Effectiveness of Online Marketing Campaigns

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An Investigation into Online Multichannel and Search Engine Advertising

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Internet advertising: The ultimate marketing machine.

—The Economist

Foreword

The importance of the Internet as a marketing and advertising medium has grown rapidly in recent years and will continue to grow. As in the offline world, the online world has generated a variety of marketing instruments of its own, but so rapidly that scholarly research in the field of business management still has only a limited knowledge of their workings.

This is the area that Sebastian Klapdor addresses in his work. The goals of his analysis lie first in improving the body of research regarding an online marketing instrument that has recently achieved dominance: search engine marketing. In this connection, he investigates the question of which factors determine the "success" of a keyword as measured by click-through rates. Secondly, he examines the interplay and interactions that occur between the different online advertising instruments.

In my view, Sebastian Klapdor's work fills important gaps in the still largely unexamined field of online marketing. His contributions lie both in his interdisciplinary approach to the issues, for example, his application of insights and theories drawn from research into linguistics, and in his analyses of a very extensive dataset and development of a systematic method for categorizing the different instruments available for use in the Internet. Through his analyses of various types of searches, Klapdor has developed a deeper understanding of the success of online advertising, and his work thus provides important knowledge for the design of an online marketing mix. This knowledge is equally valuable for practical use in the business world and in further scholarly research.

This work represents a major advance in online marketing research, and it is to be hoped that it will find widespread use in academia and in practice.

Florian v. Wangenheim

Acknowledgments

To the many people who made this thesis possible, I extend my greatest appreciation.

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I also would like to deeply thank my parents, Ursula and Jürgen, for their love, support, and encouragement—from kindergarten to the PhD. Now you can be relieved :-)

Finally, I owe my thanks to Tonia for all the emotional support and caring she provided. I love you.

Sebastian Klapdor

Summary

Internet advertising has come of age; yet little is known in research and practice about how digital channel advertising really works. The empirical research in this thesis intends to fill this gap and shed light on the effectiveness of online advertising. Two studies are conducted that focus on multichannel online advertising and search engine advertising, the single-most important online ad channel. In an interdisciplinary approach, both studies first develop comprehensive theoretical models based on existing work in related research fields—for example, marketing and information retrieval (a blend of computer science, library science, information science, cognitive psychology, and statistics). This approach pays off. When applying both models to large advertiser data sets, they explain the effectiveness of online advertising significantly better than any other previously published work and lead to new and insightful findings.

Study I, which investigates multichannel online advertising, produces initial empirical evidence about the multichannel synergies between online channels. It reveals that purchase propensity increases when consumers receive advertising messages through multiple channels. The analysis also shows that channel order plays a decisive role. For users who begin browsing on channels primarily used for information gathering and then move to navigation channels, advertiser messages lead to significantly greater uplifts than for those users who start off in navigation channels. Moreover, both synergy and channel order effects depend on the past purchasing behavior of consumers.

Study II, which focuses on the effectiveness of keywords in search engine advertising, identifies several previously unknown criteria that substantially affect click-through rates of keywords. One new element—query variation index—turns out to be an exceptionally good predictor. It indicates whether a keyword contains sufficient information to identify a user's information need correctly. Moreover, the analysis shows that keyword matching options moderate the relationship between the main predictors and a keyword's click-through rate.

As one of the first empirical studies built on a solid theoretical base, the results of this thesis constitute an important starting point for future research in online advertising. Furthermore, the results enable practitioners to improve the effectiveness of online advertising through a more differentiated campaign management approach. Based on its findings, the thesis outlines how a future integrated approach to online advertising could look like.

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List of Abbreviations

ADV	Advertiser name
B	Broad
B2B	Business-to-business
B2C	Business-to-consumer
CAGR	Compound annual growth rate
CH	Number of channels
CPA	Cost per action
CPC	Cost per click
CPM	Cost per mile
CPR	Current purchase
CR	Conversion rate
CTR	Click-through rate
DUR	Duration of user journey
ELM	Elaboration likelihood model
FCH	First channel of user journey
FL	Frequency in language
IAB	Internet Advertising Bureau
IDS	Institute for German Language
IfD	Institute for Demographics
IND	Industry
INT	Exposure intensity
IR	Information retrieval
KPI	Key performance indicator
LA	Lexical ambiguity
LCH	Last channel of user journey
LDIFF	Keyword-query length difference
LEN	Keyword length
LOC	Advertiser location
MMR	Moderated multiple regression
OVK	German Online Publisher Industry Association
P	Phrase
POS	Display position on search engine result page
PPC	Pay-per-click
PPR	Previous purchase

PR	Public relations
QS	Quality score
QVI	Query variation index
SD	Standard deviation
SEA	Search engine advertising
SEM	Search engine marketing
SEO	Search engine optimization
SERP	Search engine result page
TV	Television
US	United States
URL	Uniform resource locator
VIF	Variance inflation factor
ZAW	German Advertising Industry Association

1 Introduction

1.1 Motivation and Objective

The Internet has revolutionized how advertising works: while with traditional mass media, such as TV or newspapers, half the advertising spend is wasted on the wrong audience, advertising messages on digital channels can be tailored to individual consumers at low cost (*Economist*, 2006; Lewis, 2007). The Internet offers an unprecedented level of interactivity, allowing consumers to immediately respond to ads and connect closely with the advertiser (Pavlou & Stewart, 2000). Today, because people devote a significant amount of their daily time to digital channels, the Internet has become a highly precise, interactive mass medium (De Pelsmacker, Geuens, & Van Den Bergh, 2010).

The increasing budgets for online advertising reflect this development. Even during the economic recession (2008–2010), in which the German gross domestic product remained nearly constant with a compound annual growth rate (CAGR) of 0.1% (Statistisches Bundesamt, 2011), spending on search, display, and other forms of online marketing annually climbed by 10.5% (IAB Europe, 2009, 2011).

However, the emerging online advertising models differ from traditional mass media communication and thus require new skills of advertisers (*Economist*, 2006; Kotler, Armstrong, Wong, & Saunders, 2008). Although extensive research on traditional media advertising exists (see Vakratsas & Ambler, 1999, for a detailed review of studies on advertising effectiveness), research has been somewhat outpaced by the rapid development of advertising on digital channels. There is a growing body of published literature on online advertising, but it focuses more on analyzing selective issues and phenomena than on developing comprehensive theoretical models to understand and explain the effectiveness of online advertising.

The goal of this work is to fill this gap by focusing on two core issues of contemporary online marketing (Ha, 2008; Yao & Mela, 2008). The first project aims to investigate how different online advertising channels work together and to provide an illustration of an overarching model for online advertising effectiveness. The second project explores in-depth the effectiveness of paid search advertising, which is the single-most important online advertising channel in terms of ad spend. The following sections briefly introduce the two core issues investigated in this thesis and present the associated research questions (Figure 1).

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Research Questions

Overall Research Question
What influences the effectiveness of online advertising campaigns?

Research Questions Study I:
Effectiveness of Multichannel Online Advertising

1. *Can simultaneous advertising on multiple online channels increase purchase propensities when targeting individual users?*
2. *If so, is there a difference in the effects, depending on the sequence of the channels in the user journey of individual consumers?*
3. *Do these effects differ for existing versus new customers?*

Research Questions Study II:
Effectiveness of Search Engine Advertising

1. *What criteria can be used to select keywords and evaluate their performance in a systematic way?*
2. *How do matching options influence the effect of these criteria on keyword performance?*

Figure 1: Research Questions

1.1.1 Study I: Effectiveness of Multichannel Online Advertising

To achieve the greatest possible persuasive effect, advertisers frequently employ multiple advertising channels within a single campaign (Cho & Cheon, 2004). According to a study of 150 large US companies, this practice is also common in online advertising (Absatzwirtschaft, 2011; Efficient Frontier, 2010). Here, firms use multiple digital channels to send advertising messages to consumers, for example, in the form of display advertising on websites, e-mail marketing, or textual ads on search engines.

However, a review of the relevant literature leads to the conclusion that little is known about the role of multichannel online marketing in the consumer purchase decision (Breuer, Brettel, & Engelen, 2011). Furthermore, practitioners have failed to integrate multiple online advertising channels because they lack the required tools and knowledge (Direct Marketing News, 2008; Horizont, 2011).

As such, highly relevant issues for advertisers remain unresolved, including those addressed by **the research questions of the first study**:

1. Can simultaneous advertising on multiple online channels increase purchase propensities when targeting individual users?
2. If so, is there a difference in the effects, depending on the sequence of the channels in the user journey of individual consumers?
3. Do these effects differ for existing versus new customers?

To answer these questions, the relationship between exposure to advertising on multiple digital channels and purchasing behavior in an online shop is studied. More specifically, the study investigates how conversion rates of individual users are affected by (1) the number of involved online channels in the user journey, (2) the order of channels in the journey, and (3) users' past purchase behavior. This study therefore develops an interdisciplinary theoretical model based on previous work in marketing (advertising response, purchase decision making) and information retrieval (user search and information processing on the web). The model is estimated using a large data set from an online shop in the fashion and apparel industry that consists of more than 1.6 million user journeys.

1.1.2 Study II: Effectiveness of Search Engine Advertising

Study II focuses on the effectiveness of a single online channel: search engine advertising (or sponsored search). Search engines in particular have changed how consumers acquire information and perform transactions on the web and thus play a vital role in connecting consumers with sellers (Ghose & Yang, 2009; Peterson & Merino, 2003). With their advertising programs, search engines allow firms to display targeted textual ads next to the regular "organic" search results. Two specific features of search engine advertising are favorable from an advertiser's perspective (Hillard, Schroedl, Manavoglu, Raghavan, & Leggetter, 2010): (1) the targeting mechanism, which enables firms to send precise advertising messages to consumers searching for specific information, and (2) a performance-based pricing model, in which advertisers pay only when users actually click on the ads. The development of online advertising budgets seems to support this: investments in paid search have increased tremendously in the past several years, making search engine advertising the largest form of online marketing in mature advertising markets, including Germany or the US (IAB Europe, 2009, 2011; PwC, 2011; see also Section 2.2.1).

However, managing paid search campaigns is not a trivial task. According to Rutz and Bucklin (2007), three major activities must be executed on a continuous basis: (1) selecting relevant keywords and choosing the appropriate matching options for each keyword (parameter that defines exactly how a user query must coincide with a keyword to trigger the impression of the ad text), (2) defining and adjusting the bids on a keyword level, and (3) creating the ad texts.

Although a significant amount of research has been conducted on the latter two tasks and advertisers can draw on specialized tools (e.g., Efficient Frontier, IntelliAd, Omniture), substantially less information is available on keyword-related activities. Some empirical studies have incorporated keyword characteristics as covariates, but misunderstandings remain in both theory and practice about the underlying drivers of keyword performance.

As such, two major problems emerge for academics and advertisers, which **the research questions of the second study** address:

1. What criteria can be used to select keywords and evaluate their performance in a systematic way?
2. How do matching options influence the effect of these criteria on keyword performance?

To provide insight into these two questions, Study II analyzes the impact of keyword characteristics on the effectiveness of paid search campaigns, measured as keyword-specific click-through rate (CTR). These criteria pertain to the information a keyword carries, and thus they appear under the concept of "information content". In doing so, this study distinguishes between criteria related to intrinsic information content (defined by the keyword text itself) and extrinsic information content (induced through the advertiser's external decision on the matching option). Following an interdisciplinary approach similar to Study I, the author derives the keyword criteria from research in linguistics, information retrieval, and online marketing. To estimate the influence of these characteristics on CTR, the author develops a model and tests it on a large data set representing multiple paid search campaigns.

1.2 Contribution

This thesis makes three major contributions to research and practice in online advertising. First, it provides a **theoretical contribution** by presenting comprehensive theoretical models that explain the effectiveness of multichannel online advertising and sponsored search advertising. This fills a significant gap, as related work lacks theoretically grounded explanations for the observed phenomena (e.g., Ghose & Yang, 2009; Hollis, 2005; Ilfeld & Winer, 2002; Rutz & Bucklin, 2011). The development of the theoretical models in both studies requires an interdisciplinary approach, combining theories from research streams in marketing and information retrieval. This approach has a clear value, as the resulting models in both studies explain significantly larger shares of variance in the dependent variables than previous work (e.g., Animesh, Viswanathan, & Agarwal, 2011; Deighton, Henderson, & Neslin, 1994). Both models in this thesis develop new concepts that are powerful predictors of advertising effectiveness. For multichannel advertising, the results indicate that both the number and the order of different online channels in a user's journey drastically affect conversion rates. Furthermore, these relationships are strongly moderated by the historical purchasing behavior of the consumer. For search engine advertising, the new measure *query variation index (QVI)* is a significantly better predictor of keyword specificity than the commonly used criterion *keyword length* (Belkin et al., 2003; Finkelstein et al., 2002; Ghose & Yang, 2009; Jones, Rey, Madani, & Greiner, 2006; Xu & Croft, 1996).

Second, the study makes a **managerial contribution** by providing new and surprising insights into the successful design and execution of online advertising campaigns. On the campaign level, the major finding is that simultaneous advertising on multiple online channels can help increase conversion rates of online shops, but only if advertisers follow an integrated campaign strategy. Doing so entails sending advertising messages on different channels in the "right" order as well as considering the customer's past purchase behavior (new vs. existing customer). For paid search campaigns, the results can help advertisers better identify relevant keywords, select the appropriate matching options, and evaluate their individual performance, all of which are core tasks in the management of sponsored search campaigns.

Third, with the overall conclusions from both studies, the author proposes an **integrated framework for online advertising**, which constitutes a conceptual model for future research and practice in online advertising. The model describes how a combination of individual elements of advertising on digital channels can offer an orchestrated approach in which both effectiveness and efficiency of online advertising can be increased. It reflects the three guiding principles of *transparency*, *integration*, and *execution based on sophisticated channel knowledge*.

1.3 Structure and Approach

Figure 2 outlines the structure of this thesis. To guide the context, Chapter 2 provides an overview on online advertising and presents definitions for relevant concepts used in the course of the work. Chapter 3 follows with a review of current research on online advertising effectiveness (3.1), which shows the research gaps addressed by this thesis. The chapter then presents research from marketing and other disciplines related to online advertising that constitutes the conceptual basis of the two studies (3.2). Chapter 4 comprises Study I, which investigates the effectiveness of multichannel online advertising. After presenting the theoretical model, including the hypothesis, and touching on the research model and data, the chapter presents the results and discusses specific implications of this study for research and practice. Chapter 5 does this in a similar way for Study II, which focuses on the effectiveness of search engine advertising. In contrast with the first project, the research questions from Project 2 are examined in separate sections (5.2 and 5.3). Each section presents its own theoretical model, hypotheses, research model, data, and results, followed by the implications of the entire second study at the end of Chapter 5. Finally, Chapter 6 contextualizes the findings of both projects, derives overall conclusions from the work, and presents an integrated framework for online advertising.

