2016

Sports Content Viewership Motivations Across Digital Devices

Mark Henry
Walden University

Walden University

College of Management and Technology

This is to certify that the doctoral study by

Mark Henry

has been found to be complete and satisfactory in all respects,
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Review Committee
Dr. Christos Makrigeorgis, Committee Chairperson, Doctor of Business Administration Faculty

Dr. Thomas Schaefer, Committee Member, Doctor of Business Administration Faculty

Dr. Frederick Nwosu, University Reviewer, Doctor of Business Administration Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
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Abstract

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by

Mark Anthony Henry

MBA, University of Cincinnati, 2003

MSEE, University of Cincinnati, 2001

BSE, Walla Walla University, 1997

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

Walden University

March 2016

Abstract

U.S. advertisers spent over $2 billion on sporting events in 2014 directing advertisements towards consumers through digital devices used such as televisions, computers, smartphones, and tablets. The purpose of this cross-sectional study was to identify motivation factors that predict the intention to view sports content on digital devices. Knowing such factors is important for advertisers to prioritize distribution channels. Uses and gratification theory formed the theoretical framework for the study. The methodology adapted a survey that encapsulated 9 motives. The research questions examined what motives influenced sports viewership, what motives predicted the intention to view specific sports content, and the differences in viewing intention across sports content types. Data were collected through a survey administered to a qualified random sample of U.S. respondents with 525 responses received. Data were analyzed using exploratory factor analysis to group the questions into motivation factors, multiple linear regression to determine the significance of these factors in predicting viewership intent, and nonparametric Friedman testing to determine what demographics influenced viewership. Findings included: (a) 8 factors explained 76% of the variance; (b) 8 motives were significant in predicting viewership intention, with Escape ($\beta = .714$) ranking the highest; and (c) younger viewers had a greater intent to consume content on digital devices other than television, with smartphones ($M = .73$) ranking the highest. Social change benefits include: (a) sports content providers and advertisers could target the right content and advertisement to maximize viewership retention and revenue, and (b) users could view their desired sports content on their chosen device.

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Dedication

I would like to thank my family for allowing me to undertake this lifelong goal of completing my doctoral degree. I dedicate this document to you as an indication of my love and appreciation for the shared sacrifices.

Acknowledgments

I am indebted to many for their advice, assistance, and encouragement in the creation of this document. I would like to acknowledge a few people who went beyond the call of duty. To my mentor, Dr. Christos Makrigeorgis, who painstakingly guided me through the complex process of this doctoral study and provided vital insight. Thank you to my extended Walden University Committee, Drs. Thomas Schaefer and Frederick Nwosu (second and URR), for their help in reviewing this document, and to Dr. Freda Turner for leading and growing our DBA Program. To my immediate family, Kyna, Aliya, Owen, and Ethan for understanding that I love them although I did not spend as much time with them as they wanted and as I should. To my mother Beverly Henry and brothers Carl and Andre, thank you for your support through this process. My appreciation to the many others not mentioned by name for the contributions made in their respective ways.

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Section 1: Foundation of the Study

Traditionally, content viewers watched content such as news, shows, live sports, and movies on their home TV. In 2015, portable digital devices exist that allow users the option to view content *on the go* (Lin, 2013). Users personalize consumption and view desired content on additional screens (See-To, Papagiannidis, & Cho, 2012). For example, some consumers have the option to start a movie on one digital device and view the remainder on a different digital device.

Background of the Problem

This study was designed to address the business problem of marketing and advertising managers lacking sufficient data to increase the effectiveness of market segment prioritization for media on specific viewing devices (Bellman et al., 2013; Danaher, Dagger, & Smith, 2011). This problem was worthy of study because of the advancement in technology and availability of more portable and powerful digital devices that provide viewers with newer, alternate ways to view specific television content, sports, and movies. U.S. consumers have a choice for more personalized viewing experience with the use of mobile technologies, and the availability of content-oriented online video services such as Hulu and YouTube (See-To et al., 2012). However, at the time of this study in 2015, researchers have not provided television-viewing motives for sports content across digital devices.

The adoption of Internet-connected digital devices by consumers has demonstrated that the Internet as a delivery mechanism for sports content enables viewers to personalize their viewing experience. Such personalization has a significant potential to cause a loss of viewership for content providers on traditional platforms (Nesbit & King, 2010). As a result, many content providers no longer solely focus on delivering content to traditional television sets, but also provide viewers access to video and related content everywhere, at any time, and across multiple devices (Fleury, Pedersen, & Larsen, 2013).

Problem Statement

Between 2001 and 2010, the Super Bowl in aggregate generated $1.62 billion in advertisement revenue (Gijsenberg, 2014). In 2012, the London Olympic Games demonstrated viewership across traditional and nontraditional devices, with as many as 219.4 million television viewers and 159 million video streams (Tang & Cooper, 2013). Younger audiences prefer viewing video streams on nontraditional digital devices such as smartphones and tablets, just as older audiences prefer viewing content on traditional televisions and computers (Lin, 2013).

To keep pace with viewership migration, the proliferation of digital devices requires shifting market segment priorities from traditional distribution to nontraditional distribution. The general business problem was that uncertainty beclouds the distribution of viewership between traditional and nontraditional devices for sports content. The specific business problem was that some content providers and advertising managers lack sufficient data on sports content viewership motivations and intention to improve market segment prioritization decisions across multiple digital devices.

Purpose Statement

The purpose of this quantitative comparative cross-sectional study was to determine the factors and predictor variables that would enable content providers and advertising managers to improve market segment prioritization across four digital devices. Examination of sports viewership motives and intentions associated with specific digital device types using the identified independent variables *motives* and *device types* aided in predicting the dependent variable *intention* to watch sports content. My review of published peer-reviewed literature contained a revelation of nine major motivations associated with general content viewership across various digital devices (Cha, 2013a; Rubin, 1983). With minor modifications, I used these nine motivations in this study by analyzing and, as necessary, tailoring the motivations to focus exclusively on identifying the motives for sports content viewership on four digital devices.

I conducted a survey of randomly selected owners of all four digital devices aged 18 and older across the contiguous United States regardless of their sports content viewing habits. Analyzes of the response data aided in determining what specific survey questions best capture each motivation associated with sports content viewership. Content providers possess considerable influence and can enhance the social well-being of society by providing the desired media entertainment to viewers whenever and wherever consumers desire.

Nature of the Study

This study was quantitative comparative, as researchers lack information about sports viewership motivation by digital device types (Taneja, Webster, Malthouse, &

Ksiazek, 2012). Essentially, the design and statistical method of this research study follows previous research conducted by Cha (2013a), but with the following two differences that in turn encapsulate the distinct contributions of the study. First, modifying Cha's (2013a) survey originally designed to measure general video content motives to measure sports content by including sports content questions and extending it to four digital devices. Second, answer the same research questions stipulated by Cha (2013a) but related to sports content rather than general video content. In summary, I applied the same quantitative methodological approach for the combined quantitative comparative and factorial design to a different sample and problem domain. Namely, sports content instead of general video content. These modifications and extensions implemented with permission make this research unique.

Prior researchers who investigated television-viewing motivations chose a quantitative research approach over qualitative and mixed-methods (Cha, 2013a; Danaher et al., 2011; Rubin, 1983). Researchers who use a qualitative research method explore characteristics that are not reducible to numerical values to understand the meaning of the problem. The method allows researchers to gather data by collecting verbal and nonverbal artifacts that are organized to portray the topic of the study (Leedy & Ormrod, 2013). In like manner, a mixed-method research method uses strengths of the quantitative and qualitative approaches but requires additional time not available for the study. Researchers typically use the mixed-method approach for human behavior studies. The mixed method approach provides researchers a wholesome view of the phenomenon under study than either quantitative or qualitative would provide alone (Leedy & Ormrod, 2013).

The adoption of Cha's (2013a) design and statistical methods fits this research. Specifically, the study includes a quantitative comparative design because of its descriptive nature and ability to provide a *snapshot* of groups of individuals differing on specified criteria at the same instant in time (Leedy & Ormrod, 2013). This design bodes well for the study to aid in understanding what characteristics drive users to choose one digital device over another to view various sports content at a particular instance in time.

Research Questions

To address the specific business problem, the overarching research question of this study was: What factors and predictor variables can marketing managers employ to improve market segment prioritization across multiple digital devices?

The study also included subsidiary research questions (SRQs) related to specific statistical analyses:

- Exploratory factor analysis (EFA) was used to answer SRQ1-EFA: What subset of survey questions adequately captures the nine motives?
- Multiple regression was used to answer SRQ2-REGR: What motives adequately predict the intention to view specific sports content type on each of the subject digital devices?
- One-way repeated measures ANOVA was used SRQ3-ANOVA: What significant viewing differences exist by digital devices across each of the seven types of sports content and concerning demographic information collected in the survey?

Hypotheses

The study included statistical hypotheses for each of the subsidiary research questions. In particular, the exploratory factor analysis (EFA) hypotheses were as follows:

- H_{0k}-EFA: at least k factors (where k is the number of factors) adequately capture the nine sports content viewership motivations across all subject digital device types.
- H_{1k}-EFA: more than k factors (where k is the number of factors) adequately capture the nine sports content viewership motivations across all subject digital device types.

Multiple regression modeling addressed the following hypothesis:

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9$$

In this model, Y captured consumers' intention to use a digital device as a function of nine motives as predictors given by X_1 to X_9 representing (a) relaxation, (b) companionship, (c) habit, (d) pass time, (e) entertainment, (f) social interaction, (g) information, (h) arousal, and (i) escape. For each survey responder, the value of the i-th motive X_i represented the composite score of the set of survey questions corresponding to the i-th motive. The corresponding multiple regression hypotheses were:

- H_0-R: $R(Y \mid X) = 0$. None of the nine motives adequately predicts the intention to view specific sports content on all considered digital devices.
- H_1-R: $R(Y \mid X) = 0$. At least one of the nine motives adequately predicts the intention to view specific sports content on all considered digital devices.

Furthermore, the one-way repeated measures ANOVA hypotheses were:

- H_0-F: There are no significant viewing differences across each digital device and the seven types of sports content concerning demographic attributes.
- H_1-F: There are significant viewing differences across each digital device and the seven types of sports content concerning demographic attributes.

Theoretical Framework

I based the theoretical framework for this study on uses and gratification (U&G) theory. The origins of U&G theory start as early as 1943 with Herta Herzog (Rowland & Simonson, 2014). U&G theory was a reaction to traditional research on how users meet their needs and desires (Malik, Dhir, & Nieminen, 2015). Other U&G theorists such as Rubin (1983) and McQuail (1983) sought to explain why people use certain media, and the satisfaction received (Lou, Chea, & Chen, 2011). In 1996, the researchers of the first media study that included multiple platforms noted that users interested in a topic would access a great number of sources to obtain the information (Taneja et al., 2012). This conclusion bodes well for determining the motivations for users to view content on digital devices.

Uses and gratification consist of two types of media orientation (a) *ritualized*, which includes using a medium to pass the time; and (b) *instrumental*, using the medium for the purposes of information gathering (Bartsch & Viehoff, 2010). Stated differently: *intrinsic*, engaging in activity for pleasure and satisfaction, and *extrinsic*, engaging in activity for information, social interaction, and escapism (Lou et al., 2011). U&G theory is a theoretical framework that researchers such as Rubin and Windahl (1986) employed to explain the adoption and use of new communication mediums (Cha & Chan-Olmsted, 2012). Researchers have conducted little empirical research to address the topic of sports viewership across digital devices. U&G theory forms the theoretical anchor for this study for the examination of sports viewership motivation and intention to choose one digital device over another for viewing a particular type of sports content.

Operational Definitions

Digital device. A platform that enables a user to view live, pre-recorded, or stored content when the user desires (Fleury et al., 2013).

Tablet PC. A small portable computer that accepts input directly onto its screen rather than via a keyboard or mouse (Gerpott, Thomas, & Weichert, 2013).

Assumptions, Limitations, and Delimitations

This subsection lists the assumptions, limitations, and delimitations of the study. I used assumptions to constrain the scope of the study and assumed true but not verified. Additionally, the list of limitations outlines known weaknesses of the study. Likewise, the list of delimitations specifies the inclusions or exclusions of the study.

Assumptions

Assumptions narrow and bound the scope of this study (Leedy & Omrod, 2013) and include the following:

- that I adequately provided a theoretical framework by employing the uses and gratification theory to explain the choice between digital devices;
- that users who own all four digital devices have similar repeated behavior patterns and characteristics that determine viewership;

- that the survey did not exclude important questions and variables from the model that would provide additional significant factors;
- that exploratory factor analysis would extract key factors that drive the users to choose one digital device over another to view sports content;
- that the selected sample size would yield meaningful factors and a statistical power with a significance criterion of 5%;
- that survey participants would understand and answer the questions truthfully and accurately;
- that an adequate and willing sample from the randomly sampled population aged 18 and older throughout the contiguous United States of America would complete the survey;
- that users of the smartphone, tablet, and computer digital devices by default use WiFi connectivity to watch any and all sports content. Similarly, users of the television use local over-the-air broadcast, satellite, or cable to watch any and all sports content;
- that the study framework of uses and gratification theory amply describes how the structure of the system creates a particular user behavior;
- that content providers can use the results to provide better service to their customers; and
- that the study results would apply to new entrants to the population who own the four digital devices.

Limitations

The limitations list the potential weaknesses of this study (Leedy & Omrod, 2013). The limitations of the chosen research methodology, research design, research analysis, theoretical framework, and perspective of the researcher are implicit in the current research study. Additional limitations include:

- generalization only to the population of the contiguous United States of America who possesses all four digital devices;
- remediation steps adequately addresses missing data;
- a quantitative comparative study provides the viewing characteristics of digital device users at the time of the survey and does not account for any changes with time; and
- the survey questions adequately represent the majority of factors and are valid for collecting various characteristics for factor extraction (see Section 2).

Delimitations

Results from this study indicated the viewing habits of users across four digital devices: televisions, computers, smartphones, and tablets. Delimitations list what a researcher will not perform (Leedy & Omrod, 2013). The following aid in defining the scope of the study:

- Smartphones were defined as devices with a screen size ranging from 3 to 6 inches (7.62 to 15.24 cm).
- Tablets/tablet computers were defined as devices with a screen size ranging from 7 to 10.1 inches (17.78 to 25.65 cm)

- Portable computers were defined as devices with a screen size larger than 10.1 inches (25.65 cm).
- Nonportable computers were defined as nonlaptop devices with a screen size larger than 10.1 inches (25.65 cm).

It is possible that some users may classify digital devices differently, and that the list of digital devices specified in this study is not comprehensive. I made no attempt to examine users under the age of 18 who may have access to all four digital devices or inquire about their usage habits. The population for the study included randomly sampled users aged 18 and older who were residing in the contiguous states of the United States of America.

Multiple surveys conducted by Pew Research (2012) have shown that a growing number of Americans own all four digital device classes, demonstrating that there was a large population to examine. Users who do not have access to all four devices were not included in the study because they would not have provided a complete picture of the potential viewing habits. The scope of the study excluded manufacturer preference as this information was not directly relevant, and the data collected insufficient to make any meaningful conclusion. The scope of the study did not account for users who connect a smartphone, tablet, or computer to a TV for viewing. Questions were limited to aid in extracting viewership preference across digital devices.

Significance of the Study

In this subsection, I describe how the findings from this study were expected to fill gaps in the understanding and practice of business. Marketing and advertising managers may use this information to improve market segment prioritization across multiple digital devices for sports content viewership. Additionally, the subsection contains information on how sports content viewership information provided to content providers and advertising managers affects positive social change. Social change improves the condition of individuals and the society.

Contribution to Business Practice

Examination of the degree of shift in consumer viewing behavior of content across traditional and new digital devices is absent from the literature (Cha, 2013a). The identification of key factors that drive consumers to view sports content on specific digital devices provides benefits to digital device manufacturers, content providers, advertisers, and consumers alike. Findings and conclusions from this study may provide information for sports content viewership to advertisers to improve market segment prioritization, content providers to increase viewers, and increase revenue for both advertisers and content providers.

Results of this study may provide content providers and advertisers with the reasons viewers consume sports content, and their preferred digital device to view particular types of sports content. Advertisers may use this information to improve market prioritization for appropriate digital devices. Content providers may use this information to ensure delivery of preferred sports content to the appropriate digital device, and target advertisements to maximize revenue. In turn, viewers may receive desired content and improved user experience. Results of this study may aid content providers and marketing managers in identifying the motivations and quantify their importance across types of digital devices along with specific sports content viewed. Additionally, content providers and marketing managers may attain information from this study that explains what criteria weigh the most to determine why viewers consume sports content and on what digital device types based on the research sample. The combination of the significant factors driving viewership across types of digital devices and the specific content viewed on digital device types may provide information to media and entertainment executives that may allow them to serve their customers better. The results can provide additional data to the industry on user preferences in the four-screen viewing environment.

Implications for Social Change

Consumers in the U.S. value the ability to watch content on any device and at any time or location. Satisfying consumer needs makes the world a better place to live and allows leaders of content providers and advertisers to fulfill part of their social contract (Sastry, 2011). Corporate social responsibility represents the leaders of companies commitment to reduce harmful effects on society as a whole and increase long-term benefits (Trendafilova, Babiak, & Heinze, 2013). Consumers demand social responsibility (Saeidi, Sofian, Saeidi, Saeidi, & Saaeidi, 2015) and leaders of sports organizations responded by emphasizing the need to use their strength for social causes (Trendafilova et al., 2013). Content providers possess influence and can enhance the social well-being of society by providing the desired media entertainment to viewers whenever and wherever consumers desire. Additionally, the economic implications for identifying what motivates sports viewership on what digital device may become critical to sports content providers and advertisers for targeting the right content and advertisement to the right audience. Such behavior by content providers and advertisers may aid in both retaining viewers longer and maximize revenues; consequently providing financial resources to address social causes.

A Review of the Professional and Academic Literature

In this literature review, I present topical resources selected from business, market, and academia pertinent to the research topic. In the literature review, I explore and gathered material around four key themes: (a) digital devices, (b) statistical techniques and methodologies, (c) theoretical framework and viewing motivations, and (d) sports content types. Resources describing viewing digital devices provided prior research on consumer devices such as televisions, tablets, smartphones, and computers. The resources read included peer-reviewed journal and industry articles to establish the use of these devices for media consumption, determine the challenges in their use, and describe any prior research on usage preference.

The desired statistical techniques I used in this study to model viewing of sports content across digital devices were (a) exploratory factor analysis, (b) multiple regression, and (c) one-way repeated measures ANOVA. Exploratory factor analysis statistical technique reduces the number of variables to factors with common characteristics that in turn explains the interrelationships among the items. References such as Field (2009), Norris and Lecavalier (2010), and Sass and Schmitt (2010) described the application of EFA. Multiple regression aided to identify which of the independent variables (motives) identified by the output of EFA are useful in predicting the dependent variable of intention to view sports content on what digital device. One-way repeated measures ANOVA aided in the determination of what type of sports content consumers intend to consume on each digital device examined.

I used exploratory surveys with Likert-type scales to gather data from research participants. Researchers such as Cha (2013a) have used exploratory surveys to gather information. Cha and others analyzed the collected data using exploratory factor analysis, multiple regression, and one-way repeated measures ANOVA separately or in combination (Cha, 2013a; Hwang & Lim, 2015). Uses and gratification research forms the theoretical framework for this study and includes viewing motives (Cha, 2013a; Hwang & Lim, 2015). Viewing motivations describe the reasons users view content to meet their needs. This section elaborates on (a) digital devices considered for the study, (b) relevant statistical techniques and methodologies employed, (c) viewing motivations, and (d) various genres of sports content considered in this study.

Search Strategy

The search strategy for literature accumulation included using (a) ABI/INFORM Complete, (b) Academic Search Complete/Premier, (c) ACM Digital Library, (d) Emerald Management Journals, (e) ProQuest Central, (f) Sage Premier, and (g) Science Direct literature databases. I selected various keywords and keyword combinations to search for literature. Four themes formed the basis for these keywords, with additional keywords added to the search string based on retrieved articles: (a) digital devices, (b) relevant statistical techniques and methodologies, (c) viewing motivations, and (d) sports content.

The literature search began by using general keywords to ascertain what articles existed. Additional keywords aided in narrowing the scope of the searches using Boolean logic and quotations. I reviewed the resulting list of articles manually for appropriateness by reading their abstracts, printed the articles deemed appropriate for future reading, and discarded articles unrelated to the research topic. The utilized keywords included (a) television viewership, (b) smartphone video, (c) viewership motivation, (d) mobile television, (e) exploratory factor analysis, (f) multiple regression, (g) one-way repeated measures ANOVA, (h) sports video, (i) fantasy sports, and (j) live sports. The proposal contains 130 references total with (a) 121 references (93%) published within the last five years; and (b) 112 peer-reviewed references (86%) published within the last five years. The literature review contains 96 references total with (a) 89 references (93%) published within the last five years; and (b) 82 peer-reviewed references (85%) published within the last five years.

Application to the Applied Business Problem

The purpose of this quantitative cross-sectional study was to explore sports viewership motives associated with specific digital devices to enable content providers and advertising managers to improve market segment prioritization for media-specific viewing devices. As indicated in the purpose statement, the research has a 4-fold purpose that I fulfilled by utilizing specific statistical techniques to answer specific research questions. Completing the objectives outlined in Table 1 aided in accomplishing the purpose of this study.

Table 1

Summary of Research Purpose, Questions, and Techniques

Purpose number	Purpose description	Research question	Technique
1	Identify the best questions that capture each motivation associated with sports content viewership	What subset of survey questions adequately captures the nine motives?	EFA
2	Determine whether viewers pursue or achieve a particular motivation on one digital device over another	What motives adequately predict the intention to view specific sports content on digital devices?	Multiple Regression
3	Determine what sports content type viewers intend to watch on a digital device compared to another	What significant viewing differences by digital devices across each of the seven types of sports content concerning the nine demographic attributes?	One-way repeated measures ANOVA
4	Inform content providers what motivates their consumers' sports content viewership; providing additional information to determine what type of advertisements to target.	What motives adequately predict the intention to view specific sports content on digital devices?	Multiple Regression

Theme 1: Digital Devices

In this subsection, I explored the proliferation of digital devices capable of viewing video. Multiscreen homes comprising portable and powerful digital devices are increasingly commonplace in the United States because of increased access to the Internet (Adriaens, Damme, & Courtois, 2011). Because of the prevalence of digital devices, the U.S. media environment now includes the television, computer, as well as mobile devices such as smartphones and tablet PCs (Fleury et al., 2013). This increase in viewing device options along with accompanying social norms, economic factors, and technical issues influence the use of digital devices by consumers to view video content (Pearson, Carmon, Tobola, & Fowler, 2010).

Since 2005, advancements in technology coupled with lower pricing have led to the proliferation of various digital devices capable of displaying video content (See-To et al., 2012). These devices include a variety of smart HDTV flat screens, portable and powerful computers, tablets, and smartphones. The capabilities of most digital devices now include viewing various types of video content (Cha, 2013a; Corici, Fiedler, Magendanz, & Vingarzan, 2011; Eizmendi et al., 2012; Hess, Ley, Ogonowski, Wan, & Wulf, 2012).

Traditionally, media viewers watched content such as news, shows, live sports, and movies on their home TV. In 2014, portable digital devices existed that allow users the option to view content *on the go* (Lin, 2013). Researchers do not understand the reasons why consumers choose a particular digital device to watch sports content. However, the results from Pew Research (2012) surveys demonstrate a year-over-year increase in consumer adoption of additional types of viewing screens in the U.S. Researchers also observed users personalize consumption and view desired content on additional screens (See-To et al., 2012). Specifically, consumers have the option to start a movie on one digital device and view the remainder on a different digital device. Researchers such as Cha (2013a) have suggested that users choose the device to view content based on how the content best fits the digital device: users' choices have no dependence on choosing either content or digital device first (Cha, 2013a).

Substitution, complementary, or orthogonal relationships may exist among media choices, and audiences may substitute the functionally of similar medias for another (Sundar & Limperos, 2013). Cable TV serves as a supplement to broadcast TV, which resulted in broadening both content options and delivery capacity (Hilliard & Keith, 2010). Similarly, online media content may play a similar role rather than displacing or substituting existing media consumption methods (Cha, 2013b). Users may use any of the four digital devices examined to view sports content. By extension, each digital device may supplement rather than displace traditional consumption methods.

Media device popularity and availability have changed significantly in the last decade. In 2008, almost 99% of households with children had at least one traditional television (Adriaens et al., 2011). Despite televisions' ubiquity, only 46% of American adults viewed television as a necessity in 2010, down from 64% in 2006 (Pew Research, 2010). In 2010, approximately 40% of American households viewed television content over the Internet (Cha, 2013b). In 2012, 58% of Americans 18 and older owned a computer, nearly half of American adults owned a smartphone, and one quarter of

American adults owned tablet PCs (Pew Research, 2012). In 2014, literature described the use of each digital device for specific functions and acknowledged the growth in the use of more powerful smartphones and tablet PCs for viewing video (Hess et al., 2012). For example, 2013 prediction for smartphone adoption reached 1.6 billion users, approaching the estimated 2 billion computer users (Oulasvirta, Wahlstrom, & Ericsson, 2011).

The adoption of Internet-connected digital devices by consumers indicates that the Internet as a delivery mechanism for sports content is an enabler for viewers to personalize their viewing experience using newer devices (Nesbit & King, 2010). A switch to viewing content over the Internet could cause a loss of viewership for content providers on traditional platforms (Nesbit & King, 2010). Subsequently, content providers no longer solely focus on delivering content to traditional televisions, but provide viewers access to video and related content everywhere, at any time, and on multiple devices (Fleury et al., 2013). For instance, the London 2012 Olympic Games demonstrated viewership across traditional and nontraditional devices, with as many as 219.4 million television viewers and 159 million video streams (Tang & Cooper, 2013). As of 2014, the 2012 Super Bowl holds the record for the most-watched television show in U.S. history, and eight other sporting events comprised the top nine-watched televised events in 2012 (Gijsenberg, 2014). Because of the high viewership potential, television networks pay a financial premium for the rights to broadcast sports content. Television networks are also aware of the numerous Internet-based options fans have to access games, statistics, and other up-to-the-minute information (Nesbit & King, 2010).

Computers. The personal computer evolved since its first introduction, and multiple vendors now manufacture them across the world. Sales of personal computers in the second quarter of 2013 steadily declined with the advent of smartphones and tablet PCs, topping out at 306 million units in 2009 (Gartner, 2013). Personal computers come in two primary form factors, desktop, and laptop. Consumers use either form factor to view video content. However, users customarily use laptop computers for watching video content because of its portability. As viewers take a more active role when consuming video content, computers allow them to engage in other activities while viewing content. The rise in user multitasking activities increased the use of computers for consuming information both related and unrelated to TV content (Hess et al., 2012).

Multiple research studies show that viewers use computers to watch past programs either in part or completely, and consist primarily of episodic television series (Accenture Video Solutions, 2013; Cha, 2013a; Cha, 2013b; Ooyala, 2013). Researchers from Ooyala (2013) noted viewers use computers to view live content for extended periods; in particular live sports and news. Eighty-nine percent of personal computer owners watched video over the Internet on desktops or laptops in 2012 (Accenture Video Solutions, 2013). A survey conducted by Accenture Video Solutions (2013) also noted that 25% of consumers watch video over the Internet each day, with another 22% watching at least three times a week. Researchers from Ooyala noted that on average, viewers watched 41 minutes of continuous content with peak viewership at noon, tapering off during the evening commute and increasing later at night. The results parallel research conducted by the NPD Group (2012) that noted viewers use Internet-enabled televisions for watching over-the-top streamed video content and reduce personal computer use as a primary screen during prime-time viewership.

The above information could indicate that users watch video content on their personal computers when they are away from home at fixed locations such as an office, but watch the same content on Internet-enabled televisions when at home. No prior research indicated the motivations for viewing sports content on personal computers or the type of sports content viewed on this device. For this reason, my quantitative comparative study provided the motivations for viewing sports content, and the types of sports content consumed on personal computers.

