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Effectiveness and Efficiency of Enterprise Analytical Dashboard on Decision Support: A Case Study

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ABSTRACT

This research investigates influential factors of enterprise analytical dashboards on decision support. Factors studied include device type, a user's computer knowledge, and a user's demographic factors. Results indicate that the type of devices used influences both efficiency and effectiveness of analytical dashboard on decision support. The devices with the larger screens (desktop, laptop, and iPad) had the higher average completion rates (efficiency) and accuracy rate (effectiveness). Additional insights are also provided on the factors IT knowledge, daily mobile usage hours, years in school, country of origin, number of computer classes, and school year.

KEYWORDS: Analytical Dashboard, Scorecard, Decision Support, Mobile Analytics

1. INTRODUCTION

Data visualization often implemented as interactive analytical dashboard or scorecard intends to help people understand the significance of data by placing it in a visual context, so patterns, trends and correlations that might go undetected in text-based data can be exposed and easily recognized. A well-designed interactive visualization or dashboard can help users gain insights into their data, identify patterns, and make decisions (Elias and Bezerianos, 2012). As a result, data visualization or an interactive dashboard is becoming increasingly important in the workplace, especially for managers who are constantly surrounded by data.

Business analytical dashboards analyze critical business data and provides useful insights (Lim, et. al., 2015) through the use of graphic rich interactive dashboards and scorecards to support effective decision making and are traditionally deployed as desktop solutions (Verkooij & Spruit, 2013). As mobility has changed the way businesses operate and shifts enterprises from a wired to a wireless world (Harvard Business Review, 2012). As mobile devices are often constrained on the screen size and computing powers compared to desktop computer or a laptop, the ability of utilizing mobile and Internet-enabled devices create unique challenges and opportunities when analytical dashboards are used on a mobile device (Chen, et. al, 2012).

This research investigates and seeks insights on factors that affect the effectiveness and efficiency of an enterprise analytical dashboard on decision support. Factors studied include device type, a user's computer knowledge, and selected user demographic factors. The following sections provide a brief literature review, a description of research objectives, research questions, and research methodologies, and discussions of results, conclusions, and future research directions.

2. LITERATURE REVIEW

Although the history of mobility is relatively short in time, it has revolutionized the world of technology and the way businesses operate and competes. In the early 90's mobile hardware was improved to allow for 2G digital networks that provided mobile devices the ability to send messages over text. Mobile technology began making its way into the world of business and provided individuals with handheld capabilities that nearly matched those of a computer in the as more data services, new mobile device, and Personal Digital Assistant (PDA) became popular and with an improved 3G network 1990's. Today, mobile devices are used all throughout the workplace for anything from answering phone, checking emails, taking orders, to performing business analytics. As a result, mobility will continue to play a major role not only in personal life, but also in business operations and decision-making process.

2.1 Types of Display Devices

A dashboard is a multilayered interactive visual display built on a business intelligence and data integration infrastructure that conveys key information on a single screen to allow users to effectively measure, monitor, and manage business performance of an organization toward predefined goals (Eckerson, 2011, Lea, 2012; Few, 2013). As a result, analytical dashboards often have multiple interactive visualization objects that require high capacity GPU and adequate screen display area.

The type of devices that analytical dashboards will be displayed and used needs to be considered as it affect the choice of mobile app types, screen size, viewing area, and computing resources. For example, a desktop computer typically has bigger screen size and computing resources to render an analytical dashboard, but it is not portable and the usage typically is constrained to an office environment. On the other hand, a smart phone is portable and can be used almost everywhere, but the screen size is typical small and the computing resources are limited. Table 1 provides a list of commonly used display devices detailed with screen resolution, screen size, and usage information.

Table 1 Screen Resolution, Usage, and Screen Size of Different Device Types

Screen resolution	Display ratio	Usage	Screen size / Device Type
1366x768	16:09	19.10%	14" Notebook /15.6" Laptop/18.5" monitor
320x568	9:16	6.40%	4" iPhone 5
1280x1024	5:04	5.50%	19" monitor
320x480	2:03	5.20%	3.5" iPhone
768x1024	3:04	4.50%	9.7" iPad

