SEEKING OURSELVES ONSCREEN:

BRAND PERSONALITY, SELF-CONGRUENCE, AND MEDIA PREFERENCES

Da Eun Kim

A DISSERTATION

in

Communication

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2019

Supervisor of Dissertation

____

Michael X. Delli Carpini, Professor of Communication

Graduate Group Chairperson

____

Guobin Yang, Grace Lee Boggs Professor of Communication and Sociology

Dissertation Committee

Joseph N. Cappella, Gerald R. Miller Professor of Communication

Sandra González-Bailón, Associate Professor of Communication

DEDICATION

Here’s to the crazy ones, the fools who dream.

ACKNOWLEDGEMENT

My deepest thanks go to my advisor, Dr. Michael Delli Carpini. There are no words sufficient to express my gratitude for his guidance and support during what has been a crazy, transformative ride. Similarly, I'd also like to thank my committee members, Dr. Joseph Cappella and Dr. Sandra Gonzalez-Bailon. I am greatly thankful to all of these professors for their support of this somewhat rogue student pursuing a somewhat rogue program of research. I also extend my gratitude to Dr. Paul Messaris for his mentorship during my early days at Annenberg, and our lunches at Pod and walk through Santa Monica remain among my fondest grad school memories – you are missed.

Furthermore, I'm super grateful to Joanne Murray, who I can't recall ever having responded in the negative to the "Can I hang out for a minute?" that often followed my acquisition of a fresh cup of coffee. In addition, every adventure has a beginning, and I'd like to thank Dr. Sheila Murphy of the USC Annenberg School for Communication & Journalism. How lucky I was to have had her as my first professor in communication, in a theory class I was initially reluctant to take.

Last, but not least, I'd like to thank my parents for their unyielding support throughout the broader process. Even after I had left home for college, they struggled and poured in unspeakable hours to make sure I made it through USC – an experience without which I would never have made it to or flourished at Penn.

Financial support for this dissertation was provided by the Annenberg School for Communication and the Russell Ackoff Doctoral Student Fellowship of the Wharton Risk Management and Decision Processes Center.

ABSTRACT

SEEKING OURSELVES ONSCREEN:

BRAND PERSONALITY, SELF-CONGRUENCE, AND MEDIA PREFERENCES

Danny Da Eun Kim

Michael X. Delli Carpini

Do the media we consume reflect who we are or who we could be? Established theories of media preference implicitly presume audience knowledge of the media product's content or effects. But how does this awareness occur since, as experiential goods, the qualities and traits of media products only become known post-consumption? I argue that such an awareness results from the brands that media creators construct around their products to serve as content cues to potential consumers. Furthermore, drawing from research on brand-self congruence effects and self-management motivations for media use, I posit that individuals anthropomorphize these brands to have personalities, and prefer those with personalities paralleling how they see themselves or aspire to be seen. Through a three-part series of studies examining brands and brand-self congruence in the media context, with a focus on movies, I investigate: 1) the dimensions of brand personality across which individuals perceive media product brands; 2) whether such perceptions of media product brand personality can be predicted through computational content analysis; and 3) how brand-self congruence differs between individuals least and most preferred media products. I find the dimensions of Aggression, Heroism, and Warmth are commonly applicable across perceptions of movie, pop song, TV show, news outlet, and video game product brand personality; computational text and image features generated from movie posters and descriptions only contain information weakly predictive of movie Aggression; and that brand-self congruence is positively associated with pre-consumption interest but negatively correlated with post-consumption favoritism. I highlight the theoretical and methodological ramifications of the findings as well as directions for future research.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

CHAPTER 1 | INTRODUCTION

Media brands are increasingly important as boundaries between genres and formats blur, convergence becomes the norm, and content creators struggle to stand out in an infinitely large media landscape as they compete for finite audience attention (Malmelin & Moisander, 2014; McDowell, 2006). Yet, despite the large bodies of research in the communication literature exploring media preferences (e.g., uses and gratifications, selective exposure) and in the marketing literature examining the effects of brands and brand attributes on product selection, there has been little work at the intersection of these domains; i.e. inquiries into how the branding of media products affects media preferences and choice.

In this dissertation, I argue that understanding media preferences requires a greater understanding of how individuals perceive media products *prior* to their selection. In this regard, the integration of brand theory into theories of media preference could help bridge a key gap in the logic underlying the latter. Much as Knobloch-Westerwick (2015b) argues that media-effects theories such as the limited capacity model (Lang, 2000) and cultivation theory (Gerbner, Gross, Morgan, Signorielli, & Shanahan, 2002) often brush aside considerations of selective exposure, I argue that theories concerning media preferences, such as uses-and-gratifications (Katz, Blumler, & Gurevitch, 1973) and mood management (Zillmann, 1988; Knobloch, 2003), often brush aside considerations of how audiences perceive and think of the media products they are *considering* selecting. In short, these and similar theories of media preference essentially operate in a vacuum, implicitly presuming a degree of audience awareness of media content and potential exposure effects or gratifications prior to exposure.

But how does this awareness occur, since, as experiential goods, the qualities and traits of media products only become known post-consumption (Prior, 2013; J. Kim, Baek, & Martin, 2010)? Drawing on scholars such as Prior (2013) and J. Kim et al. (2010), I argue that this awareness results from the brands that media creators construct around their products to serve as content cues to potential consumers. The integration of brand theory into media preference research would advance the latter's theoretical and empirical foundations by bridging the logical gap described above, with the brand providing content and effect expectation cues in the case of new media selection, and reminder cues of past exposure effects in the case of repeat media selection.

More specifically, I posit that the mechanism for brand effects on media preferences operates through perceptions of "the self," arguing that media preferences are guided by perceptions of cues provided by the brand acting in interaction with perceptions of the self. This notion of "brand-self congruence effects" has been thoroughly and explicitly studied in the marketing literature. But it has implicit parallels, I argue, with notions of self-driven motivations for media choices that have been examined in the media preference literature.

Though the brand perception and brand-self congruence theories discussed and investigated are of relevance to media preferences across a range different formats, the specific medium that I most centrally examine in the present dissertation is movies. This choice was made given the role both visual and textual descriptive information commonly play in movie consumption processes (e.g. in selecting a movie on Netflix), the content of which can be studied using computational content analysis techniques, as well as the broader popularity of the format relative to other media. Though formats such as video games have overtaken movies in terms of industry revenue, movies are a far more established medium in the popular psyche and play a more central role in shaping culture (Shanley, 2017). Furthermore, such revenue-on-revenue comparisons of industry "popularity" are flawed in that video game industry sales metrics often take into account the sales of both games themselves as well as relevant hardware (e.g. video game consoles), while the movie metrics to which they are compared focus solely on box office ticket sales. Given that the average movie ticket price is $9 (Kilday, 2018) while blockbuster video games debut at $60 with even higher-priced special editions (Kain, 2018), to say the $1 billion grossing video game *Call of Duty: WWII* (Good, 2017) is as popular as the $1.3 billion grossing *Star Wars: The Last Jedi* (Box Office Mojo, 2018) is misleading.

I begin my dissertation by clarifying the definition of the brand construct as examined in the marketing literature and establishing my particular scope of inquiry, that of the "media product brand." I note similarities to other constructs more commonly examined in the communication literature and highlight the potential significance and utility of the brand construct for understanding the process by which individuals make media choices. I then foreground the theoretical parallels in the brands and the media preference literatures regarding the importance of the self, suggesting a potential approach to examining how brands may influence media preferences through the mechanism of brand-self congruence. I conclude my review by synthesizing these theoretical threads into the three research questions addressed in my dissertation.

Following this, I overview the methods to be utilized in my dissertation, starting with established statistical techniques common to the social sciences, and followed by a more extensive review of novel computational content analysis techniques. Drawing on both these theories and methods, I then turn to three empirical studies aimed at ascertaining (1) the dimensions of personality across which individuals perceive media product brands; (2) how such perceptions can be predicted from branding content; and (3) how individuals' media preferences are influenced by brand-self congruence. For each study, I detail the data collection process, the variables analyzed, and relevant analytical processes, followed by a discussion of the findings.

The results suggest the following. First, the personality dimensions of Aggression, Heroism, and Warmth are central to individuals' perception of various media products. Second, with the exception of the Aggression dimension, text and image features emerging from computational content analyses contain little information predictive of movie personality scores. Third, brand-self congruence is significantly associated with individuals' interest in watching movies that they have not yet seen. I conclude by summarizing my overall findings, discussing their broader theoretical and practical ramifications, acknowledging limitations, and outlining potential directions for future research.

CHAPTER 2 | LITERATURE REVIEW

2.1 | What is a Brand?

The American Marketing Association (1960) defined the term "brand" in the mid-20th century as a combination of words, designs, or symbols that mark one group's products to make them distinguishable from others. Since then, scholars' definitions for the brand construct have ranged from legal devices that establish ownership (Crainer, 1995; Broadbent & Cooper, 1987) to consumer risk-reduction devices (Assael, 1998) to holistic identity systems about a "product's essence, its meaning, its direction, and […] its identity in time and space" (p. 11, Kapferer, 1992; de Chernatony & Dall'Olmo Riley, 1998; Wood, 2000). Striking a balance between the functionalistic and holistic perspectives, Jones and Bonevac (2013) suggest that a brand is "a definition of a particular company or product" (p. 117) which helps consumers be aware of and identify it, and distinguishes the product from others using "promises, images, personalities, emotional characteristics, social characteristics, and various other objective and subjective qualities" (p. 118). Much as definitions give meaning to words, brands convey ideas – promises, images, personalities, or other traits – that "give meaning to names, logos, etc." (p. 118, Jones & Bonevac, 2013). I adopt this definition of brand and, while taking into consideration other components, primarily refer to brands by their name component – that is, the "part of a brand which can be vocalized" (Kotler, 1991, p. 442).

2.1.1 | Similarities to other constructs. Though brands are rarely studied in media effects research, the construct bears similarities to two others commonly examined in the field, namely the schema and the frame. Fiske and Taylor (1984) describe a schema as the mental structure representing an individual's knowledge about a concept or conceptual realm as well as the characteristics and the relationships between said characteristics. This definition could apply equally to brand perceptions, and much like brands, schema can form with regard to a wide range of concepts, including people, groups, events, or more (Price, 1992; Walsh, Clavio, Lovell & Blaszka, 2013; Grandien, 2017; Parmentier & Fischer, 2012). Similarly, though frames are typically described as the way specific issues or events are represented in the media, the framing process undoubtedly includes perceptions of the media outlet itself (e.g., the perceived brand of a particular news show or network). This holds true from both the communication frame perspective – how the brand of a media product is communicated – as well as the thought frame perspective – how the brand of a media product is understood by an individual – as outlined by Chong and Druckman (2007). Despite these conceptual similarities, the brand construct specifically presents the advantage of allowing for integration of a wealth of extant branding theory for the purposes of studying media use. For example, tying in research on topics such as brand extensions could enable more effective study of media selection beyond the traditional, single-channel context. Such a possibility is one advantage of integrating brands into selective exposure research, and the topic merits further study elsewhere.

2.2 | Media Brands

The definition of a "media brand" has varied in use as research has expanded within and across a wide range of disciplinary perspectives (McDowell, 2006). The term has been used to refer to media products, companies, services, and more. Disney – a studio – has been described as a media brand, as has *Star Wars* – a franchise – and *The New York Times* – a news outlet (Ots & Hartmann, 2015; Siegert, Förster, Chan-Olmsted, & Ots, 2015; Malmelin & Moisander, 2014). Von Rimscha (2015) proposes a three-level categorization of media brands. First are distributor brands that facilitate access to either a wide range of content (e.g., Netflix, Youtube) or niche content (e.g., ESPN-U). Second are wholesale brands that facilitate licensing and rights agreements and gain reputations for certain types of content in the process (e.g. Von Rimscha gives the example of RapidEyeMovies, which has built a reputation as a rights trader for Asian and Bollywood movies). Finally, content brands are specific shows, series, or movies (e.g. *ER, Titanic, Star Wars*).

2.2.1 | Distinguishing traits. Despite being a domain-specific subset of the larger brand construct, McDowell (2006) suggests five particular traits that, though they may play a role with other types of brands, are particularly important in distinguishing media brands from other types of brands: price insensitivity, risk minimization irrelevance, competition ease-of-access, benefit intangibility, and self-branding function. The final trait, the self-branding function, is emphasized by Ots and Hartmann (2015). They argue that the identity projection and construction function of media brands are in play regardless of whether one is consuming a media product for its social significance or out of genuine individual interest: “The magazine of your choice, whether it is *Elle, Newsweek, ComputerWorld, Guitar Player, Iron Man Magazine, Food & Wine,* or *Country Homes & Interiors* says something about you” (p. 218, Ots & Harmann, 2015). They go on to argue that the media brands individuals consume communicate something both about *and to* themselves, giving the example of how a "businesswoman who reads a certain newspaper (such as the *Frankfurter Allgemeine Zeitung* or the *Financial Times*), may signal that she is serious, knowledgeable, and sophisticated, and it may provide a personal feeling of confidence" (p. 218, Ots & Hartmann, 2015). Such assertions about the relationship between the self and media brand consumption originate in media management research, but similar claims have emerged independently in marketing and communication research. This relationship is discussed in detail in the following section.

2.2.2 | Specific scope: media product-as-brand. In selective exposure research, the term "media" generally refers to a specific media product. For example, Strizhakova and Krcmar (2007) look at media selection using video rental choices, while Knobloch and Zillmann (2002) examine music playback choice. As noted earlier, however, brands generally and media brands specifically can apply to a wide range of objects. Given my interests in applying media brand theory to media choice theory, in this dissertation I take a "products-as-brands" approach, similar to that discussed by Nienstedt, Huber, and Seelmann (2012), D. Kim (2017), and Malmelin and Moisander (2014).

Though individual media products can be derived from or extensions of existing parent brands, following the Jones and Bonevac (2013) brand construct definition discussed above, every media product, even within the same franchise, ultimately has its own brand, its own set of "promises, images, personalities, emotional characteristics, social characteristics, and various other objective and subjective qualities" (p. 118). For example, despite both deriving from the larger *Star Wars* brand and, accordingly, inheriting some associations from this parent narrative brand (Scolari, 2009), the representations of the Battle of Hoth, Yoda, and Lando Calrissian associated with *The Empire Strikes Back* are distinct from those of Rey, Kylo Ren, and Jakku associated with *The Force Awakens*. Even under the same name, the brand can still differ depending on the product – for example, the social characteristics and other qualities ascribed to the *Revenge of the Sith* movie are different from those ascribed to the licensed video-game of the same name. Consuming the video game *Star Wars: Republic Commando* is perceived differently than consuming the novelization of *Star Wars: Republic Commando*, as the two ultimately have different social characteristics – peers are more likely to have played the game than read the book – ergo, different brands.

2.3 | Brand Personality

Integrating brands into media use research makes possible the consideration of the way individuals perceive and think about media products *prior to selection*. One popular operationalization of the way individuals perceive brands takes an anthropomorphizing approach to the brand construct, centering on the idea of brand personality. Popularized in the literature by Aaker (1997), brand personality is defined as "the set of human characteristics associated with a brand" (p. 347). For example, individuals may perceive "Absolut vodka […] as a cool, hip, contemporary 25-year old, whereas Stoli's personified tends to be described as an intellectual, conservative, older man" (Aaker, 1997, p. 347). Aaker's measure put forth the dimensions of Sincerity, Excitement, Competence, Sophistication, and Ruggedness for the brand personality construct.

Scholars have conducted numerous studies building and expanding upon the brand personality construct. For example, citing concerns regarding generalizability, reliability, and cross-cultural validity with the Aaker measure, Geuens, Weijters, and de Wulf (2009) put forth a different scale for brand personality – consisting of the Responsibility, Activity, Aggressiveness, Simplicity, and Emotionality dimensions – that was found to improve upon Aaker's (1997) in all three regards. However, such a "macro" scale, which aims to be applicable to as broad a number of contexts as possible (Reynolds, 1988, S. Schwartz, 1992; Valette-Florence & de Barnier, 2013), is not without its limitations, with Valette-Florence and de Barnier (2013) arguing that because of its attempt to be so broadly applicable, the Geuens et al. (2009) scale falls short in nomological and predictive validity.

They use this shortcoming to argue the merits of the "micro" approach, which favors context-specific measures (Reynolds, 1988; S. Schwartz, 1992; Valette-Florence & de Barnier, 2013; Venable, Rose, Bush, & Gilbert, 2005), and develop a brand personality scale specifically designed for French print media (Valette-Florence & de Barnier, 2013) consisting of the dimensions of Respectability, Disingenuousness, Conviviality, Assertiveness, and Charm. A variety of micro scales exist in the media brand personality literature, each intended for different media formats, with both similarities and differences relative to each other and to macro-brand personality measures. With regard to comparisons to each other, D. Kim (2017) highlights, for example:

> Sung and Park's (2011) cable TV network personality scale and [J.]Kim et al.'s (2010) news media brand personality scale refer to similar dimensions of Ruggedness and Toughness, and the Dynamism dimension of the former seems to

parallel the Excitement dimension of the latter. The Disingenuousness dimension of the Valette-Florence and de Barnier (2013) French print media scale could be interpreted as a reverse conceptualization of the Sincerity dimension in the Sung and Park (2011) scale, while the Charm dimension of the Valette-Florence and de Barnier (2013) scale bears resemblance to the Sung and Park (2010) scale's Sophistication dimension. (p. 6)

D. Kim (2018b) also makes cross-micro comparisons as well as comparisons to Aaker's macro scale:

> Sung and Park's (2011) cable television network brand personality measure possesses a few more parallels to the Aaker (1997) measure [than does the Valette-Florence and de Barnier (2013) scale] and is conceptualized along the dimensions of Excitement, Warmness, Intelligence, Controversy, and Ruggedness. They note that the Excitement dimension is similar to that observed by Aaker but contains two subfacets, adventurous and young, capturing two different elements of excitement. They also highlight similarities between their Warmth dimension and Aaker's, but highlight the family-oriented and romantic subfacets arising from the topic domain and the nature of some channels observed like "Hallmark Channel, TV Land, and ABC Family" (p. 101, Sung & Park, 2011).
>
> Specifically with regard to news media, [J.]Kim et al. (2010) suggest that the brand personality dimensions of TV, cable, and print news media can be measured across the dimensions of Trustworthiness, Dynamism, Sincerity,

> Sophistication, and Toughness. They suggest the presence of the Trustworthiness dimension supports the idea that audiences value the credibility of media outlets, while the Dynamism dimension seems to align with Excitement as observed by Aaker (1997) and Sung and Park (2011) and the Sophistication dimension aligns with the Charm-Elegance subfacet observed by Valette-Florence and de Barnier (2013). Chan-Olmsted and Cha (2007), examining three broadcast news and three cable news outlets, posit a three-dimension conceptualization of television news brand personality consisting of Competence, Timeliness, and Dynamism, which seem to reflect similar trait emphases as the measures described above. (p. 204)

The presence of parallels in brand personality dimensions across these different micro scales, and the implied possibility of similarities in how different media products are perceived across different kinds of media products, is also reflected in the selective exposure literature. Theories of selective exposure and media use such as mood management (Knobloch, 2003; Zillmann, 1988) and eudemonia-appreciation (Vorderer & Reinecke, 2015) have both been explored with respect to a wide range of media, including movies (Oliver & Raney, 2011; Strizhakova & Krcmar, 2007), music (Knobloch & Zillmann, 2002), video games (Oliver et al., 2015), and more. That these theories of media preference are considered applicable to multiple types of media supports the possibility of a common set of personality dimensions across which media product brands of various formats are perceived.

2.4 | Brand-Self Congruence

In the marketing literature, brand-self congruence, also referred to as "self-image congruence" or "self-congruity" (Kressmann et al., 2006), has been studied for its effects on a variety of outcome variables including purchase intent (Sirgy, 1985), satisfaction (Jamal & Goode, 2001), loyalty (Kressmann et al., 2006), and more. Such effects have been observed in a variety of domains including tourism (Usakli & Baloglu, 2011), luxury products (F. Liu, Li, Mizerski, & Soh, 2012), toys (Lin, 2010), and others. Most relevant to media use, Nienstedt et al. (2012) suggest brand-self congruence is associated with loyalty to magazine brands.

Brand-self congruence is typically conceptualized and measured in one of two ways (Parker, 2009). Personality congruence asks individuals to rate their own personality and a brand's personality on a set of traits – Aaker's (1997) brand personality scale is popularly used for this purpose – and calculates congruence using the differences between the two measurements. User-imagery congruence considers congruence a gestalt-like psychological experience best measured by asking individuals to envision the typical user of a brand and rate how similar they believe themselves to be to that envisioned user (Sirgy et al., 1997; Parker, 2009).

Regardless of the particular conceptualization, such studies on brand-self congruence look at congruence singularly, or separately examine congruence with the ideal self versus congruence with the actual self. For example, Graeff (1996a) suggests that consumers' attitudes toward brands consumed in public are more influenced by congruence between the ideal self and brand image, while attitudes toward privately consumed brands are equally influenced by congruence between brand image and both actual and ideal self-image. Nienstedt et al. (2012) suggest that ideal self-congruence tends to be more explicative of online magazine brand loyalty while actual self-congruence tends to be more explicative of print magazine brand loyalty.

2.5 | Connecting Brands to Media Preference Theory

Such emphases on the effects of congruence with the self, actual and ideal, bear resemblance to recent theories integrating elements of the self into the study of media use. Knobloch-Westerwick (2015b; 2015a) cites Markus and Wurf (1987) to suggest that the situationally salient state of self – the "working self" (p. 965) – results in self-consistency, self-enhancement, and self-improvement/actualization motives for selective exposure to media. Self-consistency and self-enhancement motives arguably parallel actual self-congruence effects as observed in the marketing literature, while self-improvement motives parallel ideal self-congruence effects as observed in the marketing literature. Self-consistency and enhancement effects are also frequently observed in political communication research, where observations of news consumption driven by perceived ideological congruence with the self are numerous (e.g. Coe et al., 2008; Iyengar & Hahn, 2009) across media formats (Stroud, 2008) and topic areas (Stroud, 2011). On the other hand, self-actualization motives as put forth by Markus and Wurf (1987) have been observed in recent research examining meaning-seeking motives for media choice. Citing work by Oliver and Bartsch (2011), Oliver and Raney (2011), and Vorderer (2011), Vorderer and Reinecke (2015) suggest a eudemonic media use drive centered around "personal expressiveness, self-realization, and personal development" (p.

987, Oliver & Raney, 2011). They propose that media consumption can be driven by desire for meaning, growth, insight, and satisfaction of intrinsic needs – self-actualization – which may lead to media choices counter to hedonic optimization, such as selection of sad media (Vorderer & Reinecke, 2015).

My goal in this dissertation is to synthesize these parallel lines of self-related inquiry from the brands and the media preferences literature to examine how brand-self congruence may be associated with media preferences. The two important elements of examining brand-self congruence are individuals' perceptions of themselves and individuals' perceptions of media products. In addition, while both self and perceived brand personalities can be ascertained through surveys of potential consumers, I also test whether content analysis of materials commonly viewed prior to media selection (e.g. movie posters and summary on Netflix), may prove useful in predicting audience perceptions of media product brand personality.

2.6 | Significance and Research Questions

Brand theory can help fill a logical gap in extant media use research. As previously mentioned, existing theories examining the causes and consequences of specific media choice, such as mood management (Zillmann, 1988; Knobloch, 2003) and uses-and-gratifications (Katz et al., 1973), implicitly presume a degree of audience awareness of media content and potential exposure effects prior to exposure. The question has been how this awareness occurs, since, as experiential goods, the qualities and traits of media products only become known post-consumption (Prior, 2013; J. Kim et al., 2010).

I argue that this awareness results from the brands that media creators construct around their products to serve as content cues to potential consumers. The integration of brand theory into media preference research can advance current theoretical foundations in this area by bridging the logical gap described above, with the brand providing content and effect expectation cues in the case of new media selection and reminder cues of past exposure effects in the case of repeat media selection. I posit that media preferences and selective exposure decisions are guided by such brand cues, acting in interaction with related drives. I also propose that a key mechanism underlying the effect of brands on media preferences is brand-self congruence, bringing together similar self-centered lines of inquiry from the branding and the media preferences literature.

Methodologically, I also argue for the value of applying computational content analysis techniques, as reviewed in the following chapter, to the study of brand personality in the media context. The application of content analysis in the study of brand personality, or the utilization of computational techniques in the study of brands, are not themselves new (e.g. Ingenhoff & Fuhrer, 2010; Camiciottoli, Ranfagni, & Guercini, 2014; Tirunillai & Tellis, 2014; Santos, 2004). But prior research has largely depended on qualitative, human coding, and/or examined brand-related constructs other than brand personality. In addition, research on visual elements' effects on perceptions of brand personality or similar variables has been largely limited to experimental settings (e.g. Lieven, Grohmann, Herrmann, Landwehr, & van Tilburg, 2015; Boudreaux & Palmer, 2007; Orth & Malkewitz, 2008), reducing their generalizability to real-life contexts.

With the theories, research, and constraints discussed in this chapter in mind, I apply both self-report survey and computational content analysis techniques to the study of media-product brand personality and its relationship to self-personality, using actual media products. Specifically, I ask three research questions:

RQ1: What are the dimensions across which individuals perceive the brand personality of media products?

RQ2: What textual and visual elements of movie descriptions and posters are predictive of their brand personality?

RQ3: How is brand-self personality congruence associated with media preferences?

To answer these questions, I conducted three separate studies. The first was designed to ascertain the personality traits that individuals associate with a wide range of media products, in order to determine what specific personality dimensions apply across different media formats. The second study applies a variant of the resulting scale to explore how individuals perceive the brand personality of 250 mainstream movies, and utilizes computational content analysis to investigate how text and image attributes of movie summaries and posters may signal a media product’s brand personality to potential consumers. And the third study tests the effects of brand-self congruence on movie preference across a range of potential viewing contexts. Before turning to these studies and their findings, however, I review the various data and methods I employ and my reasons for doing so.

CHAPTER 3 | DATA & METHODS

To investigate the research questions outlined in the previous section, I utilize a wide range of statistical methods for analysis. These techniques range from more conventional methods that are long established in the social science literature, to more novel computational methods, adapted from fields such as information science and computer science, which are being increasingly adapted by other disciplines. I first discuss my data, and briefly review the more established statistical methods I use to analyze them. I then provide a more extensive review of the newer computational analysis methods employed in my research.

3.1 | Data

All ratings and survey data analyzed in this dissertation were collected from the Amazon Mechanical Turk ("mTurk") service. MTurk is a task crowdsourcing platform commonly used to conduct socio-behavioral research (Mason & Suri, 2012), with a more demographically diverse pool of participants than both Internet convenience samples and undergraduate student samples, as well as a level of reliability on par with such methodologies (Buhrmester, Kwang, & Gosling, 2011). Participants were restricted to native English speakers residing in the United States, age 18 or older, who had successfully completed at least 100 (in the Study 1 free association task) or 50 (in all other surveys included in my dissertation) tasks on mTurk. This last criteria was imposed for quality control purposes, with the initial 100 completed task threshold loosened to allow for a larger pool of participants and, accordingly, larger sample sizes in the subsequent studies.

3.2 | Conventional Methods

3.2.1 | T-tests. T-tests are a staple of statistical analysis in the social sciences. Multiple variations exist – one-sample, paired, independent sample – but are centrally about comparison of a mean to something else, either a proposed value or another mean (Field, Miles, & Field, 2012). They can also be used alongside analysis of variance, detailed below, to conduct pairwise comparisons across all possible pairs of experimental groups. In such cases, corrections to the p-value, such as via the Holm method, are necessary to account for the cumulative error concerns arising from multiple testing (Field et al., 2012). Independent sample t-tests as well as pairwise t-tests play a prominent role in the analysis of Study 3.

3.2.2 | Analysis of variance. Analysis of variance (ANOVA) allows for comparison of means across more than two groups. Much as with t-tests, there are multiple variants of ANOVA. Some of the more common variants are independent ANOVA, repeated-measures ANOVA, and mixed ANOVA, which are used in analyzing differences in between-subjects, within-subjects, and mixed designs, respectively (Field et al., 2012). Mixed ANOVAs play a prominent role in the analysis of Study 3.

3.2.3 | Regression. Regression is one of the most common analytical methods in the social sciences (Hindman, 2015). Multiple regression and related methods such as logistic regression enable examination of various predictors' effects on an outcome variable controlling for other predictors. Contemporary enhancements to regression methodology can also add a variety of functionality, such as embedded variable selection functionality in the case of LASSO (Hindman, 2015), which is discussed further in the following section. Study 2 utilizes several different approaches to regression for predictive applications, and critiques the common, saturated and un-cross-validated application of regression that is common in the social sciences. It also utilizes multi-level regression, which controls for clustering in the data (Field et al., 2012), to conduct exploratory analysis of congruence effects on responses toward media products.

3.2.4 | Factor analysis. Factor analysis is used to examine latent variable structures across a set of variables. Exploratory factor analysis takes a larger set of variables and inductively extracts a smaller set of latent variables, referred to as factors, by examining which variables tend to correlate with each other (Field et al., 2012). This is a common step in the construction of scales in general as well as brand personality scales in particular, where exploratory factor analysis reveals the latent personality dimensions pertaining to the brands under examination (e.g. Geuens et al., 2009; J. Kim et al., 2010; Sung & Park, 2011). Confirmatory factor analysis is used to test hypotheses about a factor structure (Field et al., 2012) and ascertain whether a proposed factor structure, as outlined by theory or arrived at through exploratory factor analysis, is a suitable fit for observed data. When using both exploratory and confirmatory factor analyses, Worthington and Whittaker (2006) and Cabrera-Nguyen (2010) recommend randomly splitting the dataset in half, conducting exploratory factor analysis on one half, while validating the resulting factor structure using confirmatory factor analysis on the other half. Such a process, which I use in Study 1, parallels recommendations for cross-validated regression made by Hindman (2015).

3.3 | Computational Content Analysis

Riffe, Lacy, and Fico (2014) define content analysis as "the systematic and replicable examination of symbols of communication, which have been assigned numeric values according to valid measurement rules, and the analysis of relationships involving those values using statistical methods, to describe the communication, draw inferences about its meaning, or infer from the communication to its context, both of production and consumption" (p. 19). Content analysis stands out as one of the unique methodological contributions of the communication field (Benoit, 2011). The costs associated with human-coding of large data sets, growing access to very large data sets, advances in data science, and increasing prevalence and affordability of computing power have enabled the widespread application of computational approaches to content analysis in investigating social science research questions. Computational content analysis techniques have been used in research in a range of fields, from marketing (e.g. Tirunillai & Tellis, 2014) to political science (e.g. Grimmer & Stewart, 2013) to linguistics (e.g. Jockers & Mimno, 2013) to communication (e.g. Walter, Sheafer, Nir, & Shenhav., 2016), among others.

