting trends can be highly beneficial for various industries. Therefore, the main goal of this study was to uncover trends using data analytical techniques of procrastination in online exams. Specifically, this study examined a data set related to procrastination in online exams that included task completion window and task completion time. Moreover, this study attempts to uncover specific identifiable trends in terms of task completion time, scores, gender, and academic level as time progresses during the submission window. As visualization of the data and its trends are fundamental for data analytics, two other key goal of this study were to document the process by which we developed the visualization and to provide a guide on how others can follow such processes in conducting similar studies.

Methodology

The majority of procrastination-related studies are based on surveys where information was collected post-experience (Gafni & Geri, 2010). In this study, we extracted a data set of 1,629 online exam records from an undergraduate course. Moreover, this study uses data analytics by following the interpretive research paradigms in an attempt to visualize using data analytics the phenomena and to try to infer from it causes that drive such observations. The data set was compiled from a period of five terms in an academic institution in the southeastern United States. The unit of analysis for this study was the task completed (i.e., an online exam), where each record indicated an instance of online exam completed. On average, there were about 35 students in each course, taking six online exams during each term, in a total of 10 courses distributed over the five terms. The 10 undergraduate courses were related to information systems topics for sophomore (academic year=2), junior (academic year=3), and senior (academic year=4) academic levels. All courses were structured similarly by the same instructor, and the six online exams were staged throughout the term to cover fundamental concepts discussed in the course. Two main time-related measures were extracted: task completion window and task completion time. The task completion window was a weeklong timeframe (Monday 12am to Sunday midnight), where the content tested was based on course content studied in the previous week. Procrastination was based on the proximity to due time and was measured in hours before the due time. The task completion time recorded how long each student took to complete the online exam and was measured in minutes. The time allocated for each online exam was fixed at 30 minutes, but students were informed that they could slightly exceed the limit if they wanted. Additionally, the number of questions utilized was equal for all exams.

According to Leventhal (2010), the process of data analytics begins with data preparation entailing data aggregation, organization of the data into a single file containing the records extracted, and variables. We followed the guidance provided by Leventhal (2010), and the data extracted was first organized into a single data set, then reviewed for any abnormalities and anomalies. There were instances where students logged into an exam and, due to technical issues, either lost connectivity or were not able to save their answers on the server. Such cases were removed prior to analysis. As indicated by Bose (2009), data analytics "is not a technology in and of itself, but rather, a group of tools that are used in combination with one another to gain information, analyze that information" (p. 156). Accordingly, our data set was inputted into IBM's SPSS 19 for the purpose of knowledge discovery and visualization using the SPSS syntax, while some meta-data from SPSS was inputted to Excel to augment the SPSS visualization process. Descriptive analysis was conducted on all variables, followed by specific data analytics slicing and visualization graphs. Once trends were observed in the data, Mann-Whitney U tests were conducted to test for statistical significance of the trends observed.

Results

Data Set and Sample

Our data included records captured from an undergraduate course for students attending academic year two (sophomore), three (junior), and four (senior). Out of the 1,629 online exam records extracted, 56% (913) were completed by females and 44% (716) were completed by males. Interestingly enough, these courses had more male (52%) enrollment than female (48%) on average, which suggests that there are more males and fewer females who did not complete all the required tasks throughout the term, although these tasks were part of their final grade. Table 1 shows the gender and academic level summaries.

Table 1: Descriptive Statistics and Demographics of Learners (N=1,629)

Item	Frequency	Percentage (%)
Gender		
Female	913	56.0%
Male	716	44.0%
Academic Level		
Sophomore (Year=2)	443	27.2%
Junior (Year=3)	938	57.6%
Senior (Year=4)	248	15.2%

Data Visualization

Visualization of data is a significant part of data analytics (Bose, 2009). However, due to space limitations Figure 1 provides only the summarized results of the data analytics performed, which is aggregated into a single figure. The left side of Figure 1 provides a histogram of the procrastination time (in hrs) prior to the due time, which is indicated by the red line (beneath Sunday). In the context of this work, procrastination was measured by how close to the end of the submission window the task was completed. As such, procrastination was measured by the number of hours (fractional time permitted) prior to the due time. A close review of the data indicates clear distributions of the weekdays, while several cases were observed after the due time, indicating medical or other special exceptions. The right side of Figure 1 provides a histogram of the average scores (out of 100) per day of the week, marked by the number of tasks completed per day of the week.