Television. Televisions were invented in the 1920s and provided entertainment and information to U.S. households throughout the years (Hess et al., 2012). Television is still the primary source for consuming media in U.S. living rooms (Hess et al., 2012). Before 1949, content providers primarily distributed television signals to consumers via broadcast. Starting in 1949, consumers could receive television signals from the community antenna television (CATV), which is now commonly known as cable television (Hilliard & Keith, 2010).

The key to televisions' success was in its simplicity of operation. Early television set controls consisted of a power switch, channel selector, and volume knob, which were easy for all members of a family to understand (Tsekleves, Whitham, Kondo, & Hill, 2011). These initial units of the 1920s typically had one receiver and ranged in size from nine to 20 inches (Chambers, 2011). During this period, Engineers designed televisions as furniture pieces for placement in living rooms, and the possession of a unit conveyed success and affluence (Chambers, 2011).

The concept of portable television is not new. In the mid-1950s, portable television promised personalized viewing and liberation from the living room (Chambers, 2011). Portable televisions were the size of hand luggage and promised relief for family feuds over program choice (Hilliard & Keith, 2010).

It is expensive for television networks to purchase the broadcast rights for sports content (Nesbit & King, 2010). In 1954, advertisers spent more than $800 million dollars on television commercials (Hilliard & Keith, 2010), compared to $31.5 billion for sports advertising alone in 2013 (Plunket Research, 2013). The 2012 Super Bowl holds the record for the most-watched television show in U.S. history, and eight other sporting events complete the top nine-watched televised events in 2012 (Gijsenberg, 2014). Similarly, it is expensive for advertisers to purchase advertising in these events. For example, the cost of a 30-second television commercial can cost as much as $3 million (Johnson & Lee, 2011). Although viewers have begun to shift towards the Internet, advertisers continue to target commercials based on location, lifestyle, and purchasing information (Bellman et al., 2013).

Viewer motivation to watch sporting events on other digital devices is unknown. This information could aid content providers to appropriately price commercials on these devices to maximize advertisement revenue. The information gap underscores the need for my study to explore viewership of sports content on digital devices other than traditional television.

Tablet PC. A tablet PC is a digital device equipped with a color or monochrome touch-screen that enables users to write on, speak to, or manipulate the screen (Tarek, 2014). Knight Ridder originally conceived the Tablet PC for media consumption in 1994 and was first commercially introduced in fall 2002 (El-Gayar, Moran, & Hawkes, 2011). The tablet PC did not receive widespread market acceptance until 2010 with Apples' iPad product. Since then, numerous manufacturers have introduced versions of tablet PC's to meet various needs.

Tablet PC's have found use in business, education, and pleasure. In traditional and nontraditional education applications, tablet PCs have afforded students and professors alike to transfer knowledge effectively: especially for media-rich content (El-Gayar et al., 2011; Gerard, Knott, & Lederman, 2012; Lim, 2011). Similar to laptops, tablet PCs provide the convenience of portability. Until recently, however, only tablet PCs possessed handwriting capabilities that were especially advantageous to engineering and math faculty who needed to communicate complex equations and graphs (Lim, 2011). Another advantage of Tablet PCs in education is the ability to use its functions without drawing unnecessary attention to itself (Gerard et al., 2012).

Commercial applications for Tablet PCs abound. Such applications include presentations, product information, marketing literature for use by sales persons (Koelling, Neyer, & Moeslein, 2013), and handwriting recognition: electronic clipboards for job sites in construction, manufacturing, and similar industries (Chen & Kamara, 2011; Impedovo, 2014). Healthcare professionals use tablets to access and update patient records (Klatt, 2011; Platts, Brown, Javorsky, Scalia, & MacKenzie, 2012), while product developers use tablets during the early stages of new product development (Chandrasegaran et al., 2013).

Tablet PCs are also used for leisure and entertainment. Because of their ability to display video content, consumers have begun to view such content in public and private places (Eizmendi et al., 2012). Despite this shift, most peer-reviewed research tends to examine the use of tablet PCs as a means to consume information about video rather than video viewership on the actual device (Hess et al., 2012). This gap underscores the need for my study to explore viewership of sports content on digital devices such as tablet PCs.

Smartphone. IBM and BellSouth first introduced smartphones in 1993. The device was capable of (a) sending and receiving emails, (b) sending faxes, (c) making and receiving phone calls, (d) storing addresses, (e) and calendar functions (Kalkbrenner & McCampbell, 2011). Smartphones have evolved from these early days to less expensive and even more powerful devices. They have changed the way we consume, distribute, and create information. Smartphones continuously stay connected and enable users to check for updates. Their use is habit-forming and provides quick access to rewards such as social networking, communication, and news throughout the day (Oulasvirta et al., 2011; Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013).

Because of their small size, modern smartphones are extremely portable, and users are more likely to carry them around than any other digital devices. Portability of the smartphone makes it an ideal candidate for personalized content viewing. It provides user access to various applications for business and pleasure. In 2010, the most popular applications used on smartphones in order were (a) email, (b) Facebook, (c) news, (d) data feeds, (e) music, (f) calendar, and (g) browsing (Oulasvirta et al., 2012).

In 2011, smartphones were in the hands of over 35% of Americans and as much as 52% of users aged 18-29 years owned one (Lee, 2014). Sales of smartphones increase at nearly 100% each year (Kenny & Pon, 2011) and outsold personal computers in 2011 for the first time (Little, 2011). Estimates of worldwide smartphone sales show tremendous growth rates with expected sales of 2 billion units by 2015 (Gerpott et al., 2013; Kenny & Pon, 2011).

Advertisers desire to target consumers based on lifestyle and purchasing history (Bellman et al., 2013). Equally important, consumers desire a more personalized user experience including on-demand mobile video content (Corici et al., 2011; Evens, Lefever, Valcke, Schuurman, & Marez, 2011). The intersection of these two events has created an opportunity for advertisers and content providers alike to meet the needs of consumers. The anytime anywhere desire of users to consume content for entertainment provides a demand that needs attention. Buchinger, Kriglestein, Brandt, and Hlavacs (2011) noted that mobile users want to use mobile devices to: (a) kill time while they wait; (b) stay up-to-date with events, news, and other information of interest; (c) create a private sphere; (d) relax; (e) feel less lonely; (g) create, share, and consume content; and (f) for entertainment. Users are changing from a passive viewing experience to an active one, and are seeking content created professionally and specifically for mobile devices; not just adopted standard TV content (Buchinger et al., 2011; See-To et al., 2012). Research shows that the sensory experience is an important factor for user satisfaction with mobile television (See-To et al., 2012). News, soap opera, and sports are clear content genres capable of stimulating the sensory experience (See-To et al., 2012).

It is of interest to note some researchers concluded users viewed short content only on mobile devices, and long attention demanding content is unsuitable for this medium (Haverila, 2012). However, not all researchers share this view and differ on whether users will consume long attention demanding content. Some researchers concluded users will, in fact, consume long attention demanding content on mobile devices: especially live content (Cha, 2013a; See-To et al., 2012). Sports content, especially live matches are long attention demanding content. My quantitative comparative study on sports content viewership provided additional insight on how consumers use the fast growing segment of smartphones to consume sports content.

Theme 2: Relevant Statistical Techniques and Methodologies

In this subsection, I examined the statistical techniques and methodologies undertaken in the study. Exploratory factor analysis explained what motives weigh the most in matching sports content viewed on digital devices. The resultant factors acted as independent variables in a multiple regression model that examined the significance of the motives toward predicting the dependent variable of intention to watch sports content on a specific digital device. Finally, one-way repeated measures ANOVA discovered if there are significant differences in the intention to watch specific sports content across the specified digital devices.

Survey research. Data collection by survey methods can take the form of online, mail, telephone, and face-to-face surveys. An online survey is a survey that sends and receives questions via computer (Kalantari, Kalantari, & Maleki, 2011). Kalantari et al. (2011) noted that most researchers agree online surveys are as reliable as traditional survey methods. In addition to its reliability, online surveys provide other benefits that include (a) lower cost, (b) higher response rate, (c) better response quality, (d) shorter collection time, and (e) lower interviewer bias (Fang, 2016). Additionally, online surveys provide researchers' with an assessment tool when questions have (a) restricted response types, (b) categorization, and (c) the number of research samples is below 500 (Kalantari et al., 2011).

Social science researchers commonly use rating scales such as Likert-type scales to collect responses from research participants. Developed by Rensis Likert in 1931, Likert-type scales require survey participants to respond to a series of statements selecting from options such as (a) strongly agree, (b) agree, (c) undecided, (d) disagree, or (e) strongly disagree (Croasmun & Ostrom, 2011). Researchers may present choices as words, numbers, and emoticons to research participants. Derham (2011) conducted research to ascertain user preference among presentation choices and his results indicated that survey participants prefer word scales to other scale presentations.

Although online surveys have advantages, there are drawbacks that researchers must consider when using online surveys. A drawback includes validity problems because of low Internet penetration and limited Internet access (Fang, 2016). Fang (2016) further stated that if a sample is not random, sampling errors may become problematic. I address both of these concerns in Section 2.

Exploratory factor analysis. Exploratory factor analysis is a statistical technique that researchers use to identify whether the correlation between a set of variables in a linear model occurs because of their relationship with one or more latent variables of the data set (Field, 2009). Researchers use exploratory factor analysis (EFA) when little or no supporting evidence exist for the prior structural hypothesis, or to identify common factors (Norris & Lecavalier, 2010). That is, rather than specifying the number of factors a researcher may empirically explore the number of factors. Researchers use EFA to investigate items by examining associations between items of a questionnaire to define latent variables that account for most of the variance (Senkans, McEwan, Skues, & Ogloff, 2016). EFA aims to explain the variance between the variables and account for underlying relationships (Norris & Lecavalier, 2010). A researcher groups the resulting factor scores to form factors.

Critics of EFA argued that the calculation of factor scores is difficult and, as a result, leave important research questions unanswered (Norris & Lecavalier, 2010). Heywood cases are another basis for criticism, which occurs when the variance is greater than 100%. Fabrigar, Wegener, MacCallum, and Strahan (as cited in Norris & Lecavalier, 2010) counter that such variance results are helpful in determining if Heywood cases violated EFA assumptions; acting as a support for EFA's viability. Many argue that EFA is a subjective statistical procedure because of the high number of decisions left to the researcher. Supporters of EFA refute this claim stating that many guidelines exist to aid researchers with these decisions (Norris & Lecavalier, 2010). The guidelines include

- sample size – a frequently cited rule is 5 participants per variable with at least 200 total participants or 10 participants per variable with less than 100 total participants;
- choose the correlation matrix type based on the nature of the data;
- generate communality estimates prior to extracting factors to maximize model fit;
- choose an appropriate rotation;
- decide how many factors to retain using a scree plot test, eigenvalue-greater-than-1 rule, root mean square error of approximation, Expected Cross Validation Index or parallel analysis; and
- determine the minimum item loading necessary to retain a factor – strong loadings occur at a value of .6 or higher (Norris & Lecavalier, 2010).

Many techniques exist for determining the number of factors needed. In general, the underlying goal is to use the smallest number of factors to capture the most item variation. The elbow of the scree plot is one method (Norris & Lecavalier, 2010). This technique searches for an abrupt transition from large to small eigenvalues. However, the technique becomes subjective when the transition is not evident. Researchers created stopping rules such as the Kaiser criterion to aid in the possible ambiguity of using scree plots. The Kaiser criterion sets the threshold to the arithmetic mean of the eigenvalues (Field, 2009). An eigenvalue with a value greater than one represents a factor while an eigenvalue with a value less than one is not a factor (Norris & Lecavalier, 2010). The Kaiser criterion can potentially over extract or identify too many factors and does not account for sampling error.

Parallel analysis compensates for the shortcomings of the Kaiser criterion. Parallel analysis simulates normal sampling error by calculating eigenvalues from randomly generated data sets having the same dimensions of the study data and the identity matrix as the correlation matrix (Ruscio & Roche, 2012). Methodologists agree that parallel analysis better estimates the number of factors to extract when compared to the scree test or the eigenvalue rule (Norris & Lecavalier, 2010). However, statistical software packages do not typically include parallel analysis (Norris & Lecavalier, 2010).

Sass and Schmitt (2010) reviewed multiple rotation criteria and documented important differences researchers should consider before use. They stress to resist the urge of using default software settings such as oblique and orthogonal Varimax but rather explore other rotation options to avoid an adverse impact on research results. Yates (as cited in Sass & Schmitt, 2010) comments that popular rotation choices purport that criterion are perfectly independent and easily identified, but such outputs may not represent the desired factors. Sass and Schmitt explained that placing more weight on row complexity provides a near perfect cluster configuration but may result in overemphasized row complexity reduction and higher inter-factor correlations. Conversely, placing more weight on column complexity produces a less simple structure (Sass & Schmitt, 2010). Sass and Schmitt stressed the choice of rotation criteria must consider the method to ascertain factors (model fit), as well as the rotation criteria. They continue to state that there are no “best” rotation criteria. Rather researchers have to decide on a rotation criteria considering information such as model fit statistics and prior similar research using factor analysis. Researchers also have to decide between estimating factor solutions with smaller cross-loadings and potentially larger inter-factor correlations or identifying more independent factors (i.e. smaller inter-factor correlations) and slightly larger cross-loadings (Sass & Schmitt, 2010).

Typical uses of exploratory factor analysis include (a) interdependency and pattern delineation, (b) data reduction, (c) structure discovery, (d) classification or description, (e) scale development, and (f) hypothesis testing (Field, 2009). Several authors including Cha (2013a), Karg and McDonald (2011), and Zhang et al. (2011) used factor analysis to perform hypothesis testing related to television viewership, demonstrating that EFA is a viable technique for this study.

The application of exploratory factor analysis (EFA) aided in explaining what motives (identified by a subset of survey questions) weigh the most in matching sports content viewed on what digital device. EFA reduces the survey consisting of a large set of questions to a subset that captured the nine motives (Cha, 2013a). Additionally, cross-tabulation is not an inferential statistical technique where researchers can make inferences based on significance testing. We do not know what an adequate sample size would be if we opted to use cross-tabulation. On the other hand, EFA and its conclusions aid researchers to make predictions based on sample size calculations and statistical power (Field, 2009). Researchers then apply research results to the larger population outside of the research sample (Field, 2009). The application of EFA aided in examining associations between items of the questionnaire to define latent variables that account for most of the variance in viewing motives (Senkans et al., 2016). I grouped the resulting factor scores together to form motivations.

Multiple regression. Multiple regression (MR) has evolved to address the gap between correlation and analysis of variance. Researchers use MR to examine the relationship between a single response dependent variable and several controlled independent variables (Yahaya, Abdullah, & Zainodin, 2012). Researchers use multiple regression as an analysis tool when data samples exhibit time series, censorship, or self-selection characteristics, and research questions aim to address probability related issues (Field, 2009). One of the powers of multiple regression is its ability to estimate and test the interaction between categorical or continuous variables (Yahaya et al., 2012). Businesses also use multiple regression to create a forecast or examine relationships between variables (Danaher et al., 2011).

Xenidis and Stavrakas (2013) noted disadvantages of multiple regression. Disadvantages include difficulty in deciding how to set up models for budget estimation because of no standard approach, and for computational reasons, the number of input variables cannot exceed a certain limit (Xenidis & Stavrakas, 2013). The assumptions for multiple regression include (a) assumption of a linear relationship between independent and dependent, (b) variables measured without error, (c) reliability of simple regression, and (d) reliability of multiple regression (Dumirescu, Stanciu, Tichindelean, & Vinerean, 2012).

Multiple regression aided in the analysis of relationships among various variables. Following the methodology of Cha (2013a), Danaher et al. (2011), I used multiple regression to perform hypothesis testing related to television viewership. That is, I set the resultant EFA motives as independent variables in a multiple regression model to identify which of these independent variables was useful in predicting the dependent variable of intention to watch sports content on what digital device. According to Table 2, there are 511 main and interaction effect variables. Following the methodology of Cha (2013a), the model only considered the nine main effect variables.

Similarly, using multiple regression allowed me to answer various research questions regarding user motivational differences for the four digital devices. Multiple regression also aided in determining how these motives predict consumers' intention to use a digital device to view particular sports content. The motives were unordered predictors and aided in evaluating their contribution to specific sports content viewership on the various digital devices individually and compared to each other.

My research follows a similar methodology as Cha (2013a), who also did not consider any interaction effects. Considering the 36 interactions involving two variables is expensive for regression in SPSS. As a result, the study does not contain any consideration of interaction effects. Each regression variable represents a construct, thus considering combinations of constructs dilutes the interpretation of the results significantly.

Table 2

Total Number of Main and Interaction Effect Variables for Multiple Regression Model

Formula	Count
C(9,1)	9
C(9,2)	36
C(9,3)	84
C(9,4)	126
C(9,5)	126
C(9,6)	84
C(9,7)	36
C(9,8)	9
C(9,9)	1
Total	511

Note: C(n,k) represents the notation for a binomial coefficient, where C represents the combination or choices while n and k represent the nature of the combination or choice.

One-Way Repeated Measures ANOVA. Businesses use a statistical tool known as analysis of variance (ANOVA) that aids in identifying differences between average effects in business processes (Leedy & Ormrod, 2013). ANOVA is a statistical procedure that uses the F-ratio to test the overall fit of a linear model. In experimental research, this linear model is defined in terms of group means, and the resulting ANOVA is, therefore, the overall test of whether the group means differ (Field, 2009). Three assumptions form the basis of one-way repeated measures ANOVA: (a) approximately normal distributed populations, (b) does not violate sphericity, and (c) dependent variable measured at the continuous level (Chen, Li, Shi, & Zhu, 2015; Field, 2009; Watt et al., in press). Many business processes have variations at diverse process points and physical locations, leading to challenges in comparing averages with unequal variances. Data like this violates the equal variance assumption, and traditional F-test results may render it no longer statistically justifiable (Leedy & Ormrod, 2013). Skewed or nonnormal data distribution causes the average data value not to reflect the actual value (Burch, 2011).

Several studies (Cha, 2013a; Kim & Jang, 2014; Watson, 2012; Wu & Mattila, 2013) have chosen experimental designs that include one-way repeated measures ANOVA for consumer research. Authors such as Nettelhorst and Brannon (2012) harnessed one-way repeated measures ANOVA to perform hypothesis testing related to television viewership. The application of one-way repeated measures ANOVA allowed me to test various statistical hypotheses of this study regarding statistical significance. One such hypothesis states that consumers will view particular sports content equally on all digital devices. As shown in Figure 1, the use of one-way repeated measures ANOVA as a statistical technique aided in answering the question above. In addition, one-way repeated measures ANOVA aided in examining changes in mean scores between groups and potential interactions (Field, 2009). One-way repeated measures ANOVA aided in ascertaining research participants intention to view sports content on all four digital devices by examining collected survey data. An analysis occurred for each sports content type.

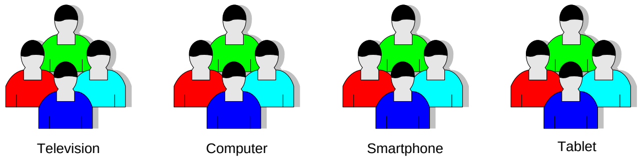

Figure 1. One-way repeated measures ANOVA performed to ascertain viewer intention for each type of sports content for each digital device.

Theme 3: Viewing Motivations

Researchers such as Blumler and Katz (1974) identified key desires that consumers want to fill with the use of media (Pearson et al., 2010). These desires became a part of the most influential theories in communication research: uses and gratification (Cha, 2014). Uses and gratification theory purport that audiences seek media and its content to meet instilled needs through a variety of motives (Bartsch, 2012).

The origins of U&G theory start as early as the 1940s with Herta Herzog (Rowland & Simonson, 2014). Research on audience motivation continued to evolve with a debate over the purposeful or unintentional use of media. Such debate was evident especially in the 1980s and early 1990s among scholars such as Rubin (1983, 1984), McQuail (1983), Rubin and Perse (1987), among others.

Uses and gratification theory aided researchers in exploring questions about how and why people use media. The reasons included: (a) information – satisfying curiosity, self-education, and learning about relevant events; (b) personal identity – reinforce personal values and gain insights about one's self; (c) integration and social interaction – a sense of belonging, substitute for real-life companionship, ability to connect with friends, family and society; and (d) entertainment – escape or diverting from problems, filling time, relaxing, and enjoyment (Joo & Sang, 2013). According to Rubin (1983), five assumptions underscore U&G theory: (a) purposed, goal-directed, and motivated user communication behavior; (b) users actively seek out a media source to meet their needs; (c) social and psychological factors dictate individual communication behavior; (d) communication mediums compete; and (e) individuals have influence on the choice of media, but not always (Wu et al., 2010).

Rubin created the Television Viewing Motives Scale (TVMS) in the 1980s (Rubin, 1983). Researchers used this scale to discover television viewing motives interrelationships, and with it have made significant contributions to audience motivation research (Bartsch & Viehoff, 2010). Rubin's (1983) work resulted in a nine-motive scale that he termed the television viewing motives scale. The nine motives are: (a) relaxation, (b) companionship, (c) habit, (d) pass time, (e) entertainment, (f) social interaction, (g) information, (h) arousal, and (i) escape. TVMS measures television viewing motivations, medium affinity, patterns of viewing, and perceived realism (Galauner, Petty, Beatty, Rudd, & Atkin, 2011).

Uses and Gratification consist of two types of media orientation: *ritualized*, which included using a medium to pass the time, and *instrumental*, using the medium for the purpose of information gathering (Joo & Sang, 2013). Stated differently: *intrinsic*, engaging in activity for pleasure and satisfaction, and *extrinsic*, engaging in activity for information, social interaction, and escapism (Lou et al., 2011). Ritualistic viewing motivations comprises of (a) relaxation, (b) pass time, (c) entertainment, (d) habit, (e) escape, and (f) companionship, while instrumental viewing motivations comprises of (a) arousal, (b) social interaction, and (c) information (Aubrey et al., 2012). Rubin (1983) used factor analysis to reduce 27 items and concluded that only five motives were significant for television viewing. These motives are (a) entertainment, (b) pass time and habit, (c) information, (d) escape, and (e) companionship.

Uses and gratifications theory is a theoretical framework that researchers widely use to explain the adoption and use of new communication mediums (Cha & Chan-Olmsted, 2012). Researchers have conducted little empirical research to address the topic of sports viewership across digital devices. Rather, explorations have involved the use of television or the Internet for video consumption. Prior researchers have used U&G theory to examine motivation as it relates to general video content (Cha, 2013a; Rubin, 1983; see also Aubrey et al., 2012; Logan, 2011). For example, Cha (2013a) used U&G theory to determine how motives influence the use of television or the Internet to consume video content. Funk, Beaton, and Alexandris (2012) applied U&G theory across sporting fan behaviors to discover the motivations for engaging in sports goal-related behavior. In this study, the application of U&G theory aided in examining motivations for sports content consumption across digital devices: (a) television, (b) computer, (c) smartphone, and (d) tablet. Figure 2 shows the relationship between viewing motivations and the four digital devices.

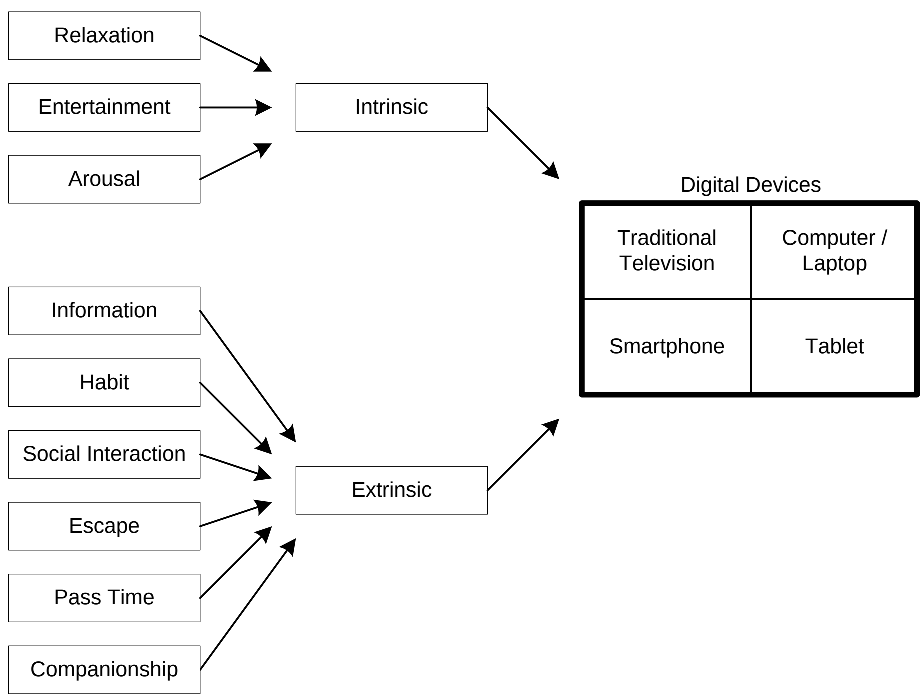

Figure 2. Model for investigating the motives that influence viewership across digital devices. Adapted from “A model of the relationship among sport consumer motives, spectator commitment, and behavioral intentions” by J. W. Kim, J. D. James, and Y. K. Kim, 2013, Sport Management Review, 16, p. 174. Copyright 2013 by Elsevier Science Publishing Co., Inc. Used with permission.

Researchers have also examined viewer motivations across various devices. Pearson et al. (2010) aimed to determine why the millennial generation used electronic devices. Pearson et al. adapted the TVMS tool, using six of the original nine motives, and found that college students primarily use their cell phones, computers, televisions, and MP3 players for (a) entertainment, (b) passing the time, (c) social interaction, and (d) companionship. Likewise, Logan (2011) studied online streaming video versus traditional television viewership and found viewers watched the same program types for the same ritualistic motives regardless of the medium; especially entertainment. Of equal importance was the determination that neither medium had any instrumental motivations; evoking low levels of viewer involvement (Logan, 2011). Similarly, a study by Hwang and Lim (2015) showed excitement as the highest viewer motivation for television viewers. Based on the findings of Hwang and Lim, instrumental motives will become more important as television converges with other devices. This conclusion underscores the need to study instrumental motives as they relate to content viewership across digital devices.

Cha (2013a) also examined viewer motivations across various devices: television and the Internet. Cha (2013a) studied (a) how viewership motives predict television and Internet use, (b) how these motives differ for watching general video content on the television and the Internet, and (c) how the choice of viewing general video content differs from that seen on television and that observed on an Internet site. Cha (2013a) concluded that motives for viewing the same general video content differ between that seen on television, and that observed on an Internet site. Cha (2013a) also discovered the popularity of certain types of content on the Internet. Research conducted by Cha (2013a) forms the basis for my study with two major differences: (a) examination of sports content types rather than general video content, and (b) digital devices such as television, computer, smartphone, and tablet rather than television and the Internet.

Other researchers adapted the TVMS to meet their research objectives and found varied viewer motivation depending on the content type and audience make-up as shown in Table 3. Researchers' such as Hwang and Lim (2015) noted that viewing motives for sports content on television only consisted of (a) information seeking, (b) entertainment and excitement seeking, and (c) social attributes. Similarly, Aubrey et al. (2012) observed that college-aged viewers in their study watched reality television to meet both ritualistic and instrumental viewing motivations.

Table 3

Selection of Previous Works That Use the Television Viewing Motivations Scale With Studied Devices

Author(s)	Motives assessed	Devices	Sample location
Cha, J. (2013a)	Information gathering, boredom relief, relaxation, entertainment, companionship, escape, social interaction	Television, The Internet	U.S. college students
Aubrey et al. (2012)	Relaxation, pass time, entertainment, companionship, arousal, social interaction, information	Television	College students in mid-western U.S.
Chua, Goh, & Lee (2012)	Leisure (escape / pass time / entertainment / relaxation), information gathering, socialization, identification	Mobile device	Singapore
Galauner et al. (2011)	Entertainment, habit/pass time, affinity, information, escape, realism	Television	College students in mid-western U.S.
Logan (2011)	Entertainment, pass time, information, social interaction, companionship, habit, arousal, relaxation, escape	Television, online streaming video	U.S. National
Pearson et al. (2010)	Escape, entertainment, information, companionship, social interaction, pass time	Television Computer, cell phones, MP3 players	College students in mid-western U.S.

