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Understanding the Movie Trailer in Generating Word-of-Mouth and Improving Box-Office Performance

by

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Declarations

I, Julia Kampani, hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in these, or any other Universities. The work described therein was carried out by myself personally, with the exception of chapter 4, 5, and 6 where the work has been done in collaboration with others:

- Chapter 4 is based on a published paper at the Journal of Advertising Research, cited below:

  Archer-Brown, C., Kampani, J., Marder, B., Bal, A., & Kietzmann, J. (2017). Conditions in Prerelease Movie Trailers For Stimulating Positive Word of Mouth. *Journal of Advertising Research, 57*(2), 159–172.

  I declare that I contributed to 70% formulation of ideas, 20% design of methodology, and 15% presentation of data in journal format

- Chapter 5 is based on a pre-printed manuscript, which will be shortly submitted for publication. I declare that I contributed to 80% formulation of ideas, 70% design of methodology, 90% experimental work, and 60% presentation of data in journal format

- Chapter 6 is based on a pre-printed manuscript, which will be shortly submitted for publication. I declare that I contributed to 90% formulation of ideas, 90% design of methodology, 80% experimental work, and 65% presentation of data in journal format.

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Abstract

This PhD aims to investigate how consumers form pre-release perceptions through trailer advertising campaigns and how movie trailers generate pre-release buzz which consequently drives audiences to the cinema on the opening weekend. This thesis is built on three studies:

1) Study 1 uses a survey to explore the relationship between understanding the movie trailer, liking, word-of-mouth intent and purchase intent. Findings from statistical analysis show that understanding what the movie is about, coupled with liking the movie trailer drives consumers to spread positive WOM online and to consider paying to see the movie.

2) Study 2 looks further into the antecedents and outcomes of understanding the movie trailer. A series of experiments assess elements of the trailer's content on consumers' objective and subjective understanding, and their effect on ad (trailer) and product (movie) liking. Findings show that the *amount* and *order of information* significantly influence consumers' understanding of what the movie is about. In addition, comparisons between objective and subjective understanding reveal that consumers are over-confident in the amount of information they feel they have understood, but it is the latter that drives ad and product liking.

3) Study 3 further tests these relationships through the collection and analysis of behavioural data. Trailers are categorised on the amount and order of information. YouTube comments collected on the respective trailers are analysed to extract different components of pre-release buzz. Confirming the findings of Study 2, results show that the *amount* and *order of information* do influence trailer liking, but relationships are further driven by movie-related parameters (e.g. genre). Analysis of pre-release buzz components demonstrate that commenting and liking are distinct activities. Among pre-release buzz components and movie-related parameters, the number of video views is the strongest predictor of opening weekend box office performance.

List of Abbreviations

BO: Box Office

eWOM: Electronic Word-of-Mouth

MPAA: Motion Picture Association of America

NFC: Need for Cognition

NLP: Natural Language Processing

OLS: Ordinary Least Squares

PLS-SEM: Partial Least Squares Structural Equation Modelling

PRCB: Pre-release Consumer Buzz

WOM: Word-of-Mouth

Chapter 1: Introduction

This chapter has seven parts. The first part introduces the background of the research (1.1), while the second part focuses on the background of the context of this thesis (1.2). The third part summarises the research problem (1.3) and the following parts provide an overview of this thesis's contribution (1.4), methodology (1.5), findings (1.6). The final part offers and overview of the structure of this thesis (1.7).

1.1 Background to Research

Word-of-mouth (WOM), is one of the most successful form of marketing (Engel, Blackwell, & Kegerreis, 1969; David Godes & Mayzlin, 2004). It is responsible for a large majority of consumers' purchase decisions (Keller & Fay, 2009; Richins & Root-Shaffer, 1988) as it is viewd to be more trustworthy and credible than other marketing techniques (Brown, Broderick, & Lee, 2007; Cheung & Thadani, 2012). The recognition of WOM as a form of marketing and its presentation as a new theoretical construct in marketing literature (Dichter, 1966), inspired a large number of studies on its antecedents (Anderson, 1998; Brown, Barry, Dacin, & Gunst, 2005; East, Uncles, Romaniuk, & Dall'Olmo Riley, 2015; Srinivasan, Anderson, & Ponnavolu, 2002), processes and outcomes (Bughin, Doogan, & Vetvik, 2010; Godes & Mayzlin, 2009). Having identified a strong impact on sales (Dellarocas, Zhang, & Awad, 2007; David Godes & Mayzlin, 2004; Sonnier, McAlister, & Rutz, 2011), research has attempted to determine what drives consumers to generate positive WOM, with the majority of studies pointing towards satisfaction with a service or product (Anderson, 1998; East et al., 2015).

The rise of the Web 2.0. completely transformed the norms of generating, sharing and receiving WOM and presented researchers with a new agenda to study WOM in the electronic environment (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Yeo, 2012). Research on electronic word-of-mouth (eWOM) has explored the structure of online communities, the spreading activity of eWOM (Balasubramanian & Mahajan, 2001; Gladwell, 2000; Goel, Watts, & Goldstein, 2012; Van Den Bulte & Lilien, 2016), the elements of online content (Berger & Milkman, 2012; Ferrara & Yang, 2015) and the effect of eWOM on consumers' online and offline purchase decisions (Dichter, 1966; Squire, 2016).

Notably, the majority of work on eWOM has focused on conversations taking place *after* the use of a product or service. As a result, a large number of products which rely on *pre-release buzz*, have been ignored in the wider eWOM research. Products in the entertainment and fashion industry need to gain traction as soon as they are introduced to the market, due to an exponentially decaying life-cycle and particular release pattern (Dellarocas et al., 2007; Hennig-Thurau, Wiertz, & Feldhaus, 2015; Karniouchina, 2011a). Specifically, these products depend on early hype that drives audience attention before market release, which contrasts the standard norms of the diffusion of innovation (Rogers, 1962). Examples of products succeeding due to pre-release buzz are evident in the media. In the context of movies, last year, "Black Panther" managed to create such buzz during its pre-release phase, that it opened to a $200 million box office, and gradually became the highest grossing movie of 2018 (www.boxofficemojo.com). In the context of consumer electronics, Apple's new products typically raise such hype, that large queues of consumers form outside Apple stores just before product launch (Weston & Duell, 2018). Despite pre-release consumer buzz (PRCB) influencing consumer decisions, PRCB was only recently recognised and theoretically separated from eWOM (Houston et al., 2018).

PRCB refers to the conversations shared *prior* to a product's release. Due to the fact that different information is available to consumers prior to their experience with a product or service, PRCB differs significantly from WOM on a number of features. Additionally, PRCB is more anticipatory (Houston et al., 2018); it is founded on speculations and it signals intentions (Craig et al., 2015). On one hand, PRCB tends to be more positive to post-release WOM, due to the absence of an actual experience with the product or service and therefore hard to shatter prior expectations (Houston et al., 2018). On the other hand, post-release WOM tends to be more credible as it is based on actual experiences (Dellarocas, 2007). The absence of an actual experience at the time of PRCB is also responsible for the differences in the antecedents between the two constructs. Since consumers have not yet used a product or experienced a service, satisfaction – which has been found as the most critical antecedent of post-release WOM (Anderson, 1998; Arndt, 1967; East et al., 2015) – is non-existent.

On this note, the antecedents of PRCB have not yet been explicitly tested. The few WOM studies that have considered conversations prior to a product's release in the market, have done so in comparison or in combination to post-release WOM (Gopinath, Chintagunta, & Venkataraman, 2013; Karniouchina, 2011a; Liu, 2006). As a result, these conversations have been deconstructed and analysed by the same metrics that have been traditionally used to measure WOM – namely, volume and valence. Yet, PRCB refers to behaviours beyond participation in WOM communications. Such activities can range from search behaviour (Ho et al., 2009; Karniouchina 2011b) to awareness and adoption intention (Craig et al., 2015; Divakaran et al., 2017). Research which focuses solely on the pre-release activities and conversations of consumers would not only shed light on the antecedents, processes and outcomes of PRCB but would also allow for the exploration of metrics that go beyond the widely researched metrics of WOM (Houston et al., 2018).

In an attempt to investigate PRCB's antecedents – where satisfaction with the product or service cannot exist – this thesis adopts the perspective that advertising can also act as an antecedent of consumers' conversations (Dichter, 1966; Keller & Fay, 2009). Following the perspective that advertising and WOM can be treated as complementary activities (Day, 1971; David Godes & Mayzlin, 2004; Hogan, Lemon, & Libai, 2004), further research into the area of persuasive advertising, revealed that *understanding* the ad leads to positive consumer response (Fernbach, Sloman, Louis, & Shube, 2013; Mick, 1992; Ratneshwar & Chaiken, 1991). However the construct of understanding, has not been specifically tested against WOM conversations or against PRCB. Additionally, while some work on persuasive advertising has investigated the elements that make communications more persuasive, understanding has rather been part of the wider information-processing model (McGuire, 1968). Another challenge with extant research on persuasive advertising, is that the stimuli used in experimental research have been either in print or audio mode, which underepresents modern ads (Mohanty & Ratneshwar, 2015) As a result, the specific antecedents of consumer understanding of a visual advertising message, and its relationship to PRCB remain unknown.

This thesis investigates the role of understanding the ad in generating positive WOM and consequently influencing purchase decisions. In doing so, it addresses substantial gaps in the theory of PRCB by investigating a real-world online phenomenon. The following section justifies the choice of context, which answers calls to conduct such research with more complex visual stimuli (Livingstone, 1990; Mohanty & Ratneshwar, 2015), and caters to an economically important industry whose success largely relies on PRCB.

1.2 Background of Problem in Practice

It is considered that no other industry can be harmed or benefitted more from WOM than the movie industry (Craig, Greene, & Versaci, 2015; Squire, 2016). The movie industry is highly economic, with revenues from the domestic box office surpassing those of all other forms of entertainment (Booth & Geis, 2006; MPAA, 2018). Still, the industry is only surviving thanks to a small percentage of movies becoming disproportionately successful (Prag & Casavant, 1994). Indeed, investing in the production of a movie is a high-risk decision with a 10% probability of the movie generating any profit (De Vany & Walls, 1999; Gong, Van der Stede, & Young, 2011). The fundamental issue with the profitability of the movie industry lies in the particularity of movies' release pattern. A movie's success is determined by its opening weekend box office performance (BO) (Earnest, 1985; Epstein, 2005; Gong et al., 2011). Thus, a movie that fails to generate the desired amount of buzz and drive audiences to the cinemas on the opening weekend, will be taken off the screens and might not be subsequently released in international markets.

In order to ensure a satisfying opening weekend performance, marketers invest huge amounts of money – often equal to the movie's production – in pre-launch campaigns (Rainey, 2016), which often start during the movie's pre-production phase and aim to generate buzz (Goldstein, 1991; Tourmarkine, 2005). Nevertheless, Hollywood is still struggling to sell movies effectively (Rainey, 2016), with the majority of movies failing to break even (Gong et al., 2011).

The above issues are responsible for attracting considerable research attention in the context of movies. Box office prediction models based on movie production and distribution factors have been developed to help studios and marketers forecast a movie's performance (Basuroy, Chatterjee, & Ravid, 2003; Gopinath et al., 2013; Hennig-Thurau et al., 2007; Swahney & Eliashberg, 1996). Among these, the effect of advertising has been taken into account in some of those models (Gong et al., 2011; Hennig-Thurau et al., 2015; Karniouchina, 2011a; Moul, 2007; Prag & Casavant, 1994). Yet, the link between trailer advertising and positive PRCB has not been researched in depth, in spite of online evidence that trailers spark heavy PRCB on social media sites. Indeed, a recent overview of studies in a movie context suggests that there is a need for further research on how the social media influence consumer decisions and movie profitability (Chisholm et al., 2015). While a number of studies in the movie industry have been concerned with the effect of online conversations on box office performance (Duan, Gu, & Whinston, 2008; Gopinath et al., 2013; Hennig-Thurau et al., 2015; Liu, 2006), the majority of them focus on post-release conversations, overlooking the effect of PRCB in raising awareness prior to the movie's release.

This thesis explores the role of the trailer in generating positive consumer response and driving audiences to the cinema. In doing so, it adopts the perspective that advertising and WOM are complementary activities (Day, 1971; Dichter, 1966; Keller & Fay, 2009) and addresses the need to conduct advertising research with visual stimuli. As movies are experiential products whose quality cannot be judged in advance, the only way to sample the movie and acquire information prior to its release, is through the movie trailer (Kernan, 2004). Indeed, the movie trailer is considered to be the most successful form of movie advertising (Eliashberg & Shugan, 1997; Friedman, 2006). For this reason, studios pay a lot of money to outsource the production of trailers in order to create the most effective promotional clips (Marich, 2013). Yet, studio marketers claim that they are unsure of whether online trailers are successful in driving audiences to the cinema (Rainey, 2016), even though trailers are tested like other ads (Basuroy, Desai, & Talukdar, 2006; Goldstein, 1991). To address this, this thesis focuses specifically on trailer-viewing and investigates antecedents of understanding the movie trailer which consequently lead audiences to share PRCB. In doing so, movies' performance (opening weekend BO) is taken into account as the ultimate objective of advertising and PRCB.

1.3 Research Problem

Following the assumption that advertising leads to PRCB, this thesis investigates the role of understanding the movie trailer in generating positive consumer response and influencing decisions to watch the upcoming movie. In view of that, it aims to answer the following research question:

"How do movie trailers generate positive PRCB and drive consumers to the cinema?"

In order to tackle the research question, this thesis is built upon three distinct studies (referred to as "papers" hereafter). The first one is an initial exploration of the effect of understanding and liking the movie trailer on WOM and purchase intent[1]. After establishing initial relationships and observing that the role of understanding combined with liking is instrumental in driving positive WOM and purchase intentions, Paper 2 investigates how understanding is formed through trailer-viewing. It tests trailers' explanatory characteristics as potential antecedents and further examines the relationship between understanding and liking, supporting the first paper. Paper 3, then, explores PRCB components through 1.5 million YouTube comments, and tests their effect on opening weekend BO, addressing possible limitations of self-report measures used in the first two papers.

More specifically, in order to address the limited literature behind the role of understanding the advertising message, Paper 1 draws from WOM literature, and especially, work carried out within the movie industry and tests the hypothesis that understanding, combined with liking leads to WOM and purchase intent. Due to the limited extant theory, the paper is exploratory in nature and aims to investigate the position of understanding in the model that predicts positive consumer intentions about an upcoming product. Therefore, it seeks to answer the following research question:

RQ 1. "What is the effect of trailer *liking* and *understanding* what a movie is about on favourable WOM and purchase intent?"

Confirming that the combination of understanding and liking the movie trailer leads to positive WOM and purchase intentions, Paper 2 draws from information-processing and persuasive advertising literature, and builds a conceptual framework which includes message

[1] Houston et al.'s (2018) recognition of PRCB as a distinct construct took place after the first paper of this thesis was published. As a result, the tested construct of the first paper is referred to as "WOM intent" or "intent to generate WOM", although it is essentially concerned only with pre-release WOM, termed as PRCB by Houston et al. (2018).

content and receiver-related parameters. It explores the heuristic cues upon which consumers' build their perceptions about upcoming movies and further explores the two perspectives of understanding (objective and subjective) which are adopted by extant relevant research. While observing fundamental differences between objective and subjective understanding, Paper 2 also investigates which of the two is more likely to lead to positive perceptions about the ad and the product. The research question that Paper 2 aims to tackle is:

> RQ 2. "How is understanding shaped through trailer-viewing and what is its effect on ad (trailer) and product (movie) liking?"

The first two papers are more exploratory in nature and investigate the position of understanding as an antecedent of positive consumer response. Following findings from the first two papers and drawing from very recent research on PRCB, Paper 3 further tests these relationships through behavioural data. Specifically, it categorises trailers according to understanding antecedents derived from Paper 2 and tests their effect on positive PRCB. It then explores components of PRCB – going beyond traditional WOM metrics – and examines their effect on opening weekend BO. Paper 3 seeks to answer the following research question:

> RQ 3. "How do trailers' explanatory characteristics shape online pre-release buzz and what is the effect of different buzz components on box office performance?"

The rationale behind the development of this thesis' conceptual framework and the design of each paper is explored in more detail in Chapter 3. The following section summarises this thesis' overall contribution.

1.4 Overview of Contribution

This research is positioned within the literature that examines the pre-release phase of new product introduction (Gelper, Peres, & Eliashberg, 2018; Houston et al., 2018; Peres, Muller, & Mhajan, 2010). More specifically, it aims to add new knowledge to very recent work on PRCB (Houston et al. 2018) and to the wider eWOM research (Duan et al., 2008; Liu, 2006; Yoon, Polpanumas, & Park, 2017). It positions understanding of the advertising message as an important PRCB antecedent, extending theory that recognises PRCB as a distinct construct to WOM and answering calls for further systematic research into its antecedents and outcomes (Houston et al., 2018). Furthermore, it extends limited research that acknowledges the complementary relationship between advertising and WOM (Day, 1971; Dichter, 1966; Keller & Fay, 2009) and supports this notion by demonstrating that trailers can lead to PRCB prior to a movie's release. Going beyond traditional WOM metrics – volume and valence – it explores other PRCB components (Houston et al., 2018), such as views and likes and offers directions to researchers and marketers towards the power of ad views in predicting early sales.

Along with contributions to the PRCB literature, this thesis aims to extend persuasive advertising theory, specifically in relation to the construct of understanding (Mick, 1992; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991). Findings from this thesis establish the role of understanding – in combination with liking – as a predictor of WOM and purchase intent, and further discover antecedents of understanding that can be manipulated by advertising researchers. It supports prior findings in information-processing research with regards to the amount and order of information in influencing consumer understanding (Eagly, 1974; Hovland, Janis, & Kelley, 1953). By measuring both objective and subjective understanding and testing their effect on ad and product liking, this thesis also extends prior work into the construct of understanding (Maheswaran & Sternthal, 1990; Mick, 1992; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991) and directs researchers and advertising managers towards a subjective understanding paradigm.

Finally, this thesis makes an important methodological contribution into the field of computational social sciences (Watts, 2013). Going beyond traditional methods in relevant eWOM and persuasive advertising literature, it embraces new technologies introduced with the pervasiveness of Big Data and computationally analyses millions of online data under a specific research agenda. It combines new and traditional data collection and analysis techniques and demonstrates how the proposed methodologies can be utilised by researchers and industry marketers alike, addressing calls to tackle social science problems utilising present-day methodologies (Snee, Hine, Morey, Roberts, & Watson, 2016a).

1.5 Overview of Methodology

This thesis adopts a pragmatic philosophy and employs data collection and analysis methods both from the interpretivist and the positivist paradigm.

Paper 1 pre-tests constructs through initial focus groups (n=18) conducted in an industry trailer-testing fashion (Goldstein, 1991). Participants are exposed to a number of trailers and discuss aspects that make them understand what the movie is about. The focus groups are video-recorded and the analysis of the results provide a basis for the selection of the trailers to be tested in a further survey designed and distributed online. Four trailers for each of the three most popular movie genres (n=12) are tested on a sample of 310 respondents, providing 1,240 unique observations. After watching each trailer online, respondents report their levels of understanding (5-item measure), liking (3-item measure), WOM intent (5-item measure) and purchase intent (3-item measure), inspired by extant WOM literature (Babin, Lee, Kim, & Griffin, 2005; Rumelhart, 1991). Statistical analysis on PLS-SEM explores the power of the paths on the conceptual model, demonstrating the strongest paths (relationships) within each genre.

Paper 2 explores the construct of understanding further through a series of experiments. In the first experiment 37 respondents watch four trailers that have been categorised on two conditions (Order of Information and Context Familiarity), providing 148 unique cases for analysis. Consistent with prior persuasive advertising and information-processing literature (Chaiken, 1980; Eagly, Wood, & Chaiken, 1978; Haugtvedt, Petty, & Cacioppo, 1992) respondents provide their thoughts on each trailer and report their level of understanding (Fernbach et al., 2013; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991). Respondents' retrospective thoughts are analysed through thematic analysis to reveal the key themes upon which consumers build their perceptions about an upcoming movie. The content from the retrospective thoughts is also used to measure objective understanding – the extent to which respondents' explanation on what the movie is about matches the official trailer synopsis. Exploratory t-tests are performed to investigate potential differences between objective and subjective understanding.

In the second experiment sequel trailers (n=4) and trailers of original movies (n=4) are tested separately, to eliminate the effect of context familiarity on consumers' understanding. The trailers are categorised on two conditions (Amount and Order of Information) and respondents are exposed to two trailers of the sequel group and two trailers of the original group (mixed design). Understanding measures are identical to the first experiment, but respondents are also asked to report their perceived informativeness, general interest in moviegoing and context familiarity (in the sequel group only). They are also tested on the Need for Cognition Scale (NCS short form; Cacioppo, Petty, & Kao, 1984), which is used to categorise individuals depending on their the tendency to elaborate on a message more. Finally, they are asked to indicate their liking of the trailer and their perceptions of liking of the movie. A series of regressions (on SPSS) tests the message-content categorisations, controlled by individual characteristics, as predictors of objective and subjective understanding. Mediation analysis is performed to examine the mediating role of perceived informativeness in the model that links trailer characteristics to subjective understanding. Further regressions on trailer and movie liking test the two understanding constructs as antecedents of positive consumer response, and mediation analyses demonstrate the mediating role of trailer liking on movie liking.

Paper 3 utilises behavioural data that was collected from YouTube and Twitter during a 2-year period (Nov 2015-Dec 2015). 1.5 million comments on 146 movies are collected from all promotional trailers of the movies in the sample. The trailers (n=416) are categorised by 3 independent raters on the same categorisations of Paper 2 (Amount and Order of Information) and are divided into "conventional" – *high amount* and *linear order of information* – and "unconventional" trailers. Sentiment analysis is performed on the online data to reveal the volume and the valence of WOM. Going beyond traditional eWOM metrics, views and likes are also extracted as suggested by recent PRCB research (Craig et al., 2015; Houston et al., 2018). Controlling for movie-related characteristics – e.g. genre, cultural familiarity, star buzz – the first study explores the extent to which conventional trailers generate more positive response. The second study examines the effect of PRCB components on opening weekend BO, along with movie-related parameters, through multiple regressions. Data for movie characteristics is collected from online sites, such as IMDb, The Numbers, Box Office Mojo.

1.6 Overview of Findings

Paper 1 shows that *understanding* the movie trailer is an important parameter in the model that links advertising to WOM and purchase intent. More specifically, it demonstrates that it is the combination of *understanding* and *liking* the movie trailer that leads consumers to spread positive WOM about the upcoming movie and to consider to pay to see the movie on the cinema. While the model for comedy and thriller movies shows that the strongest path to positive WOM intent is through understanding and liking, the model for sci-fis slightly differs in that understanding alone is enough in generating positive WOM. Findings on the other two genres demonstrate that positive WOM is highly associated with purchase intent when driven from understanding coupled with liking.

In Paper 2, seven key themes upon which consumers shape their pre-release perceptions about an upcoming movie are identified. The movie plot is the most prominent topic by which consumers build their understanding on what the movie is about, consistent with prior content analysis studies in the movie industry (Gelper et al., 2018; Nguyen & Romaniuk, 2014; Simmons, Conlon, Mukhopadhyay, & Yang, 2011). Objective and subjective understanding are found to be distinct constructs driven by different antecedents, with subjective understanding being significantly higher than consumers' objective understanding on what the movie is about. The second study demonstrates that both the amount and the order of information influence consumers' perceptions of understanding for sequel and original movies, but findings with regards to objective understanding are slightly different between the two groups (originals Vs. sequels). Perceived informativeness is found to partly mediate the relationship between message-content characteristics and subjective understanding. Testing the relationship between understanding and liking, only subjective understanding is found to influence trailer and movie liking. In the case of sequels, trailer liking fully mediates the relationship between subjective understanding and movie liking.

In Paper 3 these relationships are further tested with behavioural data. "Conventional" trailers – trailers with a high amount and a linear order of information – are the most liked and most positively talked about in about half of the cases. There is a significant association between the trailers that are most positively talked about and cultural familiarity, supporting findings from Paper 2, and a negative association of the most liked trailers and the sci-fi genre, supporting findings from Paper 1. Liking the trailer and talking positively about it are found to be two separate activities, implying that in PRCB, valence and liking are distinct constructs. The second study demonstrates that the volume of tweets is not as significant as YouTube PRCB in predicting opening weekend BO. Addressing the long-standing debate between eWOM volume and valence (Babic Rosario, Sotgiu, De Valck, & Bijmolt, 2016; Karniouchina, 2011a; Liu, 2006; You, Vadakkepatt, & Joshi, 2015), the volume and the views of PRCB are found to be better predictors of opening weekend BO compared to the valence and likes correspondingly. In particular, findings demonstrate that the number of trailer views is found to be the most significant predictor of opening weekend BO, surpassing all other movie-related variables.

1.7 Overview of Structure

This thesis constitutes seven chapters. The current chapter (Chapter 1) has introduced word-of-mouth as the research background (1.1) and the movie industry as the research context (1.2). It has outlined the research problem (1.3) and provided an overview of the contribution (1.4), methodology (1.5) and findings (1.6) of the three studies in this thesis. The rest of the thesis is structured as follows.

Chapter 2 is an account of the literature review and the context within which this thesis is positioned. The first section is a literature review on general WOM in marketing research (2.1), while the second section focuses on PRCB specifically (2.2). The concept of understanding within the information-processing and advertising literature is explained (2.3), where theories and findings of communication studies on “who says what to whom” (3.2.1), on the receiver’s cognitive ability (3.2.2) and the message content (3.2.3) are also discussed. Then, the context of movies is reviewed in detail (2.4). First the industry’s characteristics and main issues are introduced, then studies in movie research are presented (2.4.1) before focusing specifically on movie WOM research (2.4.2) and on the role of the trailer within the relevant theory and practice (2.4.3). Finally, the main research gaps are summarised (2.5).

Chapter 3 focuses on the overall research objectives and explains how the three papers address the research question. It presents the research objectives (3.1) and explains the overall research framework (3.2). It then offers a detailed account of the research methodology (3.3), presenting the chosen research methods employed within each of the three papers (3.3.1 – 3.3.3) . A summary of the three papers follows (3.4 – 3.6).

Chapter 4 presents the first empirical paper that explores the role of understanding the movie trailer in generating positive WOM and in turn, influencing consumers’ purchase intentions.

Chapter 5 presents the second empirical paper that investigates the antecedents and outcomes of understanding, through a series of experiments.

Chapter 6 presents the third empirical paper that examines different components of PRCB and tests their effect on opening weekend BO performance, through millions of digitally collected comments.

Chapter 7 is a concluding chapter which presents the theoretical contributions (7.1) in the area of PRCB (7.1.1), understanding (7.1.2) and movies (7.1.3). It also mentions the methodological contributions of this thesis (7.1.4). It then presents the managerial implications (7.2) and considers the limitations of the thesis, while offering directions for future research (7.3).

Chapter 2: Context & Literature Review

This chapter comprises of five main parts. The first section (2.1) offers and account of WOM studies in marketing literature, both in the area of traditional and electronic WOM. The second section (2.2) focuses on the recently recognised area of PRCB, explaining how the construct differs from WOM. The third section looks at persuasive advertising and information-processing literature and focuses specifically on understanding (2.3). It presents the communication model of “who says what to whom” (2.3.1) and discusses how the receiver’s cognitive ability (2.3.2) and the message content (2.3.3) influence consumers’ understanding. The fourth section is a description of the movie industry as a context for research (2.4). It first outlines the main issues that the industry is facing and then offers an account of extant research within the movie industry context (2.4.1). It then focuses specifically on WOM studies within the movie industry (2.4.2) and emphasizes the role of the trailer in movie theory and practice (2.4.3). The final section (2.5) summarises the research gaps that derive from the literature review.

2.1. Word-of-Mouth in Marketing

Word of Mouth (WOM) is a powerful marketing tool which influences purchase decisions and increases sales (Bughin, Doogan, & Vetvik, 2010; Godes & Mayzlin, 2009). Although as a concept, it has existed since the beginning of human communication, it gained attention from marketers with the work of Ernest Dichter (1966). Since then, practitioners and academics have investigated its antecedents (Anderson, 1998; Arndt, 1967; Feick & Price, 1987; Holmes & Lett, 1977), its impact on sales (Duan, Gu, & Whinston, 2008; Godes & Mayzlin, 2004; Liu, 2006), as well as its superiority to advertising (Feng & Papatla, 2011; Katz & Lazarsfeld, 1955; Rogers, 1962; Smith & Vogt, 1995; Traylor, Traylor, Mathias, & Mathias, 1983; Trusov, Bucklin, & Pauwels, 2007).

WOM studies are of an inter-disciplinary nature, borrowing theories from different fields. In order to explain how WOM forms and spreads among consumers, researchers have examined the structure of communities through social network analysis. The pattern of WOM’s spreading activity resembles that of infectious diseases and, so, WOM is often compared to epidemics (Gladwell, 2000; Godes & Mayzlin, 2004; Van Den Bulte & Lilien, 2016). WOM studies on social networks are mainly concerned with the connections among individuals and the patterns of diffusion of information (Balasubramanian & Mahajan, 2001; Goel et al., 2012; Granovetter, 1973; Watts & Dodds, 2007). By observing the flow of information within a social network, it is possible to identify influential individuals that facilitate diffusion. These individuals are characterised as 'influencers', 'opinion leaders' or 'experts' and are often the target of marketing campaigns as they play a key role in the diffusion of information, acting as intermediaries between the media and the general public (Feick & Price, 1987; Katz & Lazarsfeld, 1955; Richins & Root-Shaffer, 1988; Rogers, 1962).

A large body of WOM research, is concerned with the motives and the antecedents that drive consumers to share and to participate in conversations. A wide array of motives has been examined in the literature, but the most prominent ones include: self-enhancement, concern for others, social benefits, economic rewards and enjoyment of helping (Cheung & Lee, 2012; Dichter, 1966; Hennig-Thurau et al., 2004). WOM antecedents – which sometime overlap with motives – include constructs such as product expertise, (Feick & Price, 1987; Katz & Lazarsfeld, 1955; Rogers, 1962), product involvement (Chun & Lee, 2016; Dichter, 1966; Richins, 1983, 1984), sample involvement (Holmes & Lett, 1977), and risk of purchase (Day, 1971). The strongest WOM factor is undoubtedly product or service (dis)satisfaction (Anderson, 1998; Arndt, 1967; East et al., 2015; Holmes & Lett, 1977; Schlossberg, 1991) which, in turn, is influenced by several other parameters – such as disconfirmation of expectations, value perceptions etc.. It must be pointed out here, that the assumption that (dis)satisfaction is a necessary antecedent of WOM, has urged most researchers to focus on WOM after a product's introduction in the market. However, due to the release pattern of certain products – such as movies, cultural events etc. – some industries rely on immediate product adoption which is influenced by pre-release buzz (Hennig-Thurau et al., 2015).

The technological advancements which have made the Internet ubiquitous facilitate the spread of electronic WOM (eWOM) and have presented opportunities to conduct research under a different light. Firms offer reward strategies to advocates who introduce new customers through WOM (Goldenberg, Libai, & Muller, 2001) and researchers emphasize to organisations the importance of periodic feedback on viral and WOM referral campaigns (Brown et al., 2007; David Godes & Mayzlin, 2004; Liu, 2006). Compared to traditional (face-to-face) WOM, eWOM is superior on a number of facets. Apart from being measurable, it is easily accessible to consumers and is not restricted by time and space (Cheung & Thadani, 2012; Craig et al., 2015; Hennig-Thurau et al., 2004). It is anonymous and is often considered as more honest and credible (Bickart & Schindler, 2001; Brown et al., 2007;

Goldsmith & Horowitz, 2006). It can also reach multiple individuals and it is indefinitely available online (Hennig-Thurau et al., 2004).

The prevalence of eWOM has prompted a research shift from the offline environment to the study of online user-generated content and on how it influences product adoption (Hennig-Thurau et al., 2015; Karniouchina, 2011a). Studies within that area observe the structure of social networks and the direction of eWOM communication (Adar & Adamic, 2009; Bakshy, Hofman, Watts, & Mason, 2011; Goel et al., 2012; Leskovec, Adamic, & Huberman, 2007), or examine the motives and outcomes of eWOM (East et al., 2015; Liu, 2006; Yoon et al., 2017).

In an attempt to measure eWOM in online environments (such as social networking sites), researchers rely on two WOM metrics: volume and valence. WOM volume stands for the number of comments, tweets or conversations that consumers share, while valence stands for the overall sentiment (positive or negative) of those conversations. Such metrics can be measured manually (Nguyen & Romaniuk, 2014) or more often computationally, by applying text classification algorithms to digitally collected data (Hennig-Thurau et al., 2015; Lipizzi, Iandoli, & Marquez, 2016). There has been great effort to identify whether WOM volume and valence are of equal importance in generating sales. While some researchers emphasize the significance of WOM volume (Duan et al., 2008; David Godes & Mayzlin, 2004; Liu, 2006), others claim that valence has a stronger effect on sales (Arndt, 1967; Chintagunta, Gopinath, & Venkataraman, 2010; Forman, Ghose, & Wiesenfeld, 2008). In an attempt to address this debate, meta-analyses of eWOM studies have recently emerged to provide the scientific community with a resolution on which of the two metrics can predict sales more accurately (Babic Rosario et al., 2016; You et al., 2015). Yet, the debate still remains, since one of the studies claims that valence elasticities were higher than volume elasticities (You et al., 2015), whereas another argues that volume exerts a stronger effect on sales, compared to that of valence (Babic Rosario et al., 2016); or even that both have an equal power in predicting sales (Carrillat, Legoux, & Hadida, 2018).

2.2 Pre-release Consumer Buzz and Advertising

A number of products follow a particular release pattern, whereby immediate adoption is necessary for the product to survive in the market. Such products cannot rely on the typical diffusion of innovation pattern, where consumers start spreading WOM after they experience the product (Dellarocas et al., 2007; Rogers, 1962). The necessity of product adoption as soon as it is introduced in the market has been tackled with marketing efforts to raise pre-release buzz. While pre-release buzz exists on and off-line, it has only recently been recognised as a separate construct to WOM (Houston et al., 2018). Pre-release buzz refers to the word-of-mouth shared *prior* to a product's release. Its timing, however, is not the only differential aspect, compared to post-release WOM. Houston et al. (2018) observed the online collective behaviour of consumers prior to a product's release and concluded that PRCB consists of a number of components that go beyond typical WOM metrics (e.g. online search, likes, views). Other characteristics that differentiate PRCB from typical post-release WOM, are its anticipatory nature and its positive valence (Houston et al., 2018). Due to the fact that the construct has only recently gained researchers' attention, further research into its antecedents and outcomes is required. The key differences between post-release WOM and PRCB are summarised in Table 1.

Table 1: Differences between WOM and PRCB

	Word-of-Mouth	**Pre-release Consumer Buzz**
Timing	post-release	pre-release
Characteristics	credible, based on experience	anticipatory, based on speculations
Level	message-level	aggregate-level (collective)
Behaviours	centred around communications	involves behaviours beyond communication (search, awareness, expectations, intentions)
Adoption stage	Useful for later adoption (imitators)	Useful for early adoption (innovators)
Metrics	volume, valence	beyond volume and valence (e.g. views, likes, amounts of searches)
Sentiment	positive and negative	tends to be positive
Key antecedent	Product/service satisfaction	*unresolved*

While the antecedents of WOM have been widely studied, PRCB is necessarily driven by different factors. Naturally, the strongest WOM antecedent – product or service (dis)satisfaction – cannot occur in the pre-release period of a product's life cycle. In an attempt to understand how PRCB is shaped, this thesis follows the perspective that advertising can also act as a WOM antecedent, consistent with extant literature (Dichter, 1966; Godes & Mayzlin, 2004). Notably, the majority of extant research looks at WOM as an opposing marketing technique with a focus on proving its superiority to advertising (Feng & Papatla, 2011; Rogers, 1962; Traylor et al., 1983). Nevertheless, media advertising acts as a source of information, shapes early opinions (Katz & Lazarsfeld, 1955; Watts & Dodds, 2007) and is even a topic of discussion within WOM conversations (Nguyen & Romaniuk, 2014). Having observed the structure of information diffusion, Goel *et al.* (2012) found that the majority of posts derive directly from the seed, demonstrating thus the effectiveness of advertising in generating WOM. In fact, one fifth of WOM conversations is sparked by a relevant advertisement, and consumers who have been the target of both advertising and WOM are more likely to purchase a product (Keller & Fay, 2009). In this sense, an advertisement's goal is twofold: to lead consumers to purchase a product, and to stimulate WOM which in turn will play a key role in the product's sales (Craig et al., 2015; Keller & Fay, 2012).

2.3 Understanding

In an attempt to investigate which aspects of advertising might lead to PRCB, a review of the literature on persuasive advertising is necessary. Persuasive advertising literature has explored how different elements of communication lead to attitude or behaviour change (Hovland et al., 1953; Maheswaran & Sternthal, 1990; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991). Utilising the information-processing model, researchers have attempted to explain how receivers process information systematically and heuristically in order to accept or reject an incoming message (Chaiken, 1980; Petty & Cacioppo, 1983). Although the ultimate objective is usually the acceptance of the communication, consumer response can assume a variety of forms – one of them being positive WOM (Cheung & Thadani, 2012).

Reviewing work on persuasive advertising, it has become clear that *understanding* the advertising message leads to positive attitudes (Fernbach et al., 2013; Mohanty & Ratneshwar, 2015). In the wider marketing literature, *understanding* is often found in different terms and represents different consumer mechanisms. Although the term *understanding* has and will be used throughout this thesis for simplicity, it essentially represents the act of *comprehension* – i.e. encoding a received communication into meaning (Chaiken, 1980; McGuire, 1976). In information science studies, *comprehension* signals good quality information (Cheung, Lee, & Rabjohn, 2008; DeLone & McLean, 2003; McKinney, Yoon, & Zahedi, 2002). In viral marketing literature, *comprehensive* content is more likely to be liked and shared (Berger & Milkman, 2012).

Most studies that draw theory from information-processing measure understanding as an *objective* construct that reflects the actual comprehension of the message. They follow the rationale that messages have one meaning, and test respondents' understanding through True or False exercises or through open-ended questions (e.g. Chaiken, 1980; Eagly et al., 1978; Wright, 1973). Others are interested in the individual perceptions of understanding and therefore assign a *subjective* nature to it. They recognise that individuals interpret things differently and they rather rely on self-report scales that demonstrate respondents' feeling or confidence that they have understood the content of a message, irrespective of whether their interpretations are correct (e.g. Maheswaran & Sternthal, 1990; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991). Even so, the disparity between the two constructs was only recognised in the early 90's, when Mick (1992) observed the differences in how *understanding* had been measured in extant literature. Although Mick's work highlighted conceptual differences between objective and subjective understanding and pushed researchers towards the latter, research since then has not examined both constructs under a single conceptual framework.

Moreover, while WOM and advertising literature have both made use of the information-processing theory, where the *comprehensibility* of a message plays an important role in persuasion and behaviour change (Chaiken & Eagly, 1976; Eagly, 1974), the specific role of *understanding* an advertising message and its effect on WOM and purchase behaviour has not yet been explored in depth. In order to explore how *understanding* occurs in general – and within an advertising communication – it is first imperative to outline the norms of communication.

2.3.1 Who says what to whom?

Perhaps the most widely used communication framework is Hovland's Yale model which takes into account the following four elements: *who* says *what* to *whom* and with *what effect* (Hovland, Janis, & Kelley, 1953). According to Hovland and his colleagues, these elements influence the process of persuasion where *understanding* holds a central position (Hovland et al., 1953). Although all different elements have been studied in relation to persuasion and attitude change, Hovland (1948) suggested that enough research has been conducted around the communication source (the *who*) and that researchers should focus more on the receiver (the *whom*).

Extending Hovland's work, McGuire (1968a) focused on the receiver and constructed the six step information-processing paradigm: presentation – attention – comprehension – yielding –

retention – behaviour. McGuire's model, which is characteristically linear, placed *understanding* in the middle of the process, too.

2.3.2 Receiver's Cognitive Ability

A comprehensive message is not sufficient in building *understanding*. Each message assumes a different meaning depending on who transmits and receives it and thus, the credibility of the source and the individual characteristics of the receiver become as important as message content in a communication (Read, 1972). Consumer involvement (Chaiken, 1980; Johnson & Eagly, 1989; Park, Lee, & Han, 2007; Wright, 1973), prior or contextual knowledge (Alba, 1983; Petty & Cacioppo, 1981; Ratneshwar & Chaiken, 1991) and the need for cognition (NFC; Haugtvedt, Petty and Cacioppo, 1992; Fernbach *et al.*, 2013; Mohanty and Ratneshwar, 2015) are receiver-related variables which have been found to influence message elaboration, comprehension and, in turn, communication acceptance. The above characteristics interact with receivers' cognitive processes which have been found responsible in leading to some form of attitude change (Petty & Brock, 1981).

Models investigating cognitive response follow the foundation that two parallel activities take place in consumers' brain (e.g. Petty and Cacioppo's (1983) ELM, Chaiken's (1980) HSM, Kahneman's (2011) System 1/System 2). In these models consumers form judgements through a systematic and rational route or through a peripheral route which relies on heuristics. Because the rationale behind those models is that two possible routes can be employed, they are termed as dual-processing models. Each route is influenced by different parameters: the systematic and rational route is influenced mostly by message content parameters – such as the number and quality of arguments – while the peripheral route is affected by other cues, such as the credibility of the source (Petty & Cacioppo, 1983; Petty, Cacioppo, & Goldman, 1981; Wood, 1982; Zhang & Watts, 2003).

2.3.3 Message Content

Studies in information-processing and persuasive advertising have manipulated message content parameters to examine their effect on message comprehension and consequently, communication acceptance. Hovland and his colleagues (1953) demonstrated that the higher *the number of arguments* within a message, the easier it is to persuade the receiver. Later, Eagly and Chaiken, (1993) found that when lowering the number of arguments in a communication, participants' comprehensibility was decreased and as a result consumers became more resistant in adopting new information. Aside from the number of arguments, the *order* that they are positioned in within a message also plays an important role in message comprehension. Eagly's experiments (1974) on comprehensibility showed that randomly ordered sentences lowered participants’ ability to understand and retain a message. On this note, McCroskey and Mehrley (1969) had earlier found that a well organised message leads to greater levels of persuasion. In an experiment which manipulated the *order of arguments*, and controlled for prior knowledge and level of intelligence, Hovland and his colleagues (1953) concluded that participants with low prior knowledge and lower levels of intelligence were more easily persuaded by messages with an anti-climax argument order (strong arguments positioned first). They also pointed out that a climax order (strong arguments last) was more suitable when the message had enough attention arousal cues and could sustain the receiver’s interest until the end of the communication.

Aside from the number and order of arguments, research has also looked into the *mode* in which a message is presented. In a series of experiments on comprehensibility, Chaiken & Eagly (1976) explored messages in text, audio and video mode and found that televised communications were miscomprehended by 38% (Chaiken & Eagly, 1976). This was also supported by further experimental research that demonstrated that a very large percentage of televised communications and commercials is indeed miscomprehended (Jacoby, Nelson, & Hoyer, 1982; Lipstein, 1980). However, the statements used to test the level of miscomprehension are prone to bias as they were constructed by the researchers themselves. Recognising this limitation, the authors suggested that programmatic research should address the subject of miscomprehension in televised communications (Jacoby & Hoyer, 1982).

An important conclusion arising from the review of persuasive advertising studies is that the investigation of understanding has been carried out using stimuli in print or audio mode. The need to conduct research using more visually complex stimuli, which reflects modern ads has been highlighted in recent research (Fernbach et al., 2013; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991). The following section will outline issues with the movie industry and will justify the choice of trailers as advertising stimuli to study the effect of understanding on PRCB.

2.4. Context of Movies

Movie trailers have been chosen as advertising stimuli to explore consumer understanding for a number of reasons. First, as stated in the introduction, they satisfy calls for research to test consumer response through complex visual stimuli (Fernbach et al., 2013; Mohanty & Ratneshwar, 2015).

Second, they represent an industry that is highly reliant on pre-release buzz. Since this research is entirely focused on pre-release consumer perceptions, the chosen context should reflect an industry where pre-release buzz is not only apparent, but also crucial to its success. Like most experiential products, movies receive elaborate WOM prior to their release (Gelper et al., 2018). In fact, the movie industry highly relies on WOM (Craig et al., 2015; Squire, 2016). This is due to movies' particular release strategy, which does not follow the standard pattern of diffusion of innovations (Dellarocas et al., 2007; Rogers, 1962). Movies have an extremely short life cycle and their success is determined by the opening weekend performance (De Vany & Walls, 1997; Elberse & Eliashberg, 2003; Eliashberg & Shugan, 1997; Gong et al., 2011; Krider & Weinberg, 1998; Stapleton & Hughes, 2005). Receipts from the first three days determine the movie's length of run and the number of screens that the movie will be shown on in the following weeks. A movie's success cannot simply rely on its quality; successful advertising campaigns need to support it (Garey, 1992). For this reason, movie marketing – which costs as much as movie production (Gong et al., 2011) – aims to raise awareness and generate buzz as early as possible. As a result campaign planning starts as soon as a project is greenlighted (Medavoy, 1992).

Third, the chosen context reflects an economically important industry (Booth & Geis, 2006; Hennig-Thurau et al., 2015). Last year, the movie industry made $40.6 billion globally, surpassing revenues from all other forms of entertainment combined (MPAA, 2018). However, industry success is driven by a very small percentage of movies; in fact, only one in ten movies manages to break even and make a profit (Gong et al. 2011). As a result the mean total BO exceeds the mean total production budget (Prag & Casavant, 1994; Simonton, 2008). Since the technological revolution, growing alternatives (e.g. live streaming, movie piracy) have presented production studios and marketers with certain challenges (Griff, 2012; Tourmarkine, 2005). This environment has made it imperative for marketers to drive audiences to the cinema on the opening weekend, making pre-release advertising coupled with PRCB even more crucial in recouping costs from this high-risk investment.

Fourth, movies' short life-cycle allows researchers to examine its entire lifespan, turning the industry into a microcosm to study consumer behaviour (Chintagunta et al., 2010; Hennig-Thurau et al., 2015; Holbrook, 1999). The movie industry does not only offer numerous opportunities for research, but it can also benefit greatly from valuable insight on how to minimise risk and improve BO performance.

The key issue with the movie industry lies in the fact that the very short product life cycle requires high rates of adoption as soon as the product is introduced to the market – meaning that high attendance is necessary on the opening weekend. Attendance numbers can be increased through an effective pre-release campaign which aims to: a) drive audiences directly to the cinema, and b) generate and sustain pre-release buzz in order to beat the competition. However, the fact that only few movies manage to cover production costs proves that producers and distributors still do not have a formula for a successful marketing campaign. And although considerable research has been conducted in a movie context, movie marketers still fail to understand their audiences, claiming to be unsure of whether online advertising is effective (Rainey, 2016).

2.4.1 Movie Research

Studies in the movie industry come from a variety of disciplines, from economics and marketing to culture studies and psychology (Simonton, 2008). Two different approaches are followed in movie research studies: the economic approach and the psychological approach. Economic studies focus on the relationship between different movie characteristics (e.g. production budget, advertising spent, movie genre etc.) and BO success, which often represents opening weekend receipts or cumulative long term revenue. Economic studies have been largely influenced by the availability of data at the time that they were conducted. Before the arrival of the Internet, data was limited and so, research was conducted with small datasets that presented certain limitations (Chisholm et al., 2015). In the last two decades, however, freely available data on online websites and platforms have allowed for the exploration of larger datasets and the observation of a variety of parameters that might affect movie profitability.

The psychological approach is more customer-centric, and involves consumer behaviour studies exploring decision-making (Austin, 1981; Moller & Karppinen, 1983), or neuroscience studies examining movie preference (Boksem & Smidts, 2015). The majority of movie research studies are positivistic and the main findings on movie parameters are summarised in Table 2.

Table 2: Summary of studies on the context of movies

Author	Focus	Study Type	Contribution
De Vany and Walls, 1999	**Star Power**	Probability Modelling	*The number of stars cannot forecast a movie's success. BO depends on WOM.*
Elberse, 2007		Event Study	*The number of stars and the level of their economic and artistic reputation positively influence financial performance.*
Eliashberg and Shugan, 1997	**Critics' Reviews**	Regressions	*Critics are predictors of BO long-term success.*
Basuroy, Chatterjee and Ravid, 2003		Regressions	*Critics are influencers; both positive and negative reviews influence BO. Negative reviews have a greater (negative) effect on BO, especially in the first week of run, but stars and budgets act as moderators.*
Chakravarty, Liu and Mazumdar, 2010	**Critics' Reviews and WOM**	Online Experiments	*Infrequent moviegoers are more influenced by negative WOM, while frequent moviegoers are more influenced by critics' reviews.*
Krider and Weinberg, 1998	**Release Date/Seasonality**	Game Theory Modelling	*Changing the release date of a weaker movie to avoid competition of a 'marketable' movie, can positively influence BO.*
Radas and Shugan, 2012		Transformed-time Modelling	*Very short or very long-life movies can be released at the end of a peak season, but the optimal choice for average-life movies is to wait until the next peak season (summer).*
Einav, 2007		Benchmark Modelling	*Seasonality and demand are inter-dependent. Biggest movies are released in most popular periods, boosting the season's profitability.*

Desai and Basuroy, 2005	**Movie Genre, Star Power, Critics' Reviews**	ANOVA Test	*Star power and the valence of critics' reviews influence BO more for unfamiliar movie genres than for familiar movie genres.*
Hennig-Thurau et al., 2007	**Awards, Reviews, Advertising, Star/Director Power, Movie Quality, Seasonality**	Path Analysis	*Awards have the strongest influence on profitability. Awards and movie quality perceptions completely mediate the relationship between reviews and BO. Production budget influences only short-term BO, while advertising and seasonality influence both short and long-term BO. Star and director power do not predict BO success.*
Prag and Casavant, 1994	**Advertising**	Regressions	*Advertising expenditures is the most important factor in determining financial success.*
Gong, Van der Stede and Young, 2011	**Advertising, Sequels**	Real Options	*Advertising and BO success are inter-dependent. Sequels cost more, but have higher returns.*
Moul, 2007	**WOM**	Regressions	*WOM - along with advertising - influences consumer expectations and consumer behaviour.*
Duan, Gu and Whinston, 2008		Dynamic Simultaneous Equations	*WOM Volume mediates the relationship between WOM valence and BO but the effect diminishes quickly. BO in turn, positively influences WOM volume.*
Liu, 2006		Regressions	*WOM volume increases after release while WOM valence becomes more negative after release.*
Hennig-Thurau, Wiertz and Feldhaus, 2015		Regressions and Survey	*Negative WOM on opening night influences short-term BO, while positive WOM doesn't.*
Karniouchina, 2011a	**WOM, Star Power**	Simultaneous Equation Modelling	*Pre-release movie and star buzz are positively associated with Theatre Distribution and BO.*

Eliashberg et al., 2000	**WOM, Movie Theme, Advertising, Theatre Distribution, Movie Quality**	Markov Chain Modelling and Survey	*WOM - combined with movie theme, advertising, theatre distribution and movie quality - can forecast movie attendance.*
Gopinath, Chintagunta and Venkataraman, 2013	**Advertising and WOM**	Regressions	*Advertising influences both opening weekend and opening month BO, while WOM volume influences opening day and WOM valence influences opening month BO.*
Basuroy, Desai and Talukdar, 2006	**Advertising, Sequels, Critics' Reviews, WOM**	Dynamic Simultaneous Equations	*Controlling for the effect of critics' reviews and WOM, advertising spend has a stronger positive effect on BO for sequels, than for non-sequels.*
Elberse and Eliashberg, 2003	**Theatre Distribution and WOM**	Simultaneous Equation Modelling	*Theatre Distribution mediates the relationship between movie attributes/advertising and BO. Theatre Distribution mediates the relationship between WOM and BO.*
Clement, Wu and Fischer, 2013		Simultaneous Equation Modelling	*Theatre Distribution positively influences BO success, while WOM influences the later stages of a movie's run.*

Variables which have been explored in the studies above are production-related – such as budget and movie genre, distribution-related – such as seasonality, advertising, and theatre distribution; and reception-related – such as WOM, critics' reviews and awards.

