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PROFESSIONAL DEVELOPMENT GRANT

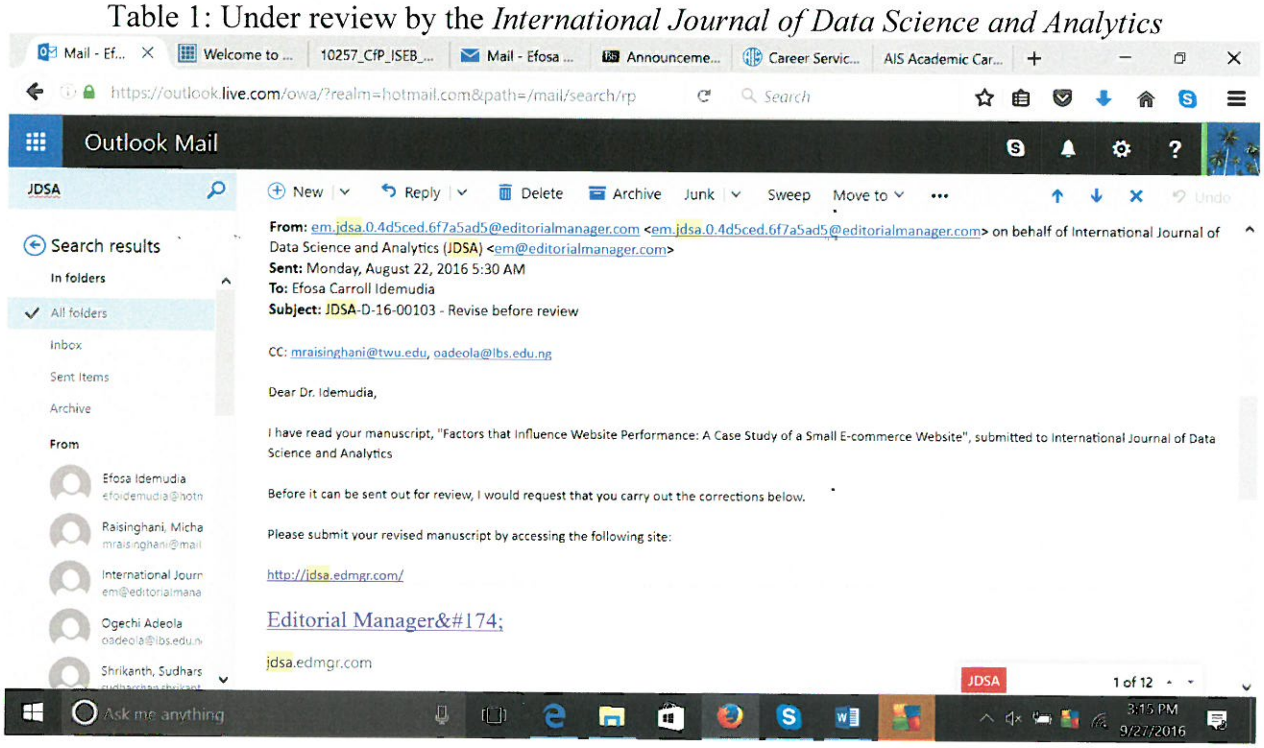
1. Professional Development Grants, Arkansas Tech University 2016, “An Empirical Taxonomy of Smartphone Users”.

Arkansas Tech University approved my professional development grant for me to present my research paper in the “HICSS 2016 : 49th HAWAII INTERNATIONAL CONFERENCE ON SYSTEM SCIENCES (HICSS)”.

Attending the conference above gave me the opportunities to share ideas, knowledge, and skills with other professors worldwide; hence, these professors gave me excellent comments and feedback on how I can improve my research papers for journal publications. Thus, my research paper is under review in the *International Journal of Data Science and Analytics*).

Table 1 shows screenshot indicating that the manuscript is under reviews in the *International Journal of Data Science and Analytics*. Also, I attached the research paper in this report.

Table 1: Under review by the *International Journal of Data Science and Analytics*



Empirical Investigation of Factors that Influence Website Performance

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Abstract

Rapid advancements in digital technology have had a significant influence on businesses' websites. Companies and organizations with well-designed websites have the potential of attracting customers, generating revenues, and increasing market share. Nevertheless, many companies and organizations that are investing billions of US dollars on websites and page development are not attracting customers or generating revenues, incomes, and profits as expected. These e-commerce firms will lose market share and online advertising revenues if their websites are not effectively managed and monitored. With big data changing the way we think about technology and making it easier to collect data and gain knowledge from a large volume of dataset to make better decisions and gain competitive advantage, it becomes necessary to understand web analytics and improve e-commerce website performance. Our study focuses on bounce rate as a measure of website effectiveness. We investigated the influence of page view, unique page view, average time on page, entrances, and percent exit on bounce rate, in the context of a small e-commerce company in the United States and developed a research model on the effect of these identified variables on the bounce rate. The results from research have practical and research implications.

Keywords: Website performance, bounce rate, page view, unique page view, average time on page, entrance, and percentage (%) exit.