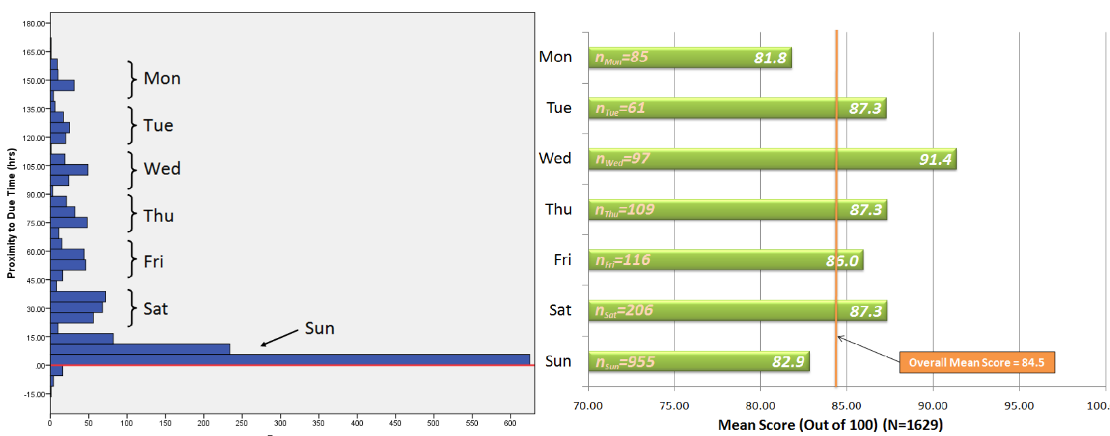
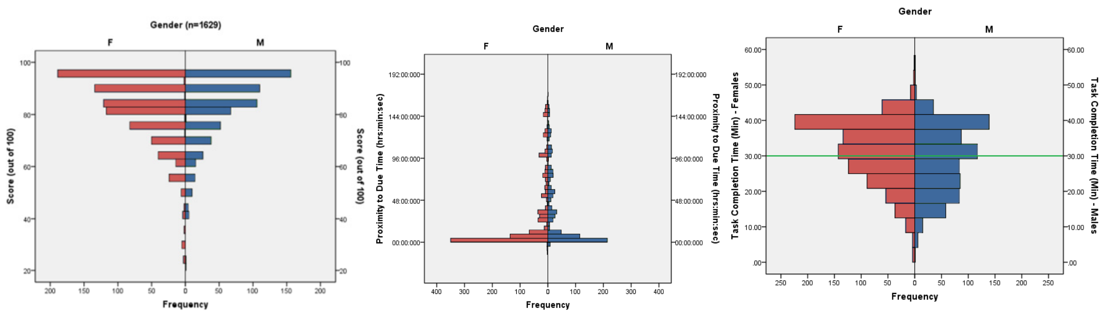


Figure 1. Descriptive Histograms of Procrastination (hrs) and Scores (N=1,629)

Figure 2 shows the distribution of scores, procrastination (measured in hours before the due time), and task completion time based on gender. Clear significant differences with $p<0.01$, using the non-parametric Mann-Whitney U test (Mertler & Vannatta, 2010), were observed. An interesting trend appears to emerge from the task completion time. It indicates that males take significantly less time to complete the task within the allocated 30 minutes, whereas females tend to take longer to complete the task, even going over the allocated 30 minutes. Given the fact that students were told they would not be penalized for going over the time, females appeared to exploit the leniency, while males appeared not to.



2a. Scores per Gender 2b. Procrastination per Gender 2c. Task Completion Time per Gender

Figure 2. Distribution of Scores, Procrastination, and Task Completion Time based on Gender (N=1629)

Due to inconsistencies in the Monday records from medical exceptions, along with the fact that weekday task completion frequencies were relatively smaller compared to those on Sunday, we decided to focus our analysis on Tuesday through Sunday. It's important to note that all exceptions to re-take the online exams were granted during Mondays due to medical reasons where individuals provided medical evidences and approval was granted by the dean's office.

For the initial analytics trend visualization, Figure 3 provides another aggregated data analytics summary of exam scores, task completion time, gender, academic level, and aggregated procrastination (i.e., Sunday vs. Tuesday-Saturday). Results indicate some observed differences for scores, academic level, gender distribution, and task completion time. Specifically, scores for procrastinated online exams (i.e., those completed on Sunday) were found to be significantly lower at p<0.001, using the non-parametric Mann-Whitney U test, than those completed between Tuesday and Saturday.

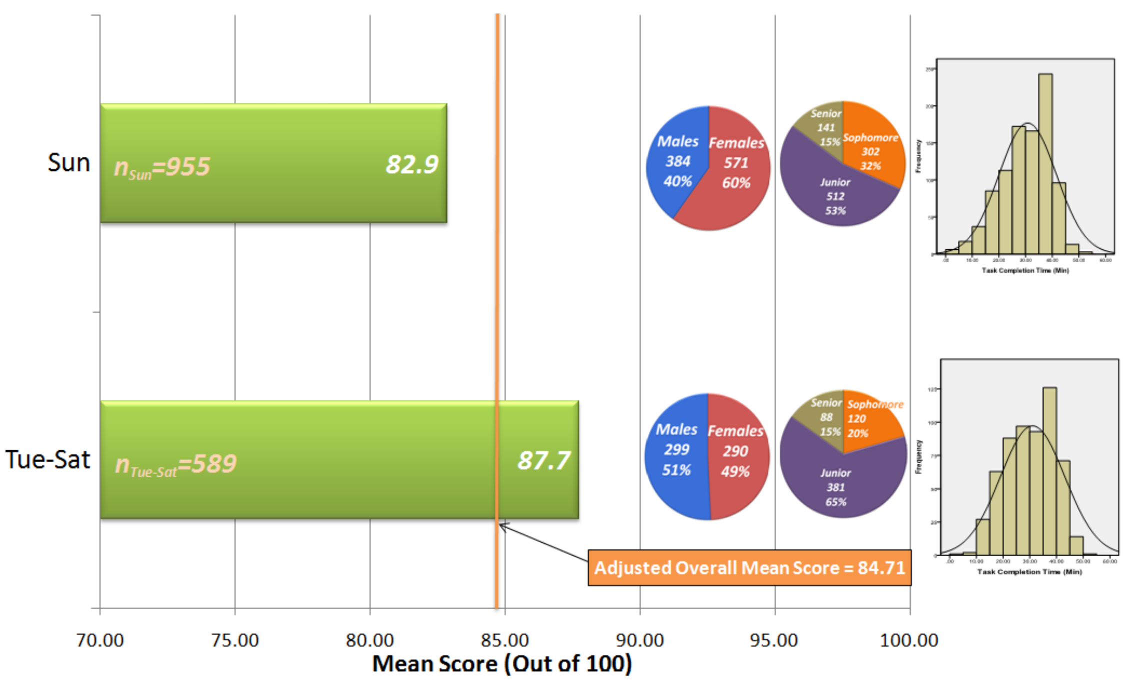


Figure 3. Data Analytics Plots of Scores, Procrastination, Task Completion Time, Gender, and Academic Level of Sunday vs. Tuesday-Saturday