In summary, prior researchers (Cha, 2013a; Pearson et al., 2010) have established the use of the television viewing motives scale for assessing viewer motivations across various types of media devices including the television. Chua et al. (2012) concluded that devices such as smartphones and tablets have taken on two new attributes: portability and mobility. As a result, it is beneficial to advertisers and content providers that new studies examine the viewing motivations for these new digital devices. For this reason, I proposed to conduct this quantitative comparative study of sports content viewership motivations across digital devices.

Theme 4: Sports Content

This subsection contains information on various sports content. Sports content types include (a) tape-delayed, (b) sports scores, (c) sports highlights, (d) live sports, (e) fantasy sports, (f) sport documentaries, and (g) sport news. I selected these sports content types as they address areas of interest to this study.

Tape-delayed. Consumers may view content at their leisure with DVRs, PVRs, or on-demand (Kerkhof & Münster, 2015) and skip advertisements (Pyun & James, 2011). Content providers may also delay original content distributed to viewers. NBC most recently delayed certain popular events in the 2012 London Olympics to air during primetime. Because of this strategy, the London Olympics had a total viewership of over 4.8 billion worldwide (Pop, 2013).

Sports scores. Viewers consume sports scores on a variety of digital devices. Their motivations may differ depending on the users' goals and use requirements (Kirk, Chiagouris, & Gopalakrishna, 2012). Because of its mobility, mobile devices are convenient to access sports scores and other services while on the go (Watson, McCarthy, & Rowley, 2013). Similarly, computers offer convenient access to sports scores and other information of personal interest especially for information seeking users while at the office (Vitak, Crouse, & LaRose, 2011).

Sports highlights. Watching sports highlight videos is a popular entertainment activity enjoyed by many viewers (Lai, Chen, Kao, & Chien, 2011). Highlight video abstracts a long game and provides viewers with a compact summary for browsing (Chen, Chou, Tsai, Lee, & Lin, 2012; Lin, Lee, Yang, Lee, & Chen, 2013).

Live sports. Watching live sporting events date back to the first Olympics and has grown into a major form of entertainment in the contemporary society (Appelbaum et al., 2012). The 2012 Super Bowl holds the record for the most-watched television show in U.S. history, and eight other sporting events comprise the top nine-watched televised events in 2012 (Gijsenberg, 2014). Viewing live sporting events accounts for 85% of the sports television consumption for male sports viewers aged 18-24 years old (Brown, Billings, & Ruihley, 2012; Wann, Grieve, Zapalac, Partridge, & Parker, 2013).

Fantasy sports. Sports enthusiast can obtain sports entertainment through fantasy sports rather than watching games (Nesbit & King, 2010). In 2012, an estimated 36 million fantasy sports enthusiasts' participants in the United States and Canada alone (Martin & Nelson, 2014). Additionally, fantasy sports influence \$3 – 4 billion on the sports industry, stimulating participants to attend or view more games and buy more team merchandise (Lee, Seo, & Green, 2013).

To participate in fantasy sports participants must (a) join a league, (b) build a team based on real players, and (c) compete with members of the league based on the players' performance. Participants spend a vast amount of time setting up and managing their teams, with football and baseball accounting for 90% of all fantasy sports activities (Brown et al., 2012). Because of their participation in fantasy sports, 55% of fantasy sports participants watch more sports on television (Nesbit & King, 2010). In fact, fantasy sports involvement increases the likelihood of watching more games weekly for both avid sports fans and nonavid sports fans (Nesbit & King, 2010).

Sports documentaries. Sports documentaries focus mostly on life stories beyond the sport (Wann et al., 2013). The content of sports documentaries are not always entirely accurate (McQuarrie, 2013). Furthermore, documentaries may serve in educational and civic functions that other genres tend to ignore (Vogan, 2012). Wann et al. (2013) confirmed that both male and female viewers who have less team identification tended to watch sports documentaries.

Sports news. Consumers view news primarily for the acquisition of information (Zhang & Zhang, 2013). For instance, young adults heavily rely on the news media for information affecting their everyday lives (Williamson, Qayyum, Hider, & Liu, 2012). Research conducted by Wann et al. (2013) indicated that live games and sports newscast account for the largest percentage of sports viewership among young adults. Print media also had high interest among young adults, with over 45% of young adults surveyed indicating their interest in reading about sports (Williamson et al., 2012).

Experts regard various types of news ideal for mobile consumption because of (a) the portability of the mobile device, (b) its ability to provide quick updates, and (c) flexibility to allow user customization (Zhang & Zhang, 2013). In addition to the consumer, both news organizations and sports leagues mutually benefit from sports news

(Zhang et al., 2011). Sports news programming provides news organizations with content that advertisers desire to promote their product or services alongside: resulting in advertising revenue for sports news organization (Zhang et al., 2011).

Transition

The specific business problem, purpose, and research questions in Section 1 of this proposal comprised the foundation and research background for exploring sports content viewership motivations across digital devices. As articulated in Section 1, a clear business need existed for further academic exploration and discovery of this topic. Specifically, advertising and marketing managers lack the information to make objective decisions on market segment prioritization of specific sports content for viewing on multiple digital devices. In Section 2, I build on the information in Section 1 and present the research design and quantitative methodology applied to this study. Section 3 contains the results with implications for business and recommendations for further research.

Section 2: The Project

In Section 2, I restate the purpose of the study, cover the steps to access the participant pool to obtain the required data, and explain the research method and research design adopted for the study. It includes an explanation of the various elements of the sampling plan including sampling unit, population, and frame, the adopted sample design and estimated sample size, the data collection process and the Likert survey instrument, and the analytic procedure used to address the research questions. Finally, Section 2 includes a discussion of the validity and reliability of the study.

Purpose Statement

The purpose of this quantitative comparative cross-sectional study was to enable content providers and advertising managers to improve market segment prioritization across four digital device types. I examined sports viewership motives and intentions associated with specific digital device types using the identified independent variables *motives* and *device types* to predict the dependent variable *intention* to watch sports content. My review of published peer-reviewed literature identified nine major motivations associated with *general* content viewership across various digital devices (Cha, 2013a; Rubin, 1983). I used these nine motivations with minor modifications in this study by analyzing and, as necessary, tailoring the motivations to focus exclusively on identifying the motives for sports content viewership on four digital device types.

I conducted a survey of randomly selected owners of all four digital device types aged 18 and older across the contiguous United States regardless of their sports content viewing habits. Analyzes of the response data aided in determining what specific survey questions best capture each motivation associated with sports content viewership. Content providers possess considerable influence and can enhance the social well-being of society by providing the desired media entertainment to viewers whenever and wherever consumers desire.

Role of the Researcher

The catalyst for this study was a research gap concerning what drives users to choose what digital device to view various types of sports content. I selected this content focus because of my industry expertise with Major League Baseball (MLB) and sports that compete for viewership market share. A further understanding of viewership motives informs content providers of the content consumer's desire for specific digital devices. This study was designed in part to produce information that will enhance content marketing and advertising managers' ability to improve marketing segment prioritization decisions and increase sports viewers' satisfaction with the availability of sports content on multiple digital devices.

My role as the researcher included (a) developing and providing information on research design, (b) creating measurable hypothesis, (c) summarizing applicable literature, (d) performing measurements, (e) documenting and interpreting results, (f) confirming or refuting prior assumptions, and (g) employing appropriate methods and rigor to properly confirm findings, as suggested by (Hamilton, 2011). This quantitative comparative study consisted of collecting primary data for analysis to enable content providers and advertising managers to improve marketing segment prioritization for media-specific viewing devices. To that end, my role as researcher included: (a) identifying, modifying, and formatting the survey instrument for administration by Qualtrics; (b) organizing and formatting the collected data; (c) analyzing and interpreting the data to make conclusions as it relates to the stated research questions and hypothesis; (d) provide limitations and guidance on the use of the results; and (e) ensuring data collection meets the guidelines of the National Institute of Health (NIH) Office of Extramural Research, Belmont Report, and Walden University's Institutional Review Board (IRB).

Participants

After I received approval from Walden University's Institutional Review Board (IRB) with approval number 08-27-15-0317462 and expiring on August 26, 2016. Qualtrics administered and collected the survey responses. Study participants consisted of a random cross-sectional sample of users aged 18 and older throughout the contiguous United States of America. I selected Qualtrics as the most effective method to ascertain a cross-section of research participants because of their low cost and ability to obtain survey results in a reasonable time. Qualtrics drew a random research sample from their diverse national database. One of the participation criteria was that members of the target audience possess all four digital devices before consideration as potential participants.

At the start of the survey, I presented each survey participant with a user agreement. A participant was ineligible to continue the survey if they did not agree with the terms of the user agreement. The user agreement informed the potential participants who provide data that their response was anonymous in nature and destroyed after 5 years. All participants equally received $1.65 from Qualtrics for a completed survey.

Research Method

This research study used a quantitative comparative design. As part of the research process, I explored the motivations for sports content viewership on types of digital devices such as televisions, computers, smartphones, and tablets using a survey as the primary research instrument. Studies based on a quantitative method determined frequency and distribution of certain characteristics in a population (Leedy & Ormrod, 2013). My research study consisted of the application of a sequence of statistical techniques to answer the research questions posed. Steps included (a) adapting an existing survey instrument by Cha (2013a) to measure the motives or end-goals that drive users to view sports content on specific digital devices; (b) executing the survey and collected data from a cross-sectional random sample of users aged 18 and older throughout the contiguous United States of America; and (c) performing data analysis using exploratory factor analysis (EFA), multiple regression, and one-way repeated measures ANOVA analysis techniques.

I considered several factors to determine the best research method for this study. For example, researchers who use qualitative methods focus on exploring characteristics that are not reducible to numerical values to understand the meaning to the problem (Leedy & Ormrod, 2013). Researchers using qualitative methods gather data by collecting verbal and nonverbal artifacts that are organized to portray the topic of the study (Leedy & Ormrod, 2013). In like manner, the mixed-methods approach uses strengths of the quantitative and qualitative approaches but requires additional time not available for the study. Researchers typically use the mixed-method approach for human behavior studies because it provides a wholesome view of the phenomenon under study than either quantitative or qualitative would provide alone (Leedy & Ormrod, 2013). A quantitative research approach examines the relationship between variables to test an objective hypothesis (Leedy & Ormrod, 2013). Prior researchers who investigated television-viewing motivations chose a quantitative research approach over qualitative and mixed-methods (Cha, 2013a; Danaher et al., 2011; Rubin, 1983). For these reasons, the quantitative methodology was the best method for this study to aid in identifying key motivations' that leads viewers to watch sports content on a specific digital device.

Research Design

I chose a quantitative comparative design for the study because of its descriptive nature and ability to provide a snapshot of groups of individuals differing on specified criteria at the same instant in time (Leedy & Ormrod, 2013; Liimatainen, Arvidsson, Hovi, Jensen, & Nykanen, 2014; Yoon et al., 2012). The quantitative comparative design bodes well for the study because the design aids in understanding what characteristics drive users to choose one digital device over another to view various sports content at a particular instance in time. I examined: (a) multiple variables to identify highly interrelated variables and derivative factors for themes, (b) focused on known variables for the study, and (c) used a web-based survey administered online to collect data from a cross-sectional random sample of users aged 18 and older throughout the contiguous United States of America for analysis using statistical techniques. Previous research studies have confirmed the validity of electronic surveys as a way to access large representative samples (Fang, 2016; Kalantari et al., 2011; Karg & McDonald, 2011).

I specifically chose a quantitative comparative design over other research designs because of (a) speed in data collection, (b) less expensive data collection compared to interviews, (c) ability to provide data in a single instance in time, and (d) application to research areas concerned with experience differences. An experimental design was not applicable because none of the participants received an intervention. A longitudinal design was not appropriate either, as the nature of the study did not include changing variables over time. Likewise, since participants did not take part in experiments, neither a causal or quasi-experimental design applies to this study.

Essentially, this research study follows an identical design and set of statistical methods as Cha (2013a), but with the following differences that in turn encapsulate the distinct contribution of the study. First, modification with permission of Cha’s (2013a) survey originally designed to measure video content motives to measure sports content and extend the survey to different digital devices; something that Cha (2013a) had not explored. Second, modify the identified motives to include questions related to sports content instead of general video content. Last, this study was designed to answer the same research questions as Cha (2013a), but for sports content rather than general video content. In summary, I applied the same methodology and design not only to a different sample but also to a different problem domain: sports video content.

Population and Sampling

Digital device ownership has gradually changed from 2005, and consumers have a choice for more personalized viewing experience on digital devices such as (a) televisions, (b) computers, (c) smartphones, and (d) tablets. My objective was to assess the motives for viewing sports content on digital devices to enable content providers, and advertising managers improve market segment prioritization for media-specific viewing devices. The information in this subsection describes the research population and sampling method.

Population

The population comprised a cross-sectional random sample of users aged 18 and older throughout the contiguous United States of America, who use each of the four types of digital devices regardless of their sports content viewing habits. Specifically at the time of completing the survey users must own a (a) television, (b) computer, (c) smartphone, and (d) tablet for consideration as members of the sampling population. I narrowed the possible vendors between Qualtrics and Survey Monkey to administer the survey. Upon ascertaining their capabilities, Qualtrics was the most appropriate choice between the two companies since Qualtrics worked extensively with academic institutions. In addition, Qualtrics product features include the capability of providing participants for the survey from an extensive population known as *panels*. Qualtrics *panels* included qualified individuals who met certain criteria and were willing to take surveys. Access to Qualtrics *panels* reduced the overall data collection time. Further steps included: (a) creating a free password-protected account with Qualtrics; (b) configuring screener questions, rules to allow for single or multiple answers per question, forced responses, and exiting the survey; (c) constructing a survey using all Likert-type questions; and (d) loading my survey using their intuitive online tool. Qualtrics management assigned a project manager who reviewed my survey and made suggestions to improve its flow.

Qualtrics project manager sent a link to the survey to a cross-sectional random sample of digital device users from their research only database. The sample comprises users aged 18 and older, and who reside in the contiguous United States. I provided Qualtrics with the pre-screening requirements of participants owning all four digital devices and requested an even split gender quota. Qualtrics project manager and its panel partners use a three-stage randomization process to match a participant with a survey the participant is likely able to complete. In the first stage, Qualtrics project manager and its panel partners randomly select participants from the *panels* and invite them to take the survey. The second stage entails a set of methodologically correct profiling questions, never affirmation questions, randomly selected for prospective participants to answer. Upon completion, the final stage matches participants with a survey they are likely able to take using further randomization selection via a *survey router*. Factors considered in the assignment performed by survey routers include the likelihood that participants can complete the survey and characteristics of the research such as survey duration. A dedicated team handles the development of the survey router parameters.

Qualtrics project management indicated an incidence rate, how many people who met the studies screening criteria, of over 70% and estimated attaining my desired completed surveys in 5 to 7 days. Completed surveys appeared real-time in my Qualtrics account and a total of 525 completed surveys in less than three days. I exported the raw survey data from my Qualtrics account in SPSS format for analysis upon attaining the desired number of responses.

Sampling

In this research study, the three statistical techniques required a specific sample size. I used two methods to determine the sample size for exploratory factor analysis. Norris and Lecavalier (2010) suggested researchers have a minimum of 200 participants or a subject-to-item ratio of at least 5:1. This study comprises of 31 EFA questions, and the subject-to-item ratio results in a minimum of 5 x 31 = 151 participants. However, this calculated figure was below the recommended minimum 200 participants. Field (2009) suggested a similar method to calculate sample size, with a subject-to-item ratio between 5 and 10 participants per variable up to 300. A sample size of 300 or above is stable regardless of the subject-to-item ratio (Field, 2009). Based on this method, the EFA sample size should range between 5 x 31 = 151 and 10 x 31 = 310. Based on Table 4 and the fact that my research has 31 variables, the desired sample size range was between 200 and 310 participants.

Table 4

Exploratory Factor Analysis Sample Size Options

Sample size ratio-empirical rule	Reference	Minimum sample size	Maximum sample size	Average
Five observations per variable	Norris & Lecavalier, 2010	200		
Five to ten observations per variable	Field, 2009	5 x 31 = 155	10 x 31 = 310	Average = 233
At least ten observations per variable	Rhode, Grobe, Hockemeyer, Carlson, & Lee, 2012	10 x 31 = 310		

The determination of sample size for multiple regression and one-way repeated measures ANOVA depends on statistical power, alpha, and effect-size (Faul, Erdfelder, Buchner, & Lang, 2009). G*Power 3.1 is a stand-alone power analysis tool for determining apriori sample size for many statistical tests and aids in calculating the required sample. In G*Power 3.1, I used the (a) *exact* linear multiple regression random model with a medium effect size value of 0.25 (Ivarsson, Anderson, Johnson, & Lindwall, 2013) to calculate the required sample size for multiple regression, (b) nine predictors (Cha, 2013a) representing the maximum number of factors, and (c) an alpha of 0.05 and power of 0.95 to calculate the required sample size of 95 participants as shown in Table 5 for multiple regression.

Table 5

Required Sample Size for Multiple Regression R^2 Random Effects Model

Input parameter		Output parameter	
Tail(s)	Two	Lower critical R^2	0.1941146
H1 ρ^2	.25	Upper critical R^2	0.1941146
H0 ρ^2	0	Total sample size	95
α err prob	0.05	Actual power	0.9526897
Power (1-β err prob)	0.95		
Number of predictors	9		

In like manner, I used the medium effect-size value of 0.25 (Ivarsson et al., 2013) to calculate the required sample size for one-way repeated measures ANOVA. The number of groups is 4 and the number of measurements 7. G*Power 3.1 configured with *F Test: ANOVA fixed effects* with an alpha of 0.05 and power of 0.95 calculated a required sample size of 164 participants as shown in Table 6 for one-way repeated measures ANOVA. Following the methodology of Cha (2013a), the model does not consider 2-way interactions.

Table 6

Required Sample Size for One-Way Repeated Measures ANOVA

Input parameter		Output parameter	
Effect size *f*	0.25	Noncentrality parameter λ	17.9375
α err prob	0.05	Critical *F*	2.6611083
Power (1-β err prob)	0.95	Numerator *df*	3.00
Number of groups	4	Denominator *df*	160
Number of measurements	7	Total sample size	164
Corr among rep measures	0.5	Actual power	0.9538445

In summary, Table 7 shows the required sample sizes for the three statistical methods employed in the study. Based on calculations, EFA requires $n1 = 233$ participants, multiple regression $n2 = 95$ participants, and one-way repeated measures ANOVA $n3 = 164$ participants. I had a single sample size and data set of $n = \text{MAX}(n1, n2, n3) = \text{MAX}(233, 95, 164) = 233$ participants to support analysis using all three statistical techniques. As a result, the Qualtrics project manager obtained a minimum of $n = 233$ valid survey responses and thus the actual response rate is irrelevant in this setting.

Table 7

Summary of Minimum Sample Size for Statistical Techniques

Statistical technique	Minimum sample size
Exploratory Factor Analysis	*n*1 = 233
Multiple Regression	*n*2 = 95
One-way repeated measures ANOVA	*n*3 = 164

Ethical Research

I collected data for this study from voluntary, anonymous participants in accordance with the guidelines of the National Institute of Health (NIH) Office of Extramural Research and Walden University's Institutional Review Board (IRB). Adhering to the following steps ensured compliance with ethical guidelines for assuring compliance with the following standards: (a) not storing identifiable personal information either during or after the study; (b) maintaining confidentiality of any information provided by the survey; (c) retaining no personal information for any reason, nor participants' names or anything else that could identify participants published in the study reports; and (d) storing data on removable media, such as a USB stick, in a password-protected folder, and locked in a fireproof safe, and keeping the data for a period of at least 5 years as required by Walden University, and subsequently destroying the data in accordance with Walden University IRB guidelines. Participating in this study was voluntary. Participants may join the study by agreeing to the content form but can change their mind during the survey. Potential participants can withdraw from the research study by not agreeing to the consent form at the start of the survey or may stop at any time during the survey. Appendix A contains a copy of the consent form presented to participants at the beginning of the survey. I authorized Qualtrics to equally provide all participants $1.65 for a completed survey.

Instrumentation

The data collection instrument was a three-part 71-question survey. The three parts were (a) motivation to watch sports content, (b) types of sports content, and (c) demographic information. Appendix B contains a copy of the survey instrument with fifty-nine Likert-type questions. The first part of the survey consisted of 8-point Likert-type questions. The scale of eight potential responses included: (a) 1- *strongly disagree*, (b) 2 - *disagree*, (c) 3 - *disagree somewhat*, (d) 4 - *undecided*, (e) 5 - *agree somewhat*, (f) 6 - *agree*, (g) 7 - *strongly agree*, or (h) 8 - *do not know - not applicable*. This scaling of responses measured latent variables in an attempt to ascertain difficult variables not easily identified. Table 8 contains a summary of the alignment of the survey questions with the research questions. The alignment of the survey questions to the research questions mirrors that in Cha's (2013a) research.

Table 8

Survey and Research Question Alignment

Survey question	Research question
Q1 – Q31	SRQ1-EFA
Q1 – Q31	SRQ2-REGR
Composite variables of Q1 – Q31, Q32 – Q70	SRQ3-ANOVA

A review of relevant literature such as Cha (2013a) and Rubin (1983) revealed that nine major motivations explain content viewership across various digital devices. Rubin created the Television Viewing Motives Scale (TVMS) in the 1980s (Rubin, 1983). Researchers used this scale to discover television viewing motives interrelationships, and with it have made significant contributions to audience motivation research (Joo & Sang, 2013). Rubin's (1983) work resulted in a nine-motive scale that he termed *the television viewing motives scale*. The nine motives were: (a) relaxation, (b) companionship, (c) habit, (d) pass time, (e) entertainment, (f) social interaction, (g) information, (h) arousal, and (i) escape. The television viewing motives scale measures (a) television viewing motivations, (b) medium affinity, (c) patterns of viewing, and (d) perceived realism (Galauner et al. 2011).

Prior researchers (Cha, 2013a; Rubin, 1983; see also Aubrey et al., 2012; Logan, 2011) used U&G theory to examine motivation as it relates to general video content. For example, Cha (2013a) used U&G theory to determine how motives influence the use of television or the Internet to consume video content. Funk et al. (2012) applied U&G theory across sporting fan behaviors to discover the motivations for engaging in sports goal-related behavior.

The survey instrument for this study was a modification and combination of two existing surveys by Cha (2013a) and Rubin (1983). I obtained permission from Cha and Rubin (see Appendix C) to modify their respective surveys. Each question maps from television viewership to sports content viewership while keeping the original structure and constructs of the existing surveys. This modification is in like manner to Cha

(2013a) who performed a similar adaptation of Rubin's survey. As a result, the adapted instrument does not require survey construct validation. Construct validity is the extent that the survey instrument measures a characteristic that is not directly measurable but exists based on patterns of people's behavior (Leedy & Ormrod, 2013). Construct validity also checks whether a test validly measures what it means to measure (Becker, Predroso, Pimenta, & Jacobi, 2015; Boag, in press; Zhi et al., 2015). Content validity is the extent that the items of the survey instrument represent the entire range of possible items that it should cover (Leedy & Ormrod, 2013). I took the following steps to ensure the content validity of the survey: (a) the literature review provided the basis for the items, (b) the dissertation chair provided feedback after reviewing the survey, (c) limit changes made to the original validated surveys, and (d) the questionnaire and survey introduction letter complied with ethical guidelines and the Walden University Institutional Review Board requirements.

Although I based this quantitative comparative study on the same methodology and statistical techniques used by Rubin (1983) and Cha (2013a), it does not provide inherent reliability. In practice, a number of external random factors can influence how respondents answer survey questions. A measurement taken with a survey contains two factors: the theoretical true score and the variation caused by random factors (Aslan, Cinar, & Yavuz, 2012). Reliability is a measure of how much of the variability in the observed scores represents variability in the underlying true score (Aslan et al. 2012). A survey is reliable if the results are consistent across different situations (Field, 2009).

The data analysis included the Split Half method for analyzing the modified instruments interim reliability. I used the Split-Half internal consistency reliability method that provides a test to determine if the modified survey items yield consistent results. The Split-Half internal consistency reliability method breaks the survey into odd and even answers to check if the answers correlate with responses (Field, 2009). I used SPSS to split the (a) odd and even questions, (b) add the responses for each grouping, and (c) calculate the Split-Half reliability coefficient to assess the consistency of scores between the two equivalent measures. The Split-Half coefficient should fall between 0 and 1. The underlying Split-Half assumption is that the odd and even responses are equivalent.

Cronbach’s alpha was another internal reliability indicator and is the mathematical equivalent to the average of all possible Split-Half estimates from the same sample (Field, 2009). I used Cronbach’s alpha to check the internal consistency and thus reliability. Cronbach’s alpha was the sum of the variance of all questions over the variance of the entire survey, and the most widely used coefficient to check for consistency (Aslan et al., 2012). Researchers noted randomly and internally distributed surveys also had a high Cronbach’s alpha (Field, 2009).

I applied the Television Viewing Motivation Scale (TVMS) to determine sports content viewership motivation. The following lists the nine major TVMS motives and a brief description: (a) RELAXATION: People want to unwind from their day or other activities; (b) COMPANIONSHIP: People do not want to be alone; (c) HABIT: People do activities because that is what they have done in the past; (d) PASS TIME: People are interested in passing the time if they have nothing better to do; (e) ENTERTAINMENT: People want exciting and amusing activities; (f) SOCIAL INTERACTION: People want to socialize and interact with others; (g) INFORMATION GATHERING: People are interested in gathering information about sports schedules, team rankings, scores, and sporting events; (h) AROUSAL: People want thrilling activities, see others push their bodies, taking risks, using a strategy, and demonstrating physical skill; and (i) ESCAPE: People want to get away from what they are doing, family, and others.

In general, it is easier to perform INFORMATION GATHERING on a computer or smartphone over the Internet than on TV without specialty channels. Therefore, it is logical to expect the achievement of INFORMATION GATHERING motivation would have a higher association with a computer and smartphone than a TV digital device. Not all motivations across digital devices are as easily deduced and hence the importance of this study. Interested parties may request raw data from the researcher.

Data Collection Technique

I used a self-administered online survey for data collection given to users aged 18 and older residing in the contiguous United States for this quantitative research study. Kalantari et al. (2011) noted that most researchers agree that online surveys are as reliable as traditional survey methods. In addition to their reliability, online surveys provided other benefits that include: (a) lower cost, (b) higher response rate, (c) better response quality, (e) shorter collection time, and (f) lower interviewer bias (Fang, 2016).

Qualtrics drew a random sample from their diverse national database. The Qualtrics project manager sent an email to the random sample of candidates inviting them to participate in the research study. I downloaded the resultant data for analysis upon receiving valid survey responses equaling the necessary sample size and mapped the questions to SPSS variables. Table 9 contains the mapping of motive questions to SPSS variables.

Table 9

Mapping of Motive Questions to SPSS Variables

Survey question	SPSS variable	SPSS measure	Sample values
Q1 – Q3	RLX1 – RLX3	Ordinal	1..8
Q4 – Q6	COMP1 – COMP3	Ordinal	1..8
Q7 – Q9	HAB1 – HAB3	Ordinal	1..8
Q10 – Q12	PAS1 – PAS3	Ordinal	1..8
Q13 – Q15	ENT1 – ENT3	Ordinal	1..8
Q16 – Q18	SOC1 – SOC3	Ordinal	1..8
Q19 – Q25	INF1 – INF7	Ordinal	1..8
Q26 – Q28	ARO1 – ARO3	Ordinal	1..8
Q29 – Q31	ESC1 – ESC3	Ordinal	1..8

Table 10 contains the mapping of content viewership questions to SPSS variables.