The effect of production-related variables on BO performance is ambiguous (Craig et al., 2015). There is a common assumption that production budget can predict a movie's success and that the more studios spend on a movie, the higher the likelihood of its profitability – which explains the large amounts of money invested in movie production. However, production budget influences only short-term BO, while other, distribution-related factors influence both short and long-term BO (Hennig-Thurau, Houston, et al., 2007).

Unfortunately, star power, which is a popular production-related parameter, has been considered an unreliable variable, not only due to the contrasting results among the various economic studies (De Vany & Walls, 1999; Elberse, 2007; Hennig-Thurau, Houston, et al., 2007; Karniouchina, 2011a), but also because the popularity of stars changes throughout time (Simonton, 2008). Nevertheless, movie stars are used as signals that help consumers form perceptions about the quality of the movie, especially because very few information is available prior to a movie's release (Hoffman, Clement, Völckner, & Hennig-Thurau, 2017; Levin, Levin, & Heath, 1997; Liu, Liu, & Mazumdar, 2014). Studies on the effect of star power can be divided into those that support the idea that it is star's artistic recognition (e.g. nominations and awards) that attracts audiences (Bagella & Becchetti, 1999; Deuchert, Adjamah, & Pauly, 2005; Hoffman et al., 2017; Rosen, 1981; Vazquez-Casielles, Suarez-Alvarez, & del Rio-Lanza, 2013) or their popularity and bankability that influences BO performance at least during the opening weekend (Carrillat et al., 2018; Desai & Basuroy, 2005; Karniouchina, 2011a; Liu et al., 2014). It is worth mentioning that stars incur higher production costs since they are expensive to hire, and therefore, it is unclear whether they actually improve or harm the BO (Simonton, 2008).

Among a number of production and distribution-related parameters, Prag and Casavant (1994) have found that advertising has the highest impact on BO success. Indeed, advertising and BO are seen as interdependent (Gong et al., 2011). Advertising influences consumer expectations and consumer behaviour (Moul, 2007) and its effect on BO is both short and long-term (Gopinath et al., 2013; Hennig-Thurau, Henning, et al., 2007). Since movie trailers are considered the most effective form of movie advertising (Austin, 1981), some studies focus specifically on trailer campaigns, identifying a positive influence on movie revenue

(Epstein, 2005; Gong et al., 2011; Hennig-Thurau, Houston, et al., 2007; Young, Gong, Van der Stede, Sandino, & Du, 2008).

Interestingly, Elberse and Eliashberg (2003) have found that the relationship between advertising and BO is mediated by another, distribution-related parameter: theatre distribution. Theatre distributors rely on pre-release buzz to determine the number of screens that the movie will be allocated on (Karniouchina, 2011a). Naturally, the higher the number of screens, the higher the revenues will be (Clement, Wu, & Fischer, 2013). The later stages of a film's run, however, have been found to be influenced by WOM rather than distribution and advertising (De Vany & Walls, 1999; Dellarocas et al., 2007).

Other parameters which have been found to influence opening weekend BO and are taken into account as control parameters in this research is the seasonality and competition of movies. Naturally, some seasons (e.g. Christmas, summer) attract higher numbers of audience attendance. As a result, these seasons are also characterised by increased competition, and researchers have attempted to find the right balance between seasonality and competition. Seasonality and demand are interdependent (Einav, 2007) and along with advertising they influence both short and long-term BO performance (Hennig-Thurau, Houston, et al., 2007). Through game theory modelling, Krider and Weinberg (1998) have found that taking competition into account, it is optimal for 'weaker' movies to change their release date. If movies do not manage to be produced and ready for release within a popular period, it is sometimes best to wait for the next peak season (Radas & Shugan, 2012).

Aside from movie-related and distribution-related variables, parameters regarding movies' reception have also been found to influence BO performance. Apart from movie WOM – which will be examined in more detail in the next section – critics' reviews and awards have a direct (Basuroy et al., 2003; Reinstein & Snyder, 2005; Zuckerman & Kim, 2003) or indirect (Hennig-Thurau, Houston, et al., 2007) effect on BO. Professional critics' reviews have sparked a debate in movie research as some researchers support the idea that critics are predictors (Eliashberg & Shugan, 1997), while others find that they are rather influencers of BO (Basuroy et al., 2003). A very recent meta-analysis on the effect of professional reviews demonstrates that professional critics are, in fact, both influencers and predictors of BO performance and that, notably, their effect on BO is equal to that of consumer reviews (Carrillat et al., 2018).

2.4.2 Movie WOM Literature

Consumer reviews, have received considerable attention in movie research in the last decade. Although the influence of WOM on movie performance has been long recognised (Eliashberg, Jonker, Swahney, & Wierenga, 2000), the availability of online data saw a shift in movie WOM research. Movies stimulate a lot of enthusiasm, fuelling online conversations on social media (Asur & Huberman, 2010; Hennig-Thurau et al., 2015), and offering important insight on audience response. To address limitations of earlier studies that measured WOM as an aggregate percentage of movie attendance on theatre distribution (Clement et al., 2013; Elberse & Eliashberg, 2003) researchers benefitted from the collection of data from social networking sites (Asur & Huberman, 2010; Hennig-Thurau et al., 2015; Rui, Liu, & Whinston, 2013).

Most movie WOM studies follow the economic approach and look at the effect of WOM in driving short and long term BO success (De Vany & Walls, 1999; Dellarocas et al., 2007; Eliashberg et al., 2000). The majority of studies on movie WOM focus on post-release conversations, which are undeniably more reliable (Dellarocas et al., 2007). This is in line with the theories that position satisfaction as the most important WOM antecedent and require consumers to already have experienced the product or service (Brown et al., 2005). Nevertheless, it is pre-release buzz that shapes audiences' decisions to go to the cinema on the opening weekend and recent research has stressed the need to examine not only how WOM builds up after an experience but also how it is generated prior to the experience (Craig et al., 2015).

The few pre-release WOM studies that exist, explore the effect of different WOM metrics in relation to BO performance. The long-standing debate on the significance of volume versus valence is apparent in the movie industry, too. Examining both metrics, Liu (2006) found that, after a movie's release, WOM volume increases but valence becomes more negative. This is in line with findings on PRCB (Houston et al., 2018), which is generally more positive compared to post-release WOM. The two metrics have also been found to be interrelated, but it is volume that directly influences BO performance (Duan et al., 2008; Liu, 2006). Differentiating between short and long term success, Gopinath *et al.* (2013) point out that the volume of WOM influences opening day receipts, while the valence of WOM influences long term BO. Going further into the study of WOM valence, recent research observed that it is only negative WOM that has an effect on short term BO receipts (Hennig-Thurau et al., 2015). Although meta-analyses on movie WOM data have attempted to resolve this debate, as demonstrated in section 2.1, a clear conclusion on which is more influential on BO is yet to be reached (Babic Rosario et al., 2016; You et al., 2015).

Going beyond volume and valence, recent research on the effect of trailers on movie WOM, demonstrated that including other WOM variables – such as awareness and intention to see – significantly improves BO prediction models (Craig et al., 2015). However, data was collected from very niche sites and only reflected consumer behaviour during a month prior to the movie’s release. Recognising that focusing on volume and valence ignores WOM’s overall dynamic pattern, Gelper et al. (2018) observed that, among other WOM characteristics, spikes in pre-release WOM conversations can significantly predict BO success. Their content analysis on pre-release WOM data revealed that consumers’ conversations revolve mainly around the storyline of the upcoming movie (Gelper et al., 2018). This supports prior content analysis research that demonstrated that the topic of storyline was the most related to consumer satisfaction after a movie’s release (Simmons et al., 2011). Although content analysis on WOM data is not a common approach in movie research, some attempts have been made to examine conversational characteristics beyond volume and valence (Lipizzi et al., 2016; Nguyen & Romaniuk, 2014). Researchers have offered considerable insight in the area of movie WOM; yet, the specific role of the movie trailer in driving positive PRCB has been overlooked.

2.4.3 The trailer

The movie trailer is characterised as the most persuasive marketing tool in the movie industry (Friedman, 2006). Offering a free sample of the movie itself, it is the most successful form of movie advertising (Eliashberg & Shugan, 1997; Friedman, 2006). Marketers release teaser trailers early in advance in order to raise initial audience awareness, and follow up with consecutive preview clips, gradually revealing more information about the movie (Goldstein, 1991). Their aim is to attract a large audience on the opening weekend and, to do so, they release trailers early on in the development phase of a movie, which results in advertising material which is not necessarily representative of the movie (Goldstein, 1991; Pollack, 1992). According to Lopez (2011), trailers are the third most watched video online. Consumers have the ability to interact with them and share them immediately after watching, generating online buzz (Fritz, 2012; Johnston, 2008; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011).

Movie trailers are very often outsourced to specialised trailer houses and their production is quite costly (Marich, 2012). To ensure the campaign’s effectiveness, trailers are tested on audiences, just like general ads (Friedman, 2006). Recent technological developments have offered studio managers the opportunity to revolutionise the process by which trailers are created. IBM's Watson went through Fox's horror movie "Morgan" and created a trailer by combining shots that featured particular characteristics (Haridy, 2016). Although a human editor completed the finalised trailer, Watson's result was quite impressive, marking an era where supercomputers can create art (Haridy, 2016). Researchers in computational social sciences have started developing tools that combine video shots and consumer-generated data to predict movie preference through trailer-viewing (Campo et al., 2018). Such research, however, is mainly data-driven and conducted under no specific theoretical framework.

In this thesis, theory from persuasive advertising is applied to trailer-viewing in an attempt to investigate how consumers form perceptions about upcoming movies and which aspects of pre-release conversations better predict movies' performance. The next section will summarise the gaps deriving from current literature and practice, which will form the basis for the research agenda.

2.5 Research Gaps

The preceding literature review outlined the most important studies in the area of WOM and advertising, as well as relevant studies conducted in the context of movies. Through the review of the literature, it has become clear that most WOM research is concerned with conversations generated and shared *after* the release and use of a product. Thus, results can only apply to products that are already introduced to the market. This disregards theory on new product introduction and overlooks a large number of products that rely on pre-release buzz. Although marketing theory and practice could highly benefit from research on pre-release consumer buzz, PRCB was only recently recognised as a separate construct to post-release WOM. Systematic research on the antecedents and outcomes of PRCB is, therefore, necessary (Houston et al., 2018).

Focusing on PRCB, this thesis will also address gaps in regards to the under-researched relationship between WOM and advertising. The connection between advertising and WOM is evident on the social media. Nevertheless, the two are usually seen as opposing marketing techniques (Feng & Papatla, 2011; Rogers, 1962; Traylor et al., 1983; Trusov et al., 2007). Overcoming restrictions imposed by the assumption that WOM is a result of (dis)satisfaction (Brown 2005), this thesis answers calls for research on how advertising can effectively engage consumers in eWOM (You et al., 2015). Specifically, it examines the effect of trailer-viewing on the production of PRCB, and their joint influence on consumers' purchase decisions.

Looking specifically into information-processing literature, the position of *understanding* in its general form is apparent; however, evidence on how the concept is formed and how it manifests itself through communication is inadequate. The few relevant comprehensibility studies have mainly employed experimental methods in an attempt to determine the antecedents and the effects of the concept. Yet the *understanding* has been measured either from an objective or a subjective perspective. Consequently, the role of *understanding* within a movie trailer context is in need of both further exploration, and systematic testing. Although the context of this study is the movie industry, the ultimate objective is to position the role of *understanding* within the general advertising and WOM literature. Additionally, while studies on information-processing of persuasive advertising examine the effect of certain parameters on consumer behaviour and attitude change, they have not used WOM as the ultimate objective. Consequently, the effect of advertising on creating and sharing PRCB is yet to be explored.

By using movie trailers to test these concepts, this research also answers calls to use more complex visual stimuli in order to reflect modern-day media (Livingstone, 1990; Mohanty & Ratneshwar, 2015). Additionally, by positioning this thesis within the context of movies, important theoretical and contextual gaps on movie WOM are addressed. Although movies' success evidently relies on PRCB, and although their short life-cycle allows for the examination of the entire pre-release phase of the movie, the majority of movie WOM studies is conducted with post-release WOM data. So far, any movie WOM research that has looked into components of pre-release conversations has been conducted utilising data collected from niche platforms (Craig et al., 2015). As a result, movie marketers claim to be unsure of whether online trailer campaigns work and production studios fail to sell movies effectively (Rainey, 2016).

The debate on the significance of WOM metrics, is another gap that this research aims to address. By collecting pre-release data on movies, it examines both the effect of volume and valence on BO success and, in a more general light, on sales.

Finally, although the study of Big Data has become conventional in the wider scientific community, marketing researchers have been reluctant in adopting methods from computational social sciences (Nguyen & Romaniuk, 2014; Snee et al., 2016a). The combination of traditional and digital methods will add this thesis alongside other studies that have attempted to solve problems in social sciences through the use of recently developed methodologies (Phil Brooker et al., 2015; Lipizzi et al., 2016; Simmons et al., 2011).

The next chapter presents the overall research design to address the aforementioned research gaps.

Chapter 3: Overall Research and Summary of Papers

This chapter aims to present the overall research objectives and to discuss the design of this thesis and, in consequence, of the three papers. It consists of six parts. The first part presents the research objectives (3.1). The second part discusses how the framework for this research was inspired by an existing framework and by extant literature in WOM and persuasive advertising (3.2). The third part gives an account of the research methodology (3.3), presenting the chosen research philosophy and discussing the research methods employed for each paper (3.3.1-3.3.3). The chapter then ends with a summary of each of the three papers (3.4 – 3.6).

3.1 Research Objectives

The gaps which arose from the literature shaped the overall research question of this thesis, which aims to address how movie trailers generate positive PRCB to drive consumers to the cinema on the opening weekend. To do so, three main research questions that correspond to the three papers have been drawn.

The first paper is of exploratory nature and focuses on the relationship between understanding the advertising message and WOM, addressing the following research question:

> RQ 1. What is the effect of trailer *liking* and *understanding* what a movie is about on favourable WOM and purchase intent?

Assuming that a positive relationship is found and that understanding the movie trailer does indeed lead consumers in producing favourable WOM and in considering to pay to see a movie, the second paper further investigates the concept of understanding in order to pin down its antecedents and its effect on trailer and movie liking. It, therefore, addresses the second research question:

> RQ 2. How is understanding shaped through trailer-viewing and what is its effect on ad (trailer) and product (movie) liking?

The first two research questions are tackled through empirical studies which utilise experimental methods. After establishing a relationship between understanding the movie trailer and positive consumer response, these relationships are further tested through behavioural data, collected from popular online platforms. Drawing from the results of the first two papers, the third paper examines the actual effect of trailer viewing on pre-release buzz and early sales. It addresses the third and final research question:

> RQ 3. How do trailers' explanatory characteristics shape online pre-release buzz and what is the effect of different buzz components on early box office performance?

The following section will explain the research framework for this thesis.

3.2 Research Framework

The present research follows the assumption that movie trailers lead to online buzz and viewing decision, consistent with extant literature (Day, 1971; Dichter, 1966; Graham & Havlena, 2007; Hogan et al., 2004). In doing so, it addresses calls for research on the complementary relationship between WOM and advertising (You et al., 2015). Drawing from persuasive advertising literature, the conceptual framework focuses on a specific information-processing mechanism – *understanding* – that has been found to drive positive consumer response (Eagly, 1974; McGuire, 1968; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991). The conceptual framework of this thesis is largely inspired by Cheung and Thadani's (2012) proposed conceptual model of communications. After a review of 47 papers on eWOM communications, the authors draw theory from information-processing and summarise all the possible relationships between communication elements and different consumer responses (See Figure 1).

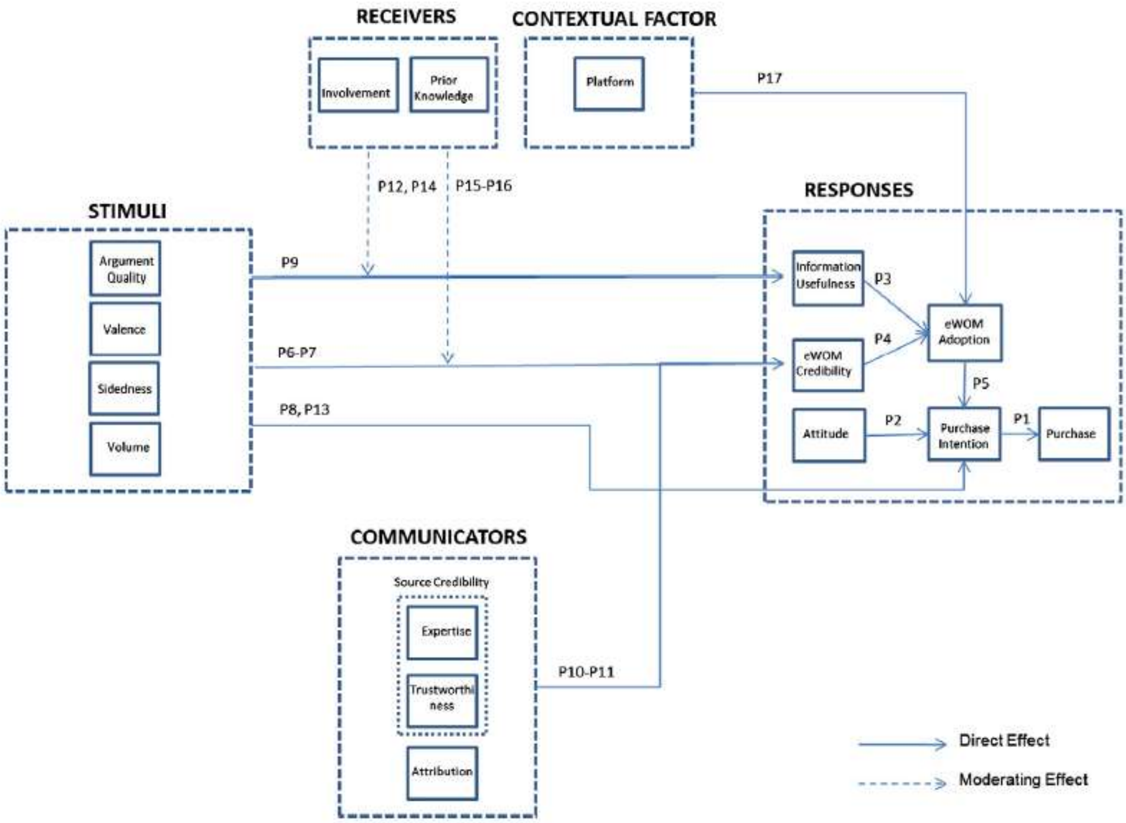

Figure 1: Cheung and Thadani's (2012) conceptual model of communication

The constructs are grouped by the elements of communication – *contextual factors, receivers, stimuli, communications, responses* – which refer to the "who says what to whom" model (Hovland et al., 1953). Since this thesis is concerned with the effect of understanding the movie trailer on positive online buzz, all trailers are tested in their natural online environment (YouTube videos). Hence, the platform remains constant all throughout this thesis, and as a result, the *contextual factor*, becomes extraneous in the proposed framework. The same applies with regards to the *communicator*. The source of communication, which has been widely researched (Hovland & Weiss, 1951; Kamins & Assael, 1987; Radighieri & Mulder, 2014; Wilson & Sherrell, 1993), is outside of the scope of this research and will remain constant throughout.

This research rather focuses on the *stimuli* (message content) and the *receivers*, borrowing relationships, relative to eWOM and purchase intention (out of all possible consumer *responses*). Adapting Cheung and Thadani's (2012) framework to the context of movie trailers, some of the parameters are naturally modified or excluded, while others, deriving from recent research on persuasive advertising, are added.

Message valence – which refers to the positive or negative aspect of a communication – and information sidedness – which refers to the objectivity of a message – are, in this case, irrelevant. Movie trailers merely offer a sample of the movie itself and these two parameters can hardly be measured or manipulated. As a result, they are not expected to have an effect on understanding and eWOM in the context of movie trailers, and so, they have been excluded.

On the other hand, adapted to the context of this thesis, the information volume can refer to the number of hints offered within a movie trailer, and is expected to have an effect on understanding and pre-release buzz. In practice, Teaser trailers offer only a taste of the actual movie, while successive trailers gradually present more information which builds on consumer understanding. For the purposes of this research, information volume has been renamed *amount* of *information* and is included as a message content (stimuli) parameter in the proposed framework.

Argument quality, which refers to the wider construct of argumentation (Chaiken, 1980; Eagly & Chaiken, 1993; Kamins & Assael, 1987) is concerned with a number of parameters regarding the arguments presented within a communication. While the quality of arguments is irrelevant in the context of trailers, the order of arguments, which has not been explicitly included in Cheung and Thadani's (2012) framework, will be taken into account. In information-processing theory, the order of arguments has been, indeed, linked to comprehension and persuasion (Eagly, 1974; Hovland et al., 1953). In the context of movie trailers, information about the plot can be presented in a linear or abstract manner. The most common one is the three-act narrative framework which sets out the characters (Act 1), presents them with a conflict (Act 2) and offers hints on how the story develops (Act 3) (Campbell, 2008; Flanagan, 2012). This linear, climaxing presentation of events may potentially make a trailer's content more comprehensive. Consequently, for the purposes of this thesis, the order of arguments has been renamed *order of information* and is included as the second message content parameter in the proposed framework.

With regards to the *receiver*, involvement and prior knowledge from Cheung & Thadani's framework have been renamed as *interest* and *context familiarity*, to apply to the context of trailers. Both involvement with the message or product (Greenwald & Leavitt, 1984; Park et al., 2007; Petty & Cacioppo, 1981; Richins & Root-Shaffer, 1988) and prior knowledge about the context of the communication (C.I. Hovland et al., 1953; Sawyer, 1981; Weiss, 1968) have been found to influence information adoption, liking and persuasion. In the context of this thesis, involvement in movies can refer to the frequency of movie-going or the general interest in movies (since moviegoing has been lately replaced with other viewing alternatives). As such, consumers with a general interest in movies, might elaborate on movie trailers for longer and might be able to derive a better understanding on what the movie is about. Additionally, prior knowledge, in this case, has been adapted to refer to the potential familiarity with a movie's context, that can be gained through the viewership of other trailers of the advertised movie or even of trailers of sequel movies. Consistent with later research on persuasive advertising, the Need for Cognition (*NFC*) which has been found to influence comprehension and communication acceptance (Fernbach et al., 2013; Mohanty & Ratneshwar, 2015) is also included as a receiver parameter. The tendency to elaborate more on a message is expected to positively influence understanding on what the movie is about.

The proposed conceptual framework for this thesis, along with the corresponding paper where each relationship is examined (P1: Paper 1 etc.), is presented in Figure 2.

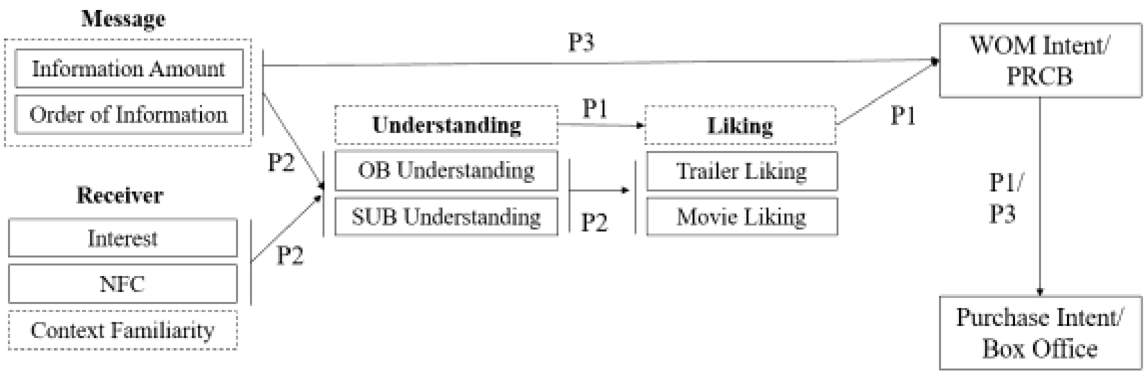

Figure 2: Conceptual framework for this thesis

Paper 1 sets out the relationship between understanding and liking and its effect on eWOM and purchase intent. Due to the limited amount of prior theory on the construct of *understanding*, Paper 2 further investigates its antecedents and its effect on ad and product liking. Once message content parameters that influence consumer understanding are identified, Paper 3 further tests these relationships on actual pre-release buzz and sales. Because the first paper is exploratory, the outcomes of understanding are the intention to share positive eWOM (*WOM intent*) and the intention to see the movie (*purchase intent*). The third paper, however, tests these constructs through behavioural data and examines the effect of trailer advertising on actual pre-release buzz (*PRCB)* and box office figures (*BO*). It should be noted here, that BO refers only to opening weekend box office receipts (rather than cummulative box office performance), since, as demonstrated in Chapter 2, only short term performance is directly influenced by both advertising and pre-release buzz.

The next section will describe the overall research philosophy and methodology and the research methods employed for each of the papers.

3.3 Research Methodology

Researchers choose the most suitable approach according to their view of the world and the research questions which they aim to answer. Most studies in movie WOM literature follow positivistic assumptions and rely on uncovering a 'universal truth' through quantitative processes. The research questions which they examine are concerned with validating relationships and explaining the effect of certain parameters on certain outcomes (e.g. Eliashberg *et al.*, 2000; Liu, 2006; Duan, Gu and Whinston, 2008; Hennig-Thurau, Wiertz and Feldhaus, 2015). They follow a deductive approach, where hypotheses are tested and supported or rejected depending on the results of statistical analysis. Their aim is to derive generalizable models and their observations represent the 'real-world' (Crotty, 1998; Gill & Johnson, 2002). This approach is ideal when the researcher's aim is to test particular relationships and to add reliability to prior theories. Although positivistic studies present many advantages, they are only suitable where there is enough prior literature to support the proposed hypotheses (Saunders, Lewis, & Thornhill, 2016). Alternatively, when the research question concerns an under-explored concept, an interpretivist approach which allows the researcher to fully explore a new construct qualitatively, is more appropriate (Saunders et al., 2016).

The present study is concerned both with establishing the concept of *understanding* as a new PRCB antecedent and with testing specific relationships between its antecedents and outcomes. In this sense, some of the questions could be tackled through an interpretivist approach, and others, through a positivist approach. As this thesis aims to tackle a research problem which is also evident in practice, the paradigm of pragmatism – which stands between positivism and interpretivism – has been deemed the most appropriate (Saunders et al., 2016). A pragmatic philosophy is ideal, when searching for practical solutions to real-world problems (Patton, 2002). Pragmatists' position between the two major epistemological views is not coincidental; they believe that it is impossible to derive meanings about the world by simply employing one scientific approach (Mertens, 2005). Being free of epistemological assumptions, pragmatism does not set any methodological restrictions and allows the researcher to tackle research questions, using any method that is deemed suitable (Mertens, 2005). The priority then, becomes the research problem, which should determine the approach and method to be followed (Saunders et al., 2016).

Consequently, pragmatism is highly associated with mixed method research. Both qualitative and quantitative methods have their advantages and limitations; the former allows the researcher to delve deep into a concept, while the latter offers the possibility of employing a larger sample and producing more reliable results (Bryman, 2012). By employing a mixed methods approach it is possible to take advantage of the opportunities that both approaches offer and to tackle their limitations. Mixed methods enhance the quality of data and allow for generalisability of the explored concepts (Bellotti, 2015). In fact, when employed for the right reasons, the combination of methods which supplement each other (Onwuegbuzie & Teddlie, 2002) can offer completeness to a study (Bryman, 2012).

Nevertheless, mixed method studies have been historically met with some criticism, and researchers specialising in both approaches are few. While quantitative and qualitative methods have been openly employed and accepted for decades, mixed methods have gained acceptance – with the first relevant published handbook – fairy recently (Tashakkori & Teddlie, 2003). Critics of pragmatism fail to accept mixed method research, as the two methods derive from different epistemological views and are, therefore, not compatible (Burrell & Morgan, 1979). However, since pragmatists are not bound by any epistemological assumptions, this argument can only be unsound (Tashakkori & Teddlie, 2003). It should be noted here that a pragmatic philosophy and a mixed methods research design should be utilised only to serve the purposes of a specific study (Patton, 2002) and only because the research questions require it so (Tashakkori & Teddlie, 2003).

Consequently, the choice of methods for this thesis, has been carried out according to the research question and objectives of each study. The following section outlines the specific research methods chosen and carried out for the purposes of the three papers.

3.3.1 Paper 1

The first paper was of exploratory nature; its purpose was to investigate potential relationships that were only implied in prior research. It assumed the psychological approach in relevant movie research (Simonton, 2008), which is more appropriate in consumer behaviour studies, as it focuses on the individual. After a review of the relevant literature, hypotheses were formed and pre-tested through exploratory focus groups.

- Collecting data through focus groups

The focus groups carried out for the collection of initial consumer opinions on trailers, resemble trailer-testing techniques, widely used in the industry. Trailers are tested just like any other kind of ad, where participants are exposed to the ad and then asked to discuss it (Basuroy et al., 2006; Lopez, 2011; Pritzker, 2009). Focus groups refer to group interviews where the focus is specified in advance and the aim is to observe or record conversations between participants (Carson, Gilmore, Perry, & Gronhaug, 2001; Krueger & Casey, 2009). The number of focus group interviews is not pre-determined; rather the researcher decides when saturation of data and insight is reached (Krueger & Casey, 2009). This data collection technique is ideal for researchers who seek a route to grounded truth, which can then be further tested quantitatively (Saunders et al., 2016). For the purposes of Paper 1, preliminary focus groups were conducted to pre-test the constructs tested in the main study.

While focus groups can offer considerable insight and have been widely used in the advertising and movie industry, they do entail certain challenges. Care needs to be taken towards the equal contribution of each participant. Issues also arise with the documentation of notes; video-recording is suggested as an alternative to tackle this (Saunders et al., 2016) and was indeed followed during the data collection for the preliminary study of Paper 1.

- Analysing qualitative data through thematic analysis

Data collected from the focus groups underwent thematic (or topic) analysis to reveal key themes that were important to participants when forming their perceptions about trailers. This analysis technique is appropriate when searching for themes and patterns in qualitative data that are often used for further exploration (Braun & Clarke, 2006). Thematic analysis is not tied to any philosophical position and can be carried out following whichever approach suits the research problem. In thematic analysis, concepts are counted and results reveal the frequency and occurrence of themes. Contrary to grounded theory, which is quite restrictive, this technique offers a flexible and accessible way to analyse qualitative data (Saunders et al., 2016).

Findings from the focus groups and insight from the literature helped shape the final model which was further tested quantitatively on a larger sample.

- Collecting data through questionnaires

An online questionnaire, which is appropriate for larger sample sizes and for research with standardized questions (Robson, 2011), was used as the data collection technique for the main part of Paper 1. Questionnaires have been widely used in information-processing and persuasive advertising research, where the aim is to collect a large amount of data to determine generalizable relationships (e.g. Jacoby, Nelson and Hoyer, 1982; Maheswaran and Sternthal, 1990). Among the various ways to distribute questionnaires, the Internet was chosen as the most appropriate mode, as the desired sample had access to it and the questions were straightforward enough to be answered through the web (Baruch & Holtom, 2008; De Vaus, 2014; Dillman, Smyth, & Christian, 2014). The Internet also allowed for trailer-testing in an environment that resembles the real world (e.g. trailers watched online). Challenges with regards to the contamination of answers (Saunders et al., 2016) were tackled through response validation techniques and attention checks to ensure that the data collected was reliable.

- Analysing data quantitatively

Quantitative methods allow for the analysis of large-scale data, where research results are more generalizable (Saunders et al., 2016). Contrary to qualitative methods, the research design needs to be carefully determined in advance. Additionally, because data is more efficient and therefore less "rich", contextual detail might be lost (Saunders et al., 2016). As previously mentioned, the majority of studies in persuasive advertising rely on quantitative methods, where respondents are exposed to a communication and are asked questions that help researchers measure specific constructs (Eagly & Chaiken, 1993; Fernbach et al., 2013; Mohanty & Ratneshwar, 2015). The relationship between these constructs is then tested through statistical analysis. Statistical analysis is used to explore differences between constructs or to test cause-and-effect relationships between variables (Saunders et al., 2016). Usually, some form of hypothesis-testing takes place even if, written-up, the explicit hypotheses are sometimes not mentioned, but rather inferred from the theoretical underpinning of the research. Statistical package software – such as SPSS or PLS-SEM – facilitates the analysis and is widely used in research. Researchers need to be careful when choosing a statistical test and to abide by its assumptions, especially when tests are parametric (Saunders et al., 2016). In the main study of Paper 1, data was analysed through the use of PLS-SEM which tests the statistical significance of paths between variables. All necessary tests were carried out to ensure that all assumptions of the statistical tests were met.

3.3.2 Paper 2

The aim of Paper 2 was to first explore how pre-release perceptions about the movie are shaped through trailer-viewing and to then test a number of variables as antecedents and outcomes of understanding. Similar to Paper 1, the focus was on consumer behaviour and therefore, the psychological approach of movie-relevant research was adopted. Experimental studies have been the core method of cognitive and consumer psychology research for decades (Eagly, 1981; Eagly et al., 1978; Hovland, Lumsdaine, & Sheffield, 1949). For the purposes of the second research question, two experiments were designed. The first was more exploratory, aiming to set the basis for the second experiment where particular hypotheses were tested.

Although questionnaires are not deemed ideal when open-ended questions are asked (Saunders et al., 2016), the nature of the study required that respondents describe their thoughts on the stimuli through an open-ended answer (Maheswaran & Sternthal, 1990; Mick, 1992; Ratneshwar & Chaiken, 1991). Data was collected through an online questionnaire – in the same way as Paper 1. The quantitative data was statistically analysed to reveal initial relationships between the constructs. Data collected from the one open-ended question, was analysed through thematic (see section 3.3.1) and content analysis. Thematic analysis studies on movie WOM are limited. Nevertheless, the few that exist have attempted to identify key themes in consumers' conversations (Gelper et al., 2018; Nguyen & Romaniuk, 2014; Simmons et al., 2011). While these studies are not limited to the pre-release phase of a movie, they have offered inspiration in terms of the techniques used to derive topics.

As the qualitative data also served for the measurement of one of the variables that was included in the statistical analysis (Objective Understanding), the data underwent content analysis, which is an appropriate technique for quantifying qualitative data (Saunders et al., 2016).

- Content Analysis

Content analysis has been historically employed to describe communication data in a quantitative way (Berelson, 1952). Generally, it is a technique that allows the researcher to make valid inferences from text to context (Popping, 2000). This methodology is particularly useful when the object of research can be expressed as an abstract concept (Diesner & Carley, 2011), as is the case of *understanding*. In content analysis, the focus is on the meaning and on its representation through communication (Popping, 2000).

Content analysis presents many similarities to thematic analysis, since coding and grouping of qualitative data takes place. However, the aim of content analysis is to quantify the data and the technique is therefore more objective and systematic, following explicit rules on how words should be coded (Saunders et al., 2016). It appears uncertain whether content analysis is traditionally a qualitative or a quantitative method. Both are found in theoretical and empirical studies and either approach can be used to analyse text data. The coding of words and the classification of concepts is typically considered to be quantitative, because words are coded and distances are measured (Popping, 2000). In contrast, assigning codes is a qualitative task and requires the researcher to be highly knowledgeable on the nature of the data. Human input is necessary when coding, although automated content analysis has certainly accelerated the procedure. Due to the fact that the dataset in Paper 2 was relatively small, respondents' descriptions were matched against official trailer synopsis and coded into true or false manually.

Findings from the first study of Paper 2 formed the hypotheses for the second part of the study, which adopted a deductive approach and statistically tested relationships between variables (see section 3.3.1 on Analysing data quantitatively).

3.3.3 Paper 3

The aim of Paper 3 was to add validity to the relationships in focus, through the collection and analysis of behavioural data. In doing so, it also addressed potential limitations of the self-report scales that were utilised in the first two papers (East et al., 2015; Romaniuk, Nguyen, & East, 2011; Watts & Dodds, 2007). Paper 3 assumed an economic approach in movie-relevant research since it was concerned with the effect of a number of parameters on BO performance (Simonton, 2008). eWOM researchers have previously collected and analysed millions of online data in an attempt to gain insight into public opinion (Beauchamp, 2013; Lin, Keegan, Margolin, & Lazer, 2014) or to explore the effect of emotion on the stock market (Zhang, Fuehres, & Gloor, 2011, 2012). Online social media sites are considered to provide more valid information when it comes to measuring the impact of WOM volume and valence on sales (You et al., 2015). Consistent with prior eWOM literature and for the purposes of Paper 3, secondary eWOM data was collected from social media platforms through the help of computational tools.

- Collecting secondary data

Secondary data refers to the data that already exists in some form. While historically such data referred to financial reports or organisational data, secondary data also alludes to consumer-generated data (Saunders et al., 2016). There are numerous advantages in working with secondary data. Because it is already available, researchers have the opportunity to judge the data's quality in advance (Stewart & Kamins, 1993). Additionally, data collection is less time-consuming (Saunders et al., 2016). A key downside, however, is that, often, datasets have been collected for other purposes and therefore the researcher has no control over the quality of the data (Saunders et al., 2016). This issue can easily be tackled when researchers compile datasets themselves, which is often the case with online data.

Due to the large size of datasets, secondary data found and collected online, have been termed as "Big Data". The study of Big Data has become increasingly popular in the past decade, with researchers designing and implementing new software tools to serve data collection and analysis purposes. Indeed, the production and availability of Big Data have completely changed the norms of research, to the point where a new – data-driven – epistemology was recently introduced, causing what Kuhn (1962) termed as a 'paradigm shift' (Kitchin, 2014). Big data are characterised by huge volume, high velocity and variety. They are flexible in that they can be combined with other datasets and exhaustive in scope as they allow researchers to capture the entire population (Boyd & Crawford, 2012; Kitchin, 2013).

While Big Data offer considerable advantages, they also present researchers with certain challenges. They are messy and uncertain, and their analysis typically derives from the data, which makes it difficult to conduct research underlined by some kind of hypothesis or assumption (Rob Kitchin, 2014). Social media analytics is still at its infancy (Brooker, Barnett, & Cribbin, 2016; Snee, Hine, Morey, Roberts, & Watson, 2016b) and the various online platforms set restrictions that inevitably influence findings (Boyd & Crawford, 2012). Additionally, 'found' data through social media platforms often represent public opinion in research, but might not always reflect consumers' opinions transparently (Manovich, 2011; Snee et al., 2016a).

For researchers concerned with the study of Big Data, it is imperative to understand how consumers use the different online platforms and how these can be combined in research (Snee, Hine, Morey, Roberts, & Watson, 2016c). In the context of movies, the majority of eWOM studies are carried out with data from Twitter, as it is the main promotional platform used by studios (Baek, Oh, Yanf, & Ahn, 2014) and can provide very useful insights on movie adoption (Hennig-Thurau et al., 2015). However, movie trailers are first posted and shared through YouTube. The two platforms are considerably different in the way that buzz is produced and shared. Due to the nature of Twitter, comments are short and have a wide reach. YouTube, on the other hand, poses no restrictions on the length of comments and allows for a richer analysis of the audience's opinions. For this reason, the main dataset for Paper 3 was compiled with comments from YouTube. However, Twitter buzz could not be disregarded and a second dataset was compiled from Twitter to control for the effect of Twitter on BO performance. Freely available movie-related data was manually compiled from various platforms – such as IMDb, the Numbers, Box Office Mojo.

Consumers' online comments underwent sentiment analysis in order to extract buzz metrics through Natural Language Processing techniques. Consistent with extant movie WOM research (Hennig-Thurau et al., 2015; Karniouchina, 2011a; Liu, 2006), relationships between buzz components and box office performance were tested through statistical analysis (see section 3.3.1 on Analysing data quantitatively).

- Analysing big data through Natural Language Processing techniques

In order to extract the volume and valence of WOM, the secondary data underwent sentiment analysis, which is a form of content analysis. Sentiment analysis has been widely used to extract the valence of WOM (the extent to which comments are positive or negative). Most movie WOM studies concerned with volume and valence have unavoidably performed some kind of sentiment analysis (e.g. Liu, 2006; Rui, Liu and Whinston, 2013; Hennig-Thurau, Wiertz and Feldhaus, 2015) – unless they have used readily available ratings (e.g. Chintagunta, Gopinath and Venkataraman, 2010; Gopinath, Chintagunta and Venkataraman, 2013). While, historically, thematic and sentiment analysis were conducted with the help of human raters (Liu, 2006; Nguyen & Romaniuk, 2014), the emergence of Big Data gave rise to computer-mediated analysis (Lipizzi et al., 2016; Snee et al., 2016a), which is considered the only option for researchers to make sense of such large-scale datasets (George, Haas, & Pentland, 2014).

For the purposes of Paper 3, the data was analysed through Natural Language Processing (NLP), which is a branch of Artificial Intelligence within the Computer Science discipline, concerned with the analysis and the understanding of the natural languages that humans use. Some of its key aspects include the identification of words, their meanings, their emotional strength, their relationships etc. (Ullah, Amblee, Kim, & Lee, 2016). As with all methods, computer-mediated NLP has certain limitations. e-bots publishing fake WOM comments (e.g. tweets) are a recurring problem in computer-mediated research (Lipizzi et al., 2016). Moreover, machine-learning processes are unable to detect sarcasm and as a result, sentiment analysis might not be entirely representative of the text’s valence (Sajuria & Fabrega, 2016). Nevertheless, the refinement of such methods is constant, and algorithms are now able to even detect emoji’s and translate them into sentiment (Knight, 2017).

A summary of the three papers will now follow.

3.4 Summary of Paper 1

The first paper was concerned with exploring initial relationships between understanding, liking, WOM and purchase intent. More specifically, it examined the power of understanding and liking the movie trailer in generating favourable WOM and consequently driving audiences to the cinema. By doing so, it followed the assumption that advertising leads to WOM and added *understanding* as an important antecedent of WOM and purchase intent. While liking has been historically linked to WOM and purchase intent (Boksem & Smidts, 2015; Vaughn, 1986; Wilson, Mathews, & Harvey, 1975; Xiong & Bharadwaj, 2014), *understanding* was a new concept to be tested in this context. *Understanding the movie trailer* had not been explicitly studied in movie literature either, although there had been mention of trailer elements that signal good quality (Campbell, 2008; Flanagan, 2012; Iida, Goto, Fukuchi, & Amasaka, 2012). The proposed conceptual framework, designed specifically for Paper 1 is presented below (See Figure 3)

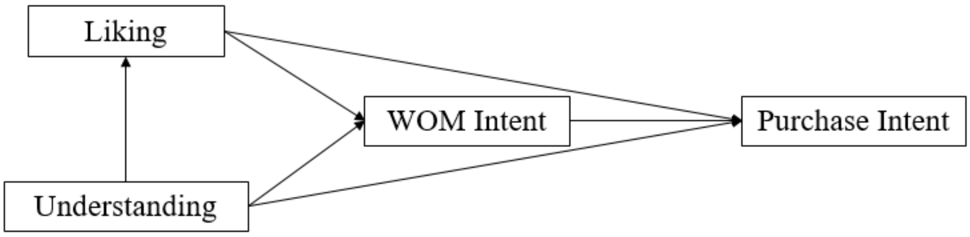

Figure 3: Conceptual framework for Paper 1

Data was collected through an online survey. Ninety-four respondents were recruited within a university environment and were exposed to trailers of 4 selected movies, providing thus 396 cases for analysis. The sample was selected to match the Motion Picture Association of America's annual report on the most frequent moviegoing age group (MPAA, 2018). Only respondents aged between 18-39 completed the survey. The movies were selected on the basis that they hadn't yet be released by the time of the survey, so essentially the trailers provided the only source of information on the upcoming movie. Genre, star power and marketing budget was taken into account. After watching each trailer, respondents reported:

1) to what extent they thought they understood what the upcoming movie was about,
2) to what extent they would spread positive WOM online,
3) to what extent they liked the trailer, and
4) to what extent they would pay to watch the movie at the cinema

Partial least squares structural equation modelling (PLS-SEM) was deemed the most suitable method for analysis, since the study was of an exploratory nature, and the sample was relatively small in size (Hair, Sarstedt, Ringle, & Mena, 2012). Interestingly, findings showed that consumers who liked the trailer but also understood it were much more likely to spread favourable WOM and to pay to see the movie.

Findings from Paper 1 offer significant implications to the wider WOM theory that has positioned product or service (dis)satisfaction as the most important WOM antecedent. They also provide directions for movie marketers to create trailers that offer a clear representation of what the movie is about. The two key limitations of this study concern the limited literature behind the concept of understanding and the use of self-report scales which has been characterised as misleading due to cognitive bias (East et al., 2015; Nguyen & Romaniuk, 2014; Watts, 2007). The former was addressed in Paper 2, with the further exploration into antecedents of understanding, while the latter was addressed in Paper 3, with the collection and analysis of online behavioural data.

3.5 Summary of Paper 2

Extending findings from Study 1 and addressing gaps in prior research in the area of understanding, Paper 2 further explored how understanding is formed through trailer-viewing and examined the antecedents and outcomes of understanding. Paper 2 was split into two studies. Study 1 investigated heuristic cues by which consumers build their perceptions, highlighting that objective and subjective understanding are two distinct constructs. Study 2 incorporated message and receiver-related characteristics and examined their effect on the two understanding constructs, which in turn were tested against ad (trailer) and product (movie) liking. The proposed conceptual framework designed specifically for the purposes of the second paper is presented below (See Figure 4).

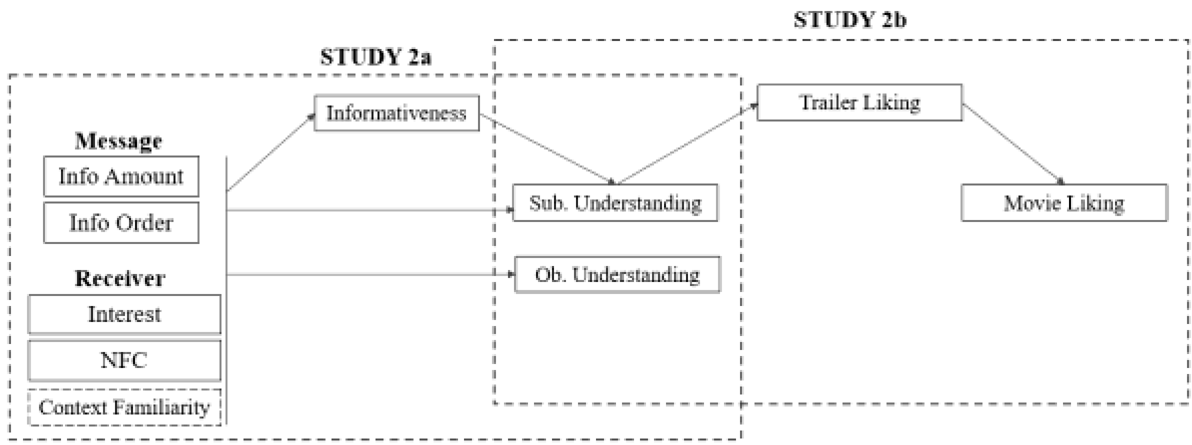

Figure 4: Conceptual framework for Paper 2

Both studies were conducted through a series of experiments, consistent with prior research in information-processing and persuasive advertising. In Study 1, respondents aged between 18-39, were exposed to four trailers and were asked to describe them and to report to what extent they thought they understood what the movie is about. Trailers were selected to match initial categorisations on *Information Order* and *Context Familiarity*. The selection of stimuli was carefully carried out to minimise bias: all trailers advertised wide-release movies that had not yet been released, included at least one star and had at least one overlapping genre (comedy). Thirty-seven usable responses provided 148 unique cases. Respondents' retrospective thoughts underwent content analysis and seven key themes through which consumers understand and explain what a movie is about were derived. The retrospective thoughts also served as a way to measure objective. T-test analysis revealed the disparity between objective and subjective understanding and the effect of both categorisations (*Information Order* and *Context Familiarity*) on the two constructs.

Study 2 manipulated further message content and receiver-related variables and divided grouped trailers by context familiarity (four sequels and four original trailers). The study design, sample and stimuli selection was similar to Study 1. One hundred and seven usable responses provided 428 unique cases. Along with questions from Study 1, respondents were asked to indicate:

- how much information they thought they derived from the trailer
- to what extent they liked the trailer and thought they would like the movie
- to what extent they had an interest in moviegoing, and
- whether they were familiar with the trailer's characters or storyline (for sequel trailers).

They were also tested on the NCS scale (short form; Cacioppo et al., 1984), as an indication of their Need for Cognition (NFC).

