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Effect Of Digital Advertising On Website Traffic At A Kentucky Comprehensive Regional University

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EFFECT OF DIGITAL ADVERTISING ON WEBSITE TRAFFIC AT A KENTUCKY COMPREHENSIVE REGIONAL UNIVERSITY

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Abstract

The purpose of this research is to quantify differences in key performance indicators between paid and organic (not paid) website traffic over a one year period of time at a regional comprehensive university in Kentucky, which is located in the southeastern United States. Two distinct sources of website traffic can be measured: paid traffic and organic traffic. Using data from website traffic analytics, this study employed multiple linear regression analysis and time series methods to understand the similarities and differences between key performance indicators of paid traffic and organic traffic as they relate to key performance indicators. Data from Google Analytics will be segmented by traffic source type and analyzed using SPSS to return descriptive statistics, multiple linear regression analysis, and time series methods. Results will quantitatively indicate tendencies of users who arrived to a website as a result of paid advertising versus the tendencies of users who arrived to a website via organic methods. Research findings will be useful for higher educational professionals who seek to optimize advertising campaigns and webpages in the student recruitment process.

Keywords: Google Analytics, digital advertising, student recruitment, higher education, website, regional comprehensive university.

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Conceptual Framework

University website traffic comes from two primary sources – paid traffic from advertising campaigns and organic traffic from search engines or other unpaid links. The intentions of each web user, theoretically, may generally be different. Users who click on a college advertisement while scrolling through social media may be curious and use the website in order to gain familiarity with the college. A user who clicks on a search engine result or email link, however, may have a more direct intent and use the website in order to take a more specific action.

Institutions of higher education actively recruit students to apply for admission using various strategies: printed publications; campus visits; college fairs; traditional advertising; social media; digital advertising; and websites, among many other approaches. The university website is the technology most frequently used during the college search process by prospective students as a way to gather information about an institution (Addington, 2012). Traffic that arrives to a college website, therefore, must be effective and efficient at communicating the necessary information in an easily digestible format.

The website plays a key role in conjunction with one of the more recent strategies for recruiting college students – digital advertising – which leverages the vast amounts of information and the abilities of technology giants (i.e., Google, Facebook, and Twitter) to deliver advertisements to specific audiences. Using the information held at these companies, advertisers are able to deliver advertising directly to 16- to 20-year-old prospective undergraduate students who meet a set of criteria defined by the advertiser.

When a user clicks on an advertisement, they are typically routed to a webpage with information pertinent to the user and/or a call to action designed to prompt the user to take a next step in the process of recruitment.

For schools that use digital advertising, a successful advertising campaign often results in an action taken by the audience, such as the user visiting a website or registering for an event. Traffic to the website is measured with a tracking code – one of the most commonly used is Google Analytics – which records an anonymous data set about each user and their visit to the website, including: pages viewed in the session, city, browser, operating system, duration of visit, and traffic flow, among other data points. These data points are available in a range of time spans – hourly, daily, weekly, and monthly. Data used in this research will be segmented into two sets – one for paid traffic and one for organic (non-paid) traffic. Independently, website usage data is useful in understanding in aggregate how users interact with the website and for understanding trends that develop over the course of time. Information derived from the research and analysis is useful for determining which aspects of an advertising campaign may be prioritized in the recruitment process and which end-user functions of a website should be given more attention for optimization depending on the goals of the organization or institution.

Multiple linear regression analysis will be used in this research due to the ability of the method to individually analyze a range of variables that are related to one another. A large sample size of daily advertising and website data across an entire calendar year will be utilized in order to capture the annual cycle of recruitment and minimize anomalies found in the two data sets. Additionally, the time series method will be used to quantify the relational nature of data over the course of time. Website usage data is available for each day of the calendar year during the period observed (fiscal year 2017-2018); digital advertising data is available for most days of the calendar year, but may not be available for every single day due to the start-and-stop nature of digital advertising campaigns. Though hourly website usage data are available, this would provide a data set of extraordinary size. Monthly data are also available, but this data set is too small for a reasonable sample size. The most effective data for this study are the daily data sets due to the size and granularity of data available. Time series will provide insight into the stochastic processes within the data set.

Resources found in the current body of literature related to this topic address website usage analytics as a singular topic instead of demonstrating the relationship between the organic traffic and advertising traffic. Website usage analytical studies generally use time series methods and focus on key performance indicators that measure website effectiveness related to user experience and interaction, website engagement features, or design elements. Advertising studies focus on the performance of campaigns related to efficiency based on factors of financial cost, user interaction, and completed actions.

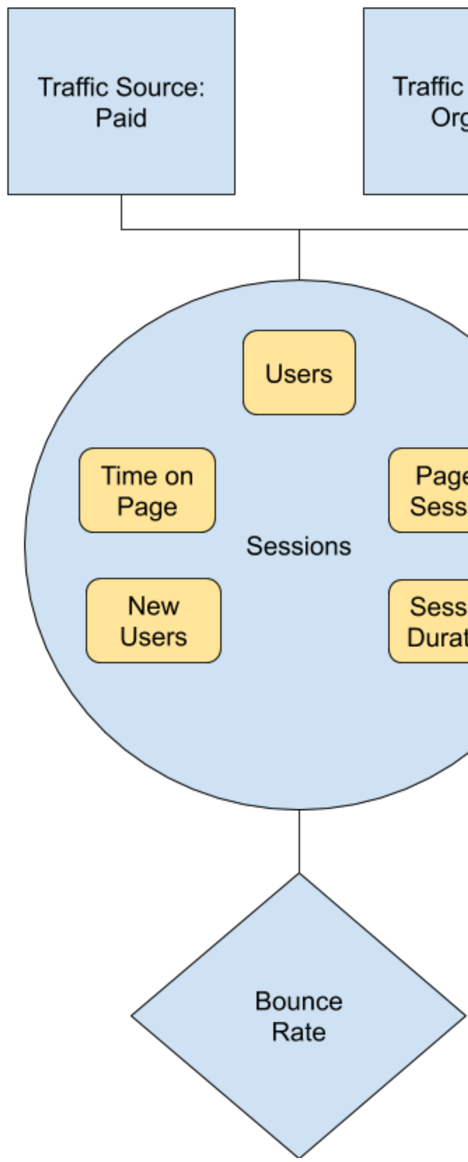
Purpose Statement

The purpose of this study is to quantify the similarities and differences between paid and organic website traffic over a period of time at a regional comprehensive university in Kentucky, offering degrees from associate level to doctoral level, with service primarily to counties within the Appalachian Regional Commission (*Counties in Appalachia - Appalachian Regional Commission*, 2020). During the time period examined by this research, this particular university had an enrollment of approximately 16,600 students. This research is an examination of the relationships between the two distinct types of website traffic for student recruitment at a regional university. Findings from this research will be useful for understanding how digital advertising is influential on website traffic. Higher education professionals may use this information in efforts to improve website designs, messaging on webpages, and digital advertising strategies. The information in this study will indicate relationships among key performance indicators over a period of time and provide insight useful to understand the prospective student experience and optimize the return on investment for institutions that invest funding into digital and web strategies.

A selection of variables specific to admissions recruitment advertising campaigns during fiscal year 2017-2018 will be used in order to capture data from an annual recruitment cycle. A selection of variables specific to the resulting website traffic will also be used, representing 365 days of data, including more than 165,000 users and 276,500 sessions, accounting for more than 670,000 pages viewed. All data are collected as part of the university's digital strategy and are anonymously representative of the activity of digital advertisement viewers and website users; no user identifiable information is available in these data sets. The data to be used in this research will be captured using Google Analytics and will be exported for multiple linear regression and time series using Statistical Package for Social Sciences (SPSS). Variables to be used include: dependent variable *bounce rate*; independent variables *sessions*, *users, pages per session, session duration, new users,* and *time on page*; and two predictor variables, *traffic source paid* and *traffic source organic*. The bounce rate is an indicator of user interaction on the page, which could include clicking on a link, completing a form, or taking another action on the webpage; a lower bounce rate is considered better for user interaction in this study (*Bounce Rate - Analytics Help*, n.d.). Some specific actions that send users to a third-party website could be recorded as a bounce, but it is not possible to delineate between a page bounce with intent to take action and a page bounce without intent to take action. This will be taken into consideration when preparing data sources for analysis. The identified key performance indicators and interactions are the base measures for this study, selected as indicators of engagement with website content and intent to take the next step in the process. All data points essentially represent different measurements of visits to the website, so all are closely related. Variables are modeled in Figure 1 to illustrate the structure of the data.

Figure 1

Data Model Illustrates the Two Types of Traffic That Result in a Session on a Website



Note. The data model represents the segmentation of website traffic data by traffic source. Each segmentation of website traffic will be measured by the five metrics inside the sessions circle. The independent variable is the bounce rate data point.

The purpose of analyzing the variables in this study is to understand the differences in user behavior when website traffic is acquired by paid methods versus organic methods, and the aggregate bounce rate associated with each. By comparing and contrasting the browsing tendencies of each type of user – both the commonalities and differences – website administrators and higher education marketers can better understand ways to effectively meet the needs of the website user, particularly the prospective student.

While the volume of traffic is expected to increase when a paid advertising campaign is in place, not all website traffic is equal. Analog research from the tourism industry indicates paid traffic quality is lower than the quality of organic traffic, as measured by the key performance indicators relative to a tourism website (Moral, Gonzalez, & Plaza, 2014). Key performance indicators are commonly shared across industries, but will not translate perfectly in different settings (Fagan, 2014). The recruitment cycle and decision-making process are significantly longer for selecting a college as opposed to searching for sources in a library or selecting a vacation, so key performance indicators should be evaluated with consideration of the purpose of the individual website.

Research Questions & Hypothesis

Given the nature of the two distinct traffic sources – organic versus paid – for a university website, it may be expected that there are statistically significant differences between the two types of traffic and their respective bounce rates. The primary question to be answered by this research is: does the referral source of website traffic – organic versus paid – have a statistically significant impact on the identified key performance indicators, particularly bounce rate? The researcher hypothesizes that quantitative analysis using multiple linear regression will demonstrate statistically significant differences among website traffic data when segmented by referral source, but that paid traffic will result in a higher bounce rate. A second question to be answered by this research is, "How does the referral source of website traffic – organic versus paid – change over the course of the recruitment cycle year?" The researcher hypothesizes that an analysis of time series will demonstrate fluctuations in both paid and organic traffic over the course of the year.

Research Methodology

The purpose of this study is to understand the differences and similarities between organic website traffic and paid website traffic on the website of a comprehensive regional university and the bounce rates of each. The results of analysis will be useful in understanding website user habits of the two distinct audiences, thereby providing information useful for optimizing website landing pages for paid traffic and standard web page for organic traffic. The university website is an essential communication platform for student recruitment, but existing studies are not specific to higher education recruitment. The findings of this research will address a gap in existing knowledge about website user behaviors specific to student recruitment for institutions of higher education.

Data is collected on a daily basis from users who visit the regional comprehensive university website across the vast majority of the website property. The potential data set is expansive, so data will be limited to a selection that is specific to student recruitment. Limiting the data set will also help avoid sampling thresholds in Google Analytics (*About Data Sampling - Analytics Help*, n.d.), which could skew raw data reporting. From the selection of data, a set of key performance indicators will be identified from a specific date range to be used for analysis, then each data point will be segmented according to traffic source – organic versus paid. Once the data has been properly selected, segmented, and scrubbed, each data set will be entered into SPSS to run descriptive statistics, multiple linear regression, and time series statistical analysis.

Three types of analysis will be performed on the data. First, descriptive statistics will be used to provide a summary of the key performance indicators identified for this study. It is necessary to understand the data contextually in order to better understand the analysis that follows. Second, multiple linear regression analysis method will be used to test the effect of multiple variables on one another and indicate the amount at which each variable is related to others in the data set. By measuring all variables using this analysis method, the researcher can identify statistically significant differences and better understand relationships among data points. Statistically significant relationships will be important to note from this analysis. But perhaps even more important are the relationships that are not statistically significant, since the data are all closely related to one another and represent the overall user sessions. Third, because data points are ordered over a period of time and measured at regular intervals, the time series method will be used to represent the stochastic processes of the key performance indicators.

Summary

Given the importance placed on the university website as a source of information during the student recruitment process, an accurate understanding of website performance is useful for enrollment professionals and other university leaders. If a website is not performing as expected, strategies may be implemented in order to address any identified shortcomings and make necessary improvements. When advertising funds are used to promote and support website and digital resources – including digital advertising strategies and website optimization resources – the priority should be even greater to ensure web pages and sites are performing as expected to encourage the desired interaction. The detailed data available regarding digital advertising and website analytics provides insight and opportunity for higher education professionals to identify areas of improvement. The flexibility of website and digital strategies afford the ability to be adjusted quickly in order to adapt to user needs and university priorities.

Website properties are not standalone entities; they are often linked to and from other website properties in ways that can both help and hinder performance. Understanding the relationships between traffic sources, key performance indicators, and interactions provides a deeper understanding of website functionality and efficacy. A statistical analysis using descriptive statistics will provide contextual information about the data, while multiple linear regression analysis will provide information about relationships between various data points. Since the data points are recorded over an extended period of time, the time series method will account for the regular intervals and structure of the data. Results of the statistical analysis will demonstrate how different traffic sources can produce different levels of engagement and results in consideration of institutional practices and goals.

The arrival of COVID-19 has amplified the necessity of digital resources and tools in higher education and most other industries. The disruption in recruitment and application processes has been so stark that deadlines have been pushed back and some colleges have adjusted acceptance criteria in order to adapt to the international pandemic (West, 2020). Colleges have shifted most instruction to digital spaces, so additional stress has been placed on virtual delivery of courses and increased use of learning management systems (Hess, 2020). Admissions and recruitment events typically held in-person have been canceled or converted to virtual events (Jaschik, 2020). While the lasting effects of COVID-19 are yet to be determined, it is certain that the short-term effects of the disease have halted much of the in-person interactions that have typically been foundational in higher education. The shift to virtual and digital interactions in the wake of initial response to the virus have forced colleges and students to think differently about delivery and interaction and depend more heavily on the digital resources available for both instruction and communication.

Definition of Key Terms

Ad Impression is a single instance of a paid advertisement appearing to an internet user. Ad impressions occur on websites external to the university; data are tracked by third parties.

Cookie is a file saved on a computer to help identify unique users and store preferences.

Bounce is a calculated integer value that represents the number of users that leave the website with no interaction. Bounces are calculated by multiplying the total users integer value by the bounce rate percentage value and rounding to the nearest whole number.

Bounce rate is the percentage of users that arrive at a web page and leave without interacting or visiting other pages.

Organic traffic consists of users that arrive to the web page by typing in the URL directly or by being referred by another non-paid means.

Pages per visit is the number of pages that are viewed within a given session.

Paid traffic consists of users that arrive to the web page by referral from paid advertising.

Pageview occurs when a user loads a web page.

Rate of Return is the percentage of users that return to the website after an initial visit.

Session is the totality of the visit to a web site, which may include browsing a single web page, multiple web pages, or taking specific actions, such as completing a form.

Session Duration is the amount of time in seconds a user stays on the website.

Chapter II – Literature Review

This section provides a review of the literature related to the research regarding quantifiable differences between organic and paid website traffic at a regional comprehensive university in Kentucky, which is located in the southeastern United States. Beginning with the topic of college enrollment in Kentucky and adjacent states, a review of data from 2000-2018 provides context central to the research purpose; enrollment efforts are heavily dependent on website and advertising strategies. Student recruitment literature provides some background information for greater context. Next is the topic of university advertising and marketing in general, and the more specific topic of digital advertising, explored as a subtopic of student recruitment more specific to the research. Next is a review of literature related to websites specific to higher education. Next is the topic of Google Analytics in general and specific to higher education websites. Finally, a review of literature regarding multiple linear regression and time series as each relates to this topic will conclude the section.

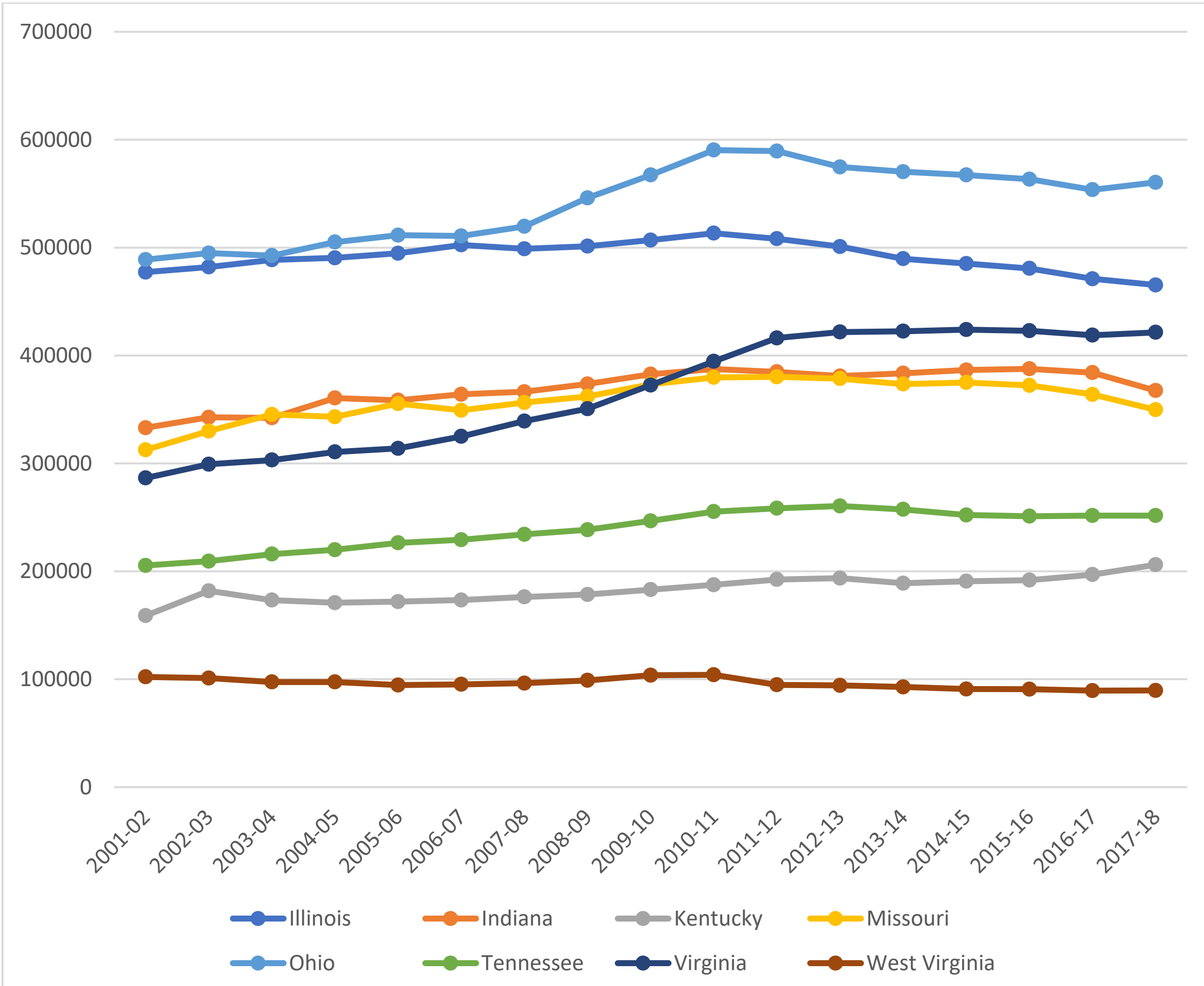
College Enrollment Trends

Website and advertising strategies are central to supporting enrollment of colleges and universities. Websites are often the starting point for the process of new student recruitment, providing a virtual front door to the university and delivering important content (e.g., scholarship/cost calculators, academic program information, admission requirements) to prospective students and other interested parties. Accurate and timely delivery of information from the website to current students supports the continued enrollment, retention, and successful progression of coursework year over year. Once a student has completed requirements for admission, the website provides a functional way to progress through additional enrollment processes, it facilitates communication for currently enrolled students to retain and progress through academic requirements, and move ahead to graduation. Beyond graduation, the college website provides additional communication resources of offices of alumni and development to nurture alumni relationships and foster financial support for institutions. Student enrollment is the primary focus of this research, so a review of enrollment data and trends in Kentucky and surrounding states helps to provide additional context for the research purposes.