Table 10

Mapping of Sports Content Viewership Questions to SPSS Variables

Survey question	SPSS variable	SPSS measure	Sample values
Q32 – Q35	SNTV, SNCP, SNSP, SNTB	Ordinal	1..8
Q36 – Q39	LSTV, LSCP, LSSP, LSTB	Ordinal	1..8
Q40 – Q43	SCTV, SCCP, SCSP, SCTB	Ordinal	1..8
Q44 – Q47	HITV. HICP, HISP, HITB	Ordinal	1..8
Q48 – Q51	TDTV, TDCP, TDSP, TDTB	Ordinal	1..8
Q52 – Q55	SDTV, SDCP, SDSP, SDTB	Ordinal	1..8
Q56 – Q59	FSTV, FSCP, FSSP, FSTB	Ordinal	1..8

Table 11 contains the mapping of demographic questions to SPSS variables.

Table 11

Mapping of Demographic Questions to SPSS Variables

Survey question	SPSS variable	SPSS measure	Sample values
Q60	AGE	Nominal	{1=18-24, 2=25-34}
Q61	EDU	Nominal	{1=High School, 2=Bachelor's degree}
Q62	ZIP	Scale	10011
Q63	GENDER	Nominal	{1=Male, 2=Female}
Q64	MSTATUS	Nominal	{1=Single, 2=Married no children}
Q65	INTERNET	Nominal	{1=Internet at home, 2= unlimited Internet at home}
Q66	SERVICE	Nominal	{1=Satellite, 2=Cable}
Q67	TVYR	Nominal	{1=Less than 3 months, 2=3 months – 1 year, 3=1 – 3 years, 4 =more than 3 years}
Q68	CPYR	Nominal	{1=Less than 3 months, 2=3 months – 1 year, 3=1 – 3 years, 4 =more than 3 years}
Q69	SPYR	Nominal	{1=Less than 3 months, 2=3 months – 1 year, 3=1 – 3 years, 4 =more than 3 years}
Q70	TBYR	Nominal	{1=Less than 3 months, 2=3 months – 1 year, 3=1 – 3 years, 4 =more than 3 years}
Q71	INCOME	Nominal	{1=Under $25,000, 2=$25,000-$49,999, 3=$50,000-$100,000, 4=more than $100,000}

In Table 12, I demonstrate the formation of possible EFA factors with various survey questions.

Table 12

Possible EFA Factors Formed by Various Survey Questions

Possible survey question forming possible factors	Possible SPSS factors	SPSS measure	Sample values
Q1 – Q3	MR_X1_RLX = Relaxation factor	Scale	20
Q4 – Q6	MR_X2_COMP = Companionship factor	Scale	20
Q7 – Q9	MR_X3_HAB = Habit factor	Scale	20
Q10 – Q12	MR_X4_PAS = Pass time factor	Scale	20
Q13 – Q15	MR_X5_ENT = Entertainment factor	Scale	20
Q16 – Q18	MR_X6_SOC = Social factor	Scale	20
Q19 – Q25	MR_X7_INF = Information factor	Scale	20
Q26 – Q28	MR_X8_ARO = Arousal factor	Scale	20
Q29 – Q31	MR_X9_ESC = Escape factor	Scale	20

I will store all survey response data on my local hard drive and the third-party service providers' website during and up to 6 months after the completion of the study. Study data will (a) remain on removable media such as a USB stick, (b) saved in a password-protected folder, (c) locked in a fireproof safe, and (d) kept for at least 5 years as required by Walden University. Destruction of study data will commence after the 5-year period in accordance with the Walden University IRB guidelines and the consent form.

Data Analysis

To address the specific business problem, the overarching research question of this study was: What factors and predictor variables can marketing media managers employ to improve market segment prioritization across multiple digital devices? I divided the overarching research question into subsidiary questions (SRQs) with the statistical technique to address each SRQ.

- I used exploratory factor analysis (EFA) to address research question: SRQ1-EFA: What subset of survey questions adequately captures the nine motives?
- I used multiple regression to answer research question: SRQ2-REGR: What motives adequately predict the intention to view a specific sports content type on each of the subject digital devices?
- I used one-way repeated measures ANOVA to answer research question: SRQ3-ANOVA: What significant viewing differences exist by digital devices across each of the seven types of sports content and concerning demographic information collected in the survey?

The study included statistical hypotheses for each of the subsidiary research questions. In particular, the exploratory factor analysis (EFA) hypotheses were as follows:

- H_{0k}-EFA: at least k factors (where k is the number of factors) adequately capture the nine sports content viewership motivations across all subject digital device types.
- H_{1k}-EFA: more than k factors (where k is the number of factors) adequately capture the nine sports content viewership motivations across all subject digital device types.

Multiple regression modeling addressed the hypothesis

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9$$

In this model, Y captured consumers' intention to use a digital device as a function of nine motives as predictors given by X_1 to X_9 representing (a) relaxation, (b) companionship, (c) habit, (d) pass time, (e) entertainment, (f) social interaction, (g) information, (h) arousal, and (i) escape. For each survey responder, the value of the i-th motive X_i represented the composite score of the set of survey questions corresponding to the i-th motive. The corresponding multiple regression hypotheses were:

- H_0-R: $R(Y \mid X) = 0$. None of the nine motives adequately predicts the intention to view specific sports content on all considered digital devices.
- H_1-R: $R(Y \mid X) = 0$. At least one of the nine motives adequately predicts the intention to view specific sports content on all considered digital devices.

Furthermore, the one-way repeated measures ANOVA hypotheses were:

- H_0-F: There are no significant viewing differences across each digital device and the seven types of sports content concerning demographic attributes.
- H_1-F: There are significant viewing differences across each digital device and the seven types of sports content concerning demographic attributes.

SPSS version 21 was the primary data analysis tool for this study, and I applied exploratory factor analysis, multiple regression, and one-way repeated measures ANOVA to determine what motivates sports content viewership, and what type of sports content viewers' intend to consume on each digital device examined. Specifically, the application of exploratory factor analysis (EFA) aided in explaining what motives (as identified by a subset of survey questions) weigh the most in matching sports content viewed on which digital device. The resultant motives fed a multiple regression model as independent variables and aided in identifying which of these variables were useful in predicting the dependent variable of intention to watch sports content on what digital device. Last, the results of the one-way repeated measures ANOVA aided in determining what type of sports content consumers intend to view on each digital device examined. I examined the descriptive statistics for each statistical technique along with their specific outputs to address the research questions, and test for sampling adequacy using the Kaiser-Meyer-Olkin (KMO) measure and for sphericity using Maulchy's test, as outlined by Field (2009).

Researchers classify missing data into three types: (a) missing completely at random (MCAR), (b) missing at random (MAR), and (c) missing not at random (MNAR) (Dong & Peng, 2013; Pantazis, Kenward, & Touloumi, 2013; Sterner, 2011). To address missing data, I (a) determined if the missing data is ignorable (MCAR and MAR) or not ignorable (MNAR), (b) selected an appropriate remediation process, (c) implemented the remediation process using SPSS, and (d) reported presence of missing data and remediation steps (Sterner, 2011). Most researchers used listwise deletion or pairwise deletion to deal with missing data in quantitative studies (Dong & Peng, 2013).

Descriptive Statistics

I generated a number of descriptive statistics for each Likert survey question to familiarize myself with the data. Several *Descriptives* options needed selecting and included (a) *minimum,* (b) *maximum,* (c) *variance,* and (d) *range* as shown in Figure 3.

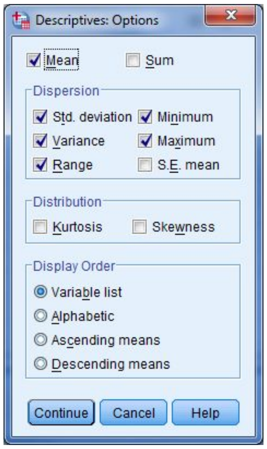

Figure 3. Selected options for descriptive statistics.

I performed a cross-tabulation of demographic questions to understand the number of surveys received by various demographic groups. More importantly, I checked various assumptions before applying multiple regression and one-way repeated measures ANOVA statistical techniques. One key assumption that must be satisfied by both one-way repeated measures ANOVA and linear regression is the normality of the independent and dependent variables (for regression). Therefore, after applying EFA to reveal the composite variables, the next step was determining the distribution of each composite variable before applying multiple regression or one-way repeated measures ANOVA. In SPSS, I checked each composite variable identified by EFA for normal distribution.

Appropriate techniques if a violation of an ANOVA assumption such as heteroscedasticity occurs include bootstrapping (Xu, Yang, Abula, Qin, 2013) and the Box-Cox (Beaumont, 2014). The Box-Cox technique transforms data from nonnormal to approximately normal (Beaumont, 2014; Costa & Crepaldi, 2014; Proietti & Lutkepohl, 2013). I performed the following steps to correct for nonnormality in SPSS: (a) find the best value of Lambda using SPSS vector and looping commands based on Box-Cox as shown in Table 13, (b) select *Transform - Compute Variable* from the menu, (c) enter the transform equation based on Box-Cox best value of Lambda as a numeric expression, and (d) check transformed variable for normality. If I was unable to normalize the data, I planned to use Friedman's test instead of one-way repeated measures ANOVA.

Table 13

Sample Box-Cox SPSS Vector and Looping Commands to Determine Best Lambda Value

SPSS Vector and Looping Commands
COMPUTE var1=num_tot-6.
execute.
VECTOR lam(31) /xl(31).
LOOP idx=1 TO 31.
COMPUTE lam(idx)=-2.1 + idx * .1.
DO IF lam(idx)=0.
COMPUTE xl(idx)=LN(var1).
ELSE.
COMPUTE xl(idx)=(var1**lam(idx) - 1)/lam(idx).
END IF.
END LOOP.

Table 14 shows a hypothetical output of the normality test. I used the Kolmogorov-Smirnov and Shapiro-Wilk tests since these tests are appropriate for datasets with less than 2000 observations (Field, 2009). For the hypothetical output, a *p*-value .220 > .10 would result in rejecting the alternate hypothesis and conclude that the data comes from a normal distribution.

Table 14

Hypothetical Test of Normality Sample Output for EFA Revealed Composite Variables

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
MR_X1_RLX	.145	20	.200[b]	.938	20	.220

Note. [a]Lilliefors Significance Correction. [b]This is a lower bound of the true significance.

Exploratory Factor Analysis

EFA requires testing two key assumptions: (a) linear relationships exist between measured variables and the factors plus errors, and (b) normally distributed measured variables (Green & Salkind, 2011). Assumption (b) relates to the measured variables, the Likert questions. In SPSS, I (a) checked each composite variable identified by EFA for normal distribution using the Kolmogorov-Smirnov and Shapiro-Wilk tests since these tests are appropriate for datasets with less than 2000 observations, (b) tested for sampling adequacy using the Kaiser-Meyer-Olkin (KMO) measure, (c) tested for sphericity using Bartlett's test, and (d) tested for linear relationships using a correlation matrix (Field, 2009).

The application of EFA aided in forming the factors corresponding to the first 31 Likert variables. In SPSS, set the extraction options that included retaining factors with

Eigenvalues > 1 as shown in Figure 4. Upon setting these options, I proceeded to analyze the data and included the: (a) total variance explained table, (b) scree plot, (c) component matrix, (d) pattern matrix, and (e) component correlation matrix.

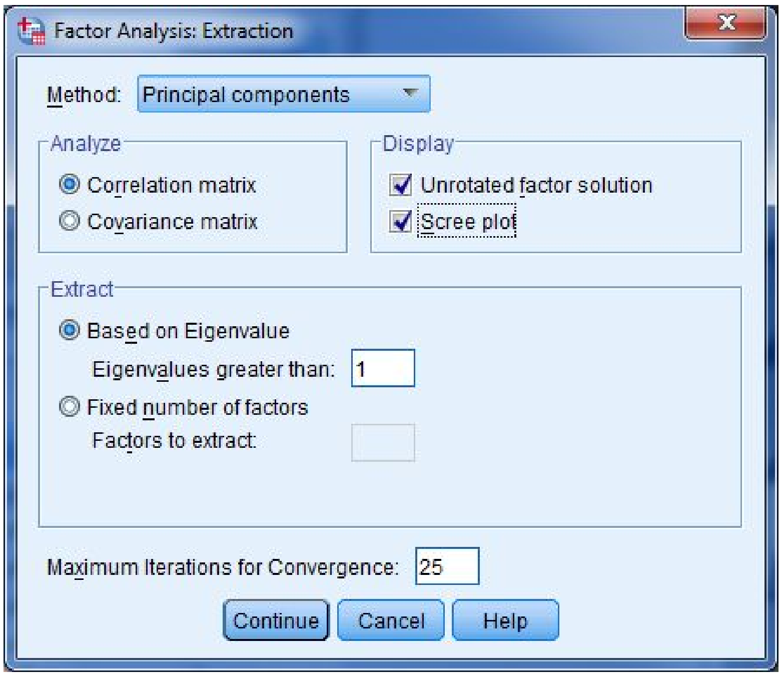

Figure 4. Extraction choices for EFA.

Next, I examined the scree plot as shown in Figure 5 and ran factor extraction to determine the inflection point visually and thus how many factors k to retain. In this hypothetical case shown in Figure 5, the inflection point occurred at k=16 factors but given that we are only interested in factors with eigenvalue > 1, retain only k=11 factors.

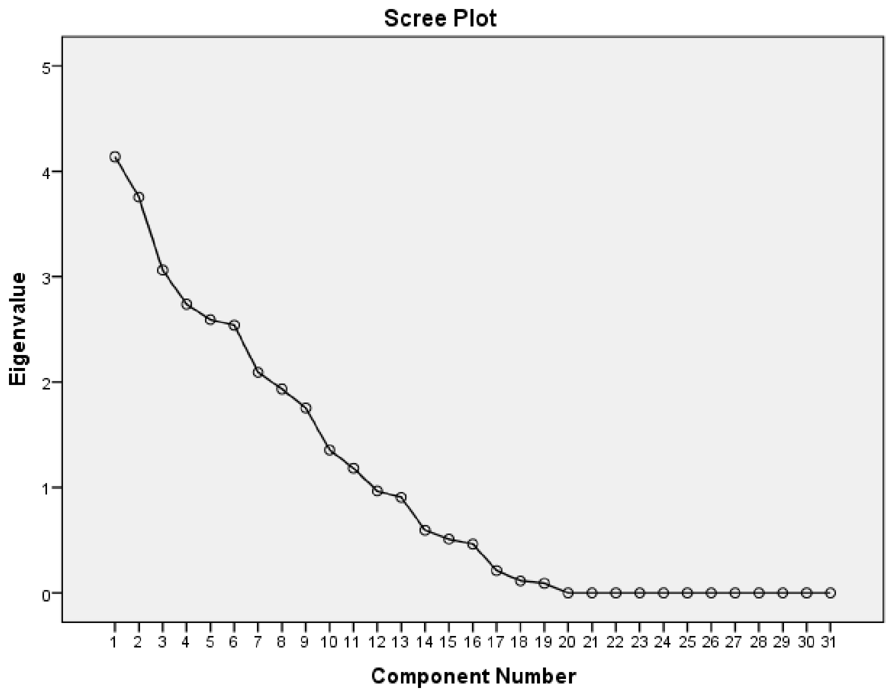

Figure 5. Example factor analysis scree plot.

In like manner, Table 15 shows a hypothetical sample component matrix that displays the eigenvalues and extracted factors. I created a composite variable representing each factor after factor extraction. For example, if F1 = RLX and it contains questions Q2 and Q3, create a composite variable RLX = Q2 + Q3.

Table 15

Partial Hypothetical Example Component Matrix for Exploratory Factor Analysis

	Component[a]						
	1	2	3	4	5	6	7
ARO1	-.781					-.105	.233
INF1	.749	.285	-.155		.342	.224	
INF3	.625	.295		.442	.362	-.242	
COMP3	.510	-.117	-.316			.381	.247
HAB3	-.281	.705	.191	.272	.147		-.145
INF5	-.398	.634			-.178	-.404	.246

Note. Extraction Method: Principal Component Analysis. [a]7 components extracted.

Multiple Regression

The assumptions for multiple regression included (a) assumption of a linear relationship between independent and dependent variables, (b) variables measured without error, (c) homoscedasticity, and (d) multicollinearity (Dumirescu et al., 2012). In SPSS, I (a) tested for linear relationships using scatterplots and partial regression plots, (b) tested for independent samples using the Durbin-Watson statistical tests, (c) tested for homoscedasticity by plotting the studentized residuals against the unstandardized predicted values, and (d) tested for multicollinearity using the correlation coefficients and variance inflation factor (Field, 2009).

I performed a reliability analysis to ensure questions can add together to form values of X_i in the multiple regression model. To do this, I selected *Analyze – Scale – Reliability Analysis*, and then moved like variables extracted by EFA and considered significant for this study. For example, Table 15 shows an example output with EFA extracting INF1 and INF3 as significant. I moved these variables to the *Items* window and performed the reliability analysis. A hypothetical Cronbach's alpha of at least .65 indicates that the variables measure the same motive, and one can add these values to create X_i variables for the multiple regression model.

Following the application of EFA, I used all my composite variables to form a linear regression model of the form below for each device

$$\hat{Y}_n = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 + B_6X_6 + B_7X_7 + B_8X_8 + B_9X_9$$

with the assumption that EFA revealed nine factors or less since Cha (2013a) and Rubin (1983) designed the survey instrument with 31 questions to capture these nine motives. Similarly, I computed variables for the value of Y_{TV} results by summing the responses for each sports content type on a particular digital device as shown in Figure 6 and repeated the computation for each of the remaining three digital devices. I checked for normality of each composite variable X_i in my regression model and defined the regression parameters. I conducted a regression analysis for each of the remaining three digital devices upon setting these options. Following the methodology of Cha (2013a), the model initially considers the nine main effect variables.

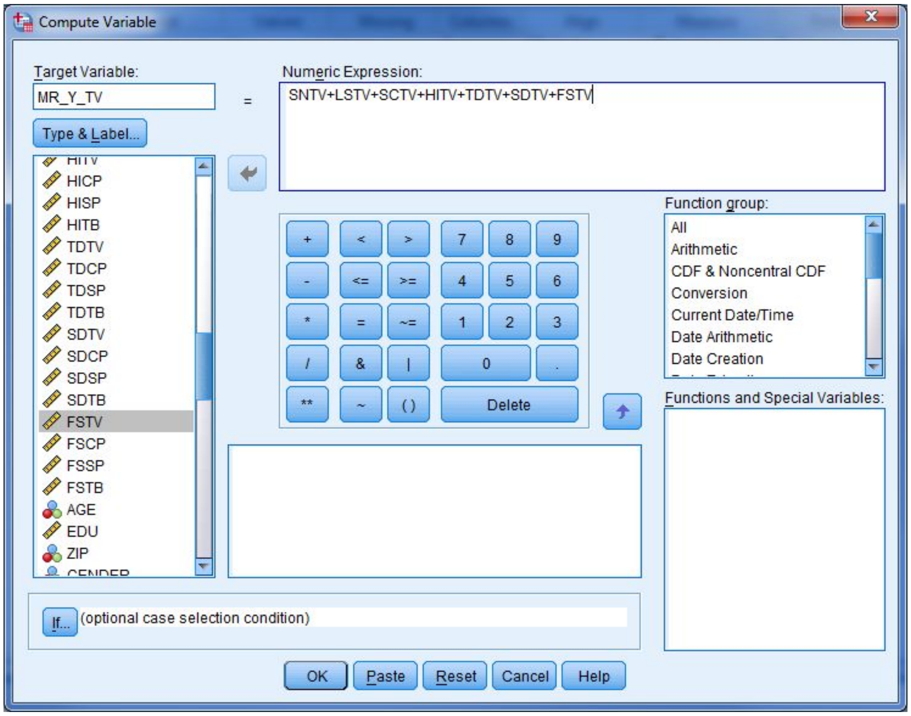

Figure 6. Add values of like variables for the Y variable in multiple regression.

One-Way Repeated Measures ANOVA

Three assumptions formed the basis of one-way repeated measures ANOVA: (a) approximately normal distributed populations, (b) does not violate sphericity, and (c) dependent variable measured at the continuous level (Chen, 2015; Field, 2009; Watt et al., in press). In SPSS, I checked for sphericity using Maulchy's test. In the event the data failed to meet this assumption, I used the Multivariate test to check for sphericity (Field, 2009) and checked each dependent variable for approximate normality by examining its distribution. I performed the following steps to correct for nonnormality in SPSS: (a) find the best value of Lambda using SPSS vector and looping commands based on Box-Cox, (b) select *Transform - Compute Variable* from the menu, (c) enter the transform equation based on Box-Cox best value of Lambda as a numeric expression, and (d) check transformed variable for normality. If I was unable to normalize the data, I planned to use Friedman's test instead of one-way repeated measures ANOVA.

I performed one-way repeated measures ANOVA by selecting (a) *Analyze – General Linear Model – Repeated Measures*, (b) entered the factor name (e.g. Television), (c) entered 7 as the number of levels, (d) and then moved the specific device survey questions (e.g. SNTV, LSTV, SCTV, HITV, TDTV, SDTV, and FSTV) to the *Within-Subjects Variables* window. I (a) changed the *Contrasts* to *Repeated*, (b) selected a plot of the factor variable, (c) defined the parameters as shown in Figure 7, (d) and performed the analysis.

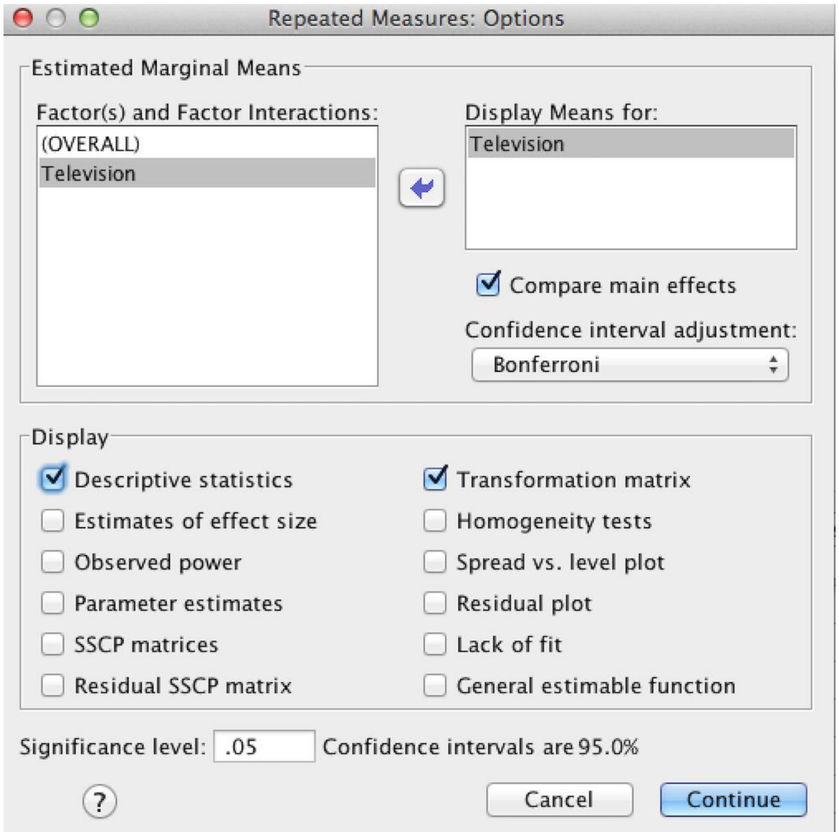

Figure 7. One-way repeated measures ANOVA options choices.

Table 16 displays a hypothetical summary of the Tests of Within-Subjects Effects. The sum of squares indicated how much of the variability is explained by the experiment, and the F-ratio indicates if the expected values in the group differ. I checked to determine if the Maulchly's test is nonsignificant which the data did not meet the sphericity condition.

Table 16

Hypothetical Example Test of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
tablet	Sphericity Assumed	125.063	6	20.844	17.675	.000
	Greenhouse-Geisser	125.063	4.522	27.655	17.675	.000
	Huynh-Feldt	125.063	4.606	27.153	17.675	.000
	Lower-bound	125.063	1.000	125.063	17.675	.000
Error(tablet)	Sphericity Assumed	1974.080	1674	1.179		
	Greenhouse-Geisser	1974.080	1261.703	1.565		
	Huynh-Feldt	1974.080	1285.055	1.536		
	Lower-bound	1974.080	279.000	7.076		

In this hypothetical case, I concluded that the data did not meet the sphericity condition because the significance value (.000) of the Maulchly's test is less than the critical value of .05. I calculated the lower limit of the Greenhouse-Geiser correction (ε = 1/(7-1), or 0.167) and compared this value to the calculated value of 0.754. Since the value is closer to the upper limit of 1, there is no substantial deviation sphericity. The significance of the F-ratio is .000, indicating that there are significant differences between sports content types. The conclusion was confirmed using the Multivariate Tests, where the significance values show that the multivariate tests are significant because *p* is .000, which is less than criterion value of .05.

Since the one-way repeated measures ANOVA indicated that there are significant differences, I examined the estimated marginal means as shown in Figure 8 that graphically displays what the intention level users have for viewing sports content across the four digital devices.

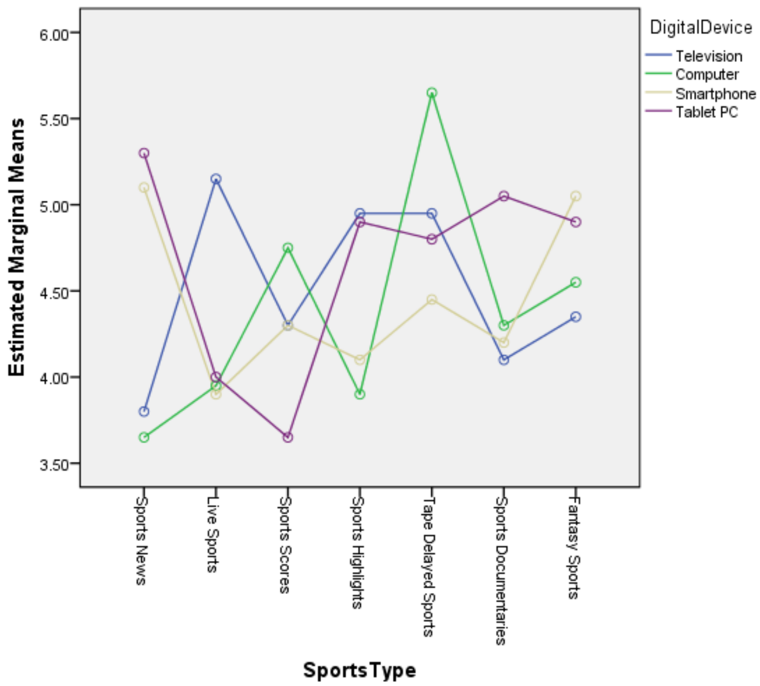

Figure 8. Hypothetical example graph of estimated marginal means of Intention

Study Validity

Validity refers to whether a study or an instrument contains the measurements the researcher intended to measure (Field, 2009). Validity also involves internal and external threats. The four key areas of validity addressed in the study include (a) *external validity*, (b) *internal validity*, (c) *empirical validity*, and (d) *conclusion validity*. For this study, I focused on determining what factors motivate sports viewership. Motivational factors include (a) relaxation, (b) companionship, (c) habit, (d) pass time, (e) entertainment, (f) social interaction, (g) information gathering, (h) arousal, and (i) escape measure sports viewership motivation. I sought to prove the validity of this measure by randomly selecting users 18 and older in the contiguous United States.

External Validity

External validity is the extent to which the results of a research study applies to a larger population outside of the research sample (Becker et al., 2015; Gonzalez-Huerta, Insfran, Abrahao, & Scanniello, 2015; Zhi et al., 2015). I took the following steps to ensure external validity: (a) ensure the random sample population comprises of users who own a television, computer, smartphone, and tablet; (b) ensure collected data has an even split gender quota; and (c) ensure sample participants reside in urban and nonurban locations.

Internal Validity

Internal validity is the extent to which a research study's design and resulting data allow the researcher to draw accurate conclusions (Becker et al., 2015; Gonzalez-Huerta et al., 2015; Zhi et al., 2015). I took the following steps to ensure internal validity: (a) randomly select participants, (b) use the same survey for all participants, and (c) only use completed surveys in the analysis.