Findings demonstrated that consumers are overconfident in the amount of information they feel they have understood, but it is this *perception* of understanding that influences ad and product liking. Statistical analysis revealed that the amount and order of information were both good predictors of subjective understanding of original and sequel trailers and that this relationship was mediated by perceived informativeness.

Findings from Paper 2 contribute new knowledge to information-processing and persuasive advertising literature and offer directions towards a subjective understanding paradigm, since it proves to be a significant predictor of ad and product liking in the model. Subjective understanding, therefore, assumes a position as an antecedent of liking, extending findings from Paper 1. Paper 2 does not only provide researchers with insight on which message content parameters are important in aiding perceptions of understanding but also offers directions to movie marketers on how to design effective and comprehensive trailers in order to ensure positive consumer response. Limitations of self-report scales were addressed in Paper 3.

3.6 Summary of Paper 3

Paper 3 investigated relationships established in the first two papers through the collection and analysis of online behavioural data. More specifically, it explored the trailer categorisations on consumers' liking manifested through PRCB on YouTube. It further tested the effect of different PRCB components on opening weekend BO. The proposed conceptual framework designed specifically for the purposes of Paper 3 is presented below (See Figure 5).

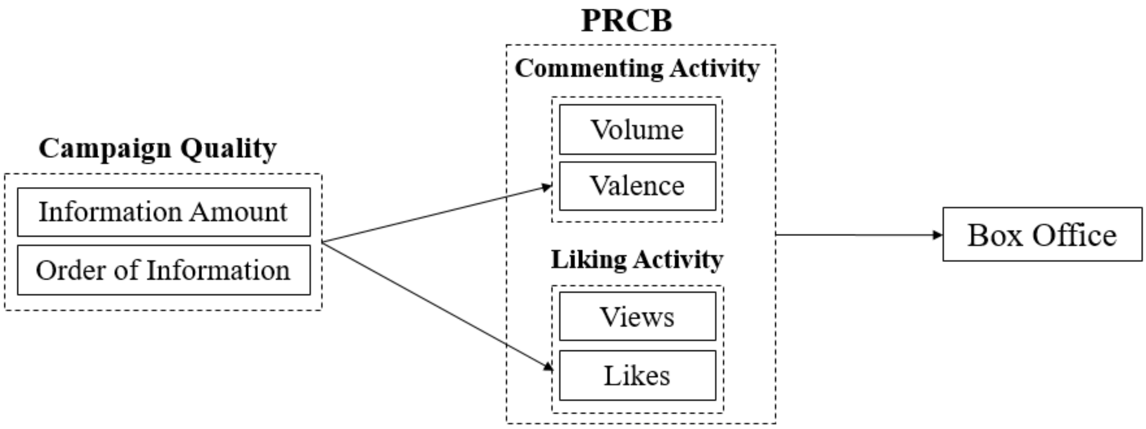

Figure 5: Conceptual framework for Paper 3

YouTube data on all wide-release movies was collected over a two-year period (Nov. 2015-Dec. 2017), forming a dataset of 1.5 million pre-release comments. Other movie-related data – such as the production budget, the opening weekend box office, the movie's genre etc. – were collected from publicly available webpages.

Paper 3 was divided in two studies. In Study 1 three independent raters categorised 416 trailers of 146 movies into the *Information Amount* and *Information Order* categorisations. Sentiment analysis on the conversations of each trailer was then performed to extract the valence of comments. Other components, such as the number of comments, views and likes for each trailer, were also included in the PRCB construct. A series of regressions tested the effect of message content parameters on commenting and liking activity. Other parameters – such as genre, star buzz etc. – were included in the model to control for movie-related effects. The trailer categorisations turned out to be significant only under certain, movie-related circumstances.

Study 2 explored the effect of various PRCB components – comments' volume and valence, views and likes – on opening weekend BO. Parameters which have been found to influence BO in prior movie research (e.g. budget, star power, theatre distribution) were also included in the model. Addressing the long-standing debate on WOM volume and valence, findings highlighted the superiority of volume and demonstrated that the number of views is the most important predictor of opening weekend BO.

Findings from Paper 3 contribute new knowledge to the recently established construct of PRCB. By demonstrating that trailers are indeed widely talked about during their pre-release phase and that the number of trailer views can predict early BO performance, emphasis is given on buzz variables beyond volume and valence. Although trailer categorisations deriving from Paper 2 were found to lead to consumer liking only under certain circumstances, findings support Paper 1 on the importance of movie genre and Paper 2 on the significance of context familiarity.

The following three chapters correspond to each of the three papers produced for this thesis.

Chapter 4: Paper 1

<table>
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<tr><td colspan="10">Conditions in Prerelease Movie Trailers for Stimulating Positive Word of Mouth: A Conceptual Model Demonstrates the Importance of Understanding as a Factor for Engagement</td></tr>
<tr><th colspan="10">Publication status (tick one)</th></tr>
<tr><td>draft manuscript</td><td></td><td>Submitted</td><td></td><td>In review</td><td></td><td>Accepted</td><td></td><td>Published</td><td>X</td></tr>
<tr><td>Publication details (reference)</td><td colspan="9">Archer-Brown, C., Kampani, J., Marder, B., Bal, A., & Kietzmann, J. (2017). Conditions in Prerelease Movie Trailers For Stimulating Positive Word of Mouth: A Conceptual Model Demonstrates the Importance Of Understanding as a Factor for Engagement. Journal of Advertising Research, 57(2), 159–172.</td></tr>
<tr><td>Candidate's contribution to the paper (detailed, and also given as a percentage).</td><td colspan="9">The candidate predominantly led the formulation of ideas.

Formulation of ideas: 70%

Design of methodology: 30%

Experimental work: 0%

Presentation of data in journal format: 15%</td></tr>
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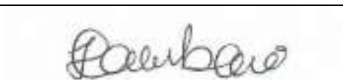
<tr><td>Signed</td><td colspan="5"></td><td>Date</td><td colspan="3">28/02/2019</td></tr>
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Data Access Statement:
Due to confidentiality agreements with research collaborators, supporting data can only be made available to bona fide researchers subject to a non-disclosure agreement. Details of the data and how to request access are available at the University of Bath Research Data Archive at: https://doi.org/10.15125/12345.

WARC
BY ASCENTIAL

Alan Saywood
Production Editor, Reports and Journals
85 Newman Street
London
W1T 3EU
01/03/2019

Dear Julia Kampani,

On behalf of WARC, I grant you permission to include the article "Conditions in Prerelease Movie Trailers For Stimulating Positive Word of Mouth: A Conceptual Model Demonstrates the Importance Of Understanding as a Factor for Engagement" from the Journal of Advertising Research in your PhD thesis.

Kind regards,

Alan

Conditions in Prerelease Movie Trailers for Stimulating Positive Word of Mouth: A Conceptual Model Demonstrates the Importance of Understanding as a Factor for Engagement[2]

Abstract

Filmmakers increasingly depend on trailers as advertising and to generate word-of-mouth (WOM). This study investigates the extent to which trailers influence WOM in the pre-release context by testing a conceptual model separately on the three most popular movie genres. Where viewers perceive greater understanding of the movie from the trailer, the prospect of liking it is significantly increased. This leads to a substantial increase in their intent to generate WOM and, ultimately, their willingness to pay to see the movie. These novel findings lead to practical implications for studios hoping to stimulate consumer interest, with wider contributions to advertising theory.

Key Words

Motion Picture Industry, Movie Trailers, Word-of-Mouth, WOM Volume and Valence

Management Slant

1. Across three main movie genres, a perception of understanding prompted by a trailer is linked with greater likelihood for viewers to believe they will like the movie.
2. In combination, these are positively related to increased intention to engage in WOM.
3. The model explains a high proportion of the variance in respondents' intention to purchase.
4. When studios ensure that audiences understand the essence of the movie from the trailer, sales may be positively affected.
5. Our findings can help studios develop pre-release engagement with the movie ahead of the critical first weekend box office.

[2] An earlier version of this chapter was presented during the Academy of Marketing Science (AMS) Annual Conference in 2014

4.1 Introduction

The movie production and distribution industry is economically and socially significant (Booth & Geis, 2006). Employing 866,000 people and generating revenues of $92 billion per year globally, the motion picture industry is a serious player for consumer dollars (IBIS World, 2014). Planning a movie is still believed to be “an enormous crapshoot” (Squire, 2006:5) into which significant costs are sunk before the product even reaches audiences.

Historically speaking, films with well-thought-out pre-release strategies often have greater audience success, so producers invest considerable people hours and funds to this end (Vogel, 2001). In the dominant model, studios take advantage of a short promotional window immediately ahead of release (Friedman, 2006). They organize their strategies into a blitz formation, whereby all marketing tactics are run simultaneously (Eliashberg, et al. 2000). Pre-release marketing campaigns are usually omni-medium communicators directly with audiences. These include: a) advertising and public relations support such as trailers and teaser campaigns (Dellarocas, et al. 2007); b) exploiting the pull of the movie’s main stars through interviews and other appearances (Elberse, 2007); and c) utilizing critical reviews from professional and amateur critics to drive interest to the movies (Chakravarty, et al. 2010). These components aim not only to increase potential consumers’ intention to pay to see the movie, but also to create personal recommendations (Eliashberg, et al. 2000) and word-of-mouth (WOM)—all key factors in generating box office success (Liu, 2006).

Movie trailers are short promotional videos (less than 2 minutes 30 seconds) that exist to excite patrons about full-length movies to come. Trailers have been shown to be particularly impactful in stimulating WOM prior to release and drive box office sales. They are an important part of the film “paratext”, a term that is borrowed from the literary world (Genette and Maclean, 1991). In this context, it refers to the information that surrounds the movie itself, including the trailer (Preece, 2011; Kernan, 2004). Originally used as advertisements shown on television and in cinemas, trailers now also are shared widely on social media (Kietzmann et al., 2011). The most popular trailers generate tens of millions of views and stimulate significant eWOM in the form of shares, “likes” and comments.

“WOM” refers to the influence exerted on consumers’ brand considerations by people within their networks (Dichter, 1966) and is noted to be an important factor in the purchasing decisions (Richins & Root-Shaffer, 1988; Keller & Fay, 2009). Although research into the phenomenon dates to the 1960s, it has been the subject of significant interest in the past decade as electronic channels have intensified the effect of personal recommendations (Hennig-Thurau et al., 2004; Yeo, 2012).

A complementary effect between advertising and WOM exists (Day, 1971), whereby WOM, coupled with advertising amplifies the efficacy and persuasiveness of the campaign threefold (Hogan et al., 2004). The same phenomenon has been tested in the movie industry (Eliashberg et al., 2006), but the focus has tended to be on the role of advertising in stimulating a direct effect on box office success and in testing WOM as a post-release phenomenon (Elberse & Eliashberg, 2003; Basuroy et al,. 2006; Clement, et al. 2013). This is because satisfaction is one of the antecedents of WOM (Brown et al., 2005), which cannot exist in the pre-release phase. Because trailers provide a free sample of the finished product (Kernan, 2004), and a significant proportion of online content references the characteristics of the movie (Nguyen and Romaniuk, 2014), it is clear that opinions on the movie can be formed prior to release. It is therefore feasible that the valence of WOM can be affected by the opinions of people who post online comments based on the trailer in isolation.

Although numerous studies have charted the influence of trailer content and timing, very limited research has been conducted regarding the relationship among trailers, WOM and box office success. This article makes three key contributions: 1) it operationalizes extant literature on trailers, which is impactful to movie producers as they commission promotional campaigns; 2) it offers a contextual extension to WOM theory, by empirically testing key antecedents that show a clear increase in intended WOM engagement; and 3) it adds to an important narrative in this and other journals that explores the complementarities between advertising and WOM.

The article is organized into four parts: first, the context of the present study is outlined through a brief overview of WOM and social media in the movie industry. Next, the production of trailers as an extended form of advertising is considered. Then, the procedure for the study is outlined and the findings are presented. Finally, the implications for theory and practice are discussed.

4.1.1 WOM in the Movie Industry

Marketing is one of the main drivers of the performance of a movie (Prag & Casavant, 1994) and positively influences box office success even if the product is poor (Basuroy et al., 2006; Hennig-Thurau et al., 2006; Elberse & Anand, 2007). The inclusion of user generated content (UCG) is noted to extend the accuracy of forecasting models, and complementary effects between advertising and this form of WOM are apparent (Dellarocas et al., 2007).

In general, although advertising can set the scene for success (Day, 1971; Allsop et al. 2007), WOM is the key factor that influences purchasing decisions (Dichter, 1966; Riegner, 2007). This particularly is true of experiential purchases such as movies (Eliashberg et al., 2000). WOM is a key antecedent to distribution decisions (Clement et al., 2013) and is associated directly with box office (BO) success (Liu, 2006; Duan et al., 2008; Karniouchina, 2011).

The *volume* of WOM has performed well consistently as a key predictor of BO success, with a direct, strong influence (Eliashberg et al., 2000; Hennig-Thurau et al., 2007; Chintagunta, 2010). Inconsistencies exist in the findings of research into the direct effect of the *valence* of pre-release WOM on BO success. Online reviews were found not to influence BO success (Liu, 2006), although this was contradicted by later findings in which valence exerted a positive, direct effect on BO success (Chintagunta, 2010). Despite this, positive WOM – where the person posting portrays a degree of empathy and interest in the movie – has a significant relationship to box office performance and consequently leads to greater volume of WOM (see Figure 6; Duan et al., 2008). In this sense, WOM is both an antecedent and an outcome of box office sales.

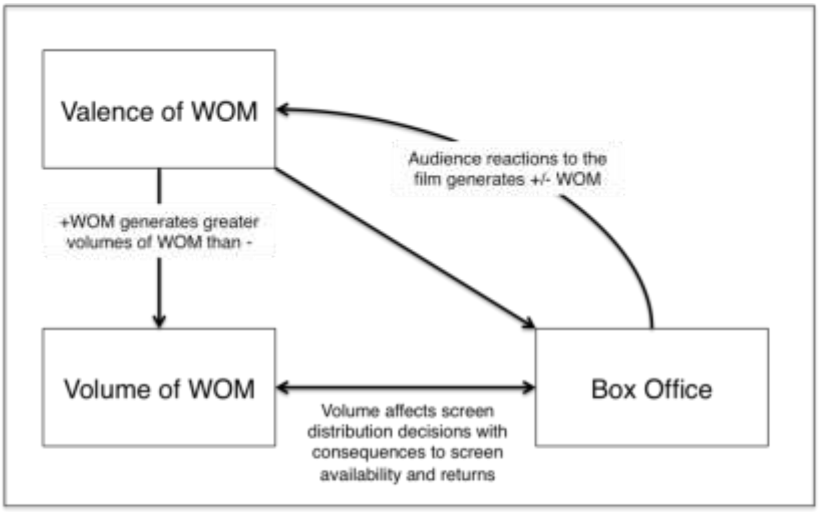

Figure 6: Theoretical model: Relationship between valence, volume and box office post-release WOM

Note: WOM = word-of-mouth; source: adapted from Chintagunta (2010); Duan et al. (2008); Eliashberg et al. (2000); Liu (2006)

The marketing campaign initiated by Lionsgate to support the release of "The Hunger Games: Catching Fire" has been regarded highly (Maloney, 2013) and is an exemplar of the current authors' theoretical model adapted from earlier studies (Chintagunta, 2010; Duan et al., 2008; Eliashberg et al., 2000; Liu, 2006; See Figure 6). The high levels of engagement with content in specially built communities and partner platforms – such as challenge for players of the online "sandbox" (free-roaming) video game Minecraft to build fictional "districts" that mirrors those in the "Hunger Games" franchise – led to a large volume of pre-release buzz. The supporting paratexts, including the trailer, were recognized to reflect the themes of economic inequality and the effects of violence that pervade the books and movies. Early viewers adjudged the movie to have delivered on the promise made in the promotional material and this contributed to the positive sentiment in the WOM generated immediately following release.

Engagement is conceptualised in these types of communities (in line with Sashi, 2012), whereby customers can develop relationships with brands and other members, thereby engaging in co-created experiences. The model supports the conclusion that this engagement perpetuated the growing volume of WOM around "The Hunger Games: Catching Fire", as well as having a direct effect on the box office revenues. Despite its importance to the movie industry, its value in generating pre-release buzz (Phelps et al., 2004; Dellarocas et al., 2007), WOM has received little attention from scholars.

4.1.2 Movie Trailers Background

The first movie trailer was produced in 1913 for the musical "The Pleasure Seekers", as an alternative to a card showing the list of upcoming shows traditionally presented at the end of the performance; hence the name "trailer". Later, trailers became previews; they were moved to the beginning of the movie and, ultimately, outside of the film experience altogether, but they kept the name "trailer". Trailers have become a key feature in that they have their own reviews, include specially composed music, and are nominated for awards (Doperalski, 2012). Over time, trailer design has gone through a number of trends, with some experts suggesting that they should be "vague and teasing", whereas others prefer a more direct approach: "not a narrative, but an abstract representation of one" (Crookes, 2011).

Trailers are promoted via social media up to a year ahead of the planned release date, often well in advance of the movie being completed, with the aim of whetting the audience's appetite for more information. By the time of release, there likely are multiple versions available, varying in timing, character focus, and theme (Crookes, 2011). Evidence of the positive role played by trailers in the direct generation of BO success is more readily available (Hennig-Thurau et al., 2007; Epstein, 2005; Young et al., 2008; Gong et al., 2011).

The literature offers general advice about producing trailers that are intended to stimulate viewing desire. One key theme is to capture the essence of the movie, being as true to its nature as possible (Flanagan, 2012). There are three key questions a trailer should answer for the audience: "Who is this person or these people? What is their problem? And why should I care?" (Campbell, 2008).

The advice to trailer designers is that there is a range of necessary traits that can be used to develop the viewer's *understanding* and *liking* of the movie itself, with the goal of achieving two positive outcome intentions: recommending the movie to friends, and paying to see it. These consequences are complementary in nature (See Figure 7).

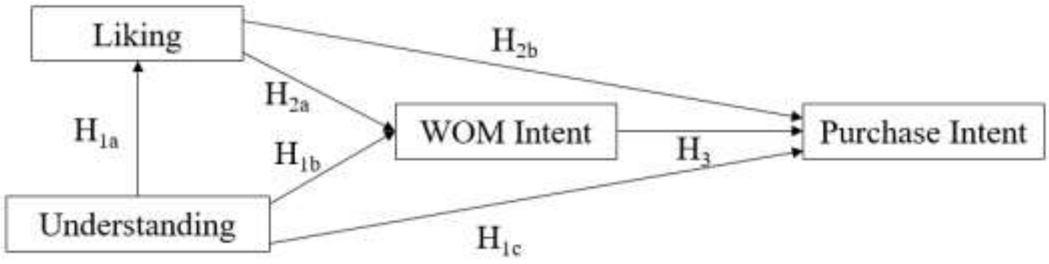

Figure 7: Conceptual Model: The potential impact of understanding and liking on WOM and purchase intent
Note: WOM = word-of-mouth

4.2 Hypotheses development

The conceptual model reflects and develops extant theory on the relationship between WOM and purchasing behavior. Unlike the majority of prior literature, the focus is on pre-release WOM leading the authors to consider the issue of self-reported measures that focus on future intentions.

4.2.1 Intention to generate WOM and purchase

There is a tradition of modeling intentions for both WOM and purchase in retailing (Maxham & Netemeyer, 2002; Babin et al, 2005) and similarly in other contexts – for example, intention to donate in the charity sector (Ford & Merchant, 2010) or WOM related to switching intention (Lee and Romaniuk, 2009). Researchers have recognized potential limitations of WOM intent measures, particularly those that are recommendation-based (Romaniuk et al, 2011; East et al, 2015), albeit noting that behavioral alternatives are also challenging (Delarocas et al, 2007). Similar reservations apply to purchase intent scales (Wright & MacRae, 2007; Mortwtiz et al, 2007) although in these studies, the choice was less problematic; because of the pre-release context of the study, intention to pay to see the movie was the only suitable measure.

The current authors concluded that although self-reported, intention-based dependent variables are imperfect, they were appropriate in this case because of: a) the exploratory nature of the study itself; b) the desire to test a single model, which required equivalent data; c) the collection of empirical data that reflects the real-world (i.e. responses from test audiences) from which costly advertising decisions are made; and d) the focus on consumer engagement rather than specifically on recommndations.

4.2.2 The role of understanding

The role of understanding a message such as one contained in a movie trailer is not well developed in the academic literature and thus formed an exploratory element of the study. Conversely, conventional wisdom in the form of expert practitioner advice tends to focus on the outcome or ‘the essence’ of the movie as captured in the trailer (Flanagan, 2012). This was supported by other research (Iida et al., 2014). In such cases, the viewer feels a heightened sense of understanding, which is defined as a representation of an individual’s knowledge of concepts based on his or her view of underlying objects, events, and actions (Rumelhart 1991).

This conceptualization is congruent with information-processing based persuasion models (McGuire, 1968), in which comprehension is the basis of ongoing consideration. In experiments on comprehension, message reception and comprehension have led to greater levels of agreement (Chaiken & Eagly, 1976; Eagly 1974; Jacoby & Hoyer, 1982). This effect has been noted especially for televised messages, as opposed to audiotaped and print messages (Chaiken & Eagly, 1976). Researchers consequently operationalized prior studies by testing the respondents’ perception of their understanding of the movie as a result of their initial viewing of its trailer. This is the starting point of the current conceptual model (See Figure 2).

4.2.3 The role of liking

When respondents understand the movie, liking the trailer increases, which is measurable as enhanced sympathy with and interest in the movie itself (Iida et al., 2012). In combination, the current authors refer to these variables as an increased liking on the part of the respondent toward the movie, which is consistent with previous perspectives (Morgan, 2000). Tests that matched electroencephalographic (EEG) results with self-reported liking, were found to predict not only individual viewing preference, but also population-wide BO success (Boksem and Smidts, 2015).

Although contradictory evidence has been reported regarding the direct effect of the valence of WOM on box office success, there is much more convergence in researchers' findings regarding its overall effect (Chintagunta, 2010; Duan et al., 2008; Eliashberg et al., 2000; Liu, 2006). As previously established, therefore, the measurement of the respondents' liking or otherwise of the movie is an important factor as this acts as an indicator of the valence of any WOM generated. This thinking informed the following hypotheses which describe the direct effects that the model illustrates:

H_1 Increased understanding of the movie perceived by the respondents as a result of viewing its trailer, will generate a positive effect on respondents':

a) Liking the movie.

b) Intention to contribute to WOM.

c) Purchase intent.

H_2 Increased levels of liking the movie as a result of viewing the trailer will lead to increased:

a) Intention to contribute to WOM.

b) Purchase intent.

H_3 Intent to engage in WOM about a movie as a result of viewing a trailer will be correlated with intention to purchase.

Theoretical contributions often can be derived from the investigation of conceptual models (See Figure 7). Extant research indicates that engagement with online communities provides a positive route for increased brand engagement (Sashi, 2012). This is supported by examples outlined previously, in which studios successfully have used WOM to develop a community following for their movie (Lang, 2014). From the consumer perspective, engagement with brands in this way is linked positively with sustained interest (Richins & Root-Shaffer, 1988). Consequently, the current authors tested the following hypotheses:

H4 WOM will mediate the relationship between:

a) The understanding of the trailer and the intention to purchase.

b) Liking of the movie and the intention to purchase.

4.3 Methodology

4.3.1 Pilot Study

A pilot study was designed to confirm: a) that the interpretation of the literature led to the development of a plausible model for testing; b) that the stimuli – movie trailers – feasibly prompted the WOM engagement inferred from the literature; and c) that the measures – particularly related to understanding and sharing behavior – were supportable.

The researchers selected a range of heavily promoted movies and, in keeping with the procedure for categorization outlined by Rich (1992), conducted a theoretical categorization of trailers. They uncovered evidence of a range of features that, in combination, contributed to the viewers' understanding of the movie as a result of viewing the trailer. These included: a) timing (Tourmarkine, 2005); b) the role of characters in developing or outlining the plot (Campbell, 2008; Flanagan, 2012); c) the nature of the narrative (Maier 2009; Crookes 2011); and d) the trailer's explanatory power (Iida et al., 2012). The research team conducted three separate focus groups (*n* = 18) in which respondents viewed a range of trailers and discussed the extent to which this would lead them to engage with the movie. The categorization of understanding related to the trailer archetypes was broadly congruent with the model, on the basis of respondents' verbal indication. This supports the notion that understanding operationalizes practitioner advice to capture the essence of the movie (Campbell, 2008) and confirmed that the stimuli and measures were appropriate. By investigating respondents' intended sharing behavior, the authors were able to validate the suitability of chosen WOM measures. On the whole, this pilot study supported the authors' interpretation of the literature and the development of the conceptual model.

4.3.2 Sample details

The sample frame was consistent with the audience segment recognized as being the most frequent visitors to movie theatres (*age* = 18-39) (MPAA, 2015). This type of purposive sampling method is acceptable where the criteria are objectively derived (e.g., age), supported by the context (in this case, the consumer segment), and where results are not generalized beyond the group from which the sample was derived (Black, 1999).

The researchers recruited participants by promoting the survey link through social media, and they encouraged participants to share the survey link, thereby creating a snowball effect. Although possible limitations of this approach are acknowledged, its application in this context is supported. First, it is impossible to acquire population lists of social media to perform randomized sampling (Tow et al., 2010). Second, this is common in the type of study in which adult Internet users are the population of interest (McMillan et al., 2003; Matook et al., 2015). Third, respondents who did not meet the exact criteria for age or who did not confirm that they had paid to view movies in the two months prior to completing the questionnaire were excluded from the data collection.

The procedures reflected those outlined in prior research (Matook et al., 2015) to counterbalance concerns of bias from snowball sampling: the survey was seeded over two disjoint social media sites, Facebook and Twitter, by researchers based in different countries with almost no overlap in their networked connections. Together these measures were aimed at reducing the likelihood of participant repetition, thereby increasing the validity of the overall study (Sudman and Kalton, 1986).

4.3.3 Survey Design & Procedure

In order to stimulate respondents' perceptions of the movie, the researchers initially selected four movies that were due for release to theatres in the late summer of 2014 in North America and Europe. Movies were initially selected from the Science Fiction and Fantasy genre (hereafter referred to as "sci-fi"). In order to test the model across different genres, the researchers replicated the study twice: first with comedies (comedy) and later with movies that fitted with the thriller classification (thriller).

Although the movie selection was centered around the studios' release schedules, bias was controlled for as rigorously as possible. All trailers were at least 3 months ahead of release at the time the survey was taken; all were big movie releases supported by big studios and a minimum of $10m advertising spend; each had at least one major movie star as part of the cast; the trailers used were official trailers rather than very early stage teasers. The authors acknowledge that controlling for endogeneity in models of this type is problematic, and only fully resolved by experimental conditions, but by testing 12 different trailers, from three genres, across three time horizons, sufficient variation to the study was introduced to minimize bias as a result of endogeneity in the model (Shugan, 2004).

In order to simulate the experience of viewing the trailer online, the researchers embedded the html code from the YouTube channel for each trailer into an online survey instrument.

The order of the trailers was randomized, which controlled for order effects. In order to establish a common experience that was similar to the norm in the chosen platform, the researchers asked respondents to watch the embedded trailer in the same window rather than open a new browser window or tab. Participants watched four trailers and answered related questions immediately after viewing each one; they were only able to move forward after the trailer had finished. Demographic and secondary questions were asked at the end of the survey.

After all four trailers, the following scales were shown: 1) understanding of the film, measured using a 5-item scale that was developed using Rumelhart's (1991) concepts, as outlined previously (Likert scale Strongly Disagree – Strongly Agree); 2) WOM intent, measured using an adapted 5-item WOM scale (Babin et al. 2005) (7-points: Strongly Disagree – Strongly Agree); 3) liking of film, trailer and story of each film, measured with a 3-item scale (6-points: Like Very Much – Dislike Very Much); 4) purchase intent, measured with a 3-item scale specific to the context (7-points: Strongly Disagree – Strongly Agree). The understanding and purchase intent scales were very particular to the context of the study and were developed with the outcomes of the pilot study. As outlined in a prior section, because the context of the study was trailers released several months ahead of release and the desire was to test a single model with equivalent data, intent scales were the only feasible option, although possible limitations were recognized. The survey instrument was designed to minimize the risk of common method bias, including: reversed questions, different Likert scales (7 and 6 points), tasks designed to offer variance in respondent activity, and clearly stated questions to avoid confusion (Mackenzie and Podsakoff, 2012).

In order to test the model, there researchers selected partial least-squares structural equation modeling (PLS-SEM), whereby relationships among multiple constructs can be measured simultaneously. The technique is often linked with exploratory studies. In this case, elements of the study previously were tested: liking, intent to generate WOM, and purchase intent. Two elements, however, were exploratory and were incorporated with the specific intention to develop theory: first, the relationship between understanding and other constructs was underexplored and second, testing this in relation to movie trailers was novel.

From a methodological perspective, the justification for the use of PLS-SEM was made on the basis of key factors. First, the goal was to predict "driver" constructs (Hair et al., 2011) which in this case refers to the extent to which WOM and purchase intent were stimulated by variables in the model. Second, the model includes both reflective and formative measures, which means that PLS-SEM was the most appropriate choice (Hair et al, 2014). Its efficacy when compared with covariance-based structural equation modeling has been found to be acceptable (Reinartz et al., 2009) and it is considered suitable for testing marketing theory (Hair et al, 2011; Fornell and Bookstein, 1982; Gruber et al., 2015). Third, although the total data pool was 310 respondents, the model was tested in each genre as part of multi-group analysis. Subsequently the small sample advantages associated with PLS-SEM meant it was the only viable option using the ratio method of 10:1 recommended by Hair et al (2014).

4.4 Results

After completing standard procedures to validate the data, the researchers included in the analysis completed surveys from 310 respondents, each responding to four trailers. This led to a total of 1,240 observations in the specified model (Sci-fi, n = 94 respondents, 376 observations; comedy, n = 104, 416 observations; thriller, n = 112, 448 observations). The sample passed the ratio-method test for significance at the 10:1 level (Hair et al., 2014) on each individual movie, in each genre and in total. The sample was made up of 62% female respondents; 76% were from Europe. A small number of survey responses was excluded from individuals whose age was outside the target range of 18 to 39, which means that the final sample was drawn from the most frequent movie-viewers range (MPAA, 2015).

4.4.1 Data and Model Validation

Tests were carried out according to procedures outlined by Hair et al. (2014) in SmartPLS version 3.0 (Ringle et al., 2014). Evaluation of outer loadings (See Table 2) exceed the threshold of .708, which indicates construct validity with the exception of one item (Und4). Consideration was given to deletion but this was rejected on basis that the outer loading was within the threshold where deletion is discretionary (.40 -.70) and because the composite reliability score was acceptable (Hair et al., 2014). Composite reliability scores (See Table 3) comfortably exceed <.800 thereby meeting the threshold for construct reliability (Nunnaly, 1978).

Table 3: Psychometric properties and measurement validity

		Understanding	Liking	Intent to Generate WOM	Purchase Intent	Composite Reliability
Und1	The story makes sense to me	.863	.469	.435	.402	.909
Und2	I understand the plot of the film	.872	.392	.344	.297	
Und3	The film seems confusing (reverse)	.817	.517	.307	.223	
Und4	The film has a clear formula	.500	.110	.146	.223	
Und5	The story is hard to comprehend (reverse)	.811	.431	.230	.271	
Aff1	Regarding the Trailer	.490	.918	.543	.480	.963
Aff2	Regarding the Film	.495	.967	.654	.592	
Aff3	Regarding the Story	.497	.955	.641	.589	
WOM1	I am likely to spread WOM about this film	.398	.674	.885	.704	.953
WOM2	I would recommend this film to my friends	.415	.652	.920	.790	
WOM3	If my friends were planning to see a film I would tell them to watch this film	.393	.621	.899	.792	
WOM4	I am likely to spread positive electronic WOM about this film	.301	.523	.890	.631	
WOM5	I would post positively about this film on social media	.292	.459	.861	.650	
IP1	In the future I intend to pay to see this film	.332	.499	.724	.904	.927
IP2	If I were planning to visit the cinema I would be likely to see this film	.362	.585	.791	.938	
IP3	When it is released I will not pay to see this film (reverse)	.289	.496	.625	.856	

Notes: Und: understanding; Aff: liking; WOM; word-of-mouth; IP: intent to purchase

Tests to assess discriminant validity were carried out in accordance with recent literature (Hair et al, 2014; See Table 4). In all cases, the square root of the average variance extracted was greater than the correlations with all other constructs. Through evaluation with the Fornell-Larcker criterion, therefore, discriminant validity was established. A further test was proposed by Hensler et al. (2014) referred to as the Heterotrait-Monotrait ratio, whereby a construct score is <.90, discriminant validity is validated (See Table 5).

Table 4: Fournell-Larcker criterion test

	1	2	3	4
1. Understanding	.785			
2. Liking	.386	.947		
3. Intent to Generate WOM	.403	.163	.877	
4. Intent to Purchase	.390	.065	.795	.899

Note: WOM: word-of-mouth

Table 5: Heterotrait-Monotrait test

	1	2	3	4
1. Understanding				
2. Liking	.553			
3. Intent to Generate WOM	.413	.671		
4. Intent to Purchase	.419	.639	.861	

Note: WOM: word-of-mouth

Constructs were tested for variance inflation factor (VIF) and data were comfortably within the rigorous thresholds of greater than .2 but less than 5.0 advocated by Hair et al. (2014) to confirm that findings are not inflated by multicollinearity. The authors used unrotated principal-components factor analysis to test independent variables, identifying three factors with Eigenvalues of above 1, none of which explained the majority of the variance. Following procedures in Gruber et al. (2015), this was validated using Harman's single factor test. Although this does not guarantee the absence of common method bias, any risk of such was mitigated by validity tests that were repeated for each genre separately, with no anomalies found.

In summary, the data-quality statistics confirmed that the data met accepted standards for convergent validity, discriminant validity, reliability and multicollinearity. Thus, the authors were confident that the findings were reflective of specified relationships rather than the result of construct mis-measurement.

There has been some discussion on the suitability of overall fit indicators in PLS-SEM, given its nature as a primarily exploratory method. The standardized root-mean-square residual (SRMR) has been recognized to indicate the suitability of the model to fit the data (Henseler et al., 2014). In this case SRMR = .07, within the most rigorous threshold referred to in the literature, which indicates that the specified model is plausible (Hu & Bentler, 1999). The multiple correlation value of the dependent variable, furthermore, indicates the overall variance explained by the antecedent constructs, and a value above .500 signifies strong explanatory value. In this case, with R^2 = .646, where key paths were significant at a level greater than 99%, the specified model is considered to be a strong indicator, explaining 65% of the variance in intention to purchase.

4.4.2 Hypothesis Testing

The authors carried out tests to assess the individual path-level multiple correlation values, along with their corresponding significance and f^2 statistics, which indicate the predictive value of the stated path (See Table 6). The focus in this section is on the findings across all three genres in order to identify generalizable findings.

Table 6: Findings from Partial Least-Squares Structural Equation Modelling (all three genres)

H#	Path Level	Path Coeff.	f^2
H1a	Understanding positively affects liking	.537***	.405
H1b	Understanding positively affects WOM intent	.072**	.006
H1c	Understanding positively affects purchase intent	.010	.000
H2a	Liking positively affects WOM intent	.607***	.454
H2b	Liking positively affects purchase intent	.119***	.020
H3	WOM intent is correlated with purchase intent	.717***	.839
	Construct Level	R^2	
	Liking	.288	
	Intent to Generate WOM	.420	
	Intent to Purchase	.645	

*Note: **p<.05, ***p<.001. The f^2 statistic establishes effect sizes for exogenous latent variables.*

The purpose of the f^2 statistic is to establish the effect size of the exogenous latent variable referred to in the respective hypothesis (Cohen, 1988; See Table 4). Note that the paths shown between "Understanding", "Liking", "Intent to Generate WOM", and "Purchase Intent" (representing H_{1a}, H_{2a} and H_3) all exhibit large effects (>.35; See Figure 8).

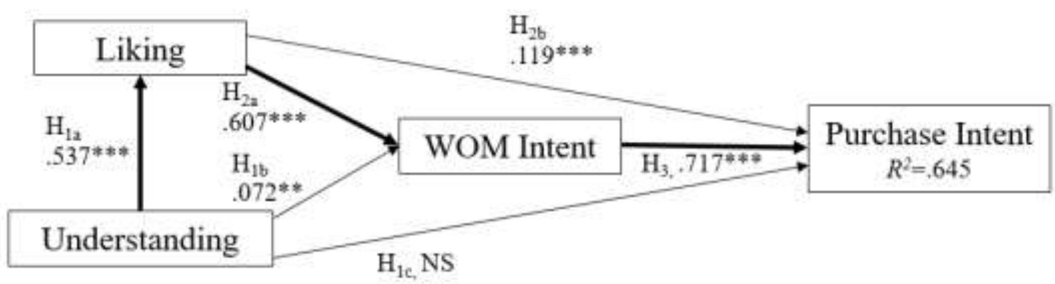

Figure 8:Measurement model with results (all three genres)

Note: Bold lines indicate the paths with large predictive value.

With consideration to the hypothesized direct effects, H_{1a} and $_b$ were supported but the former indicated a substantially larger effect and a high degree of confidence. H_{1c} was rejected, however, in the overall model, which indicates that merely understanding the trailer has no direct effect on resulting intent to purchase.

H_{2a} and $_b$ were both supported, which indicates that increased liking of the movie led to greater intent to generate WOM and to pay to see the movie, although the effect size in the case of H_{2a} also was markedly larger. The last of the direct-effect hypothess (H_3) focused on the relationship between WOM intent and purchase intent, and strong support of this notion is present in the data.

In testing the mediation effects, the authors used bootstrapping procedures outlined by Hair et al. (2014), specifying 1,000 samples and generating the Variance Accounted For (VAF). This represents the proportion of the indirect effect to the total effect, where VAF > 75% indicates the presence of mediation (Hair et al, 2014). Thus, both hypotheses were accepted as described in H_{4a} (understanding to purchase intent: VAF = 97%); and H_{4b} (liking to purchase intent: VAF = 78%). In addition, it is noted that in the case of H_{4a} full mediation was inferred on the basis that the direct relationship is non-significant and for H_{4b} partial mediation was noted (Baron & Kenny, 1986).

4.4.3 Assessing Differences between Genres

Using multigroup analysis techniques, the researchers estimated the differences among the three genres at the path level, focusing on the relationships between “Understanding”, “Liking”, “Intent to generate WOM”, and “Purchase Intent” (See Figure 2). In general, the nature of the model was the same across sci-fi, comedy and thriller genres, which indicates congruence across the three most popular movie categories. In all but one case, differences between paths did not affect the interpretation of the model.

In the case of the path represented by H_{1a} – understanding and liking – a significant difference between sci-fi and both other genres was noted ($R^2_{difference}$ = $.170_{comedy}$ and $.242_{thriller}$; p = <.002). When the comedy genre was compared with thrillers, the differences were marginal and non-significant, indicating congruence between the two.

Further inspection of the model indicated that the direct path between understanding and WOM in the sci-fi genre is larger (R^2 = .227) than in the model for comedy or thriller, where negligible effects in that path are observed. These findings are interesting for comparisons of the application of the model in different movie categories, but do not affect the overall interpretation of the model. Although understanding was important in all three genres, the effect was concentrated on the relationship with liking in comedies and thrillers, whereas it was spread between liking and WOM intent for sci-fi. Possible explanations for this effect are considered in a later section; no other significant differences were noted.

4.5 Discussion and Conclusion

The authors' findings show that although liking a particular film and understanding a trailer may be considered predictors of ultimate intent to purchase, these two constructs are mediated by WOM intent. Neither liking a particular film nor understanding of a trailer offered substantial predictive value of purchase intent without the WOM intention. Consequently, this can be seen as a form of consumer engagement. It follows that increased WOM engagement in social media leads to an increased commitment to a product or service (Sashi, 2012). The findings support the idea that liking the film alone is not a predictor of purchase intention. For filmmakers, merely making a great film will not guarantee audience members. Although trailer understanding is a must, understanding alone likewise is insufficient to entice audiences to watch a film. When liking and understanding exist in unison, however, the likelihood of WOM intention is increased, which has a strong, positive relationship with purchase intent.

The evidence strongly indicates that understanding acts as a suitable proxy for capturing the essence of the movie (Crookes, 2011). This provides a combined perspective of the viewer factors that were previously found to predict the effectiveness of a trailer: the story, the outline, and its ability to be understood. The study supports and extends these findings, indicating that understanding exerts a strong, direct effect on the respondent's liking of the movie.

These are novel findings, given that these relationships have not been included previously in prediction models. One possible explanation for the findings, however, is that although WOM classically has been linked with diffusion of innovations (Arndt, 1967; Rogers, 1962), recent research in this context has indicated that prior experience exerts a significant effect on the nature of WOM (Nguyen and Romaniuk, 2014).

In the case of sci-fi, it is clear that viewers of trailers are more inclined to engage in WOM in cases where liking of the movie was not necessarily present. It is possible that viewers wish to discuss complexities related to the plot or wish to engage with the science that underpinned the story. Perusal of the comments related to trailers for recent sci-fi blockbusters “Interstellar” and “The Martian” supports both notions: much of the discourse related to those trailers focuses on the physics that underpinned the story rather than general discussion of the plot or the performances, as was the case for “Legend” in the thrillers genre. It is not suggested that the reaction was more positive for “Legend” *per se,* simply that in the two sci-fi examples, audiences were motivated to discuss a wider range of topics in social media.

The direct influence of the respondents’ liking of the movie was tested directly with WOM and purchase intent (H_{2a} and $_{b}$). Although these direct relationships do not feature specifically in prior literature related to the model of movie success, they are implied (Iida et al. 2012). As such, the relationships are intuitive, and they may not add significant contribution in isolation. Hypothesis 3, furthermore, specifically tested the direct relationship between the respondents’ propensity to generate WOM and their intent to purchase. There is strong support for the notion that there is significant correlation between them, which provides further evidence of a complementary effect (Hogan et al., 2004).

The factors tested should be considered holistically, and the overall explanatory power of the model is strong (as attested by the SRMR and the multiple correlation of the dependent variable). This indicates that the combination of understanding and liking led to greater intention to generate WOM and that this increased purchase intent. These findings indicate that WOM from those who felt they would like the movie generated a greater effect than those who did not, whose views were included in the direct path, where a much lower effect size was noted. This offers support to notion that valence of WOM influences purchases as found by Chintagunta (2010), whose results were in contradiction to prior research that found no direct effect (Liu, 2006). This is an important contribution to the literature.

As highlighted previously, WOM is significant in the build up to the release of a movie (Dellarocas et al, 2007). Although there has been some debate on the role of the valence of

WOM, most recent research indicated that when WOM is positive, direct and indirect benefits are noted on box office success (Chakravarty et al., 2010). The role of the trailer in stimulating these effects, however, has not been tested previously. The model tests the key factors, measuring liking in terms of positive WOM (Babin et al., 2005), and proposing that a perception of understanding the movie as a result of viewing the trailer is the measurable outcome of capturing its essence (Flanagan, 2012).

This is a novel contribution to theory, because it complements significant extant research which has focused on post-release WOM, for which satisfaction is a key contributor, but is absent in cases in which the movie itself has not been released. In the traditions of research into WOM in the context of the movie-industry, the authors speculate that these findings may be applicable to a wider consumer setting. That said, considerations of practical implications are constrained to the direct context.

4.5.1 Implications

The model provides producers and marketers in the movie industry with evidence that could be operationalized in the aim to enhance engagement in the important pre-release phase of the movie. The factors in the model combine to explain a significant proportion of the variance in the intent to engage in discussion about the movie and to pay to view it. The challenge for practitioners is to stimulate and maintain consumer engagement levels to the point that the intention to view is converted to action.

This knowledge fits with the current practice of teasing movies up to a year ahead of theatrical release and producing several trailers that aim to build interest and excitement. On the basis of this evidence, studios may wish to focus on incrementally increasing audience understanding with two key benefits: a) liking appears to be improved, which means that any subsequent WOM can be assumed to be positive; and b) the volume of positive WOM explains a very significant proportion of variance in purchase intent.

The fact that the study was replicated successfully on two separate occasions gives confidence that it is broadly generalizable across the three most popular genres of movie in the largest movie-going age group. An interesting exception was noted in the case of sci-fi movies, for which the relationships vary slightly, but the key takeaway from the model itself – that understanding is the foundation – is not altered.

The model suggests that, by varying a key element of trailers depending on the stage of the movie lifecycle, filmmakers potentially can stimulate dialogue about the movie amongst potential audiences on social media. By doing so, studios can encourage discussion and opinion-sharing which data can assist with future planning of the pre-release campaign, such as determining the most appropriate release date or developing an ongoing narrative in the community that forms around the movie on social media.

4.5.2 Limitations & Future Research Directions

The current research is exploratory in nature, given the relatively scant focus on pre-release WOM in the movie industry and the lack of scholarly material on trailer design. As with all research of this type, some limitations must be acknowledged.

First, the study focused on respondents of a certain age group and, although this adds value in that it reflects the opinions across an important segment of the movie industry audience, the authors are careful not to generalize beyond this age range. Future research may extend the sample frame to include more mature respondents, because those groups may exhibit different behaviors in relation to social media and eWOM.

Second, it is necessary to reiterate the limitation of self-reported intention measures. The authors acknowledge that for prediction models, these are inadequate proxies for future behavior although this inadequacy is mitigated because the primary interest was in the relationship between the factors rather than on predicting audiences *per se*. Nevertheless, future researchers may test actual WOM valence or volume and box office revenues with pre-release understanding scores.

Studies of this nature inherently are subject to the possibility of an unidentified factor being the cause of the noted effects. The use of variation and different stimuli reduces the risk of endogeneity, but this cannot be mitigated fully without the use of experimental conditions; these may be used in future research to identify the specific drivers of understanding in trailers. Similarly, by measuring the dependent variable using the same instrument as the independent variables, the study was subject to the risk of common method bias. While the data passed appropriate tests to identify common method bias, future experimental studies may use actual BO success as the ultimate dependent variable.

Finally, the authors recognize that the personal characteristics of the viewer and even the medium in which it is viewed (e.g. movie theatre or DVD trailer) may impact the results. Future researchers may be interested to consider these in depth, perhaps using experimental methods where such variations can be considered and causation discussed.

4.6 References

Allsop, D. T., Bassett, B. R., & Hoskins, J. A. (2007). Word-of-Mouth research: principles and applications. *Journal of Advertising Research, 47*(4), 398–411.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, *4,* 291–295.

Babin, B. J., Lee, Y.-K., Kim, E.-J., & Griffin, M. (2005). Modeling consumer satisfaction and word-of-mouth: restaurant patronage in Korea. *Journal of Services Marketing*, *19*(3), 133–139.

Baron, R., & Kenny, D. (1986). The moderator-mediator variable distinction in social psychological research: conceptual, strategic and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182.

Basuroy, S., Desai, K. K., & Talukdar, D. (2006). An empirical investigation of signaling in the motion picture industry. *Journal of Marketing Research*, *43*(2), 287–295.

Black, T. (1999). *Doing Quantitative Research in the Social Sciences: An Integrated Approach to Research Design, Measurement and Statistics*. London, UK: Sage Publications.

Boksem, M. a. S., & Smidts, A. (2015). Brain responses to movie trailers predict individual preferences for movies and their population-wide commercial success. *Journal of Marketing Research, 52*(4), 482–492.

Booth, W., & Geis, S. (2006). And This Year's Oscar Goes to Social Issues. *Washington Post*, *March 5*. Retrieved 21 December 2015, from http://www.washingtonpost.com/wp-dyn/content/article/2006/03/04/AR2006030401210.html

Brown, T. J., Barry, P., P., D., & Gunst, R. (2005). Spreading the word: investigating antecedents of consumers' positive word-of-mouth intentions and behaviors in a retailing context. *Journal of the Academy of Marketing Science*, *33*(2), 123–138.

Campbell, H. (2008). The Essence of Trailers. *IndiVision*, (April). Retrieved 21 December 2015, from: http://afcarchive.screenaustralia.gov.au/newsandevents/afcnews/converse/helencampbell/newspage_463.aspx

Chaiken, S., & Eagly, A. H. (1976). Communication modality as a determinant of message persuasiveness and message comprehensibility. *Journal of Personality and Social Psychology*, *34*(4), 605–614.

Chakravarty, A., Liu, Y., & Mazumdar, T. (2010). The differential effects of online word-of-mouth and critics' reviews on pre-release movie evaluation. *Journal of Interactive Marketing*, *24*(3), 185–197.

Chintagunta, P. K. P., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: accounting for sequential rollout and aggregation across local markets. *Marketing Science*, *29*(5), 944–957.

Clement, M., Wu, S., & Fischer, M. (2013). Empirical generalizations of demand and supply dynamics for movies. *International Journal of Research in Marketing*, *31*(2), 207–223.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Mahwah, NJ: Lawrence Erlbaum Associates.

Crookes, D. (2011). The Science of the Trailer. *The Independent, August 2,* Retrieved 21 December 2015 from: http://www.independent.co.uk/arts-entertainment/films/features/the-science-of-the-trailer-2330110.html

Day, G. S. (1971). Attitude change, media and word of mouth. *Journal of Advertising Research*, *11*(6), 31–40.

Dellarocas, C., Zhang, X., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23–46.

Dichter, E. (1966). How word-of-mouth advertising works. *Harvard Business Review*, *44*(6), 147–166.

Doperalski, B. D. (2012). Passionately Promoting Pics of All Persuasions. *Variety*, *May 30*, Retrieved 21 December from: http://variety.com/2012/film/awards/passionately-promoting-pics-of-all-persuasions -1118054506.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter?: An empirical investigation of panel data. *Decision Support Systems*, *45*(4), 1007–1016.

Eagly, A. H. (1974). Comprehensibility of persuasive arguments as a determinant of opinion change. *Journal of Personality and Social Psychology*, *29*(6), 758–773.

East, R., Romaniuk, J., & Lomax, W. (2011). The NPS and the ACSI: a critique and an alternative metric. *International Journal of Market Research*, *53*(3), 327–346.

Elberse, A. (2007). The power of stars: Do star actors drive the success of movies? *Journal of Marketing*, *71*(4), 102–120.

Elberse, A., & Anand, B. (2007). The effectiveness of pre-release advertising for motion pictures: An empirical investigation using a simulated market. *Information Economics and Policy*, *19*(3–4), 319–343.