1 Introduction

Using a small e-commerce website, our study focuses on how to improve website performance. Websites are among the most innovative technological applications that have appeared in the last 25 years. The World Wide Web using the Internet platform has evolved as an essential mechanism for inter- and intra-organization information exchange [44]. The last decade has seen media delivery systems converge within single technologies such as mobile phones, personal computers, smart televisions, iPads, and other digital devices. Moreover, the Internet has led a revolution in e-commerce contributing to e-retailers like Amazon and Play.com having huge economic success in the sale of books and music. Most major commercial companies now have their own websites. This e-commerce trend has also resulted in more choices for consumers leading to increased competition, price reduction and empowers consumers who can compare prices for a large range of products and services.

According to Welling and White [49], 'the internet has been a key driver of corporate marketing during the past ten years." (p. 655). Significantly, in 2015, the US digital advertising revenue was assessed to be $59.6billion, a 20% rise from the already high 2014 revenue of $49.5billion [23]. Therefore, there are inherent opportunities in increasing the attractiveness of e-commerce websites particularly with the advantages big data presents regarding access to data on online users.

Companies worldwide harnessing the power of their websites in this Age of Big Data for activities such as advertising products to millions of customers, getting feedback from customers online on product improvement, selling goods and services to customers, expanding their market reach amongst others. Big Data should, however, mean Big Impact [50]. Such impact would include targeted marketing, business insights, client-based segmentation, sales and marketing opportunity identification, buyer preferences, customer feedback, risk analysis, data access amongst others [39, 26]. Though extraction of valuable data, however, remains a critical Big Data challenge, businesses gain many advantages by harnessing its capabilities for informed strategic directions and increased operational efficiency [30].

There are many ways web users can access webpages and websites: (1) direct traffic, i.e., directly typing the company or organization's URL, (2) indirect or referral traffic, i.e., linking through other domain websites/links, (3) search traffic, i.e., using search engines such as Google and Yahoo, (4) using a computer mouse to click on the websites/links, and (5) using advance voice recognition and eye movement. Moral et al. (2014) explain that search traffic can be classified into two main groups: (1) paid search traffic and (2) unpaid traffic. Some examples of the leading paid search traffic are Google Adwords, Facebook Ads, Outbrain Amplify, LinkedIn Ads, and Twitter Ads. Several benefits accrue for companies and organizations using paid search engines for their websites/pages: exposure in the top three search engines, immediate traffic, consistent traffic, targeted ads to potential web users and online visitors, access to web users and online visitors worldwide, perceived relevance to web users and online visitors worldwide, positive branding implications, and an ability to track both web users' and online visitors' shopping and browsing online behaviors. Also, companies that are using Adwords should implement strategies to determine if the Adwords improve the quality of paid/search traffic compared to the unpaid traffic.

For organizations to benefit from the opportunities offered by their e-commerce websites, it becomes imperative for them to improve website performance to attract and retain customers [4]. Slow websites can cause users to abandon sites and in some cases, switch to a competitor when they experience performance issues [10]. An understanding of website performance has implication for user experience and satisfaction and will lead to the achievement favorable returns on investment. Therefore, website performance has become an important element for understanding the financial and operational performance of an organization [16]. According to Ghandour et al., the nature of the website usage, which includes user behavior on the web, navigation pattern, the number of website visitors and the time spent surfing a website, are important indicators of website performance and success.

Measurement of website performance is central to website management as this will help determine the extent to which goals are achieved (Butkiewicz et al. 2011, Madhyastha & Sekar, 2011). This study focuses on one key factor influencing website performance –surfer or user or customer satisfaction, the bounce rate, which Sculley, Basu, and Bayardo (2009) found to be an effective measure of user satisfaction in online advertisement. Our study looks at the effect of bounce rate on the website of the case company, a small e-commerce North American firm, experiencing low patronage. Our in-depth investigation focused on why the company was failing to attract customers online and had high bounce rate despite the online promotions. Perplexed by the diminishing sales reports, top management of the case company were worried about the loss of market share across their range of products, despite substantial investment on the site. To address these issues and provide insights and understanding to top management on why this e-commerce website is not productive and how to improve performance, we focused on factors that affect bounce rate of this e-commerce website, as a measure of user satisfaction. The definitions of the factors our case study research focus on are shown in Table 1.

Table 1: Key performance indicators used in this study

S/N	Key performance indicator in our research model	Description
1.	Page views	"Page views" refers to the total number of pages viewed on the website and is a general measure of how much the website is used [13, 18, 27]. According to Digital Analytics Association [14], page views is "the number of times a given page was used" (p. 10).
2.	Unique page views	Unique page views refer to the number of visits or sessions during which the specified webpage or webpages was viewed at least once [21, 47].
3.	Average time on page	Average time on page is the average amount of time web users or online visitors spent viewing a specified webpage or screen, or set of webpages or screens [21, 47].
4.	Entrances	Entrances is the number of times web users or online visitors entered your website through a specified webpage or set of webpages [47].

5.	% Exit	% Exit is the percentage of website exits that happened from a specified webpage or set of webpages [47]. Mathematical it can be express as % Exit = (number of exits) / (number of pageviews) for the page or set of pages [29, 47].
6.	Bounce rate	Bounce rate refers to the number of visitors who immediately leave upon arrival at a website [16]. Booth and Jansen [6] posit that a high bounce rate "may be a reflection of unintuitive site design or misdirected advertisement."