Empirical Validity

Empirical validity, otherwise known as statistical or predictive validity, is a measure of how repeatable the results of a study are over time (Kettlers & Albers, 2013). The issue of empirical validity is not relevant to the current study based on the stated limitation that a quantitative comparative study provides the viewing characteristics of a digital device user at the time of the survey and does not account for any changes with time.

Conclusion Validity

Conclusion validity examines issues that may affect making correct conclusions about relationships and outcomes in a study (Becker et al., 2015; Paydar & Kahani, 2015; Zhi et al., 2015). The main threats to conclusion validity were the data collection, and the validity of the statistical tests applied (Gonzalez-Huerta et al., 2015). I took the following steps to ensure conclusion validity: (a) have a sufficient sample size for the statistical methods applied, (b) survey participants must own all four digital device types, and (c) apply statistical methods employed by other researchers for similar studies.

Transition and Summary

Section 2 provided the research plan propose to develop the findings and conclusions of Section 3. The plan included (a) the study purpose, (b) role of the researcher, (c) methodology, (d) design, (e) sampling, (f) data collection, (g) data analysis, and (h) validation. Section 2 outlined the roadmap to executing a successful research, and I did not collect any research data before approval from Walden University's Institutional Review Board (IRB). After receiving IRB approval, I collected and analyzed data as outlined in Section 2 for the presentation of the results in Section 3.

Section 3: Application to Professional Practice and Implications for Change

In Section 3, I (a) restate the purpose of the study, (b) present the findings of the study, (c) discussed the application to professional practice, (d) express implications to social change, (e) recommend further action, and (f) suggest further study related to improved practice in business. Finally, Section 3 includes a reflection on my experience within the DBA Doctoral Study process.

Introduction

The purpose of this quantitative comparative cross-sectional study was to answer the overarching question: Identify what motivates consumers to view specific sports content on what digital device? The study was designed to generate information that will enable content providers and advertising managers improve market segment prioritization across four digital devices. The study results extended prior research by indicating (a) what motives influenced sports viewership on digital devices, (b) what motives adequately predicted the intention to view specific sports content on digital devices, and (c) what significant viewing differences existed by digital devices across each of the seven types of sports content types.

Reviewing the results of the study, I observed eight overall motives influenced sports viewership on digital devices. Although all eight motives contributed to predicting the intention to view specific sports content on digital devices, escape and enjoyment ranked as the strongest predictors. Furthermore, the results showed possible distinguishing trends in viewership intentions between older and younger viewership groups. For example, a key finding was that younger viewers show a greater intent to consume sports content on digital devices rather than television when compared to their older counterparts. Additionally, the results of this research confirmed and expanded on Cha's (2013a) general research on movie genres, which served as a model for this study. The results of this research also confirmed that Internet-enabled devices are viable video platforms and can grow as a threat to television.

Presentation of the Findings

I took a number of steps and techniques in SPSS to prepare, transform, and assess the survey data fitness and satisfaction of various statistical assumptions before applying the various statistical techniques needed to answer the research questions and hypotheses. The first step I took was to examine the descriptive statistics of the survey questions for the entire survey population as shown in Table 17.

Table 17

Descriptive Statistics

Variable	*n*	*M*	*Mdn*	*SD*	Coefficient of Variation
RLX1	525	5.16	5.00	1.650	31.98%
RLX2	525	4.94	5.00	1.637	33.14%
RLX3	525	5.20	6.00	1.583	30.44%
COMP1	525	2.81	2.00	1.595	56.76%
COMP2	525	3.16	3.00	1.772	56.08%
COMP3	525	2.66	2.00	1.559	58.61%
HAB1	525	3.84	4.00	1.751	45.60%
HAB2	525	5.77	6.00	1.444	25.03%
HAB3	525	4.04	4.00	1.812	44.85%
PAS1	525	3.92	4.00	1.795	45.79%
PAS2	525	4.07	5.00	1.796	44.13%
PAS3	525	4.28	5.00	1.758	41.07%
ENT1	525	6.00	6.00	1.301	21.68%
ENT2	525	5.96	6.00	1.342	22.52%
ENT3	525	5.49	6.00	1.467	26.72%
SOC1	525	5.19	6.00	1.623	31.27%
SOC2	525	4.89	5.00	1.734	35.46%
SOC3	525	5.13	5.00	1.696	33.06%
INF1	525	4.64	5.00	1.770	38.15%
INF2	525	4.90	5.00	1.740	35.51%
INF3	525	4.71	5.00	1.796	38.13%
INF4	525	4.53	5.00	1.785	39.40%
INF5	525	2.83	2.00	1.672	59.08%
INF6	525	3.26	3.00	1.766	54.17%
INF7	525	3.47	3.00	1.852	53.37%
ARO1	525	5.70	6.00	1.324	23.23%
ARO2	525	5.88	6.00	1.251	21.28%
ARO3	525	5.24	6.00	1.551	29.60%
ESC1	525	3.80	4.00	1.908	50.21%
ESC2	525	2.81	2.00	1.675	59.61%
ESC3	525	3.38	4.00	1.851	54.76%

The second step I took was to examine the descriptive statistics of the survey questions by gender as shown in Table 18. There were 262 male and 263 female research participants. As originally suspected before launching the research and confirmed by Table 18, male research participants scored the survey questions differently than female research participants. These results prompted additional statistical tests as explained further below.

Table 18

Survey Questions Descriptive Statistics by Gender

	Male				Female			
Variable	*M*	*Mdn*	*SD*	Coefficient of Variation	*M*	*Mdn*	*SD*	Coefficient of Variation
RLX1	5.66	6.0	1.458	25.76%	4.67	5.0	1.685	36.08%
RLX2	5.41	6.0	1.427	26.38%	4.48	5.0	1.700	37.95%
RLX3	5.55	6.0	1.426	25.69%	4.84	5.0	1.652	34.13%
COMP1	2.71	2.0	1.576	58.15%	2.92	3.0	1.611	55.17%
COMP2	3.32	3.0	1.844	55.54%	2.99	3.0	1.684	56.32%
COMP3	2.63	2.0	1.608	61.14%	2.70	2.0	1.510	55.93%
HAB1	3.68	4.0	1.793	48.72%	4.01	5.0	1.696	42.29%
HAB2	6.05	6.0	1.287	21.27%	5.49	6.0	1.538	28.01%
HAB3	4.15	5.0	1.847	44.51%	3.94	4.0	1.773	45.00%
PAS1	4.02	5.0	1.798	44.73%	3.83	4.0	1.791	46.76%
PAS2	4.18	5.0	1.766	42.25%	3.96	5.0	1.823	46.04%
PAS3	4.36	5.0	1.709	39.20%	4.19	5.0	1.804	43.05%
ENT1	6.32	7.0	.997	15.78%	5.67	6.0	1.477	26.05%
ENT2	6.28	6.5	1.015	16.16%	5.63	6.0	1.537	27.30%
ENT3	5.67	6.0	1.342	23.67%	5.32	6.0	1.564	29.40%
SOC1	5.21	6.0	1.606	30.83%	5.17	6.0	1.643	31.78%
SOC2	4.92	5.0	1.705	34.65%	4.86	5.0	1.765	36.32%
SOC3	4.93	5.0	1.763	35.76%	5.34	6.0	1.603	30.02%
INF1	4.89	5.0	1.661	33.97%	4.39	5.0	1.842	41.96%
INF2	5.03	5.0	1.696	33.72%	4.76	5.0	1.777	37.33%
INF3	4.92	5.0	1.762	35.81%	4.50	5.0	1.807	40.16%
INF4	4.74	5.0	1.720	36.29%	4.33	5.0	1.826	42.17%
INF5	2.88	2.0	1.726	59.93%	2.77	2.0	1.618	58.41%
INF6	3.42	3.0	1.875	54.82%	3.11	3.0	1.638	52.67%
INF7	3.51	3.0	1.871	53.30%	3.43	6.0	1.835	53.50%
ARO1	5.97	6.0	1.095	18.34%	5.44	6.0	1.473	27.08%
ARO2	6.11	6.0	.988	16.17%	5.66	6.0	1.435	25.35%
ARO3	5.36	6.0	1.449	27.03%	5.13	5.0	1.640	31.97%
ESC1	3.85	4.0	1.906	49.51%	3.75	4.0	1.913	51.01%
ESC2	3.12	3.0	1.783	57.15%	2.51	2.0	1.503	59.88%
ESC3	3.60	3.0	1.892	52.56%	3.17	3.0	1.787	56.37%

The third step I took was to examine the descriptive statistics of the survey questions by age as shown in Table 19. There were 280 research participants ages 18-34, and 245 research participants ages 35 and older. As originally suspected before launching the research and confirmed by Table 19, younger research participants scored the survey questions differently than older research participants. These results prompted additional statistical tests as explained further below.

Table 19

Survey Questions Descriptive Statistics by Age

	Ages 18 - 34				Ages 35 and Older			
Variable	*M*	*Mdn*	*SD*	Coefficient of Variation	*M*	*Mdn*	*SD*	Coefficient of Variation
RLX1	5.09	5.0	1.727	33.93%	5.25	5.0	1.557	29.66%
RLX2	4.89	5.0	1.706	34.89%	5.01	5.0	1.555	31.04%
RLX3	5.23	5.0	1.604	30.67%	5.16	6.0	1.561	30.25%
COMP1	3.00	2.0	1.675	55.83%	2.60	2.0	1.472	56.62%
COMP2	3.28	3.0	1.813	55.27%	3.01	2.0	1.717	57.04%
COMP3	2.75	2.0	1.669	60.69%	2.57	2.0	1.420	55.25%
HAB1	4.15	5.0	1.711	41.23%	3.49	3.0	1.733	49.66%
HAB2	5.71	6.0	1.441	25.24%	5.84	6.0	1.448	24.79%
HAB3	4.41	5.0	1.804	40.91%	3.62	3.0	1.732	47.85%
PAS1	4.19	5.0	1.782	42.53%	3.62	3.0	1.765	48.76%
PAS2	4.37	5.0	1.767	40.43%	3.72	4.0	1.769	47.55%
PAS3	4.59	5.0	1.700	37.04%	3.92	4.0	1.760	44.90%
ENT1	5.90	6.0	1.382	23.42%	6.11	6.0	1.194	19.54%
ENT2	5.84	6.0	1.422	24.35%	6.09	6.0	1.233	20.25%
ENT3	5.60	6.0	1.421	25.38%	5.37	6.0	1.511	28.14%
SOC1	5.39	6.0	1.541	28.59%	4.96	5.0	1.686	33.99%
SOC2	5.03	6.0	1.673	33.26%	4.73	5.0	1.792	37.89%
SOC3	5.32	6.0	1.669	31.37%	4.92	5.0	1.704	34.63%
INF1	4.60	5.0	1.839	39.98%	4.69	5.0	1.690	36.03%
INF2	4.91	5.0	1.741	35.46%	4.88	5.0	1.743	35.72%
INF3	4.68	5.0	1.868	39.91%	4.75	5.0	1.713	36.06%
INF4	4.47	5.0	1.859	41.59%	4.61	5.0	1.697	36.81%
INF5	3.03	2.0	1.805	59.57%	2.59	2.0	1.475	56.95%
INF6	3.43	3.0	1.814	52.89%	3.08	3.0	1.694	55.00%
INF7	3.68	3.0	1.957	53.18%	3.22	3.0	1.695	52.64%
ARO1	5.69	6.0	1.363	23.95%	5.72	6.0	1.280	22.38%
ARO2	5.89	6.0	1.299	22.05%	5.87	6.0	1.197	20.39%
ARO3	5.29	6.0	1.622	30.66%	5.19	5.0	1.467	28.27%
ESC1	4.05	4.0	1.895	46.79%	3.51	3.0	1.885	53.70%
ESC2	2.91	2.0	1.773	60.93%	2.70	2.0	1.552	57.48%
ESC3	3.52	3.0	1.906	54.15%	3.23	3.0	1.778	55.05%
INF7	3.68	3.0	1.957	53.18%	3.22	3.0	1.695	52.64%
ARO1	5.69	6.0	1.363	23.95%	5.72	6.0	1.280	22.38%
ARO2	5.89	6.0	1.299	22.05%	5.87	6.0	1.197	20.39%
ARO3	5.29	6.0	1.622	30.66%	5.19	5.0	1.467	28.27%
ESC1	4.05	4.0	1.895	46.79%	3.51	3.0	1.885	53.70%
ESC2	2.91	2.0	1.773	60.93%	2.70	2.0	1.552	57.48%
ESC3	3.52	3.0	1.906	54.15%	3.23	3.0	1.778	55.05%

I then conducted a survey instrument reliability test using the Split-Half method that renders the Cronbach alpha. I used SPSS to split the (a) odd and even questions, (b) add the responses for each grouping, and (c) calculate the Split-Half Reliability coefficient to assess the consistency of scores between the two equivalent measures. The

Split-Half coefficient value was .947, which fell between 0 and 1 indicating the responses are equivalent as shown in Table 20. I confirmed an even split gender quota by conducting a cross-tabulation, which indicated 262 male and 263 female survey participants.

Table 20

Split-Half Reliability Statistics

Statistic	Model		Value
Cronbach's Alpha	Part 1	Value	.907
		n	30[a]
	Part 2	Value	.916
		n	29[b]
	Total *n*		59
Correlation Between Forms			.900
Spearman-Brown Coefficient	Equal Length		.947
	Unequal Length		.947
Guttman Split-Half Coefficient			.947

Note. [a]The items are: RLX1, RLX3, COMP2, HAB1, HAB3, PAS2, ENT1, ENT3, SOC2, INF1, INF3, INF5, INF7, ARO2, ESC1, ESC3, SNTV, SNSP, LSTV, LSSP, SCTV, SCSP, HITV, HISP, TDTV, TDSP, SDTV, SDSP, FSTV, FSSP. [b]The items are: RLX2, COMP1, COMP3, HAB2, PAS1, PAS3, ENT2, SOC1, SOC3, INF2, INF4, INF6, ARO1, ARO3, ESC2, SNCP, SNTB, LSCP, LSTB, SCCP, SCTB, HICP, HITB, TDCP, TDTB, SDCP, SDTB, FSCP, FSTB.

I used Cronbach's alpha to check the internal consistency and thus reliability. The overall Cronbach's alpha as .953 as shown in Table 21. Researchers noted randomly and internally distributed surveys have a high Cronbach's alpha (Field, 2009). I also examined the survey responses and found no missing data.

Table 21

Cronbach Alpha Reliability Statistic

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	*n*
.953	.955	59

The aforementioned descriptive analysis indicated that there was dispersion in the survey questions across a few specific demographics and thus importance placed on certain questions than others by such demographic segments. As such, I applied exploratory factor analysis (EFA) to determine what specific questions were key or carried more weight than others in the survey, and how I could group these questions into overarching constructs or factors. Multiple linear regression was applied to determine what constructs or factors adequately predict the intention to view specific sports content. Similarly, Friedmans test was applied to determine what type of sports content consumers intend to view on each digital device examined. Each of these statistical techniques fully aligned with specific Research Questions as explained in more detail below.

Research Question 1

Using Research Question 1 (RQ1), I addressed what subset of survey questions adequately captured the nine motives. Specifically, exploratory factor analysis (EFA) addressed the following research question, SRQ1-EFA: What subset of survey questions adequately captures the nine motives? To answer this question, I confirmed compliance to exploratory factor analysis (EFA) guidelines. The first step undertaken was to check for multivariate normality. After identifying the questions under each factor, I created eight variables representing each identified factor for use in RQ2 for multiple linear regression. The second step I took was to check for linear relationships. I performed a correlation between the eight factor variables and a scatterplot of 8x8 correlations. I tested the normality and linear relations assumptions vigorously as part of the multiple regression analysis. The third step undertaken was to choose an appropriate rotation to which I chose an oblique rotation (Promax). The fourth step I took included checking factorability. I checked the Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity. The Kaiser-Meyer-Olkin (KMO) measure, KMO = .914, verified the sampling adequacy for the analysis as superb (Field 2009). Additionally, the average communality was 0.758. Based on Kaisers rule, I extracted the recommended eight factors since the sample size exceeded 250, and the average communality was greater than 0.6 (Field, 2009). Table 22 shows the item communalities. Bartlett's test of sphericity χ^2 (465) = 11732.5, p < .001, indicated that correlation between items was sufficiently large for EFA. The EFA guideline recommended an adequate sample size of 10 participants per item. For the study, I had a total of nine initial items and 525 participants, which provided a 58:1 participant to item ratio.

Table 22

Exploratory Factor Analysis Item Communalities

Item	Initial	Extraction
RLX1	1.000	.819
RLX2	1.000	.863
RLX3	1.000	.761
COMP1	1.000	.769
COMP2	1.000	.630
COMP3	1.000	.830
HAB1	1.000	.592
HAB2	1.000	.690
HAB3	1.000	.501
PAS1	1.000	.785
PAS2	1.000	.823
PAS3	1.000	.740
ENT1	1.000	.828
ENT2	1.000	.860
ENT3	1.000	.660
SOC1	1.000	.675
SOC2	1.000	.778
SOC3	1.000	.758
INF1	1.000	.804
INF2	1.000	.813
INF3	1.000	.837
INF4	1.000	.755
INF5	1.000	.782
INF6	1.000	.790
INF7	1.000	.791
ARO1	1.000	.781
ARO2	1.000	.857
ARO3	1.000	.669
ESC1	1.000	.701
ESC2	1.000	.739
ESC3	1.000	.810

I ran an initial analysis to obtain eigenvalues for each data component. Eight components had eigenvalues over Kaiser’s criterion of 1 or higher. These eigenvalues in combination explained 75.78% of the variance as shown in Table 23.

Table 23

Total Variance Explained for Exploratory Factor Analysis

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.723	34.589	34.589	10.723	34.589	34.589	8.335
2	4.260	13.743	48.332	4.260	13.743	48.332	4.342
3	2.226	7.180	55.512	2.226	7.180	55.512	7.471
4	1.576	5.085	60.597	1.576	5.085	60.597	4.770
5	1.431	4.617	65.214	1.431	4.617	65.214	6.620
6	1.184	3.821	69.035	1.184	3.821	69.035	5.048
7	1.056	3.405	72.440	1.056	3.405	72.440	5.547
8	1.035	3.338	75.778	1.035	3.338	75.778	4.344
9	.696	2.246	78.023				
10	.596	1.924	79.947				
11	.517	1.667	81.614				
12	.494	1.592	83.207				
13	.480	1.549	84.756				
14	.430	1.387	86.143				
15	.418	1.348	87.490				
16	.406	1.308	88.799				
17	.355	1.144	89.942				
18	.343	1.107	91.050				
19	.309	.996	92.046				
20	.300	.967	93.012				
21	.278	.898	93.910				
22	.269	.867	94.777				
23	.251	.809	95.585				
24	.245	.791	96.377				
25	.210	.676	97.053				
26	.205	.662	97.715				
27	.191	.616	98.331				
28	.162	.524	98.855				
29	.145	.469	99.323				
30	.127	.410	99.733				
31	.083	.267	100.000				

Additionally, the scree plot shown in Figure 9 showed a clear inflexion that would justify retaining the first eight components as suggested by the Kaiser criterion. Given the alignment of these two criteria, I retained eight components by performing a factor extraction using principal component analysis (PCA) and factor rotation using the Promax oblique rotation. I grouped specific questions under each of the eight identified factors.

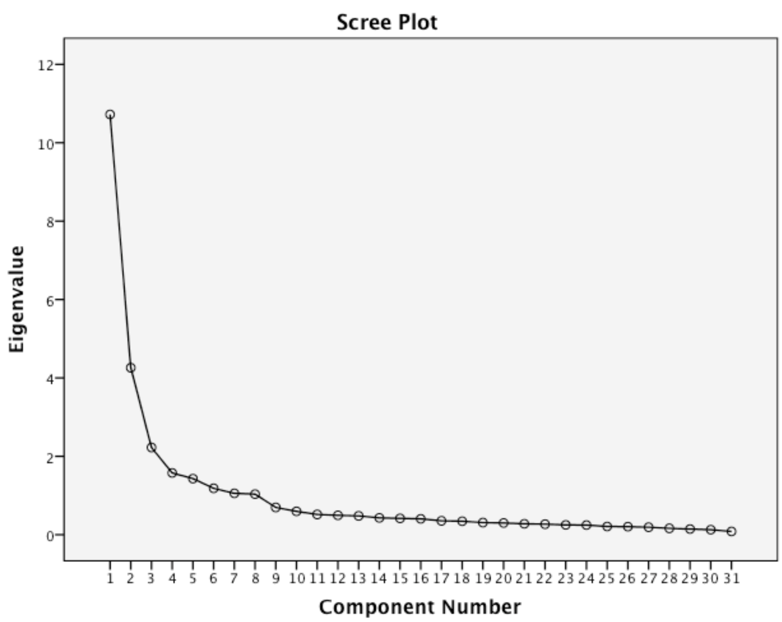

Figure 9. Factor analysis scree plot.

As shown in the Table 24, EFA generated high loadings for Factor 1 with questions (a) ARO2, (b) ARO1, (c) ENT1, (d) ENT3, (e) ENT2, (f) ARO3, (g) HAB2, (h) RLX3, and (i) SOC1. All such questions related to the “enjoyment” family of questions or construct; thus Factor 1 represents F_ENJOY.

Table 24

Exploratory Factor Analysis Pattern Matrix

	Component							
	1	2	3	4	5	6	7	8
ARO2	.942							
ARO1	.928				-.121			
ENT1	.871				.108			
ENT3	.868	.138					-.117	
ENT2	.824				.151			
ARO3	.770	-.123		.106	-.109	.126		
HAB2	.678	.124		-.118	.232			
PAS1		.918						
PAS2		.905						
PAS3		.762					.134	
HAB1		.760	-.142				-.154	.101
HAB3		.434	.105	.109	.204			.109
INF2			.948					
INF3			.923					
INF4			.865					
INF1			.815					
INF7				.898				
INF5				.869	.103			
INF6				.821				
RLX2					.951			
RLX1					.870			
RLX3	.115				.818			
SOC3						.898		
SOC2			.156	-.131		.828		
SOC1	.144					.776		
ESC3					.101		.885	
ESC2				.128		-.145	.857	
ESC1						.117	.785	
COMP3								.934
COMP1		-.105				.118		.862
COMP2		.169				-.122		.737

Note. Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization. Rotation converged in 7 iterations.

A similar rationale of naming the remaining items that clustered on the same component suggested the following seven factors: (a) Factor 2 represented Leisure (F_LEISURE), (b) Factor 3 represented Sports Information (F_SPINFO), (c) Factor 4 represented Self-Actualization Sports Information (F_MEINFO), (d) Factor 5 represented

Relaxation (F_RLX), (e) Factor 6 represented Social (F_SOC), (f) Factor 7 represented Escape (F_ESC), and (g) Factor 8 represented Companionship (F_COMP). Table 25 shows the factor, name, and clustered questions.

Table 25

Factor Summary

Factor Number	Factor Name	Questions
1	F_ENJOY	ARO2, ARO1, ENT1, ENT3, ENT2, ARO3, HAB2, RLX3, and SOC1
2	F_LEISURE	ENT3, ARO3, HAB2, PAS1, PAS2, PAS3, HAB1, HAB3, COMP1, and COMP2
3	F_SPINFO	HAB1, HAB3, INF2, INF3, INF4, INF1, and SOC2
4	F_MEINFO	ARO3, HAB2, HAB3, INF7, INF5, INF6, SOC2, and ESC2
5	F_RLX	ARO1, ENT1, ENT2, ARO3, HAB2, HAB3, INF5, RLX2, RLX1, RLX3, and ESC3
6	F_SOC	ARO3, SOC3, SOC2, SOC1, ESC2, ESC1, COMP1, and COMP2
7	F_ESC	ENT3, PAS3, HAB1, ESC3, ESC2, and ESC1
8	F_COMP	HAB1, HAB3, COMP3, COMP1, and COMP2

Research Question 2

Using Research Question 2 (RQ2), I addressed what motives adequately predicted the intention to view specific sports content on digital devices. Specifically, multiple regression answered the following research question: SRQ2-REGR: What motives adequately predict the intention to view a specific sports content type on each of the subject digital devices? To answer this question, I created eight composite variables X_i representing each identified factor as shown in Table 26 after identifying the questions under each factor from EFA.

Table 26

Computing Multiple Regression Composite Variables

Factor Name	Questions for Generating Summative Index X_i	Composite Variable
F_ENJOY	ARO2 + ARO1 + ENT1 + ENT3 + ENT2 + ARO3 + HAB2 + RLX3 + SOC1	X_1
F_LEISURE	ENT3 + ARO3 + HAB2 + PAS1 + PAS2 + PAS3 + HAB1 + HAB3 + COMP1 + COMP2	X_2
F_SPINFO	HAB1 + HAB3 + INF2 + INF3 + INF4 + INF1 + SOC2	X_3
F_MEINFO	ARO3 + HAB2 + HAB3 + INF7 + INF5 + INF6 + SOC2 + ESC2	X_4
F_RLX	ARO1 + ENT1 + ENT2 + ARO3 + HAB2 + HAB3 + INF5 + RLX2 + RLX1 + RLX3 + ESC3	X_5
F_SOC	ARO3 + SOC3 + SOC2 + SOC1 + ESC2 + ESC1 + COMP1 + COMP2	X_6
F_ESC	ENT3 + PAS3 + HAB1 + ESC3 + ESC2 + ESC1	X_7
F_COMP	HAB1 + HAB3 + COMP3 + COMP1 + COMP2	X_8

As shown in Table 26, I captured each X_i by a summative index where each survey question was weighted with the actual eigenvalues or loadings generated by EFA. Alternatively, I could weight each survey question equally with an equal weight of 1. I choose the eigenvalue weighting for each question, but both methodologies were identical and results reproducible. These eight composite variables formed the linear regression model of the form below to predict the dependent variable Y_n for the n-th device (n = 1 to 4) representing the intention to view sports content.

$$\hat{Y}_n = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 + B_6X_6 + B_7X_7 + B_8X_8$$

The computation of each of the actual Y_n's was obtained by summing the responses for the tendency to watch a specific sports content type on a particular digital device and I repeated the computation for each of the four digital devices as shown in Table 27.

Table 27

Composition of Multiple Regression Y_i Variables

Computed Variable Y_n	Responses of Each Sports Content Type
Y_{TV}	SNTV + LSTV + SCTV + HITV + TDTV + SDTV + FSTV
Y_{CP}	SNCP + LSCP + SCCP + HICP + TDCP + SDCP + FSCP
Y_{SP}	SNSP + LSSP + SCSP + HISP + TDSP + SDSP + FSSP
Y_{TB}	SNTB + LSTB + SCTB + HITB + TDTB + SDTB + FSTB

Multiple regression analysis requires that the regression residual errors have a normal distribution and as such, I tested this assumption following the application of regression. It is not necessary for each X_i to have a normal distribution before performing a multiple regression analysis. However, the normality of each X_i itself will strengthen the regression model.

Therefore, I performed a normality check on each independent variable X_i *prior* to applying multiple regression analysis and checked the well-known regression assumptions of hosmoscedacity and normality of the residual regression errors *after* completing the regression analysis. Upon checking for multivariate normality of each independent composite variable X_1 to X_8, I discovered that none of these composite variables had a normal distribution. For example, Figure 10 shows the distribution for F_ENJOY before normalization with a skewness statistic of -1.821 and .107 standard error.