Significant gender differences at $p<0.01$ were observed between males and females for procrastination. Out of the 861 online exams completed by females, 66.3% (571) were completed on Sunday, while out of the 683 completed by males, 56.2% (384) were completed on Sunday. For academic level differences, the number of online exams completed vary base on the academic years (sophomores or year=2, juniors or year=3, & seniors or year=4). Out of the 422 online exams completed by sophomores, 71.6% (302) were completed on Sunday. Out of the 229 completed by seniors, 61.6% (141) were completed on Sunday, while out of the 893 completed by juniors, 57.3% (512) were completed on Sunday. The shift in such numbers indicates that as university students mature, they tend to procrastinate more. However, as they get closer to graduation, some may be more motivated to complete their tasks earlier. Table 2 provides a summary of the gender and academic level distributions between Tuesday and Saturday versus Sunday time intervals.

Table 2: Gender and Academic Level Distributions (n=1,544)

	Gender				Academic Level					
Day	Females		Males		Sophomores (Year=2)		Juniors (Year=3)		Seniors (Year=4)	
Tue-Sat	290	33.7%	299	43.8%	120	28.4%	381	42.7%	88	38.4%
Sun	571	66.3%	384	56.2%	302	71.6%	512	57.3%	141	61.6%
Total	861	100.0%	683	100.0%	422	100.0%	893	100.0%	229	100.0%

In terms of task completion time, online exams completed during Sunday tend to take a longer time compared to those completed during the Tuesday-Saturday time frame. This indicates that procrastinating students might engage in scavenger hunts for answers to exam questions, rather than demonstrate true knowledge of the material studied. There were no observed differences of the scores based on academic level, course, or term taken.

Morningness–Eveningness Analytics

Given that procrastination was measured in hours before the due time, the comparison between the morning hours (Ante-Meridiem (AM)) and evening hours (Post-Meridiem(PM)) created another observable trend. According to Díaz-Morales et al. (2008), morningness–eveningness refers to “an individual’s preference for specific times during the day” (p. 229). Figure 4 provides the trends in the data extracted from Tuesday to Sunday (i.e., 144 hrs to 0 hrs) regarding scores and procrastination based on morningness-eveningness, while the size of the bubbles represents the number of tasks completed. Apart from Friday, the majority of the weekdays demonstrated a clear pattern where online exams completed during the AM provided significantly, at $p<.005$, higher scores then those completed during the PM hours. Moreover, it was observed that Friday appears to be a puzzling result and additional dichotomization of the data is needed to explore plausible explanations.

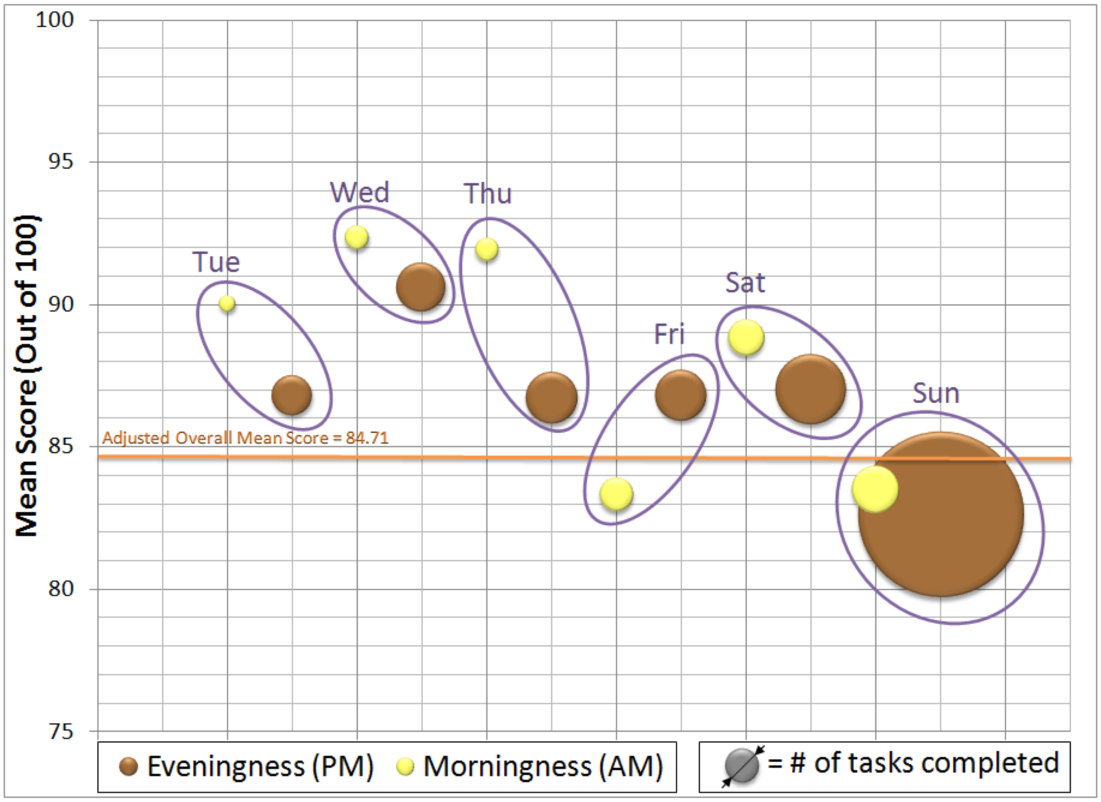


Figure 4. Distribution of Scores and Procrastination (Day) based on Morningness-Eveningness