Elberse, A., & Eliashberg, J. (2003). Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures. *Marketing Science*, *22*(3), 329–354.

Eliashberg, J., Elberse, A., & Leenders, M. A. (2006). The motion picture industry: Critical issues in practice, current research, and new research directions. *Marketing Science*, *25*(6), 638–661.

Eliashberg, J., Jonker, J.-J., Swahney, M. S., & Wierenga, B. (2000). MOVIEMOD : Implementable for prerelease motion market support system of evaluation pictures. *Marketing Science*, *19*(3), 226–243.

Epstein, E. J. (2005). *The Big Picture: The New Logic of Money and Power in Hollywood*. New York: Random House.

Flanagan, M. (2012). How to Edit a Trailer That Will Get Your Film Noticed. *MicroFilmmaker Magazine, March 13*, Retrieved 21 December 2015 from: http://www.microfilmmaker.com/tipstrick/Issue14/Edit_Trl.html

Ford, J., & Merchant, A. (2010). Nostalgia drives donations: The power of charitable appeals based on emotions and intentions. *Journal of Advertising Research*, *50*, 450–459.

Fornell, C., & Bookstein, F. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, *19*(4), 440–452.

Friedman, R. G. (2006). Motion Picture Marketing. In J. E. Squire (Ed.), *The Movie Business Book* (2nd ed., pp. 291–305). New York: Simon & Schuster.

Genette, G., & Maclean, M. (1991). Introduction to the paratext. *New Literary History*, *22*(2), 261–272.

Gong, J. J., Van der Stede, W. a., & Young, M. (2011). Real options in the motion picture industry: Evidence from film marketing and sequels. *Contemporary Accounting Research*, *28*(5), 1438–1466.

Gruber, V., Kaliauer, M., & Schlegelmilch, B. (2015). Improving the effectiveness and credibility of corporate social-responsibility messaging. *Journal of Advertising Research*, *58*(4), 397–409.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Thousand Oaks, CA: Sage.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52.

Hennig-Thurau, T., Henning, V., & Sattler, H. (2007). Consumer file sharing of motion pictures. *Journal of Marketing*, *71*(4), 1–18.

Hennig-Thurau, T., Houston, M. B., & Sridhar, S. (2006). Can good marketing carry a bad product? Evidence from the motion picture industry. *Marketing Letters*, *17*(3), 205–219.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., *et al*. (2014). Common beliefs and reality about PLS: Comments on Ronkko and Evermann (2013). *Organizational Research Methods*, *17*(2), 182–209.

Hogan, J. E., Lemon, K. N., & Libai, B. (2004). Quantifying the ripple: word-of-mouth and advertising effectiveness. *Journal of Advertising Research*, *44*(3), 271–280.

Hu, L., & Bentler, P. (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.

IBIS World. (2014). *Global Movie Production & Distribution: Market Research Report*. Retrieved 21 December 2015 from: https://www.ibisworld.com/industry/global/global-movie- production-distribution.html.

Iida, T., Goto, A., Fukuchi, S., & Amasaka, K. (2012). A study on effectiveness of movie trailers boosting consumers' appreciation desire: A customer science approach using statistics and GSR. *Journal of Business & Economics Research*, *10*(6), 375–385.

Jacoby, J., & Hoyer, W. D. (1982). Viewer miscomprehension of televised communication: selected findings. *Journal of Marketing*, *46*(4), pp. 12–26.

Karniouchina, E. V. (2011). Impact of star and movie buzz on motion picture distribution and box office revenue. *International Journal of Research in Marketing*, *28*(1), 62–74.

Keller, E., & Fay, B. (2009). The role of advertising in word of mouth. *Journal of Advertising Research*, *49*(2), 154–158.

Kernan, L. (2004). *Coming Attractions: Reading American Movie Trailers*. Austin: University of Texas Press.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, *54*(3), 241–251.

Lang, B. (2014, February 19). Guardians of the Galaxy - Trailer a Social Media Smash, Bigger than ‘Man of Steel.’ *The Wrap*. Retrieved 21 December 2015 from: http://www.thewrap.com/guardians-galaxy-trailer-social-media-smash-bigger-man-steel/

Lee, R., & Romaniuk, J. (2009). Relating switching costs to positive and negative word-of-mouth. *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, *22*, 54–67.

Liu, Y. (2006). Word of outh for movies: its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74–89.

Mackenzie, S. B., & Podsakoff, P. (2012). Common method bias in marketing: causes, mechanisms, and procedural remedies. *Journal of Retailing*, *88*(4), 542–555.

Maier, C. D. (2009). Visual evaluation in film trailers. *Visual Communication*, *8*(2), 159–180.

Maloney, D. (2013). The marketing tactics for Hunger Games: Catching Fire would make Panem’s Capitol proud. *Wired Magazine*, *November 22*, Retrieved 21 December 2015 from: http://www.wired.com/2013/ll/catching-fire-marketing/

Matook, S., Brown, S., & Rolf, J. (2015). Forming an intention to act on recommendations given via online social networks. *European Journal of Information Systems*, *24*(1), 76–92.

Maxham, J., & Netemeyer, R. (2002). Modeling customer perceptions of complaint handling over time: the effects of perceived justice on satisfaction and intent. *Journal of Retailing*, *78*(4), 239–252.

McGuire, W. (1968). Personality and attitude change: an information-processing theory. In A. G. Greenwald, T. C. Brock, & T. M. Ostrom (Eds.), *Psychological Foundations of Attitudes* (pp. 171–196). San Diego, CA: Academic Press.

McMillan, S., Hwang, J., & Lee, G. (2003). Effects of structural and perceptual factors on attitudes toward the website. *Journal of Advertising Research*, *43*(4), 400–409.

Morgan, R. (2000). A consumer-oriented framework of brand equity and loyalty. *International Journal of Market Research*, *42*(1), 65–78.

Morwitz, V. G., Steckel, J. H., & Gupta, A. (2007). When do purchase intentions predict sales? *International Journal of Forecasting*, *23*(3), 347–364.

MPAA. (2015). *Theatrical Market Statistics*. *Motion Picture Association of America*. Retrieved 21 December 2015 from http://www.mpaa.org/Resources/3037b7a4-58a2-4109-8012-58fca3abdf1b.pdf

Nguyen, C., & Romaniuk, J. (2014). Pass it on: a framework for classifying the content of word of mouth. *Australasian Marketing Journal*, *22*(2), 117–124.

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

Phelps, J. E., Lewis, R., Mobilio, L., Perry, D., & Raman, N. (2004). Viral marketing or electronic word-of-mouth advertising: examining consumer responses and motivations to pass along email. *Journal of Advertising Research*, *44*(4), 333–348.

Prag, J., & Casavant, J. (1994). An empirical study of the determinants of revenues and marketing expenditures in the motion picture industry. *Journal of Cultural Economics*, *18*(3), 217–235.

Preece, S. B. (2011). Coming soon to a live theater near you: performing arts trailers as paratexts. *International Journal of Nonprofit & Voluntary Sector Marketing*, *16*(June), 23–35.

Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Research in Marketing*, *26*(4), 332–344.

Rich, P. (1992). The organizational taxonomy: definition and design. *Academy of Management Review*, *17*(4), 758–781.

Richins, M. L., & Root-Shaffer, T. (1988). The role of involvement and opinion leadership in consumer word-of-mouth: an implicit model made explicit. *Advances in Consumer Research*, *15*, 32–36.

Riegner, C. (2007). Word of mouth on the web: the impact of web 2.0 on consumer purchase decisions. *Journal of Advertising Research*, *47*(4).

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. Bönningstedt: SmartPLS. Retrieved from http://www.smartpls.com

Rogers, E. M. (1962). Diffusion of innovations. New York: Free Press.

Romaniuk, J., Nguyen, C., & East, R. (2011). The accuracy of self-reported probabilities of giving recommendations. *International Journal of Market Research*, *53*(4), 507–521.

Rumelhart, D. (1991). Understanding understanding. In *Memories, Thoughts and Emotions: Essays in Honor of George Mandler*, pp. 257–275.

Sashi, C. M. (2012). Customer engagement, buyer-seller relationships, and social media. *Management Decision*, *50*(2), 253–272.

Shugan, S. M. (2004). Endogeneity in marketing decision models. *Marketing Science*, *23*(1), 1–3.

Squire, J. E. (2016). *The Movie Business Book*. (J. E. Squire, Ed.) (4th ed.). New York: Simon & Schuster.

Sudman, S., & Kalton, G. (1986). New developments in the sampling of special populations. *Annual Review of Sociology*, *12*, 401–429.

Tourmarkine, D. (2005). Tantalizing trailers: putting traction into coming attractions. *Film Journal International*, *108*(4), 16–20.

Tow, W., Dell, P., & Venable, J. (2010). Understanding information disclosure behaviour in Australian facebook users. *Journal of Information Technology*, *25*(2), 126–136.

Vogel, H. L. (1998). *Entertainment Industry Economics: A Guide for Financial Analysis*. New York: Cambridge University Press.

Wright, M., & MacRae, M. (2007). Bias and variability in purchase intention scales. *Journal of the Academy of Marketing Science, 35*(4), 617–624.

Yeo, T. E. D. (2012). Social-media early adopters don't count: how to seed participation in interactive campaigns by psychological profiling of digital consumers. *Journal of Advertising Research*, *52*(3), 297.

Young, M., Gong, J. J., Van der Stede, W. A., Sandino, T., & Du, F. (2008). The business of selling movies. *Strategic Finance*, (March), 35–41.

Chapter 5: Paper 2

This declaration concerns the article entitled:
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Towards a Subjective Understanding Paradigm: Investigating Consumers' Understanding and Ad Response in a Movie Trailer Context[3]

Abstract

Research on information-processing and persuasive advertising has identified that the comprehension of an advertising message creates positive attitudes. While researchers have investigated antecedents of message understanding and its effect on consumer response, understanding has been measured either from an objective (actual) or from a subjective (perceived) perspective. In this paper, the authors examine both perspectives to identify potential differences in the mechanisms that drive them. Findings from a series of experiments reveal that objective and subjective understanding are distinct constructs and that consumers are often overconfident about the amount of information they feel that they have understood. Using movie trailers as stimuli, the authors examine message content characteristics as antecedents of objective and subjective understanding and further investigate their effect on ad and product liking. Insight on the significance of subjective understanding in stimulating positive audience response is used to direct future inquiry towards a subjective understanding paradigm.

Key Words: Understanding, Advertising, Informativeness, Movie trailers, Ad response

5.1 Introduction

In the era of information overload, consumers are bombarded by an average of ten thousand advertising messages per day (Saxon, 2017). As a result, capturing consumers' attention to prompt positive ad response has become a great challenge for advertisers. In an attempt to understand how consumers receive, process and react to advertising communications, researchers have applied information-processing theory to persuasive advertising research inquiry. Examples of such research explore characteristics of communications that facilitate the processing of incoming information and lead to some form of attitude change (Eagly, 1974; Petty & Cacioppo, 1983). Models which explain consumers' positive ad response place

[3] An earlier version of this chapter was presented during the Academy of Marketing Science (AMS) annual conference in 2017.

the understanding of the advertising message at their core (Archer-Brown et al., 2017; Fernbach et al., 2013). However, the assumptions relating to the construct of understanding in these studies are significantly different.

Traditionally, information-processing literature is mainly concerned with the universal nature of message comprehension, assessed through *objective* measures imposed by the researchers – such as True/False statements on the meaning of the stimuli (Chaiken, 1980; Eagly et al., 1978; Harris, 1977). Conversely, an emerging paradigm of perceived understanding, established through the work of Mick (1992), follows the rationale that understanding is a *subjective* construct and should be measured through self-assessment measures (Mick, 1992; Fernbach et al., 2013; Ratneshwar & Chaiken, 1991). As such, the measurement of the construct has been inconsistent and findings in advertising research vary depending on the perspective adopted by the researchers. Examining both constructs is, therefore, imperative in identifying potential differences in how the two forms of understanding interact with message content characteristics and with ad response.

Another concern with the study of processing advertising communications lies in the fact that the stimuli used to manipulate certain communication parameters have been predominantly limited to print or audio mode (Fernbach et al., 2013; Ratneshwar & Chaiken, 1991). While the role of advertising to sell a product or service has remained constant, the media through which advertisers communicate their messages have significantly changed. Thus, findings on the structure of message content and on the effect of communication parameters on ad response, do not reflect modern-age media which have become primarily visual (Mohanty & Ratneshwar, 2015). Indeed, even before the emergence of the Internet as an advertising medium, a surprisingly high percentage of televised communications was in fact miscomprehended (Chaiken & Eagly, 1976; Lipstein, 1980). Given the current advertising environment and the fact that the average global advertising spend last year amounted to $534 billion (Statista, 2018), relatively little research has been conducted towards the understanding of visual ads.

The few studies that have utilised complex visual stimuli to understand consumer response, have been carried out in the context of movies (Simmons et al., 2011; Nguyen & Romaniuk, 2014; Campo et al., 2018). Content analysis of the stimuli (trailers) and of consumers' responses have helped to identify key themes that consumers focus on within their reviews (Simmons et al., 2011; Nguyen & Romaniuk, 2014) and have been found to predict product adoption (Campo et al., 2018). While such insight has been adopted by the industry (e.g. Fox Studio by Campo et al., 2018), the analysis of behavioural data has not been based on a particular theoretical framework and the role of understanding the trailer has been absent. Furthermore, consumers' reviews referred to the product itself (movie), rather than the advertising message (trailer) and were therefore reflections of opinions rather than expectations formed by trailer-viewing.

In an attempt to address these issues, we carried out a series of experiments to explore consumers' understanding of movie trailers. The choice of stimuli was aligned with calls for research to use more complex visual messages (Mohanty & Ratneshwar, 2015) and to analyse consumers' response beyond ratings (Simmons et al., 2011). In fact, recent research indicated that understanding – combined with liking – the movie trailer was more likely to lead to positive word-of-mouth and to purchase decision (Archer-Brown et al., 2017). But, while some researchers have qualitatively deconstructed and evaluated trailers (Kernan, 2004; Maier, 2009), the mechanisms through which movie trailers increase understanding remain unknown. The current research addressed gaps that emerged from persuasive advertising literature and from the study of movie trailers, and followed calls to investigate the factors behind understanding, under experimental conditions, where individual characteristics can be controlled for (Archer-Brown et al., 2017).

In the first experiment respondents were exposed to a number of trailers and asked to describe them. Their retrospective thoughts underwent thematic analysis, where seven key themes upon which consumers build their expectations were identified. The comparison between objective and subjective understanding through t-test analysis revealed significantly higher levels of the latter, implying that consumers are overconfident about the level of information they feel they have understood. Complementing extant literature, the results of the first study shaped the conceptual framework for the second empirical study, where we investigated the disparity between the two understanding paradigms further. The role of message content and individual characteristics parameters in shaping both objective and subjective understanding was examined through regression analysis. Findings showed that longer trailers with a linear structure were more likely to increase subjective understanding. A further assessment of the effect of understanding on ad and product liking, revealed that only subjective understanding was a significant predictor of positive response.

The contribution of this paper is threefold. First, we add new knowledge to the persuasive advertising literature, by providing evidence that objective and subjective understanding are distinct constructs with different antecedents and outcomes. More specifically, by demonstrating that it is the perception of understanding – and not the actual understanding – of an advertising message that leads to ad and product liking, this work encourages persuasive advertising researchers to move away from a universal way of assessing consumer understanding and focus on individual perceptions instead. Second, by incorporating message content and receiver related variables as antecedents of understanding, we identify which parameters are responsible in shaping consumers' actual and perceived interpretations about an upcoming product. Finally, this paper makes a contextual contribution to the movie industry. By identifying characteristics that render trailers more effective, we offer insight to studios and trailer-makers, for the better design of pre-release promotional material.

5.1.1 Objective and subjective understanding of persuasive communications

Although it is difficult to apply general rules of communication to mass media advertising (Lazarsfeld, 1949), marketing researchers have adopted information-processing theories to explore the effect of advertising communications on consumer decision and product adoption (Stewart, 1986; Fernbach et al., 2013; Enschot & Hoeken, 2015). The information-processing model, which explains the process between message reception and attitude change, positions message understanding at its core (McGuire, 1968). While "understanding" generally stands for the interpretation of information, the term has been found to represent different processes – from the ease of message processing (Maheswaran & Sternthal, 1990) to the comprehensibility of a message (Enschot & Hoeken, 2015; Ratneshwar & Chaiken, 1991) and from objective comprehension (Chaiken, 1980; Eagly et al., 1978; Wright, 1973) to subjective understanding (Mick, 1992; Mohanty & Ratneshwar, 2015).

Despite the fact that understanding is dependent on the individual's personal experiences, the majority of studies in persuasive advertising appoint an objective nature to understanding. Mick (1992) was the first theorist who differentiated between objective and subjective understanding in advertising and introduced a framework for the study of the subjective understanding paradigm, which stands for the individual feeling of having understood a communication. According to him, persuasive advertising studies have been leaning strongly towards the objective understanding paradigm – the extent to which a receiver's perception matches the meaning intended by the sender – because it is easier to measure. Nevertheless, subjective understanding has been linked to liking (Fernbach et al., 2013; Mick, 1992; van

Mulken & van Enschot-van Dijk, 2005), product adoption (Gatignon & Robertson, 1985; Hirschman, 1981; Rogers, 1962) and willingness to pay (Fernbach et al., 2013) in marketing research. Although some researchers have acknowledged the difference between the two forms of understanding, to date no research has examined both constructs under a single conceptual framework.

5.1.2 Understanding mechanisms and antecedents

Due to individual experiences, a message can assume two meanings: that which is intended by the sender, and that which is comprehended by the receiver (Wyer & Shrum, 2015). The disparity between these two meanings is often the result of inference-making, which is the combination of old and newly-acquired information (Kintsch & van Dijk, 1978) and is a necessary activity for humans to get by effectively with limited information (Kahneman, 2011).

In an attempt to study how individuals draw inferences while processing a message, cognitive psychologists have adopted the perspective of dual-process theories, which assumes the existence of two routes in cognitive response: an automatic and a controlled one (Chaiken, 1980; Kahneman, 2011; Petty & Cacioppo, 1983). A large body of work in consumer psychology focuses on the former, which often leads the individual to false judgements (Kahneman, 2011). Notably, the heuristic cues that might trigger inference-making activity in an advertising context, and the relationship between inference-making and understanding have not yet been explored. Further investigation into this concept might be beneficial in determining the optimal amount of information that consumers may require when processing an advertising communication (Fernbach et al., 2013).

Influential parameters that can affect consumers' understanding can be split in three categories consistent with the elements of communication: the sender, the message and the receiver (Hovland et al., 1953). Variables related to the sender (such as source credibility and likeability) have been given much attention in advertising research (Hovland & Weiss, 1951; Petty & Cacioppo, 1983; Reilly et al., 2016) and are outside the scope of this study. Focusing on the message and the receiver, consumer psychology researchers have manipulated a number of message content parameters in order to investigate their effect on communication acceptance and to understand their interaction with individual differences.

Hovland and his colleagues (1953) have focused on argumentation which relates to the number, order and quality of arguments, and found that a *higher number* and a *linear order of* *arguments* increases persuasion. Focusing specifically on comprehensibility, Eagly and Chaiken (1993) later found that lowering the number of arguments, decreased message comprehensibility and consequently increased resistance to the communication. The general consensus on the order of arguments is that a linear order of information aids the ability to understand and retain a message (Eagly, 1974) and increases persuasion (McCroskey & Mehrley, 1969). However, whether stronger arguments should be presented in the beginning or at the end of the communication depends on the receiver's individual characterics (Hovland et al., 1953).

In fact, individual characteristics have played an important role in experiments that manipulate message content variables to observe an effect on the receiver's understanding. Fernbach et al. (2013) have pointed out that the amount of information required to achieve consumer understanding varies by the message receiver. For instance, an individual's prior knowledge about the subject of communication influences the ability and motivation to elaborate on a message (Petty et al., 1981; Wood, 1982) and has been found to increase product adoption (Gatignon & Robertson, 1985). It also facilitates message comprehension (Alba, 1983; Chaiken & Stangor, 1987; Mick, 1992; Ratneshwar & Chaiken, 1991) and increases the ability to establish causal links and draw inferences (Johnson & Ahn, 2015). However, the measurement and manipulation of the parameter is often done by simply providing respondents with the title or context of communication prior to stimulus exposure, (Dooling & Lachman, 1971; Bransford & Johnson, 1972) rather than through a systematic assessment of the individuals' knowledge about the subject.

Along with prior knowledge, message or product involvement also influences the receiver's motivation to process an ad (Wright, 1973; Johnson & Eagly, 1989; Park et al., 2007). Higher message comprehension is also achieved by individuals with a high Need for Cognition (NFC), which stands for the tendency to elaborate on incoming information (Cacioppo et al., 1996; Cho & Schwarz, 2005; Haugtvedt et al., 1992).

While these studies have added significant knowledge to the field of information-processing and cognitive response, the combined effect of message and receiver-related parameters on the understanding of ads has not received much attention (Wyer & Shrum, 2015). Furthermore, the majority of these studies have been conducted with stimuli in print form, and as a result, generalizations to other types of ads (e.g. televised communications) would be problematic.

The overall aims of this research are to explore: 1) how consumers form perceptions about upcoming products through pre-release advertising; 2a) what characteristics influence these perceptions; and 2b) how these perceptions are related to ad and product liking. Two studies, where objective and subjective understanding will be treated as separate constructs, have been designed to address these research questions through content and statistical analysis.

5.2 STUDY 1: Exploring the phenomenon of objective and subjective understanding

The aim of the first study was to explore how understanding about an upcoming product is shaped through exposure to the advertising message. More specifically, our objective was to:

a) identify the key themes through which consumers' objective and subjective understanding is shaped

b) explore inference-making activity and its relationship to objective and subjective understanding

c) explore potential differences between objective and subjective understanding, and how these might be influenced by trailer and individual characteristics.

Inspired by marketing work on the analysis of consumer reviews (Nguyen & Romaniuk, 2014; Gelper et al., 2018), we followed established topic categorization methods to identify key themes upon which consumers draw general perceptions. Along with recognising the heuristic cues that shape pre-release perceptions, we also explored the role of inference-making activity in influencing objective and subjective understanding. By measuring both understanding constructs in line with extant literature (Maheswaran & Sternthal, 1990; Mohanty & Ratneshwar, 2015), we were able to identify disparities in the amount of information that respondents had understood objectively and subjectively. This study also served as an initial exploration of the possible antecedents of understanding which were further examined in Study 2. In order to form the conceptual framework for Study 2, we included a message content parameter (*order of information*) and a receiver related parameter (*context familiarity*) to observe potential effects on the two understanding constructs.

Movie trailers were chosen as the context of this study for a number of reasons. First, they satisfy calls for research in persuasive advertising, to use more complex, visual communications (Livingstone, 1990; Mohanty & Ratneshwar, 2015). Second, they play a critical role in shaping pre-release perceptions and influencing product adoption (Prag &

Casavant, 1994; Campo et al., 2018), especially because movies are experiential products, whose quality cannot be judged in advance (Joshi & Mao, 2012; Yoon et al., 2017). In fact, movies belong to a group of products with a very short life-cycle, whose success relies on fast adoption (Dellarocas et al., 2007; Gong et al., 2011). This makes pre-release advertising – which often costs as much as movie production – an important determinant of a movie's success, since it's the main driver of consumers' pre-release perceptions. Third, the movie industry is of high economic importance and has been the most profitable form of entertainment for the past decade (Packard et al., 2016; MPAA, 2018). However, while the average budget to produce a movie in 2016 was estimated at $66 million, only an average of $15.8 million was reported in the same year's domestic box office (MPAA, 2017; The Numbers, 2016). Insight on how consumers form early perceptions about upcoming movies, through pre-release advertising could help studios create more effective campaigns and reduce marketing costs.

An online survey was created and distributed to a sample of consumers aged 18-39 – the most frequent moviegoing consumer segment (MPAA, 2018). Participants were exposed to four different trailers, each followed by the same set of questions. To eliminate the possibility of additional knowledge on the movie's plot, the trailers advertised movies that at the point of the study had not yet been released. In order to control for movie-specific characteristics, all trailers advertised wide-release movies (released simultaneously in over 800 cinemas), contained at least one star and had at least one overlapping genre (comedy). To minimise bias, the order of the trailers was randomised.

5.2.1 Stimuli Categorization

To explore the effect of message content structure and context familiarity on understanding, trailers were selected and categorized on 2 (*Order of Information*) x 2 (*Context Familiarity*) conditions. Consistent with persuasive communication literature (Burton et al., 2015; Johnson & Ahn, 2015) and with context-specific work (Campbell, 2008; Flanagan, 2012), the order of events influences the ease of processing and the comprehensibility of a message. As such, trailers which followed the three-act framework[4] were categorized as *Linear*, whereas trailers that focused on the movie's atmoshere and not on the order of the events, were categorized as *Abstract*.

[4] The three-act framework is a standard structure in narratives, that can be traced back to Aristotle. In this context, the three-act framework, in commonly used by trailer-makers and follows the plot structure, where the characters are first introduced, then presented with a conflict and finally shown in some kind of action (Campbell 2008; Flanagan 2012).

Context familiarity was used as an operationalisation for prior knowledge. Extant literature on information-processing has identified that individuals with contextual knowledge about the message elaborate more consciously on the message content and are more likely to respond positively to a communication (Petty et al., 1981; Chaiken & Stangor, 1987; Ratneshwar & Chaiken, 1991; Mick, 1992). Since the trailer is the first sample of information about an upcoming movie, context familiarity can only exist in instances where the script is based on a true story, is an adaptation, a remake or a sequel. In fact, sequels or franchises have been found to have a different effect on perceptions and have consequently achieved higher box office returns (Basuroy et al., 2006; Bohnenkamp et al., 2015; Nguyen & Romaniuk, 2014; Young et al., 2008). Therefore, trailers of sequel movies were classified as *High* in the Context Familiarity categorization, while those that advertised movies with an original storyline, were classified as *Low*.

The lead author filtered all available trailers of wide-release movies of 2017 with a release date longer than two months away from the time of the study, and only selected those that featured at least one star and, among others, belonged to the comedy genre. Information on the Context Familiarity categorization (sequels/orginals), was obtained from Internet Movie Database (https://www.imdb.com). The researchers then independently watched and categorized the trailers on the Order of Information, resulting in four trailers that combined these parameters (see Table 7).

Table 7: Stimuli categorisation for Study 1

Movie	Link	Context Familiarity	Order of Information
The House	https://www.youtube.com /watch?v=bLwII6-92_Y	Low	Linear
Hitman's Bodyguard	https://www.youtube.com /watch?v=Anps6VPe0u8	Low	Abstract
Justice League	https://www.youtube.com /watch?v=qY6GqqrNBjY	High	Linear
Kingsman 2	https://www.youtube.com /watch?v=6Nxc-3WpMbg	High	Abstract

5.2.2 Variables and measures

Retrospective Thoughts and Objective Understanding In the few persuasive advertising studies focusing specifically on understanding, the construct is most often measured through open-ended thought listing tasks or through argument recall (Chaiken, 1980; Eagly et al., 1978; Harris, 1977; Haugtvedt et al., 1992; Maheswaran & Sternthal, 1990; Ratneshwar &

Chaiken, 1991; Simonson, 1989; Wright, 1973). Generally, measures imposed by thought listing tasks offer important advantages over researcher-imposed measures (Wright, 1973) and are considered to be more accurate (Simmons & Lynch, 1991; Wittrock, 1981). Consistent with Maheswaran and Sternthal's (1990) thought-listing task, to assess objective understanding (OB_UND), respondents were asked to record their thoughts as if they were describing what the movie is about to a friend interested in watching it but unfamiliar with the movie's plot. Similar to the True/False task in relevant literature (Chaiken, 1980; Eagly et al., 1978; Harris, 1977), respondents' retrospective thoughts were broken down into statements and were matched against the official trailer synopsis of each movie. Descriptions were then given a score ranging from 0 (*no major plot points mentioned*) to 1 (*all major plot points mentioned*).

Inference-making Respondents' retrospective thoughts were also used an indicator of inference-making (INF_MAKING). Responses which included events that were not explicitly shown on the trailer were given a score of 1, while the rest remained 0.

Subjective Understanding As the focus of this study was the *perception* of understanding (SUB_UND), a 9-point bipolar scale inspired by prior literature (Maheswaran & Sternthal, 1990; Mohanty & Ratneshwar, 2015; Ratneshwar & Chaiken, 1991) measured the extent of respondents' understanding on what the movie is about *(-4: did not understand at all, 4: completely understood it*). The preceding thought-listing task was also used to shatter the illusion of explanatory depth (Fernbach et al., 2013), where consumers realise their limited understanding on a subject, only *after* they are asked to describe it out loud (Keil, 2006; Rozenblit & Keil, 2002).

5.2.3 Results

Forty-three responses were collected, of which thirty-seven were usable for all four trailers, resulting in 148 unique observations. Response time and time spent watching the trailers were recorded and taken into account to eliminate all biased responses.

Key Themes Consistent with best practice on text analysis (Lipizzi et al., 2016; Gelper et al., 2018), respondents' retrospective thoughts were cleaned from stop-words (e.g. “the”, “and”). Corpus statistics analysis, revealed a list of unique words and their respective frequency. The analysis was facilitated by ConText (Diesner et al., 2015) – a computational software tool which relies on Natural Language Processing techniques. The number of unique words used to describe each movie is reported in Table 8.

Table 8: Number of unique words for each movie

Movie	Word Count
The House	73
Hitman's Bodyguard	98
Justice League	88
Kingsman: The Golden Circle	142

Topic analysis was performed computationally to provide initial suggestions, but the final topics were refined by the researchers, following Braun and Clarke's (2006) framework of thematic analysis, which has widely been used in marketing literature (McCreanor, 2008; McMackin, 2013; Nguyen & Romaniuk, 2014; Rishi & Gaur, 2012). The final topic categorization derived from a combination of prior research on movie reviews topics (Simmons et al., 2011; Nguyen & Romaniuk, 2014; Gelper et al., 2018) and from our observation of the data. Since the focus of this study was to uncover the themes upon which audiences draw their pre-release expectations, some categories (e.g. movie’s release) were not observed and were outside the scope of this research. Instead, we observed other significant topics that were frequently mentioned in the dataset and formed a separate category, unlike prior research where they were only perceived as part of a larger topic (e.g. *characters* being included in the *plot* category, in Nguyen & Romaniuk, 2014 and Gelper et al., 2018). In total, seven key topics were identified, reviewed and then given general names that could be applicable to any movie-related dataset. Table 9 reports the final topics, along with a brief description and the percentage of the dataset’s unique words that populated each topic.

Table 9: Topic categorisation and description

Topics	Summary Statistics	Description
Plot	45%	Words specific to the movie's main plot points. When grouped together, they serve as a summary of the movie.
Character	26%	Words related to the characters' names, status, characteristics and relationships.
Genre & type of movie	9%	Words indicating genre and genre-specific words (e.g. funny, scary). Also words that indicate the type of movie and the occasion for watching it (e.g. Sunday evening, summer).
Star	4%	Words related to the movie's cast, as well as their previous character work.

Other Movie/ Franchise/Sequel	6%	Titles of other movies: either with similar plot, or with overlaps of the cast. In the case of sequels or franchises, movie titles which represent the prequel or the original movie.
Movie elements	3%	Words related to secondary elements of the movie, such as the location and period that action takes place, the music, the ratings, the style, costumes and special effects.
Opinion	7%	Words indicating opinion on the movie or trailer or expressing expectations and actions towards the upcoming movie.

In general, respondents used the plot, the characters, the movie's genre, the star, the movie's relation to other movies, the movie's elements and their individual opinions to form perceptions and describe the movie to others. In line with prior research on audience's general conversations (Simmons et al., 2011; Nguyen & Romaniuk, 2014; Gelper et al., 2018), the movie's plot was by far the highest populated topic, with 45% of the dataset's words focused on the movie's storyline.

Inference-making and understanding About half of the retrospective thoughts (45%) included at least one inferred statement. The authors matched each of the inferred statements against the official movie synopsis and rated it as *True* – if the event was not shown on the trailer but did occur in the movie – or *False* – if the event was not shown on the trailer and did not occur in the movie. Out of all the inferred statements, only 47.4% were *True*, which indicates that consumers' inference-making activity did, by large, lead to false judgements.

The data for objective understanding (OB_UND) was normally distributed, with a skewness of .111 (*SE*=.199) and kurtosis of -.951 (*SE*=.396). Subjective understanding (SUB_UND) was slightly below the accepted range of -2 to +2 (George and Mallery 2010); Skewness = -2.028, (*SE*=.199), Kurtosis=4.536 (*SE*=.396). The distribution of both variables was checked through the Koglmogorov-Smirnov test, which confirmed that the distributions were normal ($p < .01$). No significant outliers were observed.

Descriptives and exploratory correlations of inference-making activity and understanding, are reported in Table 10.

Table 10: Correlations & descriptive statistics

	Mean	SD	INF_MAKING	OB_UND	SUB_UND
INF_MAKING	n/a	n/a	1		
OB_UND	.4291	.300	.002	1	
SUB_UND	2.713	1.425	-.008	.352**	1

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

Despite a considerable level of inference-making activity, no significant relationships between INF_MAKING and OB_UND, r=.002 [-.152, .158], p=.980, or between INF_MAKING and SUB_UND, r = -.008 [-.160, .145], p=.925, were observed.

The difference between objective and subjective understanding The initial exploratory correlations presented a moderate, but significant relationship, r=.352 [.212, .483], p<.01. To test this further, we conducted paired-samples t-tests, after adjusting the values of SUB_UND to match the OB_UND scales. Results showed that on average, subjective understanding was significantly higher than objective understanding, and the difference had a very large effect size (M_{SUB}=.8711, M_{OB}=.4262; p<.01; d=1.98). This indicates that respondents thought they had understood significantly more information than they actually had.

In order to formulate the conceptual framework for the consecutive study on the antecedents of understanding, we explored the effect of *Context Familiarity* and *Order of Information* on the two understanding constructs. Paired-samples t-tests were conducted first between sequels and originals. Objective understanding was higher in the original group (M_{orig}=.4764, M_{seq}=.3818; p <.05; d=.317), as was subjective understanding (M_{orig} =3.11, M_{seq}=2.43; p<.05; d=.43), but both differences represented a small effect size. With regards to the *Order of Information* categorization, objective understanding was significantly higher in the linear group (M_{lin}=.5439, M_{ab}=.3142; p<.01, d=.83), as was subjective understanding (M_{lin}=3.32, M_{ab}=2.22; p<.01; d=.73). Both categorizations presented significant differences on their effect on objective and subjective understanding and formed the basis of our conceptual framework.

5.2.4 Discussion

The topic categorization revealed seven key themes upon which consumers interpret what a movie is about and build their expectations. Consistent with research on movie WOM (Simmons et al., 2011; Nguyen & Romaniuk, 2014; Gelper et al., 2018), the movie's storyline was the most prevalent topic in consumers' trailers reviews. The most important insight from Study 1, was the disparity between objective and subjective understanding, supporting Mick's (1992) work. Subjective understanding levels were significantly higher, suggesting an overconfidence in the amount of information that respondents felt that they had understood (Moorman, 1999). Although the concept of overconfidence has been studied in a variety of contexts (Fernbach et al., 2013; Meng et al., 2017; Wood & Lynch, 2002), the effect of this phenomenon on ad response or attitude change remains yet unknown. The categorizations on message content and on context familiarity both yielded significant results, with linear trailers being better understood than abstract ones. Contrary to our expectations on context familiarity, trailers with an original storyline were better understood than sequel trailers. Although findings are inconsistent with prior work on context familiarity (Ratneshwar & Chaiken, 1991; Mick, 1992), they do suggest that original and sequel trailers are perceived differently.

Study 1 was used as an initial exploration of the heuristic cues that help consumers form perceptions through pre-release advertising. It empirically differentiated between objective and subjective understanding, while also investigating initial differences between message content and receiver related parameters. While it is clear that respondents are overconfident in their level of understanding, the effect of these mechanisms on ad response was not examined. Furthermore, receiver related parameters were not included explicitly in the exploration, leaving questions on the effect of individual differences on the two forms of understanding unanswered. These questions were further investigated in Study 2.

5.3 Conceptual Framework for Study 2a and 2b

Study 2 tested trailers' explanatory characteristics in more depth, in order to identify which message content parameters might facilitate the process of understanding and how this might consequently increase liking. Specifically, the aim of Study 2a was to determine which message content and receiver-related variables are responsible for shaping objective and subjective understanding, while the aim of Study 2b was to test the effect of the two understanding parameters on ad response – namely ad and product liking.

In light of the context of this research and the significant effect of context familiarity on the two understanding parameters, observed in the first study, sequels were deemed an important category and were grouped separately to trailers of original movies. In movie research, sequels have been found to be easier to market and to generate higher box office returns (Basuroy et al., 2006; Gong et al., 2011; Simonton, 2008); last year, 80% of the top 25 movies were indeed sequels (MPAA, 2018). Consequently, the proposed conceptual framework was tested separately on sequel movies, and on movies with an original storyline.

5.3.1 Amount and order of information as antecedents of objective and subjective understanding

Drawing upon information-processing theory, message argumentation, which stands for the number of arguments within a message has been found to increase comprehension of a communication (Bhattacherjee & Sanford, 2006; Chaiken, 1980; Eagly 1974; Percy & Rossiter, 1983). In the context of movie trailers, message argumentation was replaced with information, referring to the amount of hints provided within a trailer. In practice, Teaser trailers offer a small taste of the actual movie, while successive trailers and featurettes, gradually present more information and build on consumer understanding. While a lower amount of information is easier to process (Reber et al., 2004), researchers have found that a higher number of arguments increases comprehensibility of a message and drives opinion change (Eagly, 1974). Thus we hypothesise that trailers with a higher number of information (Official Trailers) will have a higher positive effect on understanding than trailers with a lower number of information (Teaser Trailers). Consistent with literature on the order of information (see Study 1) and with the results of the previous study, we assume that trailers with a linear structure will have a higher positive effect on understanding than trailers with an abstract order of events.

Thus, for movie trailers with an original storyline:

> *Hypothesis 1*: A higher amount of information and a linear order of events will have a positive effect on objective understanding.
>
> *Hypothesis 2*: A higher amount of information and a linear order of events will have a positive effect on subjective understanding.

Context familiarity which is explored in Study 1, is tested systematically in Study 2, to reveal the potential effect of prior knowledge on the two forms of understanding. Instead of using context familiarity as a stimuli categorization, we treated sequels as a separate group and collected specific information about respondents' viewership of the prequel. Similarly, for sequel trailers, we expect that:

> *Hypothesis 3*: A higher amount of information and a linear order of events will have a positive effect on objective understanding.
>
> *Hypothesis 4*: A higher amount of information and a linear order of events will have a positive effect on subjective understanding.

5.3.2 Perceived informativeness as mediator of the effects of message content on understanding

Although the amount of information has been determined objectively through the trailer categorizations, individuals often have different judgements on the ideal amount of information required in order to interpret a message, and advertisers strive to create messages with the right balance of informativeness and comprehensiveness (Fernbach et al., 2013). In the context of trailers, this issue is accentuated. Since movies are experiential products (Eliashberg et al., 2000; Hennig-Thurau et al., 2015) consumers rely on trailers to form perceptions about the experience of the movie. Not providing enough information ("I'm very confused with this movie. Can someone explain to me?!") creates uncertainty, while providing too much ("Why pay for movies when you can see the whole thing on youtube in under 3 minutes...for free.") eliminates the need to experience the movie (consumer generated content collected from www.youtube.com).

The order and number of information are expected to incur a sense of informativeness, which, consistent with prior research (Fernbach et al., 2013), is expected to increase perceived understanding. Notably, perceived informativeness is a subjective construct and is only expected to influence subjective, and not objective, understanding. Therefore:

> *Hypothesis 5*: For original trailers, perceived informativeness will mediate the relationship between message content and subjective understanding.

Similarly, although information on sequels might already exist due to the familiarity of context and characters, subjective understanding is still expected to increase through perceived informativeness. Thus:

> *Hypothesis 6*: For sequel trailers, perceived informativeness will mediate the relationship between message content and subjective understanding.

5.3.3 The effect of understanding on ad and product liking

The ultimate objective for marketers is to create ads that are likeable and that lead to some form of attitude change. Having identified message content characteristics that might increase understanding, and building on the results of Study 1 on consumers' overconfidence, we investigated how the two forms of understanding influence ad response. We examined both trailer liking and movie liking, consistent with prior literature that tests consumers' response towards the ad (Mick, 1992; Enschot & Hoeken, 2015) and towards the product (Boksem & Smidts, 2015; Maheswaran & Sternthal, 1990; Simmons & Lynch, 1991). Driven by a recent study on understanding and liking in the context of movie trailers (Archer-Brown et al., 2017), and by information-processing research on attitude change (Fernbach et al., 2013; Mick, 1992; Ratneshwar & Chaiken, 1991), we expect that both understanding variables will positively influence trailer and movie liking. Thus:

> *Hypothesis 7*: For original movies, objective and subjective understanding will have a positive effect on trailer liking.

> *Hypothesis 8*: For original movies, objective and subjective understanding will have a positive effect on movie liking.

Similarly:

> *Hypothesis 9*: For sequel movies, objective and subjective understanding will have a positive effect on trailer liking.

> *Hypothesis 10:* For sequel movies, objective and subjective understanding will have a positive effect on movie liking.

5.3.4 The mediating role of trailer liking

Recent research on movie trailers identified that it is the combination of understanding what the movie is about and of liking the movie trailer, that leads to positive consumer response (Archer-Brown et al., 2017). Thus we expect, that given the fact that consumers' perception of understanding will lead to trailer liking, which will consequently generate positive perceptions about the movie:

> *Hypothesis 11*: For original movies, trailer liking will mediate the relationship between subjective understanding and movie liking.

Similarly:

> *Hypothesis 12*: For sequel movies, trailer liking will mediate the relationship between subjective understanding and movie liking.

The proposed conceptual framework, for the two consecutive studies is summarised below (see Figure 9).

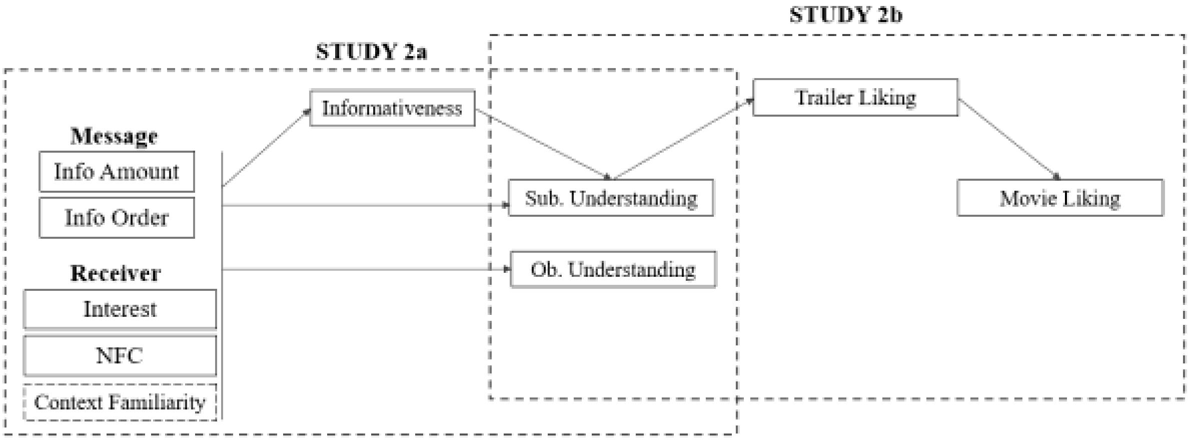

Figure 9: Proposed conceptual framework for Studies 2a and ab

5.4 STUDY 2a: Testing trailers and individual characteristics as understanding antecedents

One survey, with two groups of trailers – one for sequels and one for originals – was designed and distributed online to a sample of consumers aged 18-39 similar to Study 1. Four trailers were selected for each group and were categorized into 2 (*High or Low Amount of Information*) x 2 (*Linear or Abstract Order of Information*). The trailers were pre-tested to a sample of 15 respondents who confirmed the researchers' categorization choices. As with Study 1, all trailers advertised wide-release movies that at the point of the study had not yet been released, and contained at least one star. The experimental design was mixed; each respondent saw two trailers from the original group and two from the sequel group. To eliminate bias, trailer selection and order were randomised.

5.4.1 Variables and measures

Objective understanding (OB_UND) and subjective understanding (SUB_UND) measures were identical to the previous study. Dummy variables were created for the amount of information (INFO_AMOUNT; 1=High, 0=Low) and for the order of information (INFO_ORDER; 1=High, 0=Low).

Information-processing receiver-related variables were also incorporated in this study to control for individual differences. To account for context familiarity (CONTEXT_FAM) in the sequel group, respondents were asked to indicate specifically whether they had seen the prequel (= 1, 0 otherwise) and/or whether they were familiar with the concept and the characters of the movie (= 1, 0 otherwise).

Interest in moviegoing Personal involvement in information-processing studies is either measured through the Personal Involvement Inventory (PII; Zaichkowsky, 1985) or by deliberately creating a feeling of intrinsic involvement (e.g. offering respondents in the manipulation group some kind of reward). In the context of this study, however, involvement is concerned with respondents' general interest in movie-going. Specifically, the frequency of moviegoing is deemed managerially and theoretically relevant. The Motion Picture Association of America splits its sample by frequency of moviegoing to explore patterns in audience behaviour (MPAA, 2018). Frequent and infrequent moviegoiers might differ in the way they assess sources of information (such as advertising or WOM) on upcoming movies. Indeed, drawing from theory on product involvement and product expertise, Chakravarty et al. (2010), explore the effect of moviegoing frequency on communication acceptance. Interestingly they find that the persuasive effect of eWOM is stronger on infrequent than frequent moviegoers – especially when the communication is negative – and that the latter value professional critics' reviews more than eWOM reviews. However, due to the latest technological advancements, experiential services – such as Netflix – allow audiences to watch movies without necessarily having to go to the cinema. Thus, instead of asking respondents to state the amount of times they have visited the cinema within a certain period (Chakravarty et al., 2010; MPAA, 2018), we extract the general interest in watching movies. Consistent with prior movie literature (Hennig-Thurau et al., 2015), personal involvement (felt relevance with the experience of movies in general) was measured by the level of general interest in movies (INTEREST; 7-point scale; *not interested at all – strongly interested*).

Need for Cognition To control for individual levels of cognitive elaboration, Cacioppo's (1984) Need for Cognition Scale (NCS; short form) was used to measure respondents' Need for Cognition (NFC). The 5-point scale consists of eighteen items (α = .916), with answers ranging from *extremely uncharacteristic of me* to *extremely characteristic of me*; seven of the items are reverse-coded. Both INTEREST and NFC variables were mean-centred to categorise respondents into high/low groups.

Perceived informativeness and Liking To determine whether respondents felt that the information they received from the trailer was enough, they were asked to indicate their perception of the trailers' informativeness (INFORMATIVENESS; 7-point scale; *too little information – too much information*) (Maheswaran & Sternthal, 1990). Consistent with literature on ad liking, trailer liking (T_LIKING) was measured on a 5-point scale, ranging from “*disliked a lot*” to “*liked a lot*” (Biel & Bridgwater, 1990; Enschot & Hoeken, 2015). Movie liking, was measured by asking respondents to declare how much they thought they would like the movie (11-point; 0-10), consistent with prior research on movie preference (Boksem & Smidts, 2015).

5.4.2 Results

One hundred and thirty-five responses were collected in total. Out of those, 4 were incomplete and 14 failed the attention checks or provided senseless answers to the retrospective thoughts task. The remaining 107 responses provided 428 unique cases.

Descriptive statistics and correlations for original and sequel movies are reported in Table 11 and Table 12. Objective and subjective understanding were moderately correlated (r=.331, p<.01). We recoded the SUB_UND variable to match measures for OB_UND and performed paired-sample t-tests. Results were similar to Study 1, with subjective understanding significantly higher than objective understanding. For original movies a mean difference of -.28, BCa 95% CI [-.32, -.23], was observed. This difference was significant t(213)=-11.53, p<.01, and represented a large effect, d=.91. For sequel movies, an even larger difference was noted -.3658, BCa 95% CI [-.40, -.33], which was significant t(213)=-18.99, p<.01, and represented a very large effect, d=1.54.

Table 11: Correlations and descriptive statistics for original movies

	Mean	SD	1	2	3	4	5	6	7	8	9
1. INFO_AMOUNT	n.a.	n.a.	1								
2. INFO_ORDER	n.a.	n.a.	-.005	1							
3. OB_UND	.367	.319	.303**	.254**	1						
4. SUB_UND	5.86	2.68	.398**	.432**	.331**	1					
5. INFORMATIVENESS	3.95	1.804	.361**	.376**	.205**	.762**	1				
6. T_LIKING	3.44	1.14	.115	.027	.112	.435**	.356**	1			
7. M_LIKING	5.47	2.745	.097	.037	.066	.455**	.411**	.849**	1		
8. INTEREST	n.a.	n.a.	-.095	.031	.127	.095	.103	.139*	.182**	1	
9. NFC	n.a.	n.a.	-.109	.052	.241**	.026	-.041	.049	.059	.256**	1

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

Table 12: Correlations and descriptive statistics for sequel movies

	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. INFO_AMOUNT	n.a	n.a	1									
2. INFO_ORDER	n.a	n.a	-0.01	1								
3. OB_UND	.456	.260	0.066	.270**	1							
4. SUB_UND	7.41	1.884	.171*	.330**	.298**	1						
5. INFORMATIVENESS	4.70	1.409	.217**	.247**	.077	.597**	1					
6. T_LIKING	3.58	1.234	-.041	.226**	.024	.358**	.281**	1				
7. M_LIKING	5.60	3.154	-.08	.167*	-.025	.373**	.302**	.893**	1			
8. CONTEXT_FAM	n.a	n.a	-.051	.002	.089	.284**	.140*	.306**	.318**	1		
9. INTEREST	n.a	n.a	-.113	-.075	.091	.130	.094	.128	.161*	-.057	1	
10. NFC	n.a	n.a	.010	.010	.297**	.198**	.026	.002	-.019	.134*	.265**	1

**. Correlation is significant at the 0.05 level (2-tailed).*
***. Correlation is significant at the 0.01 level (2-tailed).*

Investigating antecedents of objective and subjective understanding

We ran four sets of OLS regressions to test for the effect of trailer and individual variables on objective (OB_UND) and subjective understanding (SUB_UND) in both the original and the sequel group. To test the first hypothesis on the antecedents of OB_UND, we entered the variables in a blockwise approach, in order to identify whether adding the message content variables increased the model fit significantly. In the first block we entered the control variables: INTEREST and NFC. Next, we entered the independent variables: INFO_AMOUNT and INFO_ORDER.