Data from the National Center for Educational Statistics (NCES) indicates enrollment at four-year Kentucky institutions is lower than most bordering states, as shown in Figure 2.

Figure 2

Number of Students Enrolled in a 4-year or More Postsecondary Institution Annually by State



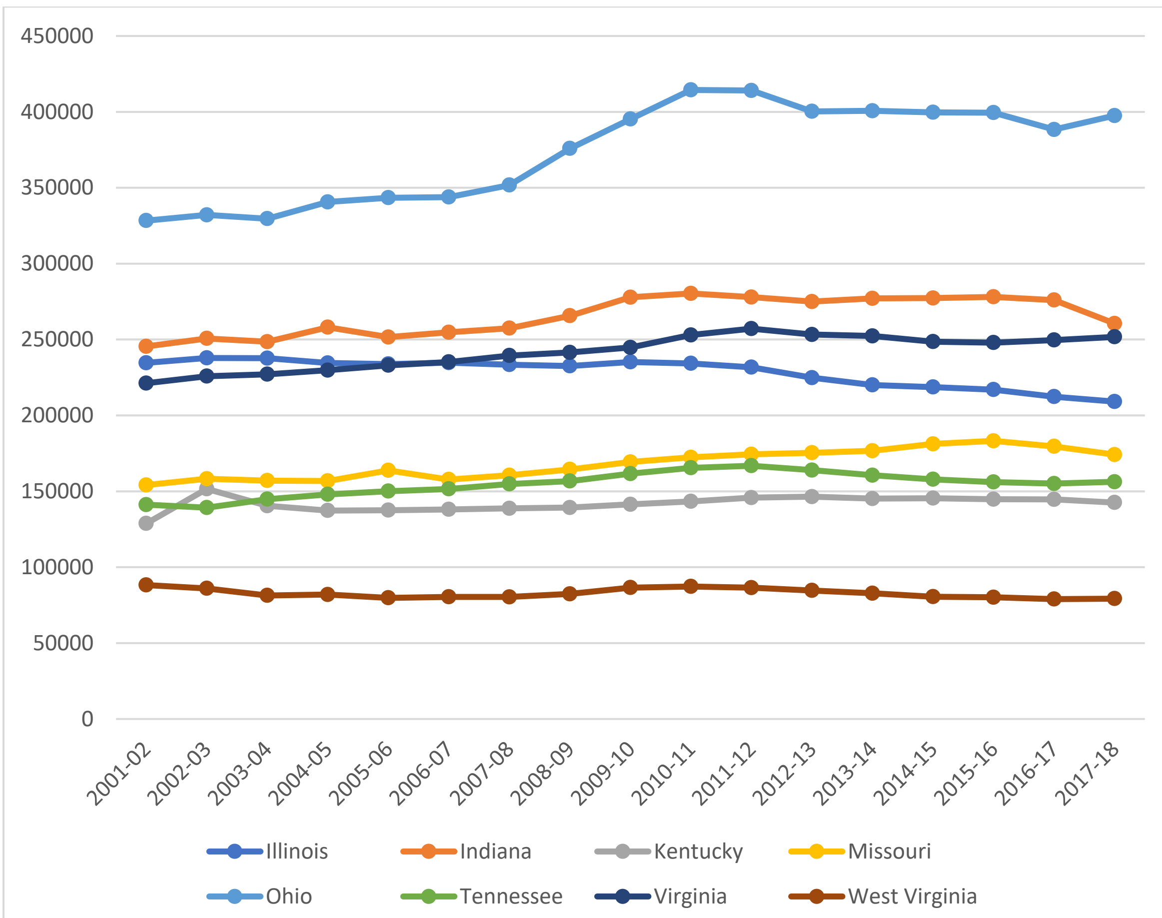
Note. In the years since 2013-2014, Ohio has the highest enrollment, followed by Illinois, Virginia, Indiana, Missouri, Tennessee, Kentucky, and West Virginia. Among these states, enrollment has generally trended upward, with some of the largest gains in Ohio and Virginia, but losses overall in Illinois and West Virginia. Kentucky enrollment has gained overall, with peaks in 2002-2003, 2012-2013, and on a current upward trend. (*Number of*

Students Enrolled in Postsecondary Institutions Annually by Level of Institution (Four or More Years), State, 2020).

Data about enrollment specific to only public 4-year colleges in Kentucky and bordering states is shown in Figure 3.

Figure 3

Number of students enrolled in postsecondary institutions annually by State, Sector of institution (Public, 4-year or above)

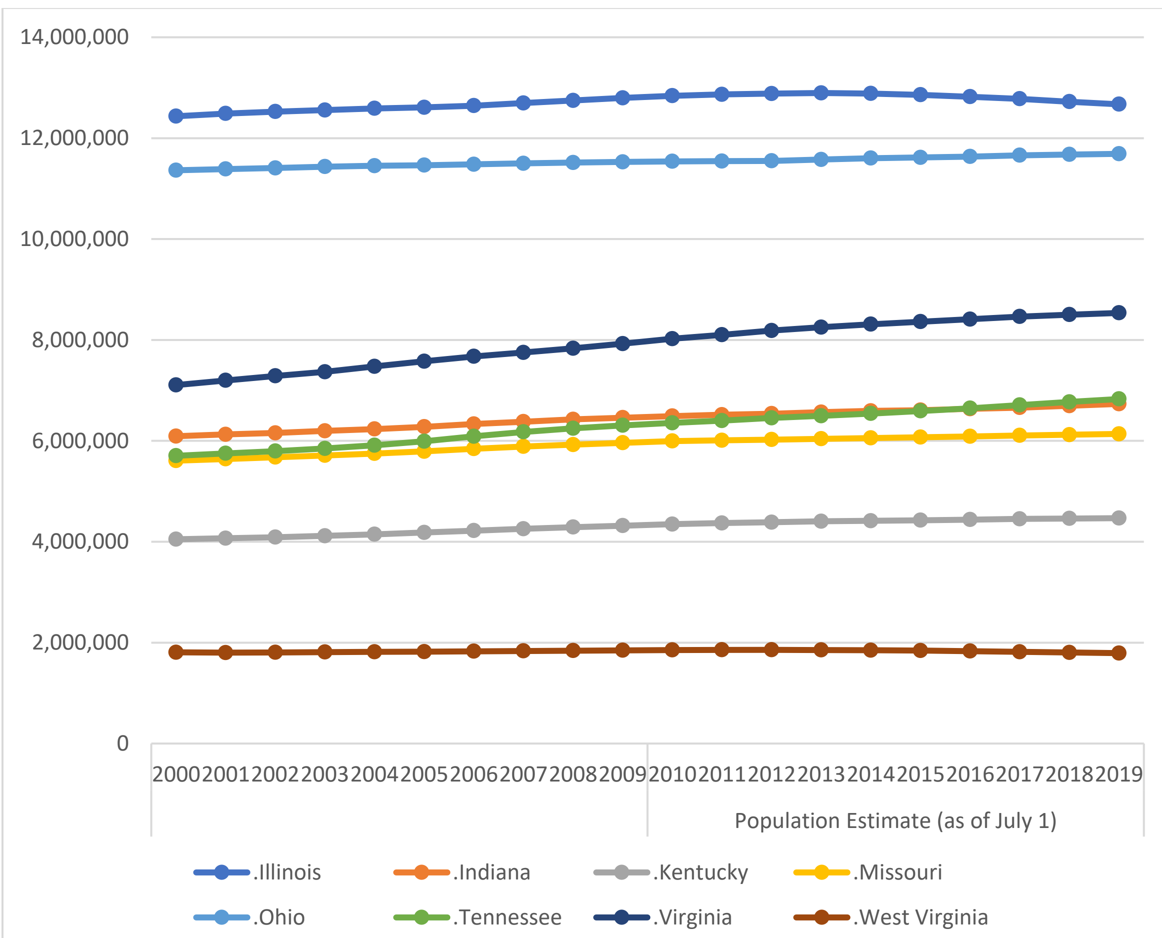


Note. Data from public four-year institutions shows Ohio has the highest enrollment numbers, followed by Indiana, Virginia, Ohio, Missouri, Tennessee, Kentucky, and West Virginia. Ohio has experienced the most dramatic gains, with generally modest variations in enrollment for other states during this period of time. (*Student Enrollment - How Many Students Enroll in Postsecondary Institutions Annually?*, n.d.).

Population estimate data for Kentucky and adjacent states can be found in Figure 4. Students typically travel less than 100 miles for college (Mattern & Wyatt, 2009); this, combined with higher out-of-state tuition costs means public 4-year colleges primarily recruit students from their respective states. By understanding public 4-year institution enrollment as relative to the state's population, we can see how states perform in recruiting students who are in-state residents.

Figure 4

State Population Data 2000-2019

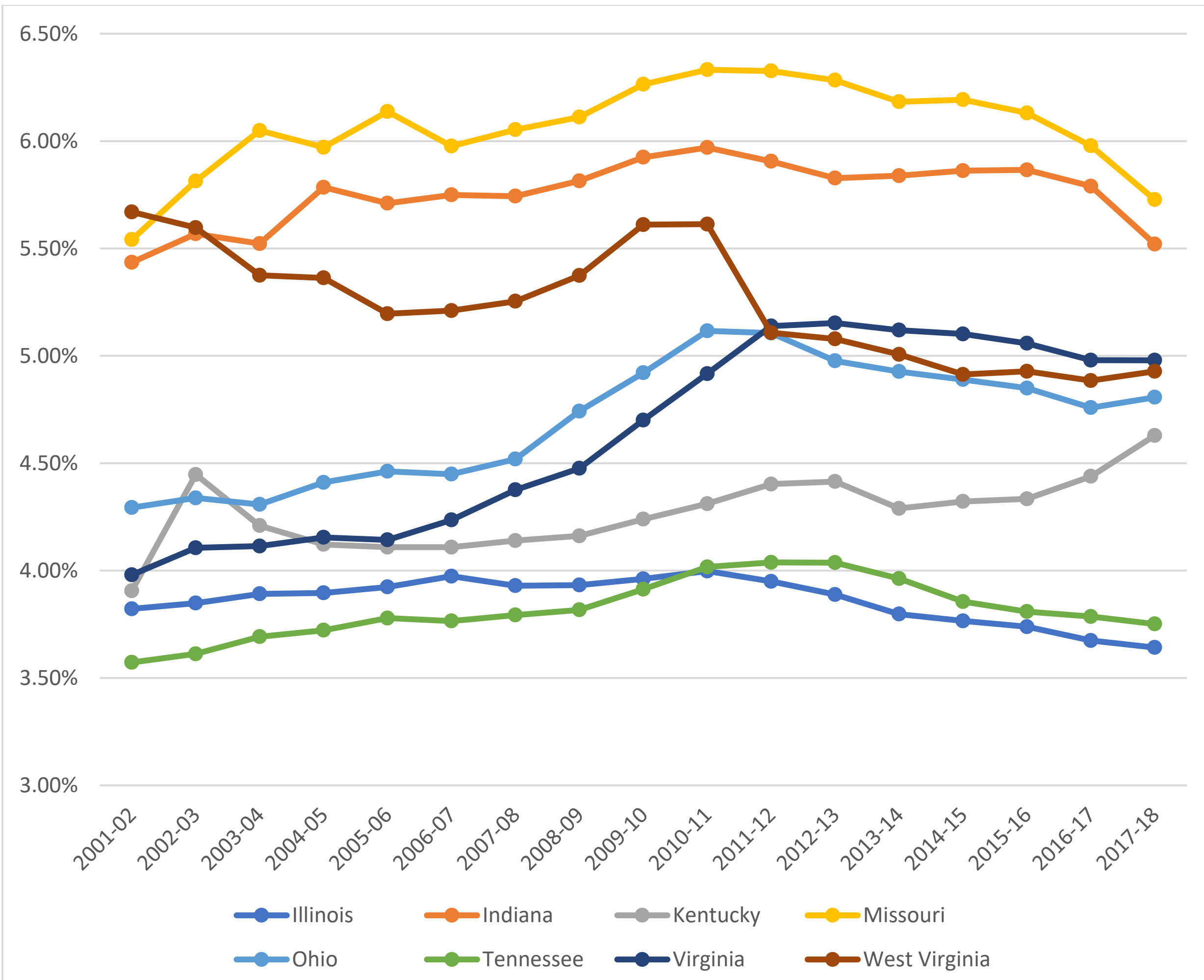


Note. Illinois has the highest population, followed by Ohio, Virginia, Tennessee, Indiana, Missouri, Kentucky, and West Virginia (Bureau, 2016, 2019).

Data from NCES is combined with population data to understand college enrollment as a percentage of state population, shown in Figure 5.

Figure 5

Public 4-Year College Enrollment as a Percentage of State Population



Note. Missouri leads all states in percentage of population enrolled, followed by Indiana, Virginia, West Virginia, Ohio, Kentucky, Tennessee, and Illinois. There were considerable gains in percentage of population enrolled in Ohio between 2007-2011 and in Virginia

2006-2012, while West Virginia dropped dramatically in 2010-2012 (Bureau, 2016, 2019; *Student Enrollment - How Many Students Enroll in Postsecondary Institutions Annually?*, n.d.).

Student Recruitment

In its most basic form, the process of college selection (from the student perspective) and student recruitment (from the college/university perspective) can be viewed as a consumer process wherein an exchange takes place between two parties (Solomon, 2017). During the process of selecting a college or university, a host of influential voices are involved in the process and can have considerable impact on the final decision, despite the fact that these influences are not the direct consumer or experiencing the decision firsthand. Demographic factors are important in the creation of advertising campaigns that deliver specific messaging to specific audiences throughout the life of the campaign. Even when advertising campaigns are effectively designed, external factors can significantly influence the decision-making process: economic factors, pricing and value propositions, general perceptions about higher education, among many other factors all influence the decisions students make to in the process of exploring higher education options. Increased competition in higher education and the instant, vast availability of information on the internet have raised the profile of the website as a student recruitment tool for universities, requiring a sizable investment in the online presence (Saichaie & Morphew, 2014).

A report from some thirty years ago provides an overview of the status of higher education and the behaviors of students enrolling in college or university at the time (Paulsen, 1990). Much of the context of this report could easily apply to the colleges and universities of today – concerns about a shrinking pool of prospective students, rising tuition costs, societal discussions of the value of higher education in the current job market, efforts by institutions to be more strategic about recruiting students and providing programs that are attractive to students, and so on. Paulsen's work provides an overview of studies at the national level, the state level, and even the institutional level, followed by guidelines and recommendations for enrollment officials. Much of the work is spent on the process of college choice from both the institutional perspective and the student perspective, and Paulsen concludes the report with recommendations and a discussion of micro- and macro-level implications pertaining to higher education recruitment.

In response to declining high school student populations across the United States and growing pressure to recruit more students, institutions of higher education increasingly employ new strategies related to branding as part of the effort to increase student enrollment (Stephenson et al., 2016). These strategies include advertising, design, and other types of media related to relaying a specific message to the audience that differentiates or distinguishes the institution from others in a highly competitive field. Effective branding and marketing practices are noted as an influential prerequisite for students to perceive the institution positively. The results of the study concluded that a few factors stood out to students: program of study/major, cost, a visit to campus, perceptions of others within the student's sphere of influence, the location of the school, the size of the student body, appearances of the campus, and a welcoming or friendly culture.

A number of technological resources are now being employed throughout the student recruitment process, including websites, social media, and a network of underlying resources that integrate the experience for prospective students (Addington, 2012; Copeland, 2009). This practice has been coupled with student demand for non-linear and on-demand messaging that gives more control to the student during the process of researching colleges and making the decision to attend a particular college or university.

Colleges and universities incur specific costs related to recruiting prospective students to enroll at their institutions. In 2018, public four-year universities reported spending a median of $536 to recruit a single undergraduate student (Ruffalo Noel Levitz, 2018), with the 25th percentile at $354 and the 75th percentile at $967. By contrast, the median cost to recruit an undergraduate student in 2015 was $578 with the 25th percentile at $407 and the 75th percentile at $775. In the 2017-2018 recruitment cycle, 70% of public institutions reported using approximately the same amount of budgeted dollars for recruitment purposes, while 23% of public institutions increased their budget and 7% decreased recruitment budget. The areas of marketing noted to see increased spending at public institutions were digital marketing, transfer recruitment, and admissions events. Some considerable efficiencies appear to be present for public 4-year institutions with larger enrollment, as shown in Figure 6. The only segment that does not hold true to this trend is for public 4-year institutions in the 25th percentile of spending and the largest third in enrollment size.

Figure 6

Cost to recruit a single undergraduate student in 2017 by enrollment

% Percentile	OVERALL	SMALLEST THIRD IN ENROLLMENT SIZE	MIDDLE THIRD IN ENROLLMENT SIZE	LARGEST THIRD IN ENROLLMENT SIZE
FOUR-YEAR PUBLIC INSTITUTIONS				
25th Percentile	$354	$582	$235	$355
Median	**$536**	**$1,149**	**$491**	**$441**
75th Percentile	$967	$2,174	$657	$594

Note. The smallest third (enrollment 8,683) spending a median $1,149 to recruit a student, the middle third spending a median of $491, and the largest third (enrollment 17,144) spending a median of $441 per student. Source: Ruffalo Noel Levitz. (2018). *2018 Cost of recruiting an undergraduate student*. https://learn.ruffalonl.com/WEB2018CosttoRecruitReport_LandingPage.html.

According to this report, digital marketing expenditures in 2017 at public 4-year schools was allocated at a median of 6% of overall budget, with a 25th percentile of 1% and a 75th percentile of 10% (Ruffalo Noel Levitz, 2018). More than 60% of schools, however, reported a plan to allocate more dollars to digital spending in the next 12-14 months, making it the most popular area of spending slated for an increase.