Morningness–Eveningness and Gender Analytics

Given the gender indicator that existed in the dataset, further analytics exploration was performed to separate the morningness-eveningness based on gender type. Results of such analytics are presented in Figure 5. Our findings indicate that aside from Wednesdays, males tend to outperform females during the AM. It is also evident that during the Tuesday to Thursday time females tend to outperform males during the PM, while from Friday to Sunday males tend to outperform females slightly in the PM. We also learned that Friday AM appears to be an out of the general female AM trend when it comes to performance. Further investigation of such female records indicated that the 18 records were mostly (73%) junior, the majority (78%) scored below the mean, and almost all (90%) went above the 30 minutes allocated time. Further dichotomization of the 18 records revealed that most of the females were mothers to school age kids and working full-time. We speculate that their out of trend results are due to the enormous demands placed on them for balancing work during the weekdays and family obligations during the weekends.

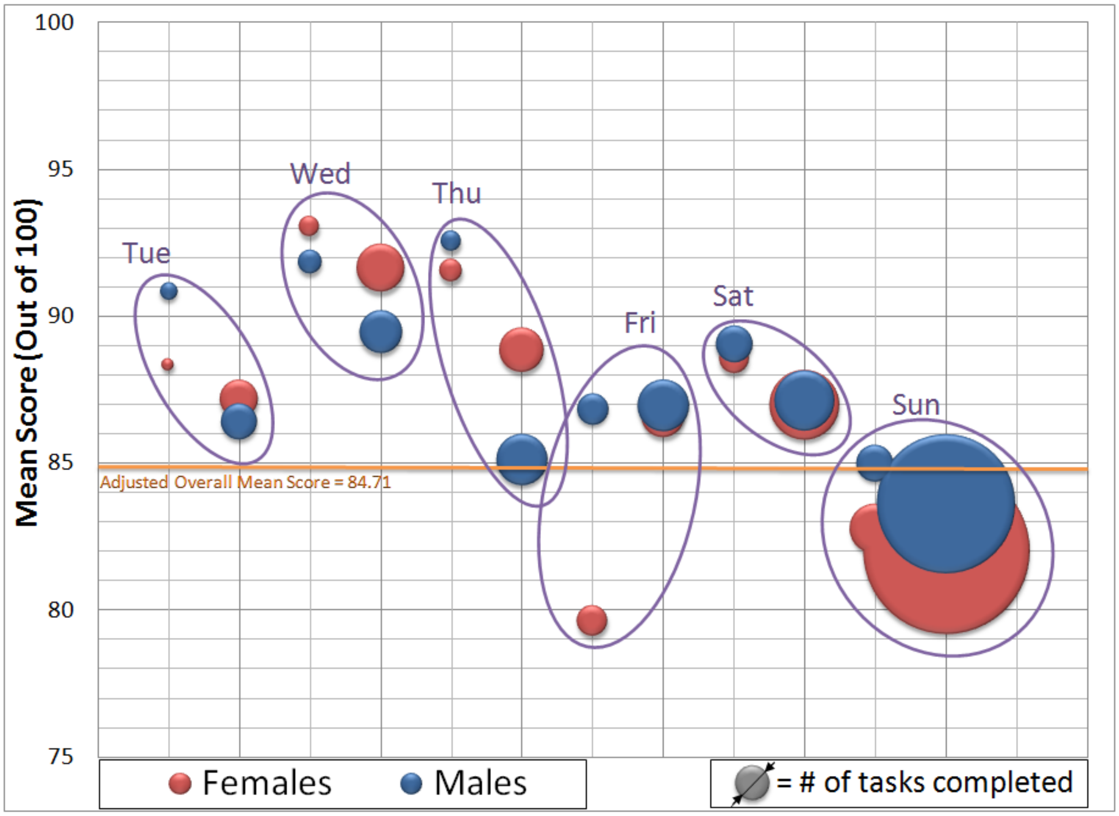
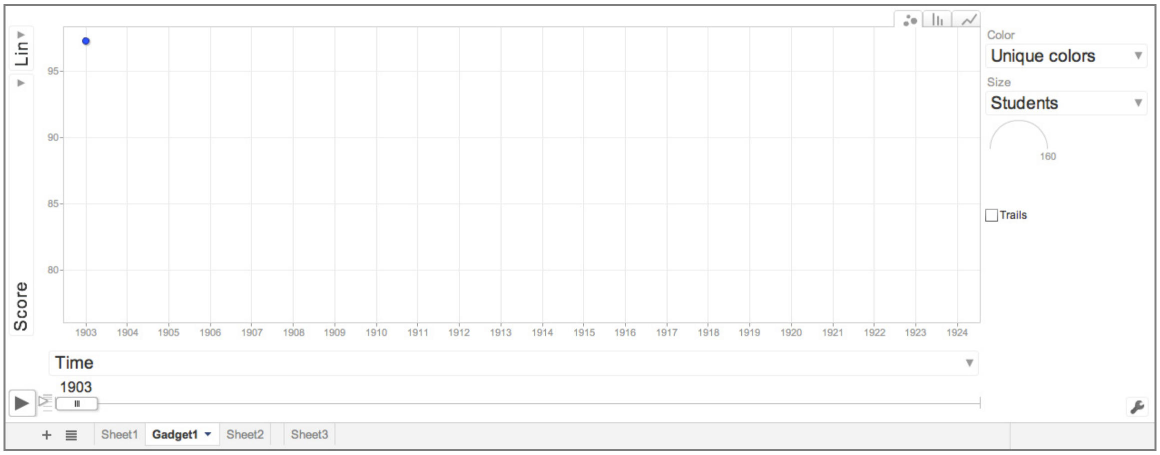