Structure of the Thesis

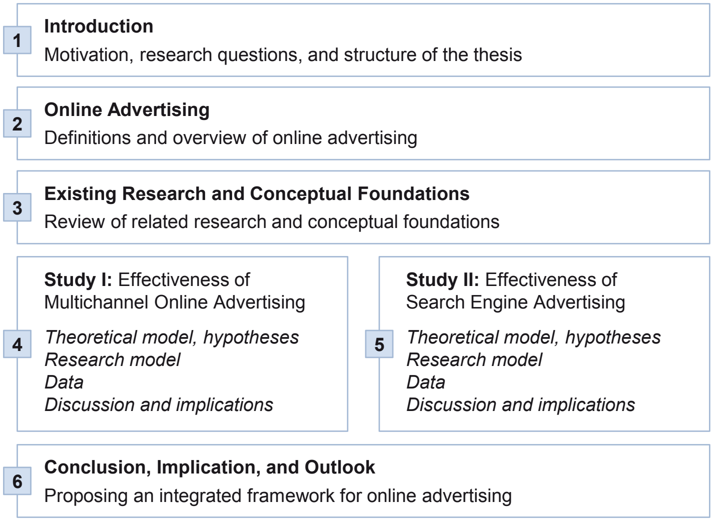

Figure 2: Structure of the Thesis

2 Overview on Online Advertising

This section provides an overview on online advertising, which is important for the course of the thesis. Key definitions for online marketing and advertising are first provided to differentiate between the individual concepts. After elaboration on the increasing relevance of online advertising, the major forms (channels) of online marketing are introduced. The chapter then continues with a brief overview on tracking mechanisms, user journeys, and privacy issues before concluding with concepts for performance evaluation of online advertising campaigns.

2.1 Definition

The American Marketing Association (2011) defines marketing as "an organizational function and a set of processes for creating, communicating, and delivering value to customers and for managing customer relationships in ways that benefit the organization and its stakeholders". To achieve these goals, marketers can control several variables, which are frequently clustered into four groups, called the "four Ps": price, product, promotion, and place (American Marketing Association, 2011; Kotler et al., 2008). Together, these instruments are also called the "marketing mix" (Homburg, Kuester, & Krohmer, 2009; Kotler et al., 2008).

Two main tools in the promotion function of marketing are *advertising* and *public relations (PR)* (Kotler et al., 2008). Advertising refers to non-personal communication activities for the presentation or promotion of ideas, goods, or services that are paid by an advertiser who can be identified as sponsor (e.g., Arens, Weigold, & Arens, 2010; Kotler et al., 2008; Moriarty, Mitchell, & Wells, 2011). In general, the primary goal of advertising is to change or influence (future) customers' attitudes to persuade them to buy the advertiser's rather than the competitor's products (Jefkins, 2000; Vakratsas & Ambler, 1999). In contrast, with PR, firms do not pay media to broadcast or print their ads. Rather, companies provide information to media and/or consumers so that they can pick it up in their coverage or conversations, respectively (Kotler et al., 2008). Therefore, the primary goal of PR is to foster a positive image through good relations with stakeholders (Kotler et al., 2008).

Online or digital marketing pertains to achieving marketing objectives with the aforementioned marketing variables over the Internet (Chaffey, Ellis-Chadwick, Mayer, & Johnston, 2009; Kotler et al., 2008). In other words, to support each of the four Ps, online marketing involves the usage of digital tools based on Internet technologies.

Online advertising and PR reside at the intersection of the promotion function and digital marketing tools (Figure 3). This thesis focuses on online advertising, which can consequently refer to the sum of all measures on the Internet to build brands or drive sales through ads appearing while consumers are surfing the Internet or using other online services, such as e-mail and instant messaging (Chaffey et al., 2009; Kotler et al., 2008). Accordingly, the objective of

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online PR is to maximize the number of mentions in favor of the firm or its brands on third-party websites with an audience consisting of the firm's primary target group (Chaffey et al., 2009).

As a final note on the understanding of online advertising in the current work, as with many other marketing activities, online promotion can also be classified according to the initiator–addressee relationship in business-to-consumer (B2C) and business-to-business (B2B) activities (Kotler et al., 2008). In line with the majority of research on advertising effectiveness, this thesis focuses on B2C relationships.

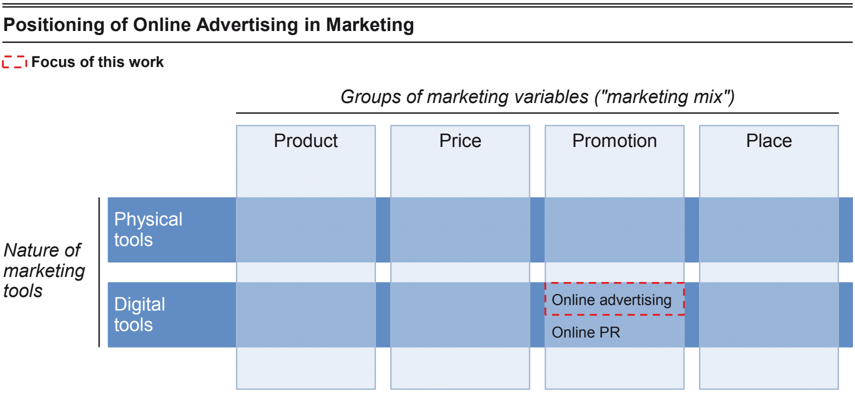


Figure 3: Positioning of Online Advertising in Marketing
Source: Based on definitions from American Marketing Association (2011), Chaffey et al. (2009), and Kotler et al. (2008).

2.2 Relevance

As mentioned in the Introduction, online advertising has gained significant importance in the past several years, as firms increasingly shift their marketing budgets to digital channels. The main reason for this dynamic development is a change in consumer behavior in terms of media usage and purchase behavior. Advertising on online channels can be highly effective, and outcomes can be easily attributed to campaigns, resulting in a high accountability.

2.2.1 Increasing Online Advertising Spends

Similar to other developed advertising markets, net spendings on online advertising have substantially increased during the past 10 years in Germany, with a CAGR of 37% (IAB Europe, 2011; Screen Digest, 2011). Market researchers expect this growth to stabilize in the future, resulting in online ad spends of nearly 5 billion EUR in 2015, as Figure 4 depicts (left-hand side).

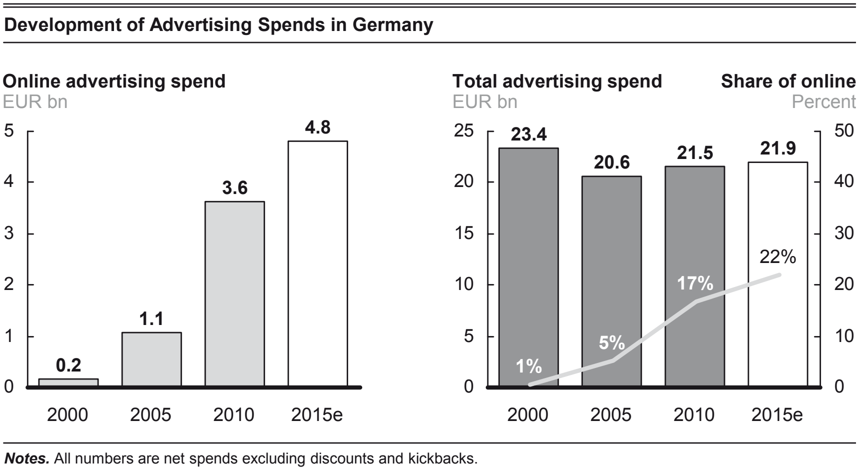
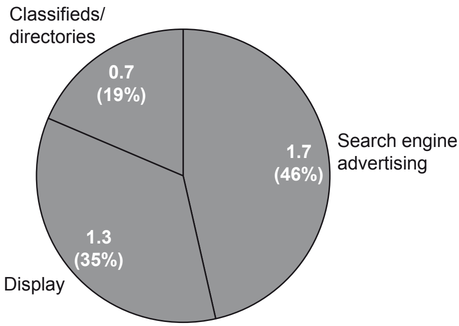


Figure 4: Development of Advertising Spends in Germany
Source: IAB Europe (2011), Screen Digest (2011), ZAW (2011a, 2011b).

This increase is considerable given a shrinking overall advertising market in the same period, shown in Figure 4 (right-hand side). Between 2000 and 2010, total ad spends (net) in Germany decreased by 0.8% per year (ZAW, 2011a). Consequently, the online share of total ad spends climbed steadily. By the end of 2010, almost every fifth advertising euro was spent for ads on digital channels. This implies that firms are continuously shifting their advertising euros from offline to online channels. According to market forecasts from ZAW (2011b) and Screen Digest (2011), this trend is expected to continue in the future, resulting in an online share of more than 20% of the entire advertising expenditures by 2015.

Figure 5 shows the split of online marketing spend across three major channels: search engine advertising, display, and classifieds/directories. (Section 2.3 provides a brief description of individual online advertising channels.) *Search engine advertising* constitutes the largest share and represents spendings for text ads on search engine result pages, often also called "sponsored search" or "paid search". However, it does not include the cost for optimizing organic search results. With a CAGR of 8% from 2008 to 2010, search engine advertising has been a major growth driver of online ad spend. *Display* is the second-largest sector, constituting 35% of online ad spendings. It includes expenditures for banner and video ads on websites and mobile devices. This sector has also strongly contributed to the growth of online ad spendings, with a CAGR of 10% between 2008 and 2010. Finally, spendings on *classifieds* *and directories* represent 19% of German online ad spendings. This segment has remained rather stable over time.

Online Advertising Spend by Channel
Germany 2010, EUR bn (Percent)



Notes. All numbers are net spends excluding discounts and kickbacks.

Figure 5: Online Advertising Spend by Channel
Source: IAB Europe (2011).

To demonstrate that the increasing importance of online advertising is not a phenomenon restricted to Germany, Figure 6 presents a country comparison of online ad spendings. It shows that the share of online spend of total advertising is on an average level in Germany, while growth of online advertising between 2010 and 2015 is predicted to be at the lower end of the peer group (eMarketer, 2010; Screen Digest, 2011). This clearly demonstrates that the rise of online advertising is occurring internationally and is not constrained to Germany. For example, in the United Kingdom online already represents 32% of the total advertising spend and is expected to almost double by 2015.

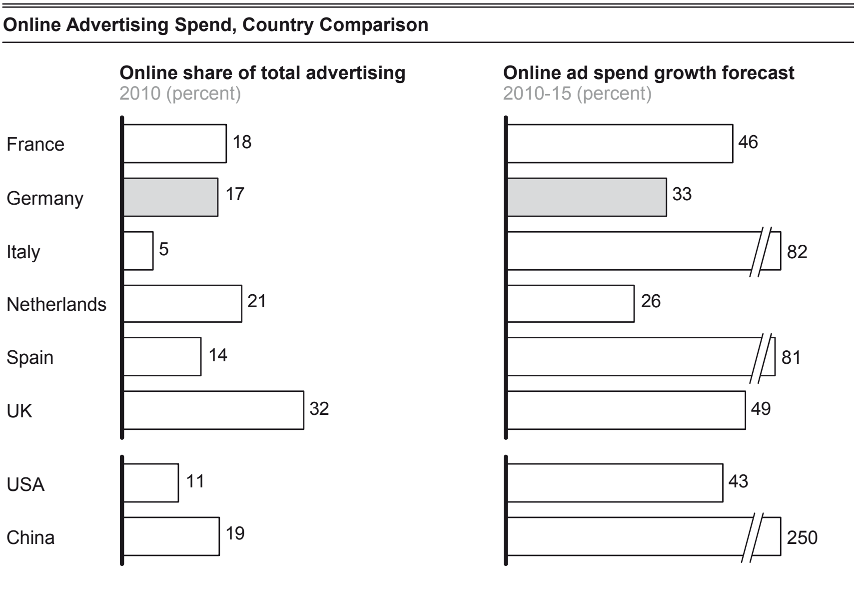


Figure 6: Online Advertising Spend, Country Comparison
Source: eMarketer (2010), Screen Digest (2011).

In summary, online ad spends have significantly increased in the past several years. In many developed countries, digital channels now represent a major part in firms' advertising activities. Still, online advertising is expected to grow at high levels, which makes it a major driver of total ad spend development. The following sections discuss the reasons for the increasing relevance of advertising on digital channels.

2.2.2 Shifting Consumer Behavior

A fundamental reason for the increase in digital advertising activities is a shift in consumer behavior. First, consumers now spend more time on the Internet, and second, their purchasing patterns have changed in such a way that they increasingly use the web both as an information source during their purchase decision-making process and to directly buy goods or services online (Homburg et al., 2009; Kotler et al., 2008).

De Pelsmacker et al. (2010) conclude that the Internet has become a mass medium and that all major target groups can now be reached online. Figure 7 substantiates this finding. It shows the development of media usage in Germany between 2000 and 2010. Whereas the shares of traditional media, including TV, radio, newspaper, and books, have continuously declined, consumers spend increasingly more time each day on the Internet (Ridder & Engel, 2010). In

2000, a German spent on average 14 minutes per day on the web. However, in 2010, this number increased fivefold to more than 80 minutes. Consequently, increasingly more consumers can be reached through the web, making digital channels more attractive and relevant for advertisers.

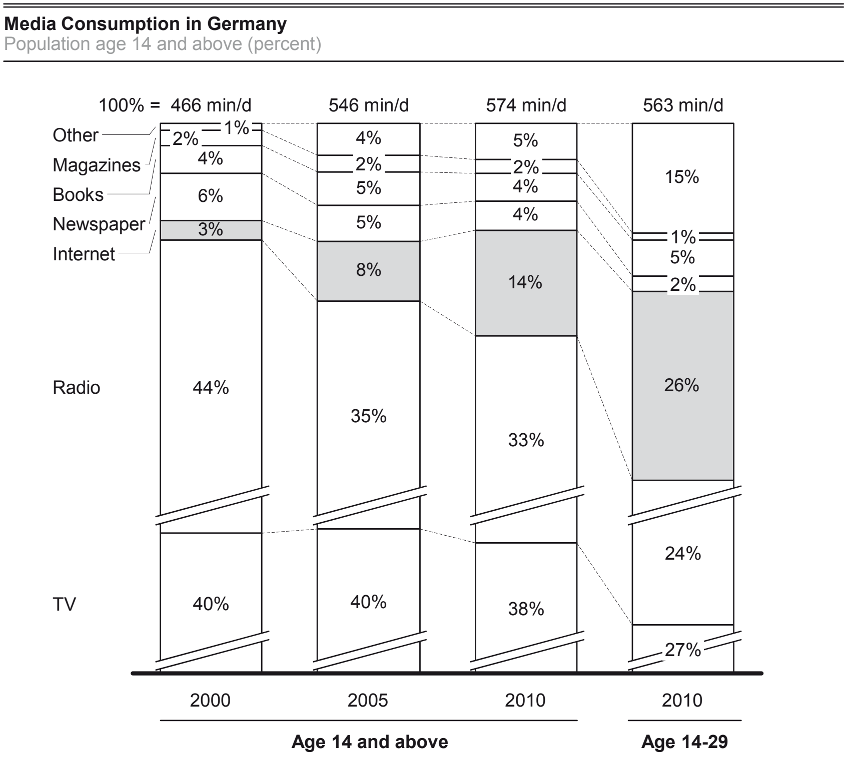


Figure 7: Media Consumption in Germany
Source: Ridder & Engel (2010).

This particularly applies to people between the ages of 14 and 29 years, often referred to as "Digital Natives" (Ridder & Engel, 2010). In this segment, the share of the Internet is almost twice as large as that in the overall adult population (14+ years) and has similar levels to TV and radio (~140 minutes per day). According to Ridder and Engel (2010), the rapid growth of the Internet as a medium can be ascribed to its twofold nature: it both offers new, unique online services (e.g., e-mail, social networks) and acts as a distribution platform for traditional media (e.g., streaming TV and radio, newspaper websites).

In addition to media usage, a change in purchasing habits has increased the relevance of digital marketing. Kotler et al. (2008, p. 839) claim that "[t]he web has fundamentally changed customers' notions of convenience, speed, price, product information and service". According to Kotler et al., this translates into two major trends: (1) an increasing share of all retail purchases is influenced by digital channels and (2) a growing number of consumers directly purchases from online shops.