2 Literature Review and Synthesis

The importance of data collection on an e-commerce site cannot be overestimated. With the huge volume of information available online, it becomes imperative for businesses to make sense of this seemly explosion of data. Big data, the game changer, aptly describes this massive amount of data (sets) available for storage, processing, analyzing, management [1, 39] , which is beyond technology's capability to do so effectively [25]. Hence, the challenge is how to devise new tools and appropriate systems for effective collection, aggregation, and analysis of these data in order to "extract relevant meaning for decision making" [25: p.995].

Data can be automatically collected on trends of people visiting the website, and this crucial information aggregated across the web visitors gives managers needed insights, allowing them to evaluate the website effectiveness [40].

According to Tarafdar and Zhang [44], website performance can be measured by the traffic it attracts and retains, i.e., the number of people and the extent to which they make repeated use of the same website. Tarafdar and Zhang, therefore, conceptualize website performance regarding visits by customers which is linked to profitability. This is in line with the views of Bharadwaj [4], Heijden [20] and Huizingh [22].

Huizingh [22] identified four antecedents of website performance: company characteristics, web initiative, website characteristics, and web strategy. The author found out that these factors affect website performance in different ways. The author made use of the number of visitors and managerial satisfaction to measure website performance. However, Tarafdar and Zhang [44] argue that there are two main measures of website performance: reach and loyalty. The authors (Tarafdar & Zhang) used website characteristics as their independent variables, with *reach* and *loyalty* as their dependent variables. The Tarafdar and Zhang study looked at the influence of website characteristics on *website Reach* and *website Loyalty,* two important website performance measures.

The Tarafdar and Zhang [44] study can be seen as broad-based in their attempt to conduct a comprehensive study on factors influencing website performance, yet it does not cover every factor influencing website performance. As suggested by Bharadwaj [4], many factors influence website performance in different ways. According to Gomez Inc. [17], "[E]enterprise stakeholders viewed Website performance in a variety of ways. Business managers have measured site performance by page views, bounce rates, and conversion rates with tools such as Google Analytics or Omniture, while technology professionals have watched site availability and response time metrics" (p. 4). This shows that there are different ways of understanding factors influencing website performance depending on the interest of an individual researcher.

Information systems researchers have demonstrated that usage is a key variable in explaining the performance impact of website or information technology [16]. User satisfaction is a major factor in assessing website quality and can be a useful measure to understand the reach and loyalty for a website by customers. Tarafdar and Zhang [44] suggest that reach and loyalty are two important measures for understanding websites success. Grigoroudis, Litos, Vassilis, Moustakis, Politis and Tsironis [19] studied website characteristics associated with website quality. In other words, the features inherent in a website will determine its quality. Also, the quality of a website will determine whether the users will leave the website immediately without clicking any page, which is called bounce rate. According to Sculley et al. [41] bounce rate, which is less studied, is an important metric of understanding the performance of a sponsored search advertisement, directed to a landing page. Bounce rate is defined by Avinash Kaushik, writing for Google Analytics as "...the number of people who entered the site on a page and left right away. They came, they said yuk and they were on their way" [41,(cited in Sculley et al., 2009, p. 1]. In other words, bounce rate refers to the number of visitors who immediately leave upon arrival at a website [16]. Booth and Jansen [6] posit that a high bounce rate "may be a reflection of unintuitive site design or misdirected advertisement" (p. 153).

Kaushik argues that bounce rate is important for advertisers to monitor because a user who bounces from a site is unlikely to perform a conversion action such as a purchase [41]. Also, of major concern is the proliferation of mobile phone users who expect web links to download as fast as on their personal computers [17]. These individuals are likely going to leave a site that does not offer them the opportunity to download on their mobiles or better still *bounce*. Therefore, businesses that take this factor into consideration may gain greater customer loyalty over those who refuse to adjust to this new phenomenon in technology space.

Poock and Bishop [38] found that most website users prefer sites that are intuitive and easy to use and that sites with these qualities are likely to be effective and have good usability. Usability is the ease of usage of an object [12]. According to Churm, [12], usability signifies the ease with which users can achieve specified goals with efficiency when visiting a website. Zhu, Vu and Proctor [51] argue that usability – the ability of individuals to easily interact with a website – is the most important characteristic to determine the success of a website.