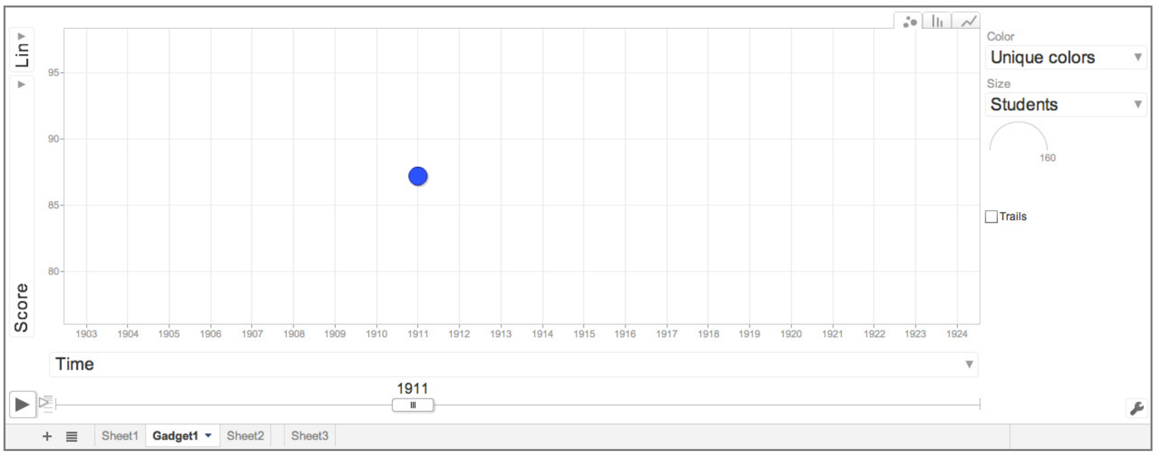
Figure 5. Distribution of Scores and Procrastination (Day) based on Morningness-Eveningness and Gender

4D Analytics of Online Exam Procrastination in the last 24 hours

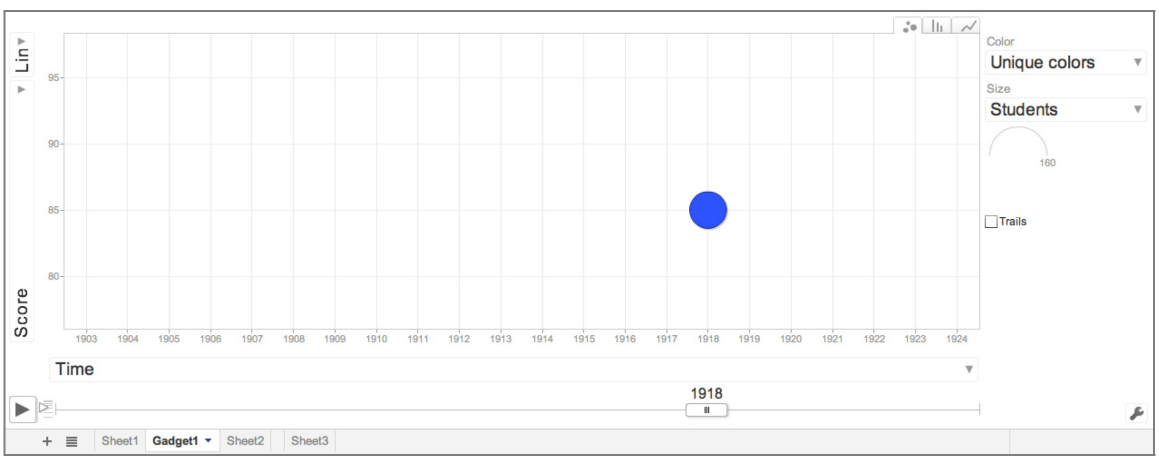
Due to the significant number of those who procrastinated until Sunday, the last day of the submission window, all records submitted in the last 24 hours prior to the due time were analyzed closely using the Google® Motion Chart data visualization (Motion Chart Gadget - http://code.google.com/apis/chart/interactive/docs/gallery/motionchart.html). Google® Motion Chart gadget is a feature that is added to any Google® spreadsheet document to enable 4D visualization of data using a 3D data graphing over time, i.e., 4D = 3D + t. Part of the preparation of the data for visualization is the layout of the data in the spreadsheet, especially the time variable. The spreadsheet for this visualization included three variables: time, mean score, and number of students. Given the limitations of the Google® Motion Chart gadget time restrictions, the time variable for the last 24 hours was noted as years starting at 1901 and ending at 1924, corresponding to the hours 01:00 (1AM) to 24:00 (Midnight). Figure 6 is a set of four captures of the data visualization for the records during the last 24 hours before the due time at 3AM, 11AM, 6PM, and midnight. The actual data visualization (without voice) is available via a YouTube® movie (http://www.youtube.com/watch?v=Bt4rHaOteoo&context=C3e76fabADOEgsToPDskLwDu1YsJZADHxbMC97mc0j). Our data visualization in Figure 6 or the YouTube® movie indicates an overall trend of growth in the number of exam takers (i.e., the size of the bubble), where the last six hours represent a significant amount. We also demonstrate that while the early hours of the last day of the submission window appear to fluctuate in grades, during the last 12 hours the grades appear to drop as time progress. Moreover, our data demonstrate that such a drop seems to be significant in the last six hours before the due time.