Studies from Verhoef, Neslin, and Vroomen (2007) and Yahoo Research & Enigma GfK (2010) present evidence for the first argument. Figure 8 displays the results of the latter study. Here, consumers were asked which information sources they used before purchasing a product. The study reveals that for many categories, the Internet is the first- or second-most important information source during the purchasing process. For example, when purchasing consumer electronics, 84% of the surveyed consumers used the Internet to perform product research before purchasing. This is also called the "research shopper phenomenon" (Verhoef et al., 2007). Advertising on digital channels can be vital to reach these consumers and influence their purchase decisions.

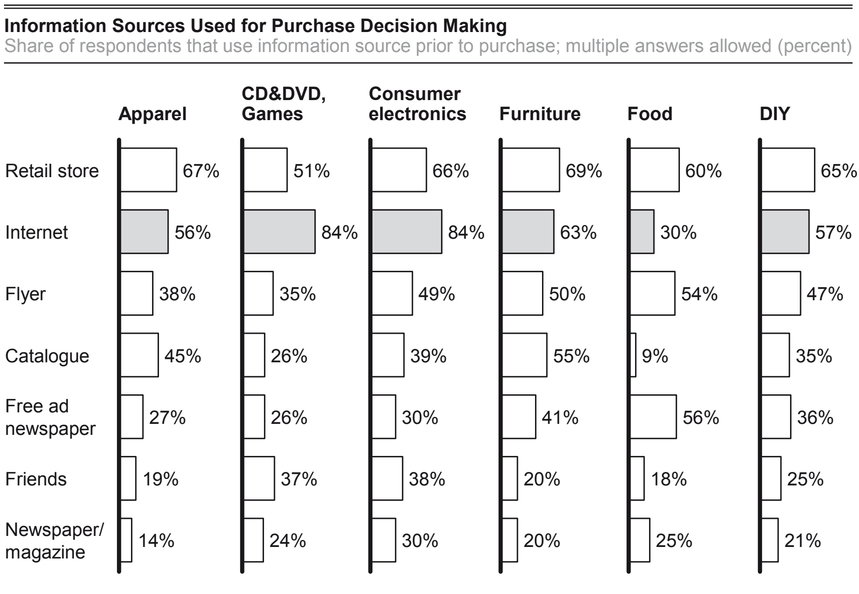


Figure 8: Information Sources Used for Purchase Decision Making
Source: Yahoo Research & Enigma GfK (2010).

Furthermore, consumers increasingly purchase goods and services directly over the Internet. Figure 9 shows the development of online shoppers in Germany as a share of the total population. According to IfD Allensbach (2010), whereas in 2000 only every 10th German purchased goods and services over the Internet, by the end of 2010, more than two-thirds of Germans were online shoppers. During the past several years, the segment of "silver surfers" in particular (Internet users between ages 50 and 64) has contributed substantially to the strong growth of e-commerce in Germany (Enigma GfK, 2010). To benefit from the growing number of online shoppers, e-commerce businesses aim to attract them to their shops. Digital advertising is a key activity to achieve this and drive online retail sales (Ansari, Mela, & Neslin, 2008; Yao & Mela, 2008).

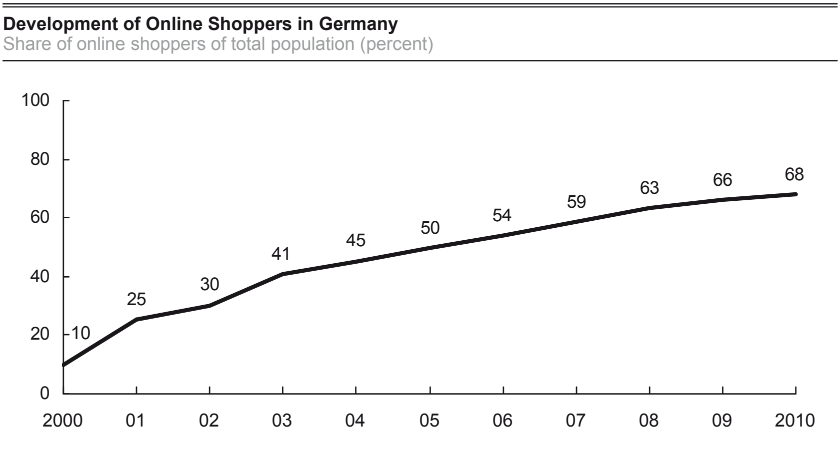


Figure 9: Development of Online Shoppers in Germany
Source: IfD Allensbach (2010).

2.2.3 Advantages of Online Advertising Instruments

Apart from the shift in consumers' purchase and media consumption behavior, digital channels have specific advantages over physical media, which may have also contributed to the immense growth of online advertising during the past years. In relevant literature from practice and research, three major themes can be identified: *interactivity*, *effectiveness*, and *accountability*.

First, according to Deighton (1996), online channels allow a considerably stronger interaction between advertiser and recipient than many forms of traditional direct response media. The contact is often initiated by the consumer, who actively seeks an experience or information. In doing so, the consumer attributes 100% of his or her attention to this task, making online a high-involvement medium. In such an environment, advertising messages are more likely to be noticed by consumers, in turn making them more effective. Chaffey et al. (2009) and De

Pelsmacker et al. (2010) explain that online channels can be used to establish “real” two-way communications between advertiser and customers, including competitions, sales promotions, and social media interaction. Hoffman and Novak (1996, 1997) find that this new form of interaction provides a better perceptual experience for customers and requires a paradigm shift in marketing activities.

Second, in traditional mass media (e.g., TV, newspaper), a significant share of advertising spend is wasted on non-relevant target audiences (Abraham & Lodish, 1990; Lodish, Abraham, Kalmenson, et al., 1995). According to estimates from the Interactive Advertising Bureau, this waste constituted approximately 50% of global ad spend in 2006 (Lewis, 2007). Unlike in traditional media, advertising messages on digital channels can be tailored to the individual consumer at low cost (Chaffey et al., 2009), which is often referred to as “targeting”. Consumers react more positively to targeted ads because they perceive the information as more useful than unspecific ads (Cho & Cheon, 2004; Edwards, Li, & Lee, 2002; Wang, Chen, & Chang, 2008). This eventually leads to a higher effectiveness of advertising and, in many cases, also to increased cost-efficiency (IAB Europe, 2011). One main objective of the current work is to develop a model to identify the underlying drivers of the effectiveness of keywords in sponsored search advertisements.

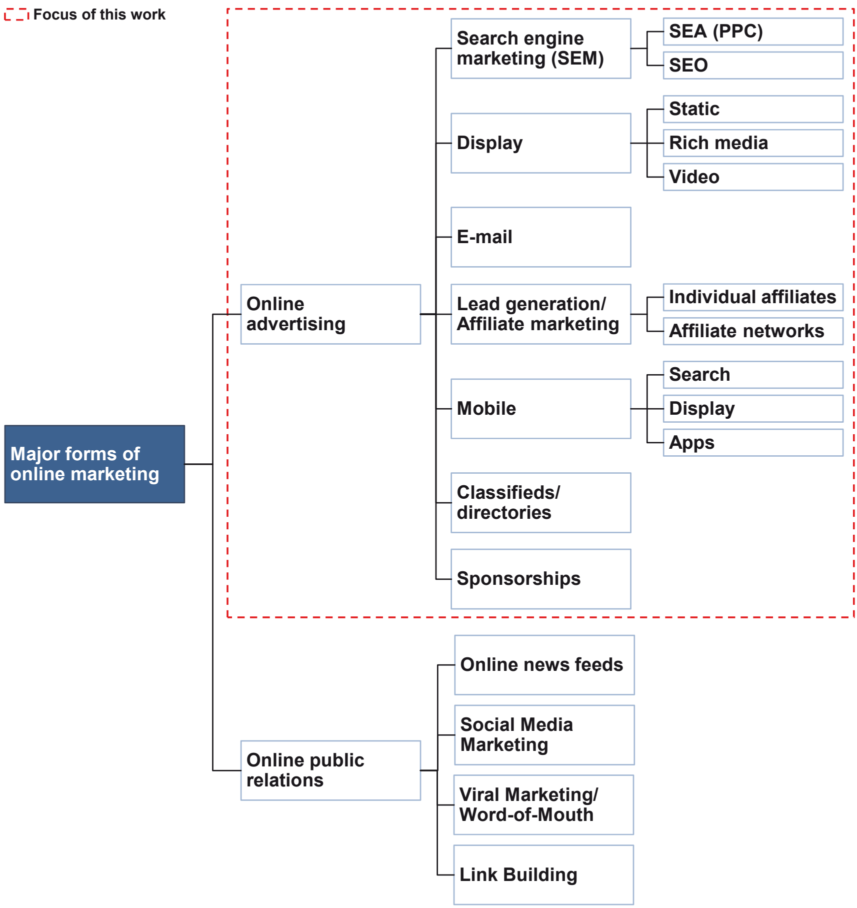
Third, digital channels support a precise measurement of advertising effectiveness (Homburg et al., 2009). Through sophisticated tracking mechanisms, behavioral outcomes, such as purchases, sign-ups, or customer calls, can be directly attributed to advertising exposure on an individual consumer level. According to industry experts (e.g., PwC, 2011), this accountability of results to ad spend is a major driver of continuous growth of online advertising budgets. The economic crisis between 2008 and 2009 provides support for this argument: during these years, advertisers heavily reduced their offline ad budgets, while maintaining online ad spends at a fairly constant level (IAB Europe, 2010a).

2.3 Forms (Channels)

With regard to different types of online marketing, this domain is still in an early stage of development. Only a few broadly accepted definitions exist for the forms of digital advertiser communication, and even the term “form” itself is not clearly defined. Where the advertising industry speaks of “advertising formats” (IAB Europe, 2011; OVK, 2011a; PwC, 2011), the web community frequently uses the term “channels” (e.g., Bundy, 2011; Fishkin, 2011; Gabe, 2011), and academic research refers to “communication techniques on digital media channels” (Chaffey et al., 2009), “types of ads” (Homburg et al., 2009), or “forms of online advertising” (Kotler et al., 2008). However, all these terms denote more or less the same thing: measures on the Internet to build brands or drive sales (Chaffey et al., 2009). Of these activities, the current work primarily focuses on advertising-related ones. According to marketing scholars, activities belonging to this group must meet the following four criteria: (1) paid by the advertiser; (2) non-personal communication; (3) presentation of promotion of ideas, goods, or services; and (4) advertiser can be identified as a sponsor (e.g., Arens et al., 2010; Kotler et al., 2008; Moriarty et al., 2011). These types of online marketing are also called "online advertising channels" in the remainder of the work.

provides an overview of the different forms of online marketing, highlighting the advertising-related ones. In addition to the advertising vehicles, online marketing comprises PR on digital channels. As discussed previously, PR is fundamentally different from advertising and is briefly covered at the end of this section.

Major Forms of Online Marketing



Notes. SEA = search engine advertising; PPC = pay per click; SEO = search engine optimization.

Figure 10: Major Forms of Online Marketing (Promotion)

Sources: Chaffey et al. (2009), IAB Europe (2011), Kaushik (2007), Kotler et al. (2008), OVK (2011), PwC (2011).

2.3.1 Search Engine Marketing

According to Chaffey et al. (2009, p. 506), search engine marketing (SEM) is an activity that promotes a firm through search engines (e.g., Bing, Google, Yahoo) by "delivering relevant content in the search listings for searchers and encouraging them to click through to a destination site". This is achieved by obtaining listings in upper positions for specific search terms that refer to the products and services of an advertiser (PwC, 2011). This targeting mechanism allows advertisers to send precise messages to consumers searching for specific information. Because SEM is a pull channel, it is more often used for sales than for branding objectives (Chaffey et al., 2009). Because of the vital role of search engines for Internet users, SEM has become one of the most important forms of online marketing, constituting almost half the European online ad spend in 2010 (IAB Europe, 2011). It can be separated into two major techniques: **SEA**, which is often referred to as pay-per-click (PPC), sponsored search, or paid search, and **search engine optimization (SEO)**. The primary difference between the two techniques is the section of the search engine result page (SERP) in which the advertiser listing appears (Figure 11).

Example of a Search Engine Result Page

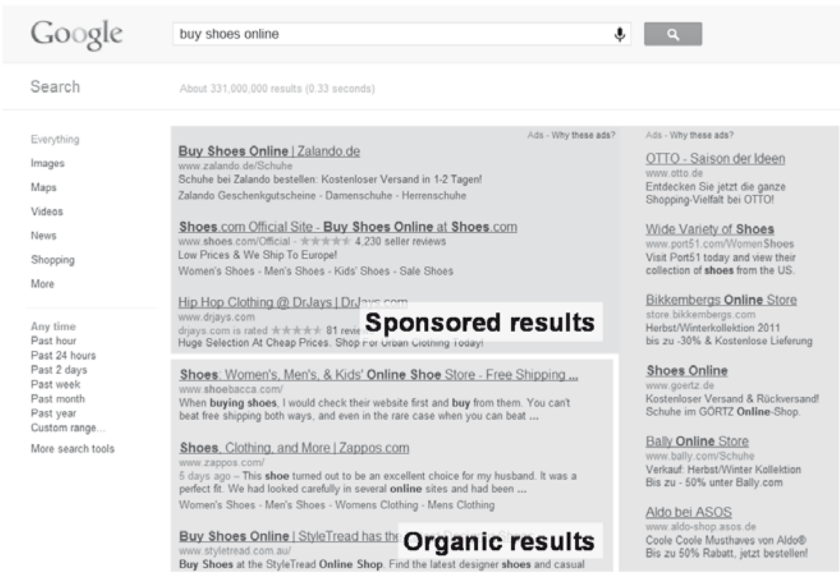


Figure 11: Example of a Search Engine Result Page
Source: Google.

Firms use **SEO** to increase the position of their listings in the natural or organic search results (Figure 11, blue area), which are generated by the search engine's proprietary raking algorithms (Chaffey et al., 2009; Google, 2011a). The ranking portrays the relevance of the match between the user's search query and the websites in the search engine's index. With SEO, advertisers try to optimize their sites so that they are perceived as more relevant by the ranking algorithms and consequently appear at higher positions (Kaushik, 2007). This is favorable for advertisers because they do not have to pay for traffic from organic search results. However, SEO is a fuzzy task and needs to be performed on an ongoing basis. The results are difficult to predict and usually take months to manifest (Chaffey et al., 2009).

In contrast, **SEA** offers advertisers a more deterministic way to appear for desired search queries at high ranks on the SERP. Here, firms can create textual advertising messages and place bids on relevant keywords. If a user's search query contains these keywords, the ad appears on the top or on the right-hand side of the organic search results (Figure 11, red area). A fee is charged only when the user clicks on the ad and is forwarded to the advertiser's website (Chaffey et al., 2009). Cost-per-click and display position of the ad are determined in an auction, when several competitors bid on the same keyword (Google, 2010a; Microsoft, 2010; Yahoo, 2010). Because it can be challenging for advertisers to identify an exhaustive list of all relevant keywords for a campaign, search engines offer *broad* and *phrase* matching options (Bartz, Murthi, & Sebastian, 2006; Gupta, Bilenko, & Richardson, 2009). Here, the keyword only needs to be related to the search query—and not match it exactly—to trigger the ad impression.[1] These generic matching options can help advertisers increase the reach of their paid search campaign substantially and are often used in practice: according to Google (2010b), one-third of all clicks are generated through *broad* match. Figure 12 illustrates how matching options work.

There is also a push variation of SEA (Chaffey et al., 2009), called "content network". Here, the text ads are displayed on third-party websites that are relevant to the ads' content (contextual advertising). However this work focuses on the primary form of search engine advertising with the ads displayed on the SERPs.

Section 5 develops and tests a model to determine the factors that drive the relevancy of keywords in "classic" paid search advertising. It also views matching options as explanatory variables.