The user experience of popular content distribution services, Netflix or Amazon Video is such that individuals are consistently exposed to representative visuals, often in the form of posters, and short descriptive texts for movies and shows available for selection. Posters and texts like these provide a corpus on which I will apply computational content analysis techniques in this dissertation to examine how the features of these images and texts may be associated with movie brand personality. In the sections to follow, I review the computational content analysis techniques that will be utilized in this dissertation, primarily as they pertain to largely to text features – commonly referred to as text mining – and with a more abbreviated review of computer vision features. In addition, I also review the computational regression techniques that I will use, which can be used with both text and image data.

3.3.1 | What is text mining? I draw on Hotho, Nürnberger, and Paaß's (2005) definition of text mining – "the application of algorithms and methods from the fields of machine learning and statistics to texts with the goal of finding useful patterns" (p. 4) with emphasis on pre-processing and feature extraction distinguishing it from regular data mining (Dörre, Gerstl, & Seiffert, 1999) – to consider the term "text mining" in this dissertation as encompassing both the feature extraction procedures necessary to arrive at a set of features to which regression/classification algorithms can be applied, as well as the development of said regression/classification algorithms. Unless otherwise noted (e.g., in my discussion of computer vision analysis), I also use the terms "text mining" and "computational content analysis" and similar terms interchangeably.

Zamith and Lewis (2015) suggest manual and computerized content analysis can be distinguished across each of the four steps of the content analysis process: coding protocol development, population triangulation/sampling, reliability measurement, and content coding. They note that with manual coding, the protocol must strike a balance between being too detailed versus too unreliable, adding to concerns voiced elsewhere (Lacy, Watson, Riffe, & Lovejoy, 2015) that much coding training is often done informally, possibly without comprehensive documentation, and with instructions that are delivered orally. This contrasts with computerized text analysis's strict unambiguity, which, in exchange for the transparency and greater replicability, lacks human adaptability and necessitates development of extensive, ideally exhaustive, combinations of classification criteria beforehand. With regard to population triangulation and sampling, larger samples require significantly more resources with manual coding. This is not the case for computational methods, with the caveat that computational methods require preprocessing prior to analysis and the associated risk of information loss (e.g. word order/relational information, Young & Soroka, 2012). Concerns related to intercoder reliability or replicability of findings present in human coding are absent for computational content analysis, since, given the same input parameters and content, a computer should return the same output every time (e.g. Young & Soroka, 2012; Zamith & Lewis, 2015; Su et al., 2017).

More broadly, computers are unable to comprehend the full range of human language – "all quantitative models of language are wrong" (p. 3, Grimmer & Stewart, 2013) – and struggle to capture subtler concepts that human coders would recognize, such as sarcasm or humor. Such underlying meanings in text are referred to as latent constructs, as opposed to manifest constructs, which are more clear-cut, objective constructs like word frequency (Riffe et al., 2014; Su et al., 2017). Benoit (2011) suggests that computer analysis is better suited for analysis of manifest content, while human coders are better suited for analysis of latent content. Similarly, Lewis, Zamith, and Hermida (2013) suggest that computational methods are best for analyzing structural variables, while human coding is necessary for more socioculturally constructed variables.

It is important to note that the latent-manifest distinction is not necessarily dichotomous, but a spectrum. Both text features prominently utilized in this dissertation are not pure manifest word counts, but instead represent more latent information derived from such manifest counts. For example, though word counts themselves may be purely manifest, topic models examine patterns in these word counts to extract latent topics that are present across multiple documents. Similarly, Linguistic Inquiry and Word Count (LIWC) variables are created based on dictionaries that sort the words present in documents into those related to latent cognitive, affective, and behavioral processes. But even in such cases, in being derived from word counts at their core, these feature extraction processes still ultimately fail to take into consideration any hidden meanings of the words that may be implied by their surrounding context – e.g. whether a word being used sarcastically or ironically is not taken into account – making them less purely manifest than word counts, but also centrally more manifest variables in nature than latent variables.

3.3.1.a | Preprocessing. With raw text data, pre-processing is necessary before analysis. Hotho et al. (2005) outline these steps, the first of which is tokenization. Tokenization means splitting a document into a list of words by removing non-text characters (punctuation, spaces, etc.). This process forms the base text on which further pre-processing occurs. The second step is filtering, which removes words from the body of documents as specified by a particular dictionary. A common example of filtering is stop-word deletion, which removes words such as, “a,” “the,” “it,” etc. that contain limited informational value (Hotho et al., 2005). The third step in pre-processing is lemmatization or stemming. Lemmatization converts verbs to infinitives and plural nouns to singular, but as such a transformation necessitates part-of-speech knowledge, the more frequently used procedure which I will apply in this dissertation is stemming, which removes prefixes and suffixes from words (“-es,” “-ize,” “-ing,” etc.) to form word stems with similar meaning (Hotho et al., 2005).

The above procedures lead to a body of words generally represented in vector-space form (Hotho et al., 2005), or spreadsheet form in lay-language, and such a body of text often referred to as term-document or document-term matrices (TDM/DTM). Commonly, the matrix is one where the rows represent separate documents and each column represents a separate word or string of words. The values in each cell can consist of a binary indicator for word usage in a document, numeric frequency in a document, weighted importance measures (e.g. term frequency-inverse document frequency [TF-IDF], Ramos, 2003; Hotho et al., 2005), or others.

Depending on the desired feature set and its extraction method, not all of these pre-processing steps may be necessary. For example, for a LIWC dictionary-based feature extraction approach as explicated below, a spreadsheet with rows of strings representing separate documents is sufficient pre-processing, with TDM construction and even filtering and stemming unnecessary. On the other hand, the term-document matrix forms the foundation from which topic modeling algorithms examine word co-occurrence patterns to extract topics. LIWC and topic models are further discussed in the following section.

Both feature extraction and regression/classification algorithm development are key steps of the computational content analysis process. Reviewed below are examples of common feature sets that can be utilized as predictors in regression/classification as well as some popular regression/classification algorithms. While the options for both are numerous, here I review prominent examples I apply in this dissertation.

3.3.1.b | Features. The most fundamental text feature is the word, commonly referred to as the unigram. When using unigrams as the feature level of interest, each unigram is extracted from documents using the pre-processing procedures described above. Within the resulting document-term matrix, each document is represented by the words contained in it (Hotho et al., 2005) without regard for their order (Blei, Ng, & Jordan, 2003) – popularly referred to as a "bag-of-words" – with the frequency of each word in the document or binary presence indicators (Pang, Lee, & Vaithyanathan, 2002) most commonly being the representative value. This makes them intuitively interpretable and useful for visualizations of word counts, such as word clouds (e.g. Chuang, Ramage, Manning, & Heer, 2012), and unigrams are computationally efficient (Blei et al., 2003; Wallach, 2006; Xia, Zong, & Li., 2011). Despite their interpretability, utility, and computational simplicity, unigrams are limited by their inability to consider context (Cui, Mittal, & Datar, 2003). But this does not necessarily undermine their significance – unigrams are the foundation on which more sophisticated features such as topic models and dictionary dimensions, discussed below, are created. A natural, commonly utilized extension of the unigram is the *n*-gram, best thought of as phrases consisting of a predefined *n* number of words, or word sequences (Fürnkranz, 1998). However, as neither unigrams nor *n*-grams are utilized in their raw form in this dissertation, with unigrams utilized primarily as the component elements to derive topic models, further discussion of the properties of unigrams and *n*-grams is omitted here.

3.3.1.b.i | Dictionary-based features – LIWC. Extracting features relating to sentiments, cognitions, or other constructs based on pre-established coding dictionaries or lexicons is one of the oldest and most straight-forward methods of feature-extraction (Stone, Dunphy, Smith, & Ogilvie, 1966; Grimmer & Stewart, 2013). To do so entails examining documents for the appearance of keywords with pre-established relevance to a set of conceptual dimensions, as established during dictionary development, to measure to what degree texts present across said dimensions. Sometimes characterized as classification methods themselves (e.g. Grimmer & Stewart, 2013), dictionary-based methods can arguably be considered a specialized form of feature extraction in that they take high-dimensional text data and convert them into numerical representations of a given set of constructs relevant to a particular domain, as determined by the particular dictionaries used. Dictionary-based techniques have been used to study sentiment (e.g. Young & Soroka, 2012) and policy positions (e.g. Laver & Garry, 2000) among other topics.

A widely used dictionary that I apply in this dissertation is the Linguistic Inquiry and Word Count (LIWC) dictionary as developed by Pennebaker, Boyd, Jordan, and Blackburn (2015). The LIWC dictionary as of its latest 2015 revision consists of 6,400 words, stems, and even some emoticons. Each item in the LIWC dictionary is labeled as being part of several categorical subdictionaries representing particular linguistic, grammatical, emotional, or psychological dimensions. For example, the word "cried" is part of the subdictionaries of "sadness, negative emotion, overall affect, verbs, and past focus" (Pennebaker et al., 2015, p.2). Documents are scored on these subdictionary dimensions based on the presence of associated words, resulting in approximately 90 measurements including both general informational variables (e.g. word count, % words captured across all dictionaries, etc.) and specific categorical variables pertaining to language use, linguistic dimensions, affective/psychological dimensions (e.g. sadness, anger, tentativeness, certainty), etc. (Pennebaker et al., 2015), all of which can be used as input in regression and classification.

3.3.1.b.ii | Topic models. Despite the limitations of unigrams discussed earlier, they remain useful as a building block of more complex features. Blei et al. (2003) note that despite the irrelevance of word order in the unigrams bag-of-words approach as well as the irrelevance of document order it implies, this exchangeability does not inherently restrict one to the use of purely frequency-based methods. They propose the latent Dirichlet allocation (LDA, not to be confused with linear discriminant analysis) model, or, as it is more commonly known, topic models.

LDA assumes that a document discusses multiple topics that are predetermined in nature, i.e. these topics would intuitively exist outside of their presence within a document. Each topic is a set of words highly representative of that topic: for example, "Computers" would have words related to computers with high probability (e.g. "CPU", “RAM”, “disk”), while the topic American History would have words related to American history with high probability (e.g. “Constitution”, “Roosevelt”, “Jefferson”) (Blei, 2012), and so on. LDA assumes that all documents in a corpus are based on a common set of topics, but that each document displays the topics to varying degrees. With such assumptions in place, topic modeling takes a reverse engineering approach, taking the documents in the corpus and using their contents to infer these hidden topics and their prominence in each document (Blei, 2012).

The output generated by this process consists of topic probabilities for each word (Steyvers & Griffiths, 2007) as well as per-topic probabilities for each document in the corpus – the latter can be used as input features during regression and classification. Blei et al. (2003) found that doing so using a 50-topic LDA model improved prediction accuracy using a support vector machine classifier compared to a 15,818 word unigram-based feature set, while lowering dimensionality by over 99%. Scholars have since built on the LDA concept to develop a range of topic model variants, such as supervised topic models (Blei & McAuliffe, 2007) and dynamic topic models (Blei & Lafferty, 2006). Utilized in this dissertation is one such variant, the correlated topic model (Blei & Lafferty, 2007), which allows for the underlying algorithm to account for cross-topic correlation in the generation of the extracted topics. The example Blei and Lafferty (2009) give is that an article about genetics is inherently more likely to be about disease than astronomy, but the LDA topic model algorithm is unable to account for this while the correlated topic model algorithm can when generating topics.

3.3.2 | Beyond text – computer vision features. Though far less commonly applied in than text features, computer vision features based on images are gaining increased attention in the social sciences. Visual elements such as color, complexity, and composition of images have been shown to impact attitudes, emotions, behavior, and more (Bakhshi & Gilbert, 2015; Detenber, Simons, & Reiss, 2000; Peng, 2017; Peng & Jemmott, 2018), and vision is a core component of media evaluation and consumption, particularly in the context of visual media such as movies. This is especially true given the design of the modern content distribution platforms, such as Netflix; audiences scroll through an endless pool of movie posters to make their selection, with these visual components taking up the majority of the screen while the text descriptions are largely relegated to a specific corner.

At the most fundamental level, vision features differ little from text features. They are computer-comprehensible numerical representations of more easily human-comprehensible non-numerical content. And much as is the case with text features, such features can represent a variety of constructs and be generated in a variety of ways.

A popularly applied computer vision method is edge detection. Edges are defined as locations of sudden change in texture or color and often demarcate object boundaries (Szeliski, 2010). Once edge detection is completed, the data can be used to calculate the prominence and density of edges within the image, as well as a range of derivative features such as adherence to the rule-of-thirds, a photographic principle where in a frame divided vertically and horizontally into equal thirds, important subjects are placed on the dividing lines or their intersection (Peng & Jemmott, 2018; Amirshahi, Hayn-Leichsenring, Denzler, & Redies, 2014; Ke, Tang, & Jing, 2006).

Color is also a commonly examined component and operationalizable in a variety of ways. Segments, or regions of sufficiently similar color, can be counted (van der Walt et al., 2014). The total number of unique hues present in an image can also be considered (Ke et al., 2006), as can the prominence of different basic colors as delineated in the English language (van de Weijer, Schmid, Verbeek, & Larlus, 2009). From these more fundamental variables, various derivative features, such as an arousing-relaxing color index (Peng & Jemmott, 2018) can be generated.

More popularly recognizable qualities can also be identified and defined as vision features. Brightness and contrast are common image settings in consumer electronics and software and frequently included as variables in computer vision analysis (L. Liu, Preotiuc-Pietro, Samani, Moghaddam, & Ungar, 2016; Peng & Jemmott, 2018). File size can also be a useful metric for image complexity across images of standardized dimensions and formats.

Many of the strengths and weaknesses of computational versus human text analyses also apply to computer vision feature-based image analysis. Computers can provide manifest variable information about images to a degree of granularity not feasible with human coding – e.g. the exact number of pixels for each color. However, latent features and their meaning – e.g. relationships between people and objects in an image and the associated meaning – are more effectively coded by humans. Nonetheless, some visual components may be more evolutionarily fundamental and less socially constructed in their meaning than text. For example, in food contexts, research suggests individuals unconsciously link the color red to sweetness and desirability, and greenness to sourness and undesirability, in line with the color shift commonly observed in fruit ripening (Spence, Levitan, Shankar, & Zampini, 2010; Harrar, Piqueras-Fiszman, & Spence, 2011; Huang & Lu, 2015; Wadhera & Capaldi-Phillips, 2014). And in sports, black uniforms have been found to be associated with perceptions of aggression (M. Frank & Gilovitch, 1988; G. Webster, Urland, & Correll, 2012), potentially pertaining to the color's innate negative associations with "night, uncertainty, and danger" (p. 1020, Sherman & Clore, 2009). Even children are more likely to presume a black box contains something negative than a white box (Stabler & Johnson, 1972). Though specific color effects may differ in the specific context of movies – Elliot and Maier (2014) compare the red of a ripe apple and the red of fresh blood to highlight the contextually variant meaning of colors – it is reasonable to posit that color elements in posters may impact, for example, perceptions of aggression and interest in a movie.

3.3.3 | Algorithms. Text and visual features such as those described above can be input into a range of algorithms intended to predict a variety of outcomes. Such algorithms may be parametric (e.g. linear regression), with underlying assumptions about variable relationships, or non-parametric (e.g. random forests), with minimal underlying assumptions. Given this, the present manuscript prefers the term "algorithm" over "model," the latter of which implies parametricity, when referring to regression and classification methods. Similarly, while "regression" refers to these methods' application with a continuous outcome variable and "classification" to their application with a categorical outcome variable, many such algorithms can be used for either purpose (Berk, 2016), and the terms are used interchangeably here. Reviewed below are common regression algorithms I will apply in this dissertation.

3.3.3.a | LASSO. Hindman (2015) notes that multiple regression as commonly applied in the social sciences presents problems pertaining to model parsimony – "any variable included in the model will produce a nonzero coefficient" (p. 56) – and that this can lead to issues with interpretability, overfitting, predictive performance, and replicability. LASSO, short for least absolute shrinkage and selection operator, is a form of penalized regression that Hindman (2015) suggests addresses such concerns with standard linear regression outlined above. It works by imposing a constraint on the sum of the absolute value of all regression coefficients, as specified by the tuning parameter *lambda*. A larger lambda means more coefficients will be shrunk to zero; a smaller lambda means more coefficients will be allowed to have non-zero values, replicating multiple regression results at lambda equals zero. As lambda decreases, variables are introduced into the model based on their degree of correlation with remaining residuals – variables introduced late into the model are less likely to be directly affecting the outcome and likely to be shrunk to zero (Hindman, 2015).

3.3.3.b | Decision trees & random forests. Decision trees, also called classification and regression trees (Berk, 2016), are simple in logic. Given a set of predictors and an outcome variable, decision trees first examine all possible binary splits that can be taken on each of the predictors. It seeks a predictor and a splitting value that, in the case of regression, most reduces the total residual sum of squares (relative to the mean) across the two new partitions compared to before the split. Once this initial split occurs, the same procedure is repeated until an insufficient reduction in residual sum of squares to merit another split or a minimum terminal partition size is reached, thresholds that are determined by the researcher. Within each terminal node, the average forms the predicted value for those observations. Tabulation and visualization of decision trees allows researchers to examine the variables and values upon which the partitioning in the tree occurred and implied associated relationships.

Random forests (Breiman, 2001) use decision trees as their building block and are fundamentally an array of decision trees, averaged over each other. However, by adding randomization at two points of the algorithm generation process and repeating the process – a random subset of observations is used to construct each tree and a random subset of variables is considered for each split – random forests allow for more stable and independent fitted values and more realistic estimates of out-of-sample performance (Berk, 2016). After training each tree with these additional randomizing steps, the tree is used to then generate predicted values ("out-of-bag" or OOB predictions) for those observations not randomly sampled to train the tree (OOB observations). The final predicted value for each observation is the average of all of its OOB predictions. There are no regression coefficients per se with random forests, and while tools like importance plots and partial dependence plots allow for consideration of variable contributions to predictive performance, they do not provide information on the directionality of the relationship between each predictor and the outcome (Berk, 2016).

3.3.3.c | Boosting. As a high-level concept, boosting works by first fitting a base algorithm (often a decision/regression tree), then, once errors based on this initial fit have been calculated, re-fitting the algorithm with the high-error observations weighted higher. This process is repeated, with the highest error observations continuously given greater weight; the goal is to take advantage of the cumulative predictive power of many such weakly predictive observations (Berk, 2016; Hastie, Tibshirani, & Friedman, 2009). There are many sub-types of boosting, and a popular option is stochastic gradient boosting (SGB) (Friedman, 2002). SGB works by fitting the base learner (often a single decision tree), then calculating the residuals from its fitted values, attaching these residuals as a new predictor to the dataset, randomly sampling the data without replacement, fitting another learner with the newly extended and sampled dataset, then repeating this process a specified number of times. As is the case with random forest, no regression coefficients as commonly understood are provided and the directionality of predictor-outcome relationships is not specified, but partial dependence plots and variable importance plots can be generated to examine the contributions of various predictors to fit (Berk, 2016).

I apply the features and algorithms presented above in Study 2 of this dissertation to examine the effects of computational text and image features extracted from movie posters and descriptive text on movie brand personality. Five-fold cross-validation – a method by which data is split into five sets, the algorithm is trained on the fours of the sets, its test error calculated with the one holdout set, this process repeated with each of sets used as the holdout set once, and the five test error values averaged to provide a cross-validated error value (James, Witten, Hastie, & Tibshirani, 2013) – is used to determine algorithm tuning parameters (e.g. lambda for LASSO) as needed. Multiple regression, as commonly utilized in the social sciences, will also be applied alongside the algorithms reviewed above, primarily to provide an accessible reference against which the predictive performance of these algorithms can be compared.

CHAPTER 4 | STUDY 1:

THE DIMENSIONS OF MEDIA PRODUCT BRAND PERSONALITY

In examining perceptions of media-product brand personality, two questions arise. The first regards the relevant dimensions of personality across which individuals assess the personality of different media product brands. The second is whether there is a common set of personality dimensions that are applicable across different media formats. Ascertaining the answers to these questions is the goal of Study 1 (**RQ1**).[1]

4.1 | Selecting Media Categories for Inclusion

As discussed in the literature review, prior research suggests the existence of similar traits that cut across various micro media brand personality scales (e.g. Valette-Florence & de Barnier, 2013; Sung & Park, 2011; and J. Kim et al., 2010). Prior research also suggests that the same selective exposure theories are applicable across different types of media. In combination, these findings suggest the possibility of a common core of brand personality traits that are perceived and influence individuals' preferences regardless of the media product format in question. Of course, creating a media brand personality scale encompassing *every* possible media format is not feasible, given the sheer number of different media types, the constant emergence of new forms, and fading of older ones. Furthermore, such an all-encompassing scale would arguably exacerbate

---

[1] This section and other sections of the present dissertation related to Study 1 are adapted with edits from the Accepted Manuscript of an article published by Taylor and Francis in the *International Journal on Media Management* on May 3, 2017, available at https://tandfonline.com/doi/abs/10.1080/14241277.2017.1306531 (D. Kim, 2017).

concerns raised regarding existing macro brand personality scales, such as the issue of nomological and predictive validity (Valette-Florence & de Barnier, 2013).

In order to find an appropriate "middle ground," the selection of media brand categories for inclusion in the present study was guided by which media are most commonly studied in extant research on media preferences. I observed that a commonly examined theory of media preference, mood management (Zillmann, 1988; Knobloch, 2003), had been studied with regard to news (e.g. Knobloch-Westerwick & Alter, 2006), movies (e.g. Strizhakova & Krcmar, 2007), music (e.g. Knobloch & Zillmann, 2002), TV shows (e.g. Bryant & Zillmann, 1984), and video games (e.g. Reinecke et al., 2012), justifying the inclusion of media product brands of these formats. Books, while not similarly examined, were also selected for inclusion due to their relative construct simplicity – except in cases of marquee authors and franchises, books arguably have less potential attitudinal confounders than do movies or TV shows, perceptions of which can easily be influenced by the actors, directors, or other creative parties involved.

4.2 | Data Collection

Data collection took place in two stages. First was a free-association task to generate candidate items for the scale, a common early step of brand-personality scale development (e.g. Aaker, 1997; J. Kim et al., 2010; Geuens et al., 2009). The second was a test of the candidate items ascertained in stage 1, to determine the factor structure of the personality traits commonly applicable across the included media formats.

4.2.1 | Free-association task. Twelve brands each from the categories of film, news, TV shows, video games, pop songs, and books were included in the free-association task survey (Table 1). The source for the film brands was the Worldwide Grosses section of Box Office Mojo as it stood in March 2016 (Box Office Mojo, 2016). News brands were adapted from those used in J. Kim et al. (2010), with popular conservative and liberal online news sites added and local news removed. The source for TV show brands was the Most Watched Series Finales in the United States list on Wikipedia (2016), a compilation of viewership data sourced from Reuters, *Variety*, Nielsen, and *USA Today* data, as it stood in March 2016. Video game brands were selected from VGChartz's (2016) Game Totals chart as it stood in March 2016. Given the wide variety of music available, and the need for a minimum degree of recognizability among participants, only pop song brands were included, chosen from the Billboard Hot 100 All-Time Top 100 Songs (Billboard, 2013). Finally, book brands were selected from Amazon Best Sellers lists from 2013 to 2015 (Amazon, 2015; Amazon, 2014; Amazon, 2013).

Table 1

Study 1, 72 Brands (6 Categories x 12 Brands) Included in Free-association Task

Video Games	Call of Duty:Black Ops III	Movies	Avatar	Pop Songs	Apologize
	Cooking Mama		8 Mile		Boom Boom Pow
	Forza Motorsport 6		Enemy of the State		Call Me Maybe
	Heavy Rain		Forrest Gump		Just the Way You Are
	Just Dance		Frozen		Low
	LA Noire		Inception		Moves Like Jagger
	LittleBigPlanet		Jumanji		Party Rock Anthem
	Madden NFL 16		Love Actually		Rolling in the Deep
	Minecraft		Sixth Sense		Somebody That I Used to Know
	Red Dead Redemption		Spirited Away		Tik Tok
	The Last of Us		Titanic		We Are Young
	The Witcher 3: Wild Hunt		XXX		We Found Love
TV Shows	Avatar:The Last Airbender	News Outlets	ABC News	Books	5 Love Languages: The Secret to Love That Lasts
	Battlestar Galactica		Breitbart		A Visit from the Goon Squad
	Dawson's Creek		CNN		All the Light We Cannot See
	ER		Fox News		Boys in the Boat: Nine Americans and Their Epic Quest for Gold at the 1936 Berlin Olympics
	Friends		Mother Jones		Hotel on the Corner of Bitter and Sweet
	Gilmore Girls		MSNBC		Jesus Calling
	JAG		Newsweek		Miss Peregrine's Home for Peculiar Children
	King of the Hill		The Drudge Report		StrengthsFinder 2.0
	Mad Men		The Huffington Post		The Goldfinch
	NYPD Blue		The New York Times		The Invention of Wings
	The Late Show with David Letterman		The Wall Street Journal		Thinking, Fast and Slow
	The Sopranos		Time		What If: Serious Scientific Answers to Absurd Hypothetical Questions

With all media categories except news, six of the 12 brands were chosen from the top half (i.e., most popular) and six were chosen from the bottom half (i.e., least popular) of either the entire available rankings or the top 500 in the rankings, whichever was smaller. This approach was used to account for any potential confounding effects of popularity. Specific most and least popular brands were selected with the aim of genre-representativeness within media categories, with a preference for post-2000 media to help ensure some degree of recognizability among participants. Finally, to control for the potential confounding effects of brand awareness in relation to media franchises rather than for a specific media product, media brands that were not and did not have widely-known sequels, prequels, spin-offs, reboots, adaptations, or known source material for adaptations at the time of the study received preference for inclusion. However, exceptions were made, particularly in the case of video games, as the vast majority of the top selling games were brands with many extensions – e.g. *Pokemon, Call of Duty, Super Mario*, etc.

All mTurk workers who indicated interest in participating in the free-association task were screened through being randomly presented, one-by-one, with up to six media brands from the 72 brands described above. At any point that a respondent indicated being sufficiently familiar with a media brand (3 or above on a category-specific 5-point scale variant of: 1 – Not at all familiar with it, 2 – Have heard of it but don't know what it's about, 3 – Have heard of it and know what it's about, 4 – Have [consumption verb] it once; 5 – Have [consumption verb] it multiple times), they were deemed eligible and brought into the main Study 1 free-association task survey. If a respondent indicated not being sufficiently familiar with any of the six randomly presented brands in the screening, they were dropped from the study. Study participants were then asked to imagine that the media brand that they indicated being familiar with "was a person," and to provide three or more personality traits that they believed described that media brand's personality. Following this task, basic demographic information was collected. The above procedure was repeated until all 72 brands had 20 responses each, for a total N of 1440. Participants in the free-association task survey were 50.42% male and 78.54% white, with a median age of 30 (minimum: 18; maximum: 77) and 53.5% possessing a college education or greater.

4.2.1.a | Determining candidate items. The free-association task data was cleaned, with all text converted to lower case, punctuation deleted, and stopwords removed, resulting in 1,882 unique unigrams. Then, synonyms within the data were compounded using an online version of *Roget's 21st Century Thesaurus, 3rd Edition* as a reference and "root" word (the words that synonyms were compounded into) priority given to words that were determined to be unipolar markers for personality as determined by Goldberg (1992). This synonym compounding led to 1,262 unique word unigrams.

The synonym-compounded data was then converted to a sparse matrix consisting of dummy variables for every word, with a 1 to indicate that a specific unigram was used in a given row and a 0 to indicate that it was not. Then, instead of using an umbrella minimum frequency threshold, only words used in at least 4 of 20 cases for at least one of the 72 brands were retained for further analysis. This two-tier selection criteria was preferred as the presence of a word in 20% of observations for a single brand suggested consistent perception of a trait in a brand across multiple individuals and avoided the possibility of a stray word appearing once for numerous brands being included in the analysis. This led to a total of 78 unigrams.

Geuens et al. (2009) highlight the construct validity concerns with brand personality scales that incorporate non-personality traits, and as such, though what is and is not a personality trait involves some element of subjectivity, unigrams qualitatively determined to be non-personality items when evaluated by McCrae and Costa’s (1997) “relatively enduring styles of thinking, feeling, and acting” standard were dropped. Such dropped items included those pertaining to age (“teenage”, “youthful”), image (“party”, “athletic”, “fast”, “creepy”, “powerful”, “funny”, “crazy”, etc.), gender (“masculine”), and others characteristics (e.g. “confusing”, “intense”). This led to a set of 52 unigrams for analysis. Contrary to Aaker’s (1997) approach in retaining only positive traits and in line with Bosnjak, Bochmann, and Hufschmidt’s (2007) critique of the restriction, both positive and negatively valenced traits were included in the analysis; Aaker’s (1997) argument regarding retaining only positive traits does not necessarily hold with media as many popular media products can be construed to possess negatively valenced traits, which may even be the attracting factors in some cases (e.g. dystopian movies, violent video games).

Principal component analysis with Quartimax rotation on the 52 unigram dummy variables resulted in a 23 component solution explaining 54.6% of variance. Bivariate correlation analysis suggested that all factor scores were associated with any one media category by +/-<.23, suggesting relatively little category bias in the applicability of the components. Going through the rotated component matrix sorted in decreasing Eigenvalue order, for each component, the two traits with the highest loadings were chosen to be carried onto the primary pre-test survey. If one of the two highest-loading words for a given component had already been selected from a component higher in the chart, only one word was selected from that component; if both of the highest-loading words for the component had already been selected, then no words were selected from that component. This step led to a pool of 41 personality traits. Six traits from the Geuens et al. (2009) brand personality scale that were not already contained in this pool of 41 – down-to-earth, responsible, stable, ordinary, dynamic, and sentimental – were added to the pool, similar to what J. Kim et al. (2010) did with traits examined by Aaker (1997), for a total of 47 traits to be carried into the next part of the study.

4.2.2 | Main survey. Twenty brands were selected from each of five different media categories (movies, TV shows, pop songs, video games, and news outlets) for inclusion in the main pre-test survey, for a total of 100 media brands (Table 2)[2]. Selection of the brands to be included in the main pre-test survey followed a slightly modified version of the brand selection protocol for the free-association task survey, with the number of brands included per category expanded to 20. With all media formats except

---

[2] An individual bypassed mechanisms put in place to ensure that each survey response came from a unique participant, overloading the book category with ~300 void responses (4 of 7 on all 47 trait questions). Due to budget limitations, additional data could not be gathered to replace the void responses. After careful consideration of available options, the decision was taken to remove the book category from the final scale.

news, 10 of the 20 brands were chosen from the top half and the other 10 were chosen from the bottom half of either the entire available rankings for the respective media category or the top 500 in the rankings for the respective media category, whichever was smaller, to control for any popularity biases[3]. Within the news category, the set of brands included in the news media brand personality scale by developed J. Kim et al. (2010) was expanded to include *The Washington Post,* three liberal leaning outlets (*Daily Kos, Mother Jones, The Huffington Post*) and three conservative leaning outlets (*Breitbart, The Blaze, The Drudge Report*).[4]

---

[3] The source ranking for the film brands was the Worldwide Grosses section of Box Office Mojo as it stood in August 2016 (Box Office Mojo, 2016). The source ranking for the TV show brands was the Most Watched Series Finales in the United States list on Wikipedia (2016) as it stood in March 2016, a compilation of viewership data sourced from Reuters, *Variety*, Nielsen, and *USA Today* data, as it stood in March 2016. Video game brands were selected from VGChartz's (2016) Game Totals chart as it stood in August 2016. Pop song brands were chosen from the Billboard Greatest of All Time Hot 100 (Billboard, 2016). Brands were selected with concern for ensuring genre-representativeness within category. Given that potential confounding effects had been accounted for at the item-selection level, the no-sequel/prequel/spin-off/adaptation rule was not strict protocol for brand selection for the main pre-test survey; still, media brands of one category that had a high probability of unintentional cognitive conflation with media of another category - e.g. *Harry Potter* movies and *Harry Potter* books – were avoided as much as possible in the brand pool for the primary pre-test survey.