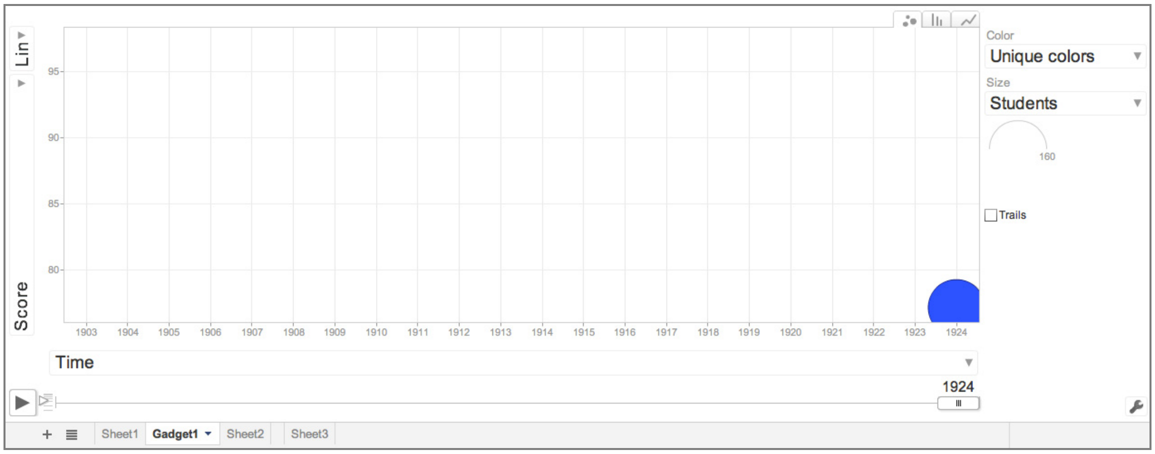
At time 03:00 (3AM)



At time 11:00 (11AM)



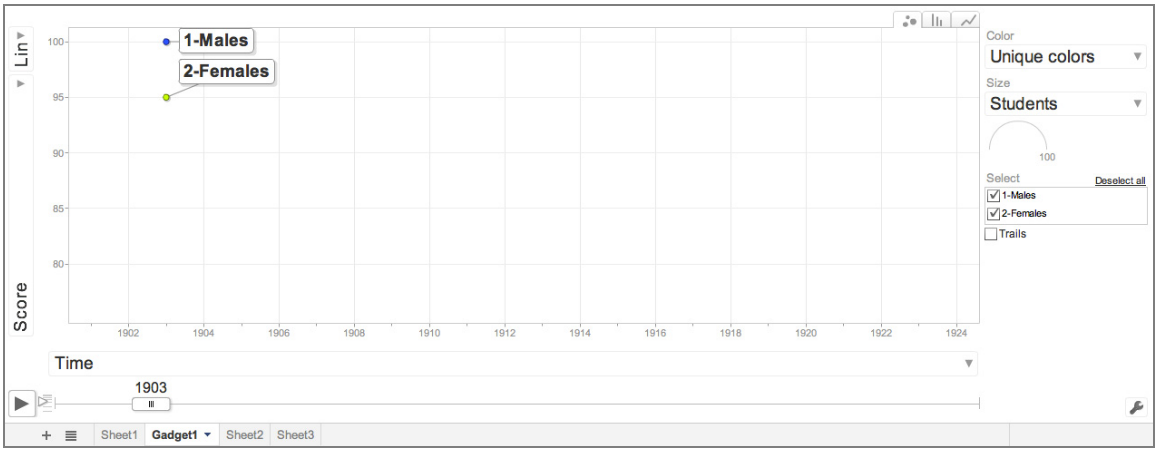
At time 18:00 (6PM)



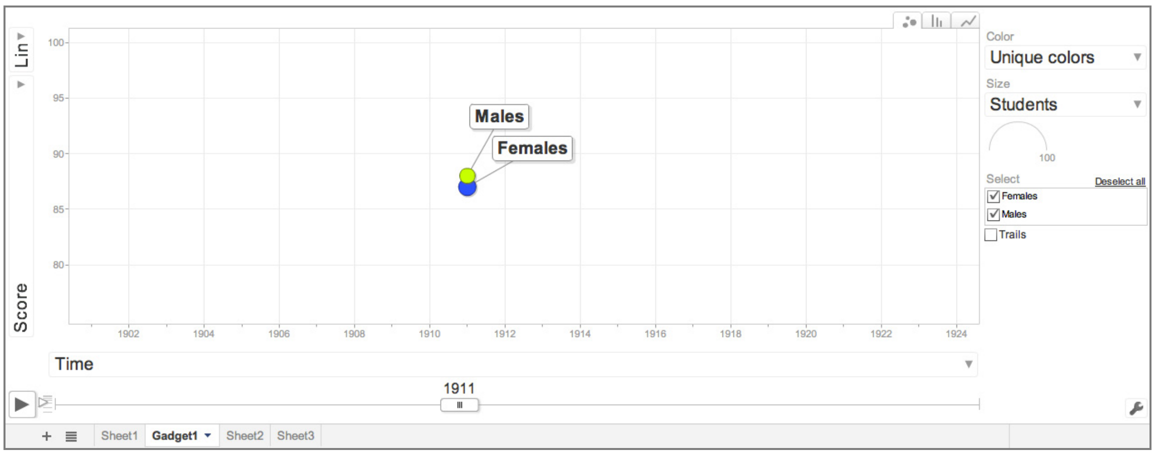
At time 24:00 (12AM)