2.2 Business Intelligence & Analytics and Visualization

While mobility has continued to develop and expand, the evolution of business analytics has done the same. Business intelligence and analytics (BI&A) are "…the technologies, systems, practices, and applications that analyze critical business data to help an enterprise better understand its business and market" (Lim, et al. 2012). Chen, et al. (2012) classified business intelligence and analytics into three stages. The first stage (or BI&A 1.0) was popular leading up to the early 2000s and often consists of structured data, collected through some sort of legacy system, and stored commercial relational database management systems (RDBMS). The techniques used in this method are, for the most part, evolutions of the “statistical methods developed in the 1970s and data mining techniques developed in the 1980s.” The second stage (or BI&A 2.0) began to evolve during the early 2000s and focuses on text and using Web 2.0 for analysis of unstructured data. The third stage (or BI&A 3.0) focus on mobile devices and sensor based data. However, Chen, et al. (2012) indicated that “although the coming of the [BI&A 3.0] era seems certain, the underlying mobile analytics [along with] location and context-aware techniques for collecting, processing, analyzing and visualizing such large-scale and fluid mobile and sensor data are still unknown."

Consequently, the utilization of interactive analytical dashboard to support highly mobile, location-aware, person-centered, and context-relevant decision-making creates challenges when such apps are running on a mobile device where the screen size and computing power are constrained. However, there are few studies examined the impact of dashboard use across a variety of display devices.

2.3 Types of Mobile Apps

A mobile App is an application software that can be executed on mobile devices. Mobile Apps have become increasingly popular in recent years, and will likely continue their rise as the popularity of mobile devices continues (Oinas-Kukkonen, et al., 2003). As more users use mobile apps to perform day-to-day business transactions and analytics, it is important to understand common types of mobile apps when design and deploy an analytical dashboard.

There are several different types of mobile applications and the most common of these include web apps, native apps, and hybrid apps. Native apps are applications installed on the mobile device, often accessed through icons on the devices home screen. The most beneficial characteristic of a native app is its ability to take advantage of features that the device has to offer and such features are made possible because the application is developed specifically for one platform (Budiu, 2013; Charland & Leroux, 2011) allowing the application to use the features necessary. Examples of these features could include camera, GPS, compass, touchscreen, or contact list. Although the ability to take advantage of a device’s features is extremely beneficial, it can also be a disadvantage. Since these apps are developed specifically for one platform, they often have issues when used on a platform that it is not designed for. The final major benefit of native apps are their ability to be accessed offline, making them more reliable than other options. There is no need to connect to the internet, which eliminates any connection errors or lag times during use. However, having an offline application also means that you cannot have online capabilities and that the user is limited to the capabilities and information that their device has access to in an offline setting.

Web apps typically coded with HTML5 are websites that look and feel like native apps, but run on a web browser. Users access them by navigating to a URL as they would any other website. Today, it is so widely used that the distinction between web apps and web pages has become blurry (Budiu, 2013). Just like native apps, web apps also have different web platforms (or browsers) to work with. Although web platforms are generally consistent, the number of built-in or SDK-included controls is limited. At least in the modern world of mobile technology, most devices include the very capable WebKit rendering engine, and only small differences from typical browsers prevail (Charland & Leroux, 2011).

The hybrid application is a combination of both the native and web application. These Apps, much like native apps, can be found in an app store, and also rely on HTML being rendered in a browser. It is similar to a web app, except that the browser is embedded in the application itself. Because of this feature, hybrid apps have cross-platform capabilities, meaning that they can be used on devices of different platforms. This reduces production costs significantly because if a company wants to create an app as a wrapper for their existing web page, all they have to do is transfer the majority of the original coding. Using the power of HTML through PhoneGap and Sencha Touch, this also means that the same code can be used on different mobile operating systems (Budiu, 2013). One of the most popular uses of hybrid Apps are in use with “the cloud”. With web Apps, someone can create an interface that is easy to access and store information on the cloud. However, this only works if you are able to connect to the internet. With a hybrid app, you can setup the application to access the cloud only when connected to the internet. Otherwise, the application will natively use the features of your device. (Oinas-Kukkonen, et al., 2003) For instance, you could have your application set to store images from your gallery at a time that you do not have internet access, but as soon as you connect, the application will automatically send your images to the cloud.

Currently, the struggle that many mobile application designers face, is deciding which type of mobile application to use. Factors to be considered when making this decision include context, device features, offline functionality, discoverability, speed, updating needs, content restrictions, costs, and user interface.