[4] Liberal and conservative outlets were selected based on a study by the Pew Research Center (Mitchell, Gottfried, Kiley, & Matsa., 2014) showing sources that were more trusted by liberals or conservatives.

Table 2

Study 1, 100 Brands (5 Categories x 20 Brands) Included in Primary Survey

Video Games	Movies	Pop Songs
Assassin's Creed: Revelations	A Beautiful Mind	Apologize
Borderlands	American Hustle	Boom Boom Pow
Cooking Mama	Black Swan	Call Me Maybe
Dance Central	Bruce Almighty	Dark Horse
FIFA 16	Catch Me If You Can	Dilemma
Halo 4	Django Unchained	Gold Digger
Heavy Rain	Elysium	Happy
LA Noire	Gladiator	How You Remind Me
Madden NFL 16	Interstellar	I Gotta Feeling
Metal Gear Solid V: The Phantom Pain	Knight and Day	Just the Way You Are
Minecraft	Love Actually	Low
Need for Speed: Underground	Signs	Moves Like Jagger
Nintendogs	Skyfall	No One
Red Dead Redemption	Spirited Away	Party Rock Anthem
Splatoon	Star Wars: The Force Awakens	Rolling in the Deep
Street Fighter IV	Super 8	Royals
The Elder Scrolls V: Skyrim	The Blind Side	Somebody That I Used to Know
The Last of Us	The Day After Tomorrow	Tik Tok
The Sims 3	Titanic	We Belong Together
Titanfall	Zootopia	We Found Love

TV Shows	News Outlets
Alias	ABC News
Avatar: The Last Airbender	Breitbart
Boardwalk Empire	CBS News
Breaking Bad	CNN
Charmed	Daily Kos
ER	Fox News
Frasier	Mother Jones
Gilmore Girls	MSNBC
House MD	NBC News
Judging Amy	Newsweek
Lost	PBS
Parks and Recreation	The Blaze
Sons of Anarchy	The Drudge Report
Stargate SG-1	The Huffington Post
The Daily Show with Jon Stewart	The New York Times
The Late Show with David Letterman	The Wall Street Journal
The West Wing	The Washington Post
Veronica Mars	Time
Will and Grace	US News and World Report
Without a Trace	USA Today

Mechanical Turk workers who indicated interest in participating in the main survey were subjected to a screening where they were randomly presented, one-by-one, with up to 10 media brands from the 100 brands described above. At any point that a respondent indicated being sufficiently familiar with a presented media brand (using the same 5-point scale used in the free association study) they were deemed eligible and brought into the main survey. If a respondent indicated not being sufficiently familiar with any of the ten randomly presented brands in the screening, they were dropped from the study. Eligible participants were asked to imagine as a person the media brand that they indicated being familiar with, and then to rate to what degree each of the 47 (randomized) traits applied to the brand, using a 7-point scale (1 – Not at all, 7 – Very much). Following this task, gender, age, race/ethnicity, education, and political ideology information were collected. The above procedure was repeated until all 100 brands had 41 to 50 responses each.

4.3 | Descriptives & Variables Analyzed

The total sample size for the main pre-test survey was 4,967. Participants in the main pre-test survey were 44.9% male and 80.6% white, with a median age of 32. 48% of participants indicated having a four-year college degree or more education, and 50.2% of participants indicated having weak to strong liberal political ideology, 25.1% indicated having moderate ideology, and 24.7% indicated having weak to strong conservative ideology. The means and standard deviations for the 47 personality traits tested are presented in Table 3. Per protocol recommended by Worthington and Whittaker (2006) and Cabrera-Nguyen (2010) and as is done by J. Kim et al. (2010), data was split randomly in two, stratifying by brand. This resulted in 2,486 observations in the subset used for exploratory factor analysis, and 2,481 observations set aside for confirmatory factor analysis. Some brands had an odd number of observations, leading to the slight disparity in counts between the two sets.

Table 3

Study 1, Means and Standard Deviations for Traits in Main Survey (1: Not at all, 7: Very much)

Trait	**Mean**	**SD**		**Trait**	**Mean**	**SD**
Active	5.37	1.42		Helpful	4.02	1.68
Aggressive	4.19	1.9		Honorable	4.29	1.62
Arrogant	3.65	1.88		Hopeful	4.42	1.65
Bold	5.15	1.52		Hostile	3.26	1.88
Brave	4.77	1.64		Ignorant	2.53	1.54
Bright	4.54	1.65		Innovative	4.58	1.63
Careless	3.18	1.72		Intellectual	4.48	1.69
Clever	4.77	1.6		Liberal	4.26	1.62
Competitive	4.79	1.69		Loving	3.85	1.77
Confident	5.33	1.38		Loyal	4.39	1.6
Conservative	3.06	1.6		Mysterious	3.8	1.91
Considerate	3.89	1.59		Optimistic	4.47	1.62
Creative	4.95	1.56		Ordinary	2.99	1.59
Curious	4.61	1.61		Persistent	5.1	1.44
Daring	4.82	1.68		Responsible	4.16	1.61
Dark	3.41	1.94		Romantic	3.35	1.84
Determined	5.23	1.45		Ruthless	3.65	1.98
Dishonest	2.8	1.69		Selfish	3.35	1.79
Down-to-earth	3.84	1.66		Sentimental	3.85	1.78
Dramatic	4.98	1.62		Simple	3.31	1.67
Dynamic	4.9	1.51		Spontaneous	4.56	1.64
Eccentric	4.3	1.75		Stable	3.93	1.63
Emotional	4.55	1.71		Violent	3.31	2.03
Extroverted	4.9	1.62				

4.4 | Modeling Approach – Exploratory Factor Analysis (EFA)

Exploratory factor analysis was conducted to inductively ascertain the underlying factor structure of the observed variables. Initial exploratory factor analysis on 47 items with nFactors (Raiche, 2010) and psych (Revelle, 2018) packages for R based on optimal coordinate criteria – which outperforms and is recommended over the standard Kaiser K1 eigenvalue>1 rule (Courtney, 2012; Raiche, Walls, Magis, Riopel, & Blais, 2013; Ruscio & Roche, 2012) – suggested a 6-factor solution explaining 48.5% of variance.

However, there were multiple items without clear focal factors, possessing high loadings on more than one factor. Therefore, three rounds of reductions took place, with items having less than +/-.65 loading on their primary factor eliminated and the analysis re-run each time, in line with steps followed by Aaker (1997) and Geuens et al. (2009) and striking a median between the commonly used .6 and .7 thresholds (Matsunaga, 2010) for item removal. This led to an 11-trait, three-factor solution with clear focal factors (>.65 loading on focal factors, <.2 loading on non-focal factors for all items) explaining 62.2% of variance: Aggression (28.7%), Heroism (17.4%), and Warmth (16.1%). The final factor loadings are presented in Table 4.

Table 4

Study 1, Factor Loading Table (Principal Axis Factoring, Promax Rotation), EFA subset

Traits	**Aggression**	**Heroism**	**Warmth**
Violent	*.83*	.02	.00
Hostile	*.83*	-.05	-.03
Ruthless	*.78*	-.02	-.05
Dark	*.77*	-.04	.19
Aggressive	*.74*	.11	-.14
Responsible	.00	*.88*	-.05
Helpful	-.04	*.76*	.04
Honorable	.06	*.69*	.10
Romantic	.07	-.17	*.81*
Loving	-.10	.14	*.75*
Sentimental	.00	.11	*.70*
Eigenvalue	4.268	2.608	1.190
% Variance	28.7%	17.4%	16.1%
% Cumulative	28.7%	46.1%	62.2%

4.5 | Analysis – Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis was conducted to validate the 3-factor model reached in EFA using the holdout subset with the lavaan package for R (Rosseel, 2012). Fit indices were highly satisfactory: χ^2 (3)=522.581, CFI=.964, TLI=.952, RMSEA=.069, SRMR=.046. Though the chi-square statistic is large and seemingly points toward problematic fit, this is to be expected given the sensitivity of the particular test to large sample size (Hooper, Coughlan, & Mullen, 2008), and other fit indices indicated no problems. The CFI and SRMR value pair met Hu and Bentler's (1999) criteria for satisfactory fit (>.95 and <.08, respectively), and all indices surpassed recommend satisfactory fit thresholds (CFI >.95, TLI >.95, RMSEA <.07, SRMR <.08) put forth by Hooper et al. (2008). The final three factor structure is presented in Table 5.

Table 5

Study 1, Dimensions of Unified Media Brand Personality Scale

Aggression	**Heroism**	**Warmth**
Dark		
Aggressive	Honorable	Sentimental
Hostile	Helpful	Romantic
Violent	Responsible	Loving
Ruthless		

4.5.1 | Reliability & construct validity. All reliability and validity calculations were conducted with the CFA subset and results. With regard to reliability, Cronbach's alpha analysis for all dimensions surpassed the .7 threshold recommended by Nunnally (1978) – Aggression: .89, Heroism: .83, Warmth: .81. For convergent validity, average variance extracted (AVE) was .63 for Aggression, .63 for Heroism, and .58 for Warmth, with all values exceeding the .5 AVE threshold for convergent validity recommended by Fornell and Larcker (1981). Fornell and Larcker (1981) also suggest that discriminant validity is achieved when the AVE values for any two constructs are both greater than the square of the correlation between the two constructs (Table 6); this was the case for all pairs of dimensions (max squared correlation = $.698^2$), suggesting discriminant validity for all dimensions.

AVE-based convergent and discriminant validity test results were reinforced with chi-square based tests used by Bagozzi, Yi, and Phillips (1991) and also by Deery, Iverson, and Erwin (1999). Results suggest that the three-factor structure fits the data better than both the null model (χ^2 (14)=13052.78, p<.000) and a one-factor solution **(**χ^2 (3)=5415.2, p<.000), lending support to convergent validity. Chi-square comparisons of a full unconstrained model and a model constraining correlation to unity for all three possible pairwise comparisons rejected the null hypothesis every time, supporting discriminant validity between all pairs of constructs (Table 7).

Table 6

Study 1, Correlation Between Media Brand Personality Factor Scores, CFA subset

Factor	**Aggression**	**Heroism**
Heroism	-.32	-
Warmth	-.38	.698

Table 7

Study 1, Chi-square Tests for Discriminant Validity Between Dimensions, CFA subset

Unconstrained Model χ^2 (41) = 522.58	**Aggression**	**Heroism**
Heroism	3773.03 (df=2, p<.000)	-
Warmth	2863.6 (df=2, p<.000)	1341.5 (df=2, p<.000)

Bivariate correlation analysis between factor scores and media category revealed weak correlations between media category and factor score. All category-factor score correlations were between -.230 and .214, suggesting overall applicability of the factors regardless of media category (Table 8).

Table 8

Study 1, Factor Score-Category Correlations, CFA subset

Media Category	**Aggression**	**Heroism**	**Warmth**
News	-.106	.040	-.230
Movies	.095	.036	.114
Pop music	-.212	-.163	.137
TV shows	.010	.116	.102
Video games	.214	-.030	-.125

4.6 | Study 1 Discussion

The goal of Study 1 was to determine what, if any, common personality dimensions across movie, video game, pop music, news, and TV show brands are identified by consumers. The results suggest the existence of three core personality dimensions that cut across all five categories of media brands: Aggression, Heroism, and Warmth. Though the large size of the holdout set resulted in seeming fit rejection by the chi-square test in confirmatory factor analysis, this is a common non-problematic occurrence due to the test's sensitivity to large sample sizes (Hooper et al., 2008), and the satisfactory values of the more sample size-agnostic fit indices suggest an overall excellent fit of this three-factor structure. Low correlations between media categories and factor scores suggest that the scale is applicable to all five categories of media examined in the study.

From a scale development perspective, the findings suggest that measurement of brand personality need not take place at strictly the macro or micro ends of a spectrum, particularly when seeking to determine common dimensions between separate but related domains as is the case with media of differing formats. What is interesting to consider is that though the three brand personality dimensions uncovered are applicable to all five of the media categories, the inherent contextual valences with regard to a specific media category differ. For example, though Aggression (dark, violent, hostile, ruthless, aggressive) may be considered a positive characteristic in the context of video games, that is not necessarily the case with pop music. Similarly, Warmth, while a positive characteristic with music, would not be considered so in the context of news. To some extent, this is reflected in the factor score-category correlation table (Table 8). The possibility of such context-dependent valence of personality dimensions lends support to

Bosnjak et al.'s (2007) questioning of Aaker's (1997) decision to retain only clearly positive traits in scale development.

4.6.1 | Comparisons to existing measures. Compared to a micro scale approach (the news media brand personality scale by J. Kim et al., 2010), the Unified Media Brand Personality Scale (UMBPS) developed here contains both parallels and differences. Trustworthiness and Toughness, which are present in the J. Kim et al. scale, are not present in the UMBPS. Elements of the Sincerity dimension from the news media scale are present in the Heroism and Warmth dimensions of the UMBPS. Elements of the Dynamism dimension from the J. Kim et al. scale are not present in the UMBPS. Compared to a macro approach scale (Geuens et al., 2009), the UMBPS seems both an expansion and a domain-specific intensification. The UMBPS Warmth dimension is a one-item expansion of the Emotionality dimension in the Geuens et al. scale, while Geuens et al.'s Responsibility dimension shares one trait with the UMBPS Heroism dimension. The UMBPS Aggression dimension could be seen as an expanded, intensified analogue to the Geuens et al. scale's Aggressiveness dimension. Similar to J. Kim et al. scale's Dynamism dimension, the Activity dimension of the Geuens et al. scale is not present in the UMBPS.

Furthermore, the emphasis on the particular domains of Aggression, Heroism, and Warmth also present a distinct but reasonable contrast to the emphasis on the commonly discussed dimensions of competence and warmth as discussed by Fiske, Cuddy, and Glick (2007). Evaluations of competence and warmth may be central in the evaluation of products in general as authors like Fiske and colleagues have suggested. However, it is sensible to posit that for products that provide an identity constructive, self-branding function as do media products (Ots & Hartmann, 2015), the Aggression-Heroism-Warmth combination may be more pertinent; mainstream media glorifies the tales of the villains, the heroes, and the romantics, not the stories of the nice and hard-working. In that regard, overall, the dimensions of the UMBPS are reflective of common narrative and thematic elements present in a variety of media. The dimensions also capture how various personality dimensions and traits may be projected onto media not explicitly possessing such content elements. For example, though reporting neutral news events, a news outlet may be perceived to be hostile or emotional in its presentation, or a pop song, though not possessing dark or romantic lyrical content, may be considered dark or romantic due to its instrumentation.

It is important to re-emphasize that the central argument here is not that the three dimensions of Aggression, Heroism, and Warmth are the sole pertinent dimensions of brand personality when considering any of these media formats. Independent formulation of a scale for any one of these formats may result in a different factor structure involving different personality dimensions. Such a possibility comes into full focus in Study 2, where analysis of solely the movie data results in a slightly different factor structure. If ascertaining the full nuances of the brand personality of media products of a particular format is desired, a more format-specific "micro" scale may be better suited. Nonetheless, the findings of the present study suggest that Aggression, Heroism, and Warmth are personality traits that cut across individuals' evaluations of product brands across all categories examined. This meso-level approach enables comparison across formats, allowing, for example, the consideration of whether a particular video game is generally perceived as more heroic than a particular movie – a key comparative dimension when considering brands in transmedia entertainment.

CHAPTER 5 | STUDY 2:

CONTENT-BASED PREDICTION OF MOVIE BRAND PERSONALITY

The goal of Study 2 was to determine how media brand personalities may be "signaled" through the ways in which they are marketed or represented to potential consumers. To explore this possibility, I ask respondents drawn from Mechanical Turk to assess the personality of movies with which they are *unfamiliar*. I then use automated content analysis to identify textual and visual patterns in movie branding materials (plot summaries and posters). Finally, I test to see if the personality dimensions identified by mTurkers correlate with identifiable aspects of the promotional texts and visuals. I focus on movies since plot summaries and visuals, such as posters, play a key role in the media selection process on content distribution services like Netflix, providing the opportunity to test whether the presence of certain computational text or image features in these materials assist potential viewers in assessing a movie's brand personality (**RQ2**).

5.1 | Data Collection

5.1.1 | Movies-only scale reanalysis. The results of Study 1 suggested that a limited number of personality dimensions (Aggression, Heroism, and Warmth) and their related traits are applicable across different media platforms and genres (e.g., news, TV series, movies, etc.). Given my exclusive focus on movies in Study 2, however, it seemed prudent to reanalyze the movie data from Study 1 to see if the same three dimensions and underlying traits emerged, or if a more movie-specific scale was in order. My initial effort to do so using the same procedures as in Study 1 (i.e, optimal coordinate criteria for factor count determination and a +/-.65 threshold for continued item inclusion between rounds of factor analysis) resulted in zero recommended factors. Dropping the threshold to +/- .60 led to a three-factor solution, but with poor fit indices (CFI: .927; TLI: .912; RMSEA: .074; SRMR: .065). Keeping the .65 threshold but switching to parallel analysis criteria resulted in a satisfactory three factor solution with satisfactory fit indices (CFI .966; TLI .954, RMSEA .061, SRMR .053) based on Hu and Bentler's (1999) recommended CFI (>.95) and SRMR (<.08) thresholds, as well as Hooper et al.'s (2008) CFI (>.95), TLI (>.95), RMSEA (<.07), and SRMR (<.08) recommendations. The resulting dimensions of the movie brand personality scale are presented in Table 9. Two of the movie-specific personality dimensions and their component traits – Aggression and Heroism – are largely the same as those found in Study 1. The third dimension of the original scale (Warmth) did not emerge however, and was replaced with what I call "Determination," with "active", "determined", and "confident" as the component traits.

That the emergence of an Aggression and a Heroism dimension, which explain the greatest amount of variance across their component traits, are largely consistent with the findings of Study 1 is not surprising. But why would the third personality dimension for movies be different, with Determination replacing Warmth? My post hoc conclusion is that as one moves from the most dominant dimensions to those explaining less variance, format differences are more likely to emerge. This suggests that while a limited number of personality traits applicable across different types of media and genres has utility (the conclusion of Study 1), it may still be necessary or wise to tailor the traits when focusing on a single medium or genre. I return to this issue in the conclusion of this dissertation.

Table 9

Study 2, Factor Structure for Movie Brand Personality Scale

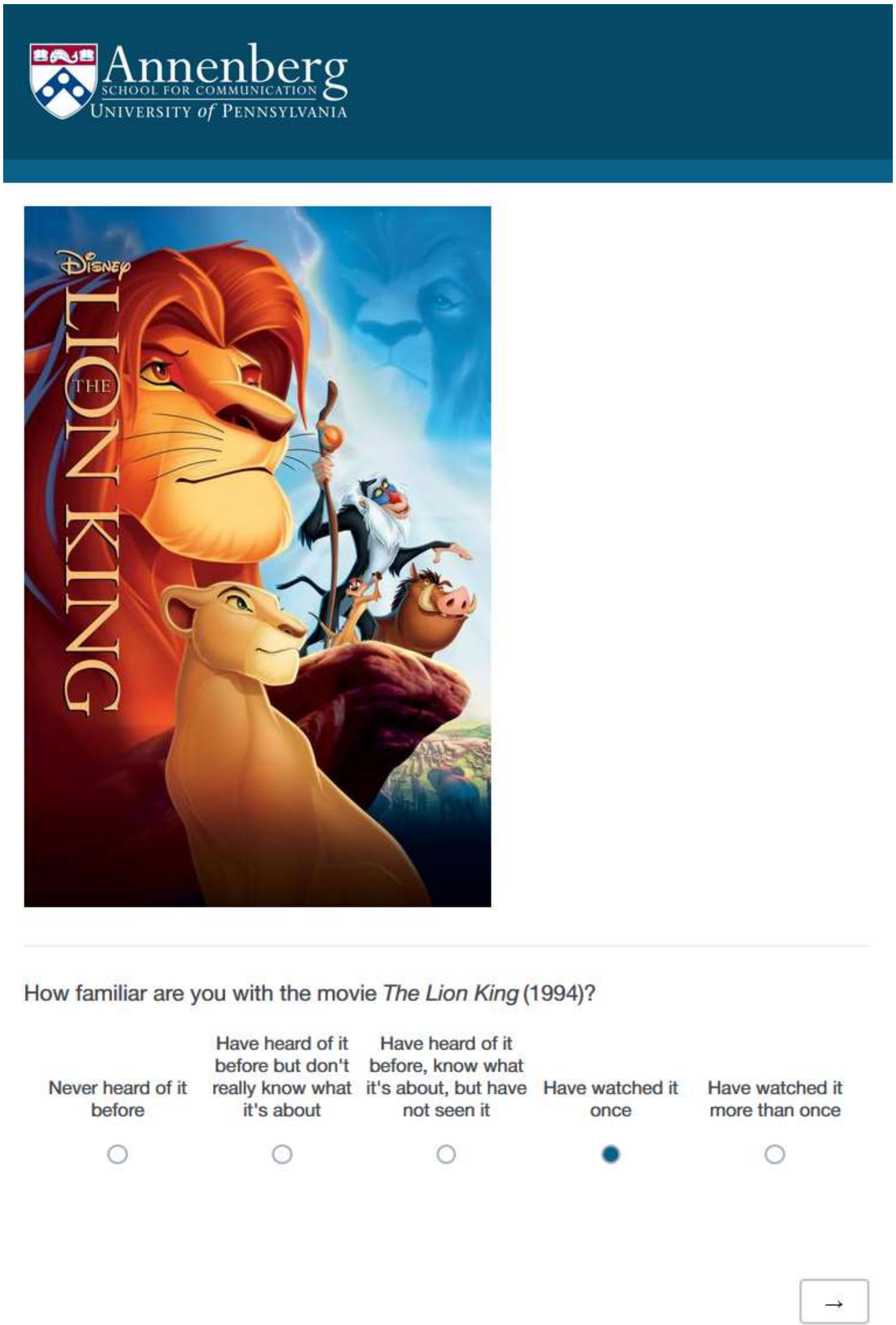
Aggression	**Heroism**	**Determination**
Dark Aggressive Hostile Violent	Honorable Considerate Helpful Responsible	Active Determined Confident

5.1.2 | Movie secondary data collection. The first step of my content analysis was data collection. To do so, I scraped the title, year, genre, and movie page links for the top 250 domestic gross films from the IMDB database (2018) as it stood in May 2018 using Python. Then, using the movie page links, I collected the generally shorter (~1-2 sentences) description text and the generally longer (~1 paragraph) synopsis text for each movie. Following this, utilizing the IMDB IDs embedded in the movie page links, I collected the movie posters through the TMDB (The Movie Database) API (TMDB, n.d.). As all movies had multiple posters in a variety of languages, the specific poster downloaded was determined by: 1) subsetting strictly English language posters; 2) sorting the posters by number of ratings; and 3) selecting a poster from among the top three most commonly rated that had the highest rating. In cases of ties for the highest rating among the three final candidates, one was randomly selected. The images were downloaded at the highest available quality, then standardized to a width of 400 pixels (heights were mildly variant as poster aspect ratios were slightly different).

5.1.3 | Movie brand personality rating collection. Movie raters again were recruited through Mechanical Turk. Upon entry, participants were presented with up to nine movie posters, accompanied by the question, "How familiar are you with the movie, [*Title*] [(Year)]?" using a five-point scale – 1: Never heard of it before; 2: Have heard of it before but don't really know what it's about; 3: Have heard of it before, know what it's about, but have not seen it; 4: Have watched it once; 5: Have watched it more than once. An example familiarity check screen is shown in Figure 1.

Figure 1

Study 2, Example Pre-Ratings Collection Familiarity Check Screen



Since Study 2 was designed to have the promotional material assessed by individuals who were *unfamiliar* with a movie, participants who indicated having seen (response of >=4) all nine presented movies were deemed ineligible and dropped. Otherwise, participants were asked to rate the first movie they indicated not having seen (response of <=3) using the movie brand personality traits that emerged from the movie-specific scale reanalysis described above (Figure 2) on a 7-point (Not at all – Very much) scale (Prompt: *We often use different personality traits (for example, responsible, innovative, genuine, etc.) to describe people we know. For a moment, imagine the movie* [Title] *[(Release Year)] as a person. If* [Title] *[(Release Year)] were a person, to what extent would you say each of the personality traits listed below describes it?*).

In addition, participants were asked about their attitudes toward the movie using a 4-item movie attitudes measure adapted from Sood and Dreze (2006) as well as their intent to watch the movie using an intent measure adapted from Smith-McLallen and Fishbein (2008). Following this, participants were asked to respond to abbreviated versions of topically relevant psychographic measures – self-monitoring (Lennox & Wolfe, 1984), sensation-seeking (Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002), need-for-affect (Appel, Gnambs, & Maio, 2012), and self-transcendence (Stern, Dietz, & Guagnano, 1998) – for secondary analysis (see Appendix A for all measures).

Figure 2

Study 2, Example Rating Collection Screen

Please examine the poster and text regarding *Pirates of the Caribbean: The Curse of the Black Pearl* (2003) presented below.

Description: Blacksmith Will Turner teams up with eccentric pirate "Captain" Jack Sparrow to save his love, the governor's daughter, from Jack's former pirate allies, who are now undead.

Summary: This swash-buckling tale follows the quest of Captain Jack Sparrow, a savvy pirate, and Will Turner, a resourceful blacksmith, as they search for Elizabeth Swann. Elizabeth, the daughter of the governor and the love of Will's life, has been kidnapped by the feared Captain Barbossa. Little do they know, but the fierce and clever Barbossa has been cursed. He, along with his large crew, are under an ancient curse, doomed for eternity to neither live, nor die. That is, unless a blood sacrifice is made.

We often use different personality traits (for example, responsible, innovative, genuine, etc.) to describe people we know. For a moment, imagine the movie *Pirates of the Caribbean: The Curse of the Black Pearl* (2003) as a person. If *Pirates of the Caribbean: The Curse of the Black Pearl* (2003) were a person, to what extent would you say each of the personality traits listed below describes it?

	Not at all						Very much
Romantic	○	○	○	○	○	○	○
Stable	○	○	○	○	○	○	○
Ordinary	○	○	○	○	○	○	○
Loving	○	○	○	○	○	○	○

Next, participants rated their own personality using items from the movie brand personality scale, doing so on a 7-point (Not at all – Very much) scale in response to one of three randomly assigned prompts intended to measure either their actual, fantasy, or ideal personality (Actual: *How do you see yourself? To what extent do the following personality attributes apply to you?*; Fantasy: *Now, imagine you could step into the shoes of anyone else for a day. Real, fictional, famous, not famous, good, bad, dead, alive - doesn't matter. If you could be anyone else for a day, what kind of person would you be, and to what extent do each of the following personality attributes apply to this person?*; Ideal: *Imagine how you would ideally like to be in your day-to-day life. To what extent do the following personality attributes apply to how you would ideally like to be in your day-to-day life?*). Actual and ideal personality question wording was adapted from Kressmann et al. (2006). A "fantasy personality" question was added to explore whether individuals may be attracted to certain entertainment media through a congruence not with their actual or ideal self, but with a more escapist (Hirschman & Holbrook, 1982; Addis & Holbrook, 2010) and perhaps less "noble" alternate self than is captured by the day-to-day nature of the ideal self measure. Participants were also asked to rate the importance of each of the traits measured (*How important is it for you that a person is…,* adapted form Kressmann et al., 2006) on a 7-point scale (Not at all – Very Much). Lastly, raters were asked to respond to a series of demographic questions adapted from the General Social Survey (Smith, Marsden, & Hout, 2016).

5.2 | Descriptives & Variables Analyzed

5.2.1 | Rater demographics. A total of 4,040 respondents participated in the Study 2 survey. Each of the 250 titles were rated by 12 to 30 participants, with a median of 16 raters (mean=16.22). Of these raters, 1,342 participants were randomly asked to also assess their own actual personality, 1,356 their own ideal personality, and 1,342 their own fantasy personality. The median age group for the entire sample was 25-34 (making up 38.6% of the sample), followed by 35-44 (24.2% of the sample). Women comprised 55.9% of participants. Given the large percentage of respondents who identified as white (75.2%) and the relatively small number of participants who identified in any one of the other eight options, the race/ethnicity measure was collapsed into a dichotomous nonwhite/white indicator. The median and modal level of education was a college degree or more at 53.9% (n=2,176).

5.2.2 | Scale as individual personality measure. It was first important to determine the continued reliability and internal validity of the scale developed in Study 1 as a measure of individual personality distinct from movie brand personality. Cronbach's alpha values for all three dimensions exceeded Nunnally's (1978) .7 recommendation (Aggression: .79; Heroism: .79; Determination: .84), suggesting good internal reliability. Although the AVE for Aggression fell slightly short of the .5 recommendation by Fornell and Larcker (1981) – Aggression, .49; Heroism, .58; Determination, .59 – overall levels of convergent validity were also reasonable. Similarly, with a max squared correlation between dimension factor scores of $.622^2$, discriminant validity was also not considered an issue as it did not exceed any of the AVE values (Fornell & Larcker, 1981).

5.2.3 | Generating movie personality ratings. After alpha analysis to confirm sufficient intra-dimensional reliability (Aggression: .89; Heroism: .83; Determination: .76) of the movie personality ratings, component trait ratings for each dimension were first averaged for each individual rater (to determine individual-level dimension ratings) to generate individual-level mean aggression, mean heroism, and mean determination ratings. These individual-level mean dimension ratings were then averaged *across* the raters for each movie, creating movie-level Aggression, Heroism, and Determination dimension scores for each movie. The resulting movie dimension scores were then used as outcome variables in the regression analyses below (see Appendix B).

5.2.4 | Computer text features. The promotional texts describing each movie that had been shown to participants were processed into machine-readable features for use in the regression analyses. Text features were generated from the combined description and synopsis text through processing in LIWC (Pennebaker et al., 2015) as well as through correlated topic model analysis (as described in Chapter 3).

While LIWC can produce approximately 90 features, the inclusion of all of them would work against the goal of dimension reduction, especially given the relatively small size of the text corpus used in this study. In addition, the structure of the LIWC dictionary is such that some higher-level variables are inherently correlated to lower-level "children" variables – for example, a word in the "anger words dictionary" also belongs in its parent "negative emotions dictionary," as well as in the even broader "affect dictionary."