Figure 6. 4D (3D+t) Visualization of Scores During the Last 24 hours of Procrastination in Online Exams (n=955)

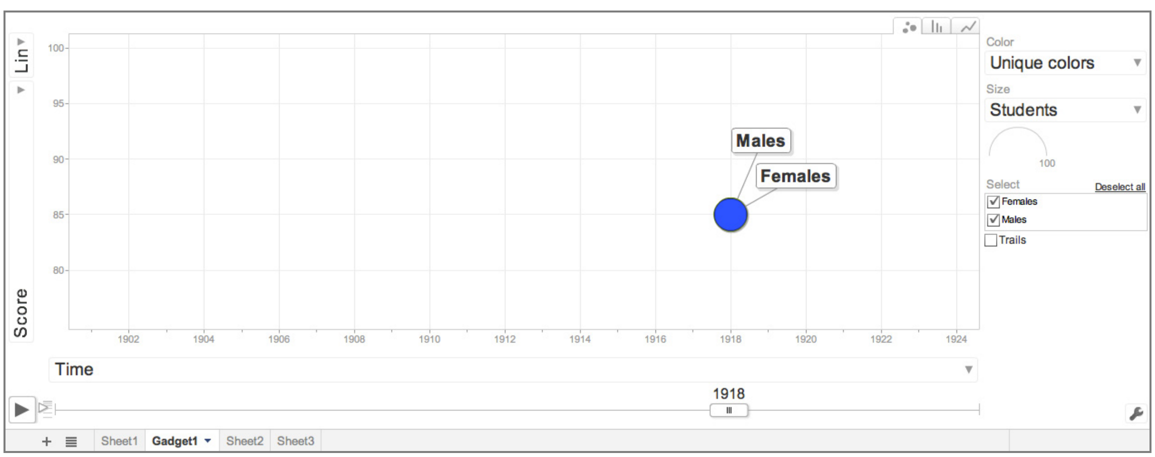
Because of the gender dichotomization of our data discussed above, an additional Google® spreadsheet was generated from the Sunday only data (n=955) for the visualization based on gender. In this case, a fourth variable was added to indicate the gender along with the time (indicated in years 1901-1924 corresponding to 01:00-24:00), the mean score for each gender in each hour, and number of students from each gender in each hour. Figure 7 is a set of four captures of the combined data visualization for the records during the last 24 hours before the due time at 3AM, 11AM, 6PM, and midnight. The actual data visualization (without voice) is available via a YouTube® movie (http://www.youtube.com/watch?v=imMeqm1K4nA&context=C379f25aADOEgsToPDskL7vxQ52aKGXCkKsCcyGfSQ). Our data visualization in Figure 7 and the YouTube® movie indicate, as in the combined genders data, an overall trend of growth in the number of exam takers (i.e., the size of the bubble), where the last six hours represent a significant amount for both females and males. However, as noted previously in the demographics information, during Sunday there were more females (~60%) in the data collected than males (~40%). Nonetheless, the gender-based visualization shows that during the majority of the day, until 8pm, there is a somewhat similar volume of online exam takers between the genders as time progresses. However, after 8PM on Sunday there is a sharp increase in the ratio of females to males taking the online exam, and in the last two hours before the due time, that ratio gets to nearly twice (~1.87:1) the number of female takers to male takers. Additionally, as observed in the aggregated data before, the gender-dichotomized data demonstrate similar characteristics regarding the fluctuation in grades during the first 12 hours, and a significant drop in both gender grades as time progresses.



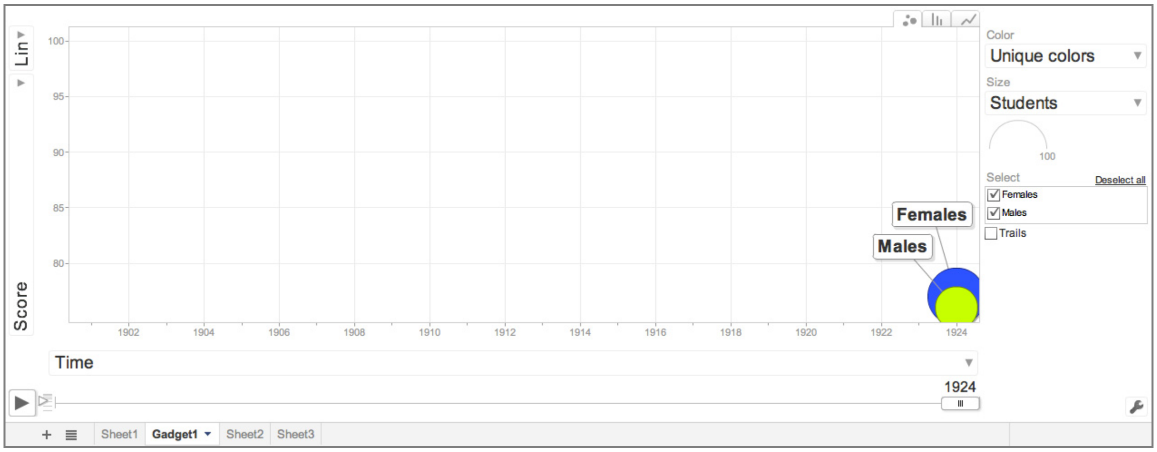
At time 03:00 (3AM)