2.4 User Demographic Factors

User demographic factors affecting technologies adoption identified by prior studies include age (Loyd & Gressard, 1984; Lala, 2014; Fatemifar, et al., 2015), gender (Loyd, B., Gressard, 1984; Badagliacco, 1990; Rowel, et al. 2003; Crews & Butterfield, 2003; Lala, 2014; Li, et. al. 2015), race (Lee & Lee, 2000; Badagliacco, 1990; Fatemifar, et al., 2015), computer experience (Loyd & Gressard, 1984; Venkatesh and Davis, 2000; Lala, 2014), academic experience (Wawrzynski, 2003). With the influence of social media and ownership of mobile devices among Millennials, it is also important to investigate whether the amount of time spend on mobile devices (Venkatesh and Davis, 2000; Lala, 2014) has influence on the use of visual analytical applications in decision support.

3. Research Objectives, Research Questions, and Research Methodologies

The objective of this research is to identify influential factors of enterprise analytical dashboards on decision support. Three research questions and their associated hypotheses investigate in this research are stated as followings

- Does the type of device used influence the efficiency and effectiveness of enterprise analytical dashboard Apps? (H_0: $Device\_Type_i = 0$)
- Do user demographics influence the efficiency and effectiveness of enterprise analytical dashboard Apps? (H_0: $Gender_i = 0$; H_0: $Age_j = 0$; H_0: $Country\_Origin_k = 0$; H_0: $School\_Year_l = 0$)
- Does a user’s computer knowledge influence the efficiency and effectiveness of enterprise analytical dashboard Apps? (H_0: $IT\_Knowledge_m = 0$; H_0: $Computer\_Classes_o = 0$; H_0: $Daily\_Mobile\_Use_n = 0$)

In this study, efficiency is measured by the completion rate and is computed as number of questions attempted divided by the total number of questions in the study. Effectiveness is measured by the accuracy rate and is computed as the number of questions answered correctly divided by the number of questions attempted.

An analytical dashboard app was developed using HTML5 for display across different devices. Although hybrid apps can be used on devices of different platforms, the HTML 5 web app is selected for this research to reduce installation and setup time needed for the experiment. Figure 1 and Figure 2 show the analytical dashboard on a desktop computer screen and on an iPhone screen.