Overall, adding the INFO_AMOUNT and INFO_ORDER as predictors of objective understanding improved the model significantly. The R-squared (adjusted R-squared) increased from .060 (.051) to .227 (.212), and the change was significant at p<.01. Multicollinearity was within standard thresholds; the variance inflation factors (VIFs) for all variables were below the acceptable limit of 5 (Ringle et al. 2015). We found a positive significant impact of the INFO_AMOUNT (b=.331, p<.01) and INFO_ORDER (b=.242 p<.01) on OB_UND. In terms of the control variables, only NFC had a positive effect on OB_UND (b=.272, p<.01) (see Table 13).

Table 13: OLS Estimation results for objective understanding; original movies

Model	1			2		
	Coeff. (Std. Err)	*b*	VIF	Coeff. (Std. Err)	*b*	VIF
DV = O*B_UND*						
Constant	.307** (.045)			.106* (.051)		
NFC	.161** (.044)	.252	1.080	.174** (.041)	.272	1.091
INTEREST	-.028 (.052)	-.038	1.080	-.019 (.047)	-.026	1.083
INFO_AMOUNT				.211** (.039)	.331	1.015
INFO_ORDER				.155** (.039)	.242	1.003
R^2 =	.060			.227		
Adj. R^2 =	.051			.212		

*Note: **p<.01, *p<.05*

We conducted an identical regression analysis for SUB_UND, to test Hypothesis 2. Similar to our results for OB_UND, the model for subjective understanding was significantly improved when adding INFO_AMOUNT and INFO_ORDER as predictor variables. The R-squared (adjusted R-squared) increased from .004 (-.006) to .353 (.341), and the change was significant at p<.01. Multicollinearity was below critical levels; all VIF's were lower than 2. A positive significant effect of the INFO_AMOUNT (b=.409, p<.01) and INFO_ORDER

(b=.430, p<.01) on SUB_UND was observed. Contrary to the model for objective understanding neither of the control variables influenced the dependent variable, indicating that the feeling of understanding was affected neither by the need for cognition nor by a general interest in movies (see Table 14).

Table 14: OLS estimation results for subjective understanding; original movies

Model	1			2		
	Coeff. (Std. Err)	*b*	VIF	Coeff. (Std. Err)	*b*	VIF
DV = *SUB_UND*						
Constant	5.572** (.391)			3.172** (.391)		
NFC	.059 (.383)	.011	1.080	.162 (.312)	.030	1.091
INTEREST	.350 (.449)	.056	1.080	.428 (.264)	.068	1.083
INFO_AMOUNT				2.191** (.301)	.409	1.015
INFO_ORDER				2.300** (.299)	.430	1.003
R^2 =	.004			.353		
Adj. R^2 =	-.006			.341		

*Note: **p<.01*

To test hypotheses 3 and 4, we followed a similar approach, but added CONTEXT_FAM in the first block along with the other receiver-related variables. For the sequel group, results for OB_UND were somewhat different compared to the original movies group. The amount of information (INFO_AMOUNT) here did not play a significant role in predicting objective understanding. In fact, only the addition of INFO_ORDER improved the model; the change of R-squared (adjusted R-squared) from .092 (.079) to .171 (.151) was significant at p<.01. Again, multicollinearity was within standard thresholds, with all VIF's assuming values around 1. We found a positive significant effect of the INFO_ORDER on OB_UND (b=.275, p<.01), but no effect of INFO_AMOUNT on the dependent variable. With regards to the control variables, similar to the model for objective understanding of original movies, only NFC had a positive significant relationship on the model (b=.268, p<.01). Interestingly, context familiarity played no particular role on objective understanding (see Table 15).

Table 15: OLS estimation results for objective understanding; sequels

Model	1			2		
	Coeff. (Std. Err)	*b*	VIF	Coeff. (Std. Err)	*b*	VIF
DV = *OB_UND*						
Constant	.356** (.037)			.257** (.044)		
CONTEXT_FAM	.027 (.036)	.049	1.018	.028 (.034)	.053	1.021
NFC	.146** (.036)	.281	1.101	.139** (.034)	.268	1.103
INTEREST	.021 (.041)	.035	1.083	.041 (.040)	.068	1.097
INFO_AMOUNT	-			.036 (.033)	.069	1.003
INFO_ORDER	-			.143** (.033)	.275	1.013
R^2 =	.092			.171		
Adj. R^2 =	.079			.151		

*Note: **p<.01*

The model for subjective understanding for the sequel group was improved both by the addition of INFO_AMOUNT and INFO_ORDER. The R-squared (adjusted R-squared) increased from .117 (.104) to .268 (.250), and the change was significant at *p*<01. Multicollinearity was below critical levels; all VIF's were close to 1. A positive significant effect of INFO_AMOUNT (*b*=.188, *p*<.01) and INFO_ORDER (*b*=.345, *p*<.01) on SUB_UND was observed. While the model for the objective understanding of sequels showed that only NFC influenced the dependent variable, an opposite result was observed here. Instead of NFC, CONTEXT_FAM (*b*=.271, p<.01) and general INTEREST (*b*=.145, *p*<.05) had a positive significant effect on subjective understanding (see Table 16).

Table 16: OLS estimation results for subjective understanding; sequels

Model	1			2		
	Coeff. (Std. Err)	*b*	VIF	Coeff. (Std. Err)	*b*	VIF
DV = *SUB_UND*						
Constant	6.435** (.267)			.5340** (.299)		
CONTEXT_FAM	1.020** (.256)	.261	1.018	1.057** (.234)	.271	1.021
NFC	.503 (.256)	.134	1.101	.436 (.234)	.116	1.103
INTEREST	.021 (.041)	.104	1.083	.637* (.272)	.145	1.097
INFO_AMOUNT	-			.707** (.223)	.188	1.003
INFO_ORDER	-			1.296** (.224)	.345	1.013
R^2 =	.117			.268		
Adj. R^2 =	.104			.250		

*Note: **p<.01, *p<.05*

The mediating role of perceived informativeness

In order to test for the mediating role of perceived informativeness between message content variables and subjective understanding, we conducted two separate mediation analyses – one on original movies and the other on sequels. We followed Zhao et al.'s (2010) procedure for mediation analysis, using the PROCESS extension. In both cases the dependent variable was subjective understanding (SUB_UND) [5]. For original trailers, we found a significant indirect effect of INFO_AMOUNT (*b*=.754, *p* < .01; 95% BCa CI [.905, 1.883]) and INFO_ORDER (*b*=.902, *p*<.01; 95% BCa CI [.943, 1.915]) on SUB_UND through perceived informativeness. Informativeness partially mediated the relationship between trailer characteristics and subjective understanding for original movies (see Figure 10).

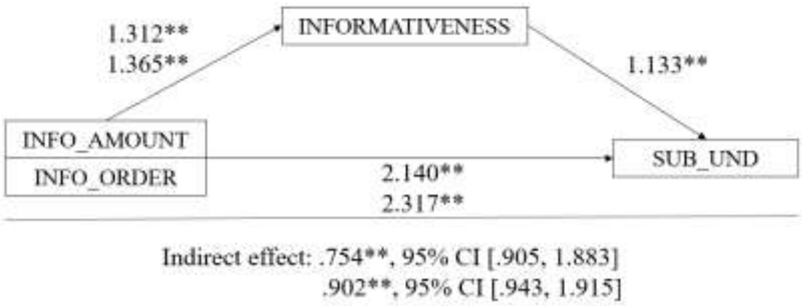

Figure 10: The mediating role of informativeness; original movies

Perceived informativeness played a similar role on the relationship between trailer characteristics and subjective understanding of sequel trailers. However, in this case, INFORMATIVENESS fully mediated the relationship between INFO_AMOUNT (*b*=.163, *p*=.443; 95% BCa CI [.177, .831] and SUB_UND. The effect of INFO_ORDER was decreased with the addition of INFORMATIVENESS, but the parameter was still a significant predictor (*b*=.730, *p*<.01; 95% BCa CI [.222, .828] (see Figure 11).

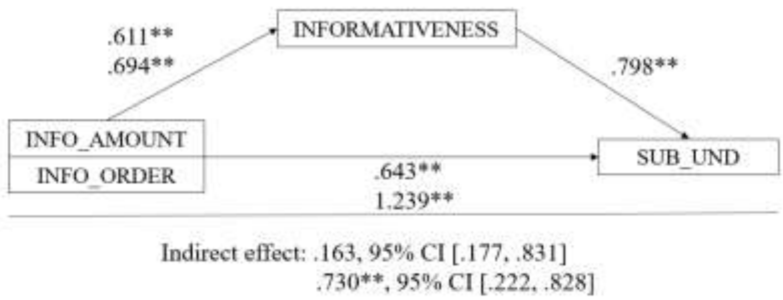

Figure 11: The mediating role of informativeness; sequels

[5] We also conducted the mediation analysis for INFORMATIVENESS, excluding the 7th data-point ("too much information"), which might have a negative connotation. However, results were more significant when including the 7th data-point. We did not – and this is outside of the scope of this study – examine the ideal amount of information in terms of ad and product liking. In the context of understanding, subjective understanding increases even with "too much" information.

5.5 STUDY 2b: The effect of understanding on consumer response

After establishing which message content and individual characteristics are responsible for shaping objective and subjective understanding, Study 2b tested the effect of the two understanding constructs on trailer and movie liking.

Model Fit

A series of OLS regressions were conducted to test the effect of the two understanding variables on trailer and movie liking, first in the original group and then in the sequel group. Overall, understanding of original movie trailers predicted trailer liking quite well. The R-squared (adjusted R-squared) was .188 (.180) and the relationship was significant at $p < .01$. Multicollinearity was within standard thresholds; the variance inflation factors (VIFs) for all variables were below 2. A positive significant effect of SUB_UND on T_LIKING (b=.444, p<.01) was observed. However, OB_UND presented a non-significant negative effect on the dependent variable (b=-.035, p=.591) (Table 17).

Table 17: OLS estimation results for trailer liking; original movies

	Coeff. (Std. Err)	*b*	VIF
DV = *T_LIKING*			
Constant	2.380** (.173)		
OB_UND	-.126 (.235)	-.035	1.123
SUB_UND	.189** (.028)	.444	1.123
R^2 =	.188		
Adj. R^2 =	.180		

*Note: **p<.01*

Similarly, only subjective understanding contributed significantly to the model for movie liking (b=.489, p<.01); the effect of objective understanding was negative and non-significant (b=-.096, p=.140). The overall model fit was quite good; the R-squared (adjusted R-squared) was .217 (.209) and was significant at p<.01. Multicollinearity was below critical levels, with both VIF's assuming values close to 1 (see Table 18).

Table 18: OLS estimation results for movie liking; original movies

	Coeff. (Std. Err)	*b*	VIF
DV = *M_LIKING*			
Constant	2.837** (.409)		
OB_UND	-.824 (.556)	-.096	1.123
SUB_UND	.500** (.066)	.489	1.123
R^2 =	.217		
Adj. R^2 =	.209		

*Note: **p<.01*

The effect of understanding on trailer and movie liking of sequel trailers was similar to the original group. We recorded a positive significant effect of SUB_UND on T_LIKING (*b*=.385, *p*<.01), while the effect of objective understanding on the dependent variable was negative and non-significant (*b*=-.091, *p*=.177). The overall model fit was good; the R-squared (adjusted R-squared) was .135 (.127) and the relationship was significant at *p*<.01. Multicollinearity was below critical levels, with both VIF's assuming values close to 1 (see Table 19).

Table 19: OLS estimation results for trailer liking; sequels

	Coeff. (Std. Err)	*b*	VIF
DV = *T_LIKING*			
Constant	1.909** (.324)		
OB_UND	-.431 (.318)	-.091	1.097
SUB_UND	.252** (.044)	.385	1.097
R^2 =	.135		
Adj. R^2 =	.127		

Note: **p<.01

We also observed a positive significant effect of SUB_UND (*b*=.417, *p*<.01), while OB_UND had a negative significant effect on M_LIKING (*b*=-.150, *p*<.05), implying that actually understanding what a sequel movie is about might decrease the perception of movie liking. The overall model fit was good; the R-squared (adjusted R-squared) was .159 (.151) and the relationship was significant at p<.01. Multicollinearity was below critical levels; all VIF values were below 2 (see Table 20).

Table 20: OLS estimation results for movie liking; sequels

	Coeff. (Std. Err)	*b*	VIF
DV = *M_LIKING*			
Constant	1.251 (.817)		
OB_UND	-1.813* (.802)	-.150	1.097
SUB_UND	.699** (.111)	.417	1.097
R^2 =	.159		
Adj. R^2 =	.151		

Note: **p<.01, *p<.05

Mediation analysis

To test the mediating role of trailer liking, we conducted two sets of mediation analysis, on original and sequel trailers. Similar to the previous study, we followed Zhao et al.'s (2010) method for mediation. For original trailers, we observed a partial mediation of trailer liking on the relationship between subjective understanding and movie liking. The effect of SUB_UND on M_ LIKING was significantly reduced, when T_LIKING was included in the model (*b*=.116, *p*<.01; 95% BCa CI [.091, 1.641]; see Figure 12).

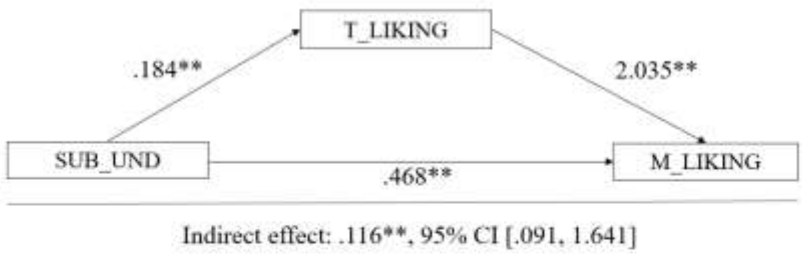

Figure 12: The mediating role of trailer liking; original movies

For sequels, trailer liking fully mediated the relationship between subjective understanding and movie liking, with SUB_UND having a non-significant effect on M_LIKING, after the addition of T_LIKING in the model (*b*=.103, *p*=.063; 95% BCa CI [.092, .342]). This indicates that for sequel trailers, liking a trailer that has been understood, automatically creates positive audience perceptions on liking the movie itself (see Figure 13). Important findings from the two studies, along with their implications, are discussed in the next section.

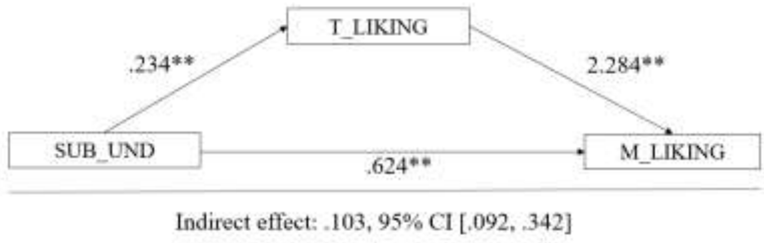

Figure 13: The mediating role of trailer liking; sequels

5.6 General Discussion & Implications

Answering calls for research on the factors behind understanding of advertisements (Archer-Brown et al., 2017), this paper offers a number of theoretical and managerial implications. Having empirically examined objective and subjective understanding under a single framework, our results demonstrate that the two constructs are indeed different mechanisms and have a different effect on ad response. Consistent with prior research on overconfidence (Moorman, 1999; Rozenblit & Keil, 2002; Wood & Lynch, 2002), we provide evidence that consumers' perception of understanding is much higher than their actual understanding, even when the illusion of explanatory depth is shattered (Fernbach et al., 2013). While this adds new knowledge to information-processing and persuasive advertising literature, it also highlights that using self-report measures for objective constructs (e.g. objective understanding) can be inaccurate and should be avoided.

Unlike prior research on the comprehension of advertising messages (Haugtvedt et al., 1992), objective (actual) understanding was not found to be a significant predictor of consumer response. Evidence that it is the *perception* of understanding that increases ad and product liking – and not the actual comprehension of a message – offers significant implications to research in persuasive advertising and information-processing. Research in this field should move beyond recall and recognition and focus on more subjective constructs, such as individual perceptions or confidence of understanding.

Inference-making activity was evident in respondents' retrospective thoughts and did indeed lead to false judgements in approximately half of the cases, consistent with prior literature (Kahneman, 2011). Although the construct was not examined in depth, exploration of its relationship to objective and subjective understanding showed that neither objective nor subjective understanding was influenced by inference-making. This indicates that while respondents jumped into – often erroneous – assumptions, this did not affect the overall perception of what a movie is about, but was rather a separate automatic brain mechanism.

Antecedents of understanding Testing of our hypotheses revealed that trailers with a higher amount of information and a linear structure increase the feeling of understanding (subjective understanding), both for original and sequel movies. However, objective understanding was driven by different factors in the two groups. Although both message content variables were significant in predicting objective understanding of original trailers, only the *order of information* was significant in the sequel group. This shows that while the amount of information in a sequel trailer does not add value to the level of audience's actual understanding, it does create an illusion of having understood what the movie is about.

Interesting findings were also noted in relation to the control variables. In original movies, where no other information is available, the need for cognition (NFC) had a positive effect on objective understanding. Consistent with prior literature on NFC (Cacioppo et al., 1996; Fernbach et al., 2013), this implies that viewers with a higher need for cognition elaborated more on the trailer and were able to achieve a higher understanding on what the movie is about. This individual characteristic, however, did not influence subjective understanding, which was affected mainly by message content parameters. The same effect was observed for sequel trailers.

Notably, having seen the prequel or being familiar with the characters, only influenced subjective understanding, indicating that context familiarity, in this sense, only affects consumers' *perceptions* of understanding. This offers important implications to researchers who are interested in the effect of prior knowledge on understanding. Again, the distinction between the two paradigms is imperative, as a different effect was observed on objective and subjective understanding.

The mediation analysis of understanding antecedents, revealed that the effect of trailer content variables on subjective understanding was partially mediated by perceived informativeness. In the case of sequel trailers, perceived informativeness fully mediated the relationship between information amount and subjective understanding. This highlights the role of perceived informativeness in the model for subjective understanding and offers significant implications to researchers who are concerned with the factors behind consumers' understanding of advertising messages. Essentially, for movies with a familiar storyline it is the perception of having received enough information that increases subjective understanding of what an upcoming movie is about.

Liking While we have already stressed the effect of *subjective* understanding on trailer and movie liking, our paper supports findings from prior work on the mediating role of trailer liking (Archer-Brown et al., 2017). Consistent with prior research on the understanding of movie trailers, we observed that trailer liking mediates the relationship between subjective understanding and perceptions of movie liking. Especially in the case of sequels, a full mediation was observed, indicating that the perception of understanding of a sequel trailer, leads to trailer liking, which automatically leads to movie liking. Perhaps, this is linked to the fact that the quality of the upcoming movie can be inferred from the prequel, and a good and comprehensive trailer alone, is enough to create positive perceptions about the movie. While these findings derived from a very specific context, it would be interesting to explore the mediating role of ad liking on other products or brand extensions where the audience has some level of context familiarity.

Thematic analysis of consumer response By identifying seven key themes through which consumers form their pre-release perceptions, we also offer contextual implications for movie-specific research. Consumers' perceptions are not only aided through the content of a communication but also through heuristic cues, peripheral to the meaning of the message. This should draw attention to secondary aspects of communications as well. Supporting prior work that focuses on movie reviews (Simmons et al., 2011; Gelper et al., 2018), the plot or storyline assumed a central role in consumers' perceptions of what the movie is about. While our focus was entirely on the pre-release phase of a movie, similar topics from prior work were observed in consumers' retrospective thoughts, indicating that the main axes of consumers' conversations before and after a movie might not be so different.

Finally, the combination of computational software and traditional statistical methods should hopefully offer methodological directions to researchers interested in analysing consumer data. Adopting new technologies, such as Natural Language Processing, to complement traditional methods, has been recommended by researchers as digital methods are increasingly becoming part of social sciences (Snee et al., 2016; Campo et al., 2018).

5.6.1 Managerial Implications

Our findings on the two different forms of understanding offer significant implications for advertising managers and movie marketers. Evidence that it is *subjective* – and not actual – understanding that leads consumers to like an ad and its featured product, should hopefully direct marketers to focus on perceptions of understanding. Advertising testing is a costly procedure (Basuroy et al., 2006). Our work offers directions on the measurement of the two constructs – objective and subjective understanding – and proposes that greater focus is given on the perception of what an ad or product is about rather than a universal comprehension of the message.

Our research demonstrates that the two understanding constructs are driven by different antecedents. As we suggest that marketers should focus on subjective understanding, important insights on the influence of information amount and order can be drawn from this work. Findings that subjective understanding is more likely increased by message content parameters rather than individual characteristics offer insight to creative advertisers who can easily manipulate the amount and order of information. The central role of perceived informativeness suggests that advertisements should offer consumers enough information to create a confident feeling of understanding of what the product is. Even in the context of movie trailers, where the plot of the movie is best left unknown, too much information was still found to be more effective in raising subjective understanding and liking. This should help trailer-makers create trailers with the ideal amount and structure of information. Confirming that the three-act framework (Campbell, 2008; Flanagan, 2012) is indeed more successful to an abstract structure and finding that the plot is key to driving consumer perceptions, should offer direction for the effective design of original and sequel trailers.

The methods employed by the researchers can also be adopted by practitioners aiming to test advertisements and analyse consumer perceptions. Although findings derive from the examination of trailers, insights can apply to other contexts where narrative based ads prevail (e.g. entertainment, fashion).

5.6.2 Limitations & Directions for future research

While our research presents novel findings through two carefully conducted studies, it is not free of limitations. We restricted our experiments to include specific information-processing parameters in relation to the message and the receiver. However, a line of work in consumer psychology and persuasive advertising takes into account the way that moods and other behavioural constructs might influence the processing of an ad (Braun-Latour et al., 2007; Forgas, 1995; Isen, 2000). While we found that general interest and contextual knowledge did not influence understanding significantly, it would be interesting to see the effect of other characteristics within the model of communication on the two forms of understanding.

Respondents were exposed to ads in an experimental environment, where they watched a trailer on their personal device and answered questions following the trailer. Focusing on the delivery of advertising, we did not take the media context in which the ad was shown into account. However, in reality, trailers – and ads in general – are watched on a variety of media. According to Puccinelli et al. (2015) the media context in which consumers watch ads can influence information-processing and attitude change. Further research could simulate different media contexts and observe their potential effects on objective and subjective understanding.

Furthermore, we used self-report measures for the two liking parameters. Whereas, this is acceptable in marketing literature (Archer-Brown et al., 2017; Enschot & Hoeken, 2015), future research could examine whether message content parameters have a similar effect on ad response, using behavioural data. Finally, this research focuses on movie trailers, as they present a narrative structure and allow for an easy manipulation of message characteristics. Further research could extend this study, using a wider variety of ads to examine the observed relationships in a wider context.

5.7 References

Alba, J. W. (1983). The Effects of Product Knowledge on the Comprehension, Retention, and Evaluation of Product Information. In R. P. Bagozzi, A. M. Tybout, & A. Abor (Eds.), *Advances in Consumer Research, Vol. 10* (pp. 577–580). MI: Association for Consumer Research.

Archer-Brown, C., Kampani, J., Marder, B., Bal, A. S., & Kietzmann, J. (2017). Conditions in Prerelease Movie Trailers For Stimulating Positive Word of Mouth. *Journal of Advertising Research*, *57*(2), 159–172.

Basuroy, S., Desai, K. K., & Talukdar, D. (2006). An Empirical Investigation of Signaling in the Motion Picture Industry. *Journal of Marketing Research*, *43*(2), 287–295.

Bhattacherjee, A., & Sanford, C. (2006). Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model. *MIS Quarterly*, *30*(4), 805–825.

Biel, A. & Bridgwater, C. A. (1990). Attributes of Likable Television Commercials. *Journal of Advertising Research*, (June/July), 38–44.

Bohnenkamp, B., Knapp, A. K., Hennig-Thurau, T., & Schauerte, R. (2015). When Does it Make Sense to Do it Again? An Empirical Investigation of Contingency Factors of Movie Remakes. *Journal of Cultural Economics*, *39*(1), 15–41.

Boksem, M. a. S., & Smidts, A. (2015). Brain Responses to Movie Tailers Predict Individual Preferences for Movies and Their Population-Wide Commercial Success. *Journal of Marketing Research*, *52*(4), 482–492.

Bransford, J. D., & Johnson, M. K. (1972). Contextual Prerequisites for Understanding: Some Investigations of Comprehension and Recall. *Journal of Verbal Learning and Verbal Behavior*, *11*(6), 717–726.

Braun-Latour, K. A., Puccinelli, N. M., & Mast, F. W. (2007). Mood, Information Congruency, and Overload. *Journal of Business Research*, *60*, 1109–1116.

Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

Brooker, P., Vines, J., Sutton, S., Barnett, J., Feltwell, T., & Lawson, S. (2015). Debating Poverty Porn on Twitter: Social Media as a Place for Everyday Socio-Political Talk. *CHI 2015, Seoul, Republic of Korea*, 3177–3186.

Burton, J. L., McAlister, L., & Hoyer, W. D. (2015). How do Consumers Respond to Storylines in Television Advertisements? A Principal-Components Analysis Tool Helps Decipher Moment-to-Moment Evaluations. *Journal of Advertising Research*, *55*(1).

Cacioppo, J. T., Petty, R. E., Feinstein, J. a., & Jarvis, W. B. G. (1996). Dispositional Differences in Cognitive Motivation: The Life and Times of Individuals Varying in Need for Cognition. *Psychological Bulletin*, *119*(2), 197–253.

Cacioppo, J. T., Petty, R. E., & Kao, C. F. (1984). The Efficient Assessment of Need for Cognition. *Journal of Personality Assessment*, *48*, 306–307.

Campbell, H. (2008). The Essence of Trailers. *IndiVision*, (April). Retrieved from http://afcarchive.screenaustralia.gov.au/newsandevents/afcnews/converse/helencampbell/newspage_463.aspx

Campo, M., Hsieh, C.-K., Nickens, M., Espinoza, J., Taliyan, A., Rieger, J., … Sherick, B. (2018). Competitive Analysis System for Theatrical Movie Releases Based on Movie Trailer Deep Video Representation. Retrieved 20 November 2018, from http://arxiv.org/abs/1807.04465

Chaiken, S. (1980). Heuristic Versus Systematic Information Processing and the Use of Source Versus Message Cues in Persuasion. *Journal of Personality and Social Psychology*, *39*(5), 752–766.

Chaiken, S., & Eagly, A. H. (1976). Communication Modality as a Determinant of Message Persuasiveness and Message Comprehensibility. *Journal of Personality and Social Psychology*, *34*(4), 605–614.

Chaiken, S., & Stangor, C. (1987). Attitudes and Attitude Change. *Annual Review of Psychology*, *38*(1), 575–630.

Chakravarty, A., Liu, Y. and Mazumdar, T. (2010) ‘The Differential Effects of Online Word-of-Mouth and Critics’ Reviews on Pre-release Movie Evaluation’, *Journal of Interactive Marketing*, 24(3), pp. 185–197.

Cho, H., & Schwarz, N. (2005). If I Don’t Understand it, it Must Be New: Processing Fluency and Perceived Product Innovativeness. *Advances in Consumer Research*, *33*, 319–320.

Dellarocas, C. N., Zhang, X. (Michael), & Awad, N. F. (2007). Exploring the Value of Online Product Revoews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing*, *21*(4), 23–45.

Diesner, J., Aleyasen, A., Chin, C., Mishra, S., Soltani, K., & Tao, L. (2015). ConText: Network Construction from Texts [Software]. Retrieved from http://context.lis.illinois.edu/

Dooling, D. J., & Lachman, R. (1971). Effects of Comprehension on Retention of Prose. *Journal of Experimental Psychology*, *88*(2), 216–222.

Eagly, A. H. (1974). Comprehensibility of Persuasive Arguments as a Determinant of Opinion Change. *Journal of Personality and Social Psychology*, *29*(6), 758–773.

Eagly, A. H., Wood, W., & Chaiken, S. (1978). Causal Inferences About Communicators and Their Effect on Opinion Change. *Journal of Personality and Social Psychology*, *36*(4), 424–435.

Eliashberg, J., Jonker, J., Swahney, M. S., & Wierenga, B. (2000). MOVIEMOD : Implementable for Prerelease Motion Market Support System of Evaluation Pictures.

Marketing Science, *19*(3), 226–243.

Enschot, R. Van, & Hoeken, H. (2015). The Occurence and Effects of Verbal and Visual Anchoring of Tropes on the Perceived comprehensibility and Liking of TV Commercials. *Journal of Advertising*, *44*(1), 25–36.

Fernbach, P. M., Sloman, S. A., Louis, R. St., & Shube, J. N. (2013). Explanation Fiends and Foes: How Mechanistic Detail Determines Understanding and Preference. *Journal of Consumer Research*, *39*(5), 1115–1131.

Flanagan, M. (2012). How to Edit a Trailer That Will Get Your Film Noticed. *MicroFilmmaker Magazine*. Retrieved from http://www.microfilmmaker.com/tipstrick/Issue14/Edit_Trl.html

Forgas, J. P. (1995). Mood and Judgment: the Affect Infusion Model (AIM). *Psychological Bulletin*, *117*(1), 39–66.

Gatignon, H., & Robertson, T. S. (1985). A Propositional Inventory for New Diffusion Research. *Journal of Consumer Research*, *11*(4), 849–867.

Gelper, S., Peres, R., & Eliashberg, J. (2018). Talk Bursts: The Role of Spikes in Pre-release Word-of-Mouth Dynamics. *Journal of Marketing Research*, *55*(6), 801-817.

Gong, J. J., Van der Stede, W. a., & Young, M. (2011). Real Options in the Motion Picture Industry: Evidence from Film Marketing and Sequels. *Contemporary Accounting Research*, *28*(5), 1438–1466.

Harris, R. J. (1977). Comprehension of Pragmatic Implications in Advertising. *Journal of Applied Psychology*, *62*(5), 603–608.

Haugtvedt, C. P., Petty, R. E., & Cacioppo, J. T. (1992). Need for Cognition and Advertising: Understanding the Role of Personality Variables in Consumer Behavior. *Journal of Consumer Psychology*, *1*(3), 239–260.

Hennig-Thurau, T., Wiertz, C., & Feldhaus, F. (2015). Does Twitter Matter? The Impact of Microblogging Word of Mouth on Consumers’ Adoption of New Movies. *Journal of the Academy of Marketing Science*, *43*(3), 375–394.

Hirschman, E. C. (1981). Technology and Symbolism as Sources for the Generation of Innovations. In A. Mitchell & A. Abo (Eds.), *Advances in Consumer Research, Vol. 9* (pp. 537–541). MI: Association for Consumer Research.

Hovland, C. I., & Janis, I. L. (1959). *Personality and Persuability*. New Haven, CT: Yale University Press.

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). *Communication and Persuasion*. New Haven, CT: Yale University Press.

Hovland, C., & Weiss, W. (1951). The Influence of Source Credibility on Communication Effectiveness. *Public Opinion Quarterly*, *15*, 635–650.

Isen, A. M. (2000). Positive Affect and Decision Making. In M. Lewis & J. Haviland (Eds.), *Handbook of Emotions* (pp. 261–277). New York: The Guilford Press.

Jacoby, J., Nelson, M. C., & Hoyer, W. D. (1982). Corrective Advertising and Affirmative Disclosure Statements: Their Potential for Confusing and Misleading the Consumer. *Journal of Marketing*, *46*(1), 61–72.

Johnson, B. T., & Eagly, A. H. (1989). Effects of Involvement on Persuasion: A Meta-Analysis. *Psychological Bulletin*, *106*(2), 290–314.

Johnson, S. G. B., & Ahn, W. (2015). Causal Networks or Causal Islands? The Representation of Mechanisms and the Transitivity of Causal Judgment. *Cognitive Science*, *39*(7), 1468–1503.

Joshi, A., & Mao, H. (2012). Adapting to succeed? Leveraging the brand equity of best sellers to succeed at the box office. *Journal of the Academy of Marketing Science*, *40*(4), 558–571.

Kahneman, D. (2011). *Thinking Fast and Slow*. New York: Farrar, Straus and Giroux.

Kardes, F. R. (1988). Spontaneous Inference Processes in Advertising: The Effects of Conclusion Omission and Involvement on Persuasion. *Journal of Consumer Research*, *15*(2), 225.

Keil, F. C. (2006). Explanation and Understanding. *Annual Review of Psychology*, *57*, 227–254.

Kernan, L. (2004). *Coming Attractions: Reading American Movie Trailers*. Austin: University of Texas Press.

Lazarsfeld, P. F. (1949). Preface. In J. T. Klapper (Ed.), *The Effects of Mass Media*. NY: Columbia Bureau of Applied Social Research.

Lipizzi, C., Iandoli, L., & Marquez, J. E. R. (2016). Combining structure, content and meaning in online social networks: The analysis of public's early reaction in social media to newly launched movies. *Technological Forecasting and Social Change*, *109*, 35–49.

Lipstein, B. (1980). Theories of Advertising and Measurement Systems. In R. W. Olshavsky (Ed.), *Attitude Research Enters the '80s*. Chicago, IL: American Marketing Association.

Livingstone, S. M. (1990). *Making Sense of Television: The Psychology of Audience Interpretation*. Oxford: Pergamon.

Maheswaran, D., & Sternthal, B. (1990). The Effects of Knowledge, Motivation, and Type of Message on Ad Processing and Product Judgments. *Journal of Consumer Research*, *17*(1), 66–73.

Maier, C. D. (2009). Visual Evaluation in Film Trailers. *Visual Communication*, *8*(2), 159–180.

McCreanor, T., Moewaka-Barns, H., Kaiwai, H., Borell, S., & Gregory, A. (2008). Creating

Intoxigenic Environments: Marketing Alcohol to Young People in Aotearoa New Zealand. *Soc. Sci. Med.*, *67*(6), 938–946.

McCroskey, J. C., & Mehrley, R. S. (1969). Effects of Disorganization and Nonfluency on Attitude Change and Source Credibility. *Speech Monographs*, *36*, 13–21.

McGuire, W. (1968). Personality and Attitude Change: An Information-Processing Theory. In A. G. Greenwald, T. C. Brock, & T. M. Ostrom (Eds.), *Psychological Foundations of Attitudes* (pp. 171–196). San Diego, CA: Academic Press.

McMackin, E., Dean, M., Woodside, J. V., & McKinley, M. C. (2013). Whole Grains and Health: Attitudes to Whole Grains Against a Prevailing Background of Increased Marketing and Promotion. *Public Health Nutrition*, *16*(4), 743–751.

Meng, X., Goodwin, P., Meeran, S., & Squire, B. (2017). Cross-Cultural Variation in Overconfidence in Judgmental Forecasting. *Journal of Behavioural Decision Making*, 1–53.

Mick, D. (1992). Levels of Subjective comprehension in Advertising Processing and their Relations to Ad Perceptions, Attitudes, and Memory. *Journal of Consumer Research*, *19*(9), 155–179.

Mohanty, P. P., & Ratneshwar, S. (2015a). Did You Get It ? Factors Influencing Subjective Comprehension of Visual Metaphors in Advertising. *Journal of Advertising*, *44*(3), 232–242.

Moorman, C. (1999). The Functionality of Knowledge Illusions. In *Association for Consumer Research Conference*. Colombus, OH.

MPAA. (2018). 2017 Theatrical Home Entertainment Market Environment (THEME) Report. Retrieved 21 December 2018, from https://www.mpaa.org/research-docs/2017-theatrical-home-entertainment-market-environment-theme-report/

MPAA. (2017). 2016 Theatrical Market Statistics. Retrieved 20 May 2018, from https://www.mpaa.org/wp-content/uploads/2018/03/MPAA-Theatrical-Market-Statistics-2016_Final-1.pdf

Nguyen, C., & Romaniuk, J. (2014). Pass it on: A Framework for Classifying the Content of Word of Mouth. *Australasian Marketing Journal*, *22*(2), 117–124.

Packard, G., Aribarg, A., Eliashberg, J., & Foutz, N. Z. (2016). The Role of Network Embeddedness in Film Success. *International Journal of Research in Marketing*, *33*(2), 328–342.

Park, D.-H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148.

Percy, L., & Rossiter, J. R. (1983). Mediating Effects of Visual and Verbal Elements in Print Advertising upon Belief, Attitude, and Intention Responses. In *Advertising and*

Consumer Psychology (pp. 171–196). Lexington, MA: D.C. Heath and Company.

Petty, R. E., & Cacioppo, J. T. (1983). Central and Peripheral Routes to Persuasion: Application to Advertising. In L. Percy & A. G. Woodside (Eds.), *Advertising and Consumer Psychology* (pp. 3–23). Lexington, MA: D.C. Heath and Company.

Petty, R. E., Cacioppo, J. T., & Goldman, R. (1981). Personal Involvement as a Determinant of Argument-Based Persuasion. *Journal of Personality and Social Psychology*, *41*(5), 847–855.

Prag, J., & Casavant, J. (1994). An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry. *Journal of Cultural Economics*, *18*(3), 217–235.

Puccinelli, N. M., Wilcox, K., & Grewal, D. (2015). Consumers ' Response to Commercials: When the Energy Level in the Commercial Conflicts with the Media Context. *Journal of Marketing*, *79*(2), 1–18.

Ratneshwar, S., & Chaiken, S. (1991). Comprehension's Role in Persuasion: The Case of Its Moderating Effect on the Persuasive Impact of Source Cues. *Journal of Consumer Research*, *18*(1), 52.

Reber, R., Schwarz, N., & Winkielman, P. (2004). Processing fluency and aesthetic pleasure: Is beauty in the perceiver's processing experience? *Personality and Social Psychology Review*, *8*(4), 364–382.

Reilly, K. O., Macmillan, A., Mumuni, A. G., & Karen, M. (2016). Extending Our Understanding of eWOM Impact: The Role of Source Credibility and Message Relevance. *Journal of Internet Commerce*, *15*(2), 77–96.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. Bönningstedt: SmartPLS. Retrieved 10 October 2018, from http://www.smartpls.com

Rishi, M., & Gaur, S. S. (2012). Emerging Sales and Marketing Challenges in the Global Hospitality Industry: a Thematic Analysis of Customer Reviews from the World's Top Two Tourist Destinations. *Tourist Themes*, *4*(2), 131– 149.

Rogers, E. M. (1962). Diffusion of innovations. New York: Free Press.

Rozenblit, L., & Keil, F. (2002). The Misunderstood Limits of Folk Science: An Illusion of Explanatory Depth. *Cognitive Science*, *26*(5), 521–562.

Saxon, J. (2017). Why Your Customers' Attention is the Scarcest Resource in 2017. *American Marketing Association*. Retrieved from https://www.ama.org/partners/content/Pages/why-customers-attention-scarcest-resources-2017.aspx

Simmons, C. J., & Lynch, J. G. J. (1991). Inference Effects without Inference Making? Effects of Missing Information on Discounting and Use of Presented Information. *Journal of Consumer Research*, *17*(4), 477–491.

Simmons, L., Conlon, S., Mukhopadhyay, S., & Yang, J. (2011). A Computer Aided Analysis of Online Reviews. *Journal of Computer Information Systems*, *52*(1), 43–55.

Simonson, I. (1989). Choice Based on Reasons: The Case of Attraction and Compromise Effects. *Journal of Consumer Research*, *16*(2), 158.

Simonton, D. K. (2008). Cinematic Success Criteria and Their Predictors: The Art and Business of the Film Industry. *Psychology & Marketing*, *26*(5), 400–420.

Snee, H., Hine, C., Morey, Y., Roberts, S., & Watson, H. (2016). Combining and Comparing Methods. In H. Snee, C. Hine, Y. Morey, S. Roberts, & H. Watson (Eds.), *Digital Methods for Social Science: An Interdisciplinary Guide to Research Innovation* (pp. 67–70). Hampshire & NY: Palgrave Macmillan.

Squire, J. E. (1992). *The Movie Business Book*. (J. E. Squire, Ed.) (2nd ed.). New York: Simon & Schuster.

Statista. (2018). Global Advertising Spending from 2010 to 2018.

Stewart, D. W. (1986). The Moderating Role of Recall, Comprehension, and Brand Differentiation on the Persuasiveness of Television Advertising. *Journal of Advertising Research*, *26*(6), 43–48.

The Numbers. (2016). The Numbers. Retrieved from http://www.the-numbers.com/

van Mulken, M., & van Enschot-van Dijk, R. (2005). Puns, Relevance and Appreciation in Advertisements. *Journal of Pragmatics, 37*(5), 707–721.

Wierenga, B. (2006). Motion Pictures: Consumers, Channels, and Intuition. *Marketing Science*, *25*(6), 674–677.

Wittrock, M. C. (1981). Reading Comprehension. In F. J. Pirozzolo & M. C. Wittrock (Eds.), *Neuropsychological and Cognitive Processes in Reading* (pp. 229–259). Academic Press.

Wood, S. L., & Lynch, Jr., J. G. (2002). Prior Knowledge and Complacency in New Product Learning. *Journal of Consumer Research*, *29*(3), 416–426.

Wood, W. (1982). Retrieval of Attitude-Relevant Information from Memory: Effects on Susceptibility to Persuasion and on Intrinsic Motivation. *Journal of Personality and Social Psychology*, *42*(5), 798–810.

Wright, P. L. (1973). The Cognitive Processes Mediating Acceptance of Advertising. *Journal of Marketing Research*, *10*(1), 53–62.

Wyer, R. S., & Shrum, L. J. (2015). The Role of Comprehension Processes in Communication and Persuasion. *Media Psychology*, *18*(2), 163–195.

Yoon, Y., Polpanumas, C., & Park, Y. (2017). The Impact of Word of Mouth via Twitter On Moviegoers' Decisions and Film Revenues. *Journal of Advertising Research*, *57*(2), 144–158.

Young, M., Gong, J. J., Van der Stede, W. A., Sandino, T., & Du, F. (2008). The Business of Selling Movies. *Strategic Finance*, (March), 35–41.

Zaichkowsky, J. L. (1985). Measuring the Involvement Construct. *Journal of Consumer Research*, *12*(3), 341–352.

Zhao, X., Lynnch, J. G. J., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*(2), 197–206.

Chapter 6: Paper 3

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“Room with a View: An Investigation of Pre-Release Movie Buzz on YouTube Trailers”

Abstract

This research provides an empirical analysis of the antecedents and outcomes of online pre-release consumer buzz (PRCB). The authors examine how advertising can generate positive perceptions and influence early consumer decisions prior to a product’s market introduction. In spite of being a crucial factor of new product adoption, PRCB has only recently gained attention in research as a separate construct from word-of-mouth. This paper further examines the PRCB construct by analyzing 1.5 million comments from YouTube on 146 upcoming movies. In the first study, the authors illustrate that PRCB comprises of various components (comments, views, likes) which are driven by different consumer behaviours. In a second study, the authors examine the effect of those components on early box office performance and find that the number of trailer views can predict early sales better than sentiment. Those results provide valuable insights for both researchers and marketers who focus on new product introduction and should direct further inquiry into the antecedents and components of PRCB.

Key Words: Pre-release buzz, Word of Mouth, Trailer advertising, Movies, New product adoption, Box office

6.1 Introduction

In 1941, Orson Wells' voiceover introduced everyone on set for the trailer of Citizen Kane. This was perhaps the most unconventional trailer in history: no hints on the movie’s storyline were given and the protagonist never appeared on screen (Shapiro, 2009). Trailers have changed considerably since then to the point where they receive equal audience attention as the movies they promote. Modern trailers include cinematic shots and music scores produced specifically for them (Shapiro, 2009), have their own awards and they are reviewed as soon as they appear online (e.g. Mendelson, 2016). But regardless of whether they do the movie justice, they typically generate large amounts of online buzz.

Few industries can be harmed or benefit more from word-of-mouth (WOM) than the movie industry (Craig et al., 2015). As the success of a movie is judged by its opening weekend performance (Gong et al., 2011), attendance needs to be at its peak as soon as a movie is released, and cannot afford to follow the standard diffusion of innovation pattern (Dellarocas et al., 2007). In order to attract large audiences to the cinemas on the opening weekend, studios spend nearly as much on advertising as on production (Rainey, 2016). Last year, the movie industry made $40.6 billion globally (MPAA, 2018). In the US alone, cinemas are still the most profitable form of entertainment, even compared to “Sports” and “Theme Parks” combined. However, the industry is only surviving because a small percentage of movies attracts a large number of moviegoers (MPAA, 2018). And although user-generated data has been available online for over a decade now, studio marketers still fail to understand their audience’s response, and translate it into their strategy (Rainey, 2016).

Recent studies on the movie industry, as well as Hollywood practitioners, have identified that movie success relies on pre-release buzz, more than studio actions (Craig et al., 2015; Squire, 2016; Divakaran et al., 2017). An overview of movie research emphasises on the need to further investigate how the social media influence consumer decisions and product success (Chisholm et al., 2015). Twitter metrics have been found to predict box office (BO) revenues (Asur & Huberman, 2010; Lipizzi et al., 2016), and the existence of tools such as Rentrak’s PreAct is proof that tracking social media reaction by studios is a standard practice (D’Alessandro, 2015). The movie industry does not only offer numerous opportunities for research, but it can also benefit greatly from valuable insights on how to minimise risk and improve early BO performance. Attendance numbers can be increased through an effective pre-release campaign which aims to: a) drive audiences directly to the cinema, and b) generate and sustain pre-release buzz in order to beat the competition (Squire, 2016). However, while pre-release buzz has proven to be critical for the early adoption of a product, most research on online reviews concerns post-release WOM.

There are two key issues with current movie WOM studies: a) the misrepresentation of WOM in research (Elberse & Eliashberg, 2003; Clement et al., 2013), which can be addressed with the collection and analysis of (reliable) behavioural data (Dellarocas et al., 2007; East et al., 2013), and b) the focus on post-release WOM, produced by consumers who have already experienced the product (Hennig-Thurau et al., 2015; Carrillat et al., 2018). The industry exhibits evidence of "shadow diffusion", where consumers make purchase (or viewing) decisions before a product even becomes available (Peres et al., 2010). However, only recently has it been recognised that pre-release consumer buzz (PRCB) exists as a separate construct to online WOM (Houston et al., 2018). Although this identification was made and tested within the context of movies, the need for a product's fast adoption is not limited to this industry. Entertainment, media and fashion products, have exponentially decaying lifecycles (Karniouchina, 2011; Campbell et al., 2017), and their fast adoption relies heavily on early hype (Hennig-Thurau et al., 2015).

This paper answers a call for research into understanding the drivers, processes and outcomes of PRCB (Houston et al., 2018), before it dynamically evolves into WOM. Focusing particularly on the pre-release phase of a movie, the authors aim to demonstrate how audiences build perceptions about a product before its use. Online data on 136 movies were collected from YouTube and Twitter over a two-year period, to explore the antecedents and effects of PRCB. In the first study, drawing from persuasive advertising literature and WOM theory, the authors explored trailer characteristics in their ability to generate favourable PRCB. In a second study, the role of the different PRCB components (comments, views, likes) in predicting early BO performance was examined. Along with extending recent work on the construct of PRCB, this research offers new insights into how marketers can gain valuable information from audience response and anticipate early sales at any stage of the pre-release campaign.

6.1.1 On pre-release buzz and word-of-mouth

In an attempt to explore PRCB in more depth, its differences to WOM will be highlighted in a brief review of relevant literature. WOM studies have typically an inter-disciplinary nature, borrowing theories from different fields. Sociologists and network scientists have explored how WOM spreads (Gladwell, 2000; Godes & Mayzlin, 2004; Van Den Bulte & Lilien, 2016) and have worked towards building and analysing the elements of social networks (Granovetter, 1973; Balasubramanian & Mahajan, 2001; Watts & Dodds, 2007). Since the recognition of WOM as a powerful marketing tool by Dichter in 1966, marketing practitioners and researchers have investigated its antecedents (Holmes & Lett, 1977; Anderson, 1998; East et al., 2015), its impact on sales (Godes & Mayzlin, 2004; Liu, 2006; Duan et al., 2008), and its comparison to other marketing techniques – mainly advertising (Katz & Lazarsfeld, 1955; Trusov et al., 2007; Feng & Papatla, 2011). The most influential factor to predict WOM is undoubtedly satisfaction with a product or service (Holmes & Lett, 1977; Anderson, 1998; East et al., 2015). While this holds true for some products, it follows the assumption that a product has already been used, and is one of the main reasons for the limited research on pre-release buzz.

Houston et al. (2018, p. 339) recently defined pre-release buzz as “the aggregation of observable expressions of anticipation by consumers for a forthcoming new product”. Pre-release buzz is not limited to words, but rather reflects a set of behaviours, translated into views and likes for online platforms. It can trigger action-based cascades (Hennig-Thurau et al., 2012) where consumers can become interested in a new product primarily for its buzz. Its main characteristic, compared to WOM, is that it is primarily positive and is responsible for the initial, rather than later adoption of a product. Due to the fact that different information is available – and the actual experience of a product is not yet possible – consumers go through different mental processes when they create, share or receive pre-release conversations (Houston et al., 2018).

While post-release WOM is undeniably more reliable (Dellarocas et al., 2007), it has lately become critical to examine not only how WOM manifests and spreads online after an experience, but also how it is created before and to what extent it can predict product adoption (Craig et al., 2015). To the authors’ knowledge, apart from one study which explores other aspects of PRCB (Craig et al., 2015), the majority of pre-release WOM research in the movie industry (Gopinath et al., 2013; Liu, 2006) is concerned with the effect of WOM metrics – namely, volume and valence – on BO performance. Furthermore, their focus is mostly on the differential effect between pre and post-release WOM, and so the WOM data that they collect, only covers a brief period of the pre-release campaign. Although the movie industry has often been used as a microcosm to study consumer behaviour (Holbrook, 1999; Chintagunta et al., 2010; Hennig-Thurau et al., 2015), to date only one study has looked at a movie’s entire pre-release advertising campaign (Gelper et al., 2018). However, the focus was more on the topics within consumers’ conversations in general, rather than the effect of trailer-viewing on those conversations.