At time 11:00 (11AM)



At time 18:00 (6PM)



At time 24:00 (12AM)

Figure 7. 4D (3D+t) Visualization of Scores During the Last 24 hours of Procrastination in Online Exams Distributed by Gender (n=955)

Discussion

Summary of the Results

Based on our data analytics of 1,629 records extracted, the results indicated that although nearly 42% of the students staged their workdays before the due time (Mon-Sat), over 58% procrastinated until the last day (Sunday), or more precisely, about 40% procrastinated until the last 12 hours of the weeklong task completion window. We found that although academic level among seniors was similar throughout the procrastination time, percentage-wise, a significant number of older students procrastinated, specifically sophomores. Additionally, we found that percentage-wise, more females procrastinated. We suspect that such results are due to the fact that enormous demand is placed on females nowadays. Some are working mothers who balance work during the weekdays and family obligations during the weekends. Our data analytics visualization of morningness-eveningness indicated that aside from Fridays, on the majority of the weekdays a clear pattern was demonstrated where online exams completed during the AM, at $p<.005$, had higher grades than those completed during the PM hours. Additional dicotomization of the data based on gender indicated that from Tuesday to Thursday females tend to outperform males during the PM, while from Friday to Sunday males tend to outperform females slightly in the PM. Furthermore, the last day before the due time, Sunday, provided interesting visualization movies both in aggregated form and in gender-dichotomization form, indicating a clearly observed trend during the last 12 hours before the due time, where grades significantly deteriorate as the due time approaches.

Study Implications

The implications of our study are significant as our results also indicate that procrastination during the week does not pay off, given that, by and large, there was an observed downwards trend during the weekdays. The general trend shows that the longer the procrastination (i.e., closer to the due time), the lower the grade. This same trend also appears to hold true for morningness-eveningness. In fact, morningness-eveningness can be considered as a daily procrastination, where students may delay completing their task throughout the early hours and eventually complete the task during the later part of the day. Here, we must caution about students who are working professionals. In their case, work hours may limit their availability to engage in morning learning activities. However, with the increased use of professionals who work from home, the issue of learning during the morning may be open to further debate and investigation. Also, the data analytics trends show that the practice does not pay off given that, by-and-large, those who completed tasks later in the day underperformed those who completed tasks earlier in the day. We believe our results have significant research value as they can give practitioners and administrators of online programs an insight into the pressure that females, especially working mothers, face daily.

Limitations and Future Research

Empirical research has its limitations (Ellis & Levy, 2009), and this study was not immune to them. The central limitation of this study is the use of data from a single institution and a single type of course. Future research using data analytical techniques can be fruitful on data available in online learning systems in order to better understand current challenges and in an attempt to identify 'at-risk' groups in other institutions as well as other cultures. Our work may provide a starting point for additional empirical research in the area of procrastination using data analytics to help validate these results in other institutions and cultures. Moreover, our results may also stimulate data analytics studies in other types of information systems including knowledge management systems (KMS), electronic medical systems (EMR), e-government systems, customer relations management (CRM) systems, enterprise resource planning (ERP) or enterprise-wide systems, military-based information systems, and/or any Web-based system. These systems accumulate considerable amount of data logging all user activities, extracting such system logs and analyzing it using data analytics as described in this study can provide better understanding for the role of employee procrastination, for example, and its impact on the organization. Furthermore, our reported out-of trend findings on Fridays and the large increase of female submissions a few hours before the due time, warrants additional investigations for the tremendous challenge that working mothers are experiencing and how it impacts their overall performances. While our findings reported that indeed more females, in general, procrastinated, we anticipate that this is mainly due to their extensive life demands, rather than their negligence. Thus, additional work is needed to investigate the underlying causes of female's challenges in online and other learning experiences when it comes to procrastination. Additionally, as noted previously, some cases were removed from our data due to technical issues, either students lost connectivity or were not able to save their answers on the server. We think that additional work is also warranted in addressing this notion. Do these individuals pursue taking the online exams elsewhere and afterwards, or use the "technical issues" as an excuse? We think that learning about the technical issues and how individuals overcome those issues in the context of procrastination is also warranted.

Conclusion

In this research, we have set out to use data analytics techniques to explore the problem of procrastination using a data set of historical records extracted from online learning systems. While to our knowledge there is much research done on the use of data analytics in the context of business organizations, also known as business intelligence (BI), in the past decade or more, it appears that much more research is needed to incorporate such advanced data visualization and slicing techniques in the context of online learning systems. The extracted data set included a total of 1,629 historical records of online exams that were later analyzed for any observed trends. Given the main focus of the exploration was in the context of procrastination, our data analytics results actually nicely support the claim made by a participant in the Beaudoin et al. (2009) study that said "the freedom to do work when you want is the best part of online learning, but also its biggest challenge" (p. 281). Nevertheless, the trends uncovered in this study appear to indicate that students who perform their online exams during the morning hours, in general, appear to do better than those during the afternoon hours. Moreover, our trends revealed that, in general, the more procrastination was observed, the lower the online exams score was documented.

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