Figure 1 Analytical Dashboard on a Desktop Computer Screen

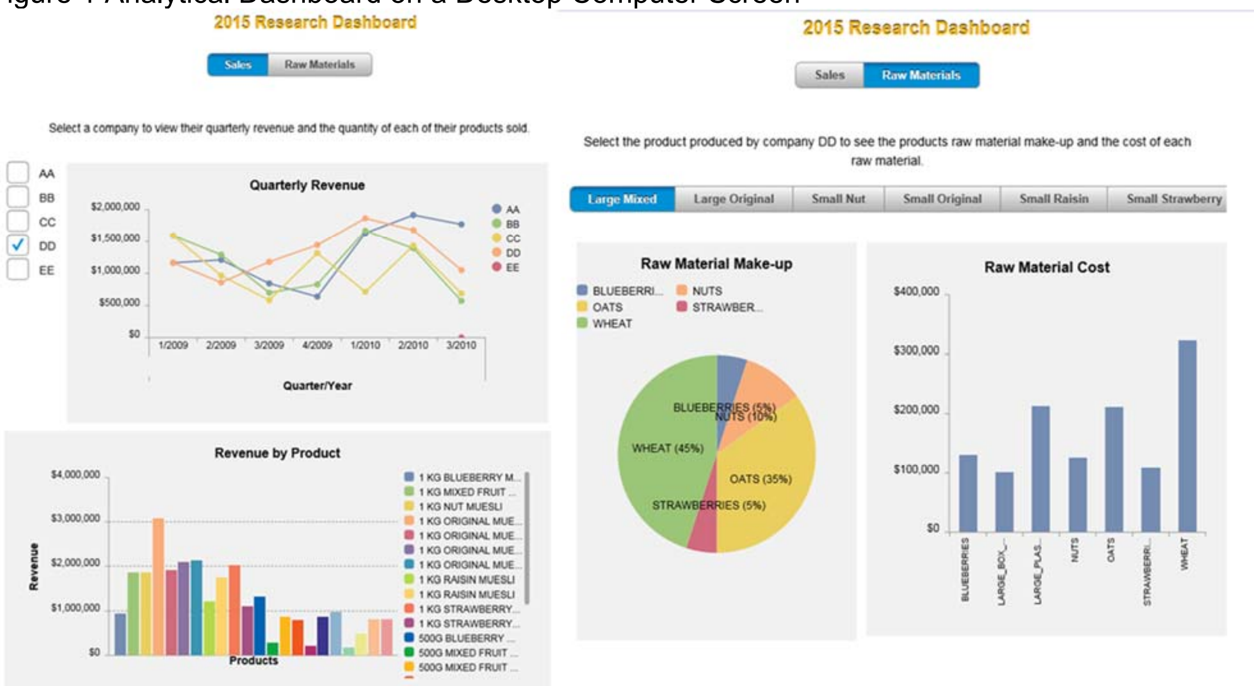
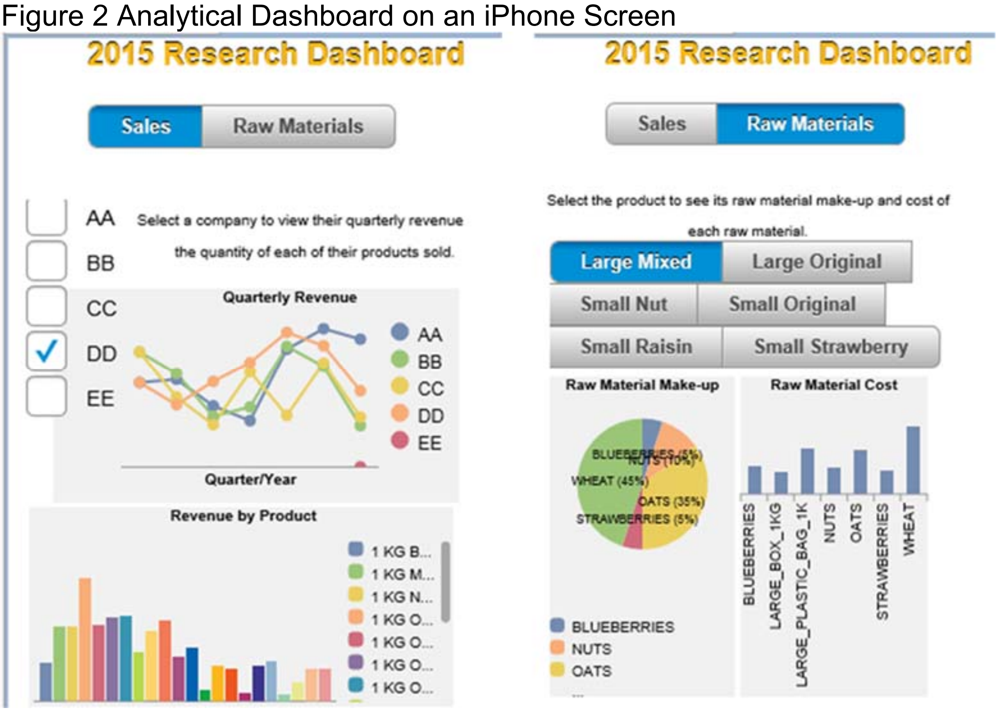


Figure 2 Analytical Dashboard on an iPhone Screen



The data were collected from eight different classes throughout the course of a week. The test itself was broken down into two parts and a script was followed to ensure that each experiment was replicated consistently. The first part of this test was a four minute timed test where the students were asked to use the analytical dashboard prototype to answer a series of questions regarding operations and performance of a case company. Four device types used in this experiment are desktop computer, laptop computer, iPad, or iPhone. Upon completion of first part, each student was asked to answer a series of questions regarding their IT knowledge, the dashboard, and the device.

4. Preliminary Results

There are 276 students participated in the experiment ranging from ages 19 and older. There are 46 females, 104 males, and one does not wish to disclose gender information. Figures 2 details the distribution of devices, student demographics such as year in school, self-reported level of IT Knowledge, daily number of hours spent on a mobile device, and number of computer courses taken. Multivariate General Liner Model (GLM) using SAS was conducted and selected results are provided in Table 2.