[1] *Phrase* match allows the user query to have additional terms (as long as the keyword terms are included in the query), and *broad* match, as the least restrictive option, also performs the matching if a query has fewer terms than a keyword or the keyword is not included at all, such as when the user enters a synonym (Google, 2010b; Gupta et al., 2009).

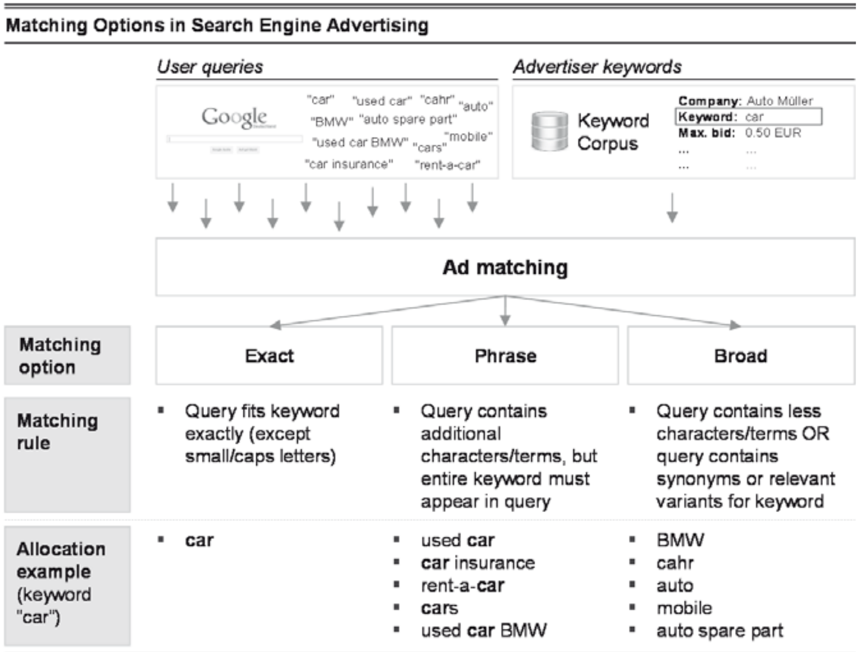


Figure 12: Matching Options in Search Engine Advertising
Source: Based on Google (2010b, 2011b).

2.3.2 Display

Display ads are "paid ad placements using graphical or rich media ad units within a web page to achieve goals of delivering brand awareness, familiarity, favorability and purchase intent. Many ads encourage interaction through prompting the viewer to interact or rollover to play videos, complete an online form or to view more details by clicking through to a site" (Chaffey et al., 2009, p. 539). Display ads are the second-largest form of online advertising, accounting for 33% of the European online ad spends (IAB Europe, 2011). Declining response rates from consumers have posed a challenge to display advertising over the years. However, innovative targeting technologies for a more precise ad delivery, especially behavioral targeting and retargeting, are expected to fuel future growth of display advertising (IAB Europe, 2011). Chaffey et al. (2009) note that payment for display ads was traditionally based on impressions (cost-per-mile), but more performance-oriented forms of funding are emerging (cost-per-click, cost-per-order).

2.3.3 E-mail

Outbound e-mail marketing is the activity in which advertisers send e-mails to existing customers or prospects that contain a link to their websites (Chaffey et al., 2009). In many countries, firms must obtain an opt-in from consumers before sending e-mail ads. Messages sent without permission are often referred to as spam or junk e-mail (Morimoto & Chang, 2006). Because retention e-mails lead to significantly better bounce and CTRs than acquisition e-mails, advertisers use this instrument more frequently for sales promotion and customer retention than for brand building and customer acquisition (Chittenden & Rettie, 2003; Direct Marketing Association, 2006). Although e-mail marketing plays an important role in the (online) marketing mix, the number of users has been declining over the last years in Germany (Deutsche Post AG, 2011).

2.3.4 Lead Generation (Affiliate Marketing)

Chaffey et al. (2009) characterize affiliate marketing as the “ultimate form of marketing communications” because of its performance-based pricing model. Here, the advertiser only pays the referring sites (also called “affiliates” or “publishers”) for transactions (sales) or qualified purchase inquiries (leads), and thus wastage is significantly smaller than with other communication media. From this definition, it is obvious that affiliate marketing is not a “real” advertising channel but rather a technique of “remunerating a marketer (based on performance)” (Prussakov, 2011, p. 24). Despite its transactional nature, affiliate marketing can also be used for branding purposes (Chaffey et al., 2009; OVK, 2011b). Multiple types of affiliates exist, including aggregators[2], review sites, blogs, and others. When a consumer comes from one of these affiliated websites to the advertiser’s shop and converts, the affiliate is reimbursed. “Affiliate networks” simplify the process of managing a multitude of (smaller) affiliates (OVK, 2011b). Here, the advertiser only needs to design an affiliate program (e.g., 5% commission for all sales) including the ads and launch it on the network (Prussakov, 2011). All interested affiliates within the network can then directly sign up for the program and incorporate the ad unit on their websites. Budgets for affiliate marketing only make up a small share of the online advertising spend. In 2010, they accounted for less than 10% of the German overall online ad spendings (OVK, 2011c). However affiliate networks have grown steadily over time and are expected to strengthen their future role in the online media mix (OVK, 2011c).

[2] Aggregators are websites that offer price comparisons for a large number of products and services, such as consumer electronics, airline tickets, or car insurance (Chaffey et al., 2009).

2.3.5 Mobile

With the proliferation of smart phones, tablets, and third-generation networks, advertising on mobile devices has become more important for firms (Pousttchi & Wiedemann, 2006). The industry association IAB defines mobile advertising as "[a]dvertising, tailored to and delivered through wireless mobile devices such as smart phones (e.g., BlackBerry, iPhone, Android) … and media tablets (e.g., iPad, Samsung Galaxy Tab)" (PwC, 2011). According to the IAB definition, mobile advertising can comprise the previously described forms of search and display ads, appear in mobile applications (apps), or use text messaging services (SMS, MMS). According to Pousttchi and Wiedemann (2006), mobile marketing campaigns can be used for both branding and sales objectives. Advertising on mobile devices is expected to be a major growth driver of online advertising spends in the next years (IAB Europe, 2011).

2.3.6 Classifieds and Directories

When firms or consumers pay third-party websites to list specific information (e.g., company profiles, job offerings, used-car ads), this type of advertising belongs to the category of classifieds and directories (IAB Europe, 2011). While US ad revenues in this segment have constantly declined in the past years (PwC, 2011), European spendings have remained stable (IAB Europe, 2011). However, the recent US development might be an indication of the decreasing significance of directory and classified services for online advertising. The main reasons for this trend might be the fixed payment (usually regardless of impressions or clicks on the ad) and the lack of transparency of the advertisers.

2.3.7 Sponsorships

Online sponsorships refers to "the linking of a brand with related content or context for the purpose of creating brand awareness and strengthening brand appeal in a form that is clearly distinguishable from a banner, button, or other standardized ad unit" (ClickZ, 2011). The IAB provides a similar definition, emphasizing that content and user experiences in online sponsorship are customized for a specific advertiser and not delivered in the form of regular display or video ads (PwC, 2011). Common forms of online sponsorships are spotlights (custom-built pages with the advertiser's brand and content around a specific theme), content/section sponsorship (section of a website or e-mail carrying the advertiser's branding), or branded sweepstakes and contests (PwC, 2011). According to Performance Research (2011), sponsorships can lead to a significantly better attitudinal response than display advertising in terms of trustworthiness, credibility, and purchase intention.

2.3.8 Online PR

The goal of PR is to establish "good relations with the company's various publics by obtaining favorable publicity, building up a good corporate image, and handling or heading off unfavorable rumors, stories and events" (Kotler et al., 2008, p. 760). As mentioned earlier, it differs from advertising in that firms do not reimburse media to send their advertising messages. Rather, firms provide content to media and/or consumers with the intention that they will refer to it in their coverage or conversations (Kotler et al., 2008). Accordingly, the objective of online PR is to maximize the number of mentions in favor of the firm or its brands on third-party websites, with an audience consisting of the firm's primary target group (Chaffey et al., 2009). Online PR comprises a broad spectrum of activities, including distribution of press releases over online news feeds, link building with other websites, social media marketing (e.g., blogging, presence on social networks, social bookmarking), and creating buzz with viral marketing campaigns (Chaffey et al., 2009). According to Kotler et al. (2008), the major advantages of (online) PR over advertising are higher reach, lower cost, and better quality of contacts, resulting in a greater message credibility. However, Chaffey et al. (2009) note that PR on digital channels also carries certain risks because it cannot be directly controlled by the firm. In addition, if executed badly (e.g., deletion of negative comments on products or bands on the coporate blog), it can backfire and damage the company's image substantially (Stanchak, 2011).

2.4 Tracking Mechanisms, User Journeys, and Privacy

A major advantage of online advertising is its accountability, enabled through the availability of highly granular data (Rürup, 2011a). Online advertising enables advertisers to precisely target their advertising messages and evaluate the results of their advertising activities for each individual recipient. According to third-party providers of tracking solutions (e.g., explido, 2011; intelliAd, 2011a), multichannel tracking data consists of

- *advertising input and the resulting user behavior,*
- *for individual consumers,*
- *on multiple online advertising channels,*
- *over time.*

This information is also frequently referred to as "user journey" or "conversion chain" (Rürup, 2011a). Figure 13 provides an example of a user journey. In this example, the first contact the user experienced with the advertiser was a click on the firm's display advertisement at t_1, which forwarded the user to the advertiser's landing page. At t_2, the user searched for a relevant keyword on a search engine and clicked on the advertiser's sponsored search ad, again reaching the advertiser's landing page. The user continued the journey on various channels until he or she finally purchased (i.e., converts) at the advertiser's online shop at t_8 after reaching it through a click on a link in the organic search results. The duration of the entire journey can be expressed as t_8–t_1.

To construct user journeys, the underlying data must be collected through complex tracking mechanisms based on cookies (Rürup, 2011b). Cookies are small text files stored on the user's computer that enable websites to identify an individual web browser (Chaffey et al., 2009). Although cookies are commonly used for online marketing purposes, they have certain technical and conceptual limitations that can affect the effectiveness of tracking and ad delivery services. Section 5.4.3 discusses this in more detail in; the corresponding analysis is based on cookie data.

Another challenge related to cookies is that they "have become a synonym for the invasion of privacy" (Hormozi, 2005). According to Hann, Hui, Lee, and Png (2007), Internet users are increasingly concerned about a potential misuse of their personal data by advertisers. Studies have shown that (perceived) invasion of privacy negatively affects purchase behavior (Brown & Muchira, 2004; Goldfarb & Tucker, 2011a). Firms try to mitigate this by quoting explicit privacy policies on their websites (Hann et al., 2007), providing users with increased control over their personal data (Tucker, 2010), and offering benefits (e.g., free services such as e-mail) to users (IAB Europe, 2010b).

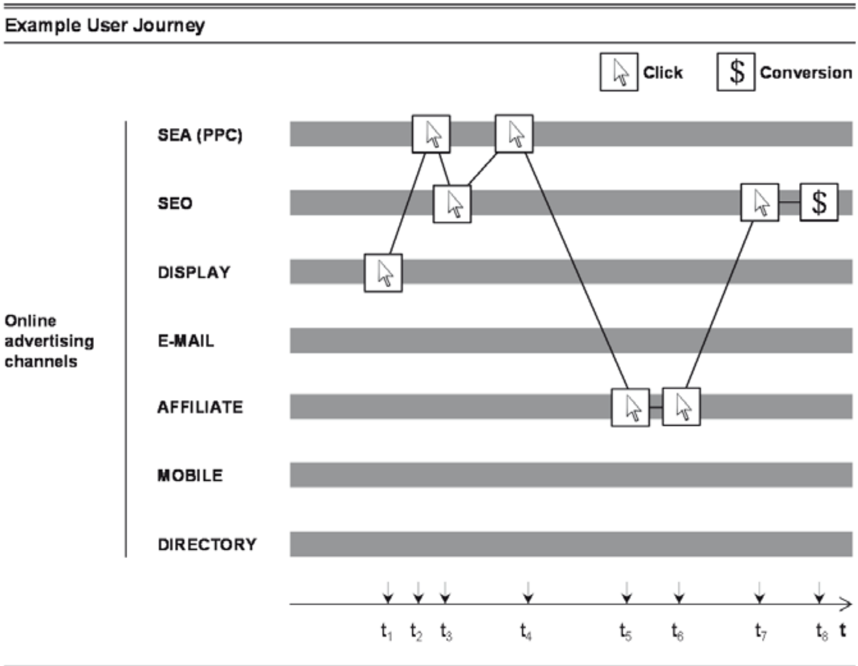


Figure 13: Example User Journey

2.5 Performance Evaluation and Key Performance Indicators

An advantage of having good-quality data on online advertising is that it provides a high level of transparency to advertisers. To evaluate the success of campaigns, firms usually employ different types of measures (Chaffey et al., 2009; Kaushik, 2007). Figure 14 shows the most relevant key performance indicators (KPIs) for online marketing campaigns, structured along the purchase decision-making process (cf. Hauser & Wernerfelt, 1990; Howard & Sheth, 1969; Roberts & Lattin, 1991), which Section 3.2.2.2 explains in more detail.

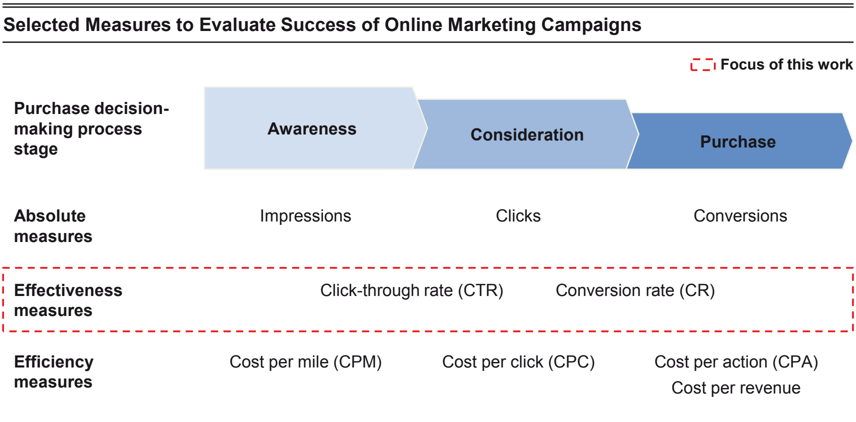


Figure 14: Selected Measures to Evaluate Success of Online Marketing Campaigns
Source: Based on Atlas Institute (2011), Chaffey et al. (2009), IAB Europe (2011), Kaushik (2007), Kotler et al. (2008), Li & Leckenby (2004), Robinson, Wysocka, & Hand (2007).