University Websites and Social Media

Among the most popular, most influential, and often first-used online resources in the college search process is the college or university website (Hendricks, 2006). While not the only resource utilized to research the institution in this particular study, internet-based sources were the primary source of information for 78% of respondents. In addition to the institution website, other sources were found to have moderate importance in the college decision process. This particular study was related to a private 4-year doctoral/research-extensive university in the mid-Atlantic region with religious affiliation, but the findings are consistent with six other cited studies. Advertisements paid for by the university, however, were found to have a moderate or significant influence for only 20% of respondents. The internet search function was frequently used by more than 50% of respondents, using the name of the institution they were interested in 45% of the time. The search detail is an important distinction because search advertising is a paid advertising strategy that is used commonly.

There is inherent potential in the internet in general, and websites in particular, to be leveraged for the communicative and dialogic benefit of institutions (Kent & Taylor, 1998). Websites can communicate to vast audiences, pull together disparate individuals into communities that might not otherwise exist, provide individuals with the means to communicate with one another, and facilitate the sharing of resources and information. University websites are often the central communication point for marketing strategies, communicating key messages and portraying a certain image about an institution (Saichaie & Morphew, 2014).

The institutional website has potential to fill a number of roles for an institution; it has the ability to facilitate communication between the institution and audience, even as far as collaboration among groups of people, enhance the educational experience, grow capacity, scale delivery of messaging, among others (Taddeo & Barnes, 2016). One study proposed two categories for websites: 1) emergent, characterized by a basic presentation of information, inconsistency in content, and incorrect or missing information, and 2) progressive, which leverages the website to meet the needs and demands of the audience, including an architecture that linked related information, consistently engaging content, and an intuitive user interface.

The nature of internet-enabled strategies, however, should be utilized as a means to an end, not an end unto itself (Porter, 2001). The introduction of the internet into existing industries has created both disruption and opportunity. The strategies that organizations employ behind the technological methods can serve to amplify and scale the strategy in expansive ways. As such, it is important that organizations design strategies and methods that are highly effective throughout. The implementation of technology does not remedy a poor strategy; instead, the ability to scale a poor strategy using technological means only serves to spread poor strategy to more people. It is necessary for organizations to get the fundamentals of marketing correct in order to execute internet-enabled strategies in the most effective ways. The internet has, however, served to reduce costs within certain industries, such as communication, which has led to an expansion of distance learning opportunities and easier and open access to information.

Because internet technologies have become more accessible to consumers and widely utilized by organizations across market sectors, the influence of competition in the marketplace has been heightened (Porter, 2001). Competitors within industries can have considerable influence on consumer choice and the marketplace strategy for each organization. Examples from some of the early internet retailers provide evidence that the influence of competition can be so strong that it has the potential to undermine the marketplace, including themselves. As markets evolve, it is necessary for organizations to understand the forces at work within the marketplace, including competitive pricing structures, the growing power of information-driven consumers, the trends related to online advertising, and current and future advancements in technology that provide new opportunities to connect with prospective audiences.

From the e-commerce business sector, literature suggests that consumer buying behaviors are heavily influenced by the online experience (Ahmad & Khan, 2017). The speed and scale at which end-users are able to access a vast array of information with a simple web search makes the online marketplace a highly competitive space. As such, the quality of websites is critical for presenting accurate and timely information in an easily consumable format – for both the end user and algorithms that produce website results. An understanding of consumer behavior related to the online experience has resulted in the creation of website quality measurement tools designed to quantify the user's experience of a website.

Students who are researching options for postsecondary education often visit institutional websites to learn more about various aspects of a college or university. Understanding the ways in which the website is utilized by traditional prospective students is especially useful for determining the topics and information to make available on a college website (Christiansen et al., 2003). Students were interested in exploring the college website to find information about academic programs, cost information, housing, and student life, but still desired to have a personal contact with someone at the institution; the website was not a replacement for relationship. These findings are consistent with the results of more recent research.

College websites are noted as the most influential resource for information related to the college search process (Ruffalo Noel Levitz & OmniUpdate, 2019), with sophomores, juniors, and seniors all ranking the website as more influential than personal contacts from a school and printed materials. Many other sources of information are certainly influential, but the university website ranks above others, so it is important that the website design and content is effective at moving the user toward their goal. More than 75% of students will use the university website to request more information using a web form, making this on of the top actions. Students who use search engines to explore college options use a number of keywords or search terms to find the information relevant to their interests, often related to the program of study. Once a prospective student arrives at the university website, certain topics are expected to be easily accessible: costs, scholarships and financial aid, and academic programs of study rank highest. Students also frequently use mobile devices to complete actions, as half of students report completing a form using a mobile device.

In a qualitative study about the use of websites by prospective students, Poock and Lefond (2001) conducted research with more than 50 high school students and found several categories to be considered in regards to the website effectiveness. Most important of all aspects of the website was the availability of anticipated content, such as athletic information, housing details, and curricular and academic offerings. Second most important to prospective students was the effective organization of information and the ability to easily navigate the website. Third most important was the orientation of the website toward the needs of the student, including photography and design, without being perceived as excessive or trying too hard to achieve a certain look.

The content and quality of university websites can vary greatly from site to site. The work of Berhow and Gordon (2007) and Rao and Hosein (2017) indicate that different institutions can present similar material in very different ways and that much of the content and presentation is left to the discretion of those responsible for creating and organizing the information. Aside from the information required to be presented in accordance with regulatory guidelines, information regarding academics and other aspects of the student experience can be quite inconsistent for students. Messaging on university websites tends to focus on the promotion of higher education as a product, the ability for individuals to get jobs, geographic location and opportunities, and ideals such as citizenship, intellectual development, and societal good. Universities should invest careful attention in the messaging found on websites and web pages to ensure consistency with university branding and an accurate portrayal of student experiences and actions taken on a website (Saichaie & Morphew, 2014).

Universities leverage social media as part of branding and recruitment efforts, and there is even evidence to support the notion that a larger social media following can be correlated to the success of student recruitment (Rutter et al., 2016). This theory proposes that a social media follow or interaction is, essentially, an endorsement of a particular institutional brand, position, or other messaging. The number of messages posted by an institution, however, is not a predictor of success; rather the relatability of content within the social media posts and an ability to interact with the audience in meaningful ways are the primary components of any associated success.

The methods for utilizing social media and college websites as strategic tools may vary from institution to institution, but a common method for delivering social media advertising to users is with a method known as retargeting (Turow, 2011). This method uses a software cookie from a website visit to track a user to other locations and deliver advertising on third-party websites. This method can also leverage a user's social media network to establish new audiences and distribute advertising to users that may not have an expressed interest, but are associated with a user who is. Another common method of digital advertising is known as geotargeting, which makes use of user locations to deliver advertising to individuals within a certain geographic location or proximity. Using these methods, social media advertising and marketing have a tremendous ability to scale exponentially and spread a message to a highly targeted set of users quickly and efficiently.

More than twenty years ago, Kent & Taylor recognized that institutions which carefully and properly leverage the website as a technological communication tool may harness the vast potential of the internet for relationship and community-building (1998). Social media as a form of marketing falls into the relatively new realm of experiential marketing, providing an immersive environment in which the user may interact with the organization and other users (Hall-Phillips et al., 2016). Aspects of education, esthetics, excitement, and escapism are also considered characteristics of experiential marketing. The exchange of information and messages within the virtual space provide a way for users to both escape from the physical space they find themselves in and craft a positive persona comprised of the messages and sentiments found in the social messages they publish on a given platform. Continued engagement in the social media space grows the educational value of a particular platform and perpetuates future interaction, all while providing organizations with knowledge and the benefit of customer perspective.

Advertising in the social media space provides another method for organizations to increase engagement with customers and potentials customers, but successful advertising and marketing campaigns should be aligned to the unique characteristics of each social media network and the sense of excitement and escapism users expect to experience on the platform.

The interaction between organizations and customers is becoming relatively commonplace with the advent of social media platforms and resources (Hanna et al., 2011). A plethora of social media platforms exist, and with the widespread usage of internet-enabled mobile devices, the platforms are highly accessible. The vast access, portability, and availability of social media platforms has changed and continues to change the marketing landscape for organizations large and small. Fundamental to social networks are the relationships built by those who participate, which in turn serve to create countless connections across the network and facilitate conversations of value for organizations. While traditional marketing was concerned with building an expansive reach in order to be seen by as many people as possible, digital marketing typically takes a more targeted approach to be seen by and interact with a highly specific selection of viewers. Traditional and digital mediums should be strategized separately, but the two should be seen as complimentary in order to work each medium as effectively as possible toward achieving the established goals for the organization.

Website Usability

Because the website is such an important factor in exploring college options and indicating interest in enrolling at a particular college, it follows that the website should be measured and made more effective toward prospective student needs. The field of usability is focused on making a product (in this case, website) by which users can accomplish contextual goals effectively and efficiently with a certain level of satisfaction (Erickson et al., 2013; Kincl & Strach, 2012). One specialist in the field of website usability also noted a website which meets usability demands should be easy to understand and remember, have few technical issues, and allow the user to accomplish the goals for their visit to the website (Bai, 2019).

Website analytics can provide some information about user experience on a technological level – data points about software, hardware, and screen resolution are readily available in most website analytics platforms (Beasley, 2013). This data provides insight into user preferences that can help inform decisions made during website development and code maintenance – decisions that have an influence on the resulting user experiences. Analytics also provide insight into the ways in which visitors are using the content on the site, including which pages are most popular, whether or not the content is clicked on, if forms are completed, pages are shared, or if the user bounces off the page. Quantitative data and analytics are useful for designing usability research and identifying pages that should be examined by usability studies.

User satisfaction is both asymmetric and non-linear, so organizations must attend to resolving the overall challenges users face related to satisfaction in order to achieve usability (Kincl & Strach, 2012). Simply refining certain attributes of a product often do not suffice to overcome user dissatisfaction, as there are elements of both emotional and visual appeal, and some dissatisfiers may be so overwhelming as to disrupt the entire experience for users. Aspects of quality, such as accuracy, timeliness, availability, and ability to obtain and ascertain information are all factors to be considered in the measurement of user satisfaction. These factors, of course, are dependent on objectives of the website – some websites are purely informational, some are purely transactional, while still others, such as college websites, are both informational and transactional in nature.

There is an inextricable link between website usability and website accessibility (Erickson et al., 2013). While the two concepts are distinct from one another and one aspect can be present in a website while the other is entirely absent, there are various points of relationship between the two (Bai, 2019). In general, websites that follow proper accessibility guidelines will be more user-friendly to more audiences; a significant positive correlation between the usability and accessibility scores of websites is notable in one study of government websites. When a website is accessible, it may be used more fully by users with limited accessibility, for example, users who rely on a screen reader to access information or users who rely solely on a keyboard to navigate the website. There are both automated and manual testing methods to identify website accessibility issues; each provides distinct advantages (Erickson et al., 2013). By utilizing both methods, a comprehensive view of the website accessibility issues may be identified and addressed by website administrators. Automated tests provide insight regarding technical accessibility issues which should be resolved in order to meet certain specifications and federal regulations.

One study used quantitative methods to examine the usability of a website in terms of user preferences and pathways when a user browses the website (Siciliano et al., 2016). Analysts can identify common sequences and patterns taken by users when browsing a website. Individual users tend to follow common paths in website navigation, so the authors were able to use quantitative records to identify common matrices and patterns in navigation. Information architecture is one of the structural features that allow users to navigate a website. Navigation is noted as one of the key elements of website quality and provides a metric by which some studies have measured ease of use and content (Kincl & Strach, 2012). Simple, clear navigation and an obvious search function are aspects that make a website more user-friendly and help users achieve the goals for a website visit. Many websites are structured to mirror organizational order, but a more useful method is to take the audience-centric approach of ordering content according to the website visitor (Erickson et al., 2013).

Content follows as another key factor in website quality (Kincl & Strach, 2012). It is necessary for content to be relevant to the user, accurate in nature, timely with current needs, and complete in explanation. Content is the primary purpose for a prospective student to visit a university's website, whether related to finances, scholarships, course schedules, program availability, housing, or other aspects of the college experience (Hoang & Rojas-Lizana, 2015). Colleges may present information on web pages in various ways that portray a particular image and message to audiences. While institutions may be intent on presenting the institution in a particular way on the website, it is also necessary to present complete details in order to help users feel confident they have the information needed to take the next action. The perception created by messaging on a website can produce specific types of responses that result in statistically significant differences in user behavior (Berliner Senderey et al., 2020).

One of the resulting resources of user experience and usability testing is the development of personas and/or demographics of website users (Beasley, 2013). This allows website administrators to identify typical audiences and segment the content, navigation, user interface design, and website strategies around more specific types of users in order to meet the needs of those users more effectively. For many websites, these types of adjustments can result in more economical website visits that translate into substantial economic gains and efficiencies. By comparing and contrasting the measurements taken from web pages both before and after making usability changes, website administrators can quantify the effects that result from usability research.

User testing may be used to assist with understand the experience of users while visiting a website and should be designed with the purpose of the website in mind (Kincl & Strach, 2012). This type of testing is often conducted using target groups consisting of users of different ability levels who are given direction to visit an identified selection of pages (Erickson et al., 2013). A range of scenarios may be provided to the users in which participants are asked to accomplish a set of tasks relevant to the purposes of the website and the study (Kincl & Strach, 2012). Once users have gone through the test scenarios, a set of measures are typically employed to quantify usability. Measurements of relevance, formatting, reliability, level and timeliness, ease of use, aesthetic appearance, navigation, terminology, readability, graphics may be used to gather feedback. Simulated target group usability testing may also be used in order to understand accessibility issues; users familiar with site and testing methods simulated the use of identified websites using screen readers, magnification technology, and other assistive/adaptive tools (Erickson et al., 2013). The aim of usability testing is to identify and remove issues and shortcomings of the website that negatively impact user satisfaction (Kincl & Strach, 2012).

University Advertising and Marketing

Only in the last thirty years have marketing departments emerged on college campuses; prior to this, universities were able to advance their mission through academic reputation, research, and community engagement (Anctil, 2008). This shift has coincided with the necessity for administrators in institutions of higher education to think of the college or university as a business, forced to answer the question: should an institution function as a *business* or as a *mission*. With declines in state funding, many institutions have been forced to think and act out the mission while being responsive to the business of the institution. By making decisions based on both principles, institutions may effectively execute the mission by being responsive to the needs of the community and society. Certainly, complexities and tensions are held within the balance of carrying out the mission and business of colleges and universities; those responsible for executing each will have challenges while navigating institutional priorities.

A foundational concept for marketing across industries is that of the 4 Ps: product, price, promotion, and place (Constantinides, 2006). Not all marketing professionals agree that this concept addresses all facets of marketing, but the model has been prevalent since the 1960s. In the time elapsed since the introduction of this concept, the landscape of economies and markets has changed considerably, especially with the introduction of the internet and related communication technologies. Modern consumers have trended toward independent and informed with high expectations and strong engagement in the purchasing process, but less responsive to traditional marketing methods. Due to the now-evolved and ever-evolving consumer, some authors argue the traditional 4 Ps marketing mix is no longer the foundational concept it once was, and it needs to be updated. Three considerations should be given to an update of the 4 Ps: the shift in customer perspective, bi-directional customer interaction enabled by digital and social media, the exchange of information, and strategic communications and content. The introduction of a new or modified marketing mix model would need to maintain the simplicity and broad application found in the 4 Ps.

According a study from the mid-1980s, the college admissions recruitment process is lengthy and can be quite involved. The advertising stage of marketing occurs late in the overall marketing plan; advertising should be viewed as a distinct aspect of marketing instead of synonymous with marketing (Kotler & Fox, 1985). Advertising is part of the action plan follows the research regarding prospective student needs and developing an understanding of the ways the institution can meet those needs. An understanding of the institutional market position compared to competitors, past trends, goals, and conversion rates are especially useful in gaining insight into the action plan and advertising messages. The college marketing and advertising strategies of today are still extended to three years or more in some cases. More specifically, advertising campaigns tend to be more targeted in a prospective student's senior year as they are finalizing decisions, accepting scholarship packages, registering for courses, and meeting enrollment deadlines.

Various forms of marketing communications may be categorized, including the two forms of communication most pertinent to this research: advertising and direct marketing (Kotler & Keller, 2012). Advertising is defined as "any paid form of nonpersonal presentation and promotion of ideas, goods, or services by an identified sponsor," and direct marketing is defined as "use of mail, telephone, fax, e-mail, or Internet to communicate directly with or solicit response or dialogue from specific customers and prospects" (Kotler & Keller, 2012, pp. 228–229). As it relates to this study, advertising is the driver behind paid traffic, while direct marketing is the driver behind organic traffic for this analysis. Kotler and Keller also categorize interactive marketing as a separate category, defined as "online activities and programs to engage customers or prospects and directly or indirectly raise awareness, improve image, or elicit sales" (Kotler & Keller, 2012, p. 229). While interactive marketing is designed to encourage a user to take an action – social media, for example – the nature of this traffic originates as an organic source, so it would not be considered a paid traffic source for this study unless the social media is specifically a paid advertising campaign and tagged as such using the Urchin tracking module (UTM) method (*Urchin Tracking Module (UTM) - Urchin Help*, n.d.).

The ability to segment is a strategy that provides a considerable return on investment in advertising and marketing (Litten, 1982). Digital strategies are often segmented in ways that allow for specific messaging to reach specific audiences. Advertisers able to leverage the ability to deliver specific messaging to a particular segment of users will see improved results.

One of the most important aspects of advertising and marketing for any type of organization is delivering the message in the right location. Students currently being recruited by colleges and universities were typically born after the year 2000 and are known by a few different names – Generation Z, iGen, and post-Millennials, to name a few (Beck & Wright, 2019). This generation is characterized by a native approach to technology, a reliance on social media, diversity in numbers, a shared experience of the 2008 recession (and the 2020 COVID-19 pandemic), violence in schools and the media, and drone parenting, which is often facilitated by technology. Students in this generation report regularly using technology, including mobile phones and tablets, even to the point that they felt more comfortable working with technology than their teachers.

Social media is widely used by post-Millennials; reports show that approximately 97% of this generation use one or more social media accounts and nearly half reporting that they are nearly always online in one form or another (Beck & Wright, 2019). The constantly connected status of these students has changed the social connectivity dynamics of these students. While strong emotional ties may be built in a virtual space, it can be challenging for these students to connect in physical spaces in real-time. Even with strong connections online, some mediums are proving to be less effective for post-Millennial students. Anecdotally, some suggest that e-mail, for example, is on the decline for these students, in favor of text messaging or other methods that are delivered more directly. Because of information overload, it is important to keep messages direct and succinct, including engaging photography and visuals.