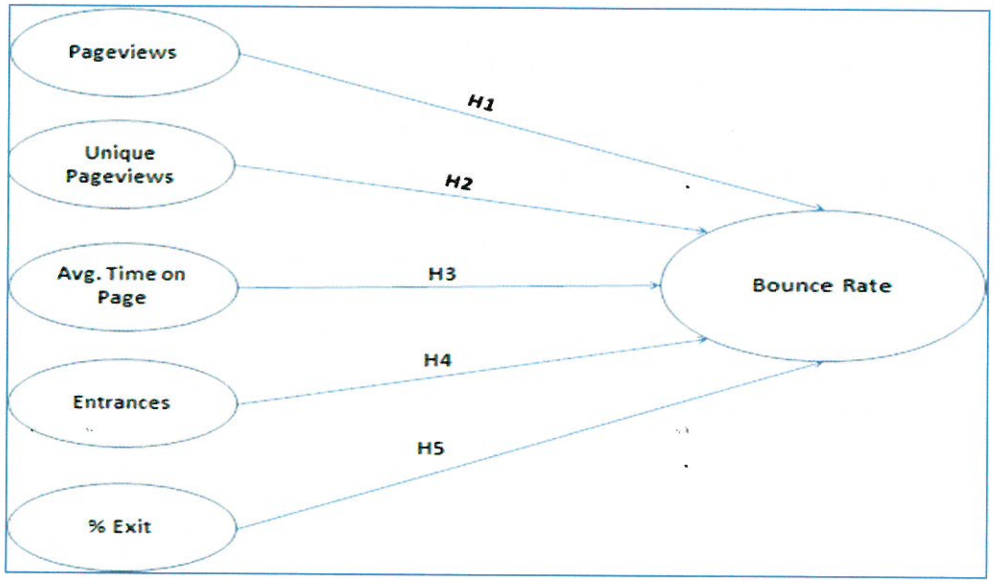
It becomes imperative for companies to improve the effectiveness of their IT capability, in this case, website performance, by capturing the value enabled by greater access to data - Big Data. Significantly, determining how to attract more potentials customers with billions of users now having access to websites and what can consist hindrances to access to their websites, should be key considerations for companies. The conceptual framework and hypotheses development section will consider the factors that have significantly influence on bounce rate using data collected via Google Analytics' e-metrics including pageviews, unique pageviews, average time on page, entrances, and % exit.

3 Conceptual Framework and Hypotheses Development

Bounce rate is considered one of the most important and overlooked performance statistics [2, 41]. A high bounce rate means that web users and online visitors do not find the landing page/web presence relevant [11]. Bounce rate reflects web users and online visitors' visual attention behavior [42]. Hence, the theoretical background for our research model is the visual attention behavior. Sha and Lu [42] argue that some example of visual attention behavior are page view, unique page view, average time on page, entrances, and percent exit on bounce rate.

The bounce rate can provide insights to companies and organization on many important things [8]. Hence, our dependent variable in our model is Bounce Rate. Based on the review of existing literature, a conceptual framework (research model) has been developed in Figure 1 below. The model shows that website performance measured in terms of bounce rate acting as a dependent variable is directly linked to page views, unique page views, average time on page, entrances and percent of exit. This implies that our dependent variable for this study, bounce rate, is directly related to our independent variables, key performance indicators (refer to Table 1 above).

Figure 1: The Research Model



3.1 Page Views and Bounce Rate

"Page views" refers to the total number of pages viewed on the website and is a general measure of how much the website is used [13, 18, 28]. Kaushik [28] avers that high bounce rate may indicate lack of user's satisfaction with the content of a page or layout and as such the user is not willing to open another page and leaves the website immediately. According to Digital Analytics Association [14], page views is "the number of times a given page was used" (p. 10). Web interfaces that use flash or AJAX may make it appear as if a particular user is visiting different pages, though the user is visiting the same or a single page [15]. According to Jansen [24] and Booth and Jansen [6], bounce rate is the proportion of visitors who exit the site after visiting only one page or the measurement of visitors that arrive at a homepage and leave immediately. Hence, the following hypothesis was developed based on the arguments above:

H1: Page views have a positive influence on bounce rate

3.2 Unique Page Views and Bounce Rate

"Unique page views" is defined as the number of sessions during which the specified webpage was viewed by webusers or online visitors at least once [47]. A unique pageview is counted for each page URL + page title combination [47]. The number of times that users are willing to view a page will depend not only on the content but may also be connected to referral by those who have visited the site. The high tendency for a specified page to be the source of traffic of users is possible. This can, therefore, help to prevent users from leaving the page or not visit the website again. The difference between unique page views and page views is that repeat viewers will only be counted once under unique page view [47]. Unlike page views, unique page views provide a more accurate count of website users as it helps prevent the counting of users more than once. An increase in the number of users will depend on how interesting these users find the site and their willingness to stay on the site, i.e., not to bounce [15]. This will have implications on whether they will encourage others to visit the site. Based on the arguments above, the following hypothesis is offered:

H2: Unique page views have a positive influence on bounce rate

3.3 Average Time on Page and Bounce Rate

The "average time on page" is a measure of the average length of time spent by users viewing a specific page or screen, or set of pages or screens [21, 29, 47]. At times, it might be difficult to measure average time on page. According to Kaushik [28], the measurement of average time on the page may be problematic when users walk away from their computers, close their web browsers or type in a URL for another site. Also, a multitasking user who leaves the web page open in one browser or tab while using another may inflate the time on the page though not actively viewing that particular page [15]. Fagan [15] suggests that these problems arise because most analytics software calculates the time on page by subtracting the time a user visited one page on the website from the time they visited the next page on the same website. Therefore, this may lead to lack of accurate measurement of average time on page. Nevertheless, irrespective of the problem inherent in calculating average time on page, the proportion of people who leave the site immediately has implications on average time on page. In other words, low or high bounce rate has implications on average time on page. Hence, the following hypothesis was proposed based on the arguments mentioned above and explanations:

H3: Average time on page has a positive influence on bounce rate

3.4 Entrances and Bounce Rate

Teixeira [47] defines "entrances" as the number of visitor entries into website pages. Teixera defines bounce rate in terms of entrances when he suggests that bounce rate is calculated by dividing bounces into entrances. He gave this illustration: When a website has a 60% bounce rate, it means that 60% of entrances left the website from the same page they entered. In other words, users did not view another page. If the user visits another page or stays longer on a page which they have entered, this may indicate low bounce rate. Thus, bounce rate may be equal to the rate of entrances if the content of the website is not satisfactory or does not meet user's expectation. Based on this explanation, this research proposes the following hypothesis:

H4: Entrances have a positive influence on bounce rate

3.5 % Exit and Bounce Rate

"% Exit" is the percentage of exits from a website and is calculated by dividing exits into page views [45]. In other words, % exit = (number of exits) / (number of page views) for a page or set of pages [45, 29, 47]. This indicates the frequency users exit from a particular page or set of pages when they view the page(s) [29]. Teixeira [45] argues that the expectation would be that entrances equal 100%, therefore % exit will also be 100% because everyone who comes into a website is expected to leave the site. However, this is not the case. This is because the way Google Analytics calculates % exit involves exits being divided into page views, multiplying all by 100% [45]. This shows that the number of exits from a website will not be equal to the number of entrances for any given page, as not everyone will leave a website on the same page from which they entered it [45]. Thus, bounce rate has implications on whether the exit rate will be equal to entrances or not. In other words, the low bounce rate will indicate that the website is relevant to the users and thus lowering the % exit. The following hypothesis is proposed owing to the explanations above:

H5: % exit has a positive influence on bounce rate

3.6 Google Analytics Data

Most e-commerce firms are collecting Big Data using Google Analytics. Big Data is the process of gaining knowledge and insights from extremely large datasets to make better decisions/competitive advantage. For our study, we collected data using Google Analytics. Google Analytics is one of the leading free website services that helps to collect datasets and then provides a rich statistics reports relating to websites' traffics, performances, efficiency, and effectiveness. Google Analytics is a tool that can provide hourly, daily, weekly, monthly, and yearly data for all the indicators used to measure the quality of websites and webpages. For our study, we selected the daily data because Moral, Gonzalez, and Plaza [33] argue that the daily data is best for the continuous monitoring of websites quality, performance, effectiveness, and efficiency. Google Analytics have been applied to various website genres including tourism [36], medical [9, 31], and libraries [5,46].

Various Google Analytics' e-metrics as shown in Table 2 can be used to analyze the quality, effectiveness, and efficiency of websites

Table 2: Google Analytics' e-metrics

e-metrics	Definitions
Visits	The total number of websites that are visited by both web users and online visitors [33, 35, 36].

Pages per visit	The average number of pages that are visited by both web users and online visitors during a session [33, 35, 36].
Length of the visit	The average duration of web users' visit that is measured in minutes [33, 35, 36].
Bounce rate	The percentage of web users that leave websites from the entrance webpage [33, 35, 36].
Return rate	The percentage of visits by web users and online visitors who visited the website before [33, 35, 36].