To narrow the set of features used in my analyses while still capturing key patterns, I first dropped from inclusion features that focused on linguistic mechanics such as punctuation, function words (e.g. pronouns, articles, prepositions), and other grammar words (verbs, adjectives, etc.). Next, I dropped four features – analytic thinking, clout, authenticity, and tone – that are composite features derived from other features.[5] Finally, of the remaining LIWC features, I limited those used in the analysis to the lowest-level subdictionary features available to reduce redundancy and associated potential for cross-predictor correlation – for example, instead of including both the broader perceptual processes measure and the component seeing, hearing, and feeling word measures, only the latter measures were included. This led to the inclusion of 47 LIWC features.

I also included a set of five correlated topic model probabilities derived from the summary text. Correlated topic models are a variant of topic models, as popularized by the original latent Dirichlet allocation (Blei et al., 2003), that allows for correlations between the underlying topics extracted through analysis of word co-occurrence patterns (Blei & Lafferty, 2009). Quantitative metrics for determining the optimal number of topics to extract from text are available (e.g. Cao, Xia, Li, Zhang, & Tang, 2009; Arun, Suresh, Madhavan, & Murthy, 2010; Griffiths & Steyvers, 2004; Deveaud, SanJuan, & Bellot, 2014). However, as Grimmer and Stewart (2013) warn, “all quantitative models of language are wrong” (p. 3), and these quantitatively optimized topic counts do not

---

[5] The process for doing so uses a formula unknown to the user, which Pennebaker et al. (2015) admit to being the only non-transparent features in the LIWC set.

inherently account for human interpretability of the resulting solutions. In the end, some qualitative evaluation by the researcher is inevitably necessary. After multiple pilot analyses to test the ideal number of topics to extract from the text, I determined that five topics produced reasonable results in terms of thematic coherence and interpretability (Table 10). The resulting topics were generally representative of the themes of Romance, Superheroics, Crisis, Youth, and Duty.

5.2.5 | Computer image features. In addition to text features, a number of computer vision features were generated from the movie posters using methods adapted from Peng and Jemmott (2018) and van der Walt et al. (2014). These included: file size; brightness; contrast; edge prominence; edge density; colorfulness; number of segments (i.e. regions of similar color); pixel count for various colors (black, brown, blue, green, grey, orange, pink, purple, red, white, yellow); an index representing the presence of arousing to relaxing colors; adherence to the rule of thirds (as represented by minimum distance from the center of all edges to one of the rule of thirds guiding line intersections); and the size of the bounding box containing 95% of edges. Tuning parameters on the Python functions for segmentation and edge detection were set after multiple rounds of pilot analyses intended to arrive at reasonably human-recognizable outcome features (i.e. an individual familiar with the *Titanic* poster should be able to see a color segmented or edge-traced version of and be able to recognize it as *Titanic*).

Table 10

Study 2, Representative Word Stems for Movie Summary Text Correlated Topic Model

Romance	**Superheroics**	**Crisis**	**Youth**	**Duty**
Back	Man	Will	Peter	World
Time	Find	Forc	Life	Must
Find	Power	Bella	Harri	War
New	World	World	Spider	Find
Love	Batman	New	Man	Boy
Year	Famili	Find	New	New
Will	Can	Must	Shrek	Hero
Name	Becom	Life	Get	Team
Friend	Human	Now	Find	Protect
Take	Stark	Destroy	Will	Home

5.2.6 | Calculating self-movie personality congruence scores. The structure of the data enabled calculation of two different types of congruence scores to measure their relationship with attitudes and intent: the more common self-referencing congruence and more novel independent congruence. Self-referencing congruence was calculated using the importance-weighted congruence formula as put forth by Kressman et al. (2006). Self-referencing congruence is essentially a ratio, with the sum of all trait congruence intermediates – for each trait, the trait importance value multiplied by the absolute value of the difference between the rater's rating of a movie on a trait and the rating of oneself on the same trait – as the numerator, and the sum of all trait importance values as the denominator. This ratio is multiplied by "-1" so that higher values indicate higher congruence.

Independent congruence was calculated using a formula similar to self-referencing congruence. In the former, however, the rater's *own* movie trait rating in the numerator was replaced by the mean trait rating across *all other* raters of that movie. With personality ratings taken on 11 traits using 7-point scales (as in the current study), the theoretical maximum score for both self-referencing and independent congruence is "0," while the theoretical minimum congruence score is "-6." Since participants were randomly asked to indicate their actual, fantasy, or ideal personality, three different types of congruence are involved. To account for this in my analyses, an indicator variable was generated to distinguish these three congruence types.

5.3 | Modeling Approach

The set of text, visual, and personality data for the 250 movies was randomly split into training (n=200) and test (n=50) sets. For each movie personality dimension score, LASSO, random forest, and stochastic gradient boosting regression algorithms were generated using 5-fold cross-validation to ascertain tuning parameter values that optimized cross-validation error with the training set. Predicted values were then generated using values from the test set and mean squared error calculated as the primary error metric of interest to compare all algorithms in their ability to predict a particular dimension score. The training and test error values for each of these algorithms are presented in Table 11 and Figure 3, as is the training time as measured by R. Multiple regression results based on a model trained without cross-validation (as is commonly done in the social sciences) are provided as reference values.

Though not the primary purpose of this study, the availability of the self-referencing and independent congruence scores as generated above also allowed for examination of congruence effects on how individuals rated their one assigned movie. This allowed for an exploratory congruence analyses on the Study 2 data using multi-level linear regression models. The goal of this analysis was to ascertain potential variables for inclusion as moderators in the analysis of Study 3.

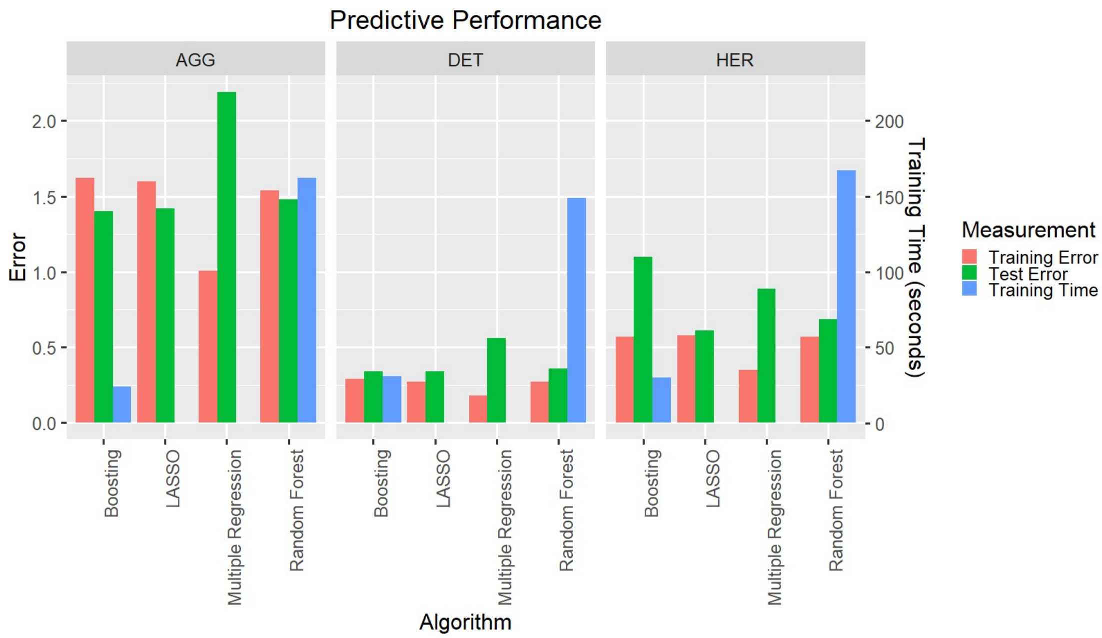
Table 11

Study 2, Regression Algorithm Performance, By Personality Dimension

	Multiple Regression			**LASSO**			**Random Forest**			**Boosting**	
	Training Err.	*Test Err.*		*Training Err.*	*Test Err.*		*Training Err.*	*Test Err.*		*Training Err.*	*Test Err.*
AGG	1.01	2.19		1.60	1.42		1.54	1.48		1.62	1.40
Train time (secs)	.01			.05			162			24	
HER	.35	.89		.58	.61		.57	.69		.57	1.1
Train time (secs)	.00			.06			167			30	
DET	.18	.56		.27	.34		.27	.36		.29	.34
Train time (secs)	.00			.05			149			31	

Figure 3

Study 2, Bar Graph of Regression Algorithm Performance, by Personality Dimension



5.4 | Analysis

5.4.1 | Primary analysis of Aggression dimension scores. The LASSO algorithm zeroed out all variables except poster grey pixel count (b=.00000000048), poster white pixel count (b=.00000024), poster file size (b=-.0000050), text present focus (b=.0066), text future focus (b=-.075), text positive emotions (b=.00102), text motion words (b=-.0088), text death words (b=-.109), text discrepancy words (b=.060), text certainty words (b=.061), and text differentiation words (b=.00079). P-values are not generated by the LASSO process as "penalized estimation is a procedure that reduces the variance of estimators by introducing substantial bias," (p. 18, Goeman, Meijer, & Chaturvedi, 2018) and the standard errors that would be used to arrive at a p-value become meaningless in such cases of high bias (Goeman et al., 2018; Goeman, 2018). Its test error (test MSE = 1.42) was substantially lower than that of the worst-performing saturated multiple regression model (test MSE = 2.19) despite having fewer predictors. The random forest algorithm also provided test error (test MSE = 1.48) that was lower than that of the reference multiple regression model but higher than that of LASSO, despite having a training time substantially longer than LASSO. Boosting provided the lowest test error (test MSE=1.40) with, compared to random forests, a relative minor increase in training time.

5.4.2 | Primary analysis of Heroism dimension scores. LASSO zeroed out all coefficients, leading to all predicted values being the mean of the outcome variable in the training set (M=3.98). Yet, it provided the lowest test error across all algorithms (test MSE = .61). The saturated multiple regression model (test MSE = .89) again performed the worst on the test set. Both random forests (test MSE=.69) and boosting (test MSE=1.1) displayed notably worse predictive performance on the test set as well as higher training times compared to LASSO.

5.4.3 | Primary analysis of the Determination dimension. LASSO once again zeroed out all coefficients, leading to all predicted values being the mean of the outcome variable in the training set (M=5.28), again providing the lowest test error (test MSE=.34), tied with boosting (test MSE=.38). Random forest performed the marginally worse (test MSE=.36) but at the cost of a significantly higher training time. Multiple regression performed the worst predictively, with a test error of .56. The saturated multiple regression model again displayed signs of overfitting, with the lowest training error (.18) but the highest test error (test MSE=.56) as happened with the other two dimensions.

5.4.4 | Exploratory analysis of the direct and interactive effects of self-referencing congruence. A multi-level regression model was created with title rated as random effect to account for title-based clustering in the data and attitude toward the movie rated as outcome, self-referencing congruence as the primary predictor of interest, and all available demographic and psychographic terms and their interactions with self-referencing congruence (Table 12; for additional information on measures, see Appendix A). The multi-item sensation seeking, need-for-affect, self-monitoring, self-transcendence, and movie attitude batteries were each averaged into one-item measures prior to inclusion, as alpha analysis indicated sufficient internal reliability for all (sensation-seeking: .81; need-for-affect: .79; self-monitoring: .88; self-transcendence: .80; movie attitudes: .91).

The results suggest no main effect of congruence (b=.0034, SE=.135, p=.98), no main effect of congruence type (Fantasy: b=.012, SE=.074, p=.87; Ideal: b=.0055, SE=.075, p=.94), and no difference in congruence effect across personality types (Fantasy: b=-.022, SE=.036, p=.54; Ideal: b=-.035, SE=.036, p=.33). Examining the interaction terms, women tended to exhibit lower congruence effects on attitudes than did men (b=-.07, SE=.031, p=.02), and congruence effects on attitudes tended to be higher among the more educated (b=.046, SE=.020, p=.024). Congruence effects also interacted with need-for-affect (b=.041, SE=.022, p=.065), which captures differences in approach and avoidance of emotion (Appel et al., 2012) and self-transcendence (b=.031, SE=.017,

$p=.066$), a measure of environmental and altruistic concern (Stern et al., 1998), though these interaction terms fell short of accepted levels of significance. In terms of main effects, the model also suggests that individuals higher in need-for-affect ($b=.22$, $SE=.048$, $p<.000$), self-transcendence ($b=.15$, $SE=.037$, $p<.000$), and age ($b=.061$, $SE=.025$, $p=.015$) tend to have more positive attitudes toward the movies rated (i.e., say it is likely to be a good movie, must see, interesting, and better than most films).

Examining a similar model with intent to view a movie as the outcome and attitude and its demographic/psychographic interactions added as predictors, once again the main effect of congruence was not significant ($b=.163$, $SE=.136$, $p=.230$) and no main effect of congruence type (Fantasy: $b=-.089$, $SE=.070$, $p=.20$; Ideal: $b=.0014$, $SE=.071$, $p=.98$) or difference in congruence effect across personality types (Fantasy: $b=-.038$, $SE=.034$, $p=.27$; Ideal: $b=.014$, $SE=.034$, $p=.69$) was present. Attitude was by far the most significant predictor in the model ($b=.72$, $SE=.134$, $p<.000$), interacting with self-monitoring – individuals' sensitivity to social cues and ability to adjust behavior (Lennox & Wolfe, 1984) – such that the effect of attitude on intent was stronger for higher self-monitors ($b=.058$, $SE=.023$, $p=.012$). An interaction between congruence and self-monitoring was present but failed to achieve statistical significance ($b=-.042$, $SE=.024$, $p=.091$). Higher self-monitors tended to indicate lower intent to see the movie rated ($b=-.29$, $SE=-.10$, $SE=.004$), while high sensation-seekers – i.e. those who indicated higher need for novel, different sensations (Hoyle et al., 2002) – tended to indicate greater intent to view ($b=.159$, $SE=.078$, $p=.042$). Higher education was associated with lower intent to view, though not to a statistically significant degree ($b=-.152$, $SE=.085$, $p=.075$).

Table 12

Study 2, Multilevel Regression Tables with Self-Referencing Congruence Effects

	Outcome: Attitude				**Outcome: Intent**		
Fixed Effects	**Estimate**	**SE**	**P**		**Estimate**	**SE**	**P**
Intercept	1.948	.284	<.000***		1.08	.553	.051^
Congruence (Self-referencing)	-.0034	.135	.98		.163	.136	.23
Congruence Type (Base: Actual)							
Fantasy	.012	.074	.87		-.089	.070	.20
Ideal	.0055	.075	.94		.0014	.071	.98
Attitude					.72	.134	<.000***
Congruence by Congruence Type Interaction							
By Fantasy	-.022	.036	.54		-.038	.034	.27
By Ideal	-.035	.036	.33		.014	.034	.69
Congruence by Psychographics Interaction							
By Sensation-seeking	-.019	.018	.29		.006	.018	.74
By Need-for-affect	.041	.022	.07^		-.008	-.022	.73
By Self-transcendence	.031	.017	.07^		-.001	-.017	.94
By Self-monitoring	-.012	.024	.62		-.041	-.024	.09^
Congruence by Demographics Interaction							
By Age	.013	.012	.30		.013	.012	.27
By Sex/Female (Base: Male)	-.07	.031	.02*		.018	.031	.57
By Race/Ethnicity (Base: White)	-.023	.034	.50		.047	.034	.17
By Education	.046	.020	.02*		-.025	-.020	.21
Attitude by Psychographics Interaction							
By Sensation-seeking					.016	.018	.37
By Need-for-affect					.009	.022	.68
By Self-transcendence					.013	.016	.42
By Self-monitoring					.058	.023	.01*

Attitude by Demographics Interaction							
By Age					.0028	.012	.82
By Sex/Female (Base: Male)					-.037	.030	.22
By Race/Ethnicity (Base: White)					-.044	.034	.19
By Education					.026	.02	.20
Sensation-seeking	.064	.038	.10		.159	.078	.04*
Need-for-affect	.224	.048	<.000***		.015	.093	.87
Self-transcendence	.148	.037	<.000***		-.064	.070	.36
Self-monitoring	.027	.052	.60		-.291	.102	.004**
Age	.061	.025	.02*		.037	.053	.49
Sex/Female (Base: Male)	-.077	.064	.23		.158	.133	.23
Race/Nonwhite (Base: White)	.050	.069	.47		.165	.145	.26
Education (1: Less than HS; 2: HS; 3: Some College; 4: College+)	.034	.042	.42		-.152	.085	.07^
Random Effects		**VAR**	**SD**			**VAR**	**SD**
Title		.069	.263			.030	.173
Residual		.723	.850			.066	.810

5.4.5 | Exploratory analysis of the direct and interactive effects of independent congruence. The results of multilevel regression models regarding the effects of independent congruence on attitudes and intent are presented in Table 13. With regard to attitude outcomes, congruence main effects were once again not significant (b=.15, SE=.20, p=.46), nor was the main effect of personality type (Fantasy: b=.128, SE=.106, p=.23; Ideal: b=.009, SE=.106, p=.93) or the interaction of congruence with personality type (Fantasy: b=-.045, SE=.056, p=.42; Ideal: b=-.023, SE=.056, p=.68). However, the model presented other suggestive and potentially interesting associations. The significance of the congruence by race/ethnicity interaction term (b=-.13, SE=.052,

$p=.01$) suggested that the effect of congruence on attitudes was weaker for nonwhites than for whites. Once again, individuals higher in need-for-affect tended to indicate more positive attitudes toward (expectations of) the movie rated ($b=.149$, $SE=.071$, $p=.04$).

Regarding intent to view a movie, attitude was again the most prominent predictor ($b=.733$, $SE=.130$, $p<.000$), also interacting with self-monitoring ($b=.051$, $SE=.022$, $p=.02$) such that greater self-monitors exhibited higher effect of attitudes on intent. High sensation-seekers ($b=.187$, $SE=.075$, $p=.01$) again tended to display greater intent to view, while higher self-monitors ($b=-.275$, $SE=.10$, $p=.01$) once more displayed lower intent. Age ($b=-.089$, $SE=.052$, $p=.09$) and sex ($b=.232$, $SE=.128$, $p=.07$) differences were also present but not statistically significant. Once again, congruence main effects were not significant ($b=-.071$, $SE=.19$, $p=.71$), nor were the main effect of personality type (Fantasy: $b=.002$, $SE=.096$, $p=.98$; Ideal: $b=-.045$, $SE=.096$, $p=.64$) or the interaction of congruence with personality type (Fantasy: $b=.011$, $SE=.050$, $p=.82$; Ideal: $b=-.008$, $SE=.050$, $p=.87$).

Table 13

Study 2, Multilevel Regression Tables with Independent Congruence Effects

	Outcome: Attitude				**Outcome: Intent**		
Fixed Effects	**Estimate**	**SE**	**P**		**Estimate**	**SE**	**P**
Intercept	2.151	.410	<.000***		1.08	.553	.051^
Congruence (Independent)	.150	.205	.46		-.071	.19	.71
Congruence Type (Base: Actual)							
Fantasy	.128	.106	.23		.002	.096	.98
Ideal	.009	.106	.93		-.045	.096	.64
Attitude					.733	.127	<.000***
Congruence by Congruence Type Interaction							
By Fantasy	-.045	.056	.42		.011	.050	.82
By Ideal	-.023	.056	.68		-.008	.050	.87
Congruence by Psychographics Interaction							
By Sensation-seeking	-.036	.028	.21		.027	.026	.30
By Need-for-affect	-.005	.036	.88		-.020	.033	.55
By Self-transcendence	-.024	.027	.38		-.007	.024	.77
By Self-monitoring	.019	.038	.62		-.048	.034	.17
Congruence by Demographics Interaction							
By Age	-.013	.019	.49		-.002	.017	.89
By Sex/Female (Base: Male)	-.011	.048	.82		.067	.043	.12
By Race/Nonwhite (Base: White)	-.131	.052	.01*		.010	.047	.83
By Education	.036	.031	.25		-.009	.028	.76
Attitude by Psychographics Interaction							
By Sensation-seeking					-.011	.017	.50
By Need-for-affect					.009	.021	.67
By Self-transcendence					.017	.016	.29
By Self-monitoring					.051	.022	.02*

Attitude by Demographics Interaction							
By Age	[redacted]				.010	.012	.39
By Sex/Female (Base: Male)	[redacted]				-.035	.029	.22
By Race/Ethnicity (Base: White)	[redacted]				-.026	.032	.41
By Education	[redacted]				.019	.019	.31
Sensation-seeking	.0009	.057	.99		.187	.075	.01*
Need-for-affect	.149	.072	.04*		.068	.093	.46
Self-transcendence	.044	.052	.40		-.086	-.071	.23
Self-monitoring	.084	.077	.27		-.275	.10	.007***
Age	.024	.037	.51		.089	.052	.09^
Sex/Female (Base: Male)	-.013	.092	.89		.232	.128	.07^
Race/Nonwhite (Base: White)	-.099	.10	.33		.044	.140	.75
Education (1: Less than HS; 2: HS; 3: Some College; 4: College+)	.010	.062	.87		-.10	.085	.24
Random Effects		**VAR**	**SD**			**VAR**	**SD**
Title		.090	.299			.029	.171
Residual		.800	.894			.660	.812

5.5 | Study 2 Discussion

The findings from Study 2 have several suggestive theoretical, empirical and methodological implications. Recall that I define a product brand as a way of helping potential consumers distinguish it from others using “promises, images, personalities, emotional characteristics, social characteristics, and various other objective and subjective qualities” (p. 118, Jones & Bonevac, 2013), with a particular emphasis in my research on “perceived personality.” Yet for both the Heroism and Determination dimensions, the results from all four of the methods suggest that *none* of the textual or visual features computationally generated from movie posters or descriptions were predictive of perceived movie personalities. LASSO analysis did find evidence that certain textual and visual qualities were predictive of participants' perceptions of movie Aggression. Nonetheless, overall my findings suggest that the visual and descriptive textual characteristics of movie promotional material (at least as measured here) play a relatively low role in the perception of at least two of the three personality dimensions examined as compared to other affective and social characteristics. And, while my method differed, the results seem to challenge previous research suggesting that changes in visual branding result in changes in perceived brand personality (e.g. Lieven et al., 2015; Boudreaux & Palmer, 2007; Orth & Malkewitz, 2008).

What should we make of these findings? One very real possibility is that the communication of a product's personality occurs through the more socially constructed *latent* qualities of text and images; qualities that are, to date at least, difficult to capture through computational content analysis (Benoit, 2011). Such a possibility aligns with Jenkins, Ford, and Green's (2013) argument that the meaning of media are not firmly set by the creators, but are crafted in interaction between content creators and audiences. Even LIWC features, which to some degree integrate more human cultural context than do pure unigram counts, are essentially topically aggregated unigram counts, and so arguably lack the ability to take broader structural and affective context into account. It is also possible that other signals regarding a movie's brand – e.g., directors, actors, studios, genres, etc. – that were not included in my analysis, are more important to consumers' expectations than those I measured.

The results of Study 2, in combination with prior research, points to three other possibilities worthy of future investigation. First is that while the manipulation of visual elements *within* a single brand may result in changes in perception, such visual effects do not generalize to perceptions *across* brands. Second, is that while the effects of textual and visual branding changes occur at the individual level, they may be cancelled out at the aggregate level. A third possibility, alluded to in the previous paragraph, is that aspects of a movie's brand not measured in my analyses – *including those not related to its personality dimensions* – may overpower any pure visual or text component effects.

A more methodological finding emerging from the computational content analysis conducted in Study 2 is that LASSO consistently showed lower test error than the saturated multiple regression model. This highlights the dangers of overfit algorithms for predictive performance, with this point further accentuated by the fact that the saturated multiple regression model generally provided the lowest training error but the highest test error. It also underscores concerns with the common single-run, single-dataset applications of multiple regression that Hindman (2015) emphasizes; application of cross-validated and penalized regression models should become more standard in the social sciences. In addition, the relatively disappointing predictive performance of random forests and stochastic gradient boosting – in spite of their consistently longer training times – underscores the need for caution in applying new predictive algorithms with the assumption that they will always provide superior outcomes. This is especially true given that some utility loss – for example, knowledge of function form – occurs upon transitioning to such more "black-box" methods.

Lastly, in anticipation of Study 3, I used the data available in Study 2 to explore the direct and interactive effects of brand-self personality congruence on attitudes toward and intent to watch a movie with which participants were unfamiliar. These exploratory findings suggested that congruence (whether with the actual, ideal, or fantasized self) played little to no direct role once controlling for various demographic and psychographic factors and their interaction with congruence; however, it is important to note that these findings pertain solely to the single movie the individuals rated. Since many of the movies included had been publicly available for several years, the accumulation of social discussion effects (e.g. L. Frank et al., 2012) over time may have impacted the outcomes.

Self-monitoring stood out for its repeatedly significant or present but statistically non-significant main effects and interactions with congruence and attitudes. That self-monitoring relates in some way to self-congruence effects is unsurprising. If, as posited by Ots and Hartmann (2015) and others, individuals utilize media to construct and project identity, it is sensible to reason that in the case of high self-monitors – as in, individuals who are highly sensitive and adaptive to surrounding social cues – self-congruence effects on media preference may become diluted by such individuals adapting their preference to surrounding social cues and norms. This supported the potential utility of the variable's inclusion as a moderator in Study 3 analysis.

However, for both self-monitoring and other variables presenting statistically significant effects in the exploratory multilevel models, two particular concerns call for caution. First, the models are un-cross-validated, raising generalizability and replicability concerns (Hindman, 2015). Secondly, with a large sample size approaching 4,000, the models present the possibility of statistical overpoweredness in their ability to capture certain effects. As a result, several regression coefficients seem to capture miniscule differences that are null in practice given their small values but nonetheless appear statistically significant (e,g. congruence-by-sex and congruence-by-education in the self-referencing congruence, attitude-outcome model). This combination of generalizability and overpoweredness underscores the need for a cautious interpretation of the results when building on the findings for future research.

CHAPTER 6 | STUDY 3:

BRAND-SELF CONGRUENCE, PRE-CONSUMPTION INTEREST, AND POST-CONSUMPTION FAVORITES

Study 3 aimed to examine the effects of media brand personality and individuals' congruence with such brand personalities on media preferences (**RQ3**). The movie-specific reanalyzed scale developed in Study 2 is again used, as are the movie mean personality ratings data from Study 2. Though analysis of congruence effects was possible in Study 2, as exhibited in the exploratory congruence analysis, the particular design poses two methodological concerns. The first involves common issues with self-report based measures, such as potential for recall bias when rating both one's own personality and a movie's personality in the case of self-referencing congruence, as well as the possibility of associated hypothesis-guessing from participants. Second, since participants were selected through a familiarity check and asked to rate the first movie with which they were unfamiliar, it is possible that prior attitudes toward the movie may have affected the results. For example, if a popular movie has been out for several years but the participant has never seen it, the underlying reasons for not having done so may impact the findings. Study 3 alleviates such concerns through a more direct measure of preference that allows participants to select multiple movies out of a set of 250 and focuses on the participants' mean congruence with those selected, as well as through utilization of an independent congruence measure that allays recall bias concerns mentioned above.

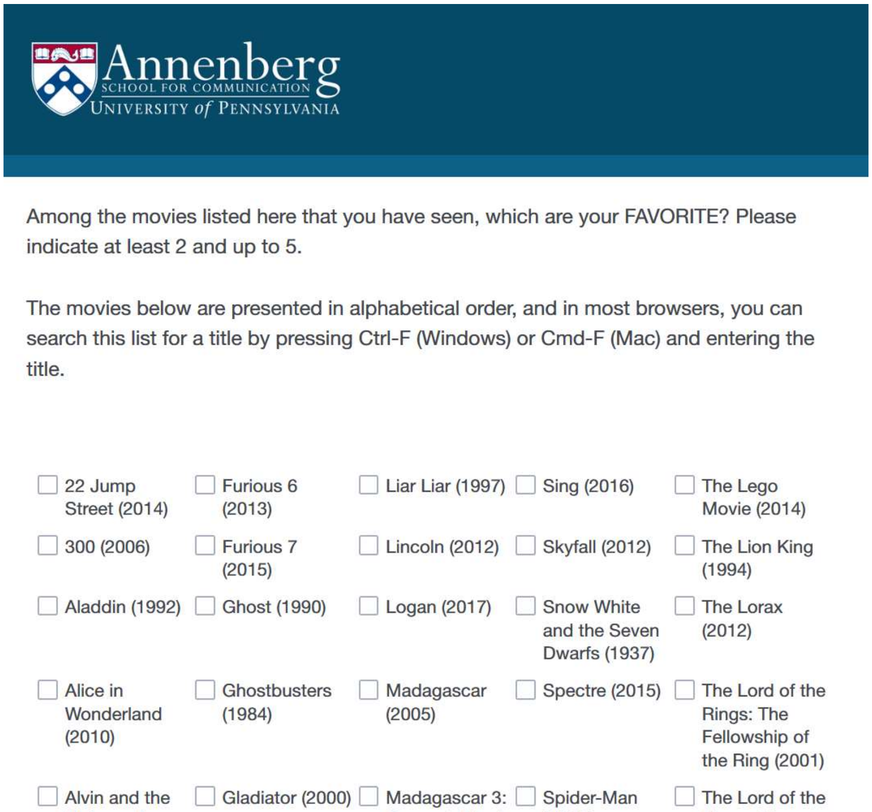
6.1 | Data Collection

Mechanical Turk workers who entered the survey were welcomed with the following prompt: *Please take a minute to examine from beginning to end the below list containing the Top 250 box office gross films in the United States. As you scan through the list, make brief mental notes of your thoughts about each of the movies - whether you like it or not, haven't seen it but want to see it, haven't seen it and aren't interested in seeing it, are likely it to see alone or with friends, etc. On the following pages, you will be provided an alphabetized list of these movies and asked to indicate your preferences in various contexts. The button to proceed to the next page will appear at the bottom of the page once at least 20 seconds have passed.* Below this prompt, participants were shown a list of the Top 250 domestic box office films rated in Study 2 in a five-by-fifty grid, with the order randomized to avoid any systematic order biases. Once 20 seconds had passed, they could proceed onto the next page.

On each of the six following pages, participants were provided the same 250 movies, this time in alphabetized checklist form, and asked to indicate two to five movies that they least or most preferred in several different preference dimensions. On the first page, participants were asked to respond with their least favorite movies among those they had seen (negative response), and on the second page, participants were asked to respond with their most favorite movies among those they had seen (positive response); together, these negative and positive responses formed the Favorites dimension (FAV). A screenshot of the most favorite seen movies response is provided in Figure 4.

Figure 4

Study 3, Most Favorite Seen Movie Response Page



Annenberg
School for Communication
University *of* Pennsylvania

Among the movies listed here that you have seen, which are your FAVORITE? Please indicate at least 2 and up to 5.

The movies below are presented in alphabetical order, and in most browsers, you can search this list for a title by pressing Ctrl-F (Windows) or Cmd-F (Mac) and entering the title.