Essentially, three different types of metrics can be differentiated: (1) absolute measures representing input or output of online advertising, (2) relative indicators measuring the effectiveness of the campaign in transferring users from one stage in the purchase decision-making process to the next, and (3) efficiency measures connecting the absolute input/output measures with the incurred cost. The first group comprises ad impressions as input measures and clicks/conversions as output-related KPIs. Impressions are the number of times a user (or a target group) has been exposed to an ad (Kaushik, 2007). Clicks and conversions denote the total number of clicks on the firm's ad, respective conversions from the user or the target group (Kaushik, 2007). Conversions constitute various types of user actions that define the advertiser's campaign (e.g., orders, qualified leads, sign-ups). As absolute numbers, these metrics are useful to evaluate the overall success of an advertising campaign; however, they do not indicate anything about its effectiveness. For this purpose, advertisers use metrics such as CTR and conversion rate. The former is the ratio of clicks to impressions; it measures the user response to an ad and thus provides insight into how effective the ad is in attracting users' attention and awakening their interests for the advertiser (Li & Leckenby, 2004; Robinson et al., 2007). Similar to this, the conversion rate connects the actual transactions with the clicks (Kaushik, 2007) and thus determines the share of consumers who arrived on the landing page of an advertiser and closed the transaction at the end of their user journey. A major advantage of these two metrics is that they cancel out the variation in numbers in previous stages and thus help compare the effectiveness of campaigns with different numbers of impressions or clicks. These metrics are the focus of the current work, whose goal is to identify the drivers of ad effectiveness. More detailed specifics of these measures are discussed in the research model sections of the respective analysis (Sections 4.2, 5.2.2 and 5.3.2). Finally, the last group of metrics measures the efficiency of online advertising campaigns. In this context, cost per mile (CPM) denotes the cost of 1,000 ad impressions (IAB, 2011), CPC denotes the actual cost per click, and CPA is the cost per action (Kaushik, 2007). Especially in the context of e-retailing, cost per revenue is also a frequently used efficiency metric. It accounts for the revenue of a transaction (basket value) and measures how much it costs the advertiser to generate 1 dollar or euro of revenue (Atlas Institute, 2011). As all these metrics focus on different aspects of online advertising campaigns, practitioners usually employ a set of various KPIs to evaluate the success of their marketing efforts (Kaushik, 2007). This set is usually part of a dashboard or balanced scorecard (Kaushik, 2007).

3 Existing Research and Conceptual Foundations

This chapter comprises the theoretical foundation of the thesis. As the overarching theme of the dissertation is the effectiveness of online advertising, the chapter begins with a review of current knowledge in this field. Section 3.1 outlines existing research on online advertising and identifies the research gap addressed by the subsequent studies. Section 3.2 introduces core theories that form the conceptual basis of the work. Whereas advertising effectiveness theory (Section 3.2.1) is relevant for both studies, Sections 3.2.2 and 3.2.3 present existing theoretical work that is specific to each of the two projects. Figure 15 illustrates the structure of this chapter.

Structure of Chapter 3

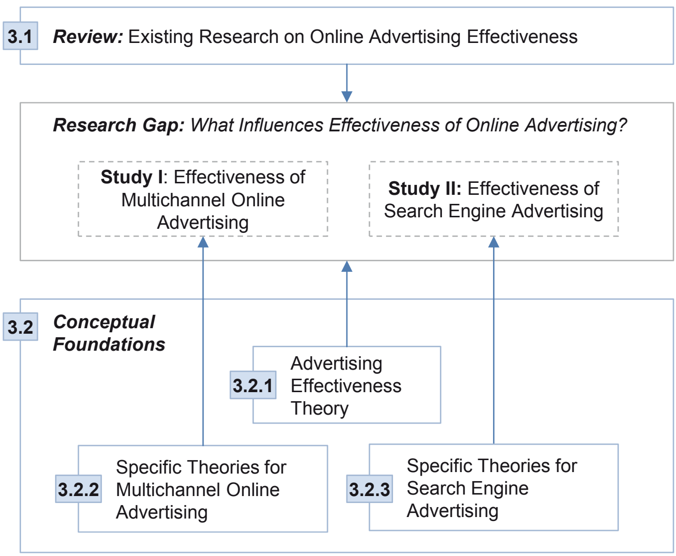


Figure 15: Structure of Chapter 3

3.1 Effectiveness of Online Advertising: What Do We Know?

Online advertising is a comparatively young research discipline that emerged with the advent of the Internet. However, researchers only became interested in the topic when firms increasingly began shifting their marketing budgets to these channels (see Section 2.2). Since then, research on online advertising emerged rapidly but still could not cope with the blustering proliferation of online advertising in practice (Ha, 2008). Thus, several gaps still remain. Ta-

S. Klapdor, *Effectiveness of Online Marketing Campaigns*,
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ble 1 shows a systematization of existing studies on online advertising effectiveness. It classifies previous work by channels and type of work (empirical versus theoretical). Furthermore, empirical research is differentiated by two criteria related to the data set. The author distinguishes whether the dependent variable represents attitudinal measures for advertising effectiveness (e.g., consideration, purchase intent) or behavioral measures (e.g., purchases, clicks). With regard to data granularity, the table shows whether a study uses aggregated data (e.g., sales by day) or individual-level data (e.g., advertising exposure and purchases for a specific consumer). The analysis shows that the majority of research focuses on single channels (e.g., display, affiliate, search). Only a small body of work has been conducted to understand how individual channels are related and affect one another in an integrated campaign.

Studies with **multiple channels** are discussed first. Many of these articles aim to prove the existence of synergies in multichannel advertising. For example, Chang and Thorson (2004) find that simultaneously advertising on TV and the Internet leads to a higher level of attention and increases positive thoughts about the advertiser. Naik and Peters (2009) prove with their integrated multimedia communications model the existence of synergies in several offline media (e.g., TV, print) as well as between offline and online media. Briggs, Krishnan, and Borin (2005) compare the effectiveness of several offline and online advertising channels during the campaign for the launch of a new car model and show that magazines and online advertising works best. Using behavioral data, Breuer et al. (2011) analyze the short- and long-term impact of different online advertising channels (display, affiliate, newsletter) on online sales. However, they use aggregated data, which might be why they do not find any interdependencies between single channels (Breuer et al., 2011). Also using aggregated data, Brettel and Spilker-Attig (2010) investigate country-specific differences of online advertising. They find that culture significantly moderates the advertising effectiveness of individual channels. From descriptive analyses, Abraham (2008) claims that simultaneously advertising on search and display channels can increase offline sales more than only focusing on one of these channels. To the best of the author's knowledge, no study so far has analyzed the impact of multichannel online advertising on purchase behavior based on individual-level data. Therefore, Study I fills this gap by developing a logit choice model on the consumer level to analyze how simultaneously advertising on multiple digital channels affects conversion rates in an online shop. The model also accounts for potential synergies from a varying sequence of individual channels.

As mentioned previously, significantly more research focusing on the effectiveness of individual channels has been conducted. With regard to **display advertising**, Drèze and Hussherr (2003) and Hollis (2005) find that exposure to banner ads can positively affect attitudinal measures, such as brand awareness and consideration. Cho (1999), Karson and Korgaonkar (2001), and SanJosé-Cabezudo, Gutiérrez-Arranz, and Gutiérrez-Cillán (2009) investigate the underlying mental processes of (early forms of) display advertising and find that the elaboration likelihood model (ELM) can be used in an Internet context. However, they also propose some extensions and modifications to the concept to better reflect the interactive nature of the Internet with its highly involved users. In doing so, Cho (1999, p. 38) introduces the concept of "voluntary exposure", or the exposure that happens on a landing page after users click on a banner. Motivated by the continuous decline of CTRs in banner advertising, Cho and Cheon (2004) develop a theoretical model to explain advertising avoidance on the Internet. They find a mismatch between the user's information need and the advertiser's information offer (goal impediment) as the main driver of ad avoidance (see also Section 3.2.1.3). The results from Goldfarb and Tucker's (2011a) study support this finding. They show that display ads work better if they match the content of the website on which they are presented (contextual targeting). However, they also find that banners that are both targeted and obtrusive do not have this positive effect, which they explain through privacy concerns. Using behavioral data, Sherman and Deighton (2001) and Ilfeld and Winer (2002) show that banner ads can increase website traffic. Moreover, Manchanda, Dubé, Goh, and Chintagunta (2006) find that display advertising positively influences purchasing behavior. Finally, Lambrecht and Tucker (2011) examine the effectiveness of retargeted display ads. Their analysis shows that retargeting only outperforms regular display advertising if consumers have well-defined product preferences.

Chittenden and Rettie (2003) investigate the effectiveness of **e-mail marketing**. By analyzing a set of previous e-mail campaigns in a qualitative research approach, they identify several factors that influence response rates (e.g., message title, length). In an experiment with students, DuFrene, Engelland, Lehman, and Pearson (2005) find that attitudes can be significantly improved through opt-in e-mail campaigns. Morimoto and Chang (2006) show that unsolicited (or spam) e-mails have the opposite effect: they are perceived as more irritating than unsolicited postal mails. Consequently, this form of e-mail marketing adversely affects consumer attitudes toward the sender.

With regard to **affiliate marketing**, Baye, Gatti, Kattuman, and Morgan (2009) conduct an analysis to identify the determinants of clicks on price comparison websites. They find that product price is the main traffic driver. However, their analysis reveals significant discontinuities, in which a small relative change in product price can lead to large changes in website traffic. Duffy (2005) analyzes the role of affiliate marketing on e-commerce websites and concludes that this form of online advertising will become a principal marketing instrument for online shops in the future.

From all online advertising channels, the largest body of research focuses on **SEA**. Much extant theoretical work from the economics community exists on the design of paid search auction mechanisms (e.g., Aggarwal, Feldman, & Muthukrishnan, 2006; Börgers, Cox, Pesendorfer, & Petricek, 2007; Edelman, Ostrovsky, & Schwarz, 2007; Feng, Bhargava, & Pennock, 2007; Varian, 2007; Xu, Chen, & Whinston, 2009). Some studies also integrate consumer decisions or advertiser competition into their models to evaluate market dynamics of paid search auctions (Animesh, Ramachandran, & Viswanathan, 2010; Athey & Ellison, 2011; Chen & He, 2006; Edelman & Ostrovsky, 2007; Ghose & Yang, 2009; Katona & Sarvary, 2010). In addition to this research from the perspective of search engines, a significant amount of work has focused on the three main advertiser activities, which, according to Rutz and Bucklin (2007), comprise the following tasks: (1) selection of relevant keywords and appropriate matching options for each keyword (parameter that defines exactly how a user query must coincide with a keyword to trigger the impression of the ad text), (2) creation of ad texts, and (3) definition and adjustment of bids. With regard to bids, Goldfarb and Tucker (2011b) show in an empirical analysis that advertisers are willing to place higher bids in the absence of offline targeting vehicles. Together with theoretical studies from Borgs, Chayes, Immorlica, Jain, Etesami, and Mahdian (2007) and Dar, Mansour, Mirrokni, Muthukrishnan, and Nadav (2009), Kitts and Leblanc (2004) examine optimal bidding strategies from an advertiser's perspective. Apart from bids, content and position of the ad texts are also determinants of campaign effectiveness. Animesh et al. (2011) show in an empirical analysis that an advertiser's unique selling proposition, as reflected by the ad text, influences the CTR. Rutz and Trusov (2011) develop a framework to describe textual properties of paid search ad texts and estimate their influence on CTR and conversion rate. They find that including the keyword or a call to action (e.g., "Click here to buy") in the headline of the ad significantly increases CTR whereas the length of an ad has a negative effect on CTRs. Jerath, Ma, Park, and Srinivasan (2011) study the extent to which clicks depend on ad position and perceived advertiser quality, whereas Agarwal, Hosanagar, and Smith (2011) analyze the profitability of display positions and find that higher positions do not necessarily yield higher revenues or profits. Significantly less research is available on the selection of keywords and matching options. Ghose and Yang (2010) analyze cross-categorical spillover effects of paid search advertising that seem to be stronger on retailer-specific keywords. Rutz and Bucklin (2011) follow a similar approach with generic and branded keywords. They find that the former can induce a spillover effect on consecutive branded searches. In a separate study, Rutz and Bucklin (2007) build a hierarchical Bayes model to predict a keyword's conversion rate in the absence of historical data. They use few keyword characteristics as covariates (length, location, and advertiser-/brand-specific information) that Study II subsequently picks up in the base model. In another paper, Rutz, Trusov, and Bucklin (2011) try to identify keywords that later lead to direct type-in visits. Therefore, they create keyword clusters in a semi-automatic approach, similar to several prior studies from information retrieval (IR) research (e.g., Carrasco, Fain, Lang, & Zhukov, 2003; Regelson & Fain, 2006; Wen, Nie, & Zhang, 2002). Finally, some empirical work has examined the interdependencies between paid listings and organic search results. Jansen and Resnick (2006) find in an experimental setting that consumers seem to prefer natural search results more often. Analyzing the relationship between organic and paid listings, Yang and Ghose (2011) show that there are positive interdependencies that can lead to higher advertiser profits if the seller appears in both result lists.

Apart from these basic keyword characteristics, no published study in marketing has analyzed the influence of keyword criteria on click-through performance. However, such criteria might be helpful to select and evaluate keywords for paid search campaigns (Ghose & Yang, 2009; Richardson, Dominowska, & Ragno, 2007). Furthermore, and to the best of the author's knowledge, no published marketing research has explicitly considered or modeled the effect of matching options on keyword effectiveness. Study II addresses this research gap by developing a model that estimates the impact of keyword criteria on CTRs. The model also accounts for the moderating effect of matching options.

The systematic review shows that there is a growing body of research on the effectiveness of online advertising. However, existing work often focuses on (1) analyzing selective phenomena (e.g., country-specific differences in online advertising effectiveness, effectiveness of retargeting campaigns) or (2) applying advanced statistical methods (e.g., in the SEA studies from Ghose & Yang [2009, 2010], Rutz & Bucklin [2011], and Rutz et al. [2011]). So far, no published work has presented comprehensive theoretical models to explain the observed effects. This thesis intends to fill this gap. Both studies therefore first develop models that are then used to explain the effectiveness of multichannel online advertising (Study I) and SEA (Study II).

Validating these models is only possible because of the highly granular data used in this thesis. Study I is based on a behavioral data set at the consumer level and is extracted from user journeys of an online shop. Study II also analyzes behavioral data. In addition to the keyword-aggregation level, which previous studies have also examined, the current data set features data on matching options. This is unique, because these types of data can only be generated when a specific campaign strategy is executed (keywords booked on all three matching options at the same time). To the best of the author's knowledge, no other published study is based on comparable data.

Existing Research on Online Advertising Effectiveness

		Data		
Channel(s)	*Type*	*Dep. var.*	*Granularity*	*Existing work*
Multiple	Empirical	Attitudinal	Individual consumer	(Y. Chang & Thorson, 2004) (Briggs et al., 2005) (Naik & Peters, 2009)
		Behavioral	Aggregated	(Abraham, 2008) (Brettel & Spilker-Attig, 2010) (Breuer et al., 2011)
			Individual consumer	**This Thesis (Study I)**
Display	Empirical	Attitudinal	Individual consumer	(Cho, 1999) (Cho & Cheon, 2004) (Drèze & Hussherr, 2003) (Goldfarb & Tucker, 2011a) (Hollis, 2005) (Karson & Korgaonkar, 2001) (SanJosé-Cabezudo et al., 2009)
		Behavioral	Individual consumer	(Ilfeld & Winer, 2002) (Lambrecht & Tucker, 2011) (Manchanda et al., 2006) (Sherman & Deighton, 2001)
E-mail	Empirical	Attitudinal	Individual consumer	(Chittenden & Rettie, 2003) (DuFrene et al., 2005) (Morimoto & Chang, 2006)
Affiliate	Empirical	Behavioral	Aggregated	(Baye et al., 2009) (Duffy, 2005)
SEA	Theoretical	-	-	(Aggarwal et al., 2006) (Animesh et al., 2010) (Athey & Ellison, 2011) (Börgers et al., 2007) (Borgs et al., 2007) (Y. Chen & He, 2006) (Dar et al., 2009) (B. Edelman & Ostrovsky, 2007) (B. Edelman et al., 2007) (Feng et al., 2007) (Katona & Sarvary, 2010) (Kitts & Leblanc, 2004) (Varian, 2007) (L. Xu et al., 2009)
	Empirical	Behavioral	Individual keyword	(A. Agarwal et al., 2011) (Animesh et al., 2011) (Ghose & Yang, 2009) (Ghose & Yang, 2010) (Goldfarb & Tucker, 2011b) (Jansen & Resnick, 2006) (Jerath et al., 2011) (Rutz & Bucklin, 2011) (Rutz & Bucklin, 2007) (Rutz & Trusov, 2011) (Rutz et al., 2011) (Yang & Ghose, 2011)
			Individual keyword + matchtype	**This Thesis (Study II)**

Note. *Dep. var.* = dependent variable; *Attitudinal* = stated beliefs from consumers (e.g., awareness, consideration, purchase intent); *Behavioral* = actual observed consumer behavior (e.g., clicks, purchases); *Aggregated* = high-level data representing multiple individual observations (e.g., impressions by day, sales by day); *Individual consumer* = data on the consumer level (i.e., exposures and sales can be linked to individual consumers); *Individual keyword* = data on the keyword level, (i.e., exposures and clicks can be linked to individual keywords); *Individual keyword + matchtype* = data on the keyword-matchtype level (three observations per keyword)—that is, exposures and clicks can be linked to individual keyword-matchtype combinations

Table 1: Existing Research on Online Advertising Effectiveness

3.2 Conceptual Foundations

This section provides the conceptual basis of this thesis. It begins with a review of advertising effectiveness research. Section 3.2.1 thus introduces two models of advertising effectiveness from "traditional" offline channels before outlining research on advertising avoidance. Both studies in this thesis transfer key concepts from this section to the online context. Afterward, Sections 3.2.2 and 3.2.3 introduce further theories used in one of the thesis's research projects.