Figure 2 Demographic Breakdown of Participants

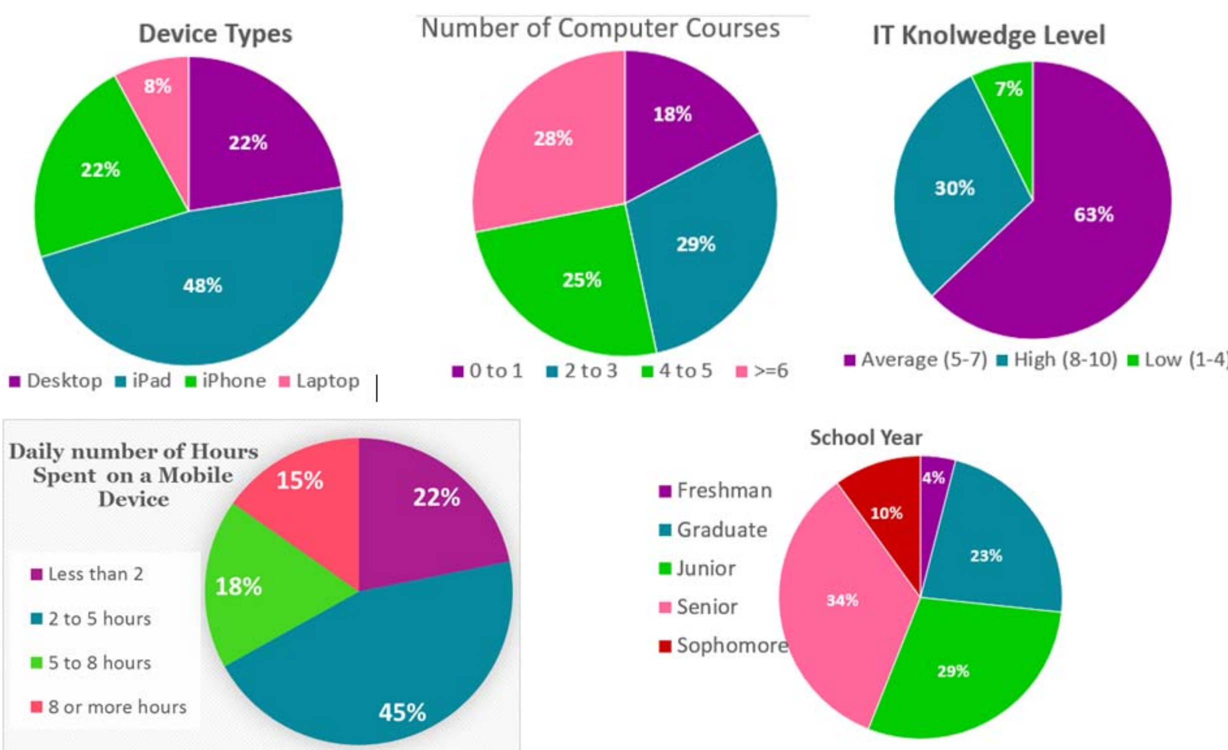


Table 2 Partial Tests of Between-Subjects Effects

Source	df	Completion Rate (Efficiency)			Accuracy Rate (Effectiveness)		
		Mean Squre	F	Sig.	Mean Squre	F	Sig.
Device_Type	3	0.178	3.915	**0.022**	0.104	9.078	**0.000**
Gender	1	0.008	0.267	0.616	0.089	4.007	0.073
Age	3	0.081	2.560	0.114	0.008	0.372	0.775
Country_Origin	6	0.046	1.017	0.432	0.079	6.876	**0.001**
IT_Knowledge	2	0.017	0.365	0.699	0.063	5.536	**0.011**
Computer_Classes	3	0.095	2.085	0.131	0.070	6.174	**0.003**
Daily_Mobile_Use	3	0.046	1.002	0.410	0.022	1.912	0.157
School_Year	4	0.104	2.283	0.093	0.038	3.305	**0.029**
Device_Type * IT_Knowledge	2	0.062	1.369	0.275	0.104	9.080	**0.001**
Device_Type * Computer_Classes	6	0.029	0.638	0.699	0.074	6.487	**0.000**
Device_Type * Daily_Mobile_Usage	4	0.058	1.283	0.307	0.125	10.939	**0.000**
Device_Type * School_Year	2	0.002	0.052	0.950	0.086	7.545	**0.003**
IT_Knowledge * Computer_Classes	1	0.250	5.499	**0.028**	0.532	46.618	**0.000**
IT_Knowledge * Daily_Mobile_Usag	2	0.125	2.746	0.086	0.052	4.515	**0.023**
IT_Knowledge * School_Year	1	0.203	4.461	**0.046**	0.080	6.978	**0.015**