22 Jump Street (2014)	Furious 6 (2013)	Liar Liar (1997)	Sing (2016)	The Lego Movie (2014)
300 (2006)	Furious 7 (2015)	Lincoln (2012)	Skyfall (2012)	The Lion King (1994)
Aladdin (1992)	Ghost (1990)	Logan (2017)	Snow White and the Seven Dwarfs (1937)	The Lorax (2012)
Alice in Wonderland (2010)	Ghostbusters (1984)	Madagascar (2005)	Spectre (2015)	The Lord of the Rings: The Fellowship of the Ring (2001)
Alvin and the	Gladiator (2000)	Madagascar 3:	Spider-Man	The Lord of the

Then, hypothesizing that peer influence effects (see Brechwald & Prinstein, 2011 for review) may differentially influence individuals' interest in unseen movies depending on context, I split measurement of interest in previously unseen movies into two additional dimensions. One dimension was likelihood of Watching By Self (WBS); on the third page, participants were asked to respond with the previously unseen movies they were least likely to watch by themselves (negative response), while on the fourth page, participants were asked to respond with the previously unseen movies they were most likely to watch by themselves (positive response). The other dimension was likelihood of Watching With Friends (WWF); on the fifth page, participants were asked to respond with the previously unseen movies they were least likely to watch with friends (negative response), while on the sixth page, participants were asked to respond with the previously unseen movies they were most likely to watch with friends (positive response). The division of these six pages into three preference dimensions, each with a negative and positive response, is shown below in Table 14.

Table 14

Study 3, Dimension and Response Table

Preference Dimension	Favorites (FAV)		Watch By Self (WBS)		Watch With Friends (WWF)	
Response	Least (-)	Most (+)	Least Likely (-)	Most Likely (+)	Least Likely (-)	Most Likely (+)

Following this, participants were asked to respond to the Lennox and Wolfe (1984) self-monitoring scale. Then, participants rated their own personality using the movie brand personality scale devised in Study 2 – once again randomly assigned to provide their actual, fantasy, or ideal personality as was the case in Study 2 – as well the importance of each of the traits from the scale, following the same prompts used in Study 2. Lastly, participants responded to a series of demographic questions adapted from the General Social Survey (Smith, Marsden, & Hout, 2016).

6.2 | Descriptives & Variables Analyzed

A total of 3,037 respondents participated in Study 3, with 1,017 participants randomly asked to rate their own actual personality; 1,006 participants randomly asked to rate their own fantasy personality; and 1,014 participants randomly asked to rate their own ideal personality. The median age group was 25-34, making up 39.7% (n=1,206) of the sample, followed by 35-44, which made up 24.3% of the sample (n=738). 56.3% of respondents (n=1,710) indicated being female, while 74.6% of respondents indicated being white; given a similar disparity in proportion across the race/ethnicity variable as observed in Study 2, the measure was collapsed into a nonwhite/white measure. The median and modal level of education was a college degree or more at 54.9% (n=1,666).

6.2.1 | Congruence scores. Prior to the main analysis, mean brand-self congruence scores with each of the six types of selected movies (LFV, MFV, LBS, WBS, LWF, WWF) were generated in a two-step process. Note that unlike the self-referencing congruence scores that are commonly used (where congruence is calculated between a respondent's personality and a brand's personality *both* as provided by the respondent themselves), here participants only rate their own personality and I measure the congruence between respondents' self-personality ratings and the movie personality ratings as collected from a separate sample in Study 2. This congruence score was calculated using a version of the Kressmann et al. (2006) formula similar to that used to calculate independent congruence in Study 2, with the mean movie trait rating across all raters from the separate Study 2 sample utilized in the numerator instead of a participant's own movie trait rating. Once more, the maximum and minimum congruence scores per movie were 0 and -6.

For each response, congruence scores were calculated between the participant and all movies listed for that response. Then, these congruence scores were averaged within response to provide a mean response congruence score. For example, if a participant selected *Titanic* and *Black Panther* as their most favorite movies, congruence between the participant and *Titanic* and congruence between the participant and *Black Panther* were separately calculated, and these two congruence scores were averaged to provide the mean most favorite movie congruence score. These mean response congruence scores (mean congruence score for favorite movies, mean congruence score for least favorite movies, mean congruence score for movies most likely to watch by self, etc.) were the primary outcome measures (i.e., dependent variables) of interest. Once again, as was the case in the exploratory analyses in Study 2, there are three different types of congruence being examined – actual, fantasy, ideal – depending on whether the participant had been randomly asked to rate their own actual/fantasy/ideal personality.

6.2.1.a | Internal reliability analysis of congruence. Because participants were required to list more than one item for each of the questions, calculating reliability of the per-movie congruence values in each question was possible. As participants had indicated anywhere from two to five movies for each of the past or likely future viewing questions, two of the congruence scores for each question were initially randomly selected for inclusion in Cronbach's alpha analysis (Table 15). This simple two-item analysis produced alphas of between .62 and .67. Expanding the reliability analysis to three randomly selected congruence scores by excluding cases that had only listed two movies led to alpha values above Nunnally's (1978) .7 recommendation across the board (see Table 15).[6]

---

[6] Though conventional assumptions are that more items automatically lead to higher alpha (Churchill & Peter, 1984), such a correlation has been suggested to be weak at best with no systematic

Table 15

Study 3, Cronbach's Alpha Results for Congruence Scores, Within-Response

Question	**Least FAV**	**Most FAV**	**Least WBS**	**Most WBS**	**Least WWF**	**Most WWF**
Two-item alpha	.67	.62	.64	.62	.64	.65
Three-item alpha (n)	.74 (2,110)	.71 (2,729)	.73 (2,065)	.71 (1,861)	.72 (1,852)	.72 (1,771)

6.3 | Analysis

6.3.1 | Primary analyses. The results for two-tailed paired-sample T-tests of the primary hypotheses of interest across all three congruence types are provided in Table 16. These t-tests, for each preference dimension, compare the mean congruence of the negative response to the mean congruence of the positive response. P-values are Holm-corrected within congruence type. Small but significant effects were observed across the board, with unexpected results in some cases. Bar plots by question and congruence type are presented in Figure 5a-c.

increase beyond three items (Peterson, 1994), and overall, the congruence scores display sufficient reliability given their highly indirectly calculated nature.

Figure 5a-c

Study 3, Boxplots for All Responses, by Preference Dimension and Congruence Type

With regard to actual personality congruence, as expected, movies that participants had not seen but were mostly likely to watch were on average slightly higher in congruence than those they had not seen and reported being least likely to watch. This was the case for movies they indicated being least ($M=-1.78$, $SD=.51$) and most ($M=-1.73$, $.51$) likely to watch by themselves ($t=3.52$, $p=.0004$, corrected $p=.001$), as well as those they indicated being least ($M=-1.77$, $SD=.50$) and most ($M=-1.73$, $SD=.50$) likely to watch with friends ($t=2.59$, $p=.0098$, corrected $p=.01$). Unexpectedly, however, the opposite pattern held true when it came to least and most favorite movies participants had already seen ($t=3.19$, $p=.0015$, corrected $p=.003$), with least favorite movies ($M=-1.73$, $SD=.48$) scoring slightly higher in congruence than did their most favorite movies ($M=-1.76$, $SD=.48$).

Similar patterns held true with both of the other congruence types included in the study. The results regarding congruence with one's fantasy personality were as expected regarding movies that participants had not seen but indicated being least and most likely to watch in the future. Congruence was higher ($t=2.84$, $p=.005$, corrected $p=.009$) for movies participants had not seen but considered most likely to watch by themselves ($M=-1.87$, $SD=.56$) than it was with movies participants had not seen but considered least likely to watch by themselves ($M=-1.91$, $SD=.57$). Likewise, congruence was higher ($t=4.83$, $p<.000$, corrected $p<.000$) for movies participants had not seen but considered most likely to watch with friends ($M=-1.87$, $SD=.56$) than it was with movies participants had not seen but considered least likely to watch with friends ($M=-1.91$, $SD=.57$). There was no significant difference, however ($t=.32$, $p=.75$, corrected $p=.75$) when it came to least (M=-1.87, SD=.55) versus most (M=-1.87, SD=.54) favorite movies that had already been seen.

As was the case with actual personality congruence, congruence with one's ideal self was higher ($t=2.71$, $p=.007$, corrected $p=.007$) with least favorite movies (M=-1.88, SD=.53) than with most favorite movies (M=-1.92, SD=.52), but other results followed expectations. Congruence was higher ($t=5.30$, $p<.000$, corrected $p<.000$) for movies participants had not seen but considered most likely to watch by themselves (M=-1.87, SD=.54) than it was with movies participants had not seen but considered least likely to watch by themselves (M=-1.94, SD=.56). Likewise, congruence was higher ($t=3.39$, $p=.001$, corrected $p=.001$) for movies participants had not seen but considered most likely to watch with friends (M=-1.88, SD=.52) than it was with movies participants had not seen but considered least likely to watch with friends (M=-1.93, SD=.55).

Table 16

Study 3, Two-tailed Paired Sample T-test Results, by Congruence Type

Test	**T-statistic**	**p-value (Holm correction)**	**M Difference**	**SE Difference**
Actual Personality Congruence (n=1,017)				
*Favorite*** (Least/Most)*	3.19	.0015 (.003)	-.037	.0116
*Watch By Self*** (Least/Most Likely)*	3.52	.0004 (.001)	.045	.0127
*Watch With Friends*** (Least/Most Likely)*	2.59	.0098 (.010)	.032	.0125
Fantasy Personality Congruence (n=1,006)				
Favorite (Least/Most)	.320	.7491 (.749)	-.004	.0115
*Watch By Self*** (Least/Most Likely)*	2.84	.005 (.009)	.036	.0128
*Watch With Friends*** (Least/Most Likely)*	4.83	<.000 (.000)	.064	.0133
Ideal Personality Congruence (n=1,014)				
*Favorite*** (Least/Most)*	2.71	.007 (.007)	-.033	.0122
*Watch By Self*** (Least/Most Likely)*	5.30	.000 (.000)	.070	.0132
*Watch With Friends*** (Least/Most Likely)*	3.39	.001 (.001)	.044	.0131

6.3.2 | Secondary analyses. The results of the exploratory congruence analyses in Study 2 suggested a set of potential moderators worth investigating in the present study. Given the computational intensity of high dimensional ANOVAs, particularly with the present mixed design and large sample size, the present secondary moderation analyses were limited to three-way analyses. No moderation effects on response category differences were present, but a range of main effects became apparent.

6.3.2.a | Self-monitoring. Self-monitoring (Lennox & Wolfe, 1984) was included as a measure in the Study 3 survey for its potential role as a moderator of self-congruence effects. Such a possibility was reinforced by self-monitoring's significant interaction with attitudes toward the movie (expectations) as well as its present, if not statistically significant ($p=.17$), interaction with congruence in the exploratory independent congruence intent-outcome multilevel model in Study 2. After alpha analysis of the responses to confirm satisfactory internal reliability – the .86 alpha exceeded Nunnally's (1978) .7 standard – the self-monitoring items were averaged and a median split (<=median, >median) conducted to generate a dichotomous low-high measure of self-monitoring. Then, for each preference dimension (FAV, WBS, WWF), 2 (between: congruence type) x 2 (between: self-monitoring low-high) x 2 (within: least [likely] vs. most [likely] response) mixed ANOVA models with congruence score as outcome were created (Table 17; Table 18).

Table 17

Study 3, 3-way (Congruence Type x Self-monitoring x Response) Mixed ANOVA Tables

Variable	**DF**	**F**	**p**
Favorite			
(Intercept)	1,3031	46943.17	<.000
Self-monitoring	1,3031	182.9	<.000
Congruence Type	2,3031	32.78	<.000
Response (Least vs Most)	1,3031	12.34	<.000
Self-monitoring:Congruence Type	2,3031	6.165	.002
Self-monitoring:Response	1,3031	0.316	0.573
Congruence Type:Response	2,3031	2.435	0.087
Self-monitoring:Congruence Type:Response	2,3031	1.510	0.220
Watch By Self			
(Intercept)	1,3031	43779.14	<.000
Self-monitoring	1,3031	181.823	<.000
Congruence Type	2,3031	31.09	<.000
Response (Least Likely vs Most Likely)	1,3031	42.59	<.000
Self-monitoring:Congruence Type	2,3031	8.892	0.0001
Self-monitoring:Response	1,3031	2.264	0.132
Congruence Type:Response	2,3031	2.072	0.126
Self-monitoring:Congruence Type:Response	2,3031	0.380	0.683
Watch with Friends			
(Intercept)	1,3031	44465.37	<.000
Self-monitoring	1,3031	162.4	<.000
Congruence Type	2,3031	29.82	<.000
Response (Least Likely vs Most Likely)	1,3031	38.11	<.000
Self-monitoring:Congruence Type	2,3031	8.593	<.000
Self-monitoring:Response	1,3031	0.125	0.723
Congruence Type:Response	2,3031	1.491	0.225
Self-monitoring:Congruence Type:Response	2,3031	1.612	0.199

Table 18

Study 3, 3-way (Congruence Type x Self-monitoring x Response) Table of Mean Congruence Scores, with Within-Congruence Holm Corrected Pairwise T-test Significance

	Actual Personality				**Fantasy Personality**				**Ideal Personality**		
	Low SM	**High SM**			**Low SM**	**High SM**			**Low SM**	**High SM**	
- FAV (LFV)	-1.63	-1.84	-.21 ***		-1.79	-1.97	-.18 ***		-1.74	-2.05	-.31 ***
+ FAV (FAV)	-1.68	-1.87	-.19 ***		-1.80	-1.97	-.17 ***		-1.77	-2.10	-.33 ***
	-.05***	-.03			-.01	.00			-.03	-.05*	
- WBS (NBS)	-1.69	-1.88	-.19 ***		-1.84	-1.99	-.15 ***		-1.79	-2.12	-.33 ***
+ WBS (WBS)	-1.64	-1.85	-.21 ***		-1.78	-1.98	-.20 ***		-1.71	-2.06	-.35 ***
	+.05***	+.03			+.06***	+.01			+.08***	+.06***	
- WWF (NWF)	-1.70	-1.86	-.16 ***		-1.83	-1.99	-.16 ***		-1.77	-2.11	-.34 ***
+ WWF (WWF)	-1.65	-1.84	-.19 ***		-1.76	-1.94	-.18 ***		-1.74	-2.05	-.31 ***
	+.05*	+.02			+.07***	+.05^			+.03	+.06***	
***: <.01, *: <.05, ^: <.10											

The significance of the response factor for Favorites (F(1,3031)=12.34, p=.0004) gave support to the primary hypotheses tests conducted earlier at a general level; it suggests that, overall controlling for self-monitoring, favorite movies tend to be lower in congruence than least favorite movies. No significant interactions between response and congruence type or self-monitoring was present. Among the between-subjects factors, both self-monitoring (F(1,3031)=182.95, p<.000) and congruence type (F(2,3031)=32.79, p<.000) had a significant effect on congruence, and the interaction between these variables was also significant (F(2,3031)=6.17, p=.002). In combination with the table of means, the results suggest that high self-monitors overall tend to have watched movies that are less congruent with themselves than do low-self-monitoring individuals, and the magnitude of this difference varies depending somewhat on the type of congruence (actual, fantasy, or ideal) in question; these differences can also be observed in Figure 6. Though the differences in self-congruence between high and low self-monitors appears roughly similar across the actual congruence and fantasy congruence sub studies, it is accentuated when it comes to ideal-self congruence.

Figure 6a-c

Study 3, Mean Congruence by Preference Dimension, Congruence Type, Self-monitoring

A nearly identical pattern of effects emerged from the Watch By Self preference dimension. The response factor was again significant ($F(1,3031)=42.60$, $p<.000$), which in combination with the primary hypothesis tests earlier suggests that, controlling for self-monitoring and congruence type, previously-unseen movies people indicate being most likely to watch are more congruent with their personality than are previously-unseen movies they indicate being least likely to watch. No interaction with congruence type or self-monitoring was present. Self-monitoring again had a significant between-subjects effect ($F(1,3031)=181.82$, $p<.000$), with higher self-monitors once more tending to list less self-congruent movies than did lower self-monitors. Congruence type ($F(2,3031)=31.10$, $p<.000$) was also a significant between-subjects factor, and its interaction with self-monitoring was also significant ($F(2,3031)=8.59$, $p=.0002$). Once again, the results suggest that self-monitoring does impact how congruent the movies people list tend to be, with the effect especially stark for ideal congruence as noted by the significant interaction term.

Finally, the Watch With Friends preference dimension once more presented support for the pattern of effects observed above. The response category factor was again significant ($F(1,3031)=38.11$, $p<.000$) with no significant interactions with congruence type or self-monitoring, reinforcing primary hypothesis test results controlling for the other variables in the model. The previously encountered pattern of self-monitoring effects was again present ($F(1,3031)=162.412$, $p<.000$), with higher self-monitors tending to list lower congruence movies across the board. Congruence type was also significant ($F(2,3031)=29.82$, $p<.000$) as was its interaction with self-monitoring ($F(2,3031)=8.59$, p=.0002), again suggesting the effect of self-monitoring on the congruence of listed movies depends on the type of congruence.

In addition to the three-way mixed ANOVAs, pairwise t-tests were run to compare individual cell means, conducted within-congruence type and preference dimension to align with the primary t-test procedures. Even though the response by self-monitoring interaction is not statistically significant across any of the preference dimensions in the ANOVA (Favorite: $F(1,3031)=0.316$, $p=.573$; Watch By Self: $F(1,3031)=2.264$, $p=.132$; Watch With Friends: $F(1,3031)=.125$, $p=.723$), examining the pairwise t-test results and the table of means reveals some notable patterns. Congruence differences generally seem to be more consistently significant across low-self-monitoring individuals than high self-monitoring individuals, and Fantasy congruence generally produced the least consistent congruence differences.

6.3.2.b | Demographic moderators: race/ethnicity, education. The exploratory congruence analyses from Study 2 also suggested two additional potential moderators for analysis. Race/ethnicity had a significant interaction with independent congruence effects on attitudes, while education had a significant interaction with self-referencing congruence effects on attitudes. Additional 3-way mixed ANOVA models were created to examine any potential moderating effects of these variables.

In a 3-way mixed ANOVA (Congruence type x race/ethnicity x response category), no significant race/ethnicity interactions with response category were present. However, the response factor was consistently significant (Favorite: $F(1,3031)=6.23$, $p=.013$; Watch By Self: $F(1,3031)=26.62$, $p<.000$; Watch With Friends:

F(1,3031)=24.95, p<.000). This supported the primary hypothesis tests controlling for race/ethnicity, with no significant race/ethnicity effect or interaction with congruence type and response differences present.

Table 19

Study 3, 3-way (Congruence Type x Education x Response) ANOVA Table, with Within-Congruence Holm Corrected Pairwise T-test Significance

Variable	**DF**	**F**	**p**
Favorite			
(Intercept)	1,3031	43904.92	<.000
Education (>=College)	1,3031	7.070	<.000
Congruence Type	2,3031	29.83	<.000
Response (Least vs Most)	1,3031	11.67	<.000
Education:Congruence Type	2,3031	0.810	0.44
Education:Response	1,3031	3.200	0.073
Congruence Type:Response	2,3031	2.626	0.072
Education:Congruence Type:Response	2,3031	0.993	0.370
Watch By Self			
(Intercept)	1,3031	40800.04	<.000
Education (>=College)	1,3031	3.331	0.068
Congruence Type	2,3031	27.57	<.000
Response (Least Likely vs Most Likely)	1,3031	43.94	<.000
Education:Congruence Type	2,3031	1.032	0.356
Education:Response	1,3031	0.753	0.385
Congruence Type:Response	2,3031	2.166	0.114
Education:Congruence Type:Response	2,3031	3.226	0.039
Watch with Friends			
(Intercept)	1,3031	41805.25	<.000
Education (>=College)	1,3031	6.456	0.011
Congruence Type	2,3031	26.91	<.000
Response (Least Likely vs Most Likely)	1,3031	37.95	<.000
Education:Congruence Type	2,3031	0.936	0.392
Education:Response	1,3031	0.701	0.402
Congruence Type:Response	2,3031	1.525	0.217
Education:Congruence Type:Response	2,3031	0.337	0.713

Table 20

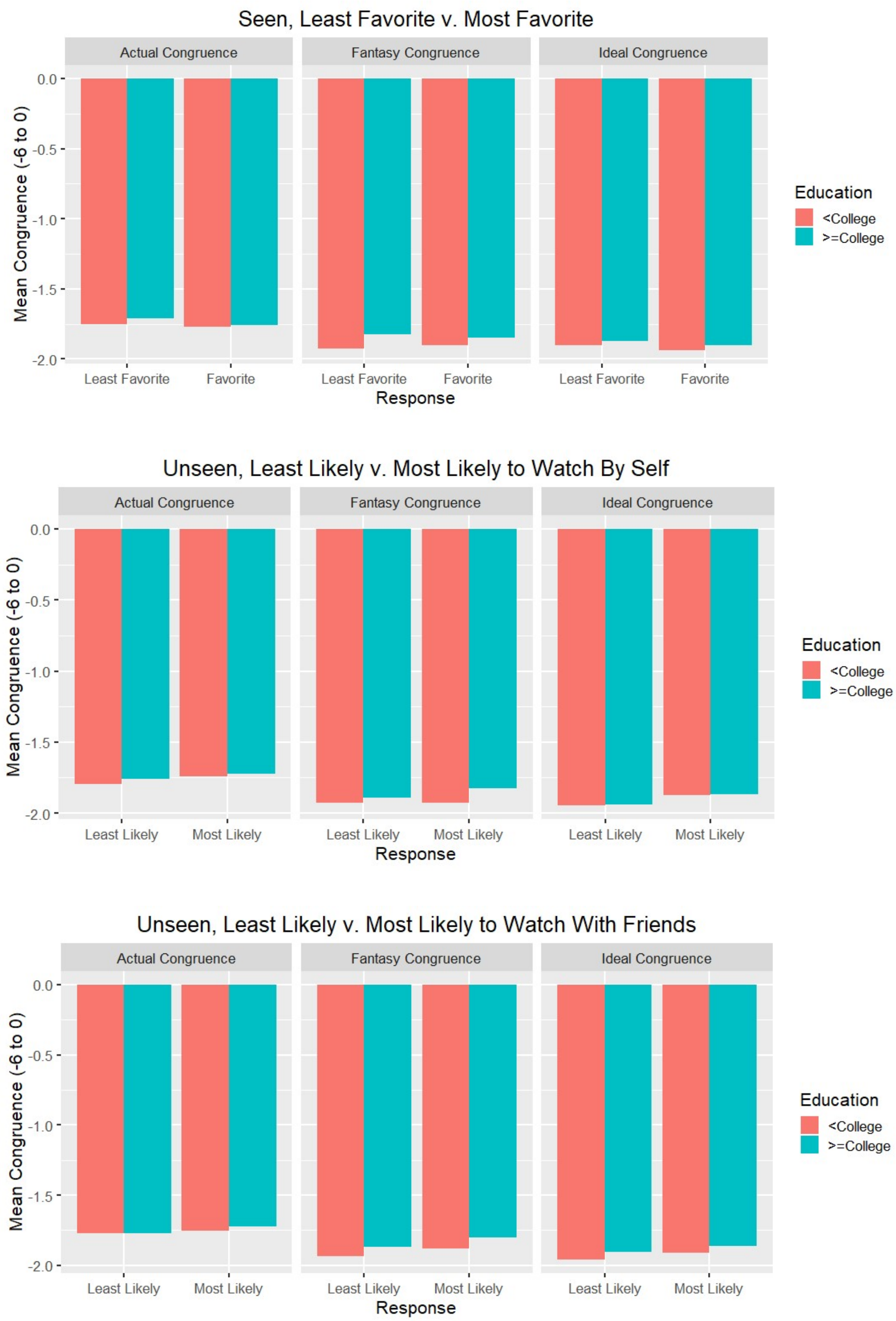
Study 3, 3-way (Congruence Type x Education x Response) Table of Mean Congruence Scores, with Within-Congruence Holm Corrected Pairwise T-test Significance

	Actual Personality			**Fantasy Personality**			**Ideal Personality**		
	<College	**College+**		**<College**	**College+**		**<College**	**College+**	
- FAV (LFV)	-1.75	-1.70	+.05	-1.92	-1.82	+.10 *	-1.90	-1.87	+.03
+ FAV (FAV)	-1.77	-1.75	+.02	-1.90	-1.84	+.06	-1.93	-1.90	+.03
	-.02	-.05*		+.02	-.02		-.03	-.03	
- WBS (NBS)	-1.80	-1.76	+.04	-1.92	-1.88	+.04	-1.94	-1.94	.00
+ WBS (WBS)	-1.74	-1.72	+.02	-1.92	-1.82	+.10 *	-1.87	-1.87	.00
	+.06*	+.04		.00	+.06***		+.07***	+.07***	
- WWF (NWF)	-1.77	-1.77	.00	-1.94	-1.87	+.07	-1.95	-1.90	+.05
+ WWF (WWF)	-1.75	-1.73	+.02	-1.88	-1.80	+.08	-1.91	-1.86	+.05
	+.02	+.04^		+.06^	+.07***		+.04	+.04	
***: <.01, *: <.05, ^: <.10									

Education proved more distinguishing (Table 19; Table 20; Figure 7). Given that both the median and modal response were the highest "college or more" category (54.86%, n=1,666), the education variable was converted to a dichotomous college no/yes variable. No moderating effects were present, as indicated by education-by-response interaction terms (Favorite: F(1,1031)=3.20, p=.07; Watch By Self: F(1,3031)=.75, p=.39; Watch With Friends: F(1,3031)=,70, p=.40). However, across all responses and congruence types, college-educated individuals generally listed movies that were higher in congruence (Favorite: F(1,1031)=7.070, p=.008; Watch By Self: F(1,3031)=3.33, p=.068; Watch With Friends: F(1,3031)=6.457, p=.011). The patterns of effects were similar to that in the self-monitoring moderation analysis, with congruence higher for least favorite movies than most favorite (F(1,3031)=7.07, p=.008), and the opposite for least and most likely to be watched by oneself ($F(1,3031)=43.94$, $p<.000$) and with friends ($F(1,3031)=37.96$, $p<.000$). There was also a significant difference across the three congruence types for all questions (Favorite: $F(2,1031)=29.84$, $p=.0006$; Watch By Self: $F(2,3031)=27.57$, $p<.000$; Watch With Friends: $F(2,3031)=26.92$, $p<.000$) such that actual personality congruence tended to be highest, followed by ideal, then fantasy. In addition, for the Watch By Self preference dimension, there was a significant three-way congruence type-education-response category interaction ($F=3.23$, $p=.04$) which suggested the effect of education on response category differences varied depending on the type of congruence.

Figure 7a-c

Study 3, Mean Congruence by Preference Dimension, Congruence Type, Education



6.4 | Study 3 Discussion

The goal of Study 3 was to compare the congruence of individuals' actual, fantasy, or ideal personalities with their most preferred and least preferred movies in various contexts – their favorite and least favorite among those they have seen, those they are most and least likely to watch by themselves among those they have not seen, and those they are most and least likely to watch with friends among those they have not seen. The results suggest that for movies individuals have not yet seen, those they are most likely to watch tend to be higher in brand-self congruence, regardless of the type of personality, than those they are least likely to watch. However, among movies they have seen, those that are their favorite tend to be lower in congruence than those that are their least favorite, again regardless of type of personality. It is important to note that all of these differences, while consistently significant statistically, were relatively small in size, raising some questions about their practical significance.

Though no significant moderators of these relationships were uncovered, the potential moderators themselves had significant main effects on self-brand personality congruence. Higher self-monitors tended to list movies lower in self-congruence and those with college education tended to list movies higher in self-congruence, regardless of type of congruence or preference dimension.

A key methodological innovation in this study is the use of independent congruence scores rather than self-referencing congruence scores. The more commonly used self-referencing congruence scores are a measure of congruence between an individual's perception of their own personality and their perception of a product's personality, but the process of collecting such data through self-report measures inherently raises response bias concerns. If an individual rates a movie's personality, their attitudes toward the movie, *and* their own personality, it is likely that their responses to any one of these questions, consciously recalled or not, could bias their responses to the others. The independent congruence score used in the present study and in the exploratory analysis in Study 2 avoid this concern by measuring the relationship between an individual's perception of their own personality and the population (as represented by the separate rater sample) mean perception of the product's personality. By using the external sample mean ratings of the movies as the comparative reference from which congruence scores are generated, the bias concerns above are allayed.

Though the results of the exploratory congruence analysis in Study 2 – namely the lack of statistical significance of congruence effects controlling for other variables and relevant interactions – may cast some doubt onto the present results, it is important to note the methodological superiority of Study 3. The design of Study 2 carries with it the usual concerns regarding self-report based studies, and each participant only rated one randomly presented movie that they indicated not seeing; many of the movies have been out for years, and the state of not having seen them for many years after release likely biases attitude and intent. The Study 3 implement sufficiently obscures the hypothesis of interest such that self-report issues such as desirability effects are not a concern, and the design nullifies the "unseen-after-years" bias alluded to above.

CHAPTER 7 | DISCUSSION AND IMPLICATIONS

Motivating this dissertation was a desire to better understand the process by which individuals select media products to consume, given that they make such choices *prior to actually experiencing them*. Drawing on brand theory and research from the marketing literature, my starting assumptions were that (1) media products have identifiable brand personalities, and (2) consumers have a preference for media that is congruent with their own personalities – what I call "brand-self congruence." To test these assumptions, I designed and conducted three studies, each of which focused on a specific research question:

- What are the dimensions across which individuals perceive the brand personality of media products (**RQ1**)?
- What textual and visual elements of movie descriptions and posters are predictive of their brand personality (**RQ2**)?
- How is brand-self personality congruence associated with media preferences (**RQ3**)?

Study 1 explored the personality traits that individuals associate with a wide range of diverse media products, identifying three personality dimensions – Aggression, Heroism, and Warmth – that applied to movies, TV shows, video games, news outlets, and pop song brands. The primary purpose of Study 2 was to investigate if computationally identified text and image features contained in the promotional material for movies could be used to predict perceptions of movie brand personality, with the results providing little evidence for this. Finally, Study 3 directly examined the relationship between three types of brand-self personality congruence and individuals' movie-viewing preferences, finding support for a positive relationship as regards future viewing intentions, but a negative relationship as regards past viewing. What follows is a discussion of what I consider to be the implications and theoretical contributions of these findings, potential directions for future research, and study limitations.

7.1 | Contributions to the Field & Directions for Future Research

7.1.1 | Study 1. The Unified Media Brand Personality Scale (UMBPS) captures common personality dimensions perceived by potential consumers across media product brands of different formats. Such a scale allows for comparisons both within and across media categories. This opens up the potential for research that instead of focusing on items of a single medium, spans media of different kinds. The ability to conduct such research is of increasing importance as the lines separating media and media formats blur, convergence becomes the norm (Malmelin & Moisander, 2014), and transmedia branding (Matteo & dal Zotto, 2015) proliferates.