3.2.1 Advertising Effectiveness Theory

For more than 100 years, research has investigated the effectiveness of advertising (Vakratsas & Ambler, 1999). Many studies have developed and empirically tested theories that constitute the basis of two major classes of advertising effectiveness models. One class is called **market response** or **stimulus–response** models (e.g., Bass & Clarke, 1972; Deighton et al., 1994; Pedrick & Zufryden, 1991; Tellis, 1988). Such models establish a direct relationship between advertising input (stimulus) and consumer reaction in terms of behavioral change (response). An advantage of these econometric models is that they use objective data—for example, advertising exposure on the one hand and purchase decisions on the other hand—that are not biased through intermediary effects (Vakratsas & Ambler, 1999). At the same time, this is also the weakness of such approaches. These models do not explain why advertising leads to a change in behavior and assume that it works similarly for all consumers. This deficiency is addressed by **stimulus–organism–response** models, which assume that advertising exposure influences intermediary mental effects, including rational thinking (cognition), emotional thinking (affect), and experience. This in turn results in a change in behavior (Kotler et al., 2008). The most common subset of these models postulates a given sequence of intermediary effects and is known as persuasive hierarchy models. Prominent examples from this class are the hierarchy-of-effects model (Lavidge & Steiner, 1961), the innovation-adoption model (Rogers, 2003), and the ELM (Petty & Cacioppo, 1986). All of these hypothesize that the cognitive stage is followed by the affective stage, which in turn is succeeded by the behavioral stage. This reflects the appealing idea that advertising must first inform and then convince to trigger a purchase decision.

Because transactional data are used in this thesis and intermediary effects cannot be observed, both studies are based on market response models. This approach is in line with previous research published in reputable outlets, in both online (e.g., Ghose & Yang, 2009; Rutz & Trusov, 2011; Rutz et al., 2011; Yang & Ghose, 2011) and offline (e.g., Deighton et al., 1994; Mela, Gupta, & Lehmann, 1997; Pedrick & Zufryden, 1991; Tellis, 1988) settings. In particular, elements from Deighton et al's (1994) comprehensive individual-level offline model are borrowed to model the basic effects of advertising effectiveness. However, to explain the new and more complex hypotheses, elements from persuasive hierarchy models—in particular the ELM—are employed. The following sections introduce these two fundamental models, followed by a brief overview on advertising avoidance research.

3.2.1.1 Model for the Effects of Advertising on Brand Switching and Repeat Purchasing

Deighton et al. (1994) develop one of the most comprehensive market response models to measure the effect of advertising on (repeat) purchasing. Their dependent variable is binary and denotes whether a specific consumer has (re)purchased the product or not. The model constitutes an important foundation of this thesis for three reasons. First, it examines the effect of advertising at the individual rather than aggregated level, which is necessary to explain how advertising works for individual consumers. Second, unlike other studies, Deighton et al.'s study analyzes how ad effectiveness differs between new and existing customers, a question Study I also intends to answer. Third and also related to Study I, the model incorporates a temporal dimension by differentiating between present and past advertising and purchasing. This makes it an ideal base for studying user journeys, which reflect advertising exposures and purchasing behavior of individual consumers over time. Apart from these three specific advantages, individual-level market response models are relatively similar to one another, with regard to both explanatory and explained variables and their methodological approach (e.g., Deighton et al., 1994; Mela, Gupta, & Lehmann, 1997; Pedrick & Zufryden, 1991; Tellis, 1988).

Figure 16 shows Deighton et al.'s (1994) framework. It consists of three major classes of influence on brand choice: exposure to advertising, previous purchase, and the interactions between these variables. Next, each class is briefly explained.

Model of the Effects of Advertising on Brand Switching and Repeat Purchasing

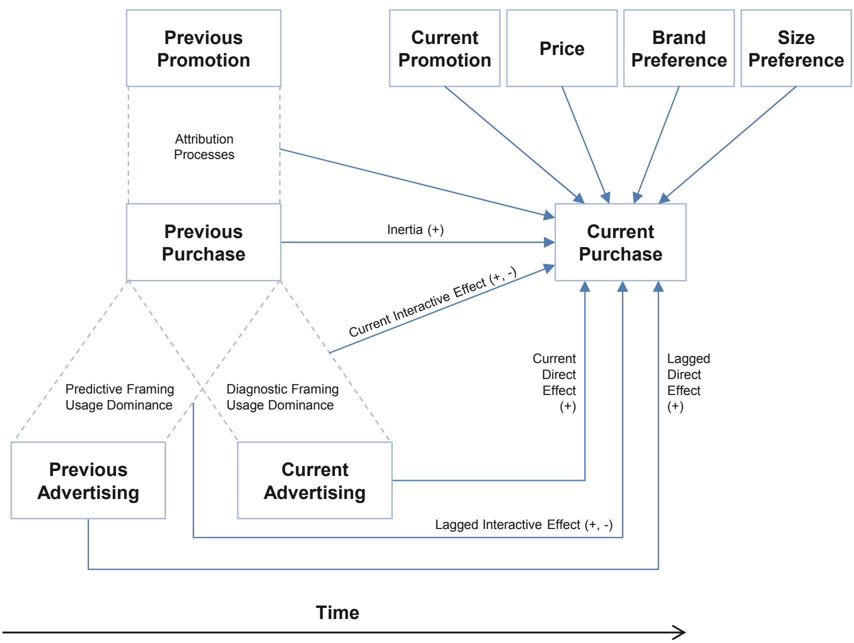


Figure 16: Model of the Effectiveness of Advertising on Brand Switching and Repeat Purchasing
Source: Deighton et al. (1994, p. 30).

Advertising Exposure. The framework accounts for the effect of advertising exposures on purchase probabilities. It differentiates into current (since the last purchase) and previous (before the last purchase) advertising to reflect short- and long-term effects of advertising (e.g., Lodish, Abraham, Livelsberger, et al. 1995; Naik & Raman 2003; Sethuraman, Tellis, & Briesch 2011; Vakratsas & Ma 2005). Deighton et al. (1994) show that both effects are positive in their model and explain this through the aforementioned persuasive hierarchy theories (e.g., hierarchy of effects, Lavidge & Steiner, 1961; innovation adoption, Rogers, 2003). However, they also show, as do other studies, that the positive effect on ad exposure diminishes with an increasing number of exposures—that is, it can be advantageous for advertisers to focus on reach, after a certain amount of exposures per individual has been achieved (e.g., Deighton et al., 1994; Tellis, 1988).

Previous Purchase. Previous purchase is the second main predictor for purchasing probability. Deighton et al. (1994) verify that consumers who already purchased the brand before show a significantly higher likelihood for repeat purchasing. This effect is also called "dynamic brand loyalty" and can be explained through inertia in consumer behavior inducing a tendency to repurchase. In contrast, more long-term and fundamental beliefs and attitudes toward a brand are reflected by the static component of brand loyalty (Lattin, 1987; Roberts & Lattin, 1991). Deighton et al. (1994) capture this effect with a separate control variable ("brand preference").

Interactions of Advertising with Previous Purchase. The model examines two interaction effects between previous purchase and advertising exposure: framing and usage dominance. These effects are opposite in direction, and according to Hoch and Ha (1986), the category of the advertised product determines which effect dominates. Framing implies that advertising can increase the probability of (re)purchase by influencing how a customer experiences a product. According to Deighton et al. (1994), the idea behind framing is based on Ehrenberg's (1974) view that advertising is more helpful for strengthening positive attitudes of existing customers than for attracting new ones. Deighton et al.'s (1994, p. 30) cognitive explanation for the framing effect is that "after the experience the advertising could suggest to the consumer how to make sense of that he or she had just experienced, resolving ambiguities and influencing what is retained in memory". The famous American art director George Lois notes this effect in a nutshell, claiming that "As a result of great advertising, food tastes better, clothes feel snugger, cars ride smoother. … It can change your perception of something" (Suplee 1987). Framing can occur before ("predictive framing") or after ("diagnostic framing") the brand usage experience (Deighton et al., 1994). Evidence for framing effects can be found in both experimental (e.g., Deighton, 1984; Ha & Hoch, 1989) and field (e.g., Hoch & Ha, 1986; Tellis, 1988) studies. Contrary to framing, usage dominance theory predicts little or no influence from advertising after a purchase because customers tend to rely more on their own experiences than on external information. Deighton et al. (1994) develop this theory on the basis of Alba, Hutchinson, and Lynch's (1991) finding that consumers prefer information that is easily accessible and promises to be useful in their decision-making process. According to Fazio and Zanna (1978), this seems to be the case more for own experience than for information from a third party. Empirical evidence for usage dominance, especially in mature, low-price categories, was found by Deighton et al. (1994), Hoch and Ha (1986), and Winter (1973). In addition to these three main classes of influence, the model contains several control variables to avoid under-specification (promotion effects, static brand preference, size preference, and product price).

3.2.1.2 Elaboration Likelihood Model

Unlike Deighton et al.'s (1994) market response model, Petty and Cacioppo's (1986) ELM is a persuasive hierarchy model, because it explains behavioral change from advertising through a sequence of cognitive and affective intermediary effects (Vakratsas & Ambler, 1999). The model originates from social science research and can be used to study the effectiveness of persuasive communication in a broad context (e.g., psychotherapy, counseling) (Cacioppo, Petty, & Stoltenberg, 1985; Petty, Cacioppo, & Heesacker, 1984) as well as in mass media advertising (Petty & Cacioppo, 1983; Petty, Cacioppo, & Schumann, 1984; Vakratsas & Ambler, 1999). It contributes to the theoretical basis of this work because of three major reasons: First, it is one of the most comprehensive persuasive models, integrating multiple (and partly contradictory) research findings into a consistent "conceptual umbrella" (Petty & Cacioppo, 1986, p. 125). Second, it has received considerable support from subsequent research, mainly because of its multipath approach, which assumes that "different people respond to different advertisements in different ways, depending on their involvement" (Vakratsas & Ambler, 1999, p. 33). Third, the multipath approach provides a good theoretical basis to explain the effects of multichannel advertising (e.g., Chang & Thorson, 2004), which Study I investigates. In addition, several studies have already used the ELM to explain the effectiveness of individual advertising channels in an Internet context (e.g., Cho, 1999; Karson & Korgaonkar, 2001; SanJosé-Cabezudo et al., 2009).

The core idea of the ELM (Figure 17) is that there are two fundamental paths for consumer reaction to persuasive communication: a central and a peripheral route to persuasion (Petty & Cacioppo, 1986). The **central route** comprises attitude formation through a careful scrutiny of the message. Here, a person cognitively processes the message arguments and forms his or her own thoughts. If positive reflections prevail, the person is likely to change his or her attitude in favor of the information presented. If negative thoughts predominate, there is a high likelihood of a negative attitude formation. In both cases, the attitude changes through the central route lead to a pervasive and enduring form of persuasion that is unlikely to change again (Cacioppo et al., 1985; Petty & Cacioppo, 1986, 1996). However, when a person evaluates the message with mere inference from peripheral clues without scrutinizing its actual content, the message is processed through a **peripheral route**. Research has identified several types of such clues, including the number of arguments in a message (Petty & Cacioppo, 1984), the perceived expertise of the message source (Petty, Cacioppo, & Goldman, 1981), and the use of celebrity endorsers for communicating the message (Petty, Cacioppo, & Schumann, 1983). If the clues induce a positive or negative affect, the attitude is formed through the peripheral route. However, this attitude formation is more susceptible, temporary, and unpredictive of behavior (Petty & Cacioppo, 1986).

Whether people form their attitudes through a central or peripheral route greatly depends on individual characteristics—namely, their motivation and ability to process the communication message. If a person is motivated and possesses the cognitive ability to elaborate on the message content, the central route is followed. When the person lacks the motivation or the capability for processing (or both), the attitude is formed through the peripheral route. The capability for message processing is mainly determined by the degree of distraction, message repetition, comprehensibility, and prior knowledge. According to Petty and Cacioppo (1986), factors influencing the motivation are personal relevance, need for cognition (willingness to structure and cognitively process information), and personal responsibility (degree of accountability a person feels for a cognitive task). Furthermore, studies have shown that motivation for message processing also increases with the number of different message sources (e.g., Chang & Thorson, 2004; Edell & Keller, 1999; Harkins & Petty, 1987). Study I builds on this finding to explain the effectiveness of online multichannel advertising.

Critics of persuasive hierarchy models—including the ELM—point out that correlations between the intermediary affective stage and behavioral outcomes are usually low (e.g., Palda, 1966; Ray, 1973). Some studies show that they are between 0 and 0.3 (Fazio, Zanna, & Cooper, 1978; Wicker, 1969). Vakratsas and Ambler (1999) suspect an inappropriate measurement of the affect dimension as a potential reason and conclude that the ELM, with its cognitive–affective–behavioral hierarchy and multipath approach, still provides an appealing and widely accepted framework for studying advertising effectiveness.