Digital advertising on social media platforms is a strategy that is commonly employed by universities and colleges. The work of Moral, Plaza, and others examines the differences between paid and organic website traffic on a tourism website and the impact paid advertising has on website traffic over time (Moral et al., 2014). Results of this study indicate that advertising does increase visits to a website, but the quality of the traffic remains about the same; advertising does not seem to have an impact on increased search/organic traffic; paid traffic tends to bounce off the site at a higher rate, spend less time on the site, and view fewer pages. The goals and traffic type for a tourism site are significantly different from that of a higher education institution, so the results found in this study should be considered in terms of specific to the industry.

User behavior related to advertising methods varies from industry-to-industry, but evidence from the financial services field suggests that users respond to advertising differently depending on the user's position within the marketing process (Hoban & Bucklin, 2015). Users who were in later stages of the purchasing process and were shown a retargeted advertisement showed a significant and positive response rate to advertising, while users who did not create an account during the first visit did not indicate the same positive or significant response. With this knowledge and by utilizing applying their own data to the model, advertisers can make more informed decisions about allocation of future advertising funds and development of new strategies related to advertising and remarketing efforts.

Academic research that examines the relationship between paid and organic website traffic are relatively sparse, but one study analyzes data about this specific area of interest using Bayesian modeling to construct a framework and Markov chain Monte Carlo methods to quantify the relationships (Yang & Ghose, 2010). The study focuses on search traffic only and concludes that paid traffic and organic traffic have a positive interdependence, demonstrating that even organizations with strong organic search results can benefit from paid search traffic. The authors theorize that this effect may be due to the idea that multiple sources are reporting a particular result, adding to the reputability of the link. Another theory is that though the paid and organic links may lead to different destinations, the organic destination is generally preferred by users because the search result is tailored to the user's search query, thus a more effective destination. An asymmetric positive relationship between paid and organic search traffic is also noted: higher-ranking search results see a greater number of paid search clicks. There is some speculation that paid search advertising has the potential to influence organic search results in some ways, but no evidence is provided to support the speculation. The outcomes of organic and paid traffic are measured in the Yang and Ghose study, with paid traffic resulting in slightly more conversions than organic traffic.

A study from the automotive industry examines the indirect or residual effects of paid search traffic on organic return traffic to a website (Rutz et al., 2011). Organizations that choose to advertise on search engines based on the keywords a user is typing in can easily see and track this type of traffic to the website, including any sales that result from this direct visit. It is more challenging, however, to understand the residual effects of paid search for users that return to the website at a later time to make a purchase. Evidence has shown that users who initially arrive at a website from an advertisement often return to the website at a later time to make the actual purchase. The ability to indirectly attribute the sale or purchase of an item is necessary to more fully understand the residual value of paid advertising that does not result in a purchase on the initial visit and more accurately attribute sources of sales and traffic. The research found that there were two categories of keywords – one larger set that was ineffective for generating return visits and a smaller set that was effective for generating return visits. The ineffective set of terms outnumbered the effective set approximately 4:1. Significant keywords tended to be more general in nature, while the insignificant ones were the more specific keywords. The effective keywords are estimated to generate 3.3 return visitors for each click, generating $0.04. At the scale of advertising in this particular scenario, the revenue amounts to an excess of $90,000, which amounts to 49% of the search advertising budget. The researchers also note that additional benefits are possible, but the research was not able to address these benefits due to data limitations. The methods proposed in the Rutz study provide a model for other organizations to use a limited data set to make inferences about the indirect effects of paid search traffic and generally understand that broader keywords are more likely to generate a return visit to the website.

The source of traffic is an important data point to track for institutions of higher education, particularly as institutions seek to quantify, refine, and improve efficiencies of marketing strategies. One study in particular indicates that all 5 of the 5 colleges that participated in the study collected data during the student application stage about how applicants learned about the institution (Shores, 2017). In addition to the data collected by Google Analytics, some university-specific customer relationship management (CRM) systems are also using technological means to integrate this information into the database and profile about applicants (*Features - Slate by Technolutions - Technolutions*, n.d.).

Google Analytics

A thorough understanding of Google Analytics is necessary to fully comprehend the data reported about the website. Plaza researched the topic in ways that closely relate to this study. In one study, Plaza and her colleagues examined the types of traffic that result in more pages viewed and more time spent on a website (Plaza, 2010; Plaza et al., 2011). The study concludes that the traffic types that are most effective are those that drive a large number of visitors to the site, keep visitors on the site for longer periods, have fewer bounces, and have visitors that return to the site later. The study by Plaza and her colleagues is useful in quantifying the assumptions that many web administrators are likely to make and provides a foundation for the further work of this study.

In a study specifically about using Google Analytics on library websites, Bhatnagar argued it is important to go beyond raw data when assessing the success of web sites and web pages (Bhatnagar, 2009). She made the case that web analytics are useful for business intelligence purposes and should be automated so the data can be mined for predictive analytics and trends that might not otherwise be known. The selection of key performance indicators can be modified for each industry or business, according to Bhatnagar, who suggests that the data collected about website usage, together with the knowledge a business has about its customer base, provides opportunities for web managers to optimize the content and structure of web properties.

Google Analytics was used to assess student recruitment in a study about summer session recruitment to a known group of students at a specific institution (Bilella, 2013). The marketing campaign for summer session recruitment can be improved by employing data mining and data analysis techniques, including predictive modeling of data, along with web analytics data from Google. By coupling the strategies for student recruitment with the resulting website data, the administrators were able to better understand which elements of the campaign were successful and which ones were not.

The process of selecting key performance indicators and the deficiencies of current website analytics tools is an important part of understanding web performance (Fagan, 2014). Even with careful selection and analysis of data points key performance indicators, the total value of a website cannot be captured in a set of data or information. The purposes of websites and the types of organizations represented by the content of websites are different enough to prevent direct analog comparisons from being productive. Data represents one aspect of the user behavior on the site, but the data is most useful when combined with other sources of information that help to complete the picture about user intentions and whether or not they have been able to achieve their goals for visiting a particular website.

Summary

College enrollment in Kentucky and surrounding states varies from year-to-year; among adjacent states, Kentucky ranks second-to-last for 4-year public and private college enrollment, but also has second-lowest population numbers. Because many colleges recruit from their home state, college enrollment as a percentage of state populations provides a more equitable comparison of numbers, but Kentucky still ranks third from last.

Student recruitment and college selection at its most basic is a consumer decision-making process that involves a number of factors, including awareness via advertising and information delivery and influence from other individuals. Part of the context of higher education are the number of individuals available in the pool of prospective students, cost of attendance, and societal discussion about the value of higher education among many factors. In light of the many factors involved in choosing to attend college, institutions employ various strategies to raise awareness, such as branding, marketing, and advertising efforts.

In more recent years, the use of technological resources and strategies have become more mainstream, providing colleges new and innovative methods for delivery of advertising and highly targeted messages to specific audiences. The university website is central to this strategy, providing a hub from which communications may be delivered and information may be gathered. Social media platforms also play a considerable role in presenting a certain branded message to prospective and current students. Technological tools provide new methods of delivery that can be amplified exponentially, so the messaging and strategy implementation must be sound and solid in order to be truly effective. Many institutions use their websites for internal audiences like current students and employees, as well as for external audiences like prospective students and community members. As such, the online experience for constituents can considerably effect behaviors related to an institution; university websites are consistently named the most influential source of information when choosing a college.

Google Analytics is a widely-used commercial product that collects anonymous data about website usage, including pageviews, time on page, bounce rate, and operating system, among many others. Businesses often identify key performance indicators (KPIs) that provide information about website efficiency and efficacy; not all business choose the same indicators.

Chapter III - Methodology

The purpose of this study is to understand the bounce rates of website traffic when segmented by traffic source – organic versus paid. Key performance indicators data will be used as a representative set of user interactions, but does not comprehensively indicate all potential actions for website users. The methodology for this research follows with research study practices established for quantitative research (Jackson, 2012). Participants in the study include a daily aggregate of visitors to admissions-specific pages of the university website over the course of a 365-day period, as tracked anonymously using the Google Analytics technology.

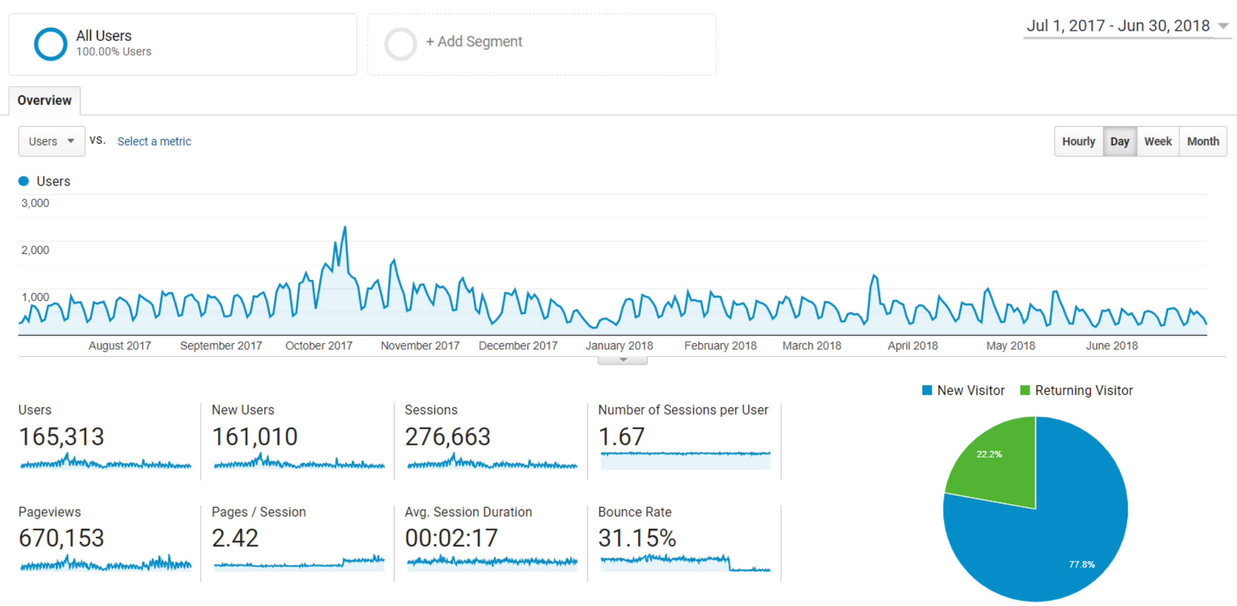
Data Collection & Procedures

Based on traditional quantitative research methods, this research follows the survey study method, except there is no survey for individual users to complete (Creswell & Creswell, 2018). Data is collected and stored in the Google Analytics online system, and may be exported into a data file and formatted for statistical analysis in SPSS. Some users may opt out of being tracked by Google Analytics by blocking the initial tracking code or rejecting the cookie. Users who opt out or reject the cookie will not be included in the data examined in this study, but it is assumed that this population is negligible.

When a visitor arrives at the site, Google Analytics places a cookie on the computer, which then anonymously logs certain technological and geographic information and tracks future activity on the website. The data set to be used in this study is from the 2017-2018 fiscal year. The website activity is collected in Google Analytics, then two data sets will be manually segmented by traffic source, resulting in one data set of paid traffic and one data set of organic traffic. The sample size for both organic traffic and paid traffic will be 365, which is the number of days aggregate data is available throughout the calendar year. The 2017-2018 fiscal year was selected because of relative stability in the website and customer relationship management system, which contributed to a more consistent data set. A sample of the raw data is indicated in Figure 7.

Figure 7

Audience Overview from Google Analytics



Note. During the course of the 365-day period, more than 165,000 users came to the website in 276,500 sessions, accounting for more than 670,000 pages viewed (*Analytics*, 2020).

Plaza has identified a set of website KPIs: sessions, pages per visit, duration of visit (in seconds), bounce rate, and rate of return (Plaza, 2010). This research will segment data into organic and paid traffic sources, so the *new users* data point will be used instead of rate of return. Within each data set, the independent variable will be *bounce rate*, and the dependent variables will be sessions, pages per visit, duration of visit, new users, and bounce rate.

There are three hypothesized rules of website analytics based on time series that have been tested with an educational tourism website (Plaza, 2010). The author proposes that: 1) return visitors spend more time on a website and view more pages, 2) a lower bounce rate means a longer visit and more time spent on the site, and 3) a lower bounce rate means a greater return visit rate. A cross-section of data is reviewed and subjected to a time series analysis to test the hypothesis, resulting in confirmation of the hypothesized rules, but a note that a statistically robust study and repeated studies would provide a more thorough analysis of the hypotheses. Plaza notes these are shortcomings of her analysis; the methodologies applied in this research will address some of those gaps.

Since the purpose of the study is to identify statistically significant and non-significant relationships among the variables related to the interaction KPIs, multiple linear regression will be used to analyze the data. Before the data can be analyzed, it must first be segmented by the source, resulting in two data sets – one for paid traffic and one for organic traffic. Each data set will be imported into SPSS to run descriptive statistics that provide context for other analyses. Multiple linear regression analysis will be calculated using bounce rate as the independent variable; the Pearson Correlation will be used, along with stepwise methods and a confidence interval of 95%. Time series will be calculated in order to illustrate relationships among the data over the course of the 365-day period.

Descriptive Statistics

Descriptive statistics will be reported first in order to examine characteristics of the data sets. A report of multiple linear regression analysis for each data set will examine any indicated correlational relationships, the models of analysis using the stepwise method, analysis of variance, and coefficients. A report of the time series analysis will include information regarding general upward or downward trends, notable fluctuations or patterns in the analysis, and any identifiable relationships among data points. The analyses will be compared and contrasted to understand the similarities and differences between the organic traffic and paid traffic related to the KPI variables, both over time and as part of the regression analysis.

Multiple Linear Regression Analysis

The statistical analysis of data will be conducted by three methods: 1) descriptive statistics and 2) multiple linear regression, and 3) time series. Each method of analysis helps to understand the data in different ways. Descriptive statistics "provide information on the central tendency of the distribution, the width of the distribution, and the shape of the distribution" (Jackson, 2012, p. 116). Descriptive statistics about the mean, mode, variation, and type of distribution provide a point of reference and context for the analysis that follows. These statistics will provide necessary context for understanding the results of the multiple linear regression and time series, which are explored in further depth below.

A foundational method used in business calculations, regression analysis is versatile and widely used in a range of applications (Hair, 2006). Regression is commonly used in forecasting, performance modeling, consumer decision-making, program effectiveness, and product feasibility, among many others. The versatility of the multiple regression analysis method lies in its ability to measure the relationship between a dependent variable and respective independent variables. Multiple regression analysis is most effective when applied to research questions related to prediction of variables and explanation of variables. As it pertains to prediction, multiple regression is most effective at measuring the predictive power of the independent variable and comparing the predictive power among a set of independent variables. As it pertains to explanation, the researcher can use the data resulting from the analysis to objectively interpret the relationships indicated by the results. The sample size of this type of research should also be carefully considered; samples of less than 30 observations may not be appropriate for multiple regression analysis and samples of more than 1,000 observations may deliver overly sensitive results. The data set for this research is solidly within these constraints, as it contains 365 data points – one for each day of the year.

An advanced form of regression analysis, multiple linear regression analysis utilizes predictor variables together in a regression equation to predict bounce rates and analyze the effects of a range of variables on a dependent variable instead of using just a single variable (Jackson, 2012; Wienclaw, 2019). The strength of the relationship between independent and dependent variables is represented as R, and the proportion of variance, or effect size, in the dependent variable is represented as R^2 (George & Mallery, 2016). Multiple regression analysis in SPSS produces a number of results for consideration: an analysis of variance (ANOVA) table, which summarizes the sources and amount of variation among the independent variables; a coefficients table, which shows coefficients of predicted values, sampling errors, and regression coefficients and z scores for independent variables; and an excluded variables table, which indicates the variables that were not included in each step of the analysis. For this study, a confidence interval of 0.05 will be used, along with Cronbach's alpha to determine internal consistency (George & Mallery, 2016).

By using a collection of variables that are potentially bounce rate predictors – in this case the key performance indicators – the multiple regression analysis will indicate statistically significant relationships between the independent variables and predictors (Weisberg, 2014). Limiting the selection of variables to a few key data points is important for maintaining the precision of the statistical analysis. This type of analysis is centered on understanding which predictor variables are active in the bounce rate and which are inactive. Because the variables in this study are related to one another, essentially all different facets of the aggregate daily user sessions, there may be some challenges in fully distinguishing between the active and inactive variables, and should be acknowledged as a limitation of this research.

The data in this study will be analyzed using multiple linear regression analysis ANOVA methods using SPSS with a Pearson correlation, an alpha level of 0.05 to determine significance, and an N=365. Cronbach's alpha will be used for data to indicate the internal consistency of data

Time Series

This particular study is well-suited for time series due to the following reasons: the research will examine two distinct sets of data over the same time period which are being compared to one another; the research will examine causal relationships; and time series is being used in supplement to another research method (*The SAGE Handbook of Applied Social Research Methods*, 2009). Time series will be used to compare the causal effects of organic versus paid website traffic as two separate data sets. Time series is a quasi-experimental method; as such, it is appropriate to be used in supplement to the multiple linear regression analysis and will not stand alone as an analytical method. One of the typical limitations of time series is that some control groups may be biased over another. That limitation is not as great of a concern in this study because nearly all website users are anonymously represented in the data by aggregate, regardless of potential bias.

The effects indicated by time series methods are dependent, on some levels, on the interventions controlled by the researcher (Gottman et al., 1969). In this case, the interventions would be advertisement delivery and frequency and the outcomes would be general increases in website traffic and improved KPI markers. The advertising data (intervention) will be overlaid with the corresponding website performance data (outcome) in order to indicate how and where the interventions were influential over the course of the entire year. In cases where regular fluctuations in website traffic are evident, the polynomial trend line will be added in order to accommodate for this pattern (Walkenbach, 2007).

Not only will the time series method allow for comparison of the two data sets, it will also illustrate how each individual data set changes over the course of the year (Kratochwill & Levin, 2010). Changes in search traffic may indicate organic popularity at certain times of the year, depending on internal and/or external events such as athletic or public relations events. Changes in paid website traffic may indicate periods of time when advertising is more or less effective, such as during a snow storm or when cultural events are taking place. Time series methods will help to indicate these changes in website traffic and provide clues regarding how may be explained.

Data from Google Analytics represents website traffic over a period of time; in order to understand the progression of data, the time series method will be used. Time series quantifies the dependence of data over evenly spaced periods of time (Box et al., 2016). There are five general applications for time series: 1) forecasting future values, 2) transfer function that illustrates the effect of output given a series of inputs, 3) assessing the effects of various events on the outcomes of a time series, 4) examining the ways variable interrelate with one another over time, and 5) controlling outcomes by adjusting inputs on a given system. The focus of this study will be on the analysis of time series data to examine the ways the multiple variables interrelate with one another over the time represented in data set for the purposes of understanding how they will interact with one another in future scenarios. Using multivariate time series will help to answer some questions about the dynamic relationships among variables and better understand how one variable influences the others within a window of time (Lütkepohl, 2013).