Indeed, this scale may enable deeper investigation of the role that brands play in transmedia entertainment storytelling. Transmedia is a "narrative structure that expands through both different languages and media" where "different media and languages participate and contribute to the construction of the transmedia narrative world" (Scolari, 2009, p. 587). Scolari (2009) emphasizes the role brands play in transmedia storytelling as "symbolic [universes] endowed with meaning" (p. 599). Giving examples of *The Matrix, 24,* and *Harry Potter,* Scolari (2009) goes on to define a "narrative brand" as being "founded on a set of characters, topics, and an aesthetic style that define the fictional world of the brand" whose "traits can be reproduced and adapted to different media and genres" (p. 600). By this definition and the product-as-brand definition of media brands utilized in the present study, media brands can be considered extensions of narrative brands, and narrative brands, though they may start as a single product, can be construed as coalescences of media brands. This suggests the potential utility of the UMBPS in measuring the personality of media brands at not just the individual product level, but also the larger franchise or series narrative brand level. Integrated with research on brand-self congruence effects as examined in the present dissertation and elsewhere (e.g. Kressmann et al., 2006), the UMBPS measure could enable novel empirical inquiries into audience behavior and attitudes in transmedia contexts.

Even beyond transmedia-specific applications, a scale such as the UMBPS that can be used to measure the personality of different media opens up many new avenues for research. For example, this scale would allow for isolation and measurement of category effects on perceptions of brand personality. Research by Batra and Homer (2004) and Maehle, Otnes, and Supphellen (2011) suggest that people tend to associate different personality traits with different types of products with different traits. Controlling for title and content cues – e.g. a plot summary – how can the proposed medium of a media product affect perceptions of its personality? And how can such category effects on perception influence responses to media messages?

Relating to the above, tie-in and licensed products are commonly released alongside major media products. Also common are adaptions of media products into another medium. How does the perception of the personality of a media brand change when it is adapted from one medium to another? Such questions could be investigated not only through the lens of category effects but also brand extension effects, as it has been shown that brand extensions can influence perceptions of the parent brand personality (Martinez & de Chernatony, 2004; Arslan & Altuna, 2010). And in cases where brand personality differences between the original and adaptation are not significant, what leads audiences to consume one but not the other? There is also the question of nested personality effects. Often, media of one category may prominently feature media of another category, e.g. a song is prominently featured in a movie. In such cases, how do the personalities of the media brands interact? Is influence on media brand personality unidirectional or bidirectional?

7.1.2 | Study 2. Study 2 showed that computer text and image features derived from movie posters and descriptions as encountered on services like Netflix are of limited value in predicting movie brand personality. The features presented some utility in predicting movie Aggression, but were of no use in predicting movie Heroism and Determination, with LASSO regression providing pure intercept-based predictions for the latter two dimensions but still providing superior test error than both random forests and boosting. This suggests that none of the text and image variables as presently operationalized contained information linearly or otherwise associated with Heroism and Determination. Returning to the latent versus manifest content distinction as discussed by Benoit (2011), with Aggression, LIWC text features – which are arguably somewhat latent in character given their links to various cognitive and affective processes – tended to be more strongly predictive both positively and negatively than image features – most of which were manifest in character. Taken as a whole, these findings suggest that the computer text and image features as presently derived from movie posters and descriptions contain little information predictive of movie brand personality, and even when they are relevant, those that are more latent leaning have more predictive value.

Methodologically, there are still insights to be gained in spite of disappointing predictive performance. Namely, that the cross-validated algorithms generally outperformed the single-fit saturated multiple regression models underscores the dangers of the popular latter practice in the social sciences. Integration of cross-validated regression model development should become standard practice, in line with recommendations made by Hindman (2015). However, despite the potential benefits offered by application of such machine learning practices in social science research, the results also underscore the fact that new-fangled methods do not always provide benefits over more conventional methods and that, factors such as training time taken into account, may even be overall detrimental. LASSO consistently outperformed random forests and boosting despite at its core relying on familiar linear model assumptions, and, in the case of predicting Heroism and Determination, using the intercept as the singular predicted value. However, there are likely to be contexts in which random forest and boosting outperform LASSO, and future research necessitating regression should consider analytic and predictive needs (e.g. is knowing the direction of association important, or is maximizing predictive performance the main goal?) in selecting the optimal regression algorithm.

7.1.3 | Study 3. Study 3 makes three major contributions to media preferences research. First, it establishes the relevance of brand-self congruence effects in media preferences research, finding significant differences in the variable across among all three preference dimensions observed, even with p-values corrected for multiple comparisons and controlling for variables such as self-monitoring, race/ethnicity, and education. Second, it demonstrates the utility of the independent congruence measure in brand-self congruence research as an alternative to the methodologically flawed and commonly used self-referencing congruence measure. By using mean trait ratings as generated by an external sample, rather than an individual's own ratings of the movie, as the reference against which congruence is calculated, concerns of question recall biasing outcomes are allayed.

In addition, unexpectedly, the findings suggest that though individuals may be more interested in movies they have not seen that are more congruent to themselves, they also suggest that among movies they have seen, individuals ultimately favor those that are incongruent with themselves. Most fundamentally, these findings suggest that the brand-self congruence effects on media preferences occur differently at two distinct levels – pre-exposure interest, and post-exposure attitudes. Returning to the self-related motives for media use as discussed by Knobloch-Westerwick (2015b), implied by the results is the possibility that pre-exposure interest in media products is driven by self-consistency motives, while post-exposure attitudes about media products are driven by their fulfillment of self-improvement or self-enhancement motives. In summary, the factors that draw individuals to movies may not necessarily be the same as those that lead to their enjoyment of it.

This possibility poses interesting implications for further research integrating targeting and tailoring theory. Thanks to digital technology, audiences have more control of exactly what they choose to be exposed to than ever before (Bennett & Iyengar, 2008; Iyengar & Kinder, 1987), and content providers are happy to play along by providing personalized content recommendations of all sorts to maximize audiences and revenue. However, it is important to consider how digital technologies like algorithmic recommendations can impact media preferences and selection not only through *what* they recommend, but *how* they recommend it, i.e. a sort of "second-level" personalized recommendation (paralleling second level agenda-setting as discussed by McCombs, 2004). For example, when an algorithm recommends *The Hunger Games* to someone, perhaps the description should read as the story of youths fighting for equality (if the individual is known to be liberal), but as the story of rebels fighting against an oppressive government (if the individual is known to be conservative). Or when an algorithm recommends news article X about a protest in one's hometown, will the customized title focus on the prosocial reasons for the protest or the disruptions it will cause?

The need to investigate such possibilities is supported by the results of Study 3, which suggest that though individuals are more drawn to self-congruent movies they have not yet seen, the movies that are their most favorite among those they have seen tend to be those less congruent than their least favorite movies. Digital technology allows for ever-increasing possibilities for group-level targeting or individual-level tailoring

(Kreuter & Wray, 2003) across a countless number of dimensions to induce or counteract media preferences and selection. The Study 3 findings, coupled with extant literature on differences in perceptions of brand personality (e.g. D. Kim, 2018a) and graphic manipulation effects on perceived brand personality (e.g. Lieven et al., 2015; Boudreaux & Palmer, 2007; Orth & Malkewitz, 2008), suggests that this tailored "me-ness" (Petty, Barden, & Wheeler, 2002) could be used to purposively manipulate media preference and selection. When drawn to the same media product by different, targeted, congruence-inducing brand material, will individuals leave having perceived the content in the same way? In the tradition of Bruner and Minturn's (1955) "13" study, a person who spends their life thinking about numbers may leave having seen "13," but the person who spends their life thinking about letters may leave having seen "B."

Finally, though there is much cross citing in the media preferences domain between research on general preference and in-the-moment selection, it is important to note that these elements are actually distinct (Knobloch-Westerwick, 2015a). The present study specifically examines the former, considering brand-self congruence differences in the context of broad stated preference rather than in the context of specific in-the-moment choice. Future research should examine how brand-self congruence effects may differ across these related but distinct contexts.

7.1.3.a | Looking beyond the self and self-congruence. The focus on the self and self-congruence also implicitly points toward four particular related avenues for further research that is in line with extant literature at increasingly specific scopes of examination. First, at the highest level is the possibility that, particularly given the small effect size observed here, though the self and personality congruence may have an effect on media preference, its amount of variance explained may be superseded by more straightforward measures of responses to a media product brand, such as love or liking (e.g. Rossiter, 2012). Additional research to parse out the effects of the self, self-congruence, simpler measures such as liking, and their relationships with each other may prove fruitful.

Second, as outlined by Knobloch-Westerwick's (2015b) SESAM model, the self is but one of two key components theorized to be relevant in media preference, the other being affect. The affect component of media preference has been examined through theories such as mood adjustment (Knobloch, 2003), and it finds a parallel in the branding literature in the form of brand affect (Chaudhuri & Holbrook, 2003). Further research on the role of media product brand affect in media preference and its interaction with brand-self congruence effects is necessary.

Focusing on the self and brand-self personality relationships, congruence and similarity may not be the only avenue of research worth further inquiry. Extant literature in social psychology has examined not only interpersonal similarity effects but also interpersonal complementarity effects on various outcomes (e.g. dominant-submissive pairs versus dominant-dominant pair performance on a task; Dryer & Horowitz, 1997; Estroff & Nowicki, 1992). Instead of always preferring media with personalities that are necessarily congruent with their personality, individuals may also prefer media with personalities that form some type of fitting complement to their personality. Additional research on brand-self personality congruence versus complementarity effects on media preference is needed.

Lastly, specifically with regard to the self, though it may indeed play a role in media preference, personality may not necessarily be the most optimal or relevant operationalization of individuals' self-attributes. Focusing on the self-concept, or the overall conceptualization an individual has of oneself ("Self-concept", n.d.) as a "physical, social, and spiritual or moral being" (Gecas, 1982), it stands to reason that personality is but one of many dimensions across which an individual considers themselves. Additional research on other elements or aspects of the self-concept as studied in the literature – e.g. academic self-concept (Marsh, 1987) – and their relationship to brands and related brand attributes in the context of media preferences is merited.

7.2 | Limitations

Several methodological limitations in the three studies presented here should be acknowledged. Most broadly applicable are the samples. Participants across all studies were limited to an American sample of mTurk users, consisting largely Caucasians in their late 20s and early 30s. Though the literature suggests that mTurk samples are reasonably reliable and more diverse than typical internet or university student samples (Buhrmester et al., 2011), racial diversity was lacking, and a more racially representative sample may have produced different results. In addition, the results are strictly applicable to native English-speaking American participants, a key fact to consider given that extant literature has shown replicability issues and differences in conceptualizations of brand personality across cultures (Azoulay & Kapferer, 2003; Bosnjak et al., 2007; Aaker, Benet-Martinez, & Garolera, 2001; Smit, van den Berge, & Franzen, 2003). Discussed below are more study-specific limitations, some of which carry across studies.

7.2.1 | Study 1. The first limitation concerns the breadth of brands examined within each of the categories considered in the construction of the unified media brand personality scale. There was an inherent tension between representativeness of the brand selection and recognizability of the brands being tested. Except in the case of news, brands were picked from top consumption lists to ensure a reasonable degree of recognizability among participants. Though they were selected from both the top and from further down such lists in an attempt to mitigate commercial success bias, this meant that less commercially driven media such as arthouse films, independent artist music, or local news brands were not included. A more extensive study with a more expansive set of media brands from across the commercial success spectrum, including more obscure media brands – e.g. indie films, indie games, etc. – may produce different results.

Furthermore, despite attempts to minimize the impact of confounding factors, they are undoubtedly present. Many individual video game brands in the study were extensions of existing franchises, opening the door to unintentional perceptive “leakage” when rating the personality of one particular entry of many in a series. With many of the media types encompassed by the UMBPS, individuals’ perceptions of the brands’ personalities may be influenced by their perceptions of the individuals involved in the media product’s creation; the personalities of individuals associated with a brand are often projected onto the brand itself (Chan-Olmsted & Cha, 2008; Aaker, 1997). Though some media brands may have fewer individual people saliently associated with them than others – it is easier to name individuals associated with *Jurassic Park* than *Halo 4* – given the complexity of many media brands and the number of associated individuals necessitated by their collaboratively creative nature, some risk of confounding factors is unavoidable.

Finally, there is the question of applicability of the UMBPS dimensions to media formats beyond the five media formats examined in the study. Though expansive, the selection of media brand categories included in this study is by no means exhaustive, and additional research is necessary to examine the applicability of this scale with media brands beyond the movie, pop music, video game, TV show, and news outlet categories. Furthermore, given the constant rise and fall in the prominence of various media formats, the scale may need to be updated and reformulated over time as the significance of particular media formats in the public mind and their corresponding effects on perceptions of media surge and fade. For example, if the relatively new augmented reality (AR) format becomes more mainstream, this continuous exposure may lead to a highlighting of certain media personality dimensions and a reduced perception of others purely due to the nature of the medium, and this AR-driven shift in perception may influence the way individuals perceive other media.

7.2.2 | Study 2. Once again, the specific set of movie brands examined here is a concern. Even putting aside the face-level concern that a sample of 250 at the movie level is relatively small, as they are from the top 250 domestic gross list, all movies included are mainstream and commercially successful. Inclusion of less commercially successful or mainstream movies – such as avant garde or arthouse movies – may have impacted the results. Future research in this direction may consider using purely upcoming movie releases, or even synopses from the industry "black list" of screenplays that have not yet been picked up, perhaps with researcher-generated posters, to minimize any attitudinal bleed-over resulting from attitudes toward associated cast or crew. In addition, though all movies were rated by individuals who had not yet seen them, many have been in public circulation for years. As a result, raters may have been influenced by long-term exposure to related ads and press discourse, as well as interpersonal discussion and social network effects (e.g. L. Frank et al., 2012; Weenig & Midden, 1991; Lazer, Rubineau, Chetkovich, Katz, & Neblo, 2010).

Another limitation of Study 2 is that the set of texts and especially computer vision features that could be utilized in predicting movie brand personality were restricted by the relative computational intensity of generating and working with more advanced features. For example, object recognition and face recognition are presently feasible and already widely applied on popular commercial platforms (e.g. Facebook) for whom computational resources are more available than for researchers such as myself. The inclusion of more advanced computer vision features may provide greater insights into perceptions of movie brand personality and higher computational predictive performance.

Lastly, the lack of notable predictive power in any of the regression algorithms suggests that there is little information in movie posters and descriptive text, at least as currently operationalized, that is associated with perceptions of brand personality. Future studies should include additional information depicted in posters, such as actors or presence of certain objects (e.g. firearms), to investigate their contribution to prediction accuracy. In addition, it is entirely possible that, paralleling Jenkins et al.'s (2013) argument that the meaning in the media realm is created in interaction between content creators and audiences, accurate measurement of brand personality perception requires consideration of both material end and viewer end considerations. Future research should examine the intersection of both branding material trait and audience characteristic effects on perceptions of brand personality.

7.2.3 | Study 3. The limitations regarding the list of 250 movies as discussed in relation to Study 2 also applies here. A different set of movies may have led to different results, and a similar approach as posited above – using purely future releases or researcher-generated materials – may be desirable in future work in the direction. Furthermore, though the design of the study is such that social desirability bias in respondents is less of a concern, it arguably still does not follow the strict, observation of selection approach of which Knobloch-Westerwick (2015a; 2015b) is a proponent. Such an observation of selection approach to brand-self congruence research in media preferences, perhaps aided by digital technologies and the relatively straightforward passive tracking they offer (de Vreese & Neijens, 2016; J. Webster, Phalen, & Lichty, 2014) may provide differing, even more methodologically sound results.

In contrast to the undersized sample concern discussed in relation to Study 2, the opposite issue presents with Study 3. The large sample size and the particularly small scope of the effects observed raise some questions with regard to statistical overpoweredness and the practical implications of the findings. The least (likely) versus most (likely) differences, while statistically significant and robust across the congruence types observed, were small, and this is evident across all figures but most clearly in Figure 5. Even controlling for third variables like self-monitoring, the differences remain statistically significant but small. With a smaller sample size, such differences in means may not have reached statistical significance. As such, though the self-congruence differences in media preferences may indeed be present and statistically significant as presently observed, they may not be of any practical significance.

Furthermore, though the independent congruence measure used does allay typical self-report associated concerns with the more commonly used self-referencing congruence, some measurement issues persist in terms of both participant-side and movie-side personality trait measurement. Ultimately, the congruence calculations rely on participants' rating their own personality, a step ripe for bias, while variation in individual experiences may also have influenced raters' evaluations of the movies. Given well-established concerns with direct self-report measures (e.g. de Vreese & Neijens, 2016), more indirect measures of participants' personality traits either using known self-report correlates (e.g. sensation-seeking and aggression; Joireman, Anderson, and Strathman, 2003), known behavioral correlates (e.g. high assertive and low submissive behavior and aggression; D. Schwartz et al., 1998), or peer evaluations may have led to differing results. Similarly, on the movie side, further research should be conducted to determine objective message features (O'Keefe, 2003) in marketing materials that correlate with perceived movie brand personality and ascertain their connections to person-side personality traits.

Putting aside trait-level measurement, the specific congruence formula used in the present study may be a concern, in multiple regards. As mentioned earlier, an alternative measure of brand-self congruence worth consideration in future research is user-imagery congruence as put forth by Sirgy et al. (1997). This approach considers congruence a gestalt-like psychological experience – instead of a trait-by-trait piecemeal process implied by difference-based approaches – best measured by asking individuals to envision the typical user of a brand and rate how similar they believe themselves to be to that envisioned user, and some argue this direct measurement of congruence has greater predictive utility (Sirgy et al., 1997; Parker, 2009).

Remaining with the difference-based approach, however, other concerns linger even taking into account the independent congruence modification. First is the singular, stationary nature of the movie personality ratings against which individuals' congruence is calculated. All movie ratings, regardless of time passed since release, were captured at roughly the same window of time. Given phenomenon like sleeper hits (Cheong & Lee, 2009; Fukuhara, Murayama, & Nishida, 2005) and cult classics (Trott & Fann, 2011) in the film industry, the dialogic nature of brand construction in entertainment (Jenkins et al., 2013), and known social discussion effects (e.g. L. Frank et al., 2012), it is possible that the driver and nature of the brand personality reference against which individuals perceive congruence shifts over time. For example, though in early period after a movie's release an individual's perceptions of its brand personality may be driven primarily by the studio's marketing efforts, over the years, peer discussions of the movie and their content may become more relevant than any studio-side marketing. Future studies on brand-self congruence differences in media preference should consider the addition of a temporal element to investigate such a possibility.

In addition, the particular difference-based congruence formula adapted from Kressmann et al. (2006) for the present study is but one of numerous possible permutations of the difference-based formula, and the application of other forms may have affected the outcome. For example, instead of opting for absolute difference-centric congruence with formulas like the Kressmann formula, some studies choose to take a Euclidean approach, putting at their center the squared differences rather than the absolute values of the differences (e.g. Graeff, 1996a; Graeff, 1996b). Even among those utilizing the more common (Hosany & Martin, 2012) absolute difference approach, importance weighting like that in the Kressmann measure is less commonly seen (e.g. Sirgy et al., 1997). Future studies should consider usage of the Sirgy et al. (1997) direct congruence measure, and in case of usage of difference-based congruence measures, consider multiple possible formulas – Euclidean distance, absolute difference, cosine similarity, etc. – in both importance weighted and unweighted forms.

7.3 | Conclusion

The findings of the present dissertation highlight multiple elements of media product brand perceptions and the effects of its interaction with the self on media preferences. Beyond ascertaining the dimensions of personality across which individuals process the brand personality of media products, this dissertation also finds that computational image and text features from posters and descriptive text alone, at least as presently operationalized, provide little information helpful to predicting mean perceived movie brand personality. In addition, deviating from the commonly utilized and arguably flawed self-referencing congruence measure, this dissertation establishes the viability of an independent measure of congruence that compares an individual's personality to the mean personality of a movie as perceived by the larger population. Lastly, the results firmly ground the relevance of brand-self congruence in the context of media preferences, finding consistent differences in brand-self congruence between movies individuals preferred and did not prefer across various contexts, in the process also uncovering notable differences in movies listed across psychographic and demographic dimensions. As a whole, the avenue of research delineated by the present dissertation offers ripe integrative potential with a range of theoretical domains for future research.

BIBLIOGRAPHY

Aaker, J. L., Benet-Martinez, V., & Garolera, J. (2001). Consumption symbols as carriers of culture: A study of Japanese and Spanish brand personality constructs. *Journal of Personality and Social Psychology*, *81*(3), 492-508. http://dx.doi.org/10.1037/0022-3514.81.3.492

Aaker, J. L. (1997). Dimensions of brand personality. *Journal of Marketing Research*, *34*(3), 347-356. https://doi.org/10.2307/3151897

Addis, M., & Holbrook, M. B. (2010). Consumers' identification and beyond: Attraction, reverence, and escapism in the evaluation of films. *Psychology & Marketing*, *27*(9), 821-845. http://dx.doi.org/10.1002/mar.20359

Amazon (2015). Amazon best sellers of 2015. Retrieved from https://www.amazon.com/gp/bestsellers/2015/books

Amazon (2014). Amazon best sellers of 2014. Retrieved from https://www.amazon.com/gp/bestsellers/2014/books

Amazon (2013). Amazon best sellers of 2013. Retrieved from https://www.amazon.com/gp/bestsellers/2013/books

American Marketing Association. (1960). *Marketing definitions: A glossary of marketing terms.* Chicago, IL: American Marketing Association.

Amirshahi, S. A., Hayn-Leichsenring, G. U., Denzler, J., & Redies, C. (2014). Evaluating the rule of thirds in photographs and paintings. *Art & Perception, 2*(1/2), 163–182. https://doi.org/10.1163/22134913-00002024

Appel, M., Gnambs, T., & Maio, G. R. (2012). A short measure of the need for affect. *Journal of Personality Assessment, 94*(4), 418–426. https://doi.org/10.1080/00223891.2012.666921

Arslan, F., & Altuna, O. (2010). The effect of brand extensions on product brand image. *Journal of Product & Brand Management, 19*(3), 170–180. https://doi.org/10.1108/10610421011046157

Arun, R., Suresh, V., Madhavan, C. V., & Murthy, M. N. (2010, June). On finding the natural number of topics with latent dirichlet allocation: Some observations. In M. J. Zaki, J. Xu Yu, B. Ravindran, & V. Pudi (Eds.), *PAKDD 2010: Advances in knowledge discovery and data mining* (pp. 391-402). Berlin: Springer.

Assael, H. (1998). *Consumer behavior and marketing action.* Cincinnati: South Western College Publishing.

Azoulay, A., & Kapferer, J. N. (2003). Do brand personality scales really measure brand personality?. *Journal of Brand Management*, *11*(2), 143-155. https://doi.org/10.1057/palgrave.bm.2540162

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly, 36*(3), 421–458. http://dx.doi.org/10.2307/2393203

Bakhshi, S., & Gilbert, E. (2015). Red, purple and pink: The colors of diffusion on Pinterest. *PLoS One, 10*(2), e0117148. https://doi.org/10.1371/journal.pone.0117148

Batra, R., & Homer, P. M. (2004). The situational impact of brand image beliefs. *Journal of Consumer Psychology*, *14*(3), 318–330. https://doi.org/10.1207/s15327663jcp1403_12

Bennett, W. L., & Iyengar, S. (2008). A new era of minimal effects? The changing foundations of political communication. *Journal of Communication, 58(*4), 707-731. https://doi.org/10.1111/j.1460-2466.2008.00410.x

Benoit, W. L. (2011). Content analysis in political communication. In E. P. Bucy & R. L. Holbert (Eds.), *The sourcebook for political communication research: Methods, measures, and analytical techniques* (pp. 268–279). Routledge.

Berk, R. (2016) *Statistical learning from a regression perspective*. New York, NY: Springer.

Billboard (2013). Hot 100 55th anniversary: The all-time top 100 Songs. Retrieved from http://www.billboard.com/articles/list/2155531/the-hot-100-all-time-top-songs

Billboard (2016). Greatest of all time hot 100 singles. Retrieved from http://www.billboard.com/charts/greatest-hot-100-singles

Blei, D. M. (2012). Introduction to probabilistic topic modeling. *Communications of the ACM*, *55*(4), 77–84. https://doi.org/10.1145/2133806.2133826

Blei, D. M., & Lafferty, J. D. (2006, June). Dynamic topic models. In *Proceedings of the 23rd International Conference on Machine Learning - ICML '06* (pp. 113–120). New York, NY: ACM. https://doi.org/10.1145/1143844.1143859

Blei, D. M., & Lafferty, J. D. (2007). A correlated topic model of Science. *The Annals of Applied Statistics, 1*(1), 17-35. http://doi.org/10.1214/07-AOAS114

Blei, D. M., & Lafferty, J. D. (2009). Topic models. In A. N. Srivastava & M. Sahami (Eds.), *Text mining: Classification, clustering, and applications* (pp. 71–89). Boca Raton, FL: Taylor & Francis.

Blei, D. M. & McAuliffe, J. D. (2007). Supervised topic models. In J. C. Platt, D. Koller, Y. Singer, & S. T. Roweis (Eds.), *Advances in neural information processing Systems, 20* (pp. 121-128).

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, *3*, 993–1022.

Bosnjak, M., Bochmann, V., & Hufschmidt, T. (2007). Dimensions of brand personality attributions: A person-centric approach in the German cultural context. *Social Behavior and Personality, 35*(3), 303−316. https://doi.org/10.2224/sbp.2007.35.3.303

Boudreaux, C. A., & Palmer, S. E. (2007). A charming little cabernet: Effects of wine label design on purchase intent and brand personality. *International Journal of Wine Business Research, 19*(3), 170–186. https://doi.org/10.1108/17511060710817212

Box Office Mojo (2016). All time box office: Worldwide grosses. Retrieved from http://www.boxofficemojo.com/alltime/world/

Box Office Mojo (2018). All time box office: Worldwide grosses. Retrieved from http://www.boxofficemojo.com/alltime/domestic.htm

Brechwald, W. A., & Prinstein, M. J. (2011). Beyond homophily: A decade of advances in understanding peer influence processes. *Journal of Research on Adolescence*, *21*(1), 166-179. https://dx.doi.org/10.1111%2Fj.1532-7795.2010.00721.x

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5-32. https://doi.org/10.1023/A:1010933404324

Broadbent, K., & Cooper, P. (1987). Research is good for you. *Marketing Intelligence & Planning,* 5(1), 3-9. https://doi.org/10.1108/eb045740

Bruner, J. S., & Minturn, A. L. (1955). Perceptual identification and perceptual organization. *The Journal of General Psychology*, *53*(1), 21-28. https://doi.org/10.1080/00221309.1955.9710133

Bryant, J., & Zillmann, D. (1984). Using television to alleviate boredom and stress: Selective exposure as a function of induced excitational states. *Journal of Broadcasting & Electronic Media, 28*(1), 1–20. https://doi.org/10.1080/08838158409386511

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, *6*(1), 3–5. https://doi.org/10.1177/1745691610393980

Cabrera-Nguyen, P. (2010). Author guidelines for reporting scale development and validation results in the Journal of the Society for Social Work and Research. *Journal of the Society for Social Work and Research, 1*(2), 99–103. https://doi.org/10.5243/jsswr.2010.8

Camiciottoli, B. C., Ranfagni, S., & Guercini, S. (2014). Exploring brand associations: An innovative methodological approach. *European Journal of Marketing*, *48*(5–6), 1092–1112. https://doi.org/10.1108/EJM-12-2011-0770

Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing, 72*(7-9), 1775-1781. http://dx.doi.org/10.1016/j.neucom.2008.06.011

Chan-Olmsted, S. M., & Cha, J. (2007). Branding television news in a multichannel environment: An exploratory study of network news brand personality. *International Journal on Media Management*, *9*(4), 135–150. https://doi.org/10.1080/14241270701632688

Chan-Olmsted, S. M., & Cha, J. (2008). Exploring the antecedents and effects of brand images for television news: An application of brand personality construct in a multichannel news environment. *International Journal on Media Management*, *10*(1), 32–45. https://doi.org/10.1080/14241270701820481

Chaudhuri, A., & Holbrook, M. (2001). The chain of effects from brand trust and brand affect to brand performance: the role of brand loyalty. *Journal of Marketing*, *65*(2), 81–93. http://doi.org/10.1509/jmkg.65.2.81.18255

Cheong, M., & Lee, V. (2009, November). Integrating web-based intelligence retrieval and decision-making from the twitter trends knowledge base. In *Proceedings of the 2nd ACM workshop on social web search and mining* (pp. 1-8). New York, NY: ACM. https://doi.org/10.1145/1651437.1651439

Chong, D., & Druckman, J. N. (2007). Framing theory. *Annual Review of Political Science*, *10*, 103–126. https://doi.org/10.1146/annurev.polisci.10.072805.103054

Chuang, J., Ramage, D., Manning, C., & Heer, J. (2012, May). Interpretation and trust: Designing model-driven visualizations for text analysis. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 443-452). New York, NY: ACM. https://doi.org/10.1145/2207676.2207738

Churchill, G. A., & Peter, J. P. (1984). Research design effects on the reliability of rating scales: A meta-analysis. *Journal of Marketing Research*, *21*(4), 360-375. https://doi.org/10.1177%2F002224378402100402

Coe, K., Tewksbury, D., Bond, B. J., Drogos, K. L., Porter, R. W., Yahn, A., & Zhang, Y. (2008). Hostile news: Partisan use and perceptions of cable news programming. *Journal of Communication*, *58*(2), 201–219. https://doi.org/10.1111/j.1460-2466.2008.00381.x

Courtney, M. G. R. (2012). Determining the number of factors to retain in EFA: using the SPSS R-menu v2.0 to make more judicious estimations. *Practical Assessment, Research & Evaluation, 18*(8), 1-14.

Crainer, S. (1995). *The real power of brands: making brands work for competitive advantage.* FT Pitman.

Cui, H., Mittal, V., & Datar, M. (2006, July). Comparative experiments on sentiment classification for online product reviews. In *Proceedings of the 21st national conference on artificial intelligence - volume 2* (pp. 1265-1270). AAAI Press.

Chernatony, L., & Dall'Olmo Riley, F. (1998). Modelling the components of the brand. *European Journal of Marketing*, *32*(11/12), 1074–1090. https://doi.org/10.1108/03090569810243721

de Vreese, C. H., & Neijens, P. (2016). Measuring media exposure in a changing communications environment. *Communication Methods and Measures*, *10*(2–3), 69–80. https://doi.org/10.1080/19312458.2016.1150441

Deery, S., Iverson, R., & Erwin, P. (1999). Industrial relations climate, attendance behaviour and the role of trade unions. *British Journal of Industrial Relations, 37*(4), 533–558. https://doi.org/10.1111/1467-8543.00141

Detenber, B. H., Simons, R. F., & Reiss, J. E. (2000). The emotional significance of color in television presentations. *Media Psychology, 2*(4), 331–355. http://dx.doi.org/10.1207/S1532785XMEP0204_02

Deveaud, R., SanJuan, E., & Bellot, P. (2014). Accurate and effective latent concept modeling for ad hoc information retrieval. *Document Numérique*, *17*(1), 61-84. http://doi.org/10.3166/dn.17.1.61-84

Dörre, J., Gerstl, P., & Seiffert, R. (1999, August). Text mining: Finding nuggets in mountains of textual data. In *KDD '99 - Proceedings of the fifth ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 398–401). New York, NY: ACM. https://doi.org/10.1145/312129.312299

Dryer, D. C., & Horowitz, L. M. (1997). When do opposites attract? Interpersonal complementarity versus similarity. *Journal of Personality and Social Psychology, 72*(3), 592-603. http://dx.doi.org/10.1037/0022-3514.72.3.592

Elliot, A. J., & Maier, M. A. (2014). Color psychology: Effects of perceiving color on psychological functioning in humans. *Annual Review of Psychology, 65,* 95–120. https://doi.org/10.1146/annurev-psych-010213-115035

Estroff, S. D., & Nowicki Jr, S. (1992). Interpersonal complementarity, gender of interactants, and performance on puzzle and word tasks. *Personality and Social Psychology Bulletin, 18*(3), 351-356. https://doi.org/10.1177/0146167292183012

Field, A., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. Sage.