6.1.2 Advertising sparks online buzz

WOM is considered as the most successful form of marketing (Engel et al., 1969; Godes & Mayzlin, 2004) and is responsible for the majority of audience decisions to see a movie (Squire 2016). The role of advertising in shaping early opinions and engaging consumers in WOM is evident (Katz & Lazarsfeld, 1955; Watts & Dodds, 2007; Nguyen & Romaniuk, 2014), especially in the pre-release phase of a product’s life-cycle, when little other information is available. Yet, aside from a few exceptions (Dichter, 1966; Godes & Mayzlin, 2004; Keller & Fay, 2012), WOM activity is very rarely associated with advertising in marketing research.

Nevertheless, pre-release buzz based on audience perceptions driven by movie advertising is apparent on social media. Indeed, research has shown that movie advertising influences consumer behaviour (Moul, 2007) and plays an important role both in the short and long term BO performance of a movie (Hennig Thurau et al., 2007; Gopinath et al., 2013). Offering a free sample of the movie itself, the trailer is perceived as the most persuasive marketing tool in the movie industry (Friedman, 1992; Eliashberg & Shugan, 1997; Campo et al., 2018). Its aim is to capture the "essence" of the movie (Campbell, 2008; Crookes, 2011), offering the right balance of information, to entice audiences to the cinemas on the opening weekend. However, trailers are complex narratives and few theorists have endeavoured to deconstruct them in an attempt to understand how their elements interact with consumer behaviour and BO performance (Maier, 2009; Campo et al., 2018; Kampani et al., 2019).

Recent research on movie trailers established that understanding what the movie is about is an important antecedent of positive buzz (Archer-Brown et al., 2017). Drawing from work on information-processing and persuasive advertising (Chaiken, 1980; Fernbach et al., 2013; Mohanty & Ratneshwar, 2015), this concept was further explored by identifying elements of movie trailers – the *amount* and the *order of information* – that are more likely to lead to pre-release buzz and to viewing decision (Kampani et al., 2019). However, studies on the effect of advertising content on ad response have been conducted in an experimental setting, using self-report data (Fernbach et al., 2013; Mohanty & Ratneshwar, 2015; Kampani et al., 2019). Answering calls for research into the effect of these constructs on actual WOM volume and valence, where box office performance is the ultimate dependent variable (Archer-Brown et al., 2017), this research examines the effect of trailer elements on pre-release buzz, using solely behavioural data.

6.1.3 Word-of-mouth metrics and beyond

The debate on whether the two main WOM metrics equally contribute to generating sales has occupied marketing researchers beyond the context of movies (Godes & Mayzlin, 2004; East et al., 2011). Research on movie WOM has explored the effect of volume (number of comments, tweets etc.) and valence (positive or negative sentiment) on BO performance. While some emphasize the superiority of volume over valence (Liu, 2006; Duan et al., 2008), others claim that valence in general has a stronger effect on movie receipts (Chintagunta et al., 2010), or even that the effect of negative valence on early movie attendance is stronger than that of positive valence (Hennig-Thurau et al., 2015). Research into movie WOM metrics has gone further to incorporate the time element of the movie's life-cycle and demonstrated that volume affects short term BO performance, while valence is more influential on long-term BO performance (Gopinath et al., 2013). In an attempt to resolve the debate between the two metrics, a recent meta-analysis on 51 WOM studies concluded that valence is, in fact, much more powerful than volume (You et al., 2015). However, the studies involved were not exclusively movie-related, nor did they focus on the pre-release period of the product.

While volume and valence have offered marketers a way to mearure WOM, Houston et al.'s (2018) recent work on PRCB, recognised that buzz comprises of components beyond WOM's metrics. Indeed, a few recent studies on movie WOM have taken advantage of data mining technologies and examined other conversational analytics, such as the structure of the conversation (Lipizzi et al., 2016), the distribution of sentiment (Lee et al., 2017), or the way that WOM spikes are formed (Gelper et al., 2018), offering significant novel insights in the area of movie WOM. None of these studies, however, focused on PRCB or considered the role of the trailer in shaping early opinions. Only one study has incorporated components beyond these metrics driven by trailer-viewing (e.g. comments, likes), but they were used as components of a principal variable and were collected from niche trailer sites which exclude a large percentage of moviegoers (Craig et al., 2015). The current study addresses this research gap by collecting and analysing data from the most popular video-viewing platform (YouTube; ComScore, 2018).

6.2 Conceptualising the effect of trailer-viewing on PRCB and BO performance

Typically, studios release more than one trailers during a movie's pre-release campaign. Trailers – as well as other advertising messages in general – can take many forms, depending on how they communicate information to the viewer. Drawing from information-processing theory and recent work on trailer buzz, the authors identified two parameters that have been found to influence audience response: *Information Amount* and *Order of Information* (Eagly, 1974; Chaiken, 1980; Kampani et al., 2019). The more "conventional" trailers last up to 2,5 minutes and present the movie's events in a linear fashion, following the three-act framework: the characters are first introduced, then presented with a conflict, before being seen in action on how the story progresses (Campbell, 2008; Flanagan, 2012). However, a group of trailers show only a small amount of information, or present events in a more abstract fashion, opting to give an idea of the movie's atmosphere, rather than its course of events. For the purposes of this research, the authors have termed these as “unconventional” trailers.

Prior research has shown that trailers with a higher (lower) amount and a linear (abstract) order of information have been found to raise (lower) viewers’ understanding on what the movie is about and are therefore more likely (less likely) to lead to positive responses (Kampani et al., 2019). While the concept of understanding the movie trailer has previously been linked to positive WOM valence (Archer-Brown et al., 2017), recent work on PRCB (Craig et al., 2015; Houston et al., 2018) has identified further components (video likes) that could signal positive audience response. For this reason, we consider both positive WOM valence (reflected in user-generated comments) and trailer liking (demonstrated through video likes).

The ultimate objective of this research is to determine the effect of PRCB components on opening weekend BO performance. Along with WOM valence and video likes, we have incorporated WOM volume (number of comments) which is a largely influential parameter of BO (e.g. Liu, 2006; Duan et al., 2008), as well as the number of video views, which has been indicated as an important PRCB component (Craig et al., 2015; Houston et al., 2018). We focus on opening weekend BO (rather than cumulative or long-term revenue), as advertising and PRCB have been found to be the strongest predictors of early performance, while post-release WOM accounts for the movie’s later performance (De Vany & Walls, 1999; Dellarocas et al., 2007; Gelper et al., 2018). The proposed conceptual framework is demonstrated in Figure 14.

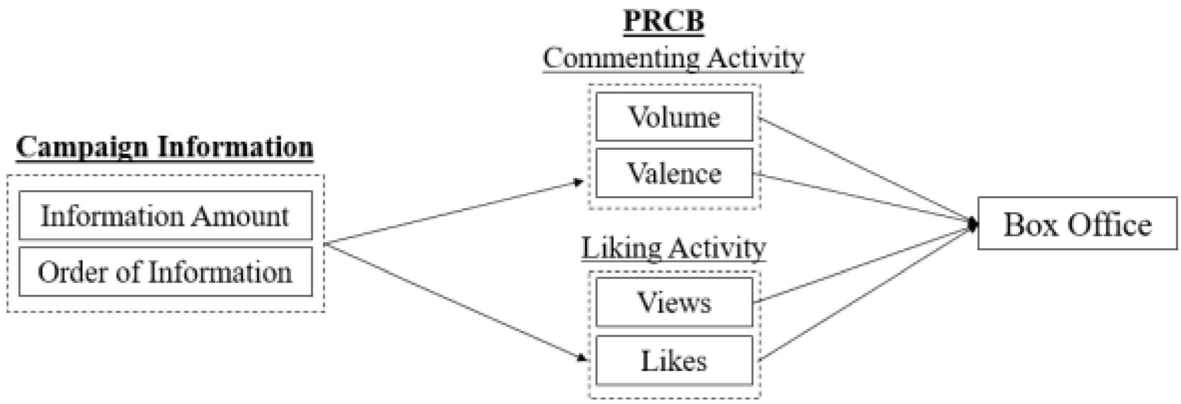


Figure 14: Proposed conceptual framework on the effect of trailer-viewing on PRCB and opening weekend BO performance

The conceptual framework was examined in two parts. The first study explored the effect of trailer campaign on positive PRCB, while the second study focused on the effect of PRCB components on opening weekend BO performance.

6.2.1 Data collection

In order to explore PRCB driven from trailer viewing, the authors collected YouTube comments 1.5 million YouTube comments for all trailers released during movies' advertising campaigns for a 2-year period (Nov 2015 – Dec 2017) on 146 movies. Consistent with Houston et al.'s (2018) work on PRCB, all wide-release movies (released in over 800 theatres) were included. Each movie's campaign was observed through Teaser-Trailer (https://teaser-trailer.com/) and a data query on YouTube URL's was prompted every time a new trailer was released on the platform. To eliminate bias in the amount of attention that a trailer had managed to generate, data was collected on all videos that had over 10,000 views and 100 comments by the day of the movie's release. The data collection process was facilitated with the help of "YouTube Data Tools" (Rieder, 2015).

Data was also collected from Twitter, to control for the effect of Twitter WOM on BO (Asur & Huberman, 2010; Rui et al., 2013; Hennig-Thurau et al., 2015). Tweets were collected during the final week before each movie's release, when marketing efforts are accentuated (Asur & Huberman, 2010; Squire, 2016). Collecting tweets during peak weeks is standard practice in WOM research (Gelper et al., 2018; Houston et al., 2018), and helps overcome the limitations of the Twitter Search API which only allows data collection for up to seven days in advance. Twitter data was scraped through Chorus Analytics (Brooker et al., 2016) – a tool specifically developed for social media research. It should be noted that the standard Twitter Search API has unavoidable limitations with regards to the messages that can be retrieved. Apart from the fact that Twitter doesn't permit the retrieval of historical data older than a week, the data that is retrieved does not fully reflect the tweets that have been shared within the week. However, this is a common limitation that many studies are facing when using a standard Twitter Search API for data scraping (Brooker et al., 2016; Bruns & Burgess, 2016).

Movie related data on the control variables was collected from various online sources – IMDb, The Numbers, Box Office Mojo, Metacritic.

6.2.2 Variables and Measures

Trailer Categorisation & Estimating Campaign Information

To determine whether a trailer follows the "conventional" or "unconventional" design, all trailers in our sample (n=416) were categorised on the *amount* and *order of information* by three independent raters. Trailers with a high (low) amount of information were classified as 1 (0). Respectively, trailers that presented the events of the movie in a linear (abstract) structure were classified as 1 (0).

In line with prior research (Liu, 2006), the categorisation was accepted when two or more raters were in agreement. Only in two trailers of the same movie ("Free State of Jones"), all three raters disagreed, and the movie was removed from the dataset completely. Trailers which scored 1 on both categorisations were deemed as "conventional". To eliminate bias that the raters might have assigned the values randomly, the Fleiss' kappa, as well as the percentage of agreement was calculated (McHugh, 2012). The percentage of agreement among the three raters was high (83%), and Fleiss' kappa showed substantial agreement (k=0.72) (Landis & Koch, 1977).

To determine a movie's overall information provided throughout the pre-release campaign (CAMP_INFO), the number of "conventional" trailers was divided by the total number of trailers for the movie. Values ranged between 0 and 1, with movies whose campaign consisted only of trailers with a high amount and a linear order of information, scoring 1.

PRCB variables selection

PRCB variables were divided into two sets. The first set was composed of the actual word-of-mouth that viewers shared after watching the trailer, consistent with most work on movie WOM. After scanning the data, and seeing that the evolution of most conversations led users to discuss completely irrelevant matters on YouTube, the authors decided to keep only top-level comments. The dataset was also filtered and comments that were not written in the English language were excluded. For each trailer of each movie, the authors extracted the number of comments (WOM_VOLUME) and the extent to which comments were positive or negative (valence). To determine each dataset's valence, sentiment analysis was performed, using a text classifier – Naïve Bayes Analyzer – which was trained on a dataset of approximately 2,000 movie reviews (Pang et al., 2002). The classifier was developed through natural language processing and machine learning techniques to assign a positive, negative or neutral classification to words and sentences. We ran the classifier on our dataset of pre-release comments and extracted the number of positive, negative and neutral comments for each trailer.

Consistent with prior movie WOM research, the ratio of positive (POS) and the ratio of negative comments (NEG) over the total number of comments was calculated (Rui et al., 2013; Hennig-Thurau et al., 2015; Hur et al., 2016; Yoon et al., 2017). We also calculated the ratio of positive over negative comments to account for the valence of comments (COM_RATIO) (Gopinath et al., 2013).

Going beyond typical WOM studies, the second set of variables was concerned with other aspects of consumer buzz behaviour (Craig et al., 2015; Oh et al., 2016; Houston et al., 2018). In order to address this, the number of views (VIEWS), likes (LIKES) and dislikes (DISLIKES) for each trailer of each movie was extracted. Similar to WOM comments, the ratio of likes over dislikes (LIKE_RATIO) was calculated to reflect overall trailer liking.

Twitter WOM

Consistent with the majority of movie WOM studies which have uncovered the influence of tweets on BO (Asur & Huberman, 2010; Rui et al., 2013; Hennig-Thurau et al., 2015), we took into account the volume of Twitter buzz (TWITTER_VOL), to control for the renowned "Twitter effect" (Corliss 2009). Since this research focuses on the effect of commenting and liking activity driven by trailer-viewing, Twitter sentiment analysis was outside the scope of this study.

Other movie-related variables

Along with trailer and PRCB variables, the authors also included movie parameters that might have an effect on early audience perceptions or on opening weekend BO performance. Movie genre (GENRE) is one of the most important characteristics of movies. It sends signals about the type of movie and is instrumental in forming expectations (Desai & Basuroy, 2005). As a result, some genres might require a different amount or order of information, to send signals about the movie. Consistent with most research on movies (Ho et al., 2009; Hennig-Thurau et al., 2015) information on each movie's genre was collected from the Internet Movie Database (IMDb.com) and a vector of the 9 most popular genres was created.

Watching a trailer of an entirely new movie can be a completely different experience to watching a trailer of a sequel, where the story and the characters are already known. Advertising spending has been found to have a stronger effect on BO for sequels than for original movies when controlling for the effect of WOM (Basuroy et al., 2006). This goes back to persuasive communications theory where the element of prior knowledge on a subject draws positive consumer attitudes (Gatignon & Robertson, 1985; Ratneshwar & Chaiken, 1991). Since sequels entail familiar signals, they have a different effect on consumer perceptions, and usually achieve higher BO returns (Joshi & Mao, 2012; Nguyen & Romaniuk, 2014; Bohnenkamp et al., 2015). In fact, sequels and franchises account for 80% of the top 25 highest-grossing movies of last year's BO revenues (MPAA, 2018). Cultural familiarity (C_FAMILIARITY) accounts for prior knowledge of a movie's context or characters and characterises movies that are sequels, adaptations, remakes or based on a true story.

Star power (STAR POWER) – which refers to the financial aspect of stars – and star buzz (STAR BUZZ) – which refers to the amount of buzz that a star raises among the audience – have both been linked to audience decisions to watch a movie (De Vany & Walls, 1999; Desai & Basuroy, 2005; Hennig-Thurau et al., 2007; Karniouchina, 2011). The effect of star power on movie receipts has been debated in movie research, since stars also incur higher production costs (De Vany & Walls, 1999; Elberse, 2007; Hennig-Thurau et al., 2007); nevertheless, the appearance on stars in movies has been found to influence at least the opening weekend BO (Desai & Basuroy, 2005; Karniouchina, 2011; Liu et al., 2014; Carrilat et al., 2018). Star buzz, on the other hand, has been found to influence WOM parameters and distributors' decisions, which in turn have a strong direct effect on BO performance (Karniouchina, 2011).

Movies' ratings imposed by the Motion Picture Association of America (MPAA) are also signals on the type of movie, complementing genre. Out of the top 25 highest-grossing movies of last year, only 3 (12%) were R-rated (MPAA, 2018). Due to the fact that R-rated movies are very often thrillers or horror movies, a higher amount of information might have a negative effect on audience response, as most of the story needs to remain unknown. Furthermore, movie ratings have been found to influence BO, since naturally a larger part of the audience is allowed to view movies that have been rated PG or PG-13 (Swami et al., 1999; Hennig-Thurau et al., 2015; Gelper et al., 2018).

Other control variables that were included in the model, consistent with prior research (Hennig Thurau et al., 2007; Karniouchina, 2011; Gopinath et al., 2013; Hoffman et al., 2017), were the production budget (BUDGET), theatre distribution (SCREEN), market competition (COMPETITION) and release date (SEASONALITY). The authors also noted whether the movie was produced by one of the major production studios (MAJOR_STUDIO), and whether it was released in the UK or in one of the theatrical festivals, before its wide release in the US. Opening weekend BO data, reflect the domestic (US) BO. Naturally, a movie released elsewhere first might exhibit a different behaviour, since some of the WOM spread between its UK and its US release will be post-release WOM. Thus, a dummy variable was created to account for movies which might have generated credible post-release WOM before their opening in the US (UK_FIRST).

A major debate in movie literature concerns the role of professional critics' reviews on BO performance. Critics' reviews (CRITICS) have been found to influence BO directly (Basuroy et al., 2003) or indirectly (Hennig Thurau et al., 2007), and they are considered to be predictors rather than influencers of the movie's performance (Eliashberg & Shugan, 1997). To shed more light into the matter, movie researchers recently conducted a meta-analysis on the effect of users' and critics' reviews on movie performance (Carrillat et al., 2018). Critics were found to be both influencers and predictors of BO success, and their role was deemed equal to user reviews (Carrillat et al., 2018), although there has been an assumption, that since the era of web 2.0. users have a greater power to influence product performance (Proserpio & Zervas, 2017). While such research focuses in the post-release phase of the product's life cycle, the authors still deemed professional opinion important, and collected data on the average movie rating of all the professional reviews that were available before the release date of the movie.

Since the focus is on the effect of PRCB, driven by trailer-viewing, two campaign-related variables were included as well: the number of trailers released during the advertising campaign (NO_TRAILERS), and the length (in months) of the campaign (CAMP_LEN). Dummy variable information was collected from Box Office Mojo (https://www.boxofficemojo.com/), The Numbers (https://www.the-numbers.com/), IMDb (https://www.imdb.com) and Metacritic (https://www.metacritic.com/). Table 21 demonstrates the operational definitions of all variables.

Table 21: Variable operationalisation

Variable	Label	Operationalisation	Source	Exemplary Studies
Campaign Information	CAMP_INFO	Ratio of "conventional" over total number of trailers in a movie's campaign	YouTube; Independent raters	*n/a*
Positive Comments	POS	Percentage of positive comments over total number of comments	YouTube; sentiment analysis	*Hennig-Thureau et al., 2015; Yoon et al., 2017; Rui et al., 2013; Hur et al., 2016; Liu, 2006*
Negative Comments	NEG	Percentage of negative comments over total number of comments	YouTube; sentiment analysis	*Hennig-Thureau et al., 2015; Yoon et al., 2017; Rui et al., 2013; Hur et al., 2016; Liu, 2006*
Commenting Ratio	COM_RATIO	Ratio of positive over negative comments	YouTube; sentiment analysis	*Gopinanth et al., 2013*
Likes	LIKES	Number of video likes	YouTube	*n/a*
Dislikes	DISLIKES	Number of video dislikes	YouTube	*n/a*
Liking Ratio	LIKE_RATIO	Ratio of video likes over video dislikes	YouTube	*n/a*
YouTube Volume	*WOM_VOLUME*	Total number of comments on all YouTube trailers of a movie throughout the pre-release period	YouTube; sentiment analysis	*Liu, 2006; Rui et al., 2013; Hennig-Thurau et al., 2015; Hur et al., 2016; Yoon et al., 2017*
YouTube Views	*VIEWS*	Total number of video views	YouTube	*Craig et al., 2015*
Twitter Volume	*TWITTER_VOL*	Number of tweets shared during the week before the movie's release	Twitter	*Liu, 2006; Rui et al., 2013; Hennig-Thurau et al., 2015; Hur et al., 2016; Yoon et al., 2017*
Opening Weekend BO	*BO*	US Opening weekend (Friday-Sunday) gross box office receipts in $	Box Office Mojo	*Dellarocas et al., 2007; Hennig-Thurau et al., 2007; Gopinath et al., 2013; Houston et al., 2018*
Production Budget	*BUDGET*	Production costs in $	Box Office Mojo	*Gelper et al., 2018; Houston et al., 2018*
Genre	*GENRE*	Vector of 9 most popular movie genres: family, comedy, drama, adventure, action, horror, thriller/crime, romance, sci-fi/fantasy	IMDb.com	*Ho et al., 2009; Hennig-Thurau et al., 2015*
Major Studio	*STUDIO*	Movie was partly or fully produced by one of the major six studios: Warner, Fox, Universal, Sony, Paramount, Disney (=1, 0 otherwise)	IMDb.com	*Elberse & Eliashberg, 2003; Hennig-Thurau et al., 2015*

Star Power	*STAR_POWER*	Movie contains at least one star who is listed in the Numbers' 100 Highest Grossing Stars in the year(s) of the movie's pre-release campaign (=1, 0 otherwise)	The Numbers	*Gong et al., 2011; Hennig-Thurau et al., 2015; Gelper et al. 2018*
Star Buzz	*STAR_BUZZ*	Movie contains at least one star who is listed in IMDB's StarMeter in the year(s) of the movie's pre-release campaign (=1, 0 otherwise)	IMDb.com	*Karniouchina, 2011*
Cultural Familiarity (sequel, adaptation etc.)	*C_FAMILIARITY*	Movie is a sequel, an adaptation, a remake, a franchise or based on a true story (=1, 0 otherwise)	Wikipedia	*Liu, 2006; Karniouchina, 2011; Bohnenkamp et al., 2015; Hennig-Thurau et al., 2015; Houston et al., 2018*
MPAA	*MPAA*	Dummy variable for the movie's age ratings imposed by the MPAA (PG, PG-13 = 1, R = 0)	Box Office Mojo	*Swami et al., 1999; Hennig-Thurau et al., 2015; Gelper et al., 2018*
UK or Earlier Festival Release	*UK_FIRST*	Movie was released earlier in the UK or in festivals (=1, 0 otherwise)	IMDb.com	*n/a*
Seasonality	*SEASON*	Movie was released during a week that is considered high season: Weeks 1-5, 9, 23-38, 49-52 in the calendar year (=1, 0 otherwise)	IMDb.com	*Einav, 2007; Karniouchina, 2011*
Competition	*COMPETITION*	Number of 20 highest grossing movies playing in the same weekend, that are between 1 and 4 weeks old and which have at least one overlapping genre or the same MPAA age rating	Box Office Mojo, IMDb.com	*Elberse & Eliashberg, 2003; Basuroy et al., 2006; Moul, 2007; Karniouchina, 2011; Clement et al., 2013*
Number of Screens	*SCREEN*	Screen count for the opening weekend	Box Office Mojo	*Gopinath et al., 2013*
Critics' Reviews	*CRITIC*	Average rating of professional critics' reviews, published prior to the movie's release	Metacritic	*Hennig-Thurau et al., 2007; Chen et al., 2012; Houston et al., 2018*
Total Number of Trailers	*NO_TRAILERS*	Total number of official trailers released	YouTube, Teaser-Trailer.com	*n/a*
Campaign Length	*CAMP_LEN*	Number of months from the release of the first trailer until the movie's release	YouTube; IMDb.com	*n/a*

6.3 Study 1: The effect of campaign information on positive PRCB

6.3.1 Isolating the impact of *amount* and *order of information* on commenting and liking

Before examining the effect of trailer campaign on PRCB, a preliminary study was conducted to explore how the *amount* and *order of information* influenced commenting and liking activity. By looking at the effect that different trailers of the same movie might have on PRCB, the authors were able to eliminate all other movie-related variables (such as movie genre or star buzz) that might influence PRCB. Since the purpose of this Pilot Study was to compare the ability of "conventional" and "unconventional" trailers in generating positive responses, the dataset was filtered to include only movies whose campaign included both types of trailers (n=79). The number of trailers for each movie ranged between 2-5.

Interestingly, the ranges of positive (POS) and negative (NEG) WOM comments were very similar. Irrespective of the type of trailer or the movie, the average positive WOM ranged between 16% to 38% and the average negative WOM ranged between 16% and 39% of the total WOM shared for the movie. Looking further into the data, we calculated the valence difference (POS – NEG) for the comments of each trailer. The maximum valence difference in the dataset was .20, showing that, at best, the proportion of positive comments produced for a trailer differed from the proportion of negative comments only by 20%. For this reason, the ratio of positive over negative WOM comments for each trailer (COM_RATIO) was deemed to be a more meaningful measure of valence.

To examine whether the *amount* and *order of information* within a trailer yielded more positive consumer response, we noted whether each movie had its highest COM_RATIO and LIKE_RATIO ratio for a "conventional" trailer. 43% of the movies followed the pattern for the COM_RATIO and 54.4% for LIKE_RATIO, implying that "conventional" trailers were more likely to generate higher liking, rather than a positive sentiment in the conversation. However, even in the cases that followed the expected pattern, no significant differences were observed between the highest and the lowest liked trailers[6].

The preliminary study revealed that "conventional" trailers were the most effective in terms of commenting and liking approximately in half of the cases. To examine the general effect

[6] Since the sample of trailers for each movie was too small (*n*=2-5), testing the mean difference through a series of t-tests was impossible. Instead, the authors opted for testing the significant difference between values, through the "simplest statistical test of significance", where: $z = \frac{a - b}{\sqrt{a - b}}$, (Pocock, 2006).

of campaign information on positive PRCB, the model included all movies in the dataset. Movie-specific variables – genre, cultural familiarity, star buzz and ratings – that might have an effect on pre-release perceptions through trailer-viewing were also taken into account.

6.3.2 Results

Descriptive Statistics

In total, the authors collected data on 146 movies, with an average production budget of $68 million and an average opening weekend box office of $29 million. After observing a skewness higher than 2, VIEWS and WOM_VOLUME were log-transformed. Outliers, which exhibited extremely high WOM _VOLUME ("Ghostbusters") or extremely positive ("The Snowman") or negative LIKE_RATIO ("Emoji", "Diary of a Wimpy Kid", "Snatched") were excluded, leaving a sample of 136 movies in the dataset. Movie genres were rated according to prior literature (Ho et al., 2009; Hennig-Thurau et al., 2015), but after an initial analysis three of the genres (romance, family and horror) were disproportionately less populated than the rest of the groups. The authors combined the first two with the Drama genre and the latter with the thriller/crime genre, resulting in 6 genres in total. Table 22 presents the frequency (in percentages) of the genres in the dataset.

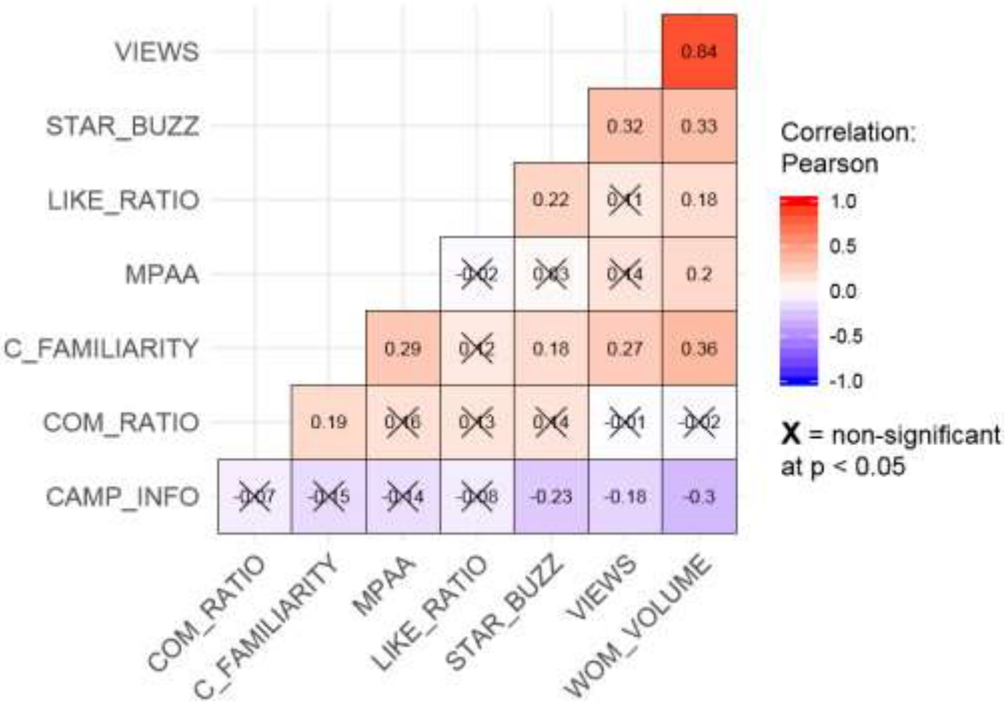
Table 22: Genre Frequency

Genre	Frequency %
Family_Drama_Romance	41.9
Action	41.2
Adventure	39.0
Comedy	36.0
Horror_Thriller	33.8
SciFi_Fantasy	22.8

Out of the 136 movies, 92 (67.6%) were culturally familiar. 42.6% of the movies included at least one star who had been featured on IMDb's top 100 StarMeter in the year(s) during the movie's pre-release campaign. 65.4% of the movies were rated PG or PG-13.

Exploratory correlations are reported in Table 23. Surprisingly, campaign information (CAMP_INFO) showed no significant relationship neither with the comment ratio nor with the liking ratio. Contrary to expectations, the overall campaign information was slightly negatively correlated both with the number of views and the number of YouTube comments, as well as with all three movie-related variables. The number of comments was highly positively correlated with the number of views, but the two ratio variables presented no significant relationship, implying that liking and talking positively about an upcoming movie, are indeed different consumer behaviours.

Table 23: Study 1 Correlations



The effect of Campaign Information on Liking and Commenting

Two sets of ordinary least squares (OLS) regressions were performed to test for the effect of campaign information on PRCB. Firstly, the effect of campaign information was tested on the liking ratio. Movie-related variables – genre, cultural familiarity, star buzz and MPAA ratings – as well as the number of views were included to control for possible effects on liking. Variables were added in two steps to illustrate differences in the model. The authors first entered the control variables (including the number of views), and added CAMP_INFO in the second step. As we report in the Appendix (Table 28), the model was not significant (R^2 = .079, F(11,124)=.966, *p* = .481), and the addition of campaign information (b = -.031, *p* = .737) did not change the model's fit at all.

The second regression estimated the effect of campaign information on commenting activity. Similar to the first regression, control variables, including the number of comments (instead of views) were inserted first, before adding CAMP_INFO in a second step. Results of the regression on COM_RATIO are reported in Table 24.

Table 24: OLS estimation results for COM_RATIO

Model	1			2		
	Coef. (Std. Error)	Beta	VIF	Coef. (Std. Error)	Beta	VIF
DV= COM_RATIO						
(Constant)	1.400** (.242)			1.424** (.260)		
COMEDY	-.164* (.083)	-.217	1.869	-.165* (.084)	-.218	1.879
FAM_DR_ROM	.094 (.072)	.128	1.493	.094 (.073)	.128	1.493
ADVENTURE	.010 (.078)	.013	1.679	.009 (.078)	.012	1.680
ACTION	-.086 (.073)	-.117	1.513	-.087 (.073)	-.117	1.513
HORROR_THRILLER	-.178* (.080)	-.231	1.661	-.178* (.080)	-.231	1.661
SCIFI_FANTASY	.047 (.086)	.054	1.523	.043 (.088)	.050	1.570
C_FAMILIARITY	.112 (.072)	.144	1.348	.112 (.073)	.144	1.348
STAR_BUZZ	.61 (.066)	.082	1.267	.058 (.067)	.079	1.289
MPAA	.043 (.069)	.056	1.268	.042 (.070)	.054	1.276
WOM_VOLUME	-.115 (.066)	-.178	1.604	-.117 (.066)	-.181	1.626
CAMP_INFO	-	-	-	-.024 (.093)	-.023	1.172
R^2 =	.195			.195		
Adjusted R^2 =	.130			.124		

*Notes: **p<.01, *p<.05*

Although the model was significant (p < .01), the model fit was quite low, R^2 = .195 (Adjusted R^2 = .124) and the addition of campaign information did not improve the model at all. In fact, only the comedy (b = -.218, p < .05) and horror/thriller (b = -.178, p < .05) genres were significant coefficients in the model.

6.3.3 Post-analysis exploration and discussion

In an attempt to investigate why in approximately half of the sample conventional trailers received a higher proportion of positive comments and likes, the authors further explored potential parameters that might explain this behaviour. For each movie with different trailers, the authors noted which trailer (in terms of CAMP_INFO) had the highest comment ratio and the highest liking ratio. Interestingly, there was only a small but significant correlation (r = .394, p < .01) between the highest talked about and the highest liked trailer, implying once more that liking and commenting activities are driven by different mental processes.

Chi-square tests against all movie-related parameters and the trailers with the highest buzz were performed to explore any possible significant relationships. Interestingly, a significant relationship between cultural familiarity and a conventional trailer being that of the highest comment ratio in the campaign was observed (X^2 (3, N=79)=14.263, p<.01). Out of all the “conventional” trailers that generated the highest comment ratio in the pre-release campaign, 70.6% were sequels, adaptations or remakes.

On the other hand, a similar effect was not observed with liking ratio (X^2 (3, N=79) = 2.291, *p*=.514). Instead, it was one of the genres that presented a significant negative relationship with a “conventional” trailer being the best liked in the campaign (X^2 (3, N=79) = 12.712, *p*<.01). Indeed, of all “conventional” trailers that generated the highest liking ratio, 85.7% were for movies that were not Sci-fi or Fantasy. This finding is in line with prior research on trailer liking and movie WOM, where compared to other movie genres (comedy, thriller) viewers of Sci-Fi/Fantasy trailers were found to engage in movie WOM irrespective of their liking the trailer (Archer-Brown et al., 2017).

Having discovered the significance of cultural familiarity and of the sci-fi genre in comment and liking ratio respectively, the authors repeated the two regressions, filtering the dataset by these two parameters. The first regression on COM_RATIO was conducted only with culturally familiar movies (n=92). The new model (Appendix, Table 29) explained an extra 2.9% of the variance (R^2 = .224, F(10,81) = 2.332, p < .05); however the addition of campaign information in the model did not improve the model fit and the parameter was not found to be a significant predictor of comment ratio (b = .009, p = .940).

The LIKE_RATIO regression was repeated on all movies that were not Sci-Fi or Fantasy (n=105). In this case the model fit was marginally higher, but again the model was not significant (R^2 = .062, F(10,94) = .624, p = .790), and campaign information did not prove to be a significant predictor (b = -.021, p = .834) (Appendix, Table 30).

The exploration of YouTube comments driven by trailer-viewing revealed that there was a small difference (up to 20%) between positive and negative valence, irrespective of the quality of the advertising message or the type of movie. Contrary to expectations, the content of trailers did not seem to be an important factor in predicting PRCB. None of the initial models presented significant results but a further analysis into movie-related variables showed that cultural familiarity, and movie genre may have an effect on commenting and liking respectively.

In general, there was a strong and significant relationship between the amount of views and the amount of comments shared on a trailer; however, no relationship was observed between comment ratio and like ratio. In fact, even looking at the most popular trailers for each movie, only in 39% of the cases the highest liked trailers were also the most positively talked about.

This is an important insight, demonstrating that engaging in positive WOM and liking a trailer are, in fact, two very different constructs. In order to examine the question of importance of positive WOM and trailer liking in predicting early BO performance, the second study tested commenting and liking activity in separate models.

6.4 Study 2: Testing the effect of PRCB activities on early BO performance

The purpose of this second study was to examine the effect of PRCB components on early BO performance, leaving the information provided in the pre-release advertising campaign aside. All movie-related variables that have been found to have an effect on opening weekend BO performance were included in the model.

Results

Descriptive statistics

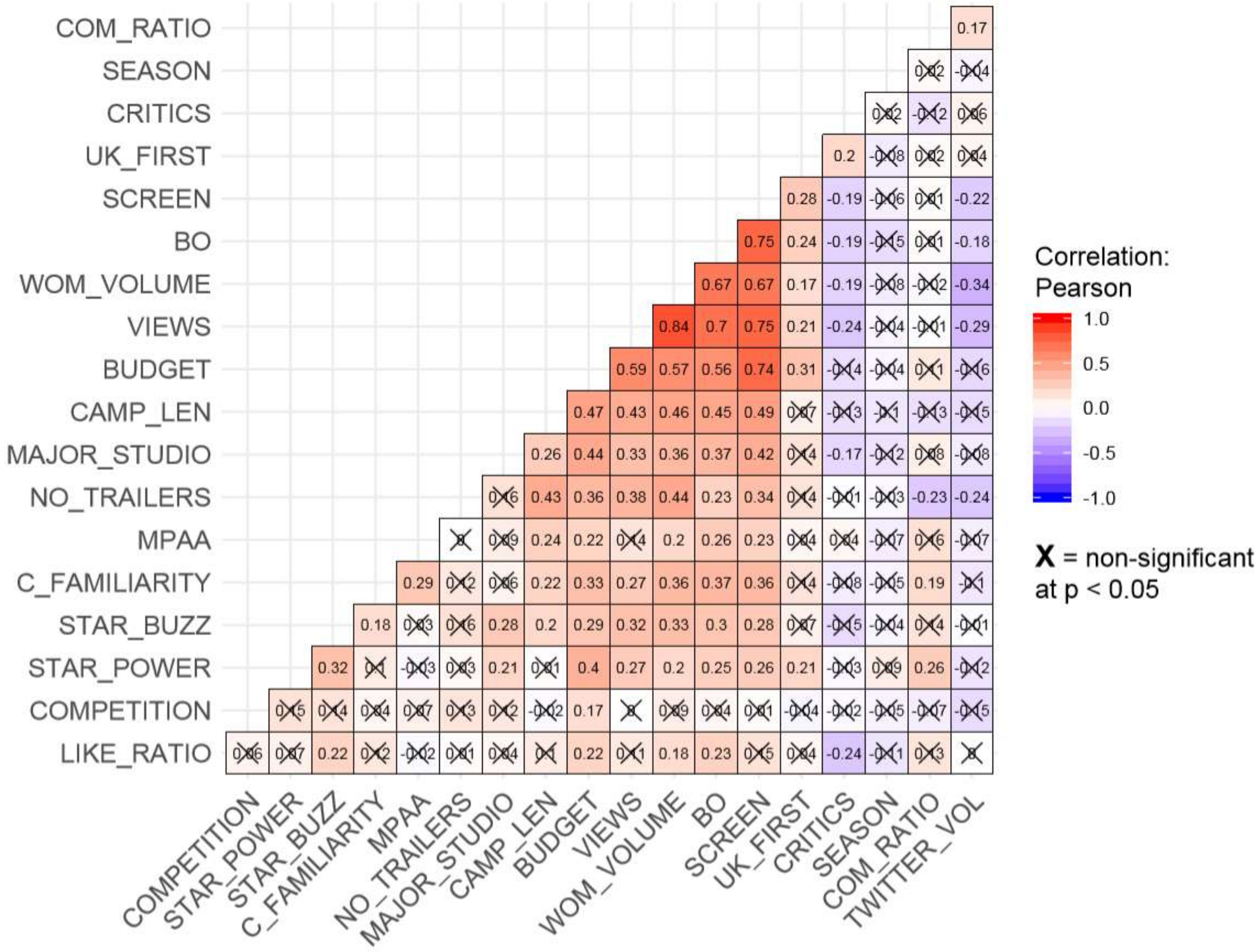
Aside from descriptive statistics on the genre, star buzz, cultural familiarity and MPAA ratings, which are reported in the previous study, we report descriptive statistics on Twitter WOM volume and the rest of movie-related parameters.

Unfortunately, due to the previously described Twitter API's restrictions (the need to start a query soon after the desired date) Twitter data was not returned for all movies in the dataset. The final Twitter dataset consisted of 26 million tweets on 106 movies. The BO, BUDGET and TWITTER_VOLUME variables presented a highly skewed distribution and were log-transformed. Only 36% of the movies were produced by a major studio. 60% of the movies featured at least one star. About half of the sample (51%) consisted of movies that were released during the peak season, and only a small percentage (19.1%) of movies were released in the UK or at a festival, before their wide US release. The average number of screens during the opening weekend, reached over three thousand. Eleven movies were not reviewed professionally before their release. The average review rating for the rest of the movies was just over 50%. The number of trailers in the pre-release campaign ranged between 1 and 5 and the length of the campaign ranged between 2 and 16 months, although the average was about 5 months.

Exploratory correlations are reported in Table 25. Opening weekend BO was significantly related with most of the variables. Contrary to prior research on seasonality and competition (Einav, 2007; Hennig-Thurau et al., 2007; Radas & Shugan, 2012), the two variables did not present any significant relationships with opening weekend BO, and so they were excluded from the final regression model. The number of YouTube comments seemed – compared to the number of Twitter comments – seemed to have a stronger relationship with BO. While both buzz volume variables (WOM_VOLUME and VIEWS) correlated with BO, out of the valence variables, only the liking ratio presented a positive relationship with BO.

Another interesting insight was the slight but significant correlation between critics' reviews and consumers' liking ratio. Although there was no evidence of a relationship between the critics' perception about the movie's quality and the audience's positive commentary, it seems that audience's perceptions of the movie, shaped by trailer-viewing, were in synch to some extent with that of critics. Finally, both campaign-related variables (the number of trailers and the length of the campaign) were positively correlated with BO. This is in line with persuasive communication theories, where repetition and increased exposure to an advertising message positively affects consumer response (Sawyer, 1981; Cacioppo & Petty, 1985).

Table 25: Study 2 Correlations



The effect PRCB on early BO performance

Consistent with prior movie literature (Hennig-Thurau et al., 2015), to test the effect of buzz, the authors ran OLS regression against opening weekend BO. Two sets of regressions were conducted to separately test the effect of comment ratio and liking ratio on BO. Similar to the first study, dummy variables were entered first, and BUZZ variables – including Twitter WOM – were added on a second step. Genre, seasonality and competition were found to be insignificant parameters and were excluded from the final model.

For the COM_RATIO regression, the second step included the amount of Twitter and YouTube comments, as well as the comment ratio. The model fit, after the first block, was good R^2 (adjusted R^2) = .561 (.504). Adding the buzz variables explained an extra 8.7 percent of the variance, bringing the R-square (adjusted R^2) to .648 (.587). Overall, the COM_RATIO model was significant ($F(14,81) = 10.636$, $p < .01$); Multicolinnearity was within limits with most VIF values below 2. When including movie-related variables and YouTube buzz, the number of tweets did not seem to be a significant predictor of opening weekend BO performance ($b = .157$, $p = .074$). Looking more closely at the two comment-related variables, the volume of YouTube comments played a more important role ($b = .288$, $p < .01$) than the valence (comment ratio) ($b = -.171$, $p < .05$), which seemed to have a negative effect on opening weekend BO performance. Interestingly, the strongest predictor in the model, even after the addition of the buzz variables, was the number of screens ($b=.374$, $<.01$) (see Table 26). This is in line with prior research which has found that theatre distribution directly affects BO (Clement et al., 2013) and is even a mediator in the relationship between advertising and BO (Elberse and Eliashberg, 2003).

Table 26: OLS estimation results for BO (COM_RATIO)

Model	1			2		
	Coef. (Std. Error)	Beta	VIF	Coef. (Std. Error)	Beta	VIF
DV = BO						
(Constant)	6.118** (.808)			5.545** (.756)		
BUDGET	-.051 (.122)	-.048	2.583	-.064 (.112)	-.061	2.625
MAJOR_STUDIO	.126 (.080)	.138	1.478	.115 (.074)	.126	1.518
C_FAMILIARITY	.124 (.078)	.136	1.392	.089 (.073)	.097	1.474
STAR_POWER	.025 (.077)	.029	1.479	.041 (.071)	.048	1.535
STAR_BUZZ	-.002 (.073)	-.003	1.309	-.030 (.068)	-.034	1.359
MPAA	.097 (.074)	.103	1.315	.130 (.070)	.145	1.384
UK_FIRST	-.013(.094)	-.011	1.253	-.020 (.089)	-.018	1.329
SCREEN	.000** (.000)	.573	2.362	.000** (.000)	.374	2.844
CRITICS	.005* (.003)	.170	1.200	.006* (.002)	.174	1.340
NO_TRAILERS	-.078 (.045)	-.142	1.267	-.121* (.044)	-.220	1.488
CAMP_LEN	.013 (.019)	.063	1.637	.008 (.018)	.037	1.647
TWITTER_VOL	-	-	-	.134 (.074)	.157	1.727
WOM_VOLUME	-	-	-	.239** (.075)	.288	1.896
COM_RATIO	-	-	-	-.199* (.091)	-.171	1.391
R^2 =	.561			.648		
Adjusted R^2 =	.504			.587		

*Notes: **p<.01, *p<.05. No genre variables, or Seasonality and Competition were significant.*

The second regression examined the effect of liking ratio on BO. Similar to the COM_RATIO regression, dummy variables were entered in the first block and the number of tweets, views and the liking ratio were added in a second step. Again, the model fit was good, R^2 (Adjusted R^2) = .561 (.504), and the addition of the buzz variables explained an extra 7.2% of the variance, bringing the R^2 (adjusted R^2) up to .633(.569).

Overall, the LIKE_RATIO model was significant (F(14,81) = 9.963, *p* <.01) and multicolinnearity was below critical limits; only two VIF values (for the budget and the number of screens) were above 2. Again, the number of tweets did not seem to be a significant predictor of opening weekend BO (b=.146, *p*=.098). Similar to the previous model, the volume of buzz – amount of views – was more significant than the valence (LIKE_RATIO). In fact, the liking ratio was not found to be a significant predictor at all (b=.051, *p*=.512). The number of views, on the other hand, was the most significant predictor in the model (b=.341, *p*<.01) and even surpassed the effect of theatre distribution (b=.305, *p*<.01) on BO (See Table 27).

Table 27: OLS estimation results for BO (LIKE_RATIO)

Model	1			2		
	Coef. (Std. Error)	Beta	VIF	Coef. (Std. Error)	Beta	VIF
DV = BO						
(Constant)	6.118** (.808)			4.034** (.975)		
BUDGET	-.051 (.122)	-.048	2.583	-.108 (.120)	.103	2.681
MAJOR_STUDIO	.126 (.080)	.138	1.478	.140 (.077)	.153	1.545
C_FAMILIARITY	.124 (.078)	.136	1.392	.136 (.073)	.148	1.416
STAR_POWER	.025 (.077)	.029	1.479	.013 (.073)	.015	1.552
STAR_BUZZ	-.002 (.073)	-.003	1.309	-.045 (.069)	-.051	1.374
MPAA	.097 (.074)	.103	1.315	.096 (.069)	.107	1.321
UK_FIRST	-.013(.094)	-.011	1.253	-.010 (.091)	-.009	1.330
SCREEN	.000** (.000)	.573	2.362	.000* (.000)	.305	3.515
CRITICS	.005* (.003)	.170	1.200	.004 (.003)	.118	1.414
NO_TRAILERS	-.078 (.045)	-.142	1.267	-.084 (.044)	-.152	1.404
CAMP_LEN	.013 (.019)	.063	1.637	.012 (.018)	.058	1.641
TWITTER_VOL	-	-	-	.124 (.074)	.146	1.679
VIEWS	-	-	-	.365** (.108)	.341	2.241
LIKE_RATIO	-	-	-	-.002 (.003)	.051	1.344
R2 =	.561			.633		
Adjusted R2 =	.504			.569		

*Notes: **p<.01, *p<.05. No genre variables, or Seasonality and Competition were significant.*

Both models turned out to be significant in predicting early BO performance. In both situations, YouTube PRCB was more significant in predicting BO, than Twitter WOM volume. This poses important implications for movie WOM research that relies solely on Twitter data. A very interesting insight lies in the fact that in both regression models, the overall volume – number of comments and views – was more important than the valence – comment and liking ratio respectively. Due to the high correlation between the number of comments and views, the authors performed two separate regressions on BO. However, comparing the volume of comments to the number of views, the latter had a stronger predictive power, and in fact outperformed all other predictors in the model. Consistent, with prior movie literature on the predictors of BO performance, theatre distribution was found to be one of the most influential predictors. Important insights derived from this research are summarised in the conceptual framework on Figure 15 and discussed in the next section.

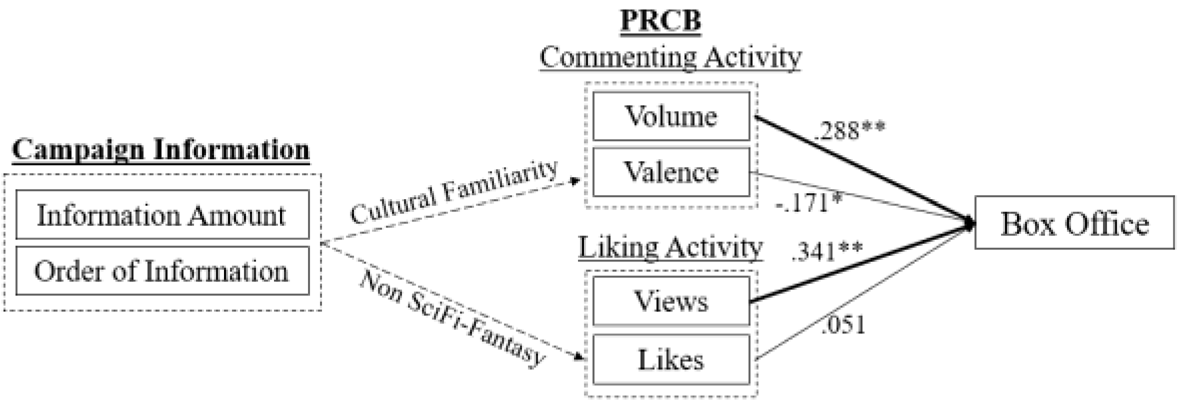


Figure 15: The effect of pre-release consumer buzz (PRCB) components on box office
*Notes: Bold lines indicate parameters with highest predictive values. **significant at p < .01, *significant at p < .05*

6.5 Discussion and Implications

This work is positioned within the marketing literature on understanding the effect of advertising on buzz and product performance. More importantly, this research aims to extend recently published work on the phenomenon of PRCB as opposed to the widely researched post-release WOM (Houston et al. 2018). The authors' aim was to uncover the antecedents of PRCB through trailer advertising, and to examine the effect of different PRCB components on early product adoption. For most experiential products, quality cannot be judged in advance (Basuroy et al., 2006; Joshi & Mao, 2012; Yoon et al., 2017); particularly for those that have not yet been introduced to the market, consumers can only speculate (Carrillat et al., 2018). Advertising plays an instrumental role in forming early audience perceptions, and this work should hopefully direct researchers' attention to the pre-release phase of a product's word-of-mouth activity.