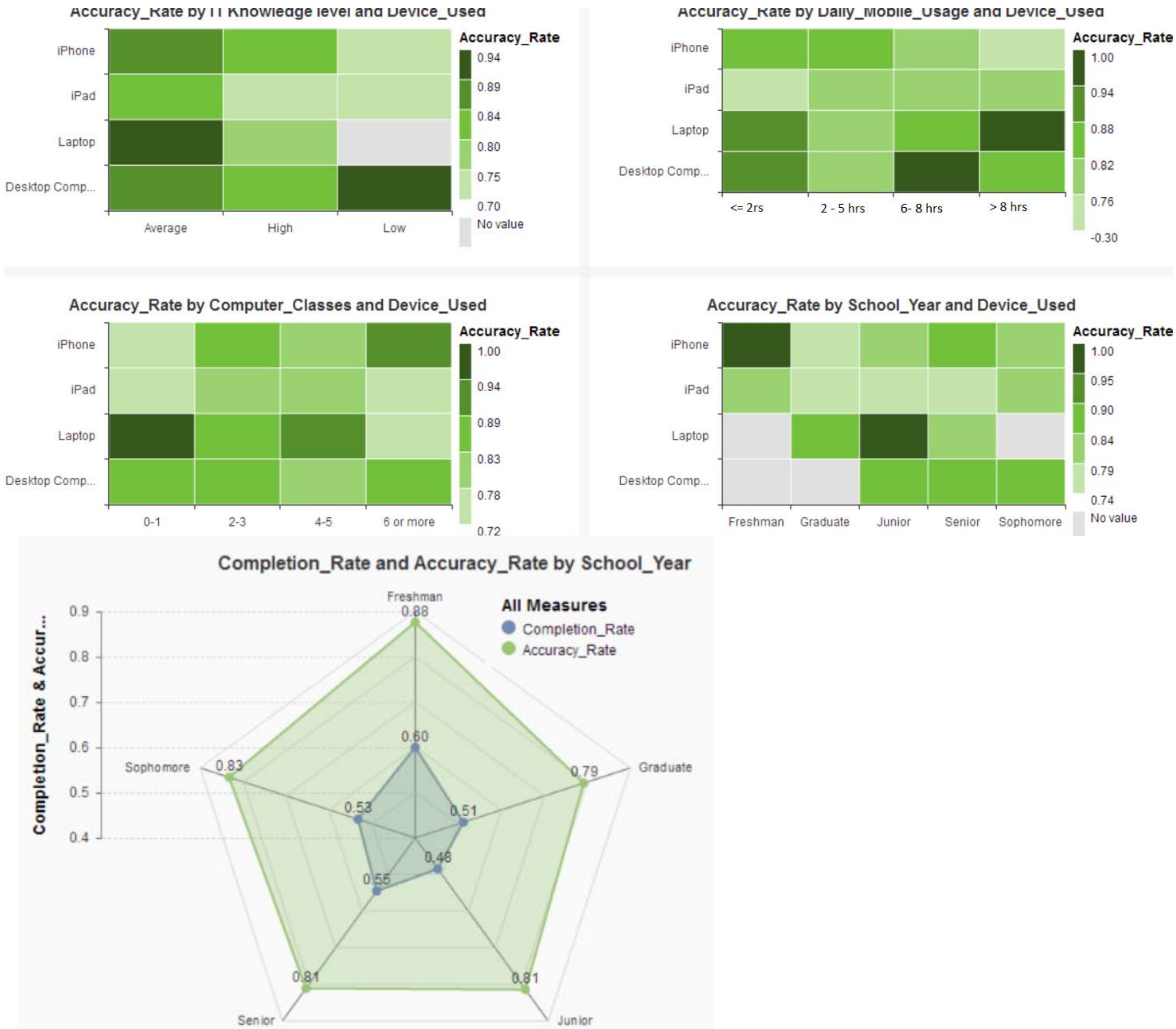
4.1 Influence of Device Types

As shown in table 2, the first research hypothesis “Does the type of devices used influence the efficiency and effectiveness of analytical dashboard” is supported at $\alpha = 0.05$ level. That is, the devices with the larger screens (desktop, laptop, and iPad) had the higher average completion rates (efficiency) and accuracy rate (effectiveness). It may due to the fact that the students would have an easier time finding and clicking on compenents on the larger the screen. As expected, a smart phone have the smallest screen and that may cause certain charts not to dispay as well as they might on other devices.

Figure 3 show intereaction between IT knowledge, daily mobile usage, number of computer classes taken, or year in school and effectiveness (accuracy) of analytical dashboard on decision support. It is observed that users with low IT knowledge, have taken fewer computer classes, or have fewer years in school perform better with larger screen sized devices.