Fiske, S. T., Cuddy, A. J., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences*, *11*(2), 77-83. https://doi.org/10.1016/j.tics.2006.11.005

Fiske, S., & Taylor S. (1984). *Social Cognition.* New York: Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

Frank, L. B., Chatterjee, J. S., Chaudhuri, S. T., Lapsansky, C., Bhanot, A., & Murphy, S. T. (2012). Conversation and compliance: Role of interpersonal discussion and social norms in public communication campaigns. *Journal of Health Communication, 17(*9), 1050–1067. https://doi.org/10.1080/10810730.2012.665426

Frank, M. G., & Gilovich, T. (1988). The dark side of self- and social perception: Black uniforms and aggression in professional sports. *Journal of Personality and Social Psychology*, *54*(1), 74–85. https://doi.org/10.1037/0022-3514.54.1.74

Friedman, J. (2002). Stochastic gradient boosting. *Computational Statistics & Data Analysis*, *38*(4), 367-378. https://doi.org/10.1016/S0167-9473(01)00065-2

Fukuhara, T., Murayama, T., & Nishida, T. (2005, May). Analyzing concerns of people using Weblog articles and real world temporal data. Paper presented at WWW 2005 2nd Annual Workshop on the Weblogging Ecosystem: Aggregation, Analysis and Dynamics, Chiba, Japan.

Fürnkranz, J. (1998). A study using n-gram features for text categorization. Austrian Research Institute for Artificial Intelligence.

Gecas, V. (1982). The self-concept. *Annual Review of Sociology*, *8*(1), 1-33. https://doi.org/10.1146/annurev.so.08.080182.000245

Gerbner, G., Gross, L., Morgan, M., Signorielli, N., & Shanahan, J. (2002). Growing up with television: Cultivation processes. In J. Bryant & D. Zillmann (Eds.), *Media effects: Advances in theory and research* (pp. 43-67). Mahwah, NJ: Lawrence Erlbaum.

Geuens, M., Weijters, B., & de Wulf, K. (2009). A new measure of brand personality. *International Journal of Research in Marketing*, *26*(2), 97–107. https://doi.org/10.1016/j.ijresmar.2008.12.002

Goeman, J. (2018). Penalized R package, version 0.9-51.

Goeman, J., Meijer, R., & Chaturvedi, N. (2018). L1 and L2 penalized regression models. R package vignette, penalized version 0.9-51.

Goldberg, L. R. (1992). Development of markers for the Big-Five factor structure. *Psychological Assessment, 4*(1), 26–42. http://dx.doi.org/10.1037/1040-3590.4.1.26

Good, O. S. (2017). Call of Duty: WWII and Destiny 2 were 2017's best-sellers. *Polygon*. Retrieved from https://www.polygon.com/2017/12/20/16801308/call-of-duty-ww2-sales-activision-destiny-2

Graeff, T. R. (1996a). Image congruence effects on product evaluations : The role of self-monitoring and public / private consumption. *Psychology & Marketing*, *13*(5), 481–499. https://doi.org/10.1002/(SICI)1520-6793(199608)13:5%3C481::AID-MAR3%3E3.0.CO;2-5

Graeff, T. R. (1996b). Using promotional messages to manage the effects of brand and self-image on brand evaluations. *Journal of Consumer Marketing, 13*(3), 4–18. https://doi.org/10.1108/07363769610118921

Grandien, C. (2017). Pulling together and tearing apart – The occupational branding of public relations and the management of tainted work. *Public Relations Inquiry*, *6*(1), 73–98. https://doi.org/10.1177/2046147X16682986

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, *101*(suppl 1), 5228-5235. https://doi.org/10.1073/pnas.0307752101

Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political Analysis*, *21*(3), 267–297. https://doi.org/10.1093/pan/mps028

Harrar, V., Piqueras-Fiszman, B., & Spence, C. (2011). There's more to taste in a coloured bowl. *Perception, 40*(7), 880–882. https://doi.org/10.1068/p7040

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. Springer.

Hindman, M. (2015). Building better odels. *The ANNALS of the American Academy of Political and Social Science*, *659*(1), 48–62. https://doi.org/10.1177/0002716215570279

Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic consumption: emerging concepts, methods and propositions. *The Journal of Marketing*, *46*(3). 92-101. https://doi.org/10.1177/002224298204600314

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*(1), 53-60. http://doi.org/10.21427/D7CF7R

Hosany, S., & Martin, D. (2012). Self-image congruence in consumer behavior. *Journal of Business Research*, *65*(5), 685–691. https://doi.org/10.1016/j.jbusres.2011.03.015

Hotho, A., Nürnberger, A., & Paaß, G. (2005). A brief survey of text mining. *LDV Forum - GLDV Journal for Computational Linguistics and Language Technology*, *20*, 19–62.

Hoyle, R. H., Stephenson, M. T., Palmgreen, P., Lorch, E. P., & Donohew, R. L. (2002). Reliability and validity of a brief measure of sensation seeking. *Personality and*

Individual Differences, 32(3), 401–414. https://doi.org/10.1016/S0191-8869(01)00032-0

Huang, L., & Lu, J. (2015). Eat with your eyes: Package color influences the expectation of food taste and healthiness moderated by external eating. *Marketing Management Journal, 25*(2), 71–87.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. https://doi.org/10.1080/10705519909540118

IMDB (2018). Feature Film (Sorted by US Box Office Descending). Retrieved from https://www.imdb.com/search/title?sort=boxoffice_gross_us&title_type=feature&view=advanced

Ingenhoff, D., & Fuhrer, T. (2010). Positioning and differentiation by using brand personality attributes. *Corporate Communications: An International Journal*, *15*(1), 83–101. https://doi.org/10.1108/13563281011016859

Iyengar, S., & Hahn, K. S. (2009). Red media, blue media: Evidence of ideological selectivity in media use. *Journal of Communication*, *59*(1), 19–39. https://doi.org/10.1111/j.1460-2466.2008.01402.x

Iyengar, S., & Kinder, D. R. (1987). *News that matters.* Chicago, IL: University of Chicago Press.

Jamal, A., & Goode, M. M. H. (2001). Consumers and brands : A study of the impact of self-image congruence on brand preference and satisfaction. *Marketing*

Intelligence & Planning, *19*(7), 482–492. http://dx.doi.org/10.1108/02634500110408286

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning*. New York: Springer.

Jenkins, H., Ford, S., & Green, J. (2013). *Spreadable media: Creating value and meaning in a networked culture*. NYU Press.

Jockers, M. L., & Mimno, D. (2013). Significant themes in 19th-century literature. *Poetics*, *41*(6), 750–769. https://doi.org/10.1016/j.poetic.2013.08.005

Joireman, J., Anderson, J., & Strathman, A. (2003). The aggression paradox: Understanding links among aggression, sensation seeking, and the consideration of future consequences. *Journal of Personality and Social Psychology, 84*(6), 1287-1302. http://dx.doi.org/10.1037/0022-3514.84.6.1287

Jones, C., & Bonevac, D. (2013). An evolved definition of the term 'brand': Why branding has a branding problem. *Journal of Brand Strategy*, *2*(2), 112–120.

Kain, E. (2018). Should video games be more expensive? 3 reasons why that doesn't make sense. *Forbes*. Retrieved from https://www.forbes.com/sites/erikkain/2018/02/13/here-are-3-reasons-why-video-games-should-actually-cost-less-than-60/

Kapferer, J. N. (1992). *Strategic brand management.* London, UK: Kogan Page.

Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and gratifications research. *Public Opinion Quarterly, 37*(4)*,* 509-523. https://doi.org/10.1086/268109

Ke, Y., Tang, X., & Jing, F. (2006, June). The design of high-level features for photo quality assessment. In *Proceedings of the IEEE computer society conference on computer vision and pattern recognition* (pp. 419–426). Washington, DC: IEEE. https://doi.org/10.1109/CVPR.2006.303

Kilday, G. (2018). Average price of a movie ticket rises to $8.97 in 2017. *The Hollywood Reporter*. Retrieved from https://www.hollywoodreporter.com/news/average-price-a-movie-ticket-soars-897-2017-1075458

Kim, D. D. E. (2017). A unified measure of media brand personality: Developing a media brand personality scale for multiple media. *International Journal on Media Management*, *19*(3), 197-221. https://doi.org/10.1080/14241277.2017.1306531

Kim, D. D. E. (2018a). Demographic differences in perceptions of media brand personality: a multilevel analysis. *International Journal on Media Management*, *20*(2), 81–106. https://doi.org/10.1080/14241277.2017.1410481

Kim, D. D. E. (2018b). My hero, your aggressor : Differences in perceptions of news media Brand Personality. *International Journal of Communication*, *12*, 200–221.

Kim, J., Baek, T. H., & Martin, H. J. (2010). Dimensions of news media brand personality. *Journalism & Mass Communication Quarterly*, *87*(1), 117–134. https://doi.org/10.1177/107769901008700107

Knobloch-Westerwick, S., & Alter, S. (2006). Mood adjustment to social situations through mass media use: How men ruminate and women dissipate angry moods. *Human Communication Research, 32*(1), 58–73. https://doi.org/10.1111/j.1468-2958.2006.00003.x

Knobloch-Westerwick, S. (2015a). *Choice and preference in media use: Advances in selective exposure theory and research.* New York, NY: Routledge.

Knobloch-Westerwick, S. (2015b). The Selective Exposure Self- and Affect-Management (SESAM) model : Applications in the realms of race , politics , and health. *Communication Research*, *42*(7), 959–985. https://doi.org/10.1177/0093650214539173

Knobloch, S. (2003). Mood adjustment via mass communication. *Journal of Communication*, *53*(2), 233–250. https://doi.org/10.1093/joc/53.2.233

Knobloch, S., & Zillmann, D. (2002). Mood management via the digital jukebox. *Journal of Communication*, *52*(2), 351–366. https://doi.org/10.1093/joc/52.2.351

Kotler, P. (1991). *Marketing management: Analysis, planning, and control* (8th ed.). Englewood Cliffs, NJ: Prentice Hall.

Kressmann, F., Sirgy, M. J., Herrmann, A., Huber, F., Huber, S., & Lee, D. (2006). Direct and indirect effects of self-image congruence on brand loyalty. *Journal of Business Research*, *59*(9), 955–964. https://doi.org/10.1016/j.jbusres.2006.06.001

Kreuter, M. W., & Wray, R. J. (2003). Tailored and targeted health communication: Strategies for enhancing information relevance. *American Journal of Health Behavior*, *27*(SUPPL. 3), S227-S232.

Lacy, S., Watson, B. R., Riffe, D., & Lovejoy, J. (2015). Issues and best practices in content analysis. *Journalism and Mass Communication Quarterly*, *92*(4), 791–811. https://doi.org/10.1177/1077699015607338

Lang, A. (2000). The limited capacity model of mediated message processing. *Journal of Communication, 50*(1)*,* 46-70. https://doi.org/10.1111/j.1460-2466.2000.tb02833.x

Laver, M., & Garry, J. (2000). Estimating policy positions from political texts. *American Journal of Political Science*, *44*(3), 619-634. https://doi.org/10.2307/2669268

Lazer, D., Rubineau, B., Chetkovich, C., Katz, N., & Neblo, M. (2010). The coevolution of networks and political attitudes. *Political Communication*, *27*(3), 248–274. https://doi.org/10.1080/10584609.2010.500187

Lennox, R. D., & Wolfe, R. N. (1984). Revision of the self-monitoring scale. *Journal of Personality and Social Psychology, 46*(6), 1349–1364. https://doi.org/10.1037/0022-3514.46.6.1349

Lewis, S. C., Zamith, R., & Hermida, A. (2013). Content analysis in an era of big data: A hybrid approach to computational and manual methods. *Journal of Broadcasting and Electronic Media*, *57*(1), 34–52. https://doi.org/10.1080/08838151.2012.761702

Lieven, T., Grohmann, B., Herrmann, A., Landwehr, J. R., & van Tilburg, M. (2015). The effect of brand design on brand gender perceptions and brand preference. *European Journal of Marketing*, *49*(1/2), 146–169. https://doi.org/10.1108/EJM-08-2012-0456

Lin, L. (2010). The relationship of consumer personality trait, brand personality and brand loyalty: an empirical study of toys and video games buyers. *Journal of*

Product & Brand Management, *19*(1), 4–17. https://doi.org/10.1108/10610421011018347

Liu, F., Li, J., Mizerski, D., & Soh, H. (2012). Self congruity, brand attitude, and brand loyalty: a study on luxury brands. *European Journal of Marketing*, *46*(7/8), 922–937. https://doi.org/10.1108/03090561211230098

Liu, L., Preotiuc-Pietro, D., Samani, Z. R., Moghaddam, M. E., & Ungar, L. (2016, May). Analyzing personality through social media profile picture choice. In *Proceedings of the tenth international AAAI conference on web and social media* (pp. 211–220). Cologne, Germany: AAAI.

Maehle, N., Otnes, C., & Supphellen, M. (2011). Consumers' perceptions of the dimensions of brand personality. *Journal of Consumer Behaviour*, *10*(5), 290-303. https://doi.org/10.1002/cb.355

Malmelin, N., & Moisander, J. (2014). Brands and branding in media management—Toward a research agenda. *International Journal on Media Management*, *16*(1), 9–25. https://doi.org/10.1080/14241277.2014.898149

Markus, H., & Wurf, E. (1987). The dynamic self-concept: A social psychological perspective. *Annual Review of Psychology, 38*(1), 299-337. https://doi.org/10.1146/annurev.ps.38.020187.001503

Marsh, H. W. (1987). The big-fish-little-pond effect on academic self-concept. *Journal of Educational Psychology, 79*(3)*,* 280-295. http://dx.doi.org/10.1037/0022-0663.79.3.280

Martinez, E., & de Chernatony, L. (2004). The effect of brand extension strategies upon brand image. *Journal of Consumer Marketing, 21*(1), 39–50. https://doi.org/10.1108/07363760410513950

Mason, W., & Suri, S. (2012). Conducting behavioral research on Amazon's Mechanical Turk. *Behavior Research Methods*, *44*(1), 1–23. https://doi.org/10.3758/s13428-011-0124-6

Matsunaga, M. (2010). How to factor-analyze your data right: Do's, don'ts, and how-wo's. *International Journal of Psychological Research, 3*(1), 97-110.

Matteo, S., & dal Zotto, C. (2015). Native advertising, or how to stretch editorial to sponsored content within a transmedia branding era. In G. Siegert, K. Förster, S. M. Chan-Olmsted, & M. Ots (Eds.), *Handbook of media branding* (pp. 157–167). Switzerland: Springer International Publishing.

McCombs, M. (2004). *Setting the agenda: The mass media and public opinion.* Cambridge: Polity.

McCrae, R., & Costa, P. (1997). Personality trait structure as a human universal. *American Psychologist*, *52*(5), 509–516. https://doi.org/10.1037/0003-066X.52.5.509

McDowell, W. S. (2006). Issues in marketing and branding. In A. B. Albarran, S. M. Chan-Olmsted, & M. O. Wirth (Eds.), *Handbook of media management and economics* (pp. 229-249). Mahwah, NJ: Routledge.

Mitchell, A., Gottfried, J., Kiley, J., & Matsa, K. E. (2014, October 21). Political polarization and media habits. Washington, DC: Pew Research Center. Retrieved from http://www.journalism.org/2014/10/21/political-polarization-media-habits/

Nienstedt, H.-W., Huber, F., & Seelmann, C. (2012). The influence of the congruence between brand and consumer personality on the loyalty to print and online issues of magazine brands. *International Journal on Media Management*, *14*(1), 3–26. https://doi.org/10.1080/14241277.2011.602033

Nunnally, J. (1978). *Psychometric methods.* New York, NY: McGraw-Hill.

O'Keefe, D. J. (2003). Message properties, mediating states, and manipulation checks: Claims, evidence, and data analysis in experimental persuasive message effects research. *Communication Theory, 13*(3), 251–274. https://doi.org/10.1111/j.1468-2885.2003.tb00292.x

Oliver, M. B., & Bartsch, A. (2011). Appreciation of entertainment. *Journal of Media Psychology*, *23*(1), 29–33. https://doi.org/10.1027/1864-1105/a000029

Oliver, M. B., Bowman, N. D., Woolley, J. K., Rogers, R., Sherrick, B. I., & Chung, M.-Y. (2015). Video games as meaningful entertainment experiences. *Psychology of Popular Media Culture*, *5(4)*, 390-405. http://dx.doi.org/10.1037/ppm0000066

Oliver, M. B., & Raney, A. A. (2011). Entertainment as pleasurable and meaningful: Identifying hedonic and eudaimonic motivations for entertainment consumption. *Journal of Communication*, *61*(5), 984–1004. https://doi.org/10.1111/j.1460-2466.2011.01585.x

Orth, U. R., & Malkewitz, K. (2008). Holistic package design and consumer brand impressions. *Journal of Marketing, 72*(3), 64–81. https://doi.org/10.1509/jmkg.72.3.64

Ots, M., & Hartmann, B. J. (2015). Media brand cultures: Researching and theorizing how consumers engage in the social construction of media brands. In G. Siegert, K. Förster, S. M. Chan-Olmsted, & M. Ots (Eds.), *Handbook of media branding* (pp. 157–167). Switzerland: Springer International Publishing.

Pang, B., Lee, L., & Vaithyanathan, S. (2002, July). Thumbs up? Sentiment classification using machine learning techniques. In *Proceedings of the ACL-02 conference on empirical methods in natural language processing* (pp. 79–86). Stroudsburg, PA: ACL. http://dx.doi.org/10.3115/1118693.1118704

Parker, B. T. (2009). A comparison of brand personality and brand user-imagery congruence. *Journal of Consumer Marketing*, *26*(3), 175–184. https://doi.org/10.1108/07363760910954118

Parmentier, M. A., & Fischer, E. (2012). How athletes build their brands. *International Journal of Sport Management and Marketing*, *11*(1/2), 106-124. https://doi.org/10.1504/IJSMM.2012.045491

Peng, Y., & Jemmott, J. B. (2018). Feast for the eyes: Effects of food perceptions and computer vision features on food photo popularity. *International Journal of Communication*, *12*, 313–336.

Peng, Y. (2017, May). Time travel with one click: Effects of digital filters on perceptions of photographs. In *Proceedings of the ACM conference on human factors in* *computing systems* (pp. 6000–6011). New York, NY: ACM. https://doi.org/10.1145/3025453.3025810

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The development and psychometric properties of LIWC2015. *UT Faculty/Researcher Works*. https://doi.org/10.15781/T29G6Z

Peterson, R. A. (1994). Meta-analysis of alpha Cronbach's coefficient. *Journal of Consumer Research*, *21*(2), 381–391. https://doi.org/10.1086/209405

Petty, R. E., Barden, J., & Wheeler, S. C. (2002). ELM: Health promotions that yield sustained behavioral change. In *Emerging theories in health promotion practice and research* (pp. 71–99). San Francisco, CA: Jossey-Bass.

Price, V. (1992). Conceptualizing opinions. In *Public Opinion* (pp. 45–71). Thousand Oaks, CA: Sage.

Prior, M. (2013). Media and political polarization. *Annual Review Political Science*, *16*, 101–127. https://doi.org/10.1146/annurev-polisci-100711-135242

Raiche, G., Walls, T. A., Magis, D., Riopel, M., & Blais, J. G. (2013). Non-graphical solutions for Cattell's scree test. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 9*(1), 23-29. https://doi.org/10.1027/1614-2241/a000051

Raiche, G. (2010). nFactors: an R package for parallel analysis and non graphical solutions to the Cattell scree test. R package version 2.3.3.

Ramos, J. (2003). *Using TF-IDF to determine word relevance in document queries.* Department of Computer Science, Rutgers University.

Reinecke, L., Tamborini, R., Grizzard, M., Lewis, R., Eden, A., & David Bowman, N. (2012). Characterizing mood management as need satisfaction: The effects of intrinsic needs on selective exposure and mood repair. *Journal of Communication*, *62*(3), 437–453. https://doi.org/10.1111/j.1460-2466.2012.01649.x

Revelle, W. (2018) psych: Procedures for Personality and Psychological Research, Northwestern University, Evanston, Illinois, USA, https://CRAN.R-project.org/package=psych Version = 1.8.4.

Reynolds, T. (1988). Implications for value research: A macro vs. micro perspective. *Psychology & Marketing, 2*(4), 297–305. https://doi.org/10.1002/mar.4220020408

Riffe, D., Lacy, S., & Fico, F. (2014). *Analyzing media messages: Using quantitative content analysis in research* (3rd ed.). New York, NY: Routledge.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1-36. http://dx.doi.org/10.18637/jss.v048.i02

Rossiter, J. R. (2012). A new C-OAR-SE-based content-valid and predictively valid measure that distinguishes brand love from brand liking. *Marketing Letters, 23*(3), 905-916. https://doi.org/10.1007/s11002-012-9173-6

Ruscio, J., & Roche, B. (2012). Determining the number of factors to retain in an exploratory factor analysis using comparison data of known factorial structure. *Psychological Assessment, 24*(2), 282-292. http://doi.org/10.1037/a0025697

Santos, C. A. (2004). Framing Portugal: Representational dynamics. *Annals of Tourism Research*, *31*(1), 122–138. https://doi.org/10.1016/j.annals.2003.08.005

Schwartz, D., Dodge, K. A., Coie, J. D., Hubbard, J. A., Cillessen, A. H., Lemerise, E. A., & Bateman, H. (1998). Social-cognitive and behavioral correlates of aggression and victimization in boys' play groups. *Journal of Abnormal Child Psychology, 26*(6), 431-440. https://doi.org/10.1023/A:1022695601088

Schwartz, S. (1992). Universals in the content and structure of values: Theoretical advances and empirical tests in 20 countries. In M. Zanna (Ed.), *Advances in experimental social psychology* (pp. 1–65). Waltham, Boston: Academic Press.

Scolari, C. A. (2009). Transmedia storytelling : Implicit consumers , narrative worlds , and branding in contemporary media production. *International Journal of Communication*, *3*, 586–606.

Self-concept (n.d.). In *APA dictionary of psychology*. Retrieved from https://dictionary.apa.org/self-concept

Shanley, P. (2017). Why aren't video games as respected as movies? *The Hollywood Reporter*. Retrieved from https://www.hollywoodreporter.com/heat-vision/why-arent-video-games-as-respected-as-movies-1067314

Sherman, G. D., & Clore, G. L. (2009). The color of sin and pollution. *Psychological Science*, *20*(8), 1019–1025. https://doi.org/10.1111/j.1467-9280.2009.02403.x

Siegert, G., Förster, K., Chan-Olmsted, S. M., & Ots, M. (2015). What is so special about media branding? Peculiarities and commonalities of a growing research area. In G. Siegert, K. Förster, S. M. Chan-Olmsted, & M. Ots (Eds.), *Handbook of media branding* (pp. 157–167). Switzerland: Springer International Publishing.

Sirgy, M. J. (1985). Using self-congruity and ideal congruity to predict purchase motivation. *Journal of Business Research*, *13*(3), 195–206. https://doi.org/10.1016/0148-2963(85)90026-8

Sirgy, M. J., Grewal, D., Mangleburg, T. F., Park, J.-O., Chon, K.-S., Claiborne, C. B., … Berkman, H. (1997). Assessing the predictive validity of two methods of measuring self-image congruence. *Journal of the Academy of Marketing Science*, *25*(3), 229–241. https://doi.org/10.1177/0092070397253004

Smith-McLallen, A., & Fishbein, M. (2008). Predictors of intentions to perform six cancer-related behaviours: Roles for injunctive and descriptive norms. *Psychology, Health & Medicine, 13*(4), 389–401. https://doi.org/10.1080/13548500701842933

Smith, T. W., Marsden, P. V., & Hout, M. (2016). General social survey, 1972–2016 cumulative file (ICPSR31521-v1) [Data file and code book]. Chicago, IL: National Opinion Research Center [Producer]; Ann Arbor, MI: Inter-university Consortium for Political and Social Research [Distributor]

Smit, E. G., Van den Berge, E., & Franzen, G. (2003). Brands are just like real people. In F. Hansen & L. B. Christensen (Eds.), *Branding and advertising* (pp. 22-43). Denmark: Copenhagen Business School Press.

Sood, S., & Dreze, X. (2006). Brand extensions of experiential goods : Movie sequel evaluations. *Journal of Consumer Research, 33*(3), 352–360. https://doi.org/10.1086/508520

Spence, C., Levitan, C. A., Shankar, M. U., & Zampini, M. (2010). Does food color influence taste and flavor perception in humans? *Chemosensory Perception, 3(*1), 68–84. http://doi.org/10.1007/s12078-010-9067-z

Stabler, J. R., & Johnson, E. E. (1972). The meaning of black and white to children. *International Journal of Symbology, 3*(3), 11-21.

Stern, P., Dietz, T., & Guagnano, G. (1998). A brief inventory of values. *Educational and Psychological Measurement, 58*(6), 984–1001. https://doi.org/10.1177/0013164498058006008

Steyvers, M., & Griffiths, T. (2007). Probabilistic topic models. In T. Landauer, S. D. McNamara, S. Dennis & W. Kintsch (Eds.), *Handbook of latent semantic analysis* (pp. 427-448). Lawrence Erlbaum Associates.

Stone, P., Dunphy, D., Smith, M., & Ogilvie, D. (1966). *The General Inquirer: A computer approach to content analysis*. Cambridge, MA: MIT Press.

Strizhakova, Y., & Krcmar, M. (2007). Mood management and video rental choices. *Media Psychology*, *10*(1), 91–112. https://doi.org/10.1080/15213260701301152

Stroud, N. J. (2008). Media use and political predispositions: Revisiting the concept of selective exposure. *Political Behavior*, *30*(3), 341–366. https://doi.org/10.1007/s11109-007-9050-9

Stroud, N. J. (2011). *Niche news: The politics of news choice.* Oxford, England: Oxford University Press.

Su, L. Y. F., Cacciatore, M. A., Liang, X., Brossard, D., Scheufele, D. A., & Xenos, M. A. (2017). Analyzing public sentiments online: combining human- and computer-based content analysis. *Information Communication and Society*, *20*(3), 406–427. https://doi.org/10.1080/1369118X.2016.1182197

Sung, Y., & Park, N. (2011). The dimensions of cable television network personality: Implications for media brand management. *International Journal on Media Management*, *13*(1), 87–105. https://doi.org/10.1080/14241277.2010.545361

Szeliski, R. (2010). *Computer vision: Algorithms and applications.* Berlin, Germany: Springer.

Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent Dirichlet allocation. *Journal of Marketing Research*, *51*(4), 463–479. https://doi.org/10.1509/jmr.12.0106

TMDB (n.d.). The Movie Database API. Retrieved from https://developers.themoviedb.org/

Trott, B., & Fann, K. (2011). Tapping into the appeal of cult fiction. *Reference & User Services Quarterly*, *51*(1), 15-18. http://dx.doi.org/10.5860/rusq.51n1.15

Usakli, A., & Baloglu, S. (2011). Brand personality of tourist destinations: An application of self-congruity theory. *Tourism Management, 32*(1), 114-127. http://dx.doi.org/10.1016/j.tourman.2010.06.006

Valette-Florence, R., & De Barnier, V. (2013). Towards a micro conception of brand personality: An application for print media brands in a French context. *Journal of Business Research*, *66*(7), 897–903. https://doi.org/10.1016/j.jbusres.2011.12.008

van der Walt, S., Schönberger, J. L., Nunez-Iglesias, J., Boulogne, F., Warner, J. D., Yager, N., . . . Yu, T. (2014). Scikit-image: Image processing in Python. *PeerJ, 2*, e453. https://doi.org/10.7717/peerj.453

van de Weijer, J., Schmid, C., Verbeek, J., & Larlus, D. (2009). Learning color names for real-world images. *IEEE Transactions on Image Processing, 18*(7), 1512-1523. https://doi.org/10.1109/TIP.2009.2019809

Venable, B. T., Rose, G.M., Bush, V.D. and Gilbert, F. W. (2005). The role of brand personality in charitable giving: An assessment and validation. *Journal of the Academy of Marketing Science*, *33*(3), 295–312. https://doi.org/10.1177/0092070305276147

VGChartz (2016). Charts: Game totals. Retrieved March 1, 2016, from: http://www.vgchartz.com/gamedb/

Von Rimscha, M. B. (2015). Branding media content: From storytelling to distribution. In G. Siegert, K. Förster, S. M. Chan-Olmsted, & M. Ots (Eds.), *Handbook of media branding* (pp. 157–167). Switzerland: Springer International Publishing.

Vorderer, P. (2011). What's next? *Journal of Media Psychology*, *23*(1), 60–63. https://doi.org/10.1027/1864-1105/a000034

Vorderer, P., & Reinecke, L. (2015). From mood to meaning: The changing model of the user in entertainment research. *Communication Theory*, *25*(4), 447–453. https://doi.org/10.1111/comt.12082

Wadhera, D., & Capaldi-Phillips, E. D. (2014). A review of visual cues associated with food on food acceptance and consumption. *Eating Behaviors, 15*(1), 132–143. https://doi.org/10.1016/j.eatbeh.2013.11.003

Wallach, H. M. (2006, June). Topic modeling: Beyond Bag of Words. In *Proceedings of the 23rd international conference on machine learning* (pp. 977–984). New York, NY: ACM. https://doi.org/10.1145/1143844.1143967

Walsh, P., Clavio, G., Lovell, M. D., & Blaszka, M. (2013). Differences in event brand personality between social media users and non-users. *Sport Marketing Quarterly*, *22*, 214–223.

Walter, D., Sheafer, T., Nir, L., & Shenhav, S. (2016). Not all countries are created equal: Foreign countries prevalence in U.S. news and entertainment Media. *Mass Communication and Society*, *19*(4), 522–541. https://doi.org/10.1080/15205436.2016.1170853

Webster, G. D., Urland, G. R., & Correll, J. (2012). Can uniform color color aggression? quasi-experimental evidence from professional ice hockey. *Social Psychological and Personality Science*, *3*(3), 274–281. https://doi.org/10.1177/1948550611418535

Webster, J. G., Phalen, P. F., & Lichty, L. W. (2014). *Ratings analysis: Audience measurement and analytics.* New York, NY: Routledge.