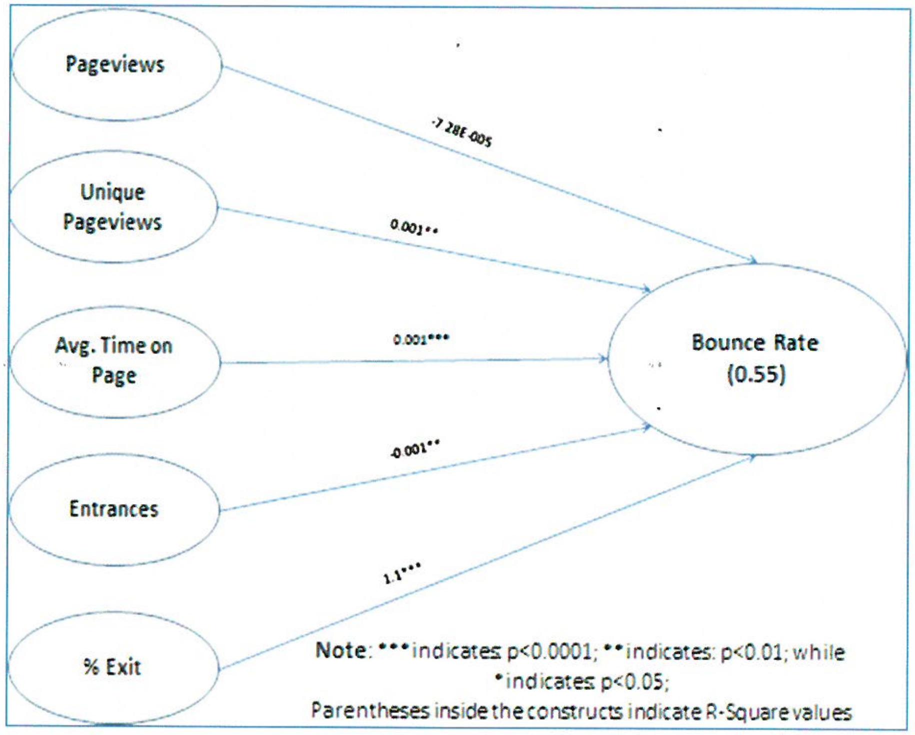
4 Research Method and Data Analysis

Most e-commerce firms are collecting Big Data using Google Analytics. Big Data is the process of gaining knowledge and insights from extremely large datasets to make better decisions/competitive advantage. The dataset for our study is provided to us by a small North American e-commerce firm that collected the data using Google Analytics and following these steps: (1) identify the issues or opportunities for data collection, (2) select the issues or opportunities for data collection, (3) set goals for data collection, (4) plan an approach and methods for data collection, (5) collect the data, (6) analyze and interpret the data, and (7) act on the results. It should be noted that the goal for our dataset by the e-commerce firm was to find the pages with the highest page views and events clicks so as to maximize advertising and set up the optimal pricing structure. The dataset collected include relevant factors that measure website effectiveness and efficiency as shown in *Table 3*. The dataset is extracted from Google Analytics, then inspected, cleaned, and transformed for relevant multiple regression analysis. It should be noted that the dataset for our study was collected from January 1, 2015, to October 21, 2015.

Table 3: Sample of the dataset

	Page	Pageviews	Unique Pageviews	Avg. Time on Page	Entrances	Bounce Ra	% Exit
2	/about.html	3358	1069	14.27	109	20.18%	5.24%
3	/rehabilitative_services.html	3191	975	19.04	958	2.19%	29.18%
4	/audiology_directory.html	3070	534	14.43	83	3.61%	3.36%
5	/resources.html	2738	531	6.51	34	2.94%	2.63%
6	/directory_listing.html	2610	618	4.62	21	0.00%	2.53%
7	/hearing_loss_statistics.html	2512	790	24.94	735	3.64%	29.38%
8	/products.html	2458	503	25.64	47	0.00%	4.88%
9	/ssd_eligibility.html	2367	1098	53.61	1096	1.09%	45.46%
10	/news.html	2303	478	12.05	95	1.06%	6.08%
11	/deafness_athletics.html	2108	676	25.84	652	2.99%	30.83%
12	/lance_allred.html	1682	720	62.72	715	0.42%	42.51%
13	/chatroom/	1591	1136	155.57	712	72.07%	53.11%
14	/explore.html	1476	466	12.51	16	0.00%	4.27%

Figure 3: Analysis with path coefficient and R-square



Note: ***indicates p<0.0001; **indicates: p<0.01; while *indicates p<0.05;
Parentheses inside the constructs indicate R-Square values

The tool we used for our multiple regression analysis is IBM SPSS Modeler as shown in Figure 2; and IBM is using IBM SPSS Modeler to process Big Data to gain insights and knowledge from Big Data to make better decisions/competitive advantage. Wang and Dinse [48] argue that multiple regression analysis is one of the most popular statistical tools that has been successfully applied in many disciplines and fields [7, 32]. To date, multiple regression models are widely used in business administration, economics, engineering, social, health, and biological sciences [34, 48]. Parvathi et al. [34] state that "Regression analysis is a methodology for analyzing phenomena in which a variable (output or response). depends on other variables called input (independent or explanatory) variables" (p. 216). Hence, in our study we used multiple regression analysis; and the result of our analysis is shown in Figures 3, 4, and 5.