It is also observed that graduate students who we assume to have the most computer skill or knowledge had accuracy rate (effectiveness) and completion rate (efficiency) that landed relatively low compared to the students of other years. In addition to this, we can see that the highest accuracy rates came from freshmen and sophomores. Additional research are needed to gain insights on this observation.

Figure 3 IT knowledge, Daily mobile usage, Computer classes taken, or Year in school and Accuracy



4.2 Demographic Factors

As detailed in Table 2, the second research question "Do user demographics influence the efficiency and effectiveness of enterprise analytical dashboard Apps?" was partially suppored at α = 0.05 level. Influence of age and gender factors are not statistically significant while the influence of country of origin and year in school are significant when the effectivenss is mesaured by accuracy. As shown in Figure 4, the highest accuracy rates came from Chinese students. It is observed that female students outperform male students from China, United States, Canada, and Saudi Arabia while male students outperform female students from India and Ukrain. Another observation is that freshmen from United States outperform students of other levels regardless of gender as shown in Figure 5.

Figure 4 Accuracy by Contry and by Gender

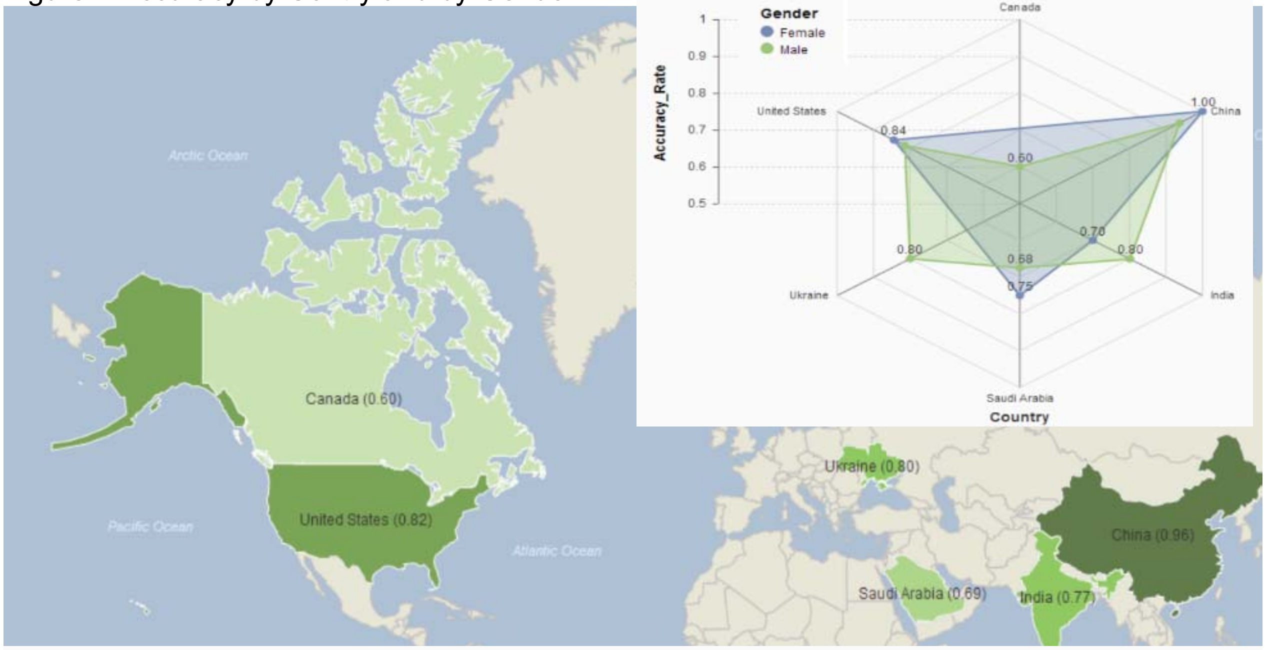
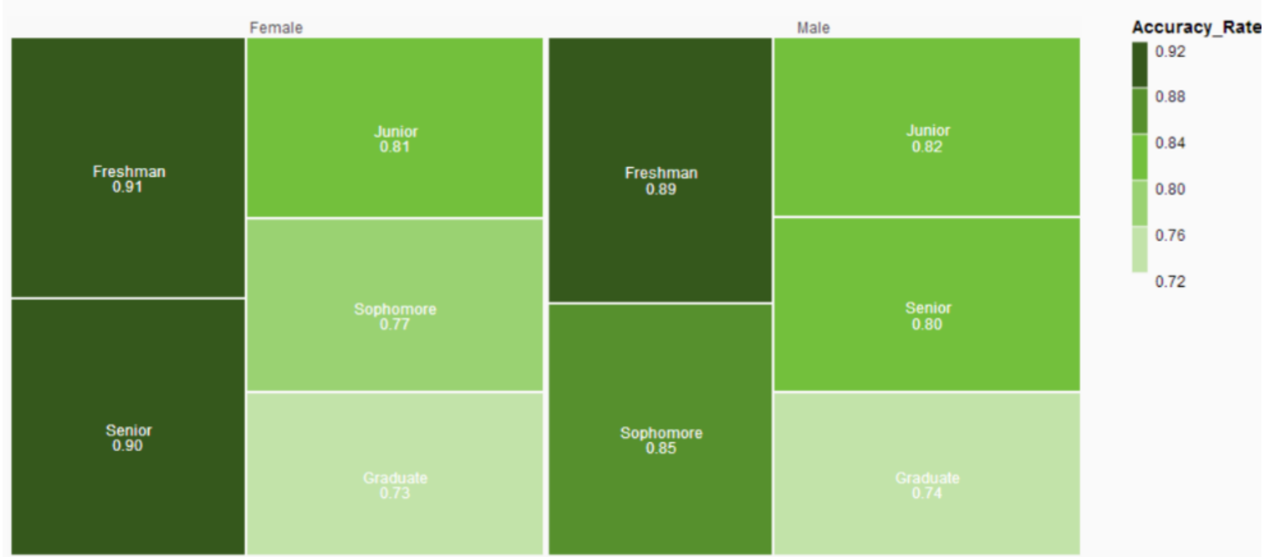