Weenig, M. W., & Midden, C. J. (1991). Communication network influences on information diffusion and persuasion. *Journal of Personality and Social Psychology, 61*(5), 734-742. http://dx.doi.org/10.1037/0022-3514.61.5.734

Wikipedia (2016). Listed of most watched television broadcasts in the United States. Retrieved March 1, 2016, from https://en.wikipedia.org/wiki/List_of_most_watched_television_broadcasts_in_the_United_States

Wood, L. (2000). Brands and brand equity: Definition and management. *Management Decision*, *38*(9), 662–669. https://doi.org/10.1108/00251740010379100

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research a content analysis and recommendations for best practices. *The Counseling Psychologist, 34*(6), 806–838. https://doi.org/10.1177/0011000006288127

Xia, R., Zong, C., & Li, S. (2011). Ensemble of feature sets and classification algorithms for sentiment classification. *Information Sciences*, *181*(6), 1138–1152. https://doi.org/10.1016/j.ins.2010.11.023

Young, L., & Soroka, S. (2012). Affective news: The automated coding of sentiment in political texts. *Political Communication*, *29*(2), 205–231. https://doi.org/10.1080/10584609.2012.671234

Zamith, R., & Lewis, S. C. (2015). Content analysis and the algorithmic coder: What computational social science means for traditional modes of media analysis. *Annals of the American Academy of Political and Social Science*, *659*(1), 307–318. https://doi.org/10.1177/0002716215570576

Zillmann, D. (1988). Mood management through communication choices. *American Behavioral Scientist*, *31*(3), 327–340. https://doi.org/10.1177/000276488031003005

APPENDIX A (MEASURES)

Appel et al. (2012) – Need for Affect Questionnaire – Short, Approach Subscale (Strongly disagree-Strongly agree)

I feel that I need to experience strong emotions regularly.

Emotions help people to get along in life.

I think that it is important to explore my feelings.

It is important for me to be in touch with my feelings.

It is important for me to know how others are feeling.

Hoyle et al. (2002) – Brief Sensation-Seeking Scale (Strongly disagree-Strongly agree)

I would like to explore strange places.

I would like to take off on a trip with no pre-planned routes or timetables.

I get restless when I spend too much time at home.

I prefer friends who are excitingly unpredictable.

I like to do frightening things.

I would like to try bungee jumping.

I like wild parties.

I would love to have new and exciting experiences, even if they are illegal.

*Lennox & Wolfe (1984) – Revised Self-monitoring Scale (Strongly disagree-Strongly agree, "Please indicate to what extent you disagree/agree with the following statements." *indicates reverse scoring)*

In social situations, I have the ability to alter my behavior if I feel that something else is called for.

I have the ability to control the way I come across to people, depending on the impression I wish to give them.

When I feel that the image I am portraying isn't working, I can readily change it to something that does.

I have trouble changing my behavior to suit different people and different situations.*

I have found that I can adjust my behavior to meet the requirements of any situation I find myself in.

Even when it might be to my advantage, I have difficulty putting up a good front.*

Once I know what the situation calls for, it's easy for me to regulate my actions accordingly.

I am often able to read people's true emotions correctly through their eyes.

In conversations, I am sensitive to even the slightest change in the facial expression of the person I'm conversing with.

My powers of intuition are quite good when it comes to understanding others' emotions and motives.

I can usually tell when others consider a joke to be in bad taste, even though they may laugh convincingly.

I can usually tell when I've said something inappropriate by reading it in the listener's eyes.

If something is lying to me, I usually know it at once from that person's manner of expression.

Smith-McLallen & Fishbein (2008) – Intent Measure, Adapted for Movie Watching (Extremely Unlikely-Extremely Likely)

How likely is it that you would watch _movie_?

Sood & Dreze (2006) – Movie Attitudes Measure (bipolar measures)

Please indicate your expectations for _movie_

1: Bad movie – 5: Good movie

1: Forget it – 5: Must see

1: Uninteresting – 5: Interesting

1: Worse than most films – 5: Better than most films

Stern et al. (1998) – Brief Inventory of Values – 3-item Self-Transcendence Inventory (Extremely Unimportant-Extremely Important, "Please indicate how important each of these is as guiding principle in YOUR life:")

Protecting the environment, preserving nature

A world at peace, free of war and conflict

Social justice, correcting injustice, care for the weak

APPENDIX B (MOVIE PERSONALITY RATINGS)

Title (Year)	AGG Mean (SD)	HER Mean (SD)	DET Mean (SD)
22 Jump Street (2014)	2.81 (1.26)	2.86 (1.14)	4.67 (1.34)
300 (2006)	6.17 (0.91)	2.98 (0.85)	6.15 (0.8)
Aladdin (1992)	2.05 (0.8)	4.36 (1.41)	4.94 (1.19)
Alice in Wonderland (2010)	3.65 (0.65)	4.07 (1.17)	5.51 (0.82)
Alvin and the Chipmunks (2007)	1.66 (1.33)	4.16 (1.2)	5.15 (1.11)
Alvin and the Chipmunks: The Squeakquel (2009)	1.5 (0.54)	3.94 (1.31)	4.6 (1.57)
American Sniper (2014)	4.89 (1.58)	4.64 (1.52)	5.65 (1.04)
Ant-Man (2015)	3.43 (1.36)	4.69 (1.26)	5.9 (1.01)
Armageddon (1998)	4.8 (1.08)	3.69 (1.28)	5.69 (1.02)
Austin Powers in Goldmember (2002)	2.8 (1.46)	3.44 (0.92)	5.15 (1.14)
Austin Powers: The Spy Who Shagged Me (1999)	2.7 (1.48)	2.7 (1.33)	4.6 (1.38)
Avatar (2009)	4.27 (1.6)	4.14 (1.57)	5.21 (1.37)
Avengers: Age of Ultron (2015)	4.53 (0.93)	4.55 (1.13)	6.15 (0.82)
Avengers: Infinity War (2018)	5.22 (0.95)	4.04 (1.44)	5.86 (0.97)
Back to the Future (1985)	2.61 (1.52)	3.66 (1.01)	4.93 (1.03)
Batman (1989)	4.33 (0.95)	4.39 (1.42)	5.43 (1.27)
Batman Begins (2005)	4.52 (1.08)	5.62 (1.25)	6.38 (0.73)
Batman Forever (1995)	5.07 (1.08)	3.92 (1.54)	5.58 (0.76)
Batman v Superman: Dawn of Justice (2016)	5.12 (0.97)	3.38 (1.31)	5.48 (1.2)
Beauty and the Beast (1991)	2.65 (1.1)	4.73 (1.1)	5.04 (1.04)
Beauty and the Beast (2017)	2.65 (1.03)	4.1 (1.02)	4.24 (1.12)
Beverly Hills Cop (1984)	4.66 (1.12)	4.09 (1.09)	5.69 (0.99)
Big Hero 6 (2014)	1.87 (1.04)	4.88 (1.09)	5.44 (0.91)

Black Panther (2018)	4.17 (1.44)	5.23 (1.37)	6.11 (1.06)
Brave (2012)	2.89 (1.38)	4.94 (1.34)	5.72 (1.03)
Bruce Almighty (2003)	2.64 (1.32)	2.95 (1.17)	4.21 (1.17)
Captain America: Civil War (2016)	4.64 (1.27)	4.22 (1.56)	5.5 (1.17)
Captain America: The First Avenger (2011)	3.51 (1.22)	4.99 (1.03)	5.89 (1.18)
Captain America: The Winter Soldier (2014)	4.72 (0.68)	4.92 (1.21)	5.83 (0.71)
Cars (2006)	1.94 (0.8)	5.03 (0.94)	5.44 (0.62)
Cars 2 (2011)	1.86 (1.1)	3.91 (1.1)	4.67 (1.38)
Cast Away (2000)	3.27 (1.32)	4.67 (1.41)	5.69 (0.81)
Charlie and the Chocolate Factory (2005)	2.73 (1.32)	3.25 (1.18)	5.27 (1.21)
Cinderella (2015)	1.86 (0.98)	4.92 (1.18)	4.9 (0.83)
Coco (2017)	2.22 (1.07)	4.55 (1.03)	5.65 (0.88)
Dances with Wolves (1990)	3.23 (1.26)	4.55 (1.6)	5.16 (1.18)
Dawn of the Planet of the Apes (2014)	5.45 (0.98)	2.77 (1.12)	5.33 (0.83)
Deadpool (2016)	5.31 (1.24)	3.77 (1.58)	6.04 (1.08)
Despicable Me (2010)	3.07 (1.55)	4.07 (1.39)	4.93 (1.12)
Despicable Me 2 (2013)	2.52 (0.94)	3.88 (0.99)	4.62 (1.13)
Despicable Me 3 (2017)	2.16 (1.16)	3.38 (1.55)	4.67 (1.45)
Doctor Strange (2016)	3.37 (1.27)	4.55 (1.39)	5.69 (1)
Dunkirk (2017)	5.24 (1.08)	4.57 (0.91)	5.43 (0.98)
E.T. the Extra-Terrestrial (1982)	2.15 (1.38)	4.58 (1.16)	4.69 (0.91)
Fantastic Beasts and Where to Find Them (2016)	3.49 (0.96)	4.17 (1.13)	5.46 (0.96)
Fast Five (2011)	5.07 (1.06)	2.47 (1.23)	5.87 (1.49)
Finding Dory (2016)	1.43 (0.81)	4.68 (1.14)	4.93 (1.24)
Finding Nemo (2003)	1.41 (0.59)	4.97 (1.19)	5.04 (1.24)
Forrest Gump (1994)	2.12 (0.93)	5.78 (0.93)	5.24 (1.04)

Frozen (2013)	2.51 (1.15)	4.53 (0.61)	4.76 (0.9)
Furious 6 (2013)	5.41 (0.86)	2.81 (0.9)	5.31 (1.49)
Furious 7 (2015)	5.83 (0.63)	2.84 (1.27)	6.1 (0.8)
Ghost (1990)	3.9 (1.7)	4.3 (1.39)	4.87 (0.88)
Ghostbusters (1984)	3.92 (1.07)	4.03 (0.85)	5.07 (1.27)
Gladiator (2000)	5.94 (0.7)	4.32 (1.1)	6.25 (0.79)
Godzilla (2014)	5.31 (1.45)	2.45 (0.81)	4.73 (1.25)
Gone with the Wind (1939)	3.86 (1.13)	3.99 (1.7)	5.2 (1.04)
Gravity (2013)	3.19 (1.1)	4.23 (1.06)	5.12 (1.08)
Grease (1978)	2.63 (1.41)	3.85 (0.94)	4.98 (1.38)
Guardians of the Galaxy (2014)	4.09 (1.32)	4.27 (1.07)	5.25 (1.41)
Guardians of the Galaxy Vol. 2 (2017)	3.78 (1.24)	4.66 (1.7)	5.62 (1.47)
Hancock (2008)	4.38 (1.51)	3.2 (1.17)	4.92 (1.41)
Happy Feet (2006)	1.47 (0.51)	4.79 (0.92)	5.47 (1.03)
Harry Potter and the Chamber of Secrets (2002)	3.27 (1.64)	3.86 (1.76)	5.15 (1.26)
Harry Potter and the Deathly Hallows: Part 1 (2010)	4.32 (1.12)	5.05 (1.09)	6.13 (0.89)
Harry Potter and the Deathly Hallows: Part 2 (2011)	4.28 (1.51)	4.31 (1.41)	5.81 (1.06)
Harry Potter and the Goblet of Fire (2005)	3 (1.15)	4.11 (1.41)	5.46 (1)
Harry Potter and the Half-Blood Prince (2009)	3.94 (1.5)	4.4 (1.15)	5.38 (1.23)
Harry Potter and the Order of the Phoenix (2007)	3.68 (1.16)	4.27 (0.95)	5.24 (0.96)
Harry Potter and the Prisoner of Azkaban (2004)	3.96 (1.53)	4 (1.48)	5.15 (1.52)
Harry Potter and the Sorcerer's Stone (2001)	2.61 (0.97)	4.14 (1.44)	4.86 (1.31)
Hitch (2005)	2 (0.86)	4 (1.07)	5.17 (1.31)
Home (2015)	1.23 (0.51)	4.77 (1.24)	5.14 (1.34)
Home Alone (1990)	2.85 (1.42)	4.04 (1.37)	5.16 (1.57)
How the Grinch Stole Christmas (2000)	3.83 (1.65)	3.11 (1.5)	4.54 (1.25)

How to Train Your Dragon (2010)	2.36 (1.22)	5.05 (1.27)	5.02 (1.36)
How to Train Your Dragon 2 (2014)	2.55 (1.13)	4.72 (0.82)	5.71 (1.08)
I Am Legend (2007)	4.61 (1.21)	4.25 (1.48)	5.44 (1)
Ice Age (2002)	2.06 (1.52)	5.65 (1.44)	5.37 (1.32)
Ice Age: Dawn of the Dinosaurs (2009)	2.26 (1.54)	3.76 (1.3)	4.8 (1.43)
Ice Age: The Meltdown (2006)	1.7 (0.69)	3.84 (1.05)	4.96 (1.07)
Inception (2010)	5.1 (1.33)	2.74 (1.54)	6.04 (0.76)
Independence Day (1996)	4.75 (1.65)	3.92 (1.61)	5.33 (1.22)
Indiana Jones and the Kingdom of the Crystal Skull (2008)	3.93 (1.48)	4.58 (1.05)	6 (0.75)
Indiana Jones and the Last Crusade (1989)	4.31 (0.84)	4.16 (1.19)	6.02 (0.76)
Indiana Jones and the Temple of Doom (1984)	3.33 (1.01)	4.42 (1.42)	5.9 (1.29)
Inside Out (2015)	2.36 (1.1)	4.59 (0.96)	4.76 (1.11)
Interstellar (2014)	2.88 (1.22)	4.62 (1.04)	5.88 (0.89)
Iron Man (2008)	3.86 (1.23)	4.3 (1.04)	6.02 (0.98)
Iron Man 2 (2010)	4.47 (1.22)	4.71 (1.32)	5.98 (1.09)
Iron Man 3 (2013)	4.59 (0.78)	4.39 (1.47)	6 (0.83)
It (2017)	6.12 (1.15)	2.68 (1.82)	4.77 (1.67)
Jaws (1975)	5.69 (1.03)	2.78 (1.29)	4.88 (1.25)
Jumanji: Welcome to the Jungle (2017)	3.9 (1.46)	3.5 (1.21)	5.35 (0.98)
Jurassic Park (1993)	4.65 (1.8)	3.07 (1.36)	5.31 (1.3)
Jurassic Park III (2001)	4.71 (1.45)	3.06 (1.26)	5.11 (1.09)
Jurassic World (2015)	5.12 (1.13)	3.03 (1.31)	5.33 (1.17)
Justice League (2017)	3.87 (1.51)	4.65 (1.34)	5.91 (1.15)
King Kong (2005)	5.08 (1.35)	3.05 (1.16)	5.5 (1.19)
Kung Fu Panda (2008)	3.08 (1.1)	4.33 (1.41)	4.91 (0.98)
Liar Liar (1997)	3 (1.3)	2.79 (1.32)	4.62 (0.99)

Lincoln (2012)	3.7 (1.26)	5.34 (1.23)	5.44 (1.01)
Logan (2017)	5.21 (0.98)	4.07 (0.98)	5.05 (1.29)
Madagascar (2005)	1.37 (0.44)	4.65 (1.48)	5.76 (0.89)
Madagascar 3: Europe's Most Wanted (2012)	1.58 (0.95)	4.03 (1.46)	5.06 (1.28)
Madagascar: Escape 2 Africa (2008)	1.88 (1.03)	3.7 (1.32)	4.84 (1.25)
Maleficent (2014)	4.64 (1.78)	3.56 (1.44)	5.12 (1.35)
Man of Steel (2013)	3.4 (1.51)	5.1 (1.29)	5.98 (0.86)
Meet the Fockers (2004)	2.03 (1.18)	3.23 (1.31)	3.9 (1.46)
Men in Black (1997)	4.61 (0.81)	4.05 (0.72)	5.62 (0.79)
Men in Black 3 (2012)	3.53 (1.11)	3.83 (1.63)	5.15 (1.04)
Men in Black II (2002)	3.62 (1.37)	3.97 (1.11)	5.25 (1.19)
Minions (2015)	2.3 (1.2)	4.38 (1.35)	5.1 (1.04)
Mission: Impossible - Ghost Protocol (2011)	4.81 (1.16)	3.34 (1.14)	5.02 (1.57)
Mission: Impossible - Rogue Nation (2015)	4.69 (1.16)	3.73 (1.28)	5.69 (1.18)
Mission: Impossible (1996)	5.09 (1.19)	4.04 (1.07)	5.86 (0.92)
Mission: Impossible II (2000)	4.51 (1.12)	4.24 (1.26)	6.11 (0.88)
Moana (2016)	2.35 (0.92)	5.12 (1.49)	5.8 (1.27)
Monsters University (2013)	1.69 (0.99)	4.63 (1.26)	4.86 (1.31)
Monsters vs. Aliens (2009)	2.89 (1.57)	4.56 (1.49)	5.19 (1.38)
Monsters, Inc. (2001)	2.39 (1.24)	4.55 (1.08)	4.73 (0.83)
Mr. & Mrs. Smith (2005)	5.53 (0.98)	3.22 (1.27)	5.73 (1.03)
Mrs. Doubtfire (1993)	2.81 (1.29)	3.94 (1.42)	5.14 (1.33)
My Big Fat Greek Wedding (2002)	1.73 (0.86)	4.58 (1.14)	5.29 (0.94)
National Treasure: Book of Secrets (2007)	3.15 (1.13)	3.81 (1.44)	4.93 (1.34)
Night at the Museum (2006)	3.4 (1.68)	4.12 (1.15)	4.73 (1.25)
Night at the Museum: Battle of the Smithsonian (2009)	2.07 (1.1)	3.82 (1.14)	4.78 (1.43)

Ocean's Eleven (2001)	4.62 (1.13)	2.66 (1.15)	5.9 (1.13)
Oz the Great and Powerful (2013)	2.78 (0.99)	4.43 (0.76)	5.11 (1.1)
Pearl Harbor (2001)	4.05 (1.35)	3.77 (0.87)	4.71 (1.18)
Pirates of the Caribbean: At World's End (2007)	5.19 (0.96)	3.25 (1.37)	5.6 (1.19)
Pirates of the Caribbean: Dead Man's Chest (2006)	4.76 (1.25)	3.12 (1.15)	5.76 (1.1)
Pirates of the Caribbean: On Stranger Tides (2011)	4.53 (1.37)	2.94 (1.29)	5.02 (1.09)
Pirates of the Caribbean: The Curse of the Black Pearl (2003)	4.83 (1.18)	3.41 (1.47)	5.15 (1.16)
Pitch Perfect 2 (2015)	2.34 (1.22)	3.81 (1.52)	4.98 (1.37)
Planet of the Apes (2001)	5.45 (0.89)	3.09 (0.97)	4.88 (1.33)
Pretty Woman (1990)	2.45 (1.31)	2.55 (1.09)	3.87 (1.43)
Raiders of the Lost Ark (1981)	4.5 (0.97)	4.46 (1.2)	5.49 (1.12)
Ratatouille (2007)	2.02 (1.56)	4.75 (1)	5.75 (0.74)
Rise of the Planet of the Apes (2011)	5.16 (1.01)	3.38 (1.07)	5.06 (0.9)
Rogue One (2016)	4.54 (1.34)	4.21 (1.7)	5.67 (1.39)
Rush Hour 2 (2001)	3.91 (1.39)	3.25 (1.44)	5.75 (1.25)
Saving Private Ryan (1998)	4.2 (1.17)	5.52 (0.79)	5.87 (0.7)
Sherlock Holmes (2009)	4.4 (1.55)	5.02 (1.21)	6.1 (0.9)
Sherlock Holmes: A Game of Shadows (2011)	4.14 (0.97)	4.52 (1.21)	5.46 (0.82)
Shrek (2001)	2.72 (1.61)	4.85 (1.24)	5.88 (0.85)
Shrek 2 (2004)	2.97 (1.88)	4.22 (1.77)	5.2 (1.28)
Shrek Forever After (2010)	2.73 (1.01)	4.29 (1.18)	5.07 (0.94)
Shrek the Third (2007)	2.36 (0.9)	4.38 (0.94)	4.73 (0.92)
Signs (2002)	3.86 (1.43)	3.19 (1.17)	4.33 (0.79)
Sing (2016)	1.8 (0.86)	4.08 (1.4)	4.36 (1.48)
Skyfall (2012)	4.53 (1.46)	3.78 (0.84)	5.76 (1.15)
Snow White and the Seven Dwarfs (1937)	2.92 (1.24)	4.37 (1.11)	4.36 (1.03)

Spectre (2015)	5.17 (0.77)	3.48 (1.11)	5.77 (1.18)
Spider-Man (2002)	3.29 (1.13)	4.84 (1.35)	5.59 (0.87)
Spider-Man 2 (2004)	3.45 (1.62)	4.7 (1.33)	5.33 (1.04)
Spider-Man 3 (2007)	5 (1.27)	3.83 (1.37)	5.65 (0.77)
Spider-Man: Homecoming (2017)	3.8 (1.51)	5.07 (1.21)	5.82 (1.01)
Star Trek (2009)	4.09 (1.11)	4.02 (0.99)	5.83 (0.97)
Star Trek: Into Darkness (2013)	4.64 (1.54)	3.98 (1.43)	5.31 (1.71)
Star Wars: Episode I - The Phantom Menace (1999)	4.8 (1.01)	4.22 (1.22)	5.47 (1.14)
Star Wars: Episode II - Attack of the Clones (2002)	4.1 (0.98)	3.45 (1.05)	4.8 (1.46)
Star Wars: Episode III - Revenge of the Sith (2005)	4.63 (0.92)	3.53 (0.89)	5.18 (0.96)
Star Wars: Episode IV - A New Hope (1977)	3.99 (1.53)	4.63 (0.93)	5.78 (1.07)
Star Wars: Episode V - The Empire Strikes Back (1980)	4.46 (1.43)	3.67 (0.84)	5.44 (0.73)
Star Wars: Episode VI - Return of the Jedi (1983)	4.37 (1.67)	3.96 (1.25)	5.45 (1.27)
Star Wars: The Force Awakens (2015)	4.47 (1.02)	3.88 (0.85)	5.77 (1.04)
Star Wars: The Last Jedi (2017)	4.55 (1.39)	3.89 (1.58)	5.28 (1.44)
Suicide Squad (2016)	5.57 (0.95)	2.69 (1.14)	5.31 (0.96)
Superman Returns (2006)	3.22 (1.03)	5.05 (1.29)	6.19 (0.87)
Tangled (2010)	1.94 (0.95)	4.75 (1.12)	5.69 (1)
Ted (2012)	3.12 (1.38)	2.5 (1.14)	4.5 (1.52)
Teenage Mutant Ninja Turtles (2014)	4 (0.83)	4.55 (1.28)	5.6 (0.99)
Terminator 2 (1991)	5.58 (1.33)	3.73 (1.67)	5.31 (1.95)
The Amazing Spider-Man (2012)	3.12 (0.89)	5.12 (1)	5.71 (0.42)
The Amazing Spider-Man 2 (2014)	3.74 (1.45)	4.94 (1.62)	5.63 (1.28)
The Avengers (2012)	4.63 (0.96)	4.67 (1.32)	5.98 (0.99)
The Blind Side (2009)	2.03 (1.54)	5.49 (1.54)	4.98 (1.61)
The Bourne Ultimatum (2007)	5.12 (0.78)	3.52 (1.06)	5.23 (1.1)

The Chronicles of Narnia: The Lion, the Witch and the Wardrobe (2005)	3.64 (1.45)	4 (1.02)	5.19 (0.84)
The Croods (2013)	2.26 (1.26)	4.09 (1.38)	4.85 (1.41)
The Da Vinci Code (2006)	3.72 (1.25)	3.35 (1.49)	4.91 (1.8)
The Dark Knight (2008)	4.79 (0.86)	4.51 (0.87)	6 (0.88)
The Dark Knight Rises (2012)	5.72 (0.76)	4.56 (1.07)	5.96 (0.62)
The Day After Tomorrow (2004)	4.7 (1.11)	3.45 (1.4)	4.48 (0.6)
The Exorcist (1973)	5.9 (0.55)	2.19 (1.09)	3.65 (1.31)
The Fate of the Furious (2017)	5.06 (1.15)	2.83 (1.18)	5.71 (1.33)
The Fugitive (1993)	5.09 (1.06)	4.25 (1.32)	5.93 (0.91)
The Hangover (2009)	2.85 (1.4)	2 (0.91)	4.13 (1.43)
The Hangover Part II (2011)	2.63 (1.33)	2.01 (0.88)	4.22 (1.18)
The Hobbit: An Unexpected Journey (2012)	3.12 (1.49)	4.74 (0.97)	5.35 (1.01)
The Hobbit: The Battle of the Five Armies (2014)	4.97 (1.01)	4.42 (1.12)	5.52 (0.79)
The Hobbit: The Desolation of Smaug (2013)	4.3 (1.58)	4.18 (1.31)	5.18 (1.53)
The Hunger Games (2012)	5.36 (1.4)	3.3 (1.14)	5.54 (0.8)
The Hunger Games: Catching Fire (2013)	5.38 (1.14)	3.79 (1.64)	5.47 (1.17)
The Hunger Games: Mockingjay - Part 1 (2014)	4.67 (1)	4.3 (1.48)	5.56 (0.88)
The Hunger Games: Mockingjay - Part 2 (2015)	4.99 (1.37)	3.82 (1.2)	5.27 (1.19)
The Incredibles (2004)	2.59 (1.2)	4.98 (1.15)	5.79 (1.11)
The Jungle Book (2016)	3.23 (1.31)	3.95 (1.05)	5.31 (1.22)
The Karate Kid (2010)	3.15 (1.18)	4.97 (1.06)	5.75 (0.63)
The Lego Movie (2014)	2.47 (1.27)	4.43 (1.11)	5.06 (1.15)
The Lion King (1994)	3.44 (1.43)	4.65 (1.05)	4.92 (0.98)
The Lorax (2012)	2.14 (1.16)	5.36 (1.05)	5.25 (0.99)
The Lord of the Rings: The Fellowship of the Ring (2001)	3.95 (1.31)	4.55 (1.62)	5.56 (1.49)
The Lord of the Rings: The Return of the King (2003)	4.69 (0.95)	4.26 (1.26)	5.52 (1.22)

The Lord of the Rings: The Two Towers (2002)	4.17 (1.09)	3.88 (1.34)	5.33 (1.25)
The Lost World: Jurassic Park (1997)	4.69 (0.99)	2.72 (0.78)	5.31 (1.03)
The Martian (2015)	2.91 (1.59)	4.34 (1.24)	5.71 (1.54)
The Matrix Reloaded (2003)	5.25 (1.06)	3.14 (1.14)	5.81 (0.85)
The Mummy Returns (2001)	4.8 (0.92)	3.2 (1.44)	4.96 (1.06)
The Passion of the Christ (2004)	4.44 (1.62)	4.31 (1.18)	5.37 (0.9)
The Perfect Storm (2000)	5.12 (1.32)	2.67 (1.27)	4.65 (0.98)
The Polar Express (2004)	1.75 (0.9)	4.92 (0.91)	4.84 (1.17)
The Revenant (2015)	5.11 (1.33)	3.81 (1.49)	5.46 (1.43)
The Secret Life of Pets (2016)	2.14 (1.57)	4.19 (1.21)	4.68 (1.3)
The Simpsons Movie (2007)	3.73 (1.57)	2.52 (1.23)	4.19 (1.33)
The Sixth Sense (1999)	3.42 (1.19)	3.69 (1.39)	4.35 (1.26)
The Twilight Saga: Breaking Dawn - Part 1 (2011)	5.07 (1.09)	3 (1.33)	4.63 (1.26)
The Twilight Saga: Breaking Dawn - Part 2 (2012)	4.52 (1.72)	3.25 (1.27)	4.81 (1.49)
The Twilight Saga: Eclipse (2010)	4.56 (1.21)	3.04 (1.58)	4.45 (1.59)
The Twilight Saga: New Moon (2009)	4.75 (1.71)	3.48 (1.62)	4.5 (1.33)
There's Something About Mary (1998)	1.68 (0.84)	3.79 (1.29)	4.76 (1.53)
Thor (2011)	4.56 (1.39)	4.34 (1.27)	5.55 (1)
Thor: Ragnarok (2017)	4.82 (1.19)	4.62 (1.69)	6.12 (0.71)
Thor: The Dark World (2013)	4.07 (1.19)	4.32 (1.77)	5.64 (1.45)
Titanic (1997)	2.63 (0.93)	3.71 (1.51)	4.22 (1.11)
Tootsie (1982)	1.99 (1.22)	3.87 (1.76)	5.04 (1.44)
Top Gun (1986)	4.6 (0.67)	3.73 (0.7)	6.42 (0.72)
Toy Story (1995)	3.02 (1.73)	4.31 (1.25)	5.26 (0.78)
Toy Story 2 (1999)	1.72 (0.94)	4.5 (1.27)	5.06 (1.25)
Toy Story 3 (2010)	1.48 (0.5)	4.87 (1.19)	5.22 (1.02)

Transformers (2007)	5.14 (1.02)	3.61 (1.32)	5.81 (0.92)
Transformers: Age of Extinction (2014)	5.09 (0.98)	3.09 (1.03)	5.44 (0.88)
Transformers: Dark of the Moon (2011)	5.17 (1.12)	3.78 (1.49)	5.69 (1.19)
Transformers: Revenge of the Fallen (2009)	4.66 (1.58)	3.16 (1.19)	5.35 (1.49)
Twilight (2008)	3.64 (1.37)	2.94 (1.37)	4.02 (1.6)
Twister (1996)	4.71 (1.11)	2.68 (1.2)	4.61 (1.55)
Up (2009)	1.98 (0.58)	4.28 (0.92)	5.1 (0.96)
Wall-E (2008)	2.25 (0.96)	5.81 (0.98)	5.38 (0.88)
War of the Worlds (2005)	5.03 (1.04)	3.12 (1.2)	5.35 (1.13)
Wedding Crashers (2005)	2.72 (0.96)	2.78 (1.02)	5.04 (1.35)
What Women Want (2000)	2.73 (1.56)	3.59 (1.31)	4.46 (1.19)
Wonder Woman (2017)	4.58 (0.96)	5.2 (0.91)	6.04 (0.97)
World War Z (2013)	4.99 (1.25)	4.24 (1.43)	5.71 (1.04)
Wreck-It Ralph (2012)	2.59 (1.04)	4.12 (1.05)	4.98 (0.98)
X-Men Origins: Wolverine (2009)	5.52 (0.96)	3.73 (1.3)	5.52 (0.92)
X-Men: Days of Future Past (2014)	4.73 (1.27)	4.36 (1.51)	5.81 (1.11)
X-Men: The Last Stand (2006)	5.03 (1.43)	3.53 (1.31)	5.83 (1.1)
X2 (2003)	5.03 (1.03)	4.15 (1.01)	5.49 (0.64)
Zootopia (2016)	2.42 (1.27)	4.92 (1.03)	5.5 (0.93)