Figure 2: IBM SPSS Modeler for Data Analysis of Big Data

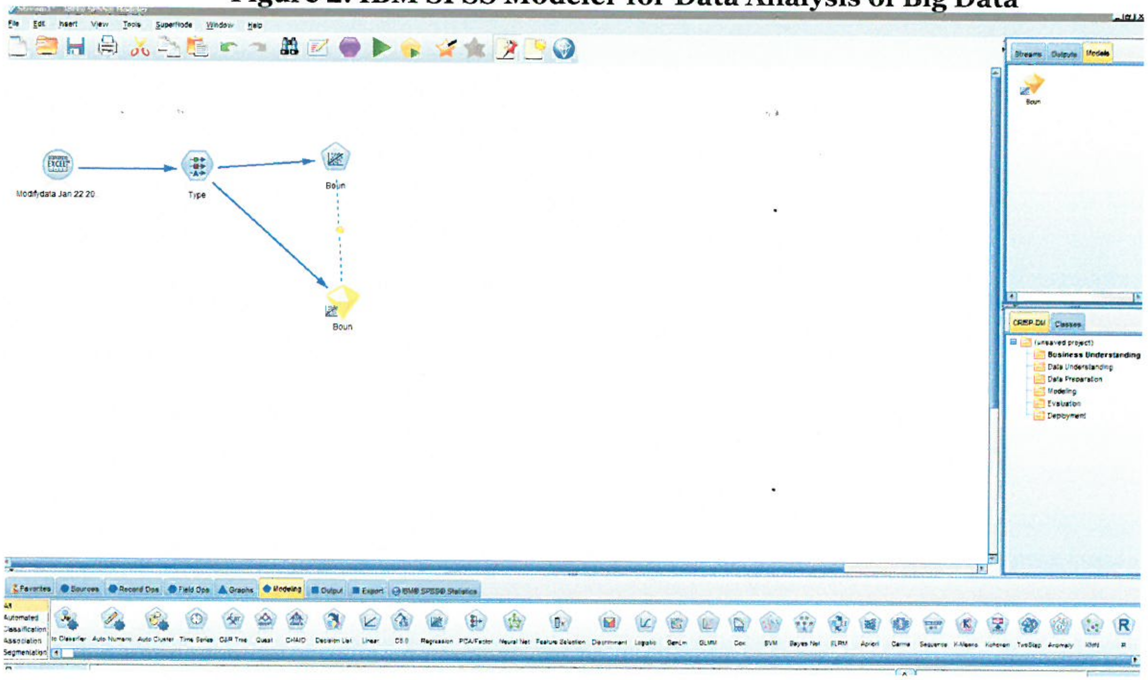
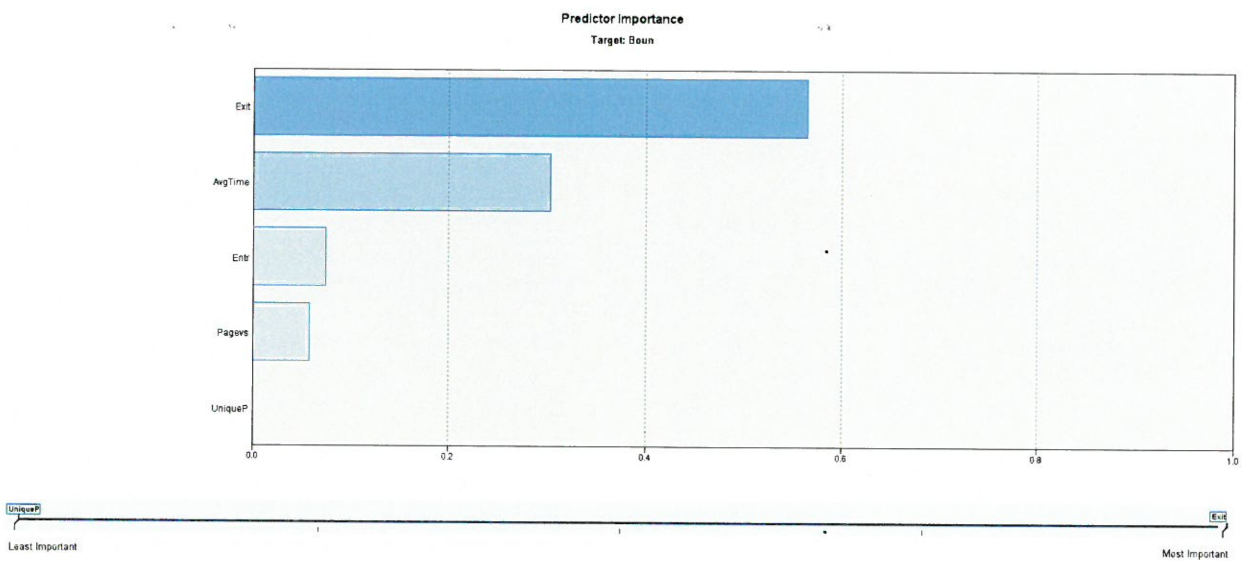


Figure 4: Predictor Importance



Notes: Variable legend:

Boun: Bounce Rate,
Exit: % Exit,
AvgTime: Avg.Time on Page,
Entr: Entrances,
Pagevs: Pageviews,
UniqueP: Unique Pageviews

Table 5: Regression Outputs

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.744(a)	.554	.550	.272722

a. Predictors: (Constant), Exit, Entr, AvgTime, Pagevs, UniqueP

ANOVA(a)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50.332	5	10.066	135.342	.000(b)
	Residual	40.536	545	.074		
	Total	90.867	550			

a. Dependent Variable: Boun

b. Predictors: (Constant), Exit, Entr, AvgTime, Pagevs, UniqueP

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.231	.025		-9.298	.000
	Pagevs	-7.28E-005	.000	-.684	-1.441	.150
	UniqueP	.001	.000	2.372	2.900	.004
	AvgTime	.001	.000	.297	9.886	.000
	Entr	-.001	.000	-1.670	-3.425	.001
	Exit	1.053	.053	.607	19.755	.000

a. Dependent Variable: Boun

Notes: Variable legend:

Boun: Bounce Rate,
Exit: % Exit,
AvgTime: Avg.Time on Page,
Entr: Entrances,
Pagevs: Pageviews,
UniqueP: Unique Pageviews

5 Discussion of Key Findings

The analysis, as shown in Figure 2, indicates that pageviews, unique pageview, average time on page, entrances, and % exit explain 55% of webpage bounce rate. Pageviews (H1) has no significant effect on bounce rate. unique page views (H2), average time on page (H3), and % exit (H5) have a positive and significant effect on bounce Rate. Entrances has a negative and significant effect on bounce rate.

5.1 Implications for Research

Triggered by the increasing number of Internet users, the growing digitalization of physical information, and the web 2.0 phenomena, there is an exponential growth of data available on the web. The contributions of this study are significant because it combines our findings with data acquired via mash-ups or composed services, thereby adding value to the existing body of knowledge and more complex, individualized, and richer information is generated.