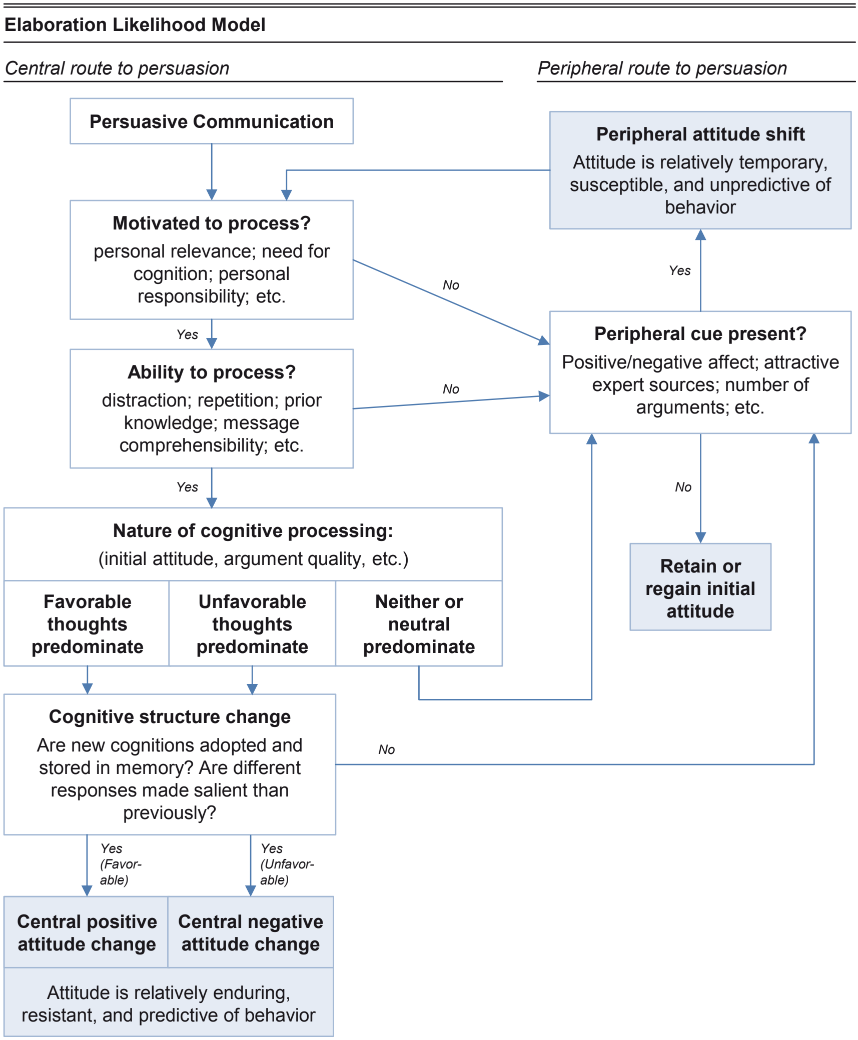


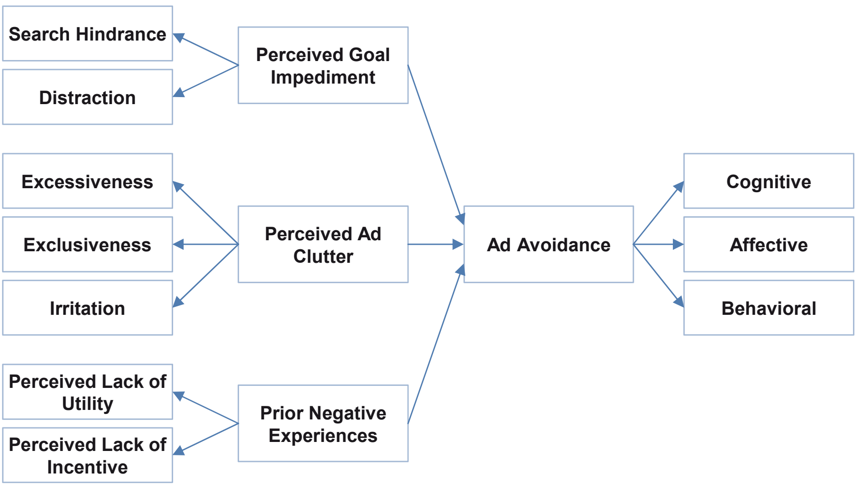
Figure 17: Elaboration Likelihood Model

Source: Petty & Cacioppo (1986).

3.2.1.3 Advertising Avoidance

The advertising effectiveness models introduced previously intend to explain how and why advertising works. However, these frameworks assume that advertiser communication is perceived by consumers who, at first, process it superficially. In the ELM, this refers to the initial check, that is, whether the recipient is motivated and able to scrutinize the message content. In this first stage, the person evaluates, among other things, the message relevance or its number of arguments (Petty & Cacioppo, 1986). However, when the person does not even notice an ad, regardless of whether this happens consciously or unconsciously, these first checks cannot be performed. Research on advertising avoidance attempts to identify the factors that make people ignore ads. Building on prior work from offline mass communications media, Cho and Cheon (2004) develop a model of advertising avoidance on the Internet (Figure 18). It constitutes the conceptual basis of Study II in this thesis.

Model of Ad Avoidance on the Internet



Notes. Only significant effects are shown.

Figure 18: Model of Ad Avoidance on the Internet
Source: Adapted from Cho & Cheon (2004).

Cho and Cheon (2004) explain ad avoidance through three latent variables: perceived goal impediment, perceived ad clutter, and prior negative experiences. **Perceived goal impediment** is the strongest predictor of advertising avoidance on the Internet. It occurs when ads hinder the users' efforts to browse the web or intrude on their search for information (Cho & Cheon, 2004). According to Li, Edwards, and Lee (2002), this often occurs on the Internet because consumers tend to use this medium in a goal-directed mode (cf. Section 3.2.2.1), and thus they perceive ads as more disturbing than on other channels. To reduce perceived goal impediment, the information presented in the ad should reflect the user's information need—that is, it needs to be relevant for the user. This can be achieved with targeting mechanisms (e.g., more specific keywords for sponsored search ads or behavioral targeting for display advertising). **Perceived ad clutter** is the second-strongest predictor of online ad avoidance. It is defined as a consumer's notion of excessive advertising on a medium (Elliott & Speck, 1998). Ad clutter can result in negative attitudes and, consequently, ad avoidance. As a result of the advertising-financed business models of many websites and online services (Pauwels & Weiss, 2008), preventing (or reducing) ad clutter is an eminent challenge in the online domain. Cho and Cheon (2004) identify **prior negative experiences** as the third root cause for ad avoidance. For information processing and decision making, consumers build on previously gained knowledge (Fazio & Zanna, 1981; Smith & Swinyard, 1982). When encountering negative experiences with Internet ads (e.g., in terms of dissatisfaction with the information provided or perceived lack of utility or incentive), they are inclined to avoid these ads in the future.

Cho and Cheon (2004) find that ad avoidance affects all three elements of Vakratsas and Ambler's (1999) framework for consumer response to advertising input: cognition, affect, and behavior. Depending on the manifestation of the three aforementioned variables, consumers may associate negative beliefs with Internet ads, intensely dislike them, and actively take actions to avoid viewing ads, for example, by scrolling down (Cho & Cheon, 2004).

These findings—in particular the concept of perceived goal impediment—are used to formulate the theoretical model for the effectiveness of search engine advertising (Study II). Here, a mismatch between the user's search query and the displayed ad is interpreted as a form of goal impediment, which eventually results in an inferior user response to the ad.

3.2.2 Specific Conceptual Foundations for Study I

In this section, two research fields that contribute to the theoretical fundament of Study I (multichannel online advertising) are introduced: research from the IR community on user intention on the Internet and purchase decision-making theory. This well reflects the interdisciplinary nature of online advertising, which lies at the intersection between marketing and computer and information sciences.

3.2.2.1 User Intention on the Internet

In contrast with other media channels, consumers often use the Internet in a goal-directed mode (Cho & Cheon, 2004; Li et al., 2002). Trying to understand this goal, with the help of available information from the users (e.g., their search queries), has been a major objective of IR research in the past years (Jansen, Booth, & Spink, 2008; Rose & Levinson, 2004). The task is to construct information systems in such way that they can better respond to users and provide an "experience tailored towards [their] goal[s]" (Rose & Levinson, 2004, p. 13). Study I of this thesis transfers insights from the IR community to multichannel online advertising. In detail, it uses Broder's (2002) framework to infer a user's goal from a web search query to link this goal to entire online advertising channels (e.g., search, affiliate). In other words, a user's goal is deduced from the channels he or she uses. This information can be exploited to optimize budget allocation and ad scheduling across multiple online ad channels.

With the aim to understand the underlying goal of search, Broder (2002) proposes a taxonomy to classify web search queries into navigational, informational, and transactional queries. Building on his work, several other researchers have refined this concept and developed algorithms to operationalize it (Jansen et al., 2008; Kellar, Watters, & Shepherd, 2007; Rose & Levinson, 2004). The result—a differentiated classification of web searches by user intent—is depicted in Figure 19.

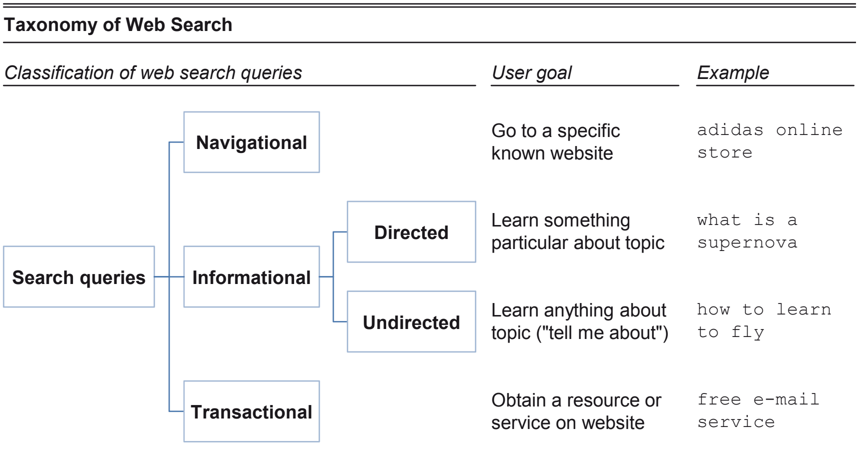


Figure 19: Taxonomy of Web Search
Source: Based on Broder (2002), Rose & Levinson (2004).

The purpose of **navigational queries** is to reach a specific website users already have in mind, because they visited it before or assume that it exists. The only reason users employ a search engine is if they do not know the target website URL or if searching is simply more convenient than typing the URL into the browser (Broder, 2002; Rose & Levinson, 2004). Examples for navigational searches are "adidas online store" or "alberto's pizza munich reservation". Most navigational queries contain the name of the firm, institution, or other target to which users intend to navigate (Rose & Levinson, 2004). In practice, this is often referred to as search on brand keywords (Boser, 2011). The underlying user goal of a navigational query is usually precise, and only one "correct" result exists (i.e., the Adidas online store or Alberto Pizza's website).

However, **informational queries** can be fuzzier. Here, users want to learn more about a specific topic and assume that corresponding information is available somewhere on the web (Broder, 2002). Several studies further differentiate informational searches into a relatively directed fact-finding and a more exploratory and undirected information gathering (e.g., Kellar et al., 2007; Navarro-Prieto, Scaife, & Rogers, 1999; Sellen, Murphy, & Shaw, 2002). Examples of directed informational queries are “what is a supernova” or “munich amateur soccer clubs”. Examples of undirected informational queries are “muse band” and “how to learn to fly”. The preciseness of the results varies with the underlying informational need. It can range from precise (i.e., the definition of a supernova) to vague (i.e., diverse information about the band Muse) (Jansen et al., 2008).

Transactional queries are formulated by users who want to reach websites on which further interaction will occur. Rose and Levinson (2004) specify four types of underlying user goals: download, entertainment, interaction, or obtainment. This encompasses a broad range of target websites—for example, online shops, webmail portals, video hosting services (e.g., youtube.com), browser games, or databases (e.g., yellowpages.com). The corresponding queries usually contain the type of interaction, for example, “download mp3” or “free e-mail service”.

Analyses of query logs show that the largest part of queries is of an informational nature (50%–90%), and the remaining share is usually split into navigational and transactional queries (Broder, 2002; Jansen et al., 2008). Although the concept of this approach is appealing and Broder (2002) empirically validates the taxonomy, some limitations exist. Perhaps the most evident one is that users can have multiple goals at the same time; however, each query can only be assigned to one class. As a remedy, Jansen et al. (2008) encourage the development of approaches that allow classification of user queries into multiple categories. At the same time, they point out that the problem is limited because approximately 75% of all queries can be safely assigned to a single category.

3.2.2.2 Purchase Decision-Making Theory

Study I analyzes the influence of multichannel online advertising on conversion rates in online shops. To explain the effects of transitions between online advertising channels over time, the model builds on purchase decision-making theory, or more precisely the concept of consideration (or evoked) sets (e.g., Hauser & Wernerfelt, 1990; Howard & Sheth, 1969; Lavidge & Steiner, 1961; Roberts & Lattin, 1991; Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991). First described by Howard and Sheth (1969), this concept assumes that consumers follow a linear process, which runs through multiple stages, before finally making their purchase decision. Consumers begin with a more or less broad set of different alternatives of which they are aware. During each stage of the process, they refine this set by reducing the number of potential alternatives through careful evaluation until one brand remains, which is finally purchased. Howard and Sheth’s model comprises five stages (or sets): all brands, awareness, consideration, purchase, and repeat purchase (Figure 20).

Consideration Set Concept

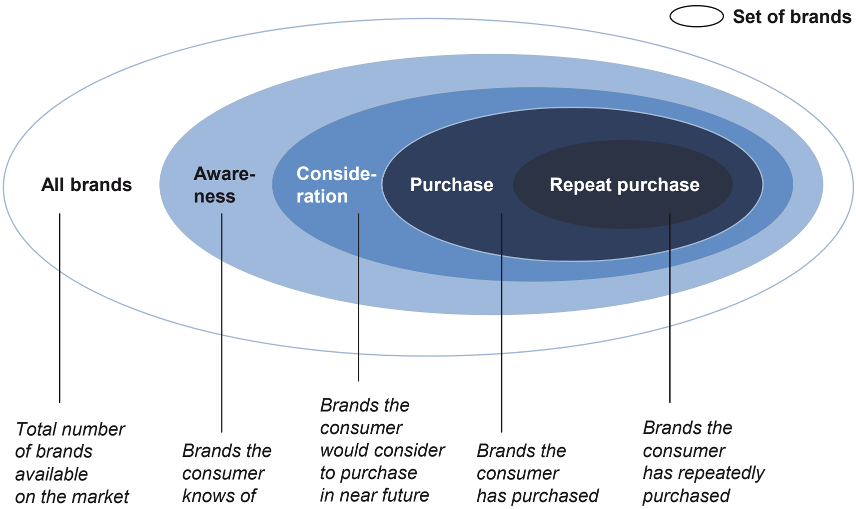


Figure 20: Consideration Set Concept
Source: Based on Howard & Sheth (1969).

All brands refer to the total number of brands available on the market. In theory, this is the largest set of potential choices. **Awareness** is the set of brands of which the consumer is aware. Depending on the consumer's level of knowledge, it can be a small or large fraction of the total number of brands. Brands that constitute a real purchasing option for the consumer (only those he or she would consider purchasing in the near future) belong to the **evoked or consideration** set. Usually, this is only a small fraction of the brands from the awareness set (Howard & Sheth, 1969; Roberts & Lattin, 1991). Finally, when the consumer becomes convinced that one of the considered brands satisfies his or her needs best, attitudes translate into behavior and **purchase** of this brand. If the brand proves satisfactory, the consumer may be inclined to consider it for **repeat purchase**, the final stage of Howard andSheth's (1969) framework.

To move brands from awareness to purchase, consumers "actively seek information from commercial and social environments" (Howard & Sheth, 1969, p. 468). They use this information for two tasks: to build a set of decision rules (i.e., what are the criteria to base the purchase decision on) and to evaluate the brands against these rules to create a ranking of brand alternatives. However, this process is not effortless. Hauser and Wernerfelt (1990) show that evaluating brands entails a certain cognitive cost for consumers. Therefore, consumers will only add further brands to their evoked sets if the expected benefit from the additional brand (resulting in a purchase decision with a higher expected utility) exceeds the perceived cognitive cost (Roberts & Lattin, 1991). Satisfied consumers, who repeatedly purchase a brand, can reduce this cost by establishing a routine decision process. In this case, an event triggering the purchasing process can directly result in a purchase, without the necessity to run through all the stages of the process (Howard & Sheth, 1969).