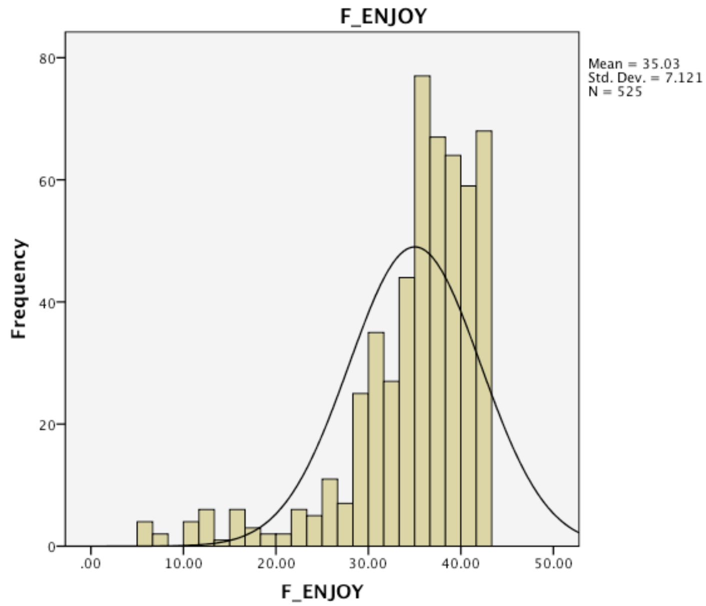

Figure 10. Distribution of composite variable F_ENJOY before normalization.

Table 28 shows the Kolmogorov-Smirnova (KS) and Shapiro-Wilk (SW) values before normalization. The significance value for each composite variable was significant, indicating nonnormality since the H_0 tested by both of these tests was given by H_0: the sample for X_i was drawn from a normal distribution.

Table 28

Test for Normality of Each Construct or Composite Variable X_i

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Construct	Statistic	*df*	Sig.	Statistic	*df*	Sig.
F_ENJOY	.153	525	.000	.830	525	.000
F_LEISURE	.077	525	.000	.969	525	.000
F_SPINFO	.092	525	.000	.948	525	.000
F_MEINFO	.094	525	.000	.954	525	.000
F_RLX	.085	525	.000	.949	525	.000
F_SOC	.085	525	.000	.945	525	.000
F_ESC	.078	525	.000	.968	525	.000
F_COMP	.107	525	.000	.950	525	.000

Note. [a]Lilliefors Significance Correction

Given that the normality tests revealed that all eight constructs represented by the eight composite X_i's were nonnormal, an attempt was made to normalize each. I first tried the Box-Cox normalization transformation method described in Table 13 with no success. I then implemented another method presented by Templeton (2011) to successfully normalize the composite variables. In summary, Templeton's method worked extremely well for skewed distributions and was applied as follows: (a) rank the composite variable, (b) compute the normal inverse distribution function, and (c) return a normal distribution for the composite variable with approximately the same mean and standard deviation of the original distribution. I performed this transformation for all composite variables and successfully created new normalized variables for use in the multiple regression analysis. Figure 11 shows the distribution for NF_ENJOY (X_1) after normalization with a skewness statistic of -.003 and .107 standard error.

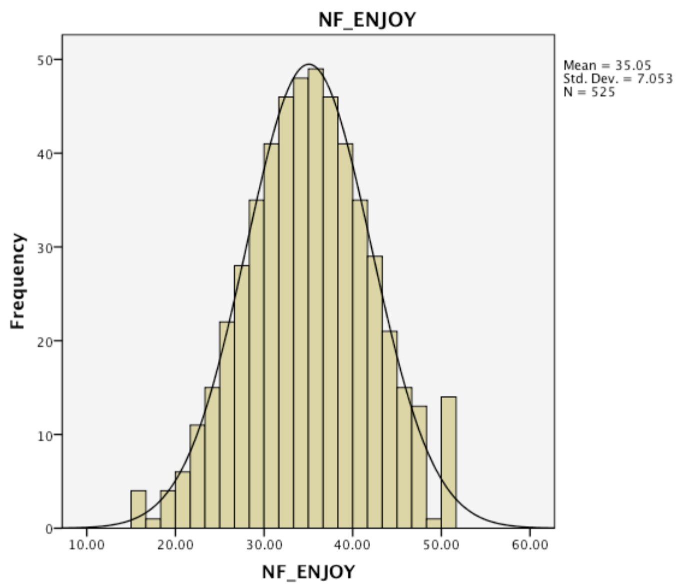

Figure 11. Distribution of composite variable NF_ENJOY after normalization.

Table 29 shows the Kolmogorov-Smirnova (KS) and Shapiro-Wilk (SW) values after normalization. The significance value for each composite variable is nonsignificant, indicating normality.

Table 29

Post-Normalization Test for Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
NF_ENJOY	.015	520	.200*	.996	520	.153
NF_LEISURE	.005	520	.200*	.999	520	1.000
NF_SPINFO	.006	520	.200*	.999	520	1.000
NF_MEINFO	.005	520	.200*	1.000	520	1.000
NF_RLX	.005	520	.200*	.999	520	1.000
NF_SOC	.006	520	.200*	.999	520	.965
NF_ESC	.012	520	.200*	.999	520	1.000
NF_COMP	.027	520	.200*	.996	520	.288

Note. *This is a lower bound of the true significance. [a]Lilliefors Significance Correction

Note that we are interested in making inferences (significance values and confidence intervals) about each regression parameter (each b coefficient) and not inferences on the response variable Y_n. Thus, we do not need to test for the normality of each Y_n. Given the eight normalized variables, I then ran a multiple regression analysis with the eight X_i and one Y_n variables for each digital device. Table 30 shows the results of the four multiple regression analyses.

Table 30

Predictors of Intention to Use Television, Computer, Smartphone, and Tablet

	Television		Computer		Smartphone		Tablet	
	β	t	β	t	β	t	β	t
NF_ENJOY	.315	1.374	.107	.459	.546*	2.357	.266	1.095
NF_LEISURE	.179	.783	-.515*	-2.203	-.058	-.250	-.378	-1.556
NF_SPINFO	-.330	-1.123	.114	.380	.051	.172	-.143	-.458
NF_MEINFO	.131	.391	.123	.359	.128	.378	-.426	-1.198
NF_RLX	.180	.700	.340	1.300	.463	1.789	.651*	2.396
NF_SOC	.254	1.070	-.437	-1.809	.102	.427	-.069	-.274
NF_ESC	.714	1.407	.616	1.190	.273	.532	.661	1.230
NF_COMP	.269	.786	.016	.045	.490	1.418	.135	.372
R^2	.321		.294		.308		.238	
Adjusted R^2	.269		.241		.256		.180	

Note: * $p < .05$

With respect to the television, NF_ESC (Escape) had the highest β value followed by NF_SPINFO (Sports Information) and NF_ENJOY (Enjoyment). However, checking the *t*-statistics yields that none of the motivations had a significant contribution to the model. As a result, we accept the null hypothesis that none of the nine motives adequately predicts the intention to view specific sports content on the television. The regression model had an R^2 value of .321, indicating that the model explains 32.1% of the variability of the intention to view sports content on digital devices. Figure 12 shows the goodness of fit for the linear model with insignificant differences between the predicted and observed values.

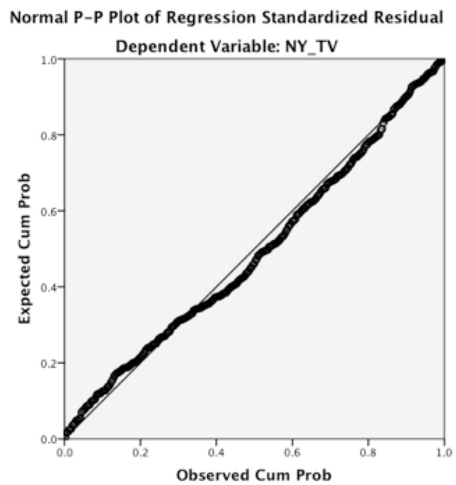

Figure 12. Normal P-P plot of regression standardized residual for NY-TV

With respect to the computer, NF_ESC (Escape) had the highest β value followed by NF_LEISURE (Leisure), NF_SOC (Social), and NF_RLX (Relaxation). Checking the *t*-statistics, only NF_LEISURE ($t(475) = -2.203$, $p < .05$) had significant contribution to the model. Interestingly, intention to use a computer for sports content viewership was negatively related to NF_LEISURE (Leisure) and NF_SOC (Social) motives. As a result, we reject the null hypothesis that none of the nine motives adequately predicts the intention to view specific sports content on the computer. The regression model had an R^2 value of .294, indicating that the model explains 29.4% of the variability of the intention to view sports content on digital devices. Figure 13 shows the goodness of fit for the linear model with insignificant differences between the predicted and observed values.

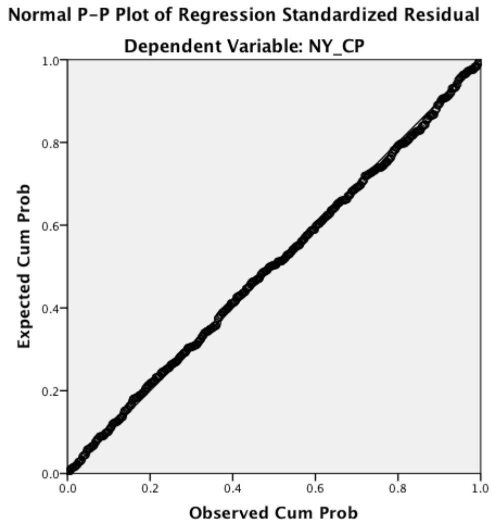

Figure 13. Normal P-P plot of regression standardized residual for NY-CP

With respect to the smartphone, NF_ENJOY (Enjoyment) had the highest β value followed by NF_RLX (Relaxation) and NF_COMP (Companionship). Checking the *t*-statistics, only NF_ENJOY ($t(475) = 2.357$, $p < .05$) had a significant contribution to the model. As a result, we reject the null hypothesis that none of the nine motives adequately predicts the intention to view specific sports content on the smartphone. The regression model had an R^2 value of .308, indicating that the model explains 30.8% of the variability of the intention to view sports content on digital devices. Figure 14 shows the goodness of fit for the linear model with insignificant differences between the predicted and observed values.

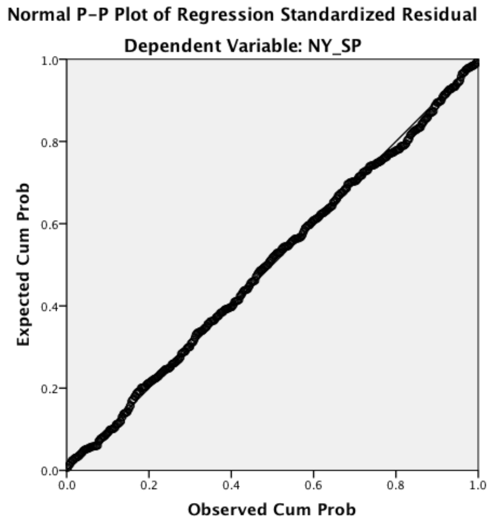

Figure 14. Normal P-P plot of regression standardized residual for NY-SP

With respect to the tablet, NF_ESC (Escape) had the highest β value followed by NF_RLX (Relaxation), NF_MEINFO (Self-Actualization Sports Information), and NF_LEISURE (Leisure). Interestingly, the intention to use the tablet to view sports content was negatively related to NF_MEINFO. However, checking the t-statistic yields only NF_RLX ($t(475) = 2.396$, $p < .05$) makes a significant contribution to the model. As a result, we reject the null hypothesis that none of the nine motives adequately predicts the intention to view specific sports content on the tablet. The regression model had an R^2 value of .238, indicating that the model explains 23.8% of the variability of the intention to view sports content on digital devices. Figure 15 shows the goodness of fit for the linear model with insignificant differences between the predicted and observed values.

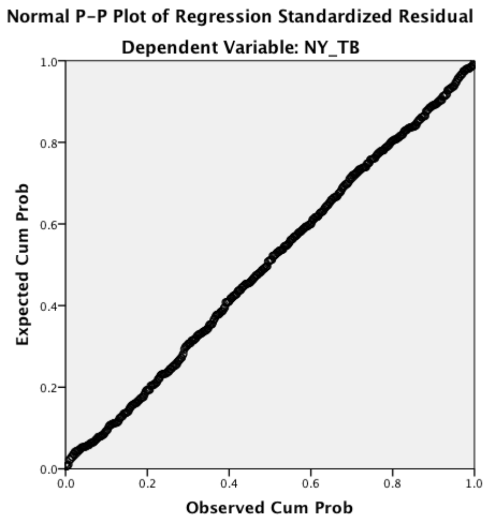

Figure 15. Normal P-P plot of regression standardized residual for NY-TB

After completing the multiple regression analysis, I tested the remaining assumptions, first testing for independent samples using the Durbin-Watson statistical tests. All Durbin-Watson statistical tests returned values close to 2 for the dependent variable Y_n as shown in Table 31, indicating independent errors were reasonable and the absence of autocorrelation (Field, 2009).

Table 31

Durbin-Watson Statistic for Each Digital Device

Dependent Variable	Durbin-Watson
NY_TV	2.072
NY_CP	2.120
NY_SP	2.044
NY_TB	1.982

Using the eight factors with two variable interactions yielded low values of R^2 as shown in Table 30. Using only eight factors with eigenvalue loadings greater than .6 and including the squares of the factors as regression terms, as well as, four factors with eigenvalue loadings greater than .6 and their respective squares made no improvement in the model's R^2 as shown in Table 32. Laicane, Blumberga, Blumberga, and Rosa (2015) noted that research involving humans have low R^2 values due to the wide variability in human behavior. However, if a low R^2 exists but the model has statistically significant predictors, researchers can still make important conclusions (Laicane, Blumberga, Blumberga, & Rosa, 2015).

Table 32

Results of Various Improvement Attempts for NY-TV R^2 Values

Factor Combinations	R^2 with All Loaded Eigenvalues	R^2 with Eigenvalue Loadings > .6
All 8 Factors with two variable interactions	.321	.294
All 8 Factors and their squares (e.g. Factor 1 * Factor 1)	.311	.312
4 Factors explaining 60% of the variance	.288	.279
4 Factors and their squares (e.g. Factor 1 * Factor 1)	.298	.292

The conclusion from the additional analysis was that only marginal improvement in the R^2 values resulted with the use of a more complex model. As a result, the simplest possible linear model is recommended. Therefore, my conclusions are based on results using the simplest linear model.

The next step was to check for linear relationships and homoscedasticity. I performed a correlation between the eight factor variables and a scatterplot of 8x8 correlations. Results showed compliance to linearity and homoscedasticity assumptions because regression plots for each device were randomly and evenly dispersed. Figure 16 shows the scatterplot for one of the four dependent variables NY_TV.

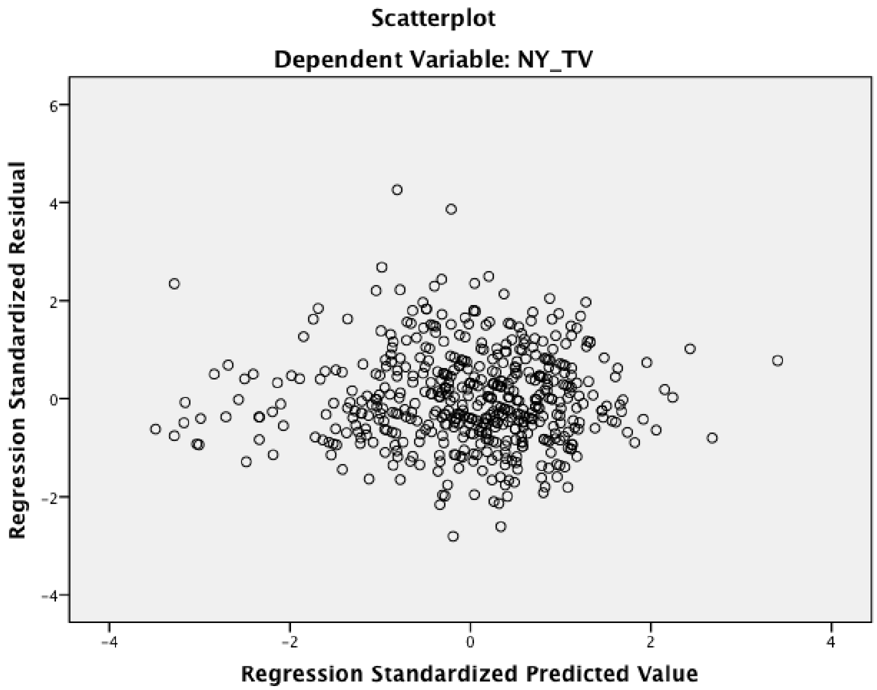

Figure 16. Scatterplot for dependent variable NY_TV.

Examining the correlation matrix yields the highest value of .651 as shown in Table 33, indicating that no predictor variables correlate highly and hence there is no multicollinearity present. I ran a reliability analysis and the Cronbach alpha for all composite variables was at least .65, which indicates that the variables measure the same motive (Field, 2009) as shown in Table 20.

Table 33

Correlation Matrix for Factors

Pearson Correlation	NY_TV	NF_ENJOY	NF_LEISURE	NF_SPINFO	NF_MEINFO	NF_RLX	NF_SOC	NF_ESC	NF_COMP
NY_TV	1.000	.426	.041	.461	.292	.408	.270	.219	.144
NY_CP	N/A	.397	.130	.415	.350	.423	.246	.330	.210
NY_SP	N/A	.422	.121	.416	.304	.414	.268	.334	.209
NY_TB	N/A	.322	.060	.359	.311	.346	.208	.268	.169
NF_ENJOY	.426	1.000	.138	.611	.263	.651	.441	.325	.171
NF_LEISURE	.041	.138	1.000	.176	.236	.226	.289	.420	.495
NF_SPINFO	.461	.611	.176	1.000	.448	.569	.397	.416	.252
NF_MEINFO	.292	.263	.236	.448	1.000	.323	.292	.467	.410
NF_RLX	.408	.651	.226	.569	.323	1.000	.349	.436	.286
NF_SOC	.270	.441	.289	.397	.292	.349	1.000	.336	.402
NF_ESC	.219	.325	.420	.416	.467	.436	.336	1.000	.462
NF_COMP	.144	.171	.495	.252	.410	.286	.402	.462	1.000

Research Question 3

Research Question 3 (RQ3) addressed what significant viewing differences exist by digital devices across each of the seven types of sports content, and concerning demographic information collected in the survey. Specifically, one-way repeated measures ANOVA addressed the following research question, SRQ3-ANOVA: What significant viewing differences exist by digital devices across each of the seven types of sports content and concerning demographic information collected in the survey? To answer this question, I first tested the dependent variables Y_n for normality. Upon checking for normality of dependent variables, I discovered that none of these variables had a normal distribution. Table 34 shows the Kolmogorov-Smirnova (KS) and Shapiro-Wilk (SW) values. The significance value for each variable was significant, indicating nonnormality. As a result, I could not use one-way repeated measures ANOVA parametric test for the analysis. Consequently, a nonparametric test such as Friedman's ANOVA was applied.

Table 34

Test of Normality

	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
SNTV	.162	525	.000	.927	525	.000
SNCP	.231	525	.000	.870	525	.000
SNSP	.248	525	.000	.836	525	.000
SNTB	.258	525	.000	.821	525	.000
LSTV	.226	525	.000	.882	525	.000
LSCP	.240	525	.000	.819	525	.000
LSSP	.265	525	.000	.751	525	.000
LSTB	.266	525	.000	.741	525	.000
SCTV	.126	525	.000	.942	525	.000
SCCP	.167	525	.000	.916	525	.000
SCSP	.140	525	.000	.924	525	.000
SCTB	.230	525	.000	.851	525	.000
HITV	.145	525	.000	.929	525	.000
HICP	.187	525	.000	.885	525	.000
HISP	.212	525	.000	.863	525	.000
HITB	.255	525	.000	.802	525	.000
TDTV	.203	525	.000	.855	525	.000
TDCP	.313	525	.000	.670	525	.000
TDSP	.345	525	.000	.629	525	.000
TDTB	.369	525	.000	.593	525	.000
SDTV	.173	525	.000	.894	525	.000
SDCP	.284	525	.000	.730	525	.000
SDSP	.353	525	.000	.610	525	.000
SDTB	.358	525	.000	.615	525	.000
FSTV	.356	525	.000	.639	525	.000
FSCP	.308	525	.000	.760	525	.000
FSSP	.306	525	.000	.747	525	.000
FSTB	.345	525	.000	.661	525	.000

I checked the assumptions of Friedman's ANOVA before applying the statistical technique. To attain compliance, I ensured (a) the group was from a random sample from the population, (b) a Likert Scale gathered the dependent data at the ordinal level, and (c) measured the group on three or more occasions. I confirmed compliance to all three assumptions and proceeded with the analysis.

I ran Friedman's test with 28 treatments, and the results indicated the viewership intention of participants changed regarding the consumption of sports content on digital devices, $\chi^2(27) = 4381.656$, $p > .05$ as shown in Table 35. Since the result was significant, I performed *post hoc* tests for these data.

Table 35

Friedman's Test

Statistic	Value
n	525
Chi-Square	4381.656
df	27
Asymp. Sig.	.000

I used Wilcoxon tests to follow up, and also a Bonferroni correction was applied. Rather than use .05 as the critical level of significance, I reported all effects at a .0018 (.05/28) level of significance. For the television, intention to view sports content changed between the various sports content types except SDTV – SCTV, where T = 34,033.50, *ns*, $r = -0.042$. Cohen's benchmark states *r* values between .3 and .5 indicate a medium to large change, and *r* values greater than .5 indicate a large change (Field, 2009). For television: (a) LSTV - SNTV, where T = 5,694.00, $p > .0018$; (b) TDTV - SNTV, where T = 13,153.50, $p > .0018$; (c) SCTV - LSTV, where T = 3,942.00, $p > .0018$; (d) HITV - LSTV, where T = 6,084.50, $p > .0018$; (e) TDTV - LSTV, where T = 5,593.00, $p > .0018$; (f) SDTV - LSTV, where T = 7,834.50, $p > .0018$; (g) FSTV - SCTV, where T = 9,059.50, $p > .0018$; (h) TDTV - HITV, where T = 11,688.00, $p > .0018$; (i) FSTV - HITV, where T = 5,914.00, $p > .0018$; (j) FSTV - TDTV, where T = 8,204.50, $p > .0018$; and (j) FSTV - SDTV, where T = 7,435.00, $p > .0018$ all indicate a medium to large change in viewing intention. Similarly, FSTV - SNTV, where T = 5,340.50, $p > .0018$, and FSTV - LSTV, where T = 2,957.50, $p > .0018$ all indicate a large change in viewing intention. We can conclude that viewership intention differed significantly on the television for the majority of sports content types as shown in Table 36.

Table 36

Wilcoxon Rank, Test Statistic, and Effect Size for Television

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-tailed)	r
LSTV - SNTV	Negative Ranks	47[a]	121.15	5,694.00	-10.650[yy]	.000	**-0.329**
	Positive Ranks	234[b]	144.99	33,927.00			
	Ties	244[c]					
SCTV - SNTV	Negative Ranks	260[d]	184.28	47,912.50	-8.965[zz]	.000	-0.277
	Positive Ranks	92[e]	154.52	14,215.50			
	Ties	173[f]					
HITV - SNTV	Negative Ranks	191[g]	165.52	31,613.50	-4.009[zz]	.000	-0.124
	Positive Ranks	126[h]	149.12	18,789.50			
	Ties	208[i]					
TDTV - SNTV	Negative Ranks	322[j]	218.27	70,282.50	-12.068[zz]	.000	**-0.372**
	Positive Ranks	86[k]	152.95	13,153.50			
	Ties	117[l]					
SDTV - SNTV	Negative Ranks	273[m]	206.26	56,308.00	-8.620[zz]	.000	-0.266
	Positive Ranks	114[n]	164.65	18,770.00			
	Ties	138[o]					
FSTV - SNTV	Negative Ranks	438[p]	244.83	107,234.5	-17.152[zz]	.000	**-0.529**
	Positive Ranks	36[q]	148.35	5,340.50			
	Ties	51[r]					
SCTV - LSTV	Negative Ranks	336[s]	199.18	66,924.00	-15.092[zz]	.000	**-0.466**
	Positive Ranks	40[t]	98.80	3,952.00			
	Ties	149[u]					
HITV - LSTV	Negative Ranks	277[v]	170.46	47,216.50	-12.237[zz]	.000	**-0.378**
	Positive Ranks	49[w]	124.17	6,084.50			
	Ties	199[x]					
TDTV - LSTV	Negative Ranks	370[y]	221.56	81,978.00	-15.523[zz]	.000	**-0.479**
	Positive Ranks	48[z]	116.52	5,593.00			
	Ties	107[aa]					
SDTV - LSTV	Negative Ranks	327[ab]	217.64	71,168.50	-13.955[zz]	.000	**-0.431**
	Positive Ranks	70[ac]	111.92	7,834.50			
	Ties	128[ad]					
FSTV - LSTV	Negative Ranks	456[ae]	250.90	11,4412.5	-18.167[zz]	.000	**-0.561**
	Positive Ranks	28[af]	105.63	2,957.50			
	Ties	41[ag]					
HITV - SCTV	Negative Ranks	94[ah]	139.44	13,107.00	-6.025[yy]	.000	-0.186
	Positive Ranks	200[ai]	151.29	30,258.00			
	Ties	231[aj]					
TDTV - SCTV	Negative Ranks	254[ak]	184.21	46,790.50	-6.697[zz]	.000	-0.207
	Positive Ranks	111[al]	180.22	20,004.50			
	Ties	160[am]					
SDTV - SCTV	Negative Ranks	200[an]	199.43	39,886.50	-1.362[zz]	.173	-0.042
	Positive Ranks	184[ao]	184.96	34,033.50			
	Ties	141[ap]					
FSTV - SCTV	Negative Ranks	381[aq]	219.44	83,605.50	-14.546[zz]	.000	**-0.449**
	Positive Ranks	49[ar]	184.89	9,059.50			
	Ties	95[as]					
TDTV - HITV	Negative Ranks	282[at]	190.26	53,653.00	-10.694[zz]	.000	**-0.33**
	Positive Ranks	79[au]	147.95	11,688.00			
	Ties	164[av]					

(table continues)

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-tailed)	r
SDTV - HITV	Negative Ranks	222[aw]	189.76	42,127.50	-5.892[zz]	.000	-0.182
	Positive Ranks	130[ax]	153.85	20,000.50			
	Ties	173[ay]					
FSTV - HITV	Negative Ranks	387[az]	219.73	85,037.00	-15.628[zz]	.000	**-0.482**
	Positive Ranks	39[ba]	151.64	5,914.00			
	Ties	99[bb]					
SDTV - TDTV	Negative Ranks	106[bc]	164.26	17,411.50	-5.781[yy]	.000	-0.178
	Positive Ranks	224[bd]	166.09	37,203.50			
	Ties	195[be]					
FSTV - TDTV	Negative Ranks	257[bf]	167.92	43,155.50	-10.644[zz]	.000	**-0.328**
	Positive Ranks	63[bg]	130.23	8,204.50			
	Ties	205[bh]					
FSTV - SDTV	Negative Ranks	328[bi]	196.88	64,575.00	-13.478[zz]	.000	**-0.416**
	Positive Ranks	51[bj]	145.78	7,435.00			
	Ties	146[bk]					

Note. [a]LSTV < SNTV. [b]LSTV > SNTV. [c]LSTV = SNTV. [d]SCTV < SNTV. [e]SCTV > SNTV. [f]SCTV = SNTV. [g]HITV < SNTV. [h]HITV > SNTV. [i]HITV = SNTV. [j]TDTV < SNTV. [k]TDTV > SNTV. [l]TDTV = SNTV. [m]SDTV < SNTV. [n]SDTV > SNTV. [o]SDTV = SNTV. [p]FSTV < SNTV. [q]FSTV > SNTV. [r]FSTV = SNTV. [s]SCTV < LSTV. [t]SCTV > LSTV. [u]SCTV = LSTV. [v]HITV < LSTV. [w]HITV > LSTV. [x]HITV = LSTV. [y]TDTV < LSTV. [z]TDTV > LSTV. [aa]TDTV = LSTV. [ab]SDTV < LSTV. [ac]SDTV > LSTV. [ad]SDTV = LSTV. [ae]FSTV < LSTV. [af]FSTV > LSTV. [ag]FSTV = LSTV. [ah]HITV < SCTV. [ai]HITV > SCTV. [aj]HITV = SCTV. [ak]TDTV < SCTV. [al]TDTV > SCTV. [am]TDTV = SCTV. [an]SDTV < SCTV. [ao]SDTV > SCTV. [ap]SDTV = SCTV. [aq]FSTV < SCTV. [ar]FSTV > SCTV. [as]FSTV = SCTV. [at]TDTV < HITV. [au]TDTV > HITV. [av]TDTV = HITV. [aw]SDTV < HITV. [ax]SDTV > HITV. [ay]SDTV = HITV. [az]FSTV < HITV. [ba]FSTV > HITV. [bb]FSTV = HITV. [bc]SDTV < TDTV. [bd]SDTV > TDTV. [be]SDTV = TDTV. [bf]FSTV < TDTV. [bg]FSTV > TDTV. [bh]FSTV = TDTV. [bi]FSTV < SDTV. [bj]FSTV > SDTV. [bk]FSTV = SDTV. [xx]Wilcoxon Signed Ranks Test. [yy]Based on positive ranks. [zz]Based on negative ranks.