The limitations of this study are with respect to the scope of this study because the goal for our dataset was to find the pages with the highest page(s) views and events clicks in order to maximize advertising and set up an optimal pricing structure. Hence, generalizability is limited to websites similar to our dataset that include page(s) views, event clicks, and relevant factors designed to measure websites' effectiveness and efficiency. Although the dataset was extracted from Google Analytics, then inspected, cleaned, and transformed for relevant multiple regression analysis, a dataset with different demographic, psychographic, and geographic profiles, and analyzed using other qualitative and quantitative tools may have generated different results.

This study can also be expanded with datasets from big data, a term commonly used to refer to techniques and technologies that are capable of manipulating vast amounts of data (in the exabyte 10^{18} and zettabyte 10^{21} ranges). Normal software applications cannot function at that level; specialized tools are required. The Internet of Things (IoTs), is highly relevant to big data given the massive quantities of data generated. The class of data in social media analytics is often unstructured and publicly available from social media outlets using common measures and tools (e.g., Google Analytics). Due to the nature of the data in social media analytics, it is difficult to quantify and index for reuse. The postings are often context dependent, leading to rich information on a variety of topics.

Future research can explore the integration and composition of information services by adding semantics and context-sensitive searches to increase the amount of time a user spends online and enhance her/his experience with a website. In this growing data market, further research has also to be done on typical market structures; the players of the data market, including users, intermediates, and suppliers; the interactions of these players as well as their business models and strategies; and other inter- and intra-organizational questions that are relevant for an efficient production and usage of web-based information services. Finally, as suggested by Baird and Raghu [3], future research could examine digital services at an even more granular level by assessing perceived value at a feature level (i.e., which specific features do I find valuable?) rather than at a system level. The interactions between feature valuations and business model attribute valuations are likely to yield interesting insights.

5.2 Implications for Management

This research has implications for strategies of e-commerce companies as these organizations can utilize the opportunities Big Data presents by Google Analytics effectively to implement online strategies that produce the best return visits, session length and set targets. Based on the findings from this study, organizations that are using Google Analytics should implement the online strategies that produce the best return visits and session length. For example, new firms such as UpCouncil (sometimes called "Uber for Attorneys") and Realty Shack can maximize the value for its current and potential customers by focusing on their targeted needs and minimizing the bounce rate. Companies that are using Adwords should implement strategies to learn if the Adwords improve the quality of paid/search traffic compared to the unpaid traffic.

By associating consumers perceived value with business models for digital services, the findings by Baird and Rahu [3] indicate that the respective digital service model/s are likely to have a significant impact on the customer's perceived value, even though perceived value may be high for generally considered digital services. Similarly in this study, comparing and contrasting mobile and social media platforms vs traditional personal computer platforms; or by comparing the consumption models among companies such as Zillow, Homesearch, and Trulia; or comparing latency measures (i.e., the time it takes a website to load) in competing digital delivery services (e.g., AT&T, Verizon, Charter Communications) could yield additional insights. Given that consumer choice is complex in digital markets characterized by many alternatives, research into how consumers perceive and value the underlying factors among such alternatives is paramount to our understanding of diffusion and adoption in this new area of consumer-oriented information systems. These considerations could help inform business strategists with a deeper understanding of the factors that influence website performance.

There are some caveats for managers/practitioners to consider. First, big data, knowledge management, and business intelligence continue to be emerging disciplines. Managers must continuously scan for new technologies. Second, making knowledge more visible is not always the objective. Managers should be cognizant of competitors seeking information on their business performance. Third, knowledge can be used to develop predictive models and develop future directions. Lastly, it is all about the people – the analysts with technical skills, the managers making better business decisions, and the employees collecting accurate data at the source. Knowledge sharing from the present research study or an expanded study that encompasses datasets from big data and social media analytics is critical to realizing value from these analyses and processes [37].

5.3 Conclusion

To stay competitive in today's highly interconnected economy, most companies must go beyond cost-cutting. They need to apply new technologies to be innovative in responding to the demands of a fast-moving, intensely competitive, global, digital economy. Technology advancements, combined with the evolution of our behavior and expectations, is affecting businesses, governments, education, and, well, just about everything. With the continuous growth of digitally-connected devices and tools enabling brands to connect with consumers and other devices (Internet of Things) in timely, relevant, and experiential ways, companies will have to empathize further with consumer wants, solving the challenges and issues for the digital customer at the time/location (physical location in the real world and/or virtual world) based on the customer's preference [43]. For management-level personnel charged with the goals of cost savings, reduced risk, improved operational efficiency, and increased revenue, what lies ahead is both a challenge and an opportunity. It is important to drive changes that are both externally focused (customer-facing) and internally focused (collaboration, process, technology, and so forth) to build a scalable infrastructure for the digital economy. For e-business intelligence (with elements that include reporting, querying, dashboards, and scorecards) and analytics to be institutionalized successfully, managers must create an environment that supports and encourages the use of performance data in decision making. The changing customer behavior/preferences, leads to a dynamic and volatile marketplace/marketspace. To lead effectively, it is critical to be proactive in understanding the what and the why of these changes. Technological innovations are rapidly incorporating near real-time data analysis, thereby improving decision making on dynamic performance data. However, an organization's only sustainable competitive advantage lies with how its employees apply their knowledge to business problems.

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