More specifically, the first study drew theory from persuasive advertising literature (Chaiken, 1980; Fernbach et al., 2013; Mohanty & Ratneshwar, 2015), to examine elements of trailer content in their ability to generate positive audience perceptions. The trailer categorization based on information-processing variables (Eagly, 1974; Chaiken, 1980; Kampani et al., 2019), offered significant insight in relation to wider advertising messages. Contrary to prior findings on advertising response, the authors provide evidence that the *amount* and *order of information* generated positive buzz only in half of the cases, demonstrating that a common advertising recipe for driving PRCB cannot exist, at least in the context of trailers. However, trailers as ads are complex narratives and it would be worth investigating whether similar findings are observed in other product categories and other types of ads.

Interestingly, the percentage of positive comments for each trailer did not differ significantly from the percentage of negative comments. Contrary to post-release WOM where consumer opinion can be significantly divided (He & Bond, 2015; Ullah et al., 2016), evidence from 1.5 million of pre-release comments shows that in anticipation of the actual product, audiences' expectations vary by a maximum of 20%. This is an important insight on PRCB valence and implies, perhaps, the need to use different valence measures in order to gain meaningful results (Houston et al., 2018).

Commenting and liking are different PRCB behaviours. The most interesting insight of the first study was the fact that commenting and liking are two distinct consumer behaviour activities. Until recently, research on the antecedents of WOM was limited to the production of post-release conversations, overlooking other consumer behaviours that might be signals of positive communications (Hennig-Thurau et al., 2004; East et al., 2015; Chen, 2017). In line with prior suggestions (Houston et al., 2018), the authors highlight differences in the production of different PRCB components. More specifically, the authors demonstrate that the most liked trailer was the same as the most positively talked about only in 39% of the cases. One of the reasons for this disparity might be that consumers who "like" a video are not necessarily the ones that write comments. Adding to Houston's work, the authors suggest that researchers who are concerned with PRCB understand that the paradigm consists of a variety of consumer behaviours. Assuming that liking and positive sentiment are identical constructs, would be inaccurate, but further research is necessary to investigate the interdependencies and outcomes of PRCB's different components.

Looking further into the elements that drive commenting and liking behaviour, the authors found that the effect of the two trailer categorizations on PRCB depended on other, product-related, variables. More specifically, empirical data showed that conventional trailers were more successful in generating positive comments when the movie was culturally familiar. On the other hand, the audience's prior knowledge did not play a role in liking activity. Conventional trailers were more likely to be liked more when they featured movies that did not belong to the Sci-fi/Fantasy genre. Although, this is in line with prior PRCB work on movie trailers (Archer-Brown et al., 2017), the reasons behind these patterns remain unknown. Nevertheless, it is obvious that audiences require a different *amount* (*and order) of* *information*, depending on the type of movie. Further investigation on the interactions between product characteristics and advertising parameters, would shed light on the antecedents of commenting and liking and would elucidate under what circumstances these hold true.

The significance of video views. Although a universal recipe for driving PRCB was not uncovered, the second study examined the effect of commenting and liking on early BO performance. Both commenting and liking activities were found to be significant predictors of early BO, but in both cases the volume (number of comments/views) rather than valence (comment ratio/liking ratio) was responsible for predicting BO. The most influential variable in predicting opening weekend BO was unquestionably the number of views; when added to the base model, it outperformed the effect of significant movie-related parameters (e.g. number of screens). Uncovering that the number of views was much more significant than liking and other PRCB components is an important novel finding, with implications both to theory and practice. Adding to the long-standing debate on the most effective WOM metric, volume (views) in both cases was found to be a better predictor of BO than its equivalent valence (liking) parameter. Contrary to prior literature, the authors did not find evidence that volume and valence equally contribute to BO success (Carrillat et al., 2018), neither that valence is superior to volume (Forman et al., 2008; Chintagunta et al., 2010; You et al., 2015).

Theatre distribution and critics' reviews. Although this paper is positioned within the PRCB literature, findings could offer valuable insight and research directions for researchers specifically concerned with the movie industry. Consistent with prior work on theatre distribution (Elberse & Eliashberg, 2003; Clement et al., 2013), the number of screens was found to be the most influential movie-related variable in predicting BO. Research has shown that movie distributors rely on pre-release buzz to determine and allocate the number of screens (Karniouchina, 2011), and although this study did not focus on theatre distribution, the authors did find support of its significance, along PRCB variables, in predicting BO.

Another interesting insight on movie parameters, was the effect of critics' reviews compared to that of consumer reviews. The analysis showed that critics do indeed play a part in predicting early BO, and are more influential than users' comments' valence, and liking activity. However, when the volume of comments was added to the model, the effect of critics' reviews slightly decreased. More importantly, when adding the number of views, the effect of critics' reviews became insignificant. This finding is in line with recent work which points out that the accessibility of user-generated content has made *post*-release WOM more effective than professional reviews in driving consumer decisions (Proserpio & Zervas, 2017). On the other hand, findings from Carrilat et al.'s (2018) meta-analysis on the equal contribution of audience and critics' reviews, were not observed in this study. Almost all extant work on the effect of critics' and consumers' reviews concerns post-release reviews (Eliashberg & Shugan, 1997; Basuroy et al., 2006; Carrillat et al., 2018); insight of this research on pre-release buzz will hopefully spark new research avenues on the relationship of professional and consumer buzz in driving purchase decisions.

New methodologies Using behavioural data, this research offers a more accurate view of the relationship between advertising, buzz and viewing decision, established in prior work through experimental research (Archer-Brown et al., 2017; Kampani et al., 2019). According to theorists, there is currently not enough insight on how the characteristics of different platforms influence the structure and use of WOM, and consumer decisions (Berger & Milkman, 2012; Berger & Iyengar, 2013; Hennig-Thurau et al., 2015). Recent research on the effect of different eWOM metrics from social networking sites on BO performance identified certain differences (Oh et al*.*, 2016). In line with these findings, only YouTube data was found to be influential; while Twitter data was only analysed in terms of volume, future research on PRCB could investigate how further components from different platforms interact and affect early product adoption. Finally, by combining Natural Language Processing techniques with traditional statistical methods to analyse large-scale text data, new ways of conducting marketing research are introduced. Online conversations are a part of complex digital social communication systems that provide countless opportunities for analysis, and the authors encourage WOM researchers to take advantage of text data richness and relevant methodologies, to lead novel research in the area of PRCB.

6.5.1 Managerial Implications

This paper offers important implications to marketing managers concerned with advertising and new product adoption. The ability to collect and understand audience response through new methodologies could inform strategic pre-release decisions and reduce costs considerably (Boksem & Smidts, 2015). The priority of studio executives is to produce and market a movie at the minimum cost possible, and to achieve a big opening at the BO. Recognising that PRCB is a critical factor of early success (Houston et al., 2018), should hopefully stir marketers' attention to monitor audience perceptions, *before* the release of a product. Newly developed marketing tools in the movie industry, provide the ability to analyse data from social media listening in an attempt to predict a movie's performance (D'Alessandro, 2015). Nevertheless, studios fail to understand customer preference and Hollywood is still struggling to sell movies (Rainey, 2016). While marketers are unsure of YouTube trailers' effectiveness (Rainey, 2016), this current study provides evidence that pre-release audience response driven by trailer viewing plays an important role in predicting early BO performance.

Undoubtedly, the aim of studio marketers, is to create effective trailers that drive audiences to the theatres. Insight on trailer elements that have an effect on PRCB, could help trailer-makers determine the ideal *amount* and *order of information*, to build trailers that generate more positive responses. Discovering that one recipe does not apply to all movies, was an important finding that should hopefully help studios tailor their trailers depending on the movie's genre and cultural familiarity.

Furthermore, the proposed methodology for analysing different components of PRCB can be adopted by the industry for marketing and audience profiling planning purposes. The most important finding – on the importance of trailer viewership in predicting early viewing decisions – will hopefully direct marketing attention on the reach of an advertising campaign. By designing effective trailers and monitoring YouTube views – as well as other components of PRCB – studio executives could minimise the risk of a slow opening weekend.

Finally, movie marketers have the opportunity to monitor PRCB on competitive movies and inform their strategic decisions accordingly. Valuable insights on advertising campaigns and social media listening can extend beyond the movie industry. Monitoring audience response early on can also be relevant to a wider group of innovative products (Craig et al., 2015), or to products that feature quality uncertainty (Carrillat et al., 2018). Findings from this research paper could apply to the broader entertainment industry where product success depends on the level of pre-release hype[7] (Hennig-Thurau et al., 2015).

[7] The success of West End shows also relies on a big opening. Shows such as "The Mousetrap" opened in 1974 and is still in theatres. On the other hand, lack of pre-release buzz, and a small opening led the musical "I Can't Sing" to leave the stage after 6 weeks, incurring losses of £6 million (Perry 2016).

6.5.2 Limitations and Suggestions for Future Research

While this paper contributes novel findings to WOM marketing literature, and especially to the work concerning pre-release buzz, it is not free of limitations. The authors highlight the most important ones, and hope that these will be addressed in future research. To minimise bias in the sample, the data only represented wide-release movies. However, the number of independent movies has increased considerably in recent years (MPAA, 2018), and more often indie movies that are released in festivals may rapidly gain popularity. Naturally, trailer campaigns for limited or slow-release movies are very different to wide-release movies, both in the content of trailers and in the aim of the campaign strategy. Taking into account the need for product dissemination, PRCB for slow-release products is an important area for investigation.

Another important characteristic of this study was the treatment of PRCB data as a “screenshot” for the whole pre-release campaign. However, studios release a number of trailers that might change opinions throughout the pre-release phase of movies. It would be valuable to explore how different advertising messages change or maintain perceptions, and how that might be related to early product success, considering the dynamic pattern of advertising and pre-release buzz.

Due to language constraints, only English-language comments were considered. While this follows the majority of digital WOM studies, it excludes a substantial group of consumers. Last year, the international moviegoing market brought $29.5 billion (MPAA, 2018). Tools that can recognise, automatically translate and analyse non-English conversations would be valuable both for the research community and the industry. It should also be emphasized that this study focused solely on online PRCB. The Internet now plays a ubiquitous role in consumer decisions; yet, the fact that most conversations still take place offline (Berger, 2013) should not be overlooked.

Due to the nature of this study utilising large-scale behavioural data, some parameters which have been identified as influential in predicting BO performance were impossible to collect and include in the models. Movie genre familiarity, for instance, has been previously linked to movie preference (Desai & Basuroy, 2005), and although genre was not found to be a significant predictor of BO, the authors did not control for genre familiarity. Finally, the present research focuses on the movie industry. While findings on PRCB can be generalised to other experiential products with similar release patterns, it would be worth exploring the relationship between pre-release advertising and PRCB in other product categories and industries.

Appendix

Table 28: OLS estimation results for LIKE_RATIO

Model	1			2		
	Coef. (Std. Error)	Beta	VIF	Coef. (Std. Error)	Beta	VIF
DV= LIKE_RATIO						
(Constant)	9.407 (18.740)			10.188 (18.950)		
COMEDY	1.235 (2.806)	.052	1.869	1.199 (2.818)	.050	1.872
FAM_DR_ROM	2.594 (2.447)	.112	1.501	2.602 (2.456)	.112	1.501
ADVENTURE	.221 (2.626)	.009	1.689	.190 (2.637)	.008	1.691
ACTION	3.364 (2.443)	.144	1.489	3.330 (2.454)	.143	1.491
HORROR_THRILLER	.177 (2.691)	.007	1.670	.171 (2.701)	.007	1.670
SCIFI_FANTASY	-1.189 (2.830)	-.043	1.452	-1.395 (2.905)	-.051	1.519
C_FAMILIARITY	2.367 (2.416)	.097	1.316	2.338 (2.426)	.095	1.317
STAR_BUZZ	4.173 (2.257)	.180	1.284	4.056 (2.292)	.175	1.314
MPAA	-1.722 (2.330)	-.071	1.265	-1.789 (2.347)	-.074	1.274
VIEWS	.761 (2.635)	.029	1.413	.760 (2.644)	.029	1.413
CAMP_INFO	-	-	-	-1.052 (3.131)	-.031	1.156
R^2 =	.078			.079		
Adjusted R^2 =	.004			-.003		

*Notes: **p<.01, *p<.05*

Table 29: OLS estimation results for COM_RATIO; Culturally Familiar movies only

Model	1			2		
	Coef. (Std. Error)	Beta	VIF	Coef. (Std. Error)	Beta	VIF
DV= COM_RATIO						
(Constant)	1.634** (.322)			1.622** (.359)		
COMEDY	-.194 (.108)	-.223	1.613	-.165* (.108)	-.224	1.614
FAM_DR_ROM	.076 (.097)	.099	1.718	.075 (.099)	.098	1.752
ADVENTURE	.001 (.096)	.001	1.707	.001 (.096)	.001	1.709
ACTION	-.126 (.099)	-.167	1.819	-.127 (.102)	-.169	1.903
HORROR_THRILLER	-.193 (.104)	-.241	1.780	-.194 (.105)	-.241	1.784
SCIFI_FANTASY	.052 (.105)	.063	1.694	.052 (.106)	.063	1.699
STAR_BUZZ	.101 (.088)	.134	1.431	.103 (.092)	.137	1.538
MPAA	.085 (.094)	.098	1.238	.085 (.095)	.098	1.239
WOM_VOLUME	-.150 (.085)	-.223	1.693	-.148 (.089)	-.220	1.834
CAMP_INFO	-	-	-	.010 (.126)	.009	1.350
R2 =	.224			.224		
Adjusted R2 =	.138			.128		

*Notes: **p<.01, *p<.05*

Table 30: OLS estimation results for LIKE_RATIO: Non-SciFi movies only

Model	1			2		
	Coef. (Std. Error)	Beta	VIF	Coef. (Std. Error)	Beta	VIF
DV= LIKE_RATIO						
(Constant)	12.810 (20.842)			13.180 (21.022)		
COMEDY	.442 (2.985)	.019	1.646	.418 (3.002)	.018	1.648
FAM_DR_ROM	.808 (2.817	.034	1.438	.815 (2.831)	.034	1.438
ADVENTURE	-1.231 (3.079)	-.050	1.568	-1.235 (3.094)	-.050	1.568
ACTION	4.650 (2.777)	.193	1.340	4.618 (2.795)	.191	1.344
HORROR_THRILLER	-0.82 (3.009)	-.003	1.604	-.088 (3.024)	-.004	1.604
C_FAMILIARITY	1.962 (2.635)	.082	1.219	1.928 (2.654)	.080	1.224
STAR_BUZZ	2.310 (2.698)	.095	1.236	2.231 (2.737)	.091	1.260
MPAA	-1.763 (2.610)	-.073	1.184	-1.814 (2.634)	-.075	1.194
VIEWS	.584 (2.940)	.021	1.184	.609 (2.957)	.022	1.186
CAMP_INFO	-	-	-	-.730 (3.476)	-.021	1.044
R2 =	.062			.062		
Adjusted R2 =	-.027			-.038		

*Notes: **p<.01, *p<.05*

6.6 References

Anderson, E. W. (1998). Customer Satisfaction and Word of Mouth. *Journal of Service Research*, *1*(1), 5–17.

Archer-Brown, C., Kampani, J., Marder, B., Bal, A., & Kietzmann, J. (2017). Conditions in Prerelease Movie Trailers For Stimulating Positive Word of Mouth: A Conceptual Model Demonstrates the Importance Of Understanding as a Factor for Engagement. *Journal of Advertising Research*, *57*(2), 159–172.

Asur, S., & Huberman, B. (2010). Predicting the Future with Social Media. *Computing*, *1*, 492–499.

Balasubramanian, S., & Mahajan, V. (2001). The Economic Leverage of the Virtual Community. *International Journal of Electronic Commerce*, *5*(3), 103–138.

Basuroy, S., Chatterjee, S., & Ravid, S. A. (2003). How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets. *Journal of Marketing*, *67*(4), 103–117.

Basuroy, S., Desai, K. K., & Talukdar, D. (2006). An Empirical Investigation of Signaling in the Motion Picture Industry. *Journal of Marketing Research*, *43*(2), 287–295.

Berger, J. (2013). *Contagious: Why Things Catch On*. New York: Simon & Schuster.

Berger, J., & Iyengar, R. (2013). Communication Channels and Word of Mouth: How the Medium Shapes the Message. *Journal of Consumer Research*, *40*(3), 567–579.

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral? *Journal of Marketing Research*, *49*(2), 192–205.

Bohnenkamp, B., Knapp, A. K., Hennig-Thurau, T., & Schauerte, R. (2015). When Does it Make Sense to Do it Again? An Empirical Investigation of Contingency Factors of Movie Remakes. *Journal of Cultural Economics*, *39*(1), 15–41.

Boksem, M. a. S., & Smidts, A. (2015). Brain Responses to Movie Tailers Predict Individual Preferences for Movies and Their Population-Wide Commercial Success. *Journal of Marketing Research*, *52*(4), 482–492.

Brooker, P., Barnett, J., Cribbin, T., & Sharma, S. (2016). Have we Even Solved the First 'Big Data Challenge?' Practical Issues Concerning Data Collection and Visual Representation for Social Media Analytics. In H. Snee, C. Hine, Y. Morey, S. Roberts, & H. Watson (Eds.), *Digital Methods for Social Science: An Interdisciplinary Guide to Research Innovation* (pp. 34–50). Hampshire & NY: Palgrave Macmillan.

Brooker, P., Vines, J., Sutton, S., Barnett, J., Feltwell, T., & Lawson, S. (2015). Debating Poverty Porn on Twitter: Social Media as a Place for Everyday Socio-Political Talk. *CHI 2015, Seoul, Republic of Korea*, 3177–3186.

Bruns, A., & Burgess, J. (2016). Methodological Innovation in Precarious Spaces: The Case of Twitter. In H. Snee, C. Hine, Y. Morey, S. Roberts, & H. Watson (Eds.), *Digital Methods for Social Science: An Interdisciplinary Guide to Research Innovation* (pp. 17–33). Hampshire & NY: Palgrave Macmillan.

Bruns, A., & Stieglitz, S. (2012). Quantitative Approaches to Comparing Communication Patterns on Twitter. *Journal of Technology in Human Services*, *30*(3–4), 160–185.

Cacioppo, J. T., & Petty, R. E. (1985). Central and Peripheral Routes to Persuasion: The Role of Message Repetition. In A. Mitchell & L. F. Alwitt (Eds.), *Psychological Processes and Advertising Effects* (pp. 91–112). Hillsdale, NJ: Lawrence Erlbaum Associates.

Campbell, A., Mayzlin, D., & Shin, J. (2017). Managing Buzz. *RAND Journal of Economics*, *48*, 203–229.

Campbell, H. (2008). The Essence of Trailers. *IndiVision*, (April). Retrieved 21 November 2018 from http://afcarchive.screenaustralia.gov.au/newsandevents/afcnews/converse/ helencampbell/newspage_463.aspx

Campo, M., Hsieh, C.-K., Nickens, M., Espinoza, J., Taliyan, A., Rieger, J., … Sherick, B. (2018). Competitive Analysis System for Theatrical Movie Releases Based on Movie Trailer Deep Video Representation. Retrieved from http://arxiv.org/abs/1807.04465

Carrillat, F. A., Legoux, R., & Hadida, A. L. (2018). Debates and assumptions about motion picture performance: a meta-analysis. *Journal of the Acadamy of Marketing Science*, *46*(2), 273–299.

Chaiken, S. (1980). Heuristic Versus Systematic Information Processing and the Use of Source Versus Message Cues in Persuasion. *Journal of Personality and Social Psychology*, *39*(5), 752–766.

Chen, Y., Liu, Y., & Zhang, J. (2012). When Do Third-Party Product Reviews Affect Firm Value and What Can Firms Do? The Case of Media Critics and Professional Movie Reviews. *Journal of Marketing*, *76*(2), 116–134.

Chen, Z. (2017). Social acceptance and word of mouth: How the motive to belong leads to divergent WOM with strangers and friends. *Journal of Consumer Research*, *44*(3), 613–632.

Chintagunta, P. K. P., Gopinath, S., & Venkataraman, S. (2010). The Effects of Online User Reviews on Movie Box Office Performance: Accounting for Sequential Rollout and Aggregation Across Local Markets. *Marketing Science*, *29*(5), 944–957.

Chisholm, D. C., Fernandez-Blanco, V., Ravid, S. A., & Walls, W. D. (2015). Economics of motion pictures: the state of the art. *Journal of Cultural Economics*, *39*(1), 1–13.

Clement, M., Wu, S., & Fischer, M. (2013). Empirical Generalizations of Demand and Supply Dynamics for Movies. *International Journal of Research in Marketing*, *31*(2), 207–223.

ComScore. (2018). Top U.S. Online Video Content Properties Ranked by Unique Video Viewers December 2018. Retrieved 25 January 2019, from https://www.comscore.com/Insights/Rankings

Corliss, R. (2009, July 13). "Bruno": Did Twitter Reviews Hurt Movie at Box Office. *TIME*. Retrieved 21 November 2018 from http://content.time.com/time/arts/article/ 0,8599,1910059,00.html

Craig, C. S., Greene, W. H., & Versaci, A. (2015). E-word of Mouth: Early Predictor of Audience Engagement: How Pre-Release "E-WOM" Drives Box-Office Outcomes of Movies. *Journal of Advertising Research*, *55*(1), 62–72.

Crookes, D. (2011, August 2). The Science of the Trailer. *The Independent*. Retrieved 21 November 2018, from http://www.independent.co.uk/arts-entertainment/films/features/the-science-of-the-trailer-2330110.html

D'Alessandro, A. (2015, April 23). How Strong is Your Film's Buzz? Rentrak's PreAct Can Tell You - CinemaCon. *Deadline*. Retrieved 21 November 2018 from https://deadline.com/2015/04/pitch-perfect-2-insidious-chapter-3-southpaw-rentrak-uta-preact-film-campaigns-1201414615/

De Vany, A., & Walls, W. D. (1999). Uncertainty in the Movie Industry: Does Star Power Reduce the Terror of the Box Office? *Journal of Cultural Economics*, *23*, 285–318.

Dellarocas, C., Zhang, X., & Awad, N. F. (2007). Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing*, *21*(4), 23–46.

Desai, K. K., & Basuroy, S. (2005). Interactive Influence of Genre Familiarity, Star Power, and Critics' Reviews in the Cultural Goods Industry: The Case of Motion Pictures. *Psychology and Marketing*, *22*(3), 203–223.

Dichter, E. (1966). How word-of-mouth advertising works. *Harvard Business Review*, *44*(6), 147–166.

Divakaran, P., Palmer, A., Søndergaard, H., & Matkovskyy, R. (2017). Pre-launch Prediction of Market Performance for Short Lifecycle Products Using Online Community Data. *Journal of Interactive Marketing*, *38*, 12–28.

Duan, W., Gu, B., & Whinston, A. (2008). The Dynamics of Online Word-of-Mouth and Product Sales: An Empirical Investigation of the Movie Industry. *Journal of Retailing*, *84*(2), 233–242.

Eagly, A. H. (1974). Comprehensibility of Persuasive Arguments as a Determinant of Opinion Change. *Journal of Personality and Social Psychology*, *29*(6), 758–773.

East, R., Romaniuk, J., & Lomax, W. (2011). The NPS and the ACSI: a Critique and an Alternative Metric. *International Journal of Market Research*, *53*(3), 327–346.

East, R., Uncles, M. D., Romaniuk, J., & Hand, C. (2013). Distortion in Retrospective Measures of Word of Mouth. *International Journal of Market Research*, *55*(4), 2–9.

East, R., Uncles, M., Romaniuk, J., & Dall'Olmo Riley, F. (2015). Factors Associated with the Production of Word of Mouth. *The Market Research Society*, *57*(3), 439–458.

Einav, L. (2007). Seasonality in the U.S. Motion Picture Industry. *RAND Journal of Economics*, *38*(1), 127–145.

Elberse, A., & Eliashberg, J. (2003). Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures. *Marketing Science*, *22*(3), 329–354.

Eliashberg, J., & Shugan, S. (1997). Film Critics: Influencers or predictors? *The Journal of Marketing*, *61*(2), 68–78.

Engel, J. E., Blackwell, R. D., & Kegerreis, R. J. (1969). How Information is Used to Adopt an Innovation. *Journal of Advertising Research*, *9*(4), 3–8.

Feng, J., & Papatla, P. (2011). Advertising: Stimulant or Suppressant of Online Word of Mouth? *Journal of Interactive Marketing*, *25*(2), 75–84.

Fernbach, P. M., Sloman, S. A., Louis, R. St., & Shube, J. N. (2013). Explanation Fiends and Foes: How Mechanistic Detail Determines Understanding and Preference. *Journal of Consumer Research*, *39*(5), 1115–1131.

Flanagan, M. (2012). How to Edit a Trailer That Will Get Your Film Noticed. *MicroFilmmaker Magazine*. Retrieved 21 November 2018 from http://www.microfilmmaker.com/tipstrick/Issue14/Edit_Trl.html

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research*, *19*(3), 291–313.

Friedman, R. G. (1992). Motion Picture Marketing. In J. E. Squire (Ed.), *The Movie Business Book* (2nd ed., pp. 291–305). New York: Simon & Schuster.

Gatignon, H., & Robertson, T. S. (1985). A Propositional Inventory for New Diffusion Research. *Journal of Consumer Research*, *11*(4), 849–867.

Gelper, S., Peres, R., & Eliashberg, J. (2018). Talk Bursts: The Role of Spikes in Pre-release Word-of-Mouth Dynamics. *Journal of Marketing Research*, *55*(6), 801-817.

Gladwell, M. (2000). *The Tipping Point: How Little Things can Make a Big Difference*. USA: Little Brown.

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, *23*(4), 545–560.

Gong, J. J., Van der Stede, W. a., & Young, M. (2011). Real Options in the Motion Picture Industry: Evidence from Film Marketing and Sequels. *Contemporary Accounting Research*, *28*(5), 1438–1466.

Gopinath, S., Chintagunta, P. K., & Venkataraman, S. (2013). Blogs, Advertising, and Local-Market Movie Box Office Performance. *Management Science*, *59*(12), 2635–2654.

Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology*, *78*(6), 1360–1380.

He, S. X., & Bond, S. D. (2015). Why Is the Crowd Divided? Attribution for Dispersion in Online Word of Mouth. *Journal of Consumer Research*, *41*(6), 1509–1527.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52.

Hennig-Thurau, T., Houston, M. B., & Walsh, G. (2007). Determinants of Motion Picture Box Office and Profitability: an Interrelationship Approach. *Review of Managerial Science*, *1*(1), 65–92.

Hennig-Thurau, T., Marchand, A., & Hiller, B. (2012). The relationship between reviewer judgments and motion picture success: Re-analysis and extension. *Journal of Cultural Economics*, *36*(3), 249–283.

Hennig-Thurau, T., Wiertz, C., & Feldhaus, F. (2015). Does Twitter Matter? The Impact of Microblogging Word of Mouth on Consumers' Adoption of New Movies. *Journal of the Academy of Marketing Science*, *43*(3), 375–394.

Ho, J. Y. C., Dhar, T., & Weinberg, C. B. (2009). Playoff Payoff: Super Bowl Advertising for

Movies. *International Journal of Research in Marketing*, *26*(3), 168–179.

Hoffman, J., Clement, M., Völckner, F., & Hennig-Thurau, T. (2017). Empirical Generalizations on the Impact of Stars on the Economic Success of Movies. *Journal of Research in Marketing*, *34*(2), 442–461.

Holbrook, M. B. (1999). Popular Appeal Versus Expert Judgments of Motion Pictures. *Journal of Consumer Research*, *26*(2), 144–155.

Holmes, J. H., & Lett, J. D. (1977). Product Sampling and Word of Mouth. *Journal of Advertising Research*, *17*(5), 35–40.

Houston, M. B., Kupfer, A., Hennig-thurau, T., Spann, M. (2018). Pre-release consumer buzz. *Journal of the Acadeny of Marketing Science, 46(2),* 338-360.

Hur, M., Kang, P., & Cho, S. (2016). Box-office Forecasting Based on Sentiments of Movie Reviews and Independent Subspace Method. *Information Sciences*, *372*, 608–624.

Joshi, A., & Mao, H. (2012). Adapting to succeed? Leveraging the brand equity of best sellers to succeed at the box office. *Journal of the Academy of Marketing Science*, *40*(4), 558–571.

Kampani, J., Archer-Brown, C., & Hang, H. (2019). *Towards a Subjective Understanding Paradigm: Investigating Consumers' Understanding and Ad Response in a Movie Trailer Context*. Working Paper

Karniouchina, E. V. (2011). Impact of Star and Movie Buzz on Motion Picture Distribution and Box Office Revenue. *International Journal of Research in Marketing*, *28*(1), 62–74.

Katz, E., & Lazarsfeld, P. F. (1955). *Personal Influence: The Part Played by People in the Flow of Mass Communications*. Glencoe, IL: Free Press.

Keller, E., & Fay, B. (2012). Word-of-mouth Advocacy: A new Key to Advertising Effectiveness. *Journal of Advertising Research*, *52*(December), 459–465.

Landis, R., & Koch, G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics*, *33*(1), 159–174.

Lee, J. H., Jung, S. H., & Park, J. H. (2017). The Role of Entropy of Review Text Sentiments on Online WOM and Movie Box Office Sales. *Electronic Commerce Research and Applications*, *22*, 42–52.

Lipizzi, C., Iandoli, L., & Marquez, J. E. R. (2016). Combining structure, content and meaning in online social networks: The analysis of public's early reaction in social media to newly launched movies. *Technological Forecasting and Social Change*, *109*, 35–49.

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*, *70*(3), 74–89.

Lopez, J. (2011, December 12). Hollywood's Two-Minute Auteurs. *Bloomberg Businessweek*, 97–101.

Maier, C. D. (2009). Visual Evaluation in Film Trailers. *Visual Communication*, *8*(2), 159–180.

McHugh, M. (2012). Interrater Reliability: The Kappa Statistic. *Biochem Med*, *22,* 3276–

3282.

Mendelson, S. (2016, March 15). Tim Burton Meets "X-Men" In "Miss Peregrine's Home For Peculiar Children" Trailer. *Forbes*. Retrieved 21 November 2018 from https://www.forbes.com/sites/scottmendelson/2016/03/15/tim-burtons-miss-peregrines-home-for-peculiar-children-gets-very-x-men-like-trailer/#7c02b0e66681

Mohanty, P. P., & Ratneshwar, S. (2015). Did You Get It ? Factors Influencing Subjective Comprehension of Visual Metaphors in Advertising, *44*(3), 232–242.

Moul, C. C. (2007). Measuring Word of Mouth's Impact on Theatrical Movie Admissions. *Journal of Economics and Management Strategy*, *16*(4), 859–892.

MPAA. (2018). 2017 Theatrical Home Entertainment Market Environment (THEME) Report. Retrieved 10 December 2018 from https://www.mpaa.org/research-docs/2017-theatrical-home-entertainment-market-environment-theme-report/

Nguyen, C., & Romaniuk, J. (2014). Pass it on: A Framework for Classifying the Content of Word of Mouth. *Australasian Marketing Journal*, *22*(2), 117–124.

Oh, C., Roumani, Y., Nwankpa, J. K., & Hu, H.-F. (2016). Beyond likes and tweets: Consumer engagement behavior and movie box office in social media. *Information & Management*, *54*(1), 25–37.

Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment Classification using Machine Learning Techniques. In *Conference on Empirical Methods in Natural Language Processing (EMNLP)* (pp. 79–86). Philadelphia, PA.

Peres, R., Muller, E., & Mhajan, V. (2010). Innovation Diffusion and New Product Growth Models. *International Journal of Research in Marketing*, *27*, 91–106.

Perry, K. E. (2016). Theatreland. *EasyJet Traveller*, 76–84. Retrieved 10 December 2018 from http://traveller.easyjet.com/features/2016/05/theatreland.

Pocock, S. J. (2006) The simplest statistical test: how to check for a difference between treatments, *BMJ*, 332(7552), 1256–1258.

Proserpio, D., & Zervas, G. (2017). Online Reputation Management: Estimating the Impact of Management Responses on Consumer Reviews. *Marketing Science*, *36*(5), 1–21.

Radas, S., & Shugan, S. M. (2012). Seasonal Product Marketing and Timing New Introductions. *Journal of Marketing Research*, *35*(3), 296–315.

Rainey, J. (2016, March). The Perils of Promotion: Pricey TV Campaigns , Fear of Change Shackles Movie Spending. *Variety*, Retrieved 10 December 2018, from https://variety.com/2016/film/features/movie-marketing-advertising-tv-campaigns-1201724468/

Ratneshwar, S., & Chaiken, S. (1991). Comprehension's Role in Persuasion: The Case of Its Moderating Effect on the Persuasive Impact of Source Cues. *Journal of Consumer Research*, *18*(1), 52.

Rieder, B. (2015). YouTube Data Tools. Retrieved 10 November 2015, from https://tools.digitalmethods.net/netvizz/youtube/index.php

Rui, H., Liu, Y., & Whinston, A. (2013). Whose and What Chatter Matters? The Effect of Tweets on Movie Sales. *Decision Support Systems*, *55*(4), 863–870.

Sawyer, A. (1981). Repetition, Cognitive Responses, and Persuasion. In R. E. Petty, T. Ostrom, & T. Brock (Eds.), *Cognitive Responses in Persuasion* (pp. 237–262). New Jersey: Lawrence Erlbaum Associates.

Shapiro, M. J. (2009). *Coming Attractions*. USA: AJK Foundation.

Squire, J. E. (2016). *The Movie Business Book*. (J. E. Squire, Ed.) (4th ed.). New York: Simon & Schuster.

Swami, S., Eliashberg, J., & Weinberg, C. B. (1999). SilverScreener: A modeling approach to movie screens management. *Marketing Science*, *18*(3), 352–372.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2007). Estimating the Dynamic Effects of Online Word-of-Mouth on Member Growth of a Social Network Site. *Journal of Marketing*, *73*(5), 90–102.

Ullah, R., Amblee, N., Kim, W., & Lee, H. (2016). From Valence to Emotions: Exploring the Distribution of Emotions in Online Product Reviews. *Decision Support Systems*, *81*, 41–53.

Van Den Bulte, C., & Lilien, G. L. (2016). Medical Innovation Revisited: Social Contagion versus Marketing Effort. *American Journal of Sociology*, *106*(5), 1409–1435.

Watts, D. J., & Dodds, P. S. (2007). Influentials, Networks, and Public Opinion Formation. *Journal of Consumer Research*, *34*(4), 441–458.

Yoon, Y., Polpanumas, C., & Park, Y. (2017). The Impact of Word of Mouth via Twitter On Moviegoers' Decisions and Film Revenues. *Journal of Advertising Research*, *57*(2), 144–158.

You, Y., Vadakkepatt, G. G., & Joshi, A. M. (2015). A Meta-Analysis of Electronic Word-of-Mouth Elasticity. *Journal of Marketing*, *79*(2), 19–39.

Chapter 7: Discussion & Conclusion

The present research contributes new knowledge both to theory and to practice. This chapter first describes the theoretical contributions of this research (7.1) to the wider PRCB literature (7.1.1) and to the particular role of understanding within persuasive advertising research (7.1.2). Theoretical implications regarding the context of movies (7.1.3) and the combination of methodologies in marketing research are also discussed (7.1.4). This chapter then demonstrates how the theoretical insight can be adopted to provide solutions to the managerial problems in the movie industry (7.2). Finally, limitations which can potentially inspire future research are mentioned (7.3).

7.1. Theoretical Contributions

7.1.1 PRCB

This research is positioned within the literature that examines new product introduction (Gelper et al., 2018; Houston et al., 2018; Peres et al., 2010). Specifically, it is concerned with how the pre-release advertising campaign for a new product can be shaped to drive positive pre-release buzz, and consequently product adoption. Although the wider eWOM marketing literature has partly been concerned with WOM shared *prior* to a product's release (Craig, Greene, & Versaci, 2015; Ho, Dhar, & Weinberg, 2009; Liu, 2006), PRCB was only recently recognised as a distinct construct (Houston et al., 2018). In an extensive research of studies concerned with the pre-release phase, Houston et al. (2018) observe substantial differences between pre and post-release WOM and have suggested that further systematic testing is conducted to identify the antecedents and outcomes of PRCB. One of the main differences lies in the fact that in post-release WOM studies consumers' reviews are shared after the product has been released and consumed. As a result, product or service (dis)satisfaction is deemed to be the most important variable in driving consumers' WOM activity (Anderson, 1998; East et al., 2015). Undeniably, this is impossible in the pre-release phase of a product (Basuroy et al., 2006; Joshi & Mao, 2012; Yoon et al., 2017). This thesis follows traditional WOM studies (Day, 1971; Dichter, 1966), as well as more recent work (Keller & Fay, 2009) which acknowledges the complementary relationship between advertising and WOM. Adding to the limited literature on PRCB, this research aims to position advertising as a PRCB antecedent.

More specifically, Paper 1 explores the initial relationship between advertising and PRCB. By testing trailers of movies that have not yet been released, it ensures that consumers' only information comes from the advertising campaign. Findings show that a specific aspect of trailer-viewing – understanding what the movie is about – combined with liking the ad (trailer) leads consumers to share positive PRCB about the movie and consider to pay to see it. Insight from this paper in the area of PRCB is twofold: not only is PRCB driven by effective advertising, but it also mediates the relationship between advertising and product adoption (purchase intention in this case). Notably, neither liking of the trailer, nor understanding what the movie is about, led to the intention of product adoption, without the intention to spread positive PRCB. This important finding demonstrates that it is PRCB, driven by advertising, that motivates consumers to adopt a product, highlighting the significance of PRCB and adding new knowledge to the recent work surrounding the concept (Houston et al., 2018).

The complementary relationship between advertising and PRCB, as well as the effect of PRCB on product adoption is thoroughly tested in Paper 3. Again, focusing only on the pre-release period of the product, the data collected for Paper 3 was directly compiled from comments on trailer-viewing ensuring that PRCB conversations were driven from the pre-release advertising campaign. In this paper, PRCB is evident, with approximately 1.5 million YouTube comments shared prior to the movies' release. Looking at different PRCB components, findings of this study show that commenting and liking are distinct activities. Indeed, the most liked trailer of the campaign, was also the most positively talked about, only in one third of the cases. This offers important implications to research on online consumer behaviour and eWOM, calling future researchers to differentiate between these two activities.

Paper 3 also demonstrates the importance of PRCB components in driving early BO performance. Notably the most important aspect in predicting opening weekend BO was not the volume and valence of comments, but the amount of trailer views throughout the pre-release period. Although the first paper demonstrated that understanding and liking lead to the intention to generate WOM and in turn, pay to see the movie, Paper 3 demonstrates that awareness (reflected through the measurement of YouTube views) is more important in predicting early sales. This is not to say that commenting activity was not a significant predictor; but to highlight that the amount of views surpasses the effect of all other movie-related variables. This finding offers important implications to literature on PRCB components and hopefully directs attention to metrics beyond volume and valence.

- Volume Vs. Valence

On the topic of volume and valence, this thesis also addresses the long-standing debate between the two metrics and their effect on BO performance (Chintagunta et al., 2010; Duan et al., 2008; Karniouchina, 2011a; Liu, 2006). A meta-analysis on eWOM metrics, beyond the context of movies, points to the significance of eWOM valence (You et al., 2015), but movie-specific meta-analyses demonstrate a stronger volume effect (Babic Rosario et al., 2016), or even an equal effect between volume and valence (Carrillat et al., 2018). Recent PRCB work (Houston et al., 2018) identifies components beyond traditional eWOM metrics and calls researchers to take these into account. Findings from this thesis elucidate debates in prior eWOM literature and add new knowledge in the area of other PRCB components.

In Paper 1, the propensity to spread positive WOM driven by trailer-viewing is found to be directly related to the intention to see the movie. In this sense, although not behaviourally measured, both the volume and valence of WOM present an association to product adoption. The analysis of behavioural data in Paper 3, however, offers slightly different insight on the production and the effect of PRCB. Notably, the percentage of positive comments on each movie did not differ significantly from the percentage of negative comments. As a result, a strong proportion of liking was not reflected in consumers' written comment activity and was not found to be a significant predictor of early BO. This offers interesting implications in the area of PRCB; it follows that in the period prior to the movie's release the audience's opinions are not significantly divided, contrary to findings on post-release movie WOM (He, Zheng, Zeng, Luo, & Zhang, 2016; Ullah et al., 2016). This might be due to the anticipatory nature of PRCB and to the fact that audiences are only capable of speculations rather than strong opinions during the pre-release phase. Nevertheless, this insight adds important new knowledge in the area of PRCB and demonstrates, once again, its difference to WOM.

In examining the effect of PRCB, volume was found to be one of the most significant predictors of early BO. Important results of Paper 3, concern the number of views which was found to predict opening weekend BO, better than all other PRCB and movie-related variables. Essentially, while researchers on movie WOM were debating the effect of WOM volume and valence (Babic Rosario et al., 2016; Carrillat et al., 2018; You et al., 2015), they overlooked other important parameters that, during the pre-release phase, are even better predictors of early performance.

7.1.2 Understanding the persuasive ad

Along with strengthening the relationship between advertising and PRCB, and adding significant new knowledge to PRCB theory, this thesis is specifically centred on understanding of the advertising message. Literature on persuasive advertising looks into the concept as part of the wider information-processing model (Eagly, 1974; McGuire, 1968; Ratneshwar & Chaiken, 1991). As a result, the particular role of understanding which is central in the model, has not gained enough attention. The few studies that examine the concept in particular have measured understanding from two different perspectives (Mick, 1992), making it problematic to generalise results to other kinds of ads or products. Moreover, the ultimate objective in information-processing models has been the adoption of communication (Chaiken, 1980; Eagly & Chaiken, 1993; Hovland et al., 1953; Petty & Cacioppo, 1983), and not specifically the production of WOM. As a result, the relationship between understanding the ad and PRCB has not been tested in advance. Findings from this thesis offer significant implications in the area of persuasive advertising theory, bridging once more the gap between advertising and WOM literature. It is also worth noting that all three papers test consumers' understanding of visually complex ads, a need that has been underlined in advertising research (Livingstone, 1990; Mohanty & Ratneshwar, 2015).

Paper 1 proposes the perception of *understanding the movie trailer* as the measurable outcome of capturing the essence of the movie (Flanagan, 2012) and tests its relationship to liking, WOM and purchase intent. Findings that liking alone does not predict WOM and purchase intent strengthen the position of understanding in the model and add the construct as a WOM antecedent. On the other hand, understanding alone does not necessarily predict WOM and purchase intent (apart from the case of scifi movies), highlighting, again, the inter-dependence of understanding and liking in predicting WOM and purchase intent.

While Paper 1 serves as an initial exploration of the position of understanding within the WOM model, Paper 2 looks more closely at its measurement, antecedents and outcomes. More specifically, Paper 2 delves deeper into the construct of understanding, measuring it both from an objective and a subjective perspective. Adding new knowledge to prior work (Mick, 1992), findings demonstrate that objective and subjective understanding are indeed distinct constructs, with subjective understanding levels being significantly higher than objective understanding. Demonstrating that audiences are overconfident in the amount of information they feel that they have understood (Moorman, 1999; Rozenblit & Keil, 2002; Wood & Lynch, Jr., 2002), this paper also offers important implications on the measurement of understanding in future research. Essentially, measuring consumers' objective understanding through self-report scales will inevitably provide inaccurate results.

Paper 2 also examines message content and receiver-related variables as antecedents of understanding. Consistent with prior research (Cheung & Thadani, 2012; Eagly, 1974; Hovland et al., 1953), it is shown that the amount and order of information are good predictors of objective and subjective understanding, but that context familiarity can influence this relationship. Examining trailers of sequels and of original movies separately, allowed for the examination of context familiarity in isolation and did indeed present some differences. When context familiarity was present, the amount of information only influenced subjective understanding, and even then, it was fully mediated by the effect of perceived informativeness. Such an effect, however, was not observed with original movies. This finding offers significant implications to research concerned with the effect of prior or contextual knowledge (Alba, 1983; Petty & Cacioppo, 1981; Ratneshwar & Chaiken, 1991), since it follows that individuals' objective understanding is only aided by the order of information, when prior knowledge is present.

An important implication of Paper 2 is the effect of understanding in predicting ad and product liking. Only subjective understanding was found to be a significant predictor of ad and product liking, a finding that offers important implications to researchers concerned with persuasive advertising and consumer response. Since it is the *feeling* of understanding which leads to positive consumer response, research attention should be turned away from the universal comprehension of an advertising message and towards the subjective understanding paradigm. The investigation of subjective understanding antecedents also demonstrated that only message-content variables were significant in instilling a feeling of understanding. This is an important finding in the area of persuasive advertising, illustrating that receiver-related parameters such as NFC or product involvement might only have an effect on objective understanding.

While Paper 3 does not necessarily examine the effect of understanding, it draws from findings from Paper 2 to study the effect of message content parameters directly on trailer liking (since the measurement of subjective understanding through behavioural data is impossible). The results of Paper 3 demonstrated that these parameters were associated with liking only in 39% of cases; nevertheless, the relationship between trailer content and liking proved to be influenced by movie-related variables (genre and context familiarity). Although these were not tested systematically and are in need of further investigation, insight is in synch with findings from Paper 1 on the particularity of sci-fi movies and findings from Paper 2 on sequel movies. In any case, it follows that understanding is a complex construct driven both by message-content variables and by product-specific elements.

7.1.3 Movie Elements

This thesis offers important contextual implications to the work surrounding movie adoption. Thanks to the availability of online data and to the fact that movies naturally stimulate a lot of WOM online, movie eWOM has drawn researchers' attention. Yet, the specific study of movies' pre-release buzz is limited. While the industry has often been used as a microcosm to study consumer behaviour (Chintagunta et al., 2010; Hennig-Thurau et al., 2015; Holbrook, 1999), no research up to date has analysed movies' PRCB throughout the entire pre-release phase. Findings from the three studies build on the fact that the pre-release advertising campaign is instrumental in forming pre-release perceptions that consequently lead to the adoption of a movie. The importance of movie PRCB becomes evident in Papers 1 and 3, extending prior research that has only looked at a fragment of a movie's PRCB (e.g. as far as three weeks in advance; Craig et al., 2015; Karniouchina, 2011a; Liu, 2006; Nguyen & Romaniuk, 2014).

The combination of two online platforms (YouTube and Twitter) in Paper 3, offers further implications with regards to prior movie WOM research. Notably, Twitter has been treated as the most significant platform in the dissemination of movie WOM and has been the source of data for the majority of studies in the area (e.g. Asur and Huberman, 2010; Rui, Liu and Whinston, 2013; Hennig-Thurau, Wiertz and Feldhaus, 2015; Lipizzi, Iandoli and Marquez, 2016). In this paper, however, the effect of YouTube PRCB was significantly stronger than the effect of Twitter WOM in predicting opening weekend BO. Although different metrics were extracted from the two platforms, comparing WOM volume from YouTube (number of comments) and from Twitter (number of tweets) presented significant results in favour of YouTube. According to theorists (Berger & Iyengar, 2013; Berger & Milkman, 2012), there is not yet enough knowledge in how the different platforms contribute to early sales; this finding should hopefully divert researchers' attention to platforms other than Twitter, or ideally to a combination of different social networking sites.

Important insights can also be gained with regards to other BO predictors, such as theatre distribution and critics' reviews. While findings on movie-related parameters are not central to this thesis, the number of screens and the effect of critics' reviews present interesting insight that should contribute to and provide directions for research on the context of movies. In Paper 3, theatrical distribution (number of screens) was found to be the most important movie-related predictor of short term BO, supporting prior work (Clement et al., 2013; Elberse & Eliashberg, 2003). However, trailer views in the PRCB model, surpassed the effect of theatre distribution. With regards to critics' reviews, the parameter has raised some debate in relation to user reviews and their effect on sales (Basuroy et al., 2003; Eliashberg & Shugan, 1997; Proserpio & Zervas, 2017). Since these parameters were not explicitly tested, findings from Paper 3 can only provide implications to research in a movie context. Findings showed that critics' reviews in the pre-release phase are generally a significant predictor of opening weekend BO. However, the addition of YouTube volume caused a decrease in the effect of critics' reviews; still more, the addition of YouTube views completely eliminated the effect of critics' reviews on early performance. Although research in movie WOM and critics' reviews has not entirely focused on the pre-release phase, researchers have highlighted the effect of critics as predictors (Eliashberg & Shugan, 1997) or influencers of BO (Basuroy et al., 2003) and have compared the influence of user versus critics' reviews (Chakravarty, Liu, & Mazumdar, 2010; Proserpio & Zervas, 2017). Findings from Study 3 are inconsistent with findings from recent meta-analysis on the equal effect of critics and consumers in predicting BO (Carrillat et al., 2018) and rather support the view from a post-release WOM study which points to the superiority of consumer reviews (Proserpio & Zervas, 2017).

7.1.4 Combination of methods

The contributions of this thesis are not limited to PRCB and persuasive advertising theory, and to the movie context. Important methodological insight can be gained by the combination of traditional and new methodologies. The gap of computational research methods in marketing literature is evident; researchers have been reluctant in adopting methodologies from the computational social sciences (Nguyen & Romaniuk, 2014; Snee et al., 2016a). The availability of Big Data has introduced the necessity to utilise recently developed methodologies based on new technologies (George et al., 2014). In keeping in synch with the latest methodological developments, this thesis combines traditional marketing methods (e.g. focus groups and experiments) and newer computational methods (e.g. data mining, sentiment analysis).

By combining these methods, it was possible to test the conceptual framework in different ways, which increases the validity of findings. Going beyond traditional WOM research and comparing this thesis to prior work in movie WOM where raters manually coded a few thousands of data (Liu, 2006; Nguyen & Romaniuk, 2014), computational methods in Paper 3 allowed for the collection and analysis of 26 million data-points. Such insight should hopefully attract the attention of social science researchers and increase the number of studies in this recent field of computational social sciences (Rob Kitchin, 2014; Watts, 2007).