For the computer, intention to view sports content changed between the various sports content types with the exception of SDCP - TDCP, where T = 10,012.00, *ns*, r = -0.055. Cohen's benchmark states r values between .3 and .5 indicate a medium to large change, and r values greater than .5 indicate a large change (Field, 2009). For computers: (a) SCCP - LSCP, where T = 8,026.00, p > .0018, r = -0.335; (a) TDCP - SCCP, where T = 6,987.50, p > .0018, r = -0.392; (a) SDCP - SCCP, where T = 7,411.50, p > .0018, r = -

0.396; (a) TDCP - HICP, where T = 7,411.50, *p* > .0018, *r* = -0.396; (a) SDCP - HICP, where T = 7,520.00, *p* > .0018, *r* = -0.324, all indicate a medium to large change in viewing intention. We can conclude that viewership intention differed significantly on the computer for the majority of sports content types as shown in Table 37.

Table 37

Wilcoxon Rank, Test Statistic, and Effect Size for Computers

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-Tailed)	r
LSCP - SNCP	Negative Ranks	157[a]	111.59	17,519.00	-5.311[yy]	.000	-0.164
	Positive Ranks	67[b]	114.64	7,681.00			
	Ties	301[c]					
SCCP - SNCP	Negative Ranks	89[d]	146.07	13,000.50	-8.687[zz]	.000	-0.268
	Positive Ranks	244[e]	174.63	42,610.50			
	Ties	192[f]					
HICP - SNCP	Negative Ranks	105[g]	125.90	13,219.50	-3.920[zz]	.000	-0.121
	Positive Ranks	163[h]	140.04	22,826.50			
	Ties	257[i]					
TDCP - SNCP	Negative Ranks	255[j]	159.96	40,789.50	-9.373[yy]	.000	-0.289
	Positive Ranks	65[k]	162.62	10,570.50			
	Ties	205[l]					
SDCP - SNCP	Negative Ranks	248[m]	164.13	40,704.00	-8.502[yy]	.000	-0.262
	Positive Ranks	78[n]	161.50	12,597.00			
	Ties	199[o]					
FSTV - SNCP	Negative Ranks	270[p]	172.39	46,544.50	-7.500[yy]	.000	-0.231
	Positive Ranks	88[q]	201.32	17,716.50			
	Ties	167[r]					
SCCP - LSCP	Negative Ranks	52[s]	154.35	8,026.00	-10.853[zz]	.000	**-0.335**
	Positive Ranks	268[t]	161.69	43,334.00			
	Ties	205[u]					
HICP - LSCP	Negative Ranks	70[v]	133.64	9,355.00	-7.624[zz]	.000	-0.235
	Positive Ranks	207[w]	140.81	29,148.00			
	Ties	248[x]					
TDCP - LSCP	Negative Ranks	192[y]	136.93	26,291.00	-6.308[yy]	.000	-0.195
	Positive Ranks	79[z]	133.73	10,565.00			
	Ties	254[aa]					
SDCP - LSCP	Negative Ranks	183[ab]	136.62	25,002.00	-5.101[yy]	.000	-0.157
	Positive Ranks	89[ac]	136.25	12,126.00			
	Ties	253[ad]					
FSCP - LSCP	Negative Ranks	169[ae]	135.00	22,815.00	-2.022[zz]	.000	-0.062
	Positive Ranks	154[af]	191.63	29,511.00			
	Ties	202[ag]					
HICP - SCCP	Negative Ranks	179[ah]	137.10	24,540.50	-6.131[yy]	.000	-0.189
	Positive Ranks	83[ai]	119.43	9,912.50			
	Ties	263[aj]					
TDCP - SCCP	Negative Ranks	306[ak]	179.05	54,788.50	-12.709[yy]	.000	**-0.392**

(table continues)

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-Tailed)	r
	Positive Ranks	45al	155.28	6,987.50			
	Ties	174[am]					
SDCP - SCCP	Negative Ranks	304[an]	188.19	57,208.50	-12.837[yy]	.000	**-0.396**
	Positive Ranks	55[ao]	134.75	7,411.50			
	Ties	166[ap]					
FSCP - SCCP	Negative Ranks	250[aq]	186.95	46,736.50	-6.582[yy]	.000	-0.203
	Positive Ranks	116[ar]	176.07	20,424.50			
	Ties	159[as]					
TDCP - HICP	Negative Ranks	257[at]	148.71	38,217.50	-11.202[yy]	.000	**-0.346**
	Positive Ranks	39[au]	147.14	5,738.50			
	Ties	229[av]					
SDCP - HICP	Negative Ranks	251[aw]	157.18	39,451.00	-10.508[yy]	.000	**-0.324**
	Positive Ranks	55[ax]	136.73	7,520.00			
	Ties	219[ay]					
FSCP - HICP	Negative Ranks	206[az]	160.23	33,006.50	-3.220[yy]	.001	-0.099
	Positive Ranks	125[ba]	175.52	21,939.50			
	Ties	194[bb]					
SDCP - TDCP	Negative Ranks	91[bc]	110.02	10,012.00	-1.795[zz]	.073	-0.055
	Positive Ranks	124[bd]	106.52	13,208.00			
	Ties	310[be]					
FSCP - TDCP	Negative Ranks	94[bf]	100.82	9,477.50	-6.445[zz]	.000	-0.199
	Positive Ranks	169[bg]	149.34	25,238.50			
	Ties	262[bh]					
FSCP - SDCP	Negative Ranks	109[bi]	101.02	11,011.50	-5.664[zz]	.000	-0.175
	Positive Ranks	160[bj]	158.15	25,303.50			
	Ties	256[bk]					

Note. [a]LSCP < SNCP. [b]LSCP > SNCP. [c]LSCP = SNCP. [d]SCCP < SNCP. [e]SCCP > SNCP. [f]SCCP = SNCP. [g]HICP < SNCP. [h]HICP > SNCP. [i]HICP = SNCP. [j]TDCP < SNCP. [k]TDCP > SNCP. [l]TDCP = SNCP. [m]SDCP < SNCP. [n]SDCP > SNCP. [o]SDCP = SNCP. [p]FSCP < SNCP. [q]FSCP > SNCP. [r]FSCP = SNCP. [s]SCCP < LSCP. [t]SCCP > LSCP. [u]SCCP = LSCP. [v]HICP < LSCP. [w]HICP > LSCP. [x]HICP = LSCP. [y]TDCP < LSCP. [z]TDCP > LSCP. [aa]TDCP = LSCP. [ab]SDCP < LSCP. [ac]SDCP > LSCP. [ad]SDCP = LSCP. [ae]FSCP < LSCP. [af]FSCP > LSCP. [ag]FSCP = LSCP. [ah]HICP < SCCP. [ai]HICP > SCCP. [aj]HICP = SCCP. [ak]TDCP < SCCP. [al]TDCP > SCCP. [am]TDCP = SCCP. [an]SDCP < SCCP. [ao]SDCP > SCCP. [ap]SDCP = SCCP. [aq]FSCP < SCCP. [ar]FSCP > SCCP. [as]FSCP = SCCP. [at]TDCP < HICP. [au]TDCP > HICP. [av]TDCP = HICP. [aw]SDCP < HICP. [ax]SDCP > HICP. [ay]SDCP = HICP. [az]FSCP < HICP. [ba]FSCP > HICP. [bb]FSCP = HICP. [bc]SDCP < TDCP. [bd]SDCP > TDCP. [be]SDCP = TDCP. [bf]FSCP < TDCP. [bg]FSCP > TDCP. [bh]FSCP = TDCP. [bi]FSCP < SDCP. [bj]FSCP > SDCP. [bk]FSCP = SDCP. [xx]Wilcoxon Signed Ranks Test. [yy]Based on positive ranks. [zz]Based on negative ranks.

For smartphones, intention to view sports content changed between the various sports content types with the exception of FSSP - SNSP, where T = 24,597.50, *ns*, *r* = -

0.029, and SDSP - TDSP, where T = 7,200.00, *ns*, $r = -0.016$. Cohen's benchmark states r values between .3 and .5 indicate a medium to large change, and r values greater than .5 indicate a large change (Field, 2009). For smartphones: (a) SCSP - SNSP, where T = 7,646.50, $p > .0018$, $r = -0.353$; (b) TDSP - SNSP, where T = 6,219.50, $p > .0018$, $r = -0.335$; (c) SDSP - SNSP, where T = 5,359.00, $p > .0018$, $r = -0.343$; (d) SCSP - LSSP, where T = 4,215.50, $p > .0018$, $r = -0.442$; (e) HISP - LSSP, where T = 4,709.00, $p > .0018$, $r = -0.315$; (f) TDSP - SCSP, where T = 3,125.50, $p > .0018$, $r = -0.467$; (g) SDSP - SCSP, where T = 3,999.50, $p > .0018$, $r = -0.469$; (h) FSSP - SCSP, where T = 11,687.00, $p > .0018$, $r = -0.300$; (i) TDSP - HISP, where T = 3,366.50, $p > .0018$, $r = -0.387$; and (j) SDSP - HISP, where T = 3,983.00, $p > .0018$, $r = -0.387$, all indicate a medium to large change in viewing intention. We can conclude that viewership intention differed significantly on the smartphone for the majority of sports content types as shown in Table 38.

Table 38

Wilcoxon Rank, Test Statistic, and Effect Size for Smartphones

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-tailed)	r
LSSP - SNSP	Negative Ranks	179[a]	108.93	19,499.00	-8.898[yy]	.000	-0.275
	Positive Ranks	36[b]	103.36	3,721.00			
	Ties	310[c]					
SCSP - SNSP	Negative Ranks	58[d]	131.84	7,646.50	-11.448[zz]	.000	**-0.353**
	Positive Ranks	270[e]	171.52	46,309.50			
	Ties	197[f]					
HISP - SNSP	Negative Ranks	101[g]	110.13	11,123.50	-3.933[zz]	.000	-0.121
	Positive Ranks	147[h]	134.37	19,752.50			
	Ties	277[i]					
TDSP - SNSP	Negative Ranks	252[j]	147.40	37,145.50	-10.841[yy]	.000	**-0.335**
	Positive Ranks	42[k]	148.08	6,219.50			
	Ties	231[l]					
SDSP - SNSP	Negative Ranks	249[m]	144.45	35,969.00	-11.116[yy]	.000	**-0.343**
	Positive Ranks	38[n]	141.03	5,359.00			
	Ties	238[o]					
FSSP - SNSP	Negative Ranks	185[p]	149.88	27,728.50	-.947[yy]	.344	-0.029
	Positive Ranks	138[q]	178.24	24,597.50			
	Ties	202[r]					
SCSP - LSSP	Negative Ranks	34[s]	123.99	42,15.50	-14.332[zz]	.000	**-0.442**
	Positive Ranks	322[t]	184.26	59,330.50			
	Ties	169[u]					
HISP - LSSP	Negative Ranks	43[v]	109.51	4,709.00	-10.196[zz]	.000	**-0.315**
	Positive Ranks	215[w]	133.50	28,702.00			
	Ties	267[x]					
TDSP - LSSP	Negative Ranks	178[y]	125.13	22,273.50	-5.842[yy]	.000	-0.18
	Positive Ranks	73[z]	128.12	9,352.50			
	Ties	274[aa]					
SDSP - LSSP	Negative Ranks	162[ab]	114.26	18,510.50	-5.973[yy]	.000	-0.184
	Positive Ranks	64[ac]	111.57	7,140.50			
	Ties	299[ad]					
FSSP - LSSP	Negative Ranks	133[ae]	127.32	16,934.00	-4.211[zz]	.000	-0.13
	Positive Ranks	172[af]	172.85	2,9731.00			
	Ties	220[ag]					
HISP - SCSP	Negative Ranks	224[ah]	150.65	33745.50	-9.682[yy]	.000	-0.299
	Positive Ranks	62[ai]	117.67	7295.50			
	Ties	239[aj]					
TDSP - SCSP	Negative Ranks	341[ak]	187.79	64,035.50	-15.145[yy]	.000	**-0.467**
	Positive Ranks	25[al]	125.02	3,125.50			
	Ties	159[am]					
SDSP - SCSP	Negative Ranks	352[an]	196.46	69,153.50	-15.194[yy]	.000	**-0.469**
	Positive Ranks	30[ao]	133.32	3,999.50			
	Ties	143[ap]					
FSSP - SCSP	Negative Ranks	266[aq]	176.56	46,966.00	-9.737[yy]	.000	-0.3
	Positive Ranks	76[ar]	153.78	11,687.00			
	Ties	183[as]					
TDSP - HISP	Negative Ranks	259[at]	148.80	38,538.50	-12.552[yy]	.000	**-0.387**
	Positive Ranks	30[au]	112.22	3,366.50			
	Ties	236[av]					

(table continues)

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-tailed)	r
SDSP - HISP	Negative Ranks	270[aw]	152.47	41,167.00	-12.541[yy]	.000	**-0.387**
	Positive Ranks	30[ax]	132.77	3,983.00			
	Ties	225[ay]					
FSSP - HISP	Negative Ranks	201[az]	156.16	31,389.00	-3.499[yy]	.000	-0.108
	Positive Ranks	119[ba]	167.82	19,971.00			
	Ties	205[bb]					
SDSP - TDSP	Negative Ranks	92[bc]	85.34	7,851.00	-.511[yy]	.609	-0.016
	Positive Ranks	81[bd]	88.89	7,200.00			
	Ties	352[be]					
FSSP - TDSP	Negative Ranks	71	92.38	6,559.00	-7.989[zz]	.000	-0.247
	Positive Ranks	178	138.01	24,566.00			
	Ties	276					
FSSP - SDSP	Negative Ranks	66	87.46	5,772.50	-8.270[zz]	.000	-0.255
	Positive Ranks	176	134.26	23,630.50			
	Ties	283					

Note. [a]LSSP < SNSP. [b]LSSP > SNSP. [c]LSSP = SNSP. [d]SCSP < SNSP. [e]SCSP > SNSP. [f]SCSP = SNSP. [g]HISP < SNSP. [h]HISP > SNSP. [i]HISP = SNSP. [j]TDSP < SNSP. [k]TDSP > SNSP. [l]TDSP = SNSP. [m]SDSP < SNSP. [n]SDSP > SNSP. [o]SDSP = SNSP. [p]FSSP < SNSP. [q]FSSP > SNSP. [r]FSSP = SNSP. [s]SCSP < LSSP. [t]SCSP > LSSP. [u]SCSP = LSSP. [v]HISP < LSSP. [w]HISP > LSSP. [x]HISP = LSSP. [y]TDSP < LSSP. [z]TDSP > LSSP. [aa]TDSP = LSSP. [ab]SDSP < LSSP. [ac]SDSP > LSSP. [ad]SDSP = LSSP. [ae]FSSP < LSSP. [af]FSSP > LSSP. [ag]FSSP = LSSP. [ah]HISP < SCSP. [ai]HISP > SCSP. [aj]HISP = SCSP. [ak]TDSP < SCSP. [al]TDSP > SCSP. [am]TDSP = SCSP. [an]SDSP < SCSP. [ao]SDSP > SCSP. [ap]SDSP = SCSP. [aq]FSSP < SCSP. [ar]FSSP > SCSP. [as]FSSP = SCSP. [at]TDSP < HISP. [au]TDSP > HISP. [av]TDSP = HISP. [aw]SDSP < HISP. [ax]SDSP > HISP. [ay]SDSP = HISP. [az]FSSP < HISP. [ba]FSSP > HISP. [bb]FSSP = HISP. [bc]SDSP < TDSP. [bd]SDSP > TDSP. [be]SDSP = TDSP. [bf]FSSP < TDSP. [bg]FSSP > TDSP. [bh]FSSP = TDSP. [bi]FSSP < SDSP. [bj]FSSP > SDSP. [bk]FSSP = SDSP. [xx]Wilcoxon Signed Ranks Test. [yy]Based on positive ranks. [zz]Based on negative ranks.

For tablets, intention to view sports content changed between the various sports content types with the exception of HITB - SNTB, where T = 14,084.00, *ns*, $r = -0.004$, and SDTB - TDTB, where T = 4,392.50, *ns*, $r = -0.027$. Cohen's benchmark states r values between .3 and .5 indicate a medium to large change, and r values greater than .5 indicate a large change (Field, 2009). For tablets: (a) TDTB – SNTB, where T = 5,316.00, $p > .0018$, $r = -0.345$; (b) SDTB - SNTB, where T = 5,433.50, $p > .0018$, $r = -$

0.332; (c) TDTB - SCTB, where T = 3,981.50, $p > .0018$, $r = -0.375$; (d) SDTB - SCTB, where T = 4,035.50, $p > .0018$, $r = -0.378$; (e) TDTB - HITB, where T = 3,365.00, $p > .0018$, $r = -0.326$; (f) SDTB - HITB, where T = 3,739.50, $p > .0018$, $r = -0.315$; and (g) SDTB - HITB, where T = 3,739.50, $p > .0018$, $r = -0.315$, all indicate a medium to large change in viewing intention. We can conclude that viewership intention differed significantly on tablets for the majority of sports content types as shown in Table 39.

Table 39

Wilcoxon Rank, Test Statistic, and Effect Size for Tablets

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-tailed)	r
LSTB - SNTB	Negative Ranks	152[a]	98.48	14,969.00	-7.010[yy]	.000	-0.216
	Positive Ranks	44[b]	98.57	4,337.00			
	Ties	329[c]					
SCTB - SNTB	Negative Ranks	96[d]	113.72	10,917.50	-5.873[zz]	.000	-0.181
	Positive Ranks	173[e]	146.81	25,397.50			
	Ties	256[f]					
HITB - SNTB	Negative Ranks	132[g]	108.77	14,357.00	-.133[yy]	.894	-0.004
	Positive Ranks	106[h]	132.87	14,084.00			
	Ties	287[i]					
TDTB - SNTB	Negative Ranks	252[j]	140.63	35,439.00	-11.187[yy]	.000	**-0.345**
	Positive Ranks	33[k]	161.09	5,316.00			
	Ties	240[l]					
SDTB - SNTB	Negative Ranks	241[m]	138.37	33,347.50	-10.755[yy]	.000	**-0.332**
	Positive Ranks	37[n]	146.85	5,433.50			
	Ties	247[o]					
FSTB - SNTB	Negative Ranks	212[p]	142.19	30,143.50	-4.392[yy]	.000	-0.136
	Positive Ranks	94[q]	179.02	16,827.50			
	Ties	219[r]					
SCTB - LSTB	Negative Ranks	51[s]	116.75	5,954.00	-9.520[zz]	.000	-0.294
	Positive Ranks	213[t]	136.27	29,026.00			
	Ties	261[u]					
HITB - LSTB	Negative Ranks	70[v]	101.31	7,092.00	-5.550[zz]	.000	-0.171
	Positive Ranks	150[w]	114.79	17,218.00			
	Ties	305[x]					
TDTB - LSTB	Negative Ranks	175[y]	115.08	20,139.00	-7.068[yy]	.000	-0.218
	Positive Ranks	55[z]	116.84	6,426.00			
	Ties	295[aa]					
SDTB - LSTB	Negative Ranks	169[ab]	110.87	18,737.50	-6.435[yy]	.000	-0.199
	Positive Ranks	56[ac]	119.42	6,687.50			
	Ties	300[ad]					
FSTB - LSTB	Negative Ranks	154[ae]	121.42	18,699.00	-.433[yy]	.000	-0.013
	Positive Ranks	115[af]	153.18	17,616.00			
	Ties	256[ag]					
HITB - SCTB	Negative Ranks	160[ah]	111.59	17,855.00	-6.389[yy]	.000	-0.197
	Positive Ranks	59[ai]	105.68	6,235.00			
	Ties	306[aj]					
TDTB - SCTB	Negative Ranks	261[ak]	146.41	38,213.50	-12.159[yy]	.000	**-0.375**
	Positive Ranks	29[al]	137.29	3,981.50			
	Ties	235[am]					
SDTB - SCTB	Negative Ranks	263[an]	148.42	39,035.50	-12.255[yy]	.000	**-0.378**
	Positive Ranks	30[ao]	134.52	4,035.50			
	Ties	232[ap]					
FSTB - SCTB	Negative Ranks	228[aq]	144.39	32,921.00	-8.117yy	.000	-0.25
	Positive Ranks	64[ar]	154.02	9,857.00			
	Ties	233[as]					
TDTB - HITB	Negative Ranks	212[at]	120.54	25,555.00	-10.555[yy]	.000	**-0.326**
	Positive Ranks	28[au]	120.18	3,365.00			
	Ties	285[av]					

(table continues)

Ranks					Test Statistic		Effect Size
Viewership Intention Difference	Rank Type	*n*	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-tailed)	r
SDTB - HITB	Negative Ranks	210[aw]	119.91	25,180.50	-10.209[yy]	.000	**-0.315**
	Positive Ranks	30[ax]	124.65	3,739.50			
	Ties	285[ay]					
FSTB - HITB	Negative Ranks	185[az]	128.75	23,818.00	-4.674[yy]	.000	-0.144
	Positive Ranks	83[ba]	147.33	12,228.00			
	Ties	257[bb]					
SDTB - TDTB	Negative Ranks	62[bc]	70.85	4,392.50	-.891[zz]	.373	-0.027
	Positive Ranks	76[bd]	68.40	5,198.50			
	Ties	387[be]					
FSTB - TDTB	Negative Ranks	77[bf]	84.44	6,502.00	-4.844[zz]	.000	-0.149
	Positive Ranks	128[bg]	114.16	14,613.00			
	Ties	320[bh]					
FSTB - SDTB	Negative Ranks	75[bi]	78.29	5,871.50	-4.577[zz]	.000	-0.141
	Positive Ranks	118[bj]	108.89	12,849.50			
	Ties	332[bk]					

Note. [a]LSTB < SNTB. [b]LSTB > SNTB. [c]LSTB = SNTB. [d]SCTB < SNTB. [e]SCTB > SNTB. [f]SCTB = SNTB. [g]HITB < SNTB. [h]HITB > SNTB. [i]HITB = SNTB. [j]TDTB < SNTB. [k]TDTB > SNTB. [l]TDTB = SNTB. [m]SDTB < SNTB. [n]SDTB > SNTB. [o]SDTB = SNTB. [p]FSTB < SNTB. [q]FSTB > SNTB. [r]FSTB = SNTB. [s]SCTB < LSTB. [t]SCTB > LSTB. [u]SCTB = LSTB. [v]HITB < LSTB. [w]HITB > LSTB. [x]HITB = LSTB. [y]TDTB < LSTB. [z]TDTB > LSTB. [aa]TDTB = LSTB. [ab]SDTB < LSTB. [ac]SDTB > LSTB. [ad]SDTB = LSTB. [ae]FSTB < LSTB. [af]FSTB > LSTB. [ag]FSTB = LSTB. [ah]HITB < SCTB. [ai]HITB > SCTB. [aj]HITB = SCTB. [ak]TDTB < SCTB. [al]TDTB > SCTB. [am]TDTB = SCTB. [an]SDTB < SCTB. [ao]SDTB > SCTB. [ap]SDTB = SCTB. [aq]FSTB < SCTB. [ar]FSTB > SCTB. [as]FSTB = SCTB. [at]TDTB < HITB. [au]TDTB > HITB. [av]TDTB = HITB. [aw]SDTB < HITB. [ax]SDTB > HITB. [ay]SDTB = HITB. [az]FSTB < HITB. [ba]FSTB > HITB. [bb]FSTB = HITB. [bc]SDTB < TDTB. [bd]SDTB > TDTB. [be]SDTB = TDTB. [bf]FSTB < TDTB. [bg]FSTB > TDTB. [bh]FSTB = TDTB. [bi]FSTB < SDTB. [bj]FSTB > SDTB. [bk]FSTB = SDTB. [xx]Wilcoxon Signed Ranks Test. [yy]Based on positive ranks. [zz]Based on negative ranks.

Table 40 shows the median and range values for the various conditions.

Table 40

Condition Median and Range Values

	Television		Computer		Smartphone		Tablet	
Sports Content Type	Median	Range	Median	Range	Median	Range	Median	Range
Sports News	5.00	7	2.00	6	2.00	6	2.00	7
Live Sports	6.00	7	2.00	7	2.00	7	2.00	7
Sports Scores	4.00	7	3.00	7	3.00	7	2.00	7
Highlights	4.00	7	2.00	6	2.00	7	2.00	7
Tape-delayed	2.00	7	1.00	7	1.00	7	1.00	7
Sports Documentaries	3.00	7	1.00	7	1.00	7	1.00	7
Fantasy Sports	1.00	7	1.00	7	1.00	7	1.00	7

Table 41 shows the mean to use digital devices according to types of sports content. Except for fantasy sports (M = 2.04, SD = 1.813), the television was the most likely digital device to consume all other sports content types. Live sports (M = 5.21, SD = 1.663) had the highest intention of viewership on the television, followed by sports news (M = 4.52, SD = 1.776), sports highlights (M = 4.16, SD = 1.907), sports scores (M = 3.79, SD = 1.786), sports documentaries (M = 3.65, SD = 2.115), and tape-delayed sports (M = 3.11, SD = 2.121).

Table 41

Marginal Viewership Intention Mean to Use Digital Devices According to Sports Type

Sports Type	Digital Device	Intention to use platform
Sports News	Television	4.52 (1.776)
	Computer	2.56 (1.414)
	Smartphone	2.53 (1.595)
	Tablet	2.36 (1.469)
Live Sports	Television	5.21 (1.663)
	Computer	2.33 (1.482)
	Smartphone	2.09 (1.453)
	Tablet	2.08 (1.474)
Sports Scores	Television	3.79 (1.786)
	Computer	3.11 (1.691)
	Smartphone	3.39 (1.830)
	Tablet	2.70 (1.756)
Sports Highlights	Television	4.16 (1.907)
	Computer	2.76 (1.617)
	Smartphone	2.76 (1.758)
	Tablet	2.36 (1.604)
Tape Delayed Sports	Television	3.11 (2.121)
	Computer	1.97 (1.567)
	Smartphone	1.81 (1.426)
	Tablet	1.75 (1.422)
Sports Documentaries	Television	3.65 (2.115)
	Computer	2.03 (1.475)
	Smartphone	1.77 (1.415)
	Tablet	1.77 (1.398)
Fantasy Sports	Television	2.04 (1.813)
	Computer	2.56 (2.069)
	Smartphone	2.51 (2.068)
	Tablet	2.13 (1.873)

The computer was the second most likely device used to consume all sports content with the exception of sports scores (*M* = 3.11, *SD* = 1.691). Interestingly, among the sports types, sports scores had the highest intention of viewership for the computer. Sports highlights (*M* = 2.76, *SD* = 1.617) were computers next highest intention of viewership followed by sports news (*M* = 2.56, *SD* = 1.414) and fantasy sports (*M* = 2.56, *SD* = 2.069). Live sports (*M* = 2.33, *SD* = 1.482), sports documentaries (*M* = 2.03, *SD* =

1.475), and tape-delayed sports (*M* = 1.97, *SD* = 1.567) complete the remaining sports types viewed on a computer.