Figure 5 Accuracy_Rate and Accuracy_Rate by Gender and School_Year



4.3 Influence of Computer Knowledge

The third research question investigates whether or not a user's computer knowledge affects the effectiveness and efficiency of analytical dashboards on decision support. As detailed in Table 2, number of computer classes taken and level of IT Knowledge have influence on the effectiveness (accuracy rate) of but not on the efficiency (completion rate) of analytical dashboards on decision support. Daily mobile usage does not appear to have influence on effectiveness or efficiency measures based on data collected. The students with the highest accuracy rate (effectiveness) had taken more computer intensive courses. Similarly, students with a higher level of IT Knowledge had higher accuracy rate.

5. Conclusions, Contribution, and Future Research Directions

This project has yielded numerous interesting results. The first is that the type of device does affect the efficiency and effectiveness of enterprise analytical dashboards on decision support. It is likely attribute to the devices screen size. The second finding is that country of origin is the only demographic factor that affects effectiveness of an enterprise analytical dashboard on decision support. Results from this study showed that students from China is more effective in using dashboard boards in decision support than students of other know countries. One of possible explanations is the mathematical skills that Chines students often exhibit. However, as literature suggested, in order to take country of origin into account, it would also be necessary to understand the students' complete ethnic background (origin, race, and ethnic make-up), because these factors may be more influential as a group, rather than on their own.

Another finding is that a higher daily mobile use and year in school did not have an effect on efficiency and effectiveness measures. However, freshmen and sophomore showed higher effectiveness in using analytical dashboard to support decision than other type of students. The more predictable conclusions came from IT knowledge and number of computer courses taken. In both instances, as the number grew (level of knowledge, and number of classes) so did the efficiency and effectiveness. One of explanations is that a higher level of knowledge and more computer classes would both allow the students to be more familiar with dashboards and how to use them, regardless of device types used.

Results of this research can provide remedies to the problem of lacking of knowledge in the areas of data and analytics. According to a study done by McKinsey Global Institute, the United States have a shortage of 140,000 to 190,000 people with deep analytical skills, as well as a lack of around 1.5 million data-savvy managers with the ability understand and use the information from that data by the year 2018. In addition to the need for data knowledge, there is a need for research in the way devices work with other tools and software - in this case, data visualization. "The ability of such mobile and Internet-enabled devices to support highly mobile, location-aware, person-centered, and context-relevant operations and transactions will continue to offer unique research challenges and opportunities throughout the 2010s." (Chen, Chiang, & Storey, 2012).

A research that deploys analytical dashboards using a hybrid app approach could be valuable as it reduces browser display inconsistency that observed in HTML 5 app developed for this research. Factor or dimension reduction on demographic factors and computer knowledge factors may yield additional insights and may help to generalize the research results. Additional analysis on the usability factors on the analytical dashboard used for the research is also valuable in the future.

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