This method was used to analyze the effectiveness of website traffic segmented by traffic source and improve website strategies (Plaza, 2009). Using static data from Google Analytics, a data set of more than 4,700 data points from 730 days was analyzed using stationary time series (ARMA) to test the number of page views for new users versus returning users and the traffic sources that result in return visits more frequently. The experiment results indicated that return visitors viewed more pages and stayed on the website longer than new visitors. Visitors who typed in the web address proved most effective, followed by search engine traffic and in last place, links from other sites.

Time series regression analysis was utilized in a study of an artist website in Iran (Omidvar et al., 2011). A large set of Google Analytics data was used to analyze fifteen independent variables against fifteen dependent variables. The study found that direct acquisition was a primary source of website traffic and viewed approximately 3 more pages per visit than users who came to the website from a referral source. As a result of this, returning visitors had more of an effect on page views than did new visitors. The authors found the time series methodology useful for understanding relationships between variables and identified opportunities for further research using this method.

Time series was also used in a study of social media influence on website traffic over a 212-day span at a university in the American southwest (Wilcox & Kyungok, 2012). Website pageviews and website visitors were used as the dependent variables, while the predictor variables used were social media reach, frequency, and engagement. Wilcox and Kyungok found that reach, frequency, and engagement were significantly related to the website traffic pageviews and visitors. One notable finding was the negative relationship between Twitter replies to pageviews and Facebook friends to website visitors.

Research Shortcomings and Opportunities

Data used in this research represents only one year of website data and is subject to the regular fluctuations in yearly traffic. An expanded set of data that incorporates additional years may be used to accommodate for regular fluctuations in website traffic. This level of research would require a greater level of control over the website infrastructure, advertising campaigns, landing pages, and other variables that are necessary for a consistent data set. This data set also represents only one university, so additional data sets from other universities could be used for future and replicated research.

User experience is not factored into this study, but is an important aspect of overall website usage. Users who do not find the information they seek will often bounce off the website back to search results or another website. Additional tracking tools like screen recordings, scrollmaps, heatmaps, and clickmaps, can provide this additional insight into the user experience in ways that raw data or statistical analysis cannot provide. Further research using these methods would add a layer of complexity and understanding that are necessary for a more complete understanding of website and advertising efficacy.

This research methodology does not capture all potential interactions for a website user. While the KPIs analyzed in this study will provide some insight into the end result for aggregate users, some users may be seeking information not indicated in the recorded Google Analytics data. Users may be in search of a phone number or social media account link, for example, which would not be recorded in the data. Or a user may find information they did not originally intend to find, which results in a bounce instead of page interaction. Establishing more strict controls on the campaigns, goals, and interactions of users would make for a stronger study, even if not entirely a true representation of the advertising and website strategies a college might employ.

Summary

Data from Google Analytics will be selected and segmented according to website traffic source. Each data set will be analyzed first using descriptive statistics in order to provide contextual information about the data. A multiple linear regression analysis in SPSS will be model the relationships that exist among the data points in the set and will identify statistically significant or non-significant relationships among data points using a CI of 0.05. Cronbach alpha will be used to measure the internal consistency of the data.

Time series methodology will be used to analyze data relative to regular periods of time and provide results that explain activities over that period of time. Time series will examine the performance of the website over time as it relates to the KPIs and website traffic sources. The relationships between these data points help to inform about strategies that may be used to improve money spent on advertising campaigns, organic social media efforts, and increase website effectiveness and efficiency. Using data from the course of an entire year of time assists with understanding website traffic on a macro level and providing a perspective in ways that cannot be achieved when analyzing smaller data sets or shorter periods of time.

The research conducted will provide strategic and valuable information to higher education administrators, marketing professionals, and website managers regarding the efficacy and performance of websites related to paid advertising campaigns and organic website traffic. The results indicated in this research will guide the practices of advertising and marketing to prospective students, the management of college websites, and institutional priorities related to the website and advertising platforms.

Chapter IV – Analysis

Raw data produced from Google Analytics exports were classified into two primary traffic categories: paid and organic. Once the traffic sources were categorized, any traffic that did not qualify as either organic or paid traffic or that did not have accompanying advertising data was filtered out of the data used in analysis. Filtering out this data allowed the researcher to maintain strict control over the classification of data sets and ensure data included in the analysis was, in fact, qualified as one of the two primary traffic sources. Data removed for these analyses represented traffic from 5,375 users over 5,534 sessions. Observations used in the analyses are representative of 518,104 organic users over 576,103 sessions and 22,313 paid users over 24,132 sessions. Excel pivot tables provided a display of data according to each category. The variables *Users, New Users, and Sessions* were each tabulated as a daily sum, while variables *bounce rate, session duration, pages per session, and time on page* were tabulated as a daily average in order to maintain the integrity and proper representation of each variable.

Descriptive Statistics

Descriptive statistics provided a general context for understanding the data to be analyzed. The resulting data set contained N=365 for organic website traffic and N=365 for paid website traffic. Paid website traffic was not available for all dates of the observation period, so blank or zero data was recorded for dates without paid website traffic. This was necessary in order to keep the time series dates order in sync with organic traffic; the subset of days that did not have traffic data was 38 of the 365 days.

Organic users (M=1419.46, SD 494.629) and paid users (M=61.13, SD=104.186); organic new users (M = 953.53, SD = 316.222) and paid new users (M = 52.98, SD =

92.814); organic sessions (M = 1578.36, SD = 556.272) and paid sessions (M = 66.12, SD = 113.999); organic bounce rate (M = 32.444, SD = 14.453) and paid bounce rate (M = 65.014, SD 35.362); organic session duration (M = 115.027, SD = 27.302) and paid session duration (M = 26.611, SD = 90.854); organic pages per session (M = 2.427, SD = .738) and paid pages per session (M = 1.206, SD = .681); organic time on page (M = 73.757, SD = 26.741) and paid time on page (M = 62.866, SD = 105.651). Ad impressions (M = 7120.170, SD = 9257.444) is included in linear regression analysis.

Figure 8

Descriptive Statistics Table

Descriptive Statistics

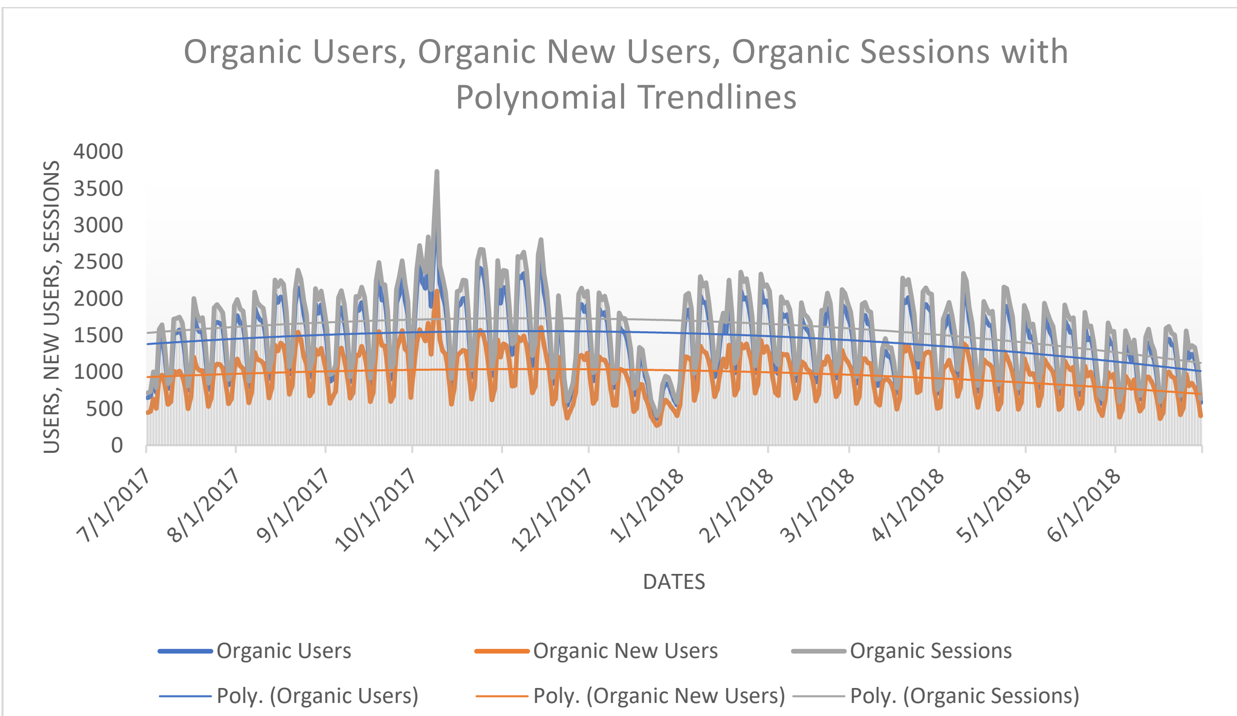
	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Organic Users	365	2915	363	3278	1419.46	494.629	244658.145
Organic New Users	365	1835	268	2103	953.53	316.222	99996.212
Organic Sessions	365	3331	404	3735	1578.36	556.272	309439.067
Organic Bounce Rate	365	50.797%	3.237%	54.034%	32.44443%	14.453139%	208.893
Organic Session Duration	365	189.512	59.202	248.715	115.02684	27.301973	745.398
Organic Pages/Session	365	3.230	1.433	4.663	2.42742	.737509	.544
Organic Time on Page	365	138.549	20.642	159.192	73.75665	26.740651	715.062
Paid Users	365	557	0	557	61.13	104.186	10854.680
Paid New Users	365	541	0	541	52.98	92.814	8614.401
Paid Sessions	365	594	0	594	66.12	113.999	12995.685
Paid Bounce Rate	365	100.000%	0.000%	100.000%	65.01373%	35.362005%	1250.471
Paid Session Duration	365	1255.000	.000	1255.000	26.61145	90.854105	8254.468
Paid Pages/Session	365	5.500	.000	5.500	1.20571	.681026	.464
Paid Time on Page	365	673.000	.000	673.000	62.86597	105.650612	11162.052
Ad Impressions	365	46063.000	.000	46063.000	7120.16986	9257.44414	85700272.0
Valid N (listwise)	365						

Time Series

Data was segmented by classification in Microsoft Excel and used to produce time series line graphs that indicate the daily sequence of the data and illustrate patterns or trends. Variables have been grouped together to show how specific variables are similar in scale, but distinct. Polynomial trendlines have been added to illustrate the general trends of the variables. Figure 9 shows the scale and volume of organic website traffic, which peaked mid-observation and decreased over the remainder of the fiscal year. Generally, weekends are the regular dips throughout the plot of the data. More sizable drops occur around the holidays of Thanksgiving and Christmas through the New Year. A second-degree polynomial trend line is used to illustrate the trend of regular weekday/weekend fluctuations in traffic during the fiscal year (Walkenbach, 2007).

Figure 9

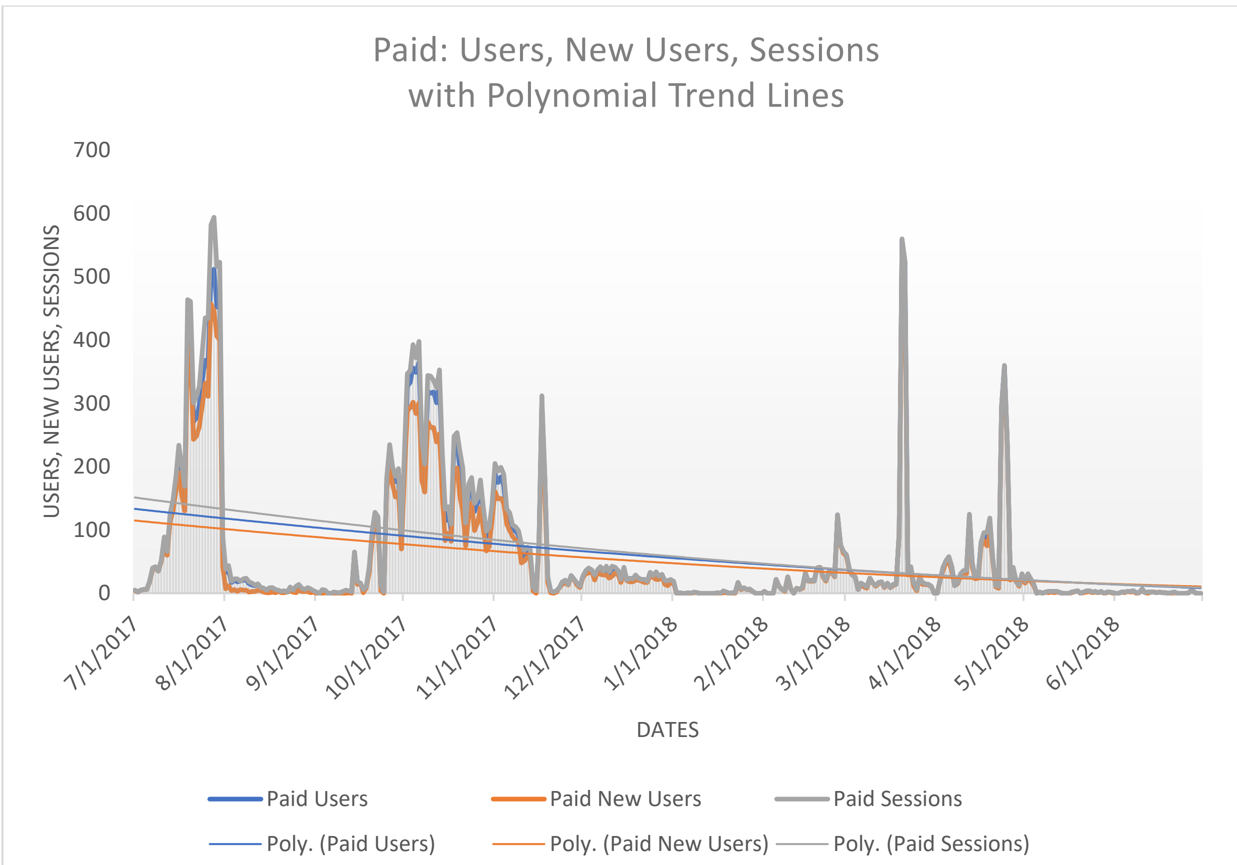
Organic: Users, New Users, Sessions with Polynomial trendline



Paid website traffic is more irregular with seasonalities and trends, though the traffic trends more downward. Interventions shown in Figures 15, 16, and 17 illustrate the ability for advertisement impressions to directly influence the website traffic volume. Spikes in traffic early in the recruitment cycle, leading up to the holidays, and from late March through early May follow with recruitment emphases throughout the year.

Figure 10

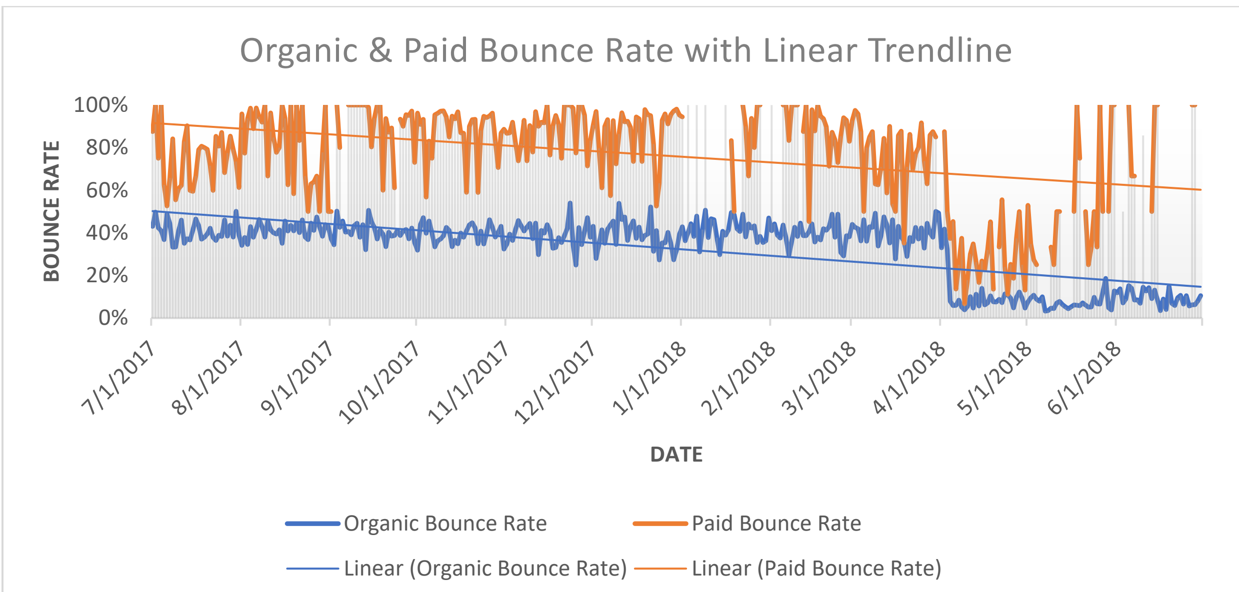
Paid: Users, New Users, Sessions



Shown in Figure 11 is the bounce rate recorded for both paid and organic website traffic. Paid website traffic almost always bounces at a higher rate than organic website traffic, but a considerable drop in bounce rate for all traffic occurs in early April 2018, coinciding with updates in the information architecture and navigational structure of the admissions website. The updates served to lower the bounce rate for both paid and organic website traffic.

Figure 11

Organic Bounce Rate and Paid Bounce Rate with linear trend lines

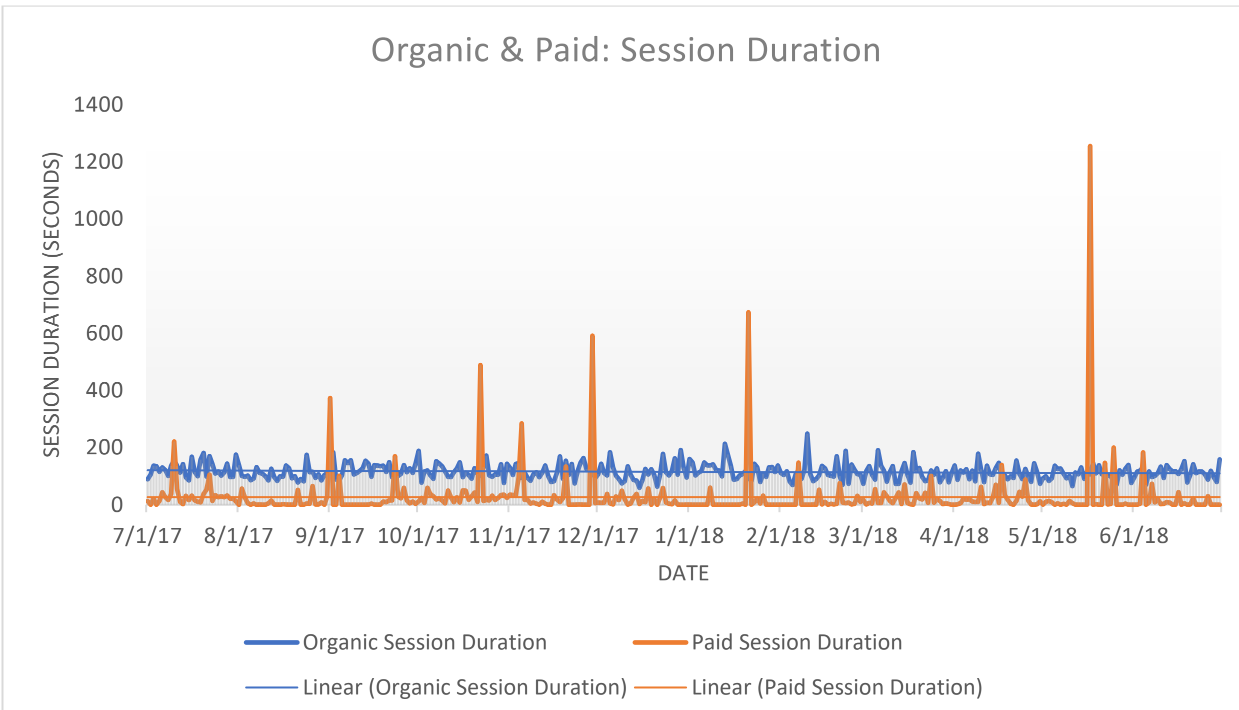


Note. Periods without paid traffic are shown as blank areas in the chart.