With the exception of having the same viewership intention for sports documentaries (*M* = 1.77, *SD* = 1.415) as the tablet, the smartphone was the solid third place digital device for consuming all sports content types. The smartphone had the second highest intention of viewing sports scores (*M* = 3.39, *SD* = 1.830), with television taking first place. Sports highlights (*M* = 2.76, *SD* = 1.758), sports news (*M* = 2.53, *SD* = 1.595), fantasy sports (*M* = 2.51, *SD* = 2.068), live sports (*M* = 2.09, *SD* = 1,453), and tape-delayed sports (*M* = 1.81, *SD* = 1.426) complete viewership intention for the smartphone. Figure 17 shows the means for intention where (a) DeviceType 1 is the television, (b) DeviceType 2 is the computer, (c) DeviceType 3 is the smartphone, and (d) DeviceType 4 is the tablet. Similarly, shows the various sports content types where (a) SportsType 1 is sports news, (b) SportsType 2 is live sports, (c) SportsType 3 is sports scores, (d) SportsType 4 is sports highlights, (e) SportsType 5 is tape delayed sports, (f) SportsType 6 is sports documentation, and (g) SportsType 7 is fantasy sports.

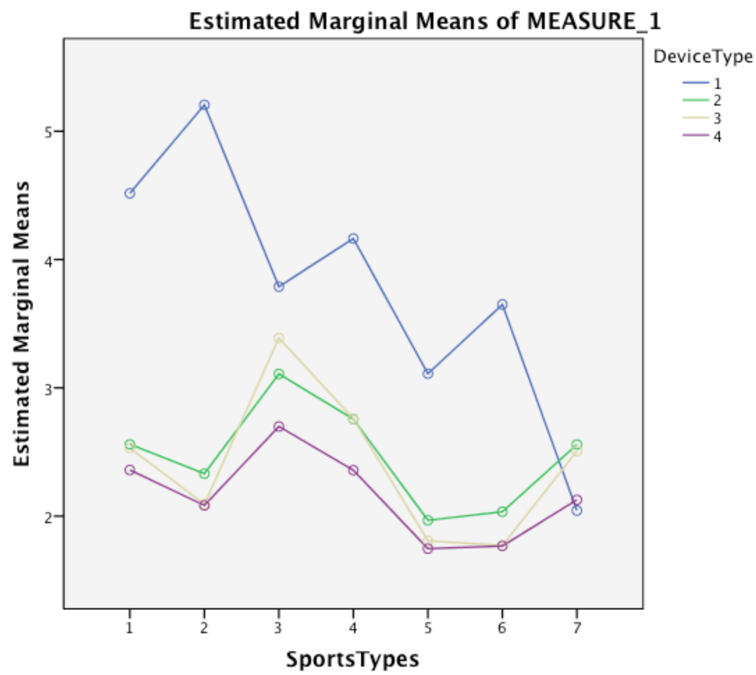

Figure 17. Estimated marginal viewership intention means for all four digital devices.

Survey participants owned the tablet for the least number of years, which may account for why the tablet was the least used to view sports content. Sports scores (*M* = 2.70, *SD* = 1.756) had the highest intention of viewership on the tablet. Sports news (*M* = 2.36, *SD* = 1.469) and sports highlights (*M* = 2.36, *SD* = 1.604) have a similar likelihood for viewership on the tablet. Fantasy sports (*M* = 2.13, *SD* = 1.873), live sports (*M* = 2.08, *SD* = 1.474), sports documentaries (*M* = 1.77, *SD* = 1.398), and tape delayed sports (*M* = 1.75, *SD* = 1.422), complete the remaining list of sports content types most likely viewed on the tablet.

Table 42 shows another Friedman's test I ran for participant's ages 18 to 34, a key demographic for content providers (Goldsmith & Walker, 2015), and Table 43 shows another Friedman test I ran for ages 35 and over. Examining the difference between intention means to view sports content for ages 35 and older and the 18 to 34 age group revealed possible trends as shown in Table 44. Except sports scores (*M* = 3.5, *SD* = 1.796) and fantasy sports (*M* = 2.17, *SD* = 1.919), the intention mean to view all other sports content types is lower on the television for the 18 to 34 age group when compared to the 35 and over age group. Additionally, overall intention mean to view sports content on smartphones had the greatest increase for the 18 to 34 age groups.

Table 42

Marginal Viewership Intention Mean to Use Digital Devices According to Sports Type for Ages 18 to 34

Sports Type	Digital Device	Intention to use platform
Sports News	Television	4.38 (1.792)
	Computer	2.68 (1.485)
	Smartphone	2.78 (1.727)
	Tablet	2.45 (1.621)
Live Sports	Television	5.10 (1.768)
	Computer	2.48 (1.521)
	Smartphone	2.25 (1.506)
	Tablet	2.21 (1.588)
Sports Scores	Television	3.50 (1.796)
	Computer	3.10 (1.747)
	Smartphone	3.73 (1.847)
	Tablet	2.71 (1.792)
Sports Highlights	Television	3.83 (1.889)
	Computer	2.96 (1.716)
	Smartphone	3.08 (1.817)
	Tablet	2.52 (1.718)
Tape Delayed Sports	Television	3.08 (2.157)
	Computer	2.20 (1.797)
	Smartphone	2.09 (1.655)
	Tablet	1.97 (1.673)
Sports Documentaries	Television	3.59 (2.103)
	Computer	2.31 (1.706)
	Smartphone	2.04 (1.691)
	Tablet	2.00 (1.634)
Fantasy Sports	Television	2.17 (1.919)
	Computer	2.72 (2.124)
	Smartphone	2.75 (2.154)
	Tablet	2.29 (1.940)

Table 43 shows the intention to view sports content for 35 and older age groups.

Table 43

Marginal Viewership Intention Mean to Use Digital Devices According to Sports Type for Ages 35 and over

Sports Type	Digital Device	Intention to use platform
Sports News	Television	4.68 (1.748)
	Computer	2.42 (1.318)
	Smartphone	2.24 (1.378)
	Tablet	2.26 (1.269)
Live Sports	Television	5.33 (1.529)
	Computer	2.17 (1.420)
	Smartphone	1.91 (1.370)
	Tablet	1.94 (1.320)
Sports Scores	Television	4.12 (1.720)
	Computer	3.11 (1.628)
	Smartphone	3.00 (1.734)
	Tablet	2.69 (1.718)
Sports Highlights	Television	4.55 (1.858)
	Computer	2.53 (1.467)
	Smartphone	2.39 (1.615)
	Tablet	2.18 (1.445)
Tape Delayed Sports	Television	3.15 (2.083)
	Computer	1.70 (1.203)
	Smartphone	1.49 (1.023)
	Tablet	1.49 (1.011)
Sports Documentaries	Television	3.72 (2.131)
	Computer	1.71 (1.071)
	Smartphone	1.47 (.926)
	Tablet	1.51 (1.007)
Fantasy Sports	Television	1.90 (1.676)
	Computer	2.37 (1.993)
	Smartphone	2.22 (1.932)
	Tablet	1.94 (1.779)

Table 44 shows the difference in means between intention to view sports content for 18 to 34 and 35 and older age groups.

Table 44

Marginal Viewership Intention Mean Differences Between Ages 18 to 34 and Ages 35 and Over

Sports Type	Television Difference	Computer Difference	Smartphone Difference	Tablet Difference
Sports News	-0.30	0.26	0.54	0.19
Live Sports	-0.23	0.31	0.34	0.27
Sports Scores	0.38	-0.01	0.73	0.02
Sports Highlights	-0.72	0.43	0.69	0.34
Tape Delayed Sports	-0.07	0.5	0.6	0.48
Sports Documentaries	-0.13	0.6	0.57	0.49
Fantasy Sports	0.27	0.35	0.53	0.35

Study findings further extends the overall knowledge of prior research by indicating (a) what motives influence sports viewership on digital devices, (b) what motives adequately predict the intention to view specific sports content on digital devices, and (c) what significant viewing differences exist by digital devices across each of the seven types of sports content types. Additionally, results show possible changing trends in viewership intentions between older and younger viewership groups. Results of the study also confirm and expand on Cha’s (2013a) research that Internet-enabled devices are viable video platforms and can grow as a threat to television. Finally, trends observed in the study confirm that younger audiences enjoy viewing video streams on nontraditional digital devices such as smartphones and tablets, just as older audiences enjoy viewing content on traditional televisions and computers (Lin, 2013).

Applications to Professional Practice

The findings of the study have applicability to the professional practice of business by giving content providers and advertisers information on what motivates sports content viewership and on what devices viewers prefer to consume sports content.

All 31 survey questions were deemed good to aid in capturing each motivation associated with sports content viewership. Statistical techniques indicated eight motives best encapsulated the motivations for sports content viewership on digital devices. These motives include: (a) Enjoyment; (b) Leisure; (c) Sports Information; (d) Self-Actualization Sports Information; (e) Relaxation; (f) Social; (g) Escape; and (h) Companionship.

I was able to determine whether viewers pursue or achieve a particular motivation on one digital device over another with eight factors. Using the eight factors with two variable interactions yielded low values of R^2 as shown in Table 30. In an attempt to improve the low R^2 values, I conducted other interactions resulting in no improvement in the model's R^2 as shown in Table 32. Laicane et al. (2015) noted that it is normal to have low R^2 values for research involving humans because of difficulty in predicting human behavior. However, if a low R^2 exists but the model has statistically significant predictors, researchers can still make important conclusions (Laicane et al., 2015). I proceeded to analyze the results and concluded Escape was the primary reason for viewing sports content on the television, computer, and tablet. Similarly, Enjoyment was the primary reason for viewing sports content on the smartphone. Content providers can use this information to ensure that the sports content delivered to consumers allow them to escape fully from their daily activities. Advertisers can also target escape and enjoyment activities to sports content viewers to potentially maximize advertisement effectiveness.

However, not all motivations had a positive reason for sports content viewership. Some motivations had a negative relationship to viewing sports content and included (a) seeking sports information with the television and tablet, (b) participating in leisure activities for sports viewership with the computer, smartphone, and tablet, (c) social interaction for sports viewership with the computer, smartphone, and tablet, and (d) self-actualization information with sports viewership with the tablet. As an example, advertisers could use this negative relationship information to avoid promoting leisure activities for viewers watching sports content on the computer, smartphone, and tablet.

Except for fantasy sports, the television holds the primary viewing position for all sports content types examined. The television has a significantly higher intention to view sports content than any other digital device when examining the entire sample population. In particular, the television has a commanding position as it pertains to live sports viewership when compared to the computer, smartphone, and tablet. Only regarding sports scores do the other digital devices come close to television with respect to intention to view sports content.

However, the television is not invisible. Examining the 18 to 34 age group of the sample population highlights a weakening position of the television across all sports content types. Although the television still maintains a substantial position regarding viewership intent, mobile viewing devices show promise in this younger demographic. Evens et al. (2011) and others also agree with the position that mobile viewing devices will take a more prominent role in content viewership as these devices become popular and access to sports content on mobile devices becomes more prevalent. As the prime target viewing demographic of ages 18 to 34 increase their intention to view sports content on mobile digital devices, content providers can use this information as justification to distribute more sports content to these devices. Similarly, advertisers can target the elusive 18 to 34 demographic (Goldsmith & Walker, 2015) on mobile devices with advertisements that promote Escape and Enjoyment.

Implications for Social Change

In this study, I assessed the motives for sports content viewership across various digital devices based on various surveys that indicated viewers tend to consume content on their mobile devices (Accenture Video Solutions, 2013; Lin, 2013; Ooyala, 2013; Tang & Cooper, 2013). The analysis of motives was used to predict viewership intention to watch the sports content on a particular digital device. For example, results of the study confirmed participants ages 18 to 34 also consumed more sports content on mobile devices. Additionally, Escape and Enjoyment ranked as the highest motivations for viewing sports content on all four digital devices.

Content providers can use findings from the study to justify delivering more sports content on mobile devices, which in turn can enhance the social well-being of society. These changes could also have an economic benefit by allowing sports content providers and advertisers to target the right content and advertisement to the appropriate audience. In turn, content providers and advertisers may retain viewers longer and maximize revenue; providing financial resources to address social issues.

Recommendations for Action

Sports content viewership on mobile devices continues to demonstrate increased acceptance. Content providers and advertisers should continue to focus on distributing desired sports content to viewers on all digital devices but with renewed focus on mobile digital devices. Such an endeavor may become increasingly lucrative to content providers and advertisers as sports content viewership across multiple mobile digital devices continues to gain acceptance. Additionally, I will provide summary findings to known executives of sports content providers with the desire that they will use the results to justify and increase sports content delivery across multiple digital devices.

The topic of sports content viewership on digital devices is a current topic for the media industry. I would like to present these findings at professional conferences such as the National Association of Broadcasters (NAB) and the Sports Video Group (SVG). Additionally, it is my intent to publish these results in peer-reviewed journals such as *Telematics and Informatics* and industry journals such as *Broadcasting and Cable*.

Recommendations for Further Study

The first recommendation for further study includes examining subsamples in isolation of a larger survey population that may achieve a higher R^2. The current study generalizes to approximately 30% of the population. A larger R^2 may give business leaders a higher confidence level regarding the recommended actions. When combining all the data with high variability, the general regression model involving all data will result in a low R^2. However, as an example, if we slice the sample by gender and demographic information such as a female high-income sub-sample, I would expect stronger EFA and multiple regression results. Future researchers can conduct said multiple regression specific to various demographic sub-samples. The results would provide a specific model based on demographics.

The scope of the study does not account for users who connect a smartphone, tablet, or computer to a television to view sports content. Neither does it examine the delivery mechanism of the content to the viewing device. The second recommendation for further study consists of ascertaining if viewers connect mobile devices directly to the television and if mobile viewers use WiFi connectivity to access sports content. This information may provide insight into if customers (a) prefer the larger screen size while in the home, (b) the convenience of the mobile device, and (c) the ease of having only one device to acquire content. Third, further study should also analyze the collected data to determine if any significant trends exist between motivation factors and devices. For example, what digital device does socially motivated users prefer to consume sports content? Forth, discovering if viewers have a preference on the delivery mechanism, whether by (a) traditional cable, (b) satellite providers, or (c) over the Internet (over the top), may aid content providers and advertisers determine if an over the top model that can target both home and mobile devices holds promise. Fifth, exploring additional demographics such as job type and technology prowess may provide additional insight on the reasons viewers choose certain devices over others. Sixth, the inclusion of time-of-day and location of digital device usage for viewership of sports content could provide insight into the reasons for device preference. Seventh, the inclusion of privacy and other motivations not included in the current survey. Finally, future research should include examining if the type of team sports matters for viewing on a particular digital device. The type of team sports should include professional sports such as baseball, football, soccer, hockey, as well as, amateur sports such as college football, high school sports, among others.

Reflections

Working in the media and entertainment industry resulted in potential bias regarding what digital device types viewers prefer to consume sports content. I was pleasantly surprised on how strong a hold the television has on both young and older viewers. However, it was good to confirm a change in younger viewers device preference to consume sports content. The viewership trends of younger viewers should awaken the industry on the shift in device preference. Additionally, Escape and Enjoyment rank as the highest motivations for viewing sports content on all four digital devices.

Summary and Study Conclusions

The results of the study had low R^2 values. However, I can conclude from additional analysis that there was a marginal improvement in R^2 values using a more complex model. As a result, the simplest possible linear model is recommended.

Results of the study confirmed the proliferation of digital devices has caused a shift in viewing habits of sports content consumers as younger audiences enjoy viewing video streams on nontraditional digital devices such smartphones and tablets. Content providers and advertisers must follow the users to maintain profitability and relevance in this multiscreen world. Although the television still holds a firm grasp on sports content viewership, trends demonstrate that viewership shifts for some sports content types exist for younger audiences. Additionally, the sports content provided to audiences must provide a means for Escape and Enjoyment to ensure continued engagement.

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Appendix A: Consent Form

You are invited to take part in a research study to ascertain what motivates people to view various sports content types on four specific digital devices. Sports content types include live games, scores, sports highlights, sports news, sports documentaries, delayed games, and fantasy sports. The researcher is inviting potential participants who own a television, computer, smartphone, and tablet to participate in the study. This form is part of a process called "informed consent" to allow you to understand this study before deciding whether to take part.

Mark Henry, a doctoral student at Walden University, will conduct this research study.

Background Information:

The purpose of this study is to explore sports content viewership motives associated with specific digital devices such as televisions, computers, smartphones, and tablets. Additionally, the researcher would like to determine what sports content type viewers watch on a digital device compared to another.

Procedures:

If you agree to be in this study, you will be asked to:

- Complete a one-time 20-minute survey consisting of 50 questions

Here are some sample questions:

- I view sports content so I won't have to be alone;
- I view sports content because it is something I do when friends come over;

- I view sports content to find constantly updated event information;
- I view sports content because it is exciting; and
- I view sports content so that I can get away from the rest of the family or others

Voluntary Nature of the Study:

This study is voluntary. Your decision of whether or not you choose to be in the study will be respected. No one at Walden University will treat you differently if you decide not to be in the study. If you choose to join the study now, you can still change your mind later. You may stop at any time.

Risks and Benefits of Being in the Study:

Being in this type of study involves some risk of the minor discomforts that may occur in daily life, such as fatigue, stress or becoming upset. Being in this study would not pose any significant risk to your safety or well-being.

The information garnered from your participation could aid content producers in delivering sports content that you value on digital devices such as televisions, computers, smartphones, and tablets.

Payment:

All participants will equally receive between $1 and $2 for a completed survey.

Privacy:

The researcher will keep confidential any information you provide. The researcher will not use your personal information for any purposes outside of this research project. In addition, the researcher will not include your name or anything else that could identify you in the study reports. The researcher will keep data secured on removable media, such as a USB stick, in a password-protected folder, and locked in a fireproof safe. The researcher will keep the data for a period of at least 5 years, as required by the university.

Contacts and Questions:

You may ask any questions you have now. In the event you have questions later; you may communicate with the researcher via email at mark.henry@waldenu.edu. If you want to talk privately about your rights as a participant, you can call Dr. Leilani Endicott. She is the Walden University representative who can discuss this with you. Her phone number is 612-312-1210. Walden University's approval number for this study is IRB will enter approval number here and it expires on IRB will enter an expiration date.

Please print or save this consent form for your records.

Statement of Consent:

I have read the above information, and I feel I understand the study well enough to make a decision about my involvement. I understand that I am agreeing to the terms described above by clicking the link below.

Appendix B: Survey

The new survey combines questions from both Rubin (1983) and Cha (2013a). As a result, a rerun of EFA is required because of the variation of old instruments to create the new instrument, as well as a different sample and problem domain. Table B1 shows the first 31 questions of the new survey pertaining to viewing motivation and consists of questions adapted from Rubin (1983) and Cha (2013a). Table B2 shows the following seven questions of the new survey pertaining to sports content types. Table B3 shows the remaining 12 demographic survey questions.

Table 45

Viewing Motivation Questions

Please answer the following questions with responses from 1 to 8								
	1	2	3	4	5	6	7	8
Question	Strongly disagree	Disagree	Disagree somewhat	Undecided	Agree somewhat	Agree	Strongly agree	Do not know / not applicable
Motive: Relaxation								
I view sports content because it allows me to unwind								
I view sports content because it relaxes me								
I view sports content because it is pleasant rest								
Motive: Companionship								
I view sports content so I won't have to be alone								
I view sports content because it relaxes me								

(table continues)

Please answer the following questions with responses from 1 to 8								
	1	2	3	4	5	6	7	8
Question	Strongly disagree	Disagree	Disagree somewhat	Undecided	Agree somewhat	Agree	Strongly agree	Do not know / not applicable
I view sports content because it is pleasant rest								
Motive: Habit								
I view sports content so just because it's there								
I view sports content because I just like to watch								
I view sports content because it is a habit, just something to do								
Motive: Pass Time								
I view sports content when I have nothing better to do								

(table continues)

Please answer the following questions with responses from 1 to 8								
Question	1 Strongly disagree	2 Disagree	3 Disagree somewhat	4 Undecided	5 Agree somewhat	6 Agree	7 Strongly agree	8 Do not know / not applicable
I view sports content because it passes time when I am bored								
I view sports content because it give me something to do to occupy my time								
Motive: Entertainment								
I view sports content because it entertains me								
I view sports content because it is enjoyable								
I view sports content because it amuses me								
Motive: Social Interaction								

(table continues)

Please answer the following questions with responses from 1 to 8								
Question	1 Strongly disagree	2 Disagree	3 Disagree somewhat	4 Undecided	5 Agree somewhat	6 Agree	7 Strongly agree	8 Do not know / not applicable
I view sports content because it is something to do when friends come over								
I view sports content so I can talk with other people about what’s on								
I view sports content so I can be with other members of the family or friends who are watching								
Motive: Information								
I view sports content to find constantly updated event information								

(table continues)

Please answer the following questions with responses from 1 to 8								
Question	1 Strongly disagree	2 Disagree	3 Disagree somewhat	4 Undecided	5 Agree somewhat	6 Agree	7 Strongly agree	8 Do not know / not applicable
I view sports content because I am interested in current events								
I view sports content to find breaking sports new events								
I view sports content because I am interested in the immediacy with which information can be obtained								
I view sports content so I could learn about what could happen to me								

(table continues)

Please answer the following questions with responses from 1 to 8								
	1	2	3	4	5	6	7	8
Question	Strongly disagree	Disagree	Disagree somewhat	Undecided	Agree somewhat	Agree	Strongly agree	Do not know / not applicable
I view sports content because it helps me learn things about myself and others								
I view sports content so I can learn how to do things which I haven't done before								
Motive: Arousal								
I view sports content because it is thrilling								
I view sports content because it is exciting								
I view sports content because it peps me up								
Motive: Escape								

(table continues)

Please answer the following questions with responses from 1 to 8								
Question	1 Strongly disagree	2 Disagree	3 Disagree somewhat	4 Undecided	5 Agree somewhat	6 Agree	7 Strongly agree	8 Do not know / not applicable
I view sports content so I can forget about school or other things								
I view sports content so I can get away from the rest of the family or others								
I view sports content so I can get away from what I am doing								

Table 46

Sports Content-Type Questions

Please answer the following questions for each digital device with responses from 1 to 8				
	Digital device			
	Television	Computer	Smartphone	Tablet
	1 – Never	1 – Never	1 – Never	1 – Never
	2 – Rarely, less than 10% of the time	2 – Rarely, less than 10% of the time	2 – Rarely, less than 10% of the time	2 – Rarely, less than 10% of the time
	3 – Occasionally, about 30% of the time	3 – Occasionally, about 30% of the time	3 – Occasionally, about 30% of the time	3 – Occasionally, about 30% of the time
	4 – Sometimes, about 50% of the time	4 – Sometimes, about 50% of the time	4 – Sometimes, about 50% of the time	4 – Sometimes, about 50% of the time
	5 – Frequently, about 70% of the time	5 – Frequently, about 70% of the time	5 – Frequently, about 70% of the time	5 – Frequently, about 70% of the time
	6 – Usually, about 90% of the time	6 – Usually, about 90% of the time	6 – Usually, about 90% of the time	6 – Usually, about 90% of the time
	7 – Every time	7 – Every time	7 – Every time	7 – Every time
Sport Content Type	8 – Do not know / Not Applicable	8 – Do not know / Not Applicable	8 – Do not know / Not Applicable	8 – Do not know / Not Applicable
Sports news				
Live sports				
Scores				
Highlights				
Tape-delayed sports				
Sports documentaries				
Fantasy sports				

Table 47

Demographic Questions

Demographic question	Possible responses			
What is your age?	18 – 24	25 - 34	35 - 55	>55
What is your highest degree attained?	High School or less	Bachelor's degree	Master's degree	Doctorate degree
What is the zip code of where you live?				
What is your Gender?	Male		Female	
What is your marital status?	Single	Married no children	Married with children	Separated / Widowed
What type(s) of Internet service do you have (check all that apply)?	Have Internet at home	Have unlimited bandwidth at home	Have phone data plan	Have unlimited phone data plan
What type of television service do you have (check all that apply)?	Satellite	Cable	IPTV/Telco	Other
How long have you had a television?	Less than 3 months	3 months – 1 year	1 – 3 years	More than 3 years
How long have you had a computer?	Less than 3 months	3 months – 1 year	1 – 3 years	More than 3 years
How long have you had a smartphone?	Less than 3 months	3 months – 1 year	1 – 3 years	More than 3 years
How long have you had a tablet PC?	Less than 3 months	3 months – 1 year	1 – 3 years	More than 3 years
What do you expect your 2013 family income from all sources? before taxes to be?	Under $25,000	$25,000 – $49,999	$50,000 - $100,000	Over $100,000

Appendix C: Permission to Adapt Surveys and Figures

Permission From Jiyoung Cha

Hi Mark,

I am sorry I couldn't get back to you earlier. You can adapt my survey.

Best,

Jiyoung

Jiyoung Cha, Ph.D.

Assistant Professor

Film and Video Studies

College of Visual and Performing Arts

George Mason University

From: Mark Henry <mark.henry@waldenu.edu>

Sent: Sunday, November 24, 2013 11:18 AM

To: Jiyoung Cha

Subject: Permission Request to Adapt Survey

Dr. Cha,

I am a doctoral student at Walden University and am writing you this email to seek permission to adapt your survey from the article entitled "Does genre type influence choice of video platform? A study of college student use of internet and television for specific video genres".

I look forward to hearing from you.

Best regards,

Mark Henry

DBA Student

Walden University

Permission From Alan Rubin

Mark, feel free to publish your work that includes the adapted survey, providing you provide explicit citation of the origins of the measure. Best if luck with your research.

Sincerely, Alan Rubin

Hi Dr. Rubin,

I am a doctoral student at Walden University. You previously gave me permission to adapt your survey from the article entitled "Television uses and gratification: The interactions of viewing patterns and motivations". I was informed that I also need explicit permission to publish the adapted survey.

With this email I seek your permission to publish the adapted survey mentioned above.

Respectfully,

Mark Henry

DBA Student

Walden University

Hello, Mark.

Dr. Haridakis forwarded your request to me (see below). Feel free to use and adapt the TV Uses & Gratifications measure you mention in your email. Make sure you provide appropriate attribution to the original measure and its published source.

Best of luck with your research.

Best regards,

Alan Rubin

From: Mark Henry [mailto:mark.henry@waldenu.edu]

Sent: Sunday, November 24, 2013 12:03 PM

To: HARIDAKIS, PAUL

Subject: Permission Request: Dr. Rubin Survey Instrument

Dr. Haridakis,

I am a doctoral student at Walden University and am writing you this email to locate Dr. Rubin so that I may seek his permission to adapt his survey from the article entitled "Television uses and gratifications: The interactions of viewing patterns and motivations". I have not been able to contact him directly thus far and was wondering if you could provide me with his contact information. Additionally, I discovered that he is now retired and did not know if Kent University could provide the permission I seek.

I look forward to hearing from you.

Best regards,

Mark Henry

DBA Student

Walden University

Permission From Jun Kim

Hello Mark,

Thank you for the email. There is no problem to adapt the model, and you can use any of published works as long as you cite a source (i.e., reference).

Regards,

Dr. Kim

From: Mark Henry <mark.henry@waldenu.edu>

Sent: Sunday, January 19, 2014 5:00 PM

To: jko7e@my.fsu.edu; jk07e@fsu.edu

Subject: Doctoral Study: Permission Request to Adapt Figure

Dr. Kim,

I am a doctoral student at Walden University and am writing you this email to seek permission to adapt Figure 1 on page 174 in the Sport Management Review article entitled "A model of the relationship among sport consumer motives, spectator commitment, and behavioral intentions". The figure is entitled "The model of sport consumer motivations, spectator commitment, and behavior intentions".

I look forward to hearing from you.

Best regards,

Mark Henry

DBA Student

Walden University

Appendix D: Literature Review Matrix

The Various Types of Literature Reviewed for This Study

Counts	References within last 5 years from anticipated graduation	References older than 5 years	Total refs	%
Books	2	2	4	50%
Dissertations	0	0	0	0%
Peer-Reviewed Articles	112	5	117	96%
Web Pages	5	1	6	83%
Other resources (e.g., gov)	2	1	3	67%
Total	121	9	130	93%
Peer-Reviewed Articles & <= 5 years	112		130	86%