7.2. Managerial Implications

Naturally, insight from this thesis offers numerous managerial implications to the movie industry and to the wider marketing area. While movie marketers invest large amounts of money in movies' pre-release campaigns, they claim to be uncertain on whether their online campaigns are effective in selling movies (Rainey, 2016). This research is centred entirely around the power of the advertising campaign to generate positive PRCB and to drive people to the cinema. Not only does it demonstrate that trailer-viewing in general is likely to generate PRCB but also that engaging in PRCB is highly related with consumers' purchase decisions. By turning to PRCB, movie marketers are able to monitor consumers' early perceptions and make strategic decisions on how the campaign should unfold. Since movies are experiential products with a very short life-cycle, it is critical to turn marketing attention to the pre-release phase. Monitoring audience insight only after a movie is released would be fruitless. This thesis is one of the very few research projects that focus solely on the pre-release phase of a movie.

Demonstrating that PRCB driven by trailer-viewing is evident in the pre-release period, this thesis looks specifically into the effect of different PRCB components on BO. While volume and valence have been found to be important predictors of consumers' purchase intentions, analysis of behavioural data in Paper 3 highlights the effect of YouTube views in predicting early BO. This important finding should hopefully direct movie marketers' attention to audience awareness, and the reach of an advertising campaign. This, in comparison to the fact that the volume of Twitter WOM was not proved to be a significant predictor of early audience attendance, could be of value to those who develop social media listening industry tools (D'Alessandro, 2015). Monitoring the components of PRCB and deriving early audience insight, thus, would also cut considerable costs from trailer testing.

Findings from the three papers highlight the importance of understanding what the movie is about through trailer-viewing. Paper 2 illustrates the importance of subjective understanding – which refers to individual perceptions of understanding. Since studios spend a lot of money on trailer-testing which can be costly, it is important to be aware of what responses to look for. Rather than aiming for a universal understanding of the trailer, studio market researchers should aim for a *feeling* of understanding what the movie is about. Important insight in relation to understanding also provides directions on trailer elements that are more likely to increase subjective understanding. The *amount* and *order of information* were both found to be significant predictors of subjective understanding in Paper 2. While studios strive to hit the right balance between providing enough information and keeping things unknown, Paper 2 showed that even too much information within the trailer increased consumer understanding and had a positive effect on trailer liking. This should give directions to trailer-makers for the effective design of trailers.

Findings from the three papers also offer important insight in relation to context familiarity and to movie genre. This thesis provides evidence that sequel movies present slightly different patterns to movies with an original storyline, supporting findings from prior movie research (Basuroy et al., 2006; Bohnenkamp, Knapp, Hennig-Thurau, & Schauerte, 2015; Nguyen & Romaniuk, 2014; Young et al., 2008). Taking this into account, along with findings on the different behaviour of SciFi (or non-Scifi) movies, could be used as a foundation to customise trailers accordingly and to tailor social media listening tools further. Ultimately, by designing effective trailers and monitoring YouTube views, studio marketers will be able to predict opening weekend performance.

Aside from insight on PRCB and understanding of the trailer campaign, this thesis also offers methodological insight to movie marketers, and to online advertising managers in general. The proposed methodologies used to extract PRCB components in Paper 3, can be adopted by industry managers. Natural language processing techniques employed in Papers 2 and 3 to analyse text data, can be used to inform social media listening tools, while all aforementioned methodologies can assist managers in analysing PRCB on competitive products and adjusting strategic decisions.

Although this research is carried out in a movie context, which presents a particular release pattern, findings can be insightful to other industries too. Among others, the wider entertainment and fashion industries largely rely on new product introduction. Findings that advertising raises PRCB about upcoming products should apply to other industries whose success relies on early hype (Craig et al., 2015; Hennig-Thurau et al., 2015), especially those that feature quality uncertainty (Carrillat et al., 2018). Although advertising campaigns of other products are not necessarily trailer-based, some do feature narrative-based ads (e.g. Burberry's 2016 campaign). The amount and order of information, thus, could be manipulated to increase consumers' subjective understanding of what the product is about and consequently raise PRCB and product adoption.

The next section will address the limitations of this thesis and provide directions for future research.

7.3. Limitations and Opportunities for Future Research

Each of the papers that contribute towards this thesis was carefully designed, taking into account the research context and the relevant extant literature. In doing so, certain limitations arose.

The focus on the movie industry determined the age group in the sample of the first two papers. Consistent with the MPAA's report of the most frequent movie-going age groups (MPAA 2018), the experiments in Papers 1 and 2 were conducted with participants aged between 18-39. While Paper 3 relied on behavioural data from online social networking sites that heavily feature trailer campaigns, findings cannot be generalised to the whole population. Other age groups, representing different generations, might present different behavioural patterns and it would be interesting to investigate whether understanding antecedents and outcomes still apply in that case. Furthermore, being centred around eWOM, this thesis addresses the proportion of the audience that is present and active on the social media. However, this does not imply that findings also apply to consumers with no Internet access. Although the fact that not all WOM takes place online is acknowledged (Berger, 2013; Keller & Fay, 2012), the focus of this thesis is on electronic buzz, and by examining the whole population of YouTube commenters, attempts have been made to generalise to the wider moviegoing population who actively engages in eWOM.

To minimise bias on the release-pattern of movies, only wide-release movies were tested in all three papers. This ensured that the sample belongs to the group of products that need to gain traction as soon as they are introduced to the market. By doing so, movies with limited-release patterns were excluded from the sample. However, a shift towards online production studios that also offer streaming services (e.g. Amazon, Netflix) has been observed, and movies are gradually being released and watched online. Moreover, independent movies which usually follow a limited-release pattern have been consistently increasing in the past years, driving industry revenues (MPAA 2018). While wide-release movies still prevail in the top 25 box office earnings (MPAA 2018), it would be interesting to examine the effect of PRCB on short and long-term sales on products with a limited or sequential release strategy.

Naturally all studies were conducted in the English language[8]. However, the international market is continuously bringing billions of dollars to the movie industry, with the Chinese market in particular earning $7.9 billion last year (MPAA, 2018). Ignoring these consumer groups would be unwise; research into the effect of international PRCB, or even into the development of tools that automatically detect and translate foreign-language comments would be highly appreciated.

Arguably, in this thesis, both experimental data (Papers 1 and 2) and behavioural data (Paper 3) were treated as a snapshot of the whole pre-release campaign. Yet, online conversations dynamically change. Taking into account that studios release a number of trailers throughout the pre-release campaign, future research could investigate how components of these conversations change throughout time and how they affect early movie adoption. Text data is rich in information and could be further analysed – beyond the natural language processing methods used in this thesis. As an example, machine-learning methods (e.g. support vector machines, neural networks) could be used to build more advanced classifiers for predicting movie performance.

Finally, the present research focuses on how movie trailers might induce positive PRCB. While attempts have been made to generalise to other products that rely on early hype, future research could extend insight from this thesis by investigating these relationships within other industries.

[8] Only English-language trailers were used in the experiments in Papers 1 & 2, and only English-language comments were analysed through the NLP techniques in Papers 2 & 3.

Bibliography

Adar, E., & Adamic, L. A. (2009). Tracking Information Epidemics in Blogspace. In *Proceedings of the 10th ACM Conference on Electronic Commerce* (pp. 325–334).

Alba, J. W. (1983). The Effects of Product Knowledge on the Comprehension, Retention, and Evaluation of Product Information. In R. P. Bagozzi, A. M. Tybout, & A. Abor (Eds.), *Advances in Consumer Research, Vol. 10* (pp. 577–580). MI: Association for Consumer Research.

Anderson, E. W. (1998). Customer Satisfaction and Word of Mouth. *Journal of Service Research*, *1*(1), 5–17.

Arndt, J. (1967). Role of Product-related Conversations in the Diffusion of a New Product. *Journal of Marketing Research*, *4*, 291–295.

Asur, S., & Huberman, B. (2010). Predicting the Future with Social Media. In *International Conference on Web Intelligence and Intelligent Agent Technology* (pp. 492–499).

Austin, B. (1981). Film Attendance: Why College Students Chose to See their Most Recent Film. *Journal of Popular Film and Television*, *9*(1), 43–49.

Babic Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. (2016). The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors. *Journal of Marketing Research*, *53*(June 2016), 297–318.

Babin, J., Lee, Y., Kim, E., & Griffin, M. (2005). Modeling Consumer Satisfaction and Word-of-Mouth: Restaurant Patronage in Korea. *Journal of Services Marketing*, *19*(3), 133–139.

Baek, H., Oh, S., Yanf, H.-D., & Ahn, J. (2014). Chronological Analysis of the Electronic Word- of-Mouth Effect of Four Social Media Channels on Movie Sales: Comparing Twitter, Yahoo!Movies, Youtube, and Blogs. In *The 18th Pacific Asia Conference on Information Systems, Chengdu 2014* (Paper 65).

Bagella, M., & Becchetti, L. (1999). The Determinants of Motion Picture Box Office Performance: Evidence from Movies Produced in Italy. *Journal of Cultural Economics*, *23*, 237–256.

Bakshy, E., Hofman, J. M., Watts, D. J., & Mason, W. A. (2011). Everyone's an Influencer: Quantifying Influence on Twitter. In *Proceedings of the 4th ACM International Conference on Web Search and Data Mining* (pp. 65–74).

Balasubramanian, S., & Mahajan, V. (2001). The Economic Leverage of the Virtual Community. *International Journal of Electronic Commerce*, *5*(3), 103–138.

Baruch, Y., & Holtom, B. C. (2008). Survey response rate levels and trends in organizational research. *Human Relations*, *61*, 1139–1160.

Basuroy, S., Chatterjee, S., & Ravid, S. A. (2003). How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets. *Journal of Marketing*, *67*(4), 103–117.

Basuroy, S., Desai, K. K., & Talukdar, D. (2006). An Empirical Investigation of Signaling in the Motion Picture Industry. *Journal of Marketing Research*, *43*(2), 287–295.

Beauchamp, N. (2013). Predicting and Interpolating State-Level Polling Using Twitter Textual Data. In *Meeting on Automated Text Analysis*. London: London School of Economics.

Bellotti, E. (2015). *Qualitative Networks: Mixed Methods in Sociological Research*. Abingdon: Routledge.

Berelson, B. (1952). *Content Analysis in Communication Research*. Glencoe, IL: Free Press.

Berger, J. (2013). *Contagious: Why Things Catch On*. New York: Simon & Schuster.

Berger, J., & Iyengar, R. (2013). Communication Channels and Word of Mouth: How the Medium Shapes the Message. *Journal of Consumer Research*, *40*(3), 567–579.

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral? *Journal of Marketing Research*, *49*(2), 192–205.

Bickart, B., & Schindler, R. M. (2001). Internet Forums As Influential Sources of Consumer Information. *Journal of Interactive Marketing*, *15*(3), 31–40.

Bohnenkamp, B., Knapp, A. K., Hennig-Thurau, T., & Schauerte, R. (2015). When Does it Make Sense to Do it Again? An Empirical Investigation of Contingency Factors of Movie Remakes. *Journal of Cultural Economics*, *39*(1), 15–41.

Boksem, M. a. S., & Smidts, A. (2015). Brain Responses to Movie Tailers Predict Individual Preferences for Movies and Their Population-Wide Commercial Success. *Journal of Marketing Research*, *52*(4), 482–492.

Booth, W., & Geis, S. (2006, March 5). And This Year's Oscar Goes to Social Issues. *Washington Post*. Retrieved on 29 May 2016, from http://www.washingtonpost.com/wp-dyn/content/article/2006/03/04/AR2006030401210.html

Boyd, D., & Crawford, K. (2012). Critical Questions for Big Data. *Information, Communication & Society*, *15*(5), 662–679.

Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

Brooker, P., Barnett, J., & Cribbin, T. (2016). Doing Social Media Analytics. *Big Data & Society*, *3*(2), 1–11.

Brooker, P., Vines, J., Sutton, S., Barnett, J., Feltwell, T., & Lawson, S. (2015). Debating Poverty Porn on Twitter: Social Media as a Place for Everyday Socio-Political Talk. *Proceedings of CHI 2015, Seoul, Republic of Korea* (pp. 3177–3186).

Brown, J., Broderick, A., & Lee, N. (2007). Word of Mouth Communication Within Online Communities: Conceptualizing the Online Social Network. *Journal of Interactive Marketing*, *21*(3), 2–20.

Brown, T., Barry, P., Dacin, P., & Gunst, R. (2005). Spreading the Word: Investigating Antecedents of Consumers' Positive Word-of-Mouth Intentions and Behaviors in a Retailing Context. *Journal of the Academy of Marketing Science*, *33*(2), 123–138.

Bryman, A. (2012). *Social Research Methods* (4th ed.). New York: Oxford Univeristy Press.

Bughin, J., Doogan, J., & Vetvik, O. J. (2010). A New Way to Measure Word-of-Mouth

Marketing. *McKinsey Quarterly*. Retrieved on 20 December 2015, from http://www.mckinseyquarterly.com/A_ new_way_to_measure_word-of-mouth_ marketing_2567

Burrell, G., & Morgan, G. (1979). *Sociological Paradigms and Organisational Analysis*. London: Heinemann.

Cacioppo, J. T., Petty, R. E., & Kao, C. F. (1984). The Efficient Assessment of Need for Cognition. *Journal of Personality Assessment*, *48*, 306–307.

Campbell, H. (2008). The Essence of Trailers. *IndiVision*, (April). Retrieved on 11 October 2015, from http://afcarchive.screenaustralia.gov.au/newsandevents/afcnews/converse/helencampbell /newspage_463.aspx

Campo, M., Hsieh, C.-K., Nickens, M., Espinoza, J., Taliyan, A., Rieger, J., … Sherick, B. (2018). Competitive Analysis System for Theatrical Movie Releases Based on Movie Trailer Deep Video Representation. Retrieved from http://arxiv.org/abs/1807.04465

Carrillat, F. A., Legoux, R., & Hadida, A. L. (2018). Debates and assumptions about motion picture performance: a meta-analysis. *Journal of the Acadamy of Marketing Science*, *46*(2), 273–299.

Carson, D., Gilmore, A., Perry, C., & Gronhaug, K. (2001). *Qualitative Marketing Research*. London: Sage.

Chaiken, S. (1980). Heuristic Versus Systematic Information Processing and the Use of Source Versus Message Cues in Persuasion. *Journal of Personality and Social Psychology*, *39*(5), 752–766.

Chaiken, S., & Eagly, A. H. (1976). Communication Modality as a Determinant of Message Persuasiveness and Message Comprehensibility. *Journal of Personality and Social Psychology*, *34*(4), 605–614.

Chakravarty, A., Liu, Y., & Mazumdar, T. (2010). The Differential Effects of Online Word-of-Mouth and Critics' Reviews on Pre-release Movie Evaluation. *Journal of Interactive Marketing*, *24*(3), 185–197.

Cheung, C. M. K., & Lee, M. K. O. (2012). What Drives Consumers to Spread Electronic Word of Mouth in Online Consumer-Opinion Platforms. *Decision Support Systems*, *53*(1), 218–225.

Cheung, C. M. K., Lee, M. K. O., & Rabjohn, N. (2008). The Impact of Electronic Word-of-Mouth: The Adoption of Online Opinions in Online Customer Communities. *Internet Research*, *18*(3), 229–247.

Cheung, C. M. K., & Thadani, D. R. (2012). The Impact of Electronic Word-of-Mouth Communication: A Literature Analysis and Integrative Model. *Decision Support Systems*, *54*(1), 461–470.

Chintagunta, P. K. P., Gopinath, S., & Venkataraman, S. (2010). The Effects of Online User Reviews on Movie Box Office Performance: Accounting for Sequential Rollout and Aggregation Across Local Markets. *Marketing Science*, *29*(5), 944–957.

Chisholm, D. C., Fernandez-Blanco, V., Ravid, S. A., & Walls, W. D. (2015). Economics of motion pictures: the state of the art. *Journal of Cultural Economics*, *39*(1), 1–13.

Chun, J. W., & Lee, M. J. (2016). Increasing Individuals' Involvement and WOM Intention on Social Networking Sites: Content Matters! *Computers in Human Behavior*, *60*, 223–232.

Clement, M., Wu, S., & Fischer, M. (2013). Empirical Generalizations of Demand and Supply Dynamics for Movies. *International Journal of Research in Marketing*, *31*(2), 207–223.

Craig, C., Greene, W., & Versaci, A. (2015). E-word of Mouth: Early Predictor of Audience Engagement: How Pre-Release "E-WOM" Drives Box-Office Outcomes of Movies. *Journal of Advertising Research*, *55*(1), 62–72.

Crotty, M. (1998). *The Foundations of Social Research: Meaning and Perspective in the Research Process*. London: Sage.

D'Alessandro, A. (2015, April 23). How Strong is Your Film's Buzz? Rentrak's PreAct Can Tell You - CinemaCon. *Deadline*. Retrieved on 17 July 2018, from https://deadline.com/2015/04/pitch-perfect-2-insidious-chapter-3-southpaw-rentrak-uta-preact-film-campaigns-1201414615/

Day, G. S. (1971). Attitude Change, Media and Word of Mouth. *Journal of Advertising Research*, *11*(6), 31–40.

De Vany, A. S., & Walls, W. D. (1997). The Market for Motion Pictures: Rank, Revenue, and Survival. *Economic Inquiry*, *35*(4), 783–797.

De Vany, A., & Walls, W. (1999). Uncertainty in the Movie Industry: Does Star Power Reduce the Terror of the Box Office? *Journal of Cultural Economics*, *23*, 285–318.

De Vaus, D. A. (2014). *Surveys in Social Research* (6th ed.). London: Routledge.

Dellarocas, C., Zhang, X., & Awad, N. (2007). Exploring the Value of Online Product Revoews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing*, *21*(4), 23–45.

DeLone, W. H., & McLean, E. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, *19*(4), 9–30.

Desai, K. K., & Basuroy, S. (2005). Interactive influence of genre familiarity, star power, and critics' reviews in the cultural goods industry: The case of motion pictures. *Psychology and Marketing*, *22*(3), 203–223.

Deuchert, E., Adjamah, K., & Pauly, F. (2005). For Oscar Glory Or Oscar Money? *Journal of Cultural Economics*, *29*(3), 159–176.

Dichter, E. (1966). How Word-of-Mouth Advertising Works. *Harvard Business Review*, *44*(6), 147–166.

Diesner, J., & Carley, K. (2011). Word & Networks. In G. Barnett (Ed.), *Encyclopedia of Social Networking* (pp. 958–961). Thousand Oaks, CA: Sage Publications.

Dillman, D. A., Smyth, J. D., & Christian, J. M. (2014). *Internet, Phone, Mail and Mixed Mode Surveys: The Tailored Design Method* (4th ed.). Hoboken, NJ: Willey.

Divakaran, P., Palmer, A., Søndergaard, H., & Matkovskyy, R. (2017). Pre-launch Prediction of Market Performance for Short Lifecycle Products Using Online Community Data.

Journal of Interactive Marketing, *38*, 12–28.

Duan, W., Gu, B., & Whinston, A. (2008a). The Dynamics of Online Word-of-Mouth and Product Sales: An Empirical Investigation of the Movie Industry. *Journal of Retailing*, *84*(2), 233–242.

Eagly, A. H. (1974). Comprehensibility of Persuasive Arguments as a Determinant of Opinion Change. *Journal of Personality and Social Psychology*, *29*(6), 758–773.

Eagly, A. H. (1981). Recipient Characteristics as Determinants of Responses to Persuasion. In R. E. Petty, T. M. Ostrom, & T. Brock (Eds.), *Cognitive Responses in Persuasion* (pp. 173–198). New Jersey: Lawrence Erlbaum Associates.

Eagly, A. H., & Chaiken, S. (1993). *The Psychology of Attitudes*. Fort Worth, TX: Harcourt Brace Jovanovich.

Eagly, A. H., Wood, W., & Chaiken, S. (1978). Causal Inferences About Communicators and Their Effect on Opinion Change. *Journal of Personality and Social Psychology*, *36*(4), 424–435.

Earnest, O. J. (1985). A Case Study of Motion Picture Marketing. In B. A. Austin (Ed.), *Current Research in Film: Audiences, Economics and Law* (pp. 1–18). New Jersey: Ablex Publishing.

East, R., Uncles, M., Romaniuk, J., & Dall'Olmo Riley, F. (2015). Factors Associated with the Production of Word of Mouth. *The Market Research Society*, *57*(3), 439–458.

Einav, L. (2007). Seasonality in the U.S. Motion Picture Industry. *RAND Journal of Economics*, *38*(1), 127–145.

Elberse, A. (2007). The Power of Stars: Do Star Actors Drive the Success of Movies? *Journal of Marketing*, *71*(4), 102–120.

Elberse, A., & Eliashberg, J. (2003). Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures. *Marketing Science*, *22*(3), 329–354.

Eliashberg, J., Jonker, J.-J., Swahney, M. S., & Wierenga, B. (2000). MOVIEMOD : Implementable for Prerelease Motion Market Support System of Evaluation Pictures. *Marketing Science*, *19*(3), 226–243.

Eliashberg, J., & Shugan, S. (1997). Film Critics: Influencers or predictors? *The Journal of Marketing*, *61*(2), 68–78.

Engel, J. E., Blackwell, R. D., & Kegerreis, R. J. (1969). How Information is Used to Adopt an Innovation. *Journal of Advertising Research*, *9*(4), 3–8.

Epstein, E. J. (2005). *The Big Picture: The New Logic of Money and Power in Hollywood*. New York: Random House.

Feick, L. F., & Price, L. L. (1987). The Market Maven: A Diffuser of Information Marketplace. *Journal of Marketing*, *51*(1), 83–97.

Feng, J., & Papatla, P. (2011). Advertising: Stimulant or Suppressant of Online Word of Mouth? *Journal of Interactive Marketing*, *25*(2), 75–84.

Fernbach, P. M., Sloman, S. A., Louis, R. St., & Shube, J. N. (2013). Explanation Fiends and

Foes: How Mechanistic Detail Determines Understanding and Preference. *Journal of Consumer Research*, *39*(5), 1115–1131.

Ferrara, E., & Yang, Z. (2015). Measuring Emotional Contagion in Social Media. *Plos One*, *10*(11), 1–10. Retrieved from http://arxiv.org/abs/1506.06021v1

Flanagan, M. (2012). How to Edit a Trailer That Will Get Your Film Noticed. *MicroFilmmaker Magazine*. Retrieved on 12 October 2015, from http://www.microfilmmaker.com/tipstrick/Issue14/Edit_Trl.html

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research*, *19*(3), 291–313.

Friedman, R. G. (2006). Motion Picture Marketing. In J. E. Squire (Ed.), *The Movie Business Book* (2nd ed., pp. 291–305). New York: Simon & Schuster.

Fritz, B. (2012, April). Movie Trailers Have Become a Main Event. *The Lost Angeles Times*. Retrieved on 13 October 2015, from http://articles.latimes.com/print/2012/apr/10/business/la-fi-ct-trailers-20120410

Garey, N. H. (1992). Elements of Feature Financing. In J. E. Squire (Ed.), *The Movie Business Book* (2nd ed., pp. 139–149). New York: Simon & Schuster.

Gelper, S., Peres, R., & Eliashberg, J. (2018). Talk Bursts: The Role of Spikes in Pre-release Word-of-Mouth Dynamics. *Journal of Marketing Research*, *55*(6), 801–817.

George, G., Haas, M., & Pentland, A. (2014). Big Data and Management. *The Academy of Management Journal*, *57*(2), 321–326.

Gill, J., & Johnson, P. (2002). *Research Methods for Managers* (3rd ed.). London: Sage Publications.

Gladwell, M. (2000). *The Tipping Point: How Little Things can Make a Big Difference*. USA: Little Brown.

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, *23*(4), 545–560.

Godes, D., & Mayzlin, D. (2009). Firm-Created Word-of-Mouth Communication: Evidence from a Field Test. *Marketing Science*, *28*(4), 721–739.

Goel, S., Watts, D. J., & Goldstein, D. G. (2012). The Structure of Online Diffusion Networks. *Proceedings of the 13th ACM Conference on Electronic Commerce*, *1*(212), (pp. 623–638).

Goldenberg, J., Libai, B., & Muller, E. (2001). A Complex Systems Look at the Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth. *Marketing Letters*, *12*(3), 211–223.

Goldsmith, R. R. E., & Horowitz, D. (2006). Measuring Motivations for Online Opinion Seeking. *Journal of Interactive Advertising*, *6*(2), 2–14.

Goldstein, P. (1991, August 25). Naked Trailers. *Los Angeles Times*. Retrieved on 13 October 2015, from http://articles.latimes.com/1991-08-25/entertainment/ca-2005_1_teaser-trailer

Gong, J. J., Van der Stede, W. a., & Young, M. (2011). Real Options in the Motion Picture Industry: Evidence from Film Marketing and Sequels. *Contemporary Accounting Research*, *28*(5), 1438–1466.

Gopinath, S., Chintagunta, P. K., & Venkataraman, S. (2013). Blogs, Advertising, and Local-Market Movie Box Office Performance. *Management Science*, *59*(12), 2635–2654.

Graham, J., & Havlena, W. (2007). Finding the "Missing Link": Advertising's Impact on Word of Mouth, Web Searches, and Site Visits. *Journal of Advertising Research*, *47*(4), 427–435.

Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Greenwald, A. G., & Leavitt, C. (1984). Audience Involvement in Advertising: Four Levels. *Journal of Consumer Research*, *11*(1), 581.

Griff, C. (2012). Film Audience Testing in Australia: Capturing the Audience Before it Bites. *Studies in Australasian Cinema*, *6*(2), 159–174.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research. *Journal of the Acadamy of Marketing Science*, *40*, 414–433.

Haridy, R. (2016, August 31). IBM's Watson Supercomputer Creates a Movie Trailer. *New Atlas*. Retrieved on 29 October 2016, from http://newatlas.com/ai-movie-trailer-morgan/45202/

Haugtvedt, C. P., Petty, R. E., & Cacioppo, J. T. (1992). Need for Cognition and Advertising: Understanding the Role of Personality Variables in Consumer Behavior. *Journal of Consumer Psychology*, *1*(3), 239–260.

He, S., Zheng, X., Zeng, D., Luo, C., & Zhang, Z. (2016). Exploring Entrainment Patterns of Human Emotion in Social Media. *Plos One*, *11*(3), 1-19.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52.

Hennig-Thurau, T., Henning, V., Sattler, H., Eggers, F., & Houston, M. B. (2007). The Last Picture Show? Timing and Order of Movie Distribution Channels. *Journal of Marketing*, *71*(4), 63–83.

Hennig-Thurau, T., Houston, M. B., Walsh, G. (2007). Determinants of Motion Picture Box Office and Profitability: an Interrelationship Approach. *Review of Managerial Science*, *1*(1), 65–92.

Hennig-Thurau, T., Wiertz, C., & Feldhaus, F. (2015). Does Twitter Matter? The Impact of Microblogging Word of Mouth on Consumers' Adoption of New Movies. *Journal of the Academy of Marketing Science*, *43*(3), 375–394.

Ho, J. Y. C., Dhar, T., & Weinberg, C. B. (2009). Playoff Payoff: Super Bowl Advertising for Movies. *International Journal of Research in Marketing*, *26*(3), 168–179.

Hoffman, J., Clement, M., Völckner, F., & Hennig-Thurau, T. (2017). Empirical Generalizations on the Impact of Stars on the Economic Success of Movies. *Journal of*

Research in Marketing, *34*(2), 442–461.

Hogan, J. E., Lemon, K. N., & Libai, B. (2004). Quantifying the Ripple: Word-of-Mouth and Advertising Effectiveness. *Journal of Advertising Research*, *44*(3), 271–280.

Holbrook, M. B. (1999). Popular Appeal Versus Expert Judgments of Motion Pictures. *Journal of Consumer Research*, *26*(2), 144–155.

Holmes, J. H., & Lett, J. D. (1977). Product Sampling and Word of Mouth. *Journal of Advertising Research*, *17*(5), 35–40.

Houston, M. B., Kupfer, A., Hennig-thurau, T., Spann, M. (2018). Pre-release consumer buzz. *Journal of the Acadeny of Marketing Science*, *46*(2), 338–360.

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). *Communication and Persuasion*. New Haven, CT: Yale University Press.

Hovland, C. I., Lumsdaine, A. A., & Sheffield, F. D. (1949). *Experiments on Mass Communication*. Princeton, N.J.: Princeton University Press.

Hovland, C., & Weiss, W. (1951). The Influence of Source Credibility on Communication Effectiveness. *Public Opinion Quarterly*, *15*, 635–650.

Iida, T., Goto, A., Fukuchi, S., & Amasaka, K. (2012). A Study on Effectiveness of Movie Trailers Boosting Consumers' Apreciation Desire: A Customer Science Approach Using Statistics And GSR. *Journal of Business & Economics Research*, *10*(6), 375–385.

Jacoby, J., & Hoyer, W. D. (1982). Viewer Miscomprehension of Televised Communication: Selected Findings. *Journal of Marketing*, *46*(4), 12–26.

Jacoby, J., Nelson, M. C., & Hoyer, W. D. (1982). Corrective Advertising and Affirmative Disclosure Statements: Their Potential for Confusing and Misleading the Consumer. *Journal of Marketing*, *46*(1), 61–72.

Johnson, B. T., & Eagly, A. H. (1989). Effects of Involvement on Persuasion: A Meta-Analysis. *Psychological Bulletin*, *106*(2), 290–314.

Johnston, K. M. (2008). "Three Times As Thrilling!" The Lost History of 3-D Trailer Production, 1953-4. *Journal of Popular Film and Television*, *36*(4), 150–160.

Joshi, A., & Mao, H. (2012). Adapting to succeed? Leveraging the brand equity of best sellers to succeed at the box office. *Journal of the Academy of Marketing Science*, *40*(4), 558–571.

Kahneman, D. (2011). *Thinking Fast and Slow*. New York: Farrar, Straus and Giroux.

Kamins, M. a., & Assael, H. (1987). Two-Sided Versus One-Sided Appeals: A Cognitive Perspective on Argumentation, Source Derogation, and the Effect of Disconfirming Trial on Belief Change. *Journal of Marketing Research*, *24*(1), 29.

Karniouchina, E. V. (2011a). Impact of Star and Movie Buzz on Motion Picture Distribution and Box Office Revenue. *International Journal of Research in Marketing*, *28*(1), 62–74.

Karniouchina, E. V. (2011b). Are Virtual Markets Efficient Predictors of New Product Success? The Case ofthe Hollywood Stock Exchange. *Journal of Product Inovation Management*, *18*, 470–484.

Katz, E., & Lazarsfeld, P. F. (1955). *Personal Influence: The Part Played by People in the*

Flow of Mass Communications. Glencoe, IL: Free Press.

Keller, E., & Fay, B. (2009). The Role of Advertising in Word of Mouth. *Journal of Advertising Research*, *49*(2), 154–158.

Keller, E., & Fay, B. (2012). Word-of-mouth Advocacy: A new Key to Advertising Effectiveness. *Journal of Advertising Research*, *52*(December), 459–465.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the Functional Building Blocks of Social Media. *Business Horizons*, *54*(3), 241–251

Kitchin, R. (2013). Big data and human geography: Opportunities, challenges and risks. *Dialogues in Human Geography*, *3*(3), 262–267.

Kitchin, R. (2014). Big Data, New Epistemologies and Paradigm Shifts. *Big Data & Society*, *1*(1), 1-12.

Knight, W. (2017, August 3). An Algorithm Trained on Emoji Knows When You're Being Sarcastic on Twitter. *MIT Technology Review*. Retrieved on 3 December 2018, from https://www.technologyreview.com/s/608387/an-algorithm-trained-on-emoji-knows-when-youre-being-sarcastic-on-twitter/

Krider, R. E., & Weinberg, C. B. (1998). Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game. *Journal of Marketing Research*, *35*, 1–15.

Krueger, R. A., & Casey, M. A. (2009). *Focus GRoups: A Practical Guide for Applied Research* (4th ed.). Thousand Oaks, CA: Sage.

Kuhn, T. (1962). *The Structure of Scientific Revolutions*. Chicago: University of Chicago Press.

Leskovec, J., Adamic, L. a., & Huberman, B. a. (2007). The Dynamics of Viral Marketing. *ACM Transactions on the Web*, *1*(1), 1-39..

Levin, A. M., Levin, I. P., & Heath, C. E. (1997). Movie stars and authors as brand names: Measuring brand equity in experiential products. *Advances in Consumer Research*, *24*(1), 175–181.

Lin, Y. R., Keegan, B., Margolin, D., & Lazer, D. (2014). Rising Tides or Rising Stars?: Dynamics of Shared Attention on Twitter During Media Events. *PLoS ONE*, *9*(5), 1-12.

Lipizzi, C., Iandoli, L., & Marquez, J. E. R. (2016). Combining structure, content and meaning in online social networks: The analysis of public's early reaction in social media to newly launched movies. *Technological Forecasting and Social Change*, *109(3)*, 35–49.

Lipstein, B. (1980). Theories of Advertising and Measurement Systems. In R. W. Olshavsky (Ed.), *Attitude Research Enters the '80s*. Chicago, IL: American Marketing Association.

Liu, A., Liu, Y., & Mazumdar, T. (2014). Star power in the eye of the beholder: A study of the influence of stars in the movie industry. *Marketing Letters*, *25*(4), 385–396.

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*, *70*(3), 74–89.

Livingstone, S. M. (1990). *Making Sense of Television: The Psychology of Audience*

Interpretation. Oxford: Pergamon.

Lopez, J. (2011, December 12). Hollywood's Two-Minute Auteurs. *Bloomberg Businessweek*, 97–101.

Maheswaran, D., & Sternthal, B. (1990). The Effects of Knowledge, Motivation, and Type of Message on Ad Processing and Product Judgments. *Journal of Consumer Research*, *17*(1), 66–73.

Manovich, L. (2011). Trending: The Promises and the Challenges of Bog Social Data. In M. K. Gold (Ed.), *Debates in the Digital Humanities* (pp. 460–475). Minneapolis: University of Minessota Press.

Marich, B. R. (2012). Trailer trends capitalize on a sense of deja vu. *Variety*, 14, 21.

Marich, R. (2013). *Marketing to Moviegoers: A Handbook of Strategies and Tactics* (3rd ed.). Illionis: Southern Illinois University Press.

McCroskey, J. C., & Mehrley, R. S. (1969). Effects of Disorganization and Nonfluency on Attitude Change and Source Credibility. *Speech Monographs*, *36*, 13–21.

McGuire, W. (1968). Personality and Attitude Change: An Information-Processing Theory. In A. G. Greenwald, T. C. Brock, & T. M. Ostrom (Eds.), *Psychological Foundations of Attitudes* (pp. 171–196). San Diego, CA: Academic Press.

McGuire, W. (1976). Some Internal Psychological Factors Influencing Consumer Choice. *Journal of Consumer Research*, *2*(March), 302–319.

McKinney, V., Yoon, K., & Zahedi, F. (2002). The Measurement of Web-Customer Satisfaction: An Expectation and Disconfirmation Approach. *Information Systems Research*, *13*(3), 296–315.

Medavoy, M. (1992). A Chairman's Perspective. In J. E. Squire (Ed.), *The Movie Business Book* (2nd ed., pp. 169–178). New York: Simon & Schuster.

Mertens, D. M. (2005). *Research and Evaluation in Education and Psychology: Integrating Diversity with Quantitative, Qualitative, and Mixed Methods* (2nd ed.). Thousand Oaks, CA: Sage.

Mick, D. (1992). Levels of Subjective comprehension in Advertising Processing and their Relations to Ad Perceptions, Attitudes, and Memory. *Journal of Consumer Research*, *19*(9), 155–179.

Mohanty, P. P., & Ratneshwar, S. (2015). Did You Get It? Factors Influencing Subjective Comprehension of Visual Metaphors in Advertising. *Journal of Advertising*, *44*(3), 232–242.

Moller, K. E. K., & Karppinen, P. (1983). Role of Motives and Attributes in Consumer Motion Picture Choice. *Journal of Economic Psychology*, *4*(3), 239–262.

Moorman, C. (1999). The Functionality of Knowledge Illusions. In *Association for Consumer Research Conference*. Colombus, OH.

Moul, C. C. (2007). Measuring Word of Mouth's Impact on Theatrical Movie Admissions. *Journal of Economics and Management Strategy*, *16*(4), 859–892.

MPAA. (2018). 2017 Theatrical Home Entertainment Market Environment (THEME)

Report. Retrieved on 10 May 2018, from https://www.mpaa.org/research-docs/2017-theatrical-home-entertainment-market-environment-theme-report/

Nguyen, C., & Romaniuk, J. (2014). Pass it on: A Framework for Classifying the Content of Word of Mouth. *Australasian Marketing Journal*, *22*(2), 117–124.

Onwuegbuzie, A., & Teddlie, C. (2002). A Framework for Analysing Data in Mixed Methods Research. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of Mixed Methods in Social and Behavioral Research* (pp. 351–334). Thousand Oaks, CA: Sage.

Park, D.-H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148.

Patton, M. Q. (2002). *Qualitative Research and Evaluation Methods*. Thousand Oaks, CA: Sage.

Peres, R., Muller, E., & Mhajan, V. (2010). Innovation Diffusion and New Product Growth Models. *International Journal of Research in Marketing*, *27*, 91–106.

Petty, R. E., & Brock, T. (1981). Thought Disruption and Persuasion: Assessing the Validity of Attitude Change Experiments. In R. E. Petty, T. M. Ostrom, & T. Brock (Eds.), *Cognitive Responses in Persuasion* (pp. 55–80). New Jersey: Lawrence Erlbaum Associates.

Petty, R. E., & Cacioppo, J. T. (1981). Issue Involvement as a Moderator of the Effects on Attitude of Advertising Content and Context. In Ke. B. Monroe & A. Arbor (Eds.), *Advances in Consumer Research, Vol. 8* (pp. 20–24). MI: Association for Consumer Research.

Petty, R. E., & Cacioppo, J. T. (1983). Central and Peripheral Routes to Persuasion: Application to Advertising. In L. Percy & A. G. Woodside (Eds.), *Advertising and Consumer Psychology* (pp. 3–23). Lexington, MA: D.C. Heath and Company.

Petty, R. E., Cacioppo, J. T., & Goldman, R. (1981). Personal Involvement as a Determinant of Argument-Based Persuasion. *Journal of Personality and Social Psychology*, *41*(5), 847–855.

Pollack, S. (1992). The Director. In J. E. Squire (Ed.), *The Movie Business Book* (2nd ed., pp. 44–56). New York: Simon & Schuster.

Popping, R. (2000). *Computer-Assisted Text Analysis*. London: Sage Publications.

Prag, J., & Casavant, J. (1994). An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry. *Journal of Cultural Economics*, *18*(3), 217–235.

Pritzker, S. R. (2009). Marketing Movies: An Introduction to the Special Issue. *Psychology & Marketing*, *26*(5), 397–399.

Proserpio, D., & Zervas, G. (2017). Online Reputation Management: Estimating the Impact of Management Responses on Consumer Reviews. *Marketing Science*, *36*(5), 1–21.

Radas, S., & Shugan, S. M. (2012). Seasonal Product Marketing and Timing New Introductions. *Journal of Marketing Research*, *35*(3), 296–315.

Radighieri, J. P., & Mulder, M. (2014). The Impact of Source Effects and Message Valence on Word of Mouth Retransmission. *International Journal of Market Research*, *56*(2), 249.

Rainey, J. (2016, March). The Perils of Promotion: Pricey TV Campaigns , Fear of Change Shackles Movie Spending. *Variety*. Retrieved 15 January 2017, from https://variety.com/2016/fil/features/movie-marketing-advertising-tv-campaigns-1201724468/

Ratneshwar, S., & Chaiken, S. (1991). Comprehension's Role in Persuasion: The Case of Its Moderating Effect on the Persuasive Impact of Source Cues. *Journal of Consumer Research*, *18*(1), 52-62.

Read, H. (1972). *Communication: Methods for All Media*. Chicago, IL: University of Illinois Press.

Reinstein, D. a, & Snyder, C. M. (2005). The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics. *The Journal of Industrial Economics*, *53*(1), 27–51.

Richins, M. L. (1983). Negative Word-of-Mouth by Dissatisfied Consumers: A Pilot Study. *Journal of Marketing*, *47*(1), 68–78.

Richins, M. L. (1984). Word of Mouth Communications as Negative Information. In T. C. Kinnear (Ed.), *Advances in Consumer Research, Vol. 11* (pp. 697–702). Provo, UT: Association for Consumer Research.

Richins, M. L., & Root-Shaffer, T. (1988). The Role of Involvement and Opinion Leadership in Consumer Word-of-Mouth: An Implicit Model Made Explicit. *Advances in Consumer Research*, *15*, 32–36.

Robson, C. (2011). *Real World Research: A Resource for Users of Social Research Methods in Applied Settings* (3rd ed.). Chichester: John Willey.

Rogers, E. M. (1962). Diffusion of innovations. New York: Free Press.

Romaniuk, J., Nguyen, C., & East, R. (2011). The Accuracy of Self-Reported Probabilities of Giving Recommendations. *International Journal of Market Research, 53*(4), 507–521.

Rosen, S. (1981). The Economics of Superstars. *American Economic Review*, *71*(5), 845–858.

Rozenblit, L., & Keil, F. (2002). The Misunderstood Limits of Folk Science: An Illusion of Explanatory Depth. *Cognitive Science*, *26*(5), 521–562.

Rui, H., Liu, Y., & Whinston, A. (2013). Whose and What Chatter Matters? The Effect of Tweets on Movie Sales. *Decision Support Systems*, *55*(4), 863–870.

Rumelhart, D. (1991). Understanding understanding. In W. Kessen, A. Ortony & F. Craik (Eds.), *Memories, thoughts and emotions: Essays in honor of George Mandler* (pp. 257–275). London: Psychology Press.

Sajuria, J., & Fabrega, J. (2016). Do We Need Polls? Why Twitter Will Not Replace Opinion Surveys but Can Complement Them. In H. Snee, C. Hine, Y. Morey, S. Roberts, & H. Watson (Eds.), *Digital Methods for Social Science: An Interdisciplinary Guide to Research Innovation* (pp. 87–104). Hampshire & NY: Palgrave Macmillan.

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research Methods for Business Students*

(7th ed.). New York: Pearson Education.

Sawyer, A. (1981). Repetition, Cognitive Responses, and Persuasion. In R. E. Petty, T. Ostrom, & T. Brock (Eds.), *Cognitive Responses in Persuasion* (pp. 237–262). New Jersey: Lawrence Erlbaum Associates.

Schlossberg, H. (1991, June 10). Customer Satisfaction: Not a Fad, But a Way of Life. *Marketing News*, 18-19.

Silver, C., & Lewins, A. (2014). *Using Software in Qualitative Research A Step-by-Step Guide* (2nd ed.). London: Sage Publications.

Simmons, L., Conlon, S., Mukhopadhyay, S., & Yang, J. (2011). A Computer Aided Analysis of Online Reviews. *Journal of Computer Information Systems*, *52*(1), 43–55.

Simonton, D. K. (2008). Cinematic Success Criteria and Their Predictors: The Art and Business of the Film Industry. *Psychology & Marketing*, *26*(5), 400–420.

Smith, R. E., & Vogt, C. A. (1995). The Effects of Integrating Advertising and Negative WOM Communications. *Journal of Consumer Psychology*, *4*(2), 133–151.

Snee, H., Hine, C., Morey, Y., Roberts, S., & Watson, H. (2016a). Big Data, Thick Data: Social Media Analysis. In H. Snee, C. Hine, Y. Morey, S. Roberts, & H. Watson (Eds.), *Digital Methods for Social Science: An Interdisciplinary Guide to Research Innovation* (pp. 13–16). Hampshire & NY: Palgrave Macmillan.

Snee, H., Hine, C., Morey, Y., Roberts, S., & Watson, H. (2016b). Combining and Comparing Methods. In H. Snee, C. Hine, Y. Morey, S. Roberts, & H. Watson (Eds.), *Digital Methods for Social Science: An Interdisciplinary Guide to Research Innovation* (pp. 67–70). Hampshire & NY: Palgrave Macmillan.

Snee, H., Hine, C., Morey, Y., Roberts, S., & Watson, H. (2016c). Digital Methods as Mainstream Methodology: An Introduction. In H. Snee, C. Hine, Y. Morey, S. Roberts, & H. Watson (Eds.), *Digital Methods for Social Science: An Interdisciplinary Guide to Research Innovation* (pp. 1–11). Hampshire & NY: Palgrave Macmillan.

Sonnier, G. P., McAlister, L., & Rutz, O. J. (2011). A Dynamic Model of the Effect of Online Communications on Firm Sales. *Marketing Science*, *30*(4), 702–716.

Squire, J. E. (2016). *The Movie Business Book*. (J. E. Squire, Ed.) (4th ed.). New York: Simon & Schuster.

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer loyalty in e-commerce: An exploration of its antecedents and consequences. *Journal of Retailing*, *78*(1), 41–50.

Stapleton, C. B., & Hughes, C. E. (2005). Mixed Reality and Experiential Movie Trailers: Combining Emotions and Immersion to Innovate Entertainment Marketing. *IEEE*, *25*(6), 24–30.

Stewart, D. W., & Kamins, M. A. (1993). *Secondary Research: Information Sources and Methods* (2nd ed.). Newbury Park, CA: Sage.

Swahney, M. S., & Eliashberg, J. (1996). A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures. *Marketing Science*, *15*(2), 113–131.

Tashakkori, A., & Teddlie, C. (2003). *Handbook of Mixed Methods in Social and Behavioral Research*. (A. Tashakkori & C. Teddlie, Eds.). Thousand Oaks, CA: Sage.

Tourmarkine, D. (2005). Tantalizing Trailers: Putting Traction into Coming Attractions. *Film Journal International*, *108*(4), 16–20.

Traylor, M. B., Traylor, M. B., Mathias, A. M., & Mathias, A. M. (1983). The Impact of TV Advertising versus Word of Mouth on the Image of Lawyers: a Projective Experiment. *Journal of Advertising*, *12*(4), 42–49.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2007). Estimating the Dynamic Effects of Online Word-of-Mouth on Member Growth of a Social Network Site. *Journal of Marketing*, *73*(5), 90–102.

Ullah, R., Amblee, N., Kim, W., & Lee, H. (2016). From Valence to Emotions: Exploring the Distribution of Emotions in Online Product Reviews. *Decision Support Systems*, *81*, 41–53.

Van Den Bulte, C., & Lilien, G. L. (2016). Medical Innovation Revisited: Social Contagion versus Marketing Effort. *American Journal of Sociology*, *106*(5), 1409–1435.

Vaughn, R. (1986). How Adevertising Works: A Planning Model Revisited. *Journal of Advertising Research*, *26*(February/March), 57–66.

Vazquez-Casielles, R., Suarez-Alvarez, L., & del Rio-Lanza, A.-B. (2013). The Word of Mouth Dynamic: How Positive (and Negative) WOM Drives Purchase Probability: An Analysis of Interpersonal and Non-Interpersonal Factors. *Journal of Advertising Research*, *53*(1), 43.

Watts, D. J. (2007). A Twenty-First Century Science. *Nature*, *445*(7127), 489–489.

Watts, D. J. (2013). Computational Social Science: Exciting Progress and Future Directions. *The Bridge*, *43*(4), 5–10.

Watts, D. J., & Dodds, P. S. (2007). Influentials, Networks, and Public Opinion Formation. *Journal of Consumer Research*, *34*(4), 441–458.

Weiss, R. F. (1968). An Extension of Hullian Learning Theory to Persuasive Communication. In A. G. Greenwald, T. C. Brock, & T. M. Ostrom (Eds.), *Psychological Foundations of Attitudes*. New York: Academic Press.

Weston, P. and Duell, M. (2018) 'Frenzy for the iPhone XS as thousands of Apple fans queue worldwide overnight for new device - despite it being the most expensive model EVER at £1,449', *Mail Online*, 21 September. Accessed 12 April 2019, from: https://www.dailymail.co.uk/news/article-6192393/The-wait-Hundreds-Apple-fans-queue-outside-hands-new-iPhone-XS.html.

Wilson, D. T., Mathews, H. L., & Harvey, J. W. (1975). An Empirical Test of the Fishbein Behavioral Intention Model. *Journal of Consumer Research*, *1*(March), 39–48.

Wilson, E. J., & Sherrell, D. L. (1993). Source Effects in Communication and Persuasion Research: a Meta-Analysis of Effect Size. *Journal of the Acadamy of Marketing Science*, *21*, 101–112.

Wood, S. L., & Lynch, Jr., J. G. (2002). Prior Knowledge and Complacency in New Product Learning. *Journal of Consumer Research*, *29*(3), 416–426.

Wood, W. (1982). Retrieval of Attitude-Relevant Information from Memory: Effects on Susceptibility to Persuasion and on Intrinsic Motivation. *Journal of Personality and*

Social Psychology, *42*(5), 798–810.

Wright, P. L. (1973). The Cognitive Processes Mediating Acceptance of Advertising. *Journal of Marketing Research*, *10*(1), 53–62.

Xiong, G., & Bharadwaj, S. (2014). Prerelease Buzz Evolution Patterns and New Product Performance. *Marketing Science*, (January 2015), 1–22.

Yeo, T. E. (2012). Social-Media Early Adopters Don’t Count: How to Seed Participation in Interactive Campaigns by Psychological Profiling of Digital Consumers. *Journal of Advertising Research*, *52*(3), 297-308.

Yoon, Y., Polpanumas, C., & Park, Y. (2017). The Impact of Word of Mouth via Twitter On Moviegoers’ Decisions and Film Revenues. *Journal of Advertising Research*, *57*(2), 144–158.

You, Y., Vadakkepatt, G. G., & Joshi, A. M. (2015). A Meta-Analysis of Electronic Word-of-Mouth Elasticity. *Journal of Marketing*, *79*(2), 19–39.

Young, M., Gong, J. J., Van der Stede, W. A., Sandino, T., & Du, F. (2008, March). The Business of Selling Movies. *Strategic Finance*, 35–41.

Zhang, W., & Watts, S. (2003). Knowledge Adoption in Online Communities of Practice. *ICIS 2003 Proceedings*, (pp. 96–109).

Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting Stock Market Indicators Through Twitter “I hope it is not as bad as I fear.” *Procedia - Social and Behavioral Sciences*, (pp. 55–62).

Zhang, X., Fuehres, H., & Gloor, P. A. (2012). Predicting Asset Value Through Twitter Buzz. *Advances in Intelligent and Soft Computing*, *113*, 23–34.

Zuckerman, E. W., & Kim, T. Y. (2003). The critical trade-off: Identity assignment and box-office success in the feature film industry. *Industrial and Corporate Change*, *12*(1), 27–67.