Session duration for both paid and organic users is indicated in Figure 12. Aside from the anomalous spikes in paid session duration, organic users generally spend more time on the website in a session than paid website users. The trendline for both paid and organic traffic shows a relative flatline trend from the beginning of observations to the end of observations.

Figure 12

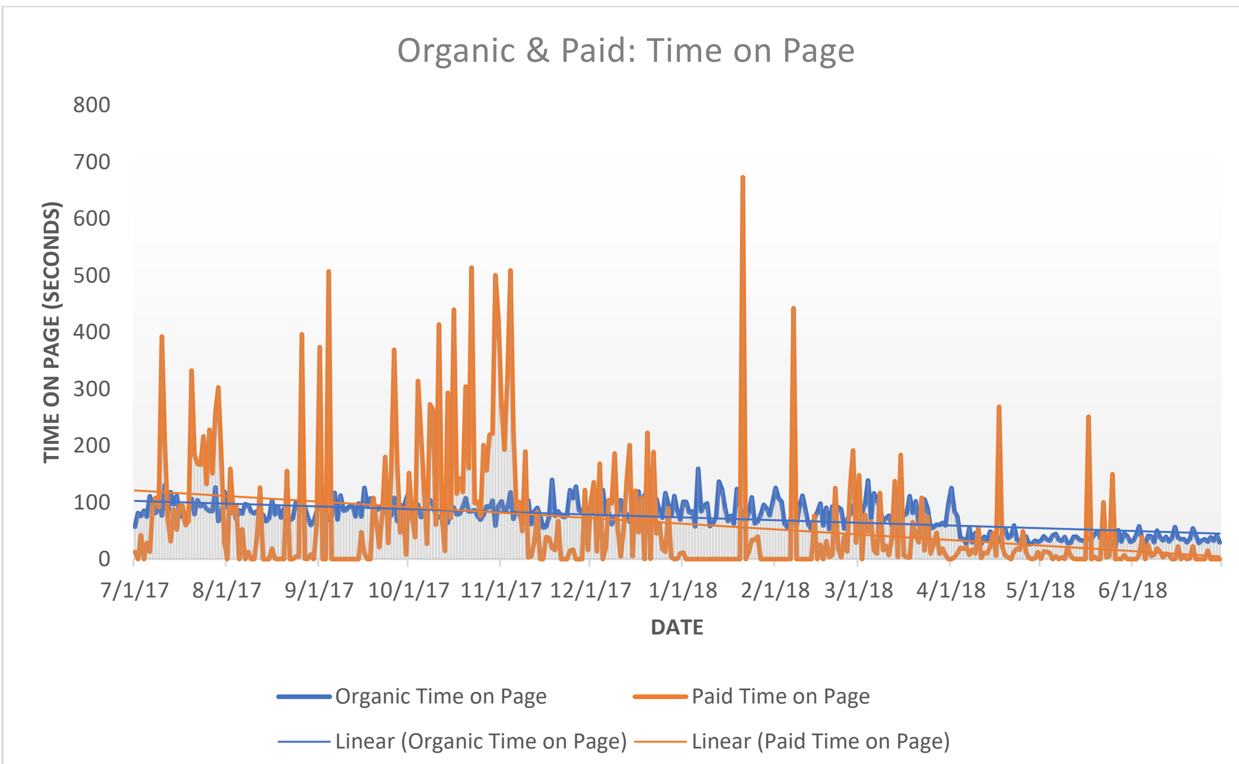
Organic & Paid: Session Duration with linear trend lines



Observations about time on the page indicates that paid traffic resulted in a slightly longer amount of time spent browsing an individual page early in the observation period, as shown in Figure 13. This trend decreased below the organic time spent on the page by November, however. Organic time on page decreased slightly over the duration of the observations, but the linear trend line was above the paid time on page from November through the end of June.

Figure 13

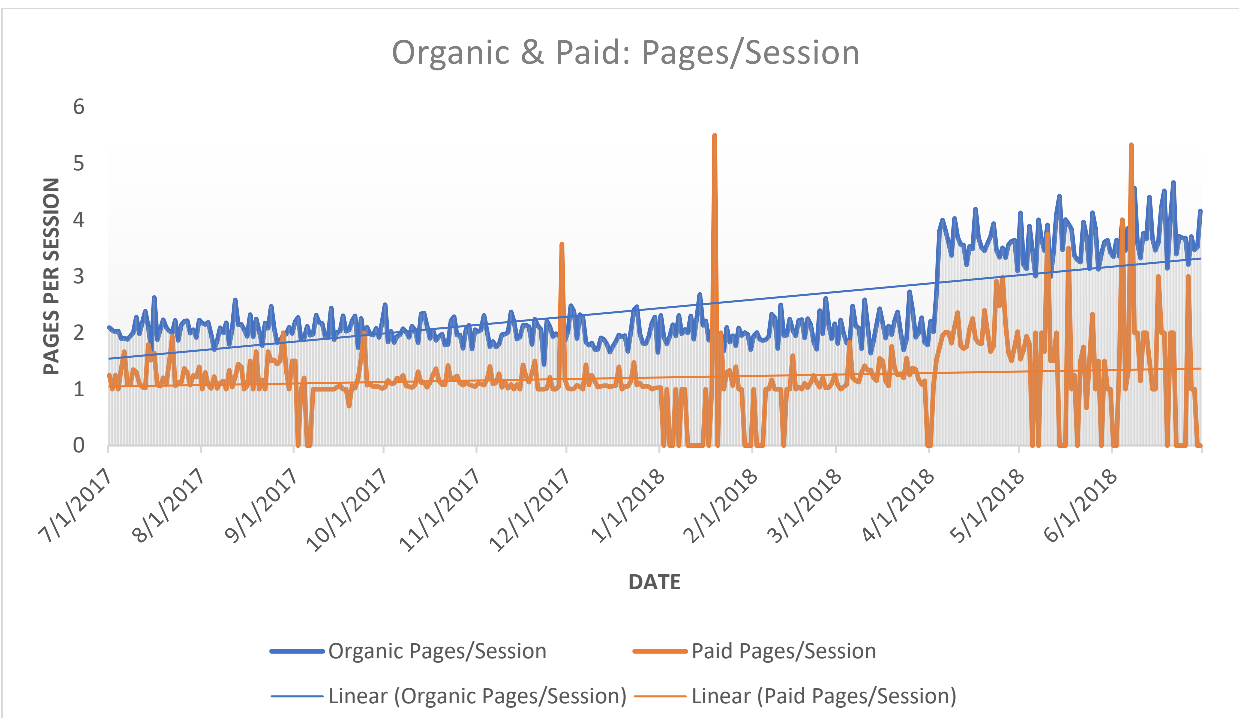
Time on Page with linear trend lines



Pages per session observations showed relatively steady numbers from July 2017 through April 2018, shown in Figure 14. Both paid and organic pages per session increased visibly from the beginning of April through the end of the observations. Again, this notable change in traffic behavior coincides with navigational architecture changes on the website that were intended to improve the user experience. The general trend for both paid and organic traffic over the observation period is an increase from the beginning of the period to the end of the period, though organic traffic saw a greater increase in pages viewed per session than did paid traffic.

Figure 14

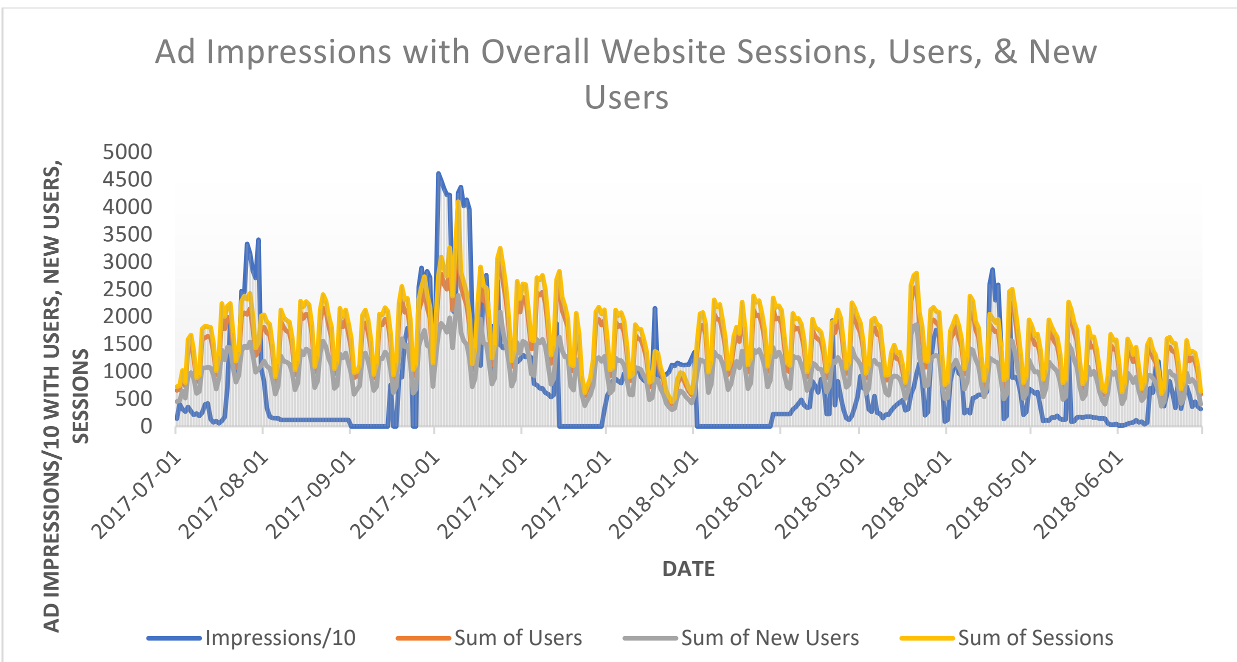
Organic & Paid: Pages per Session with linear trend lines



The purpose of advertising impressions in this study is to drive traffic to the website so the user may learn more and/or take an action. Advertising impression numbers are overlaid with data about website sessions, new users, and users to illustrate the ways advertising can influence website traffic in Figure 15, which shows advertising traffic at a factor of 10. The most notable point of advertising data coinciding with an increase in sessions, users, and new users can be seen in early October when the data points are at their highest points in the graph. A similar point of coinciding traffic increase with ad impressions increase is in late July; this point is more visible in Figure 16.

Figure 15

Ad Impressions/10 with Overall Website Sessions, Users, & New Users

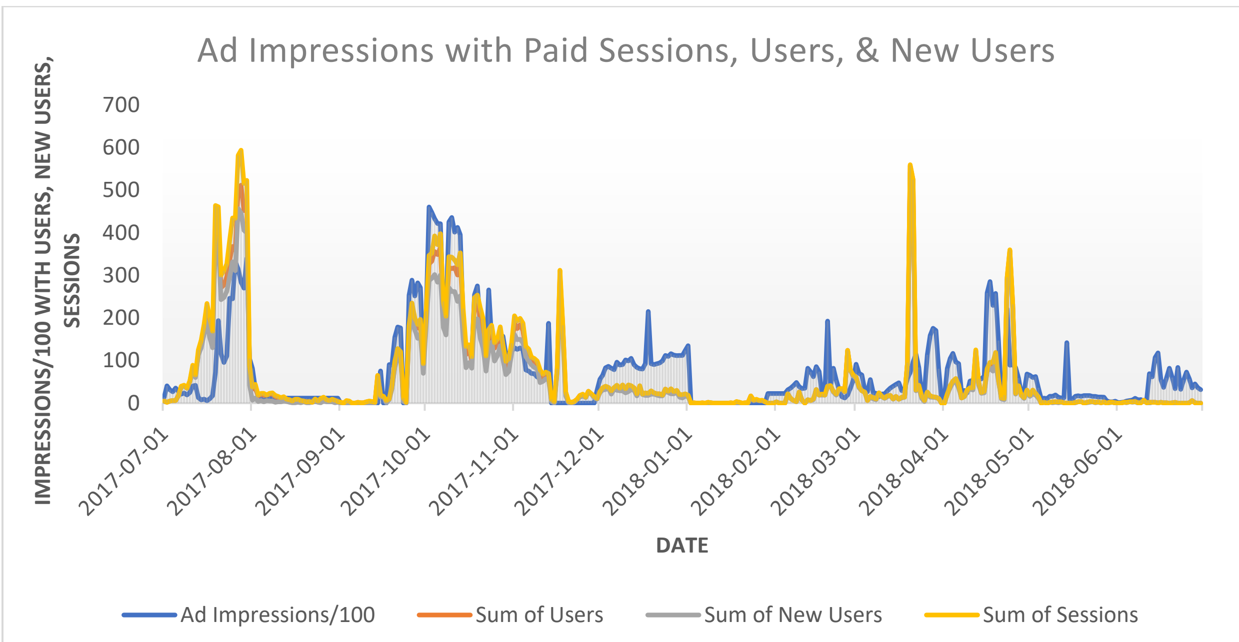


Note. Ad impressions are shown as a factor of 10 in this graph to coincide with the scale of the overall website data

The influence of advertising impressions on paid website traffic during the observation period can be seen in Figure 16, which shows advertising traffic at a scale of 1:100. The paid website traffic generally mirrors that of the advertising impressions, which can be seen at most points in the graph, with the exception of December 2017-January 2018, when overall website traffic was down and in late March 2018 through the end of observations when sessions tended to outpace that of ad impressions.

Figure 16

Ad Impressions/100 with Paid Sessions, Users, & New Users



Note. *Ad impressions are scaled 1:100 to coincide with the scale of the paid website data*

Multiple Linear Regression: Organic Traffic

A multiple linear regression was used to examine the influence of organic website traffic on the organic bounce rate. Figure 17 shows the variables entered/removed table for this analysis, which ran with two models – one for organic pages/session and one for organic session duration.

Figure 17

SPSS variables entered/removed table; organic traffic/bounce rate dependent.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Organic Pages/Session	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Organic Session Duration	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: Organic Bounce Rate

In model 1, a significant regression equation was found ($F(1,363) = 2405.451$, $p < .001$), with an adjusted R^2 of .869. The predicted organic bounce rate is equal to 76.687 - 18.2867 (organic pages/session). Organic bounce rate decreased 18.267 percent for each page visited. Organic pages/session ($p < .001$) was a significant predictor of bounce rate. Figure 18 shows the coefficients table output from SPSS for this analysis.

In model 2, a significant regression equation was found ($F(2,362) = 1236.763$, $p < .001$), with an adjusted R^2 of .872. The predicted organic bounce rate is equal to 73.374 – 18.339 (organic pages/session) + .031 (organic session duration). Organic bounce rate decreased 18.339 percent for each page visited and for each additional .031 second the user remained on the website. Both organic pages/session ($p < .001$) and organic session duration ($p = .002$) were significant predictors or organic bounce rate. Figure 18 shows the coefficients table output from SPSS for this analysis.

Figure 18

SPSS coefficients table for organic traffic/bounce rate dependent.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	76.787	.945		81.272	.000	74.929	78.645
	Organic Pages/Session	-18.267	.372	-.932	-49.045	.000	-19.000	-17.535
2	(Constant)	73.374	1.435		51.118	.000	70.552	76.197
	Organic Pages/Session	-18.339	.369	-.936	-49.735	.000	-19.064	-17.614
	Organic Session Duration	.031	.010	.059	3.130	.002	.012	.051

a. Dependent Variable: Organic Bounce Rate

Figure 19 shows the linear regression analysis of variance table and model summary, including the amount of variance in the organic bounce rate that can be explained by the variables in model 1 and model 2. The adjusted R^2 of 86.9% in model 1 and 87.2% in model 2 indicate a particularly high percentage of total variance of organic bounce rate explained by organic pages per session.

Figure 19

SPSS Analysis of variance table and model summary for organic traffic/bounce rate dependent.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	66067.127	1	66067.127	2405.451	.000[b]
	Residual	9970.008	363	27.466		
	Total	76037.135	364			
2	Regression	66329.785	2	33164.893	1236.763	.000[c]
	Residual	9707.350	362	26.816		
	Total	76037.135	364			

a. Dependent Variable: Organic Bounce Rate

b. Predictors: (Constant), Organic Pages/Session

c. Predictors: (Constant), Organic Pages/Session, Organic Session Duration

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.932[a]	.869	.869	5.24076%
2	.934[b]	.872	.872	5.17841%

a. Predictors: (Constant), Organic Pages/Session

b. Predictors: (Constant), Organic Pages/Session, Organic Session Duration

The correlations table in Figure 20 provides a data regarding the relationships between each variable in the analysis. Organic users shows correlation with organic new users ($p < .001$, $R = .995$), organic sessions ($p < .001$, $R = 1.000$), organic bounce rate ($p < .001$, $R = .221$), and organic pages/session ($p < .001$, $R = -.213$). Organic users does not show correlation with organic session duration ($p = .343$, $R = -.050$) and organic time on page ($p = .136$, $R = .078$).

Organic new users shows correlation with organic sessions ($p < .001$, $R = .994$), organic bounce rate ($p < .001$, $R = .218$), and organic pages/session ($p < .001$, $R = -.208$). Organic new users does not show correlation with organic session duration ($p = .382$, $R = -.046$) and organic time on page ($p = .161$, $R = .074$). Organic sessions has a correlation with organic bounce rate ($p < .001$, $R = .220$) and organic pages/session ($p < .001$, $R = -.212$). Organic sessions does not have a correlation with organic session duration ($p = .355$, $R = -.049$) and organic time on page ($p = .133$, $R = .079$).

Organic bounce rate has a correlation with organic pages/session ($p < .001$, $R = -.932$) and organic time on page ($p < .001$, $R = .714$), but not with organic session duration ($p = .985$, $R = .001$). Organic session duration has a correlation with organic time on page ($p < .001$, $R = .439$), but not with organic pages/session ($p = .238$, $R = .062$). Organic pages/session has a correlation with organic time on page ($p < .001$, $R = -.729$).

Figure 20

SPSS Pearson Correlations table for organic traffic/bounce rate dependent

Correlations

		Organic Users	Organic New Users	Organic Sessions	Organic Bounce Rate	Organic Session Duration	Organic Pages/Session	Organic Time on Page
Organic Users	Pearson Correlation	1	.995**	1.000**	.221**	-.050	-.213**	.078
	Sig. (2-tailed)		.000	.000	.000	.343	.000	.136
	N	365	365	365	365	365	365	365
Organic New Users	Pearson Correlation	.995**	1	.994**	.218**	-.046	-.208**	.074
	Sig. (2-tailed)	.000		.000	.000	.382	.000	.161
	N	365	365	365	365	365	365	365
Organic Sessions	Pearson Correlation	1.000**	.994**	1	.220**	-.049	-.212**	.079
	Sig. (2-tailed)	.000	.000		.000	.355	.000	.133
	N	365	365	365	365	365	365	365
Organic Bounce Rate	Pearson Correlation	.221**	.218**	.220**	1	.001	-.932**	.714**
	Sig. (2-tailed)	.000	.000	.000		.985	.000	.000
	N	365	365	365	365	365	365	365
Organic Session Duration	Pearson Correlation	-.050	-.046	-.049	.001	1	.062	.439**
	Sig. (2-tailed)	.343	.382	.355	.985		.238	.000
	N	365	365	365	365	365	365	365
Organic Pages/Session	Pearson Correlation	-.213**	-.208**	-.212**	-.932**	.062	1	-.729**
	Sig. (2-tailed)	.000	.000	.000	.000	.238		.000
	N	365	365	365	365	365	365	365
Organic Time on Page	Pearson Correlation	.078	.074	.079	.714**	.439**	-.729**	1
	Sig. (2-tailed)	.136	.161	.133	.000	.000	.000	
	N	365	365	365	365	365	365	365

**. Correlation is significant at the 0.01 level (2-tailed).

Multiple Linear Regression: Paid Traffic

A linear regression analysis using the stepwise method was also used to examine the influence of paid website traffic on the dependent variable paid bounce rate. Figure 21 shows the variables entered/removed table for this analysis, which ran with four models – one with paid sessions entered, one with paid new users entered, one with paid users entered, and one with paid sessions removed.

Figure 21

SPSS variables entered/removed table; paid traffic/bounce rate dependent.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Paid Sessions	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Paid New Users	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Paid Users	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	.	Paid Sessions	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: Paid Bounce Rate

All four models in this analysis are statistically significant.

In model 1, a significant regression equation was found ($F(1,363) = 17.173$, $p < .001$), with an adjusted R^2 of .043. The predicted paid bounce rate is equal to 60.655 + .066 (paid sessions). Paid bounce rate increased .066 percent for each paid session. Paid sessions ($p < .001$) was a significant predictor of paid bounce rate. Figure 22 shows the coefficients table output from SPSS for this analysis.

In model 2, a significant regression equation was found ($F(2,362) = 11.988$, $p < .001$), with an adjusted R^2 of .057. The predicted paid bounce rate is equal to 60.437 - .438 (paid new users) + .420 (paid sessions). Paid bounce rate decreased .438 for each paid new user and increased .420 for each paid session. Both paid sessions ($p = .003$) and paid new users ($p = .011$) were significant predictors of paid bounce rate. Figure 22 shows the coefficients table output from SPSS for this analysis.

In model 3, a significant regression equation was found ($F(3, 361) = 9.966$, $p < .001$), with an adjusted R^2 of .069. The predicted paid bounce rate is equal to 59.435 + .984 (paid users) - .844 (paid new users) - .149 (paid sessions). Paid bounce rate increased .984 for each paid user, decreased .844 for each paid new user, and decreased .149 for each paid session. Paid users ($p = .001$) and paid new users ($p = .018$) were both significant predictors of paid bounce rate, but paid sessions ($p = .590$) was not a significant predictor of bounce rate. Figure 22 shows the coefficients table output from SPSS for this analysis.

In model 4, a significant regression equation was found ($F(2, 362) = 14.833$, $p < .001$), with an adjusted R^2 of .071. The predicted bounce rate is equal to 59.578 + .790 (paid users) - .809 (paid new users). Paid bounce rate increased .790 for each paid user and decreased .809 for each paid new user. Paid users ($p < .001$) and paid new users ($p = .001$) were both significant predictors of paid bounce rate. Figure 22 shows the coefficients table output from SPSS for this analysis.

Figure 22

SPSS coefficients table for paid traffic/paid bounce rate dependent.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	60.655	2.094		28.960	.000	56.536	64.774
	Paid Sessions	.066	.016	.213	4.144	.000	.035	.097
2	(Constant)	60.437	2.080		29.051	.000	56.346	64.528
	Paid Sessions	.420	.139	1.354	3.014	.003	.146	.694
	Paid New Users	-.438	.171	-1.149	-2.558	.011	-.774	-.101
3	(Constant)	59.435	2.110		28.169	.000	55.286	63.585
	Paid Sessions	-.149	.277	-.482	-.539	.590	-.695	.396
	Paid New Users	-.844	.241	-2.215	-3.495	.001	-1.319	-.369
	Paid Users	.984	.415	2.900	2.370	.018	.167	1.801
4	(Constant)	59.578	2.091		28.491	.000	55.466	63.691
	Paid New Users	-.809	.233	-2.124	-3.480	.001	-1.267	-.352
	Paid Users	.790	.207	2.329	3.815	.000	.383	1.198

a. Dependent Variable: Paid Bounce Rate

Figure 23 shows the linear regression analysis of variance table and model summary, including the amount of variance in the organic bounce rate that can be explained by the variables in model 1, model 2, model 3, and model 4.

Figure 23

SPSS Analysis of variance table and model summary for paid traffic/bounce rate dependent.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20560.626	1	20560.626	17.173	.000[b]
	Residual	434610.953	363	1197.275		
	Total	455171.580	364			
2	Regression	28274.228	2	14137.114	11.988	.000[c]
	Residual	426897.352	362	1179.274		
	Total	455171.580	364			
3	Regression	34813.498	3	11604.499	9.966	.000[d]
	Residual	420358.082	361	1164.427		
	Total	455171.580	364			
4	Regression	34475.717	2	17237.859	14.833	.000[e]
	Residual	420695.862	362	1162.143		
	Total	455171.580	364			

a. Dependent Variable: Paid Bounce Rate

b. Predictors: (Constant), Paid Sessions

c. Predictors: (Constant), Paid Sessions, Paid New Users

d. Predictors: (Constant), Paid Sessions, Paid New Users, Paid Users

e. Predictors: (Constant), Paid New Users, Paid Users

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.213[a]	.045	.043	34.601667%	.045	17.173	1	363	.000
2	.249[b]	.062	.057	34.340566%	.017	6.541	1	362	.011
3	.277[c]	.076	.069	34.123699%	.014	5.616	1	361	.018
4	.275[d]	.076	.071	34.090222%	-.001	.290	1	361	.590

a. Predictors: (Constant), Paid Sessions

b. Predictors: (Constant), Paid Sessions, Paid New Users

c. Predictors: (Constant), Paid Sessions, Paid New Users, Paid Users

d. Predictors: (Constant), Paid New Users, Paid Users

The Pearson Correlation Table for paid website traffic is shown in Figure 24. Paid users shows correlation with paid new users ($p < .001$, $R = .997$), Paid sessions ($p < .001$, $R = .998$), paid bounce rate ($p < .001$, $R = .212$), and paid time on page ($p < .001$, $R = .410$). Paid users does not show correlation with Paid session duration ($p = .702$, $R = 0.20$) or paid pages/session ($p = .177$, $R = .071$). Paid new users shows correlation with paid sessions ($p < .001$, $R = .994$), paid bounce rate ($p < .001$, $R = .196$), and paid time on page ($p < .001$, $R = .393$). Paid new users does not show correlation with paid session duration ($p = .721$, $R = .019$) or paid pages/session ($p = .140$, $R = .077$).

Paid sessions shows correlation with paid bounce rate ($p < .001$, $R = .213$) and paid time on page ($p < .001$, $R = .418$), but is not significantly correlated with paid session duration ($p = .696$, $R = .021$) or paid pages/session ($p = .213$, $R = .065$). Paid bounce rate shows a correlation with paid time on page ($p = .002$, $R = .165$), but it is not significantly correlated with paid session duration ($p = .165$, $R = -.073$) or paid pages/session ($p = .980$, $R = .001$). Paid session duration shows a correlation with paid pages/session ($p < .001$, $R = .333$) and paid time on page ($p < .001$, $R = .464$). Paid pages/session is not significantly correlated with paid time on page ($p = .109$, $R = 0.84$).

Figure 24

Paid Website Traffic Pearson Correlation Table

Correlations

		Paid Bounce Rate	Paid Users	Paid New Users	Paid Sessions	Paid Session Duration	Paid Pages/Session	Paid Time on Page
Pearson Correlation	Paid Bounce Rate	1.000	.212	.196	.213	-.073	.001	.165
	Paid Users	.212	1.000	.997	.998	.020	.071	.410
	Paid New Users	.196	.997	1.000	.994	.019	.077	.393
	Paid Sessions	.213	.998	.994	1.000	.021	.065	.418
	Paid Session Duration	-.073	.020	.019	.021	1.000	.333	.464
	Paid Pages/Session	.001	.071	.077	.065	.333	1.000	.084
	Paid Time on Page	.165	.410	.393	.418	.464	.084	1.000
Sig. (1-tailed)	Paid Bounce Rate	.	.000	.000	.000	.082	.490	.001
	Paid Users	.000	.	.000	.000	.351	.089	.000
	Paid New Users	.000	.000	.	.000	.360	.070	.000
	Paid Sessions	.000	.000	.000	.	.348	.107	.000
	Paid Session Duration	.082	.351	.360	.348	.	.000	.000
	Paid Pages/Session	.490	.089	.070	.107	.000	.	.055
	Paid Time on Page	.001	.000	.000	.000	.000	.055	.
N	Paid Bounce Rate	365	365	365	365	365	365	365
	Paid Users	365	365	365	365	365	365	365
	Paid New Users	365	365	365	365	365	365	365
	Paid Sessions	365	365	365	365	365	365	365
	Paid Session Duration	365	365	365	365	365	365	365
	Paid Pages/Session	365	365	365	365	365	365	365
	Paid Time on Page	365	365	365	365	365	365	365

Chapter V – Summary, Implications, Conclusions

Summary of Analysis

Each data set was segmented according to traffic source and analyzed using three methods. The analysis methods employed in this study address different aspects of the data: on a broad scale, the data is time-oriented and subject to patterns and trends, but the data points measure the aggregate behavior of individual users on the website and are subject to be influenced by a number of factors both internal and external to the website. Descriptive statistics provided information about each data set and established a general context for the time series and linear regression analyses. Time series ordered the data points on a chronological timeline to illustrate patterns, trends, and seasonality of the data for each segment. A polynomial trend line was added for the data points related to users, new users, and sessions due to the regular fluctuation of data from week to weekend and holidays (Walkenbach, 2007). Linear trend lines were added to each of the other data sets to indicate the general trend from the beginning of the observation window to the end. Multiple linear regression analysis was used with paid and organic data sets to analyze how each of the data points were influential on the bounce rate variable.

Descriptive Statistics Summary

The organic and paid data sets varied greatly in number and scale, particularly in the number of users, new users, and sessions. This was not unexpected because organic website traffic sources have historically been the primary source of website traffic for the university website. Paid website traffic tends to be much smaller in number, but more focused on accomplishing specific tasks; users do not browse the site in search of information. Organic website traffic had an N=365 that represented 518,104 organic users during 576,103 sessions. Paid website traffic included N=365 that represented 22,313 users over 24,132 sessions. Organic sessions (M = 1578.36, SD = 556.272) outnumbered paid sessions (M = 66.12, SD = 113.999) by more than 1512.24 and the standard deviation range of organic sessions was greater by a margin of 442.273. Organic users (M=1419.46, SD 494.629) had a mean higher than paid users (M=61.13, SD=104.186) by 1,358.33 and a standard deviation greater than paid users by a margin of 390.443. Organic new users (M = 953.53, SD = 316.222) comprised 67.2% of all organic users, while paid new users (M = 52.98, SD = 92.814) comprised 86.7% of all paid users, demonstrating the effectiveness of gaining new website users through paid methods.

The bounce rate measures the percentage of users that leave the site without interacting with a page, duration of sessions measures the entirety of the time spent on the page during a session, pages per session measures the number of pages a user visits during a session, and time on page measures the time that is spent on a single page; all are indicators of user engagement and efficiency of the user session. Organic bounce rate (M = 32.444, SD = 14.453) was approximately half the bounce rate of paid website traffic (M = 65.014, SD 35.362), but the standard deviation of paid website traffic was more than twice that of organic website traffic. Organic session duration (M = 115.026838, SD = 27.3019732) was nearly four and a half times as much as paid session duration (M = 26.6114472, SD = 90.8541053) but the standard deviation was not as great. Organic pages per session (M = 2.42741636, SD = .737508505) was double that of paid pages per session (M = 1.20570708, SD = .681025907). The difference between standard deviation of organic pages per session and paid pages per session was very close, at only 0.057. Organic time on page (M = 73.7566511, SD = 26.7406509) was higher than that of paid time on page (M = 62.8659719, SD = 105.650612) by a margin of 10.89 seconds, but the standard deviation of paid time on page was much greater than that of organic time on page, at a margin of 78.91 seconds.

Descriptive statistics indicate that organic users tend to be much larger in number, but paid traffic drives a higher percentage of new users to the website. Though paid traffic was smaller in number, the range indicated by standard deviation was typically greater than its organic counterpart. Organic user sessions last longer and comprise visits to a larger number of pages, but paid users tend to stay on a single page for a longer amount of time. The visit of paid users is typically more focused to a landing page, which is specific to a singular task; often users are not given an option to visit another page. Because of the design of landing pages as a single source of information to accomplish a specific task, paid users do not need to browse the site to find the information they need. Further research into user experience would provide additional qualitative data regarding visitor behaviors and provide insight regarding why organic users tend to spend more time on a site than paid users.

Time Series Summary

Plotting the data in a time series graph assists with identifying patterns or trends over a chronological timeline. Figure 9 indicated that organic users followed a regular pattern of larger numbers of users and sessions on the weekdays and smaller numbers of users and sessions during the weekends. Larger drops in website traffic can be seen around holidays, such as Thanksgiving, Christmas, and New Year's Day, as well as during the mid-March university spring break. The polynomial trendline arched slightly upward mid-year and ultimately ended slightly lower for each variable measured: organic users, organic new users, and organic sessions.

Paid traffic, as indicated in Figure 10, however, did not follow the same weekday and weekend pattern. Paid users, paid new users, and paid sessions were all irregular with very little pattern or seasonality over a chronological timeline. An overall downward polynomial trendline indicates paid website traffic decreased over the course of the fiscal year. The advertising impressions data overlaid with paid website traffic, discussed later in this section, provide more information about the external factors that drive the patterns of paid users, paid new users, and paid sessions.

Organic bounce rate averages are plotted alongside paid bounce rate averages in Figure 11; in most cases a lower bounce rate is better because it indicates the user has interacted with the web page. The time series in this study indicates paid traffic bounce rates are consistently higher than the bounce rate of organic traffic. A notable and sustained drop in bounce rate occurred in April 2018, when a number of website architecture changes were made in order to improve website performance and user experience. These changes resulted in an visual change in user behavior, dropping the bounce rate well below 20% for organic website traffic and below 60% for paid website traffic over the course of the first month. The bounce rate for paid website traffic did go back up at points mid-May 2018 through the rest of the fiscal year.

The average session duration for organic and paid website traffic is plotted in a time series in Figure 12. The session duration for organic website traffic is generally higher than the session duration for paid website traffic, though both have relatively flat trendline over the course of the fiscal year. There are spikes at various points in paid session duration during the course of the year. While these spikes may be an accurate measurement of users staying on the page for a long period of time, the Google Analytics documentation does not provide any additional information to explain spikes in session duration (*Session Duration, Avg - Analytics Help*, n.d.).

The average time on page for organic and paid website traffic is plotted in a time series in Figure 13. Organic time on page fluctuated daily, but held a relatively steady line between 40-160 seconds. Paid time on page, however, was much more irregular, fluctuating from zero to 673 seconds, commonly in the 400-500 second range. Both organic time on page and paid time on page decreased over the fiscal year, but paid time on page, which started with a trendline above organic time on page at over 100 seconds, decreased much more than organic time on page, ending the fiscal year near zero seconds. The irregularity of paid time on page was expected, but not at this amount of variation. Qualitative user experience research would help identify any usability or technology issues a user may encounter, resulting in these vast variations in average time on page. Again, the organic time on page dropped around the April 2018 mark, coinciding with the website changes that were intended to improve the user experience.

Pages per session for both organic and paid website traffic is plotted in a time series in Figure 14. Organic pages per session were consistently higher than pages per session over the duration of the fiscal year, with the exception of three spikes – on in November 2017, one in January 2018, and one in June 2018. The linear trendline illustrates that both organic and paid pages per session increased over the fiscal year. The changes implemented to improve information architecture and user experience were also evident following April 2018, as pages per session for both organic and paid traffic increased visibly.

Advertising impression data is external to the website session, but is a primary data point used in measuring the visibility of an advertisement. In all cases related to this study, the goal of an ad impression is to send traffic to the website so the user may take an action. Figure 15 shows advertising impression data overlaid with the combined website sessions, users, and new users – both paid and organic. There is an increase in paid website traffic that corresponds with an increase in advertising impressions in October 2017, but other advertising impression peaks and valleys appear to have a negligible effect on the overall website traffic.

The time series in Figure 16, however, overlays ad impression data against the paid sessions, paid users, and paid new users. Generally, the website traffic follows the pattern of ad impressions. This is a logical connection between ad impressions and paid traffic: the only source of paid traffic would be the advertisements. Despite website traffic generally following ad impressions, there are three windows of time in Figure 16 where ad impressions do not correspond closely with advertising data. The first chronological area is December 2017, a time in which the holidays would be the most logical factor. A second chronological area where ad impressions do not correspond closely with website traffic is March 21-22, 2017, a time in which paid direct email campaign was the primary driver of traffic and outperformed the ad impressions at other points of the time series; some advertising methods are simply more effective than others. This campaign was especially effective in driving paid users, paid new users, and paid sessions to the website. Finally, a third point at which ad impressions were not very effective at driving paid users, paid new users, and paid sessions to the website was in the last half of June 2018. The ad impression numbers indicated ads were visible during this time, but no visible increase in website traffic was recorded. An analysis of data from additional years would help determine if this is an isolated event or if it is a pattern of user behavior.

Linear Regression: Organic Summary

Multiple linear regression analysis of organic website traffic using SPSS and the stepwise method, with organic bounce rate as the dependent variable, ran with two models. Model 1 entered organic pages per session as the only variable and returned an adjusted R^2 of 86.9% with $p < .001$. Such a high value for adjusted R^2 indicates organic pages per session is a particularly adept predictor of organic bounce rate. Model 2 added organic session duration to the analysis and returned an adjusted R^2 at a slightly higher 87.2% with $p < .001$. By adding organic session duration into the regression model, the ability to predict organic bounce rate increases slightly by .3%. Variables excluded from the analysis in Model 1 were organic users ($p = .234$), organic new users ($p = .190$), organic sessions ($p = .246$), organic session duration ($p = .002$), and organic time on page ($p = .007$). Variables excluded from the analysis in Model 2 were organic users ($p = .186$), organic new users ($p = .152$), organic sessions ($p = .198$), and organic time on page ($p = .470$).

The correlations table provides an analysis of statistically significant relationships among all data points. The organic users variable is correlated with organic new users, organic sessions, organic bounce rate, and organic pages/session, but not with organic session duration or organic time on page. It is expected that organic users are tied to new users and sessions, but the correlations with organic bounce rate and pages/session is insightful, as it indicates possible relationships for further experimentation and exploration.

The organic new users variable is correlated with organic sessions, organic bounce rate, and organic pages/session, but not with organic session duration or organic time on page. The relationship between organic new users and organic sessions is expected, but the relationships between organic new users and organic bounce rate and organic page/session were not expected, so these variables are a possible area for future study. Organic sessions is correlated with organic bounce rate and organic pages/session, but not with organic session duration or organic time on page. The relationship between organic sessions and organic pages/session is not expected, but the relationship with organic bounce rate is somewhat unexpected.

Organic bounce rate has a correlation with organic pages/session and organic time on page, which is expected because visiting more than one page and staying on a page are two ways to avoid a bounce. The lack of a correlation between organic bounce rate and organic session duration, however, indicates that getting the user to stay on the website does not necessarily mean the user will not ultimately bounce. Organic session duration is correlated with organic time on page, which is expected because a longer session visit often means a user stays on a page for a longer amount of time. The lack of statistically significant relationship between organic session duration and organic pages/session indicates users may visit more than one page in a short amount of time. The correlation between organic pages/session and organic time on page indicates users may have a tendency to both visit multiple pages and spend a longer amount of time on a webpage.

Linear Regression: Paid Summary

Linear regression analysis of paid website traffic using the stepwise method ran in four models with paid bounce rate as the dependent variable. In model 1, paid sessions was the entered variable and returned an adjusted R^2 of 4.3% with a $p < .001$. In model 2, paid new users was entered into the analysis and returned an adjusted R^2 of 5.7% with a $p < .001$. In model 3, paid users was entered into the analysis and returned an adjusted R^2 of 6.9% with a $p < .001$. Finally, in model 4, paid sessions was removed from the analysis, leaving only paid new users and paid users and returning an adjusted R^2 of 7.1% with a $p < .001$.

In model 1, variables excluded from the analysis were: paid users ($p = .877$), paid new users ($p = .011$), paid session duration ($p = .132$), paid pages/session ($p = .807$), and paid time on page ($p = .103$). In model 2, variables excluded from the analysis were: paid users ($p = .018$), paid session duration ($p = .120$), paid pages/session ($p = .969$), and paid time on page ($p = .268$). In model 3, variables excluded from the analysis were: paid session duration ($p = .115$), paid pages/session ($p = .986$), and paid time on page ($p = .300$). In model 4, paid session duration ($p = .114$), paid pages/session ($p = .983$), paid time on page ($p = .331$), and paid sessions ($p = .590$).

The correlations table provides an analysis of statistically significant relationships among all data points in the analysis. Paid users is correlated with paid new users, paid sessions, paid bounce rate, and paid time on page, but not with paid session duration or paid pages/session. The correlation between paid users, paid new users, and paid sessions is expected because the data types are closely related, but the correlation with bounce rate and time on page are points that are notable because the data types are unrelated. Similarly, paid new users is correlated with paid users, paid sessions, paid bounce rate, and paid time on page, but not paid session duration or paid pages/session. Much like paid users and paid new users, paid sessions is correlated with paid users, paid new users, paid bounce rate, and paid time on page, but not paid session duration or paid pages/session.

Paid bounce rate is also correlated with correlated with paid users, paid new users, paid sessions, and paid time on page, but not with paid session duration or paid pages/session. These correlations are of interest because paid bounce rate is a data type that is typically more closely associated with spending time on a website and interacting with the information. The lack of correlation with paid session duration and paid pages/session are expected because a bounce rate is defined as leaving a website without interacting or visiting another page.

Paid session duration is correlated with paid pages/session and paid time on page, but not with paid users, paid new users, paid sessions, or paid bounce rate, which makes logical sense because a longer session duration may include visits to additional pages. Paid pages/session is correlated only with paid session duration and not with any other variable, not even paid time on page. This lack of correlation indicates that users who browse multiple pages may do so quickly. Finally, paid time on page is correlated with paid users, paid new users, paid sessions, paid bounce rate, and paid session duration, but not with paid pages/session.

Paid & Organic Comparisons

The Pearson Correlation table of each linear regression analysis provided information about significant and non-significant relationships among variables. Table 1 combines this information and organizes the significant and insignificant relationships in a consolidated format.

Table 1

Table of combined paid and organic correlations; differences highlighted.

Key: ● Organic, significant ◉ Organic, not significant

■ Paid, significant □ Paid, not significant

	Users	New Users	Sessions	Bounce Rate	Session Duration	Pages/ Session	Time on Page
Users		● ■	● ■	● ■	◉ □	● □	◉ ■
New Users	● ■		● ■	● ■	◉ □	● □	◉ ■
Sessions	● ■	● ■		● ■	◉ □	● □	◉ ■
Bounce Rate	● ■	● ■	● ■		◉ □	● □	● ■
Session Duration	◉ □	◉ □	◉ □	◉ □		◉ ■	● ■
Pages/ Session	● □	● □	● □	● □	◉ ■		● □
Time on Page	◉ ■	◉ ■	◉ ■	● ■	● ■	● □	

The data points for users, new users, and sessions are all tied closely together by definition. When a user arrives at a website, the entire visit is defined as a session, and the user may be classified as a new user if the Google Analytics tracking code has not seen this particular user before. As these data points are so closely related, it is expected that there are significant correlations among users, new users, and sessions for both paid and organic website traffic.

Bounce rate, the dependent variable in the analyses, also has a significant relationship with users, new users, and sessions for both paid and organic website traffic.

This indicates that as the number of users, new users, and sessions rises and falls, so does the bounce rate. While the raw numbers and descriptive statistics indicated a higher bounce rate for paid website traffic, the bounce rate tracked closely with the users, new users, and sessions for corresponding visits. Similarly, though organic website traffic raw data and descriptive statistics indicated that organic users, new users, and sessions bounced at a lower rate, the bounce rate corresponded closely with these data points. This is an important observation because the analyses signify that a higher quantity of traffic of both types –paid and organic – does not result in a negative divergence or lack of relationship with bounce rate. A non-significant finding in one category of traffic would have been a differentiating point between the two categories of traffic. In the cases of bounce rate and users, new users, and sessions, however, there was no differentiating factor in the quality of traffic based on these key performance indicators.

Session duration consistently showed insignificant relationships with users, new users, sessions, and bounce rate. This indicates that the quantity of users, new users, and sessions did not correspond in either paid or organic traffic. The insignificant relationship with bounce rate, however, is expected because a high bounce rate is typically associated with a lower amount of time on a page. The two variables work in inverse, so there should not be a corresponding relationship between these two variables, and this is true for both paid and organic website traffic.

Correlations with pages/session is where more substantial differences between paid and organic website traffic become more evident. Pages/session is the measurement of how many individual pages a user loads during the entire visit to the website. Organic pages/session has correlation with organic users, organic new users, organic sessions, organic bounce rate, and organic time on page, but not with organic session duration. Paid pages/session shows exactly the opposite - it does not have a correlation with paid users, paid new users, paid sessions, paid bounce rate, and time on page, but it does have a correlation with session duration. The correlations among data points of organic website traffic indicate how closely tied organic traffic is to each other variable, with the exception of session duration. The lack of significance between pages/session and session duration is a point of interest because more pages/session tends to be associated time spent on the site, but the analysis in this case indicates this may not necessarily be the case. The lack of a significant relationship in paid website traffic among these KPIs, with the exception of session duration, indicates that paid website traffic does not generate the type of traffic that visits multiple pages, but that paid users have a tendency to stay on a single page for a longer amount of time.

Time on page has a significant relationship with bounce rate and session duration for both paid and organic traffic. These correlations follow with the expectations for user behavior – if a user spends time on a page, then the session duration should follow along in measurement of time and the bounce rate is likely to correspond as well. There are differences, however, in the way paid and organic traffic is correlated among the data points for time on page with users, new user, sessions, and pages/session. A discussion of the relationship between pages/session and time on page was noted previously. Organic time on page does not have a correlation with organic users, organic new users, and organic sessions, but paid time on page is correlated with paid users, paid new users, and paid sessions. This differentiator between paid and organic traffic is notable because it indicates paid time on a page has a tendency to follow the number of paid users, paid new users, and paid sessions in this study, but organic time on page does not follow organic users, organic new users, or organic sessions.

Research Implications

The research conducted in this study resulted in findings that contribute to the body of knowledge related to digital advertising and website traffic at a regional comprehensive university, particularly as it relates to digital strategies for student recruitment. The research has implications for the student recruitment cycle and understanding website user behaviors. Findings may be applicable to the work of college administrators, marketing teams, website managers, admissions teams, and college educators interested in strategies for institutional improvement or program growth.

Data presented in the descriptive statistics and time series illustrated positive performance early in the observation period, particularly July through November. The performance during this period of time indicate the importance of leveraging advertisements and organic methods during July through November and shifting budgets to favor this time period. This is not to say an advertising budget should not be sustained for the entire calendar year. This is only to say July through November have a tendency to result in more traffic and generally higher quality traffic during these months. This period of time is typically earlier in the college exploration process, which is focused on building awareness of choices and generating interest in specific opportunities, so users are exploring programs, gathering information, and learning about the college options available. While the later months in this study did not generate as much website traffic, there were indicators that the performance of paid traffic, generated a higher level of user engagement than organic traffic in the last quarter of observation. This insight regarding user behavior may be helpful during the months of March through June, when users are expected to take more specific actions regarding their college enrollment (e.g., scholarship acceptance, housing application, pay deposits, etc.). Continual improvement of websites and webpages is a necessary and important undertaking, as indicated by this drastic change in performance. The performance could have just as easily have gotten worse, however, so the practice of assessment after such a change is just as important as the making the change.

Descriptive statistics indicated that paid website traffic does not generate as many pages/session as organic website traffic. A contributing factor to this is that there is a vast amount of search-and-find traffic that originates from organic search engine results pages versus the more targeted and specific action-oriented nature of paid website traffic. There may be opportunities to increase pages/session for both paid users by providing suggested pages based on responses to a survey or general popularity. The ability to engage a user who is on the website is as important as helping the user to find the information they need or complete the action they intend to complete.

Descriptive statistics also indicated that paid users have a tendency to remain on a single page for a longer period of time. This may be indicative of the user's intent to complete an action on a particular page (e.g., completing an inquiry form, scheduling a visit, completing an application). For paid users in particular, this is an important metric that measures the user's ability to complete an action that is related to their ability to move forward in the college selection process. The pages where paid users arrive from paid campaigns are critical for the success of student recruitment, so this is a valuable insight for student recruitment.

The linear regression analyses of this study further signify there are statistically significant similarities and differences between organic user behaviors and paid user behaviors – though there are some behaviors among the data points that follow similar patterns, the two user groups do not demonstrate monolithic behaviors on a website. This research suggests one method of lowering the bounce rate for organic users is to encourage engagement with additional pages of the website, for example – read another story or view another program page. For paid website users, however, the better strategy for lowering bounce rate appears to be engaging the user during their entire session – a landing page and confirmation page, for example. For all users, however, the research suggests that spending too much time on a single page is more likely to result in a bounce from the website.

There are statistically significant relationships among all data points for the users, new users, sessions, and bounce rate variables for both paid and organic traffic. While the users, new users, and sessions variables are similar in nature and this significance was to be expected, it is interesting that bounce rate correlated with these as well. It was not expected that more users would correlate with a higher bounce rate. One of the goals of adding new traffic to a website – not only in higher education, but in other industries as well – is to engage new customers or new users in the content. This finding suggests that gaining new audiences requires more than delivering new paid users to a website, but that website administrators and content managers must design an engaging site and provide specialized content that encourages user interaction.

Bounce rate correlates with users, new users, sessions and time on page for both paid and organic website traffic. There is no correlation between bounce rate and session duration for either paid or organic traffic. Bounce rate, however, correlates with organic pages/session, but not with paid pages/session, which suggests that organic users who view more pages/session bounce less frequently than paid users who view more pages/session. Session duration does not have statistically significant relationships with users, new users, sessions, or bounce rate for either paid or organic traffic.

Organic pages/session correlates differently with every paid pages/session relationship in Table 1. This insight is useful for setting expectations and goals related to paid website traffic, building advertising campaigns and designing landing pages. The findings suggest that organic users behave very differently from paid users in terms of pages viewed per session on the website.

Organic time on page does not have a statistically significant relationship with organic users, organic new users, or organic sessions, but does have a statistically significant relationship between organic bounce rate, organic session duration, and organic pages/session. Paid time on page, however, has a statistically significant relationship with paid users, paid new users, paid sessions, paid bounce rate, and paid session duration, but not paid pages/session. This finding suggests that paid and organic users behave differently in terms of time spent on a single page.

The tendencies of paid and organic user behaviors indicated in this study provide some insight regarding the ways paid users and organic users are similar and the ways they differ. More specifically, paid users tend to view fewer pages, but spend more time on the pages they view. Early performance of advertising campaigns and the pattern indicated in time series graphs indicates the first half of the fiscal year is important for gaining interest and inquiries that carry forward throughout the remainder of the fiscal year and recruitment cycle. The substantial shift in bounce rate seen in time series graphs for this particular year signifies the importance of continual improvement and making changes that benefit the end user. The ability for the website content and design to engage the website user is one of the factors that drives bounce rate down. For paid users, the session duration was the key variable that showed a negative correlation with bounce rate. For organic users, however, pages per session was the key variable that showed a negative correlation with bounce rate. All other factors and variables should be taken into consideration, of course, because none of the variables can be measured alone.

Insights gained from this research may be applied in various scenarios. College marketing and advertising professionals may shift the focus of campaigns throughout the course of the year to address user tendencies at various points of the recruitment cycle. Continual website improvements may be made to address the needs of users as they learn about a college, get ready to apply, learn about financial aid, register for housing, and plan to arrive on campus, among the many other steps a prospective student takes prior to enrollment. Further emphasis may be placed on advertising campaigns that drive new users to the website earlier in the fiscal year, while later points in the recruitment cycle may focus more on admitted students who would be engaged in other more specific actions on the website.

Research Limitations

During the course of research, it became apparent that some of the variables included were quite similar to one another and nature – particularly users, new users, and sessions. The variables, by definition, represent different characteristics of website traffic, but for the purposes of this study one of the variables would have been sufficient for analyzing user or session traffic in a more general manner. Had the research been more specific to new or returning user traffic or the analysis of sessions, for example, all three variables would have been more useful. There were also some data that could be considered outliers in the data set for paid session duration and paid time on page that could have been modified or removed in the course of analysis. This would have provided a cleaner data set and improved the analysis.

Data used in this research was from one regional comprehensive state university in Kentucky, with data observations over the course of a single fiscal year. While the research indicated certain tendencies for website traffic and user behaviors, additional research is necessary to reinforce or compare for differences. Additional studies are necessary to provide additional insight and analysis that could be compared and contrasted with this research. Studies of website traffic from additional periods of time a this school, research done at both smaller and larger schools, along with additional public and private institutions, R1 universities, and other types of educational institutions would provide insight into user behaviors and website at different types of institutions and contribute to the body of knowledge.

The time series analysis conducted as part of this research was relatively limited in nature. Further time series research could be conducted to understand the traffic behaviors over the duration of the observation period. More advanced models of time series could produce data visualizations that highlight particular seasonalities, trends, or patterns that exist within the data.

Opportunities for Future Research

During the course of research several points were noted in regards to expanded or adjusted methods of research that lead to further advancing knowledge on the topic of website user behaviors. Because some of the variables in this study are similar in nature (i.e., users, new users, sessions), it may be beneficial to remove some of the similar variables in order to reduce the overall number of variables or introduce other variables in an effort to further refine the analyses or understand other facets of user behavior. Additionally, the outliers could be adjusted or otherwise removed.

The time series data modeling method was useful for identifying chronological patterns and trends and were quite insightful for this research. Additional time series data modeling methods may be used to provide different types of information and introduce forecasting data that takes a number of variables into consideration. Multiple years of data may be used in both time series and linear regression analyses. By including data from more than a single year, any positive or negative factors related to a specific year (i.e., a pandemic, weather events, or the economy) may be balanced out by the factors of the data sets from other years.

Returning user traffic would be an interesting topic of study, particularly return users whose initial visit can be attributed to an advertisement. These user behaviors would be particularly valuable because the return organic visit is one the site owner/advertiser does not have to pay for, so optimizing advertisements to find more users like these can make advertising campaigns more efficient. Google Analytics also provides the ability to create goals or set an action value within the system that tracks the user's journey from beginning to the completion of a goal, such as completing an application.

The research conducted in this study provided a wealth of quantitative data about the user visit, but the researcher also encountered a number of additional questions that may be answered though qualitative user experience research, a topic that was touched on briefly in the literature review. This research has indicated some factors related to the user bounce rate, but there are underlying questions as to why a user will bounce from a website. There are likely to be a number of answers to this question, but qualitative research regarding the user experience on the website may help identify some common themes that users identify as an issue. Further research into user experience could also provide qualitative data regarding the visit of both paid and organic users and provide insight regarding why organic users tend to spend more time on a site than paid users.

The advertising impressions data was useful for seeing chronological patterns in the data. Additional research could be conducted using other variables from the advertising system, such as clicks, click through rate, cost per thousand impressions, frequency, and many others. Further experimentation with advertising data would be useful for further understanding the relationships that exist between advertisement performance and website user behaviors. A combination of these two research topics could result in powerful insights that drive efficacy and efficiency of advertisements and the websites that serve users.

Finally, a data collective for website data from other colleges would be useful for aggregating data and classifying it according to institution classification. This data warehouse could be used for providing benchmark numbers, understanding how website performance compares with other institutions, and establishing standards by which colleges and universities can expect from their web properties. With the current and growing trend toward digital resources for institutions, particularly in light of the COVID-19 pandemic, colleges can and should expect more from digital solutions, a data collective that provides this type of information would be useful for providing context for performance expectations.

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