A major implication of the consideration set theory is that advertising needs to fulfill different roles along the process (Lavidge & Steiner, 1961). While it is important in the beginning to create awareness for a brand (and ensure it is included in the awareness set), communication messages at later stages should convince the user that the brand is suited best to fulfill his or her needs. It is helpful for advertisers to understand the consumer's decision rules because they can use this information to precisely stress the relevant brand benefits in their communication (Howard & Sheth, 1969; Roberts & Lattin, 1991).

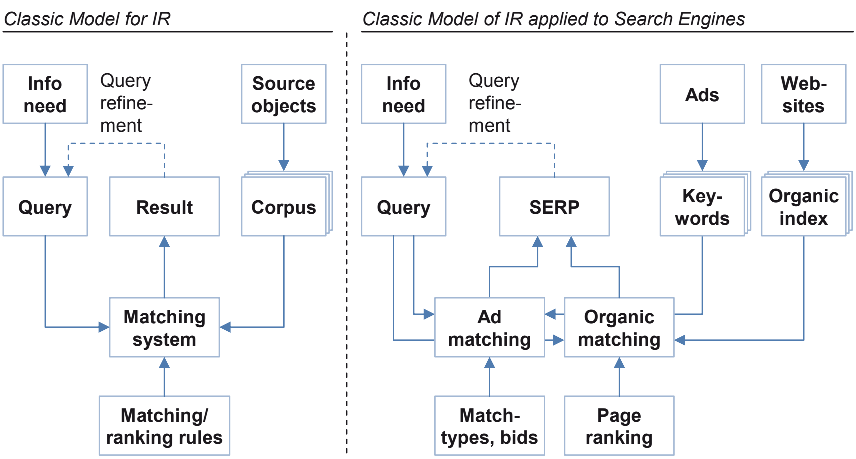
The original concept of consideration sets has been widely accepted. For example, Hauser and Wernerfelt (1990, p. 395) state that it is "real, important to practical applications, and consistent with prevailing views of how consumers process information". Several academics have built on or refined this framework. For example, Lavidge and Steiner (1961) propose seven instead of five different stages. However the basic principles of the framework remain the same. Hauser and Wernerfelt (1990) and Roberts and Lattin (1991) both analyze the trade-off between marginal cognitive cost and expected benefits during the composition of consideration sets. Practitioners also have picked up on the concept. Perhaps one of the most famous practitioner tools built around the concepts of consideration sets is the purchasing funnel. In contrast with Howard and Sheth's (1969) framework, the funnel includes an additional stage between awareness and consideration called "familiarity" (Court, Elzinga, Mulder, & Vetvik, 2009). The funnel is frequently used to measure and benchmark brand strengths on the different stages of the purchasing process. Despite its popularity, the concept of consideration sets has also received some criticism (Lambrecht & Tucker, 2011). For example Court et al. (2009) and Edelman (2010) argue that the underlying linear model does not truly reflect the complex and circular nature of many purchase processes. They therefore propose a model that includes "diversions and circuitous routes" (Lambrecht & Tucker, 2011, p. 6).

3.2.3 Specific Conceptual Foundation for Study II

As mentioned previously, online advertising is an interdisciplinary research area, mainly covered by marketing and information retrieval. This applies in particular to search engines, which are instantiations of IR systems. According to Frakes (1992, p. 6), such a system "matches user queries—formal statements of information needs—to documents stored in a database". This is why search engines have been covered extensively in IR research, which usually focuses on the perspective of search engine vendors. The main areas of interest to the IR community have been the analysis and modeling of user search behavior and classification of user queries (Hölscher & Strube, 2000; Lau & Horvitz, 1998; Muramatsu & Pratt, 2001; Navarro-Prieto et al., 1999; for query classification, see Section 3.2.2.1), the development and empirical evaluation of algorithms for retrieval (Bartz et al., 2006; Gupta et al., 2009; Jones et al., 2006; Radlinski, Broder, Ciccolo, Gabrilovich, Josifovski, & Riedel, 2008), and the selection of revenue-maximizing ads in paid search advertising (Hillard et al., 2010; Regelson & Fain, 2006; Richardson et al., 2007).

The theoretical model of Study II builds on existing research on the design of IR systems. Therefore, this section introduces the classic IR model and applies it to the context of search engines.

IR Models



Notes. IR = Information retrieval; SERP = Search engine result page.

Figure 21: IR Models
Source: Adapted from Broder (2002), Buckland & Plaunt (1994), van Rijsbergen (1979).

3.2.3.1 Classic Model for Information Retrieval

Figure 21 (left-hand side) shows the elements of a basic IR system as described by several IR researchers (e.g., Buckland & Plaunt, 1994; Frakes, 1992; van Rijsbergen, 1979). It begins with a user, who is driven by a goal that triggers an **information need**. The user translates this need into a user **query**, which serves as input to the system. Depending on the capability and nature of the IR system, the query may be submitted in natural language (Buckland & Plaunt, 1994). However, there are also systems that require a formal query, which already uses the internal representations of the source object. The representations can contain parts or all of the original **source objects** (e.g., documents, images, videos, recordings), which the system creates on the basis of representation making rules. Together with a searchable index, the internal representations constitute the **corpus** of an IR system (Broder, 2002). The **matching system** selects the document representations from the corpus, which coincide with the query. The matching system can be parameterized with **matching/ranking rules** that further specify what "matching" actually means for the system (e.g., textual match vs. conceptual match; Garcés, Olivas, & Romero, 2006). The system also includes rules for sorting the retrieved set of representations (Frakes, 1992). This is of particular importance, especially if the result list contains a large number of document representations. The user is then presented with the **result**, that is, the sorted list of retrieved document representations. If the result does not satisfy the user's information need, he or she can refine the query and resubmit it to the system (Broder, 2002).

3.2.3.2 Classic Model for Information Retrieval Applied to Search Engines

Figure 21 (right-hand side) shows the application of the classic IR model to search engines. It is mainly based on Broder's (2002) augmented IR model for the web. On the user side, there is virtually no difference from the classic model: in the context of web search, users also have goals that translate into **information needs**.[3] They verbalize this need in natural language—the **query—**and submit it to a search engine. However, as explained in Section 2.3, search engines provide two types of results: organic and paid (or sponsored) results. For each one, there is a separate retrieval system with its own corpora and matching systems. The focus of Broder's (2002) augmented model is on the organic part. Here, the queries are matched by the **organic matching** system to the **organic index**. It includes representations of websites. The representations in the index are generated by web crawlers (Kobayashi & Takeda, 2000), or small pieces of software that index the web autonomously. The organic matching system uses the **page ranking** to sort the result list by relevance. The proprietary ranking algorithms of search engines are well-protected secrets. However, it is known that the most important factor determining the relevance of websites is the number and quality of links from other websites pointing to that site (Page, Brin, Motwani, & Winograd, 1998). Finally, the ranked representations of the websites matching the user query are displayed on the **SERP**. Displayed alongside these organic results on the SERP are paid placements (see Figure 11). These sponsored search results are generated by a separate retrieval system. Here, the same user **query** is matched to **keywords** that constitute the corpus of this IR system. Keywords are manually selected by advertisers for a specific **ad**. Multiple keywords can be assigned to one ad; however, one keyword can only be ascribed to one ad (1:n relationship). **Match types and bids** represent the matching and sorting rules for the **ad matching** system. For each keyword, the

[3] As discussed in Section 3.2.2.1, the actual need of web users does not necessarily need to be of an informational nature. Users can also have navigational or transactional goals. However, this makes no difference for the concept presented here, because users also translate these goals into queries.

advertiser must choose one of three match types (also called matching options), which determine how precisely the query must match a keyword to trigger the ad (Google, 2010b; Gupta et al., 2009). For each keyword-matching option combination, advertisers specify a bid, which in turn determines the ranking position, in case several advertisers select the same keyword for their campaigns. In the case of unsatisfactory results, users also refine their queries in a web search context (Lau & Horvitz, 1998). This model significantly contributes to the conceptual basis of Study II, which is presented in Chapter 5.1.

4 Study I: Effectiveness of Multichannel Online Advertising

Chapter 2 shows that consumers increasingly use the Internet to purchase goods and services. To benefit from this growth, firms increasingly invest in digital advertising, and budgets have climbed steadily over the past several years. This rapid development has outpaced related research. The review of existing work on online advertising in Chapter 3.1 showed that a clear understanding of the effectiveness of multichannel online advertising is lacking. Multichannel online advertising occurs when a firm simultaneously uses multiple digital channels, such as display advertising on websites, e-mail, and SEM, to send advertising messages to consumers. This leaves the following questions unanswered, which are addressed by the first study of the thesis:

1. Can simultaneous advertising on multiple online channels increase purchase propensities when targeting individual users?
2. If so, is there a difference in the effects, depending on the sequence of the channels in the user journey of individual consumers?
3. Do these effects differ for existing versus new customers?

The study attempts to answer these questions by investigating the relationship between advertising exposure and purchasing behavior. It thus fills a gap; to the best of the author's knowledge, no comprehensive, theory-based model exists to explain how multichannel digital advertising affects online conversion rates. In the following sections, the study analyzes how consumers react to advertiser messages in different channels and particularly how conversion rates of individual users depend on (1) the number of online channels in their user journey, (2) the order of these channels in the journey, and (3) their past purchase behavior.

Section 4.1 presents the theoretical framework and hypotheses. Chapters 4.2 and 4.3 offer an overview of the model operationalization and the data set. After the results of the estimation (Section 4.4) and an additional robustness test (Section 4.5) are presented, Chapter 4.6 discusses the implications of the findings and concludes the study.

4.1 Model for the Effectiveness of Multichannel Online Advertising

Figure 22 displays the theoretical model of this study. In essence, it attempts to explain conversion behavior using two key predictors, which represent elements of a user journey[4]: the channel-related characteristics of advertising exposure (also called "multichannel effects") and "traditional" advertising variables (e.g., How often has the consumer been exposed to

[4] A user journey (or browsing journey) specifies on which channels and at what point in time an individual consumer is exposed to communication messages from the advertiser. It also includes information on whether the consumer has purchased something at the end of the journey (also see Section 2.4).

S. Klapdor, *Effectiveness of Online Marketing Campaigns,*
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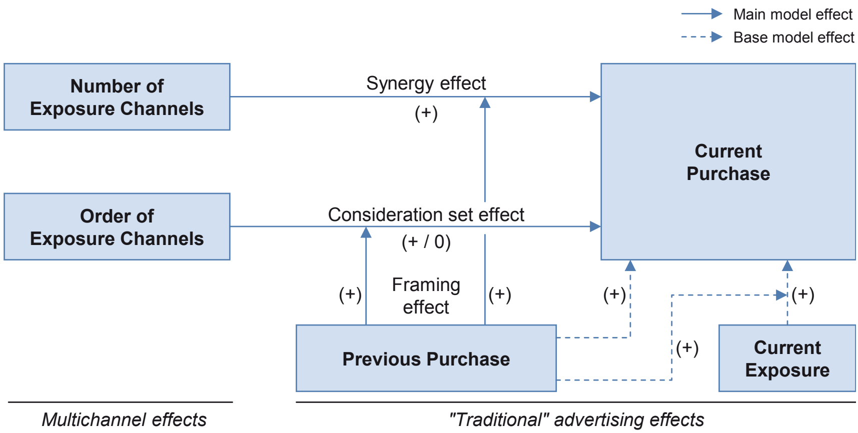
ads? Has the consumer purchased from the advertiser before?). Because consumer-related aspects have been extensively studied in offline advertising effectiveness research, they are included in the base model. According to Vakratsas and Ambler's (1999) taxonomy, the framework belongs to the class of market response models. Such theories assume a direct relationship between advertising measures and purchasing behavior.

Model for the Effectiveness of Multichannel Online Advertising



Notes. The plus and minus signs denote the direction of the hypothesized effects.

Figure 22: Model for the Effectiveness of Multichannel Online Advertising
Source: "Traditional" advertising effects are adapted from Deighton et al. (1994).

Before the main model is presented with hypotheses for multichannel effects, the base model is introduced, which includes traditional advertising variables. They are used as controls in the study.

4.1.1 Base Model

This part of the theoretical framework features three traditional advertising variables: (1) previous purchase, (2) current exposure to advertising, and (3) their interaction, as frequently used in relation to offline channels (e.g., Deighton et al., 1994; Pedrick & Zufryden, 1991; Tellis, 1988). Section 3.2.1 provides a comprehensive overview on advertising effectiveness research. Elements from this work, which are relevant for this study, are briefly recapped next.

4.1.1.1 Previous Purchase

As indicated in Section 3.2.1.1, marketing research postulates a close relationship between brand loyalty and purchasing behavior (e.g., Chintagunta, 1993; Jacoby & Kyner, 1973; Tellis, 1988). According to Lattin (1987) and Roberts and Lattin (1991), brand loyalty can be disaggregated into a static and a dynamic component. Whereas the former captures more long-term and fundamental beliefs and attitudes toward a brand, dynamic brand loyalty entails previous purchases. Deighton et al. (1994) assert that previous purchases strongly influence current purchases because consumer behavior is characterized by inertia. In their empirical study, they find strong evidence for this repurchase effect in offline retailing; the author of this thesis expects the relationship to hold in an online/e-commerce context as well.

4.1.1.2 Current Exposure to Advertising

Many empirical studies show that exposure to advertiser messages has positive short- and long-term effects on consumer purchasing behavior (e.g., Lodish, Abraham, Livelsberger, et al., 1995; Naik & Raman, 2003; Sethuraman et al., 2011; Vakratsas & Ma, 2005). This study focuses on short-term effects because it is based on cookie data. Cookies usually are limited to a period of approximately 30 days—too short to observe long-term effects (Assmus, Farley, & Lehmann, 1984; Clarke, 1976; Dekimpe & Hanssens, 1995). The effect of advertising exposures on purchase behavior might reflect persuasive hierarchy theories (Vakratsas & Ambler, 1999), such as the hierarchy of effects (Aaker & Day, 1974; Lavidge & Steiner, 1961) or innovation adoption (Rogers, 2003; see also Section 3.2.1). According to these models, the primary goal of advertising is to increase brand awareness and induce positive beliefs about the brand (Deighton et al., 1994). This outcome leads to certain intermediate effects (cognition, affect, experience), which eventually influence actual behavior, such as brand choice or repurchase. Several empirical studies verify this relationship and show that advertising response increases with the number of exposures (e.g., Jones, 2007; Pedrick & Zufryden, 1991; Tellis, 1988). In this application to an online context, the author posits that exposure to advertiser messages increases the probability of purchase.

4.1.1.3 Interaction of Previous Purchase with Exposure Intensity

As introduced in Section 3.2.1.1, Deighton et al. (1994) examine two interaction effects: diagnostic framing and usage dominance. These effects move in opposite directions—that is, diagnostic framing enhances the effect of advertising, and usage dominance diminishes it—and the product category determines which one dominates (Hoch & Ha, 1986). Both effects should emerge in an online context. The product category of the focal advertiser (fashion and apparel) is ambiguous and complex, however, so framing should outweigh usage dominance, resulting in a positive overall interaction. This prediction is in line with Hoch and Ha (1986), who use polo shirts as products from an ambiguous category in their experiments.

4.1.2 Main Model and Hypotheses

To investigate the influence of online multichannel communication on individual purchasing behavior, the author includes three characteristics in the model to describe advertiser communication in multiple channels: (1) number of channels involved in a user journey, (2) channel order in the journey, and (3) their interactions with previous purchase. The analysis includes six digital channels: SEO links (organic search); SEA links (paid search); links from e-mails (newsletter); links from affiliated websites, such as fashion blogs (affiliate); links established through sponsorship agreements from other websites, such as from beauty and fashion magazines (link); and display advertising on various websites (display). Except for mobile and classifieds, the study covers all major online advertising channels as introduced in Section 2.2. Table 2 provides specific examples of the channels in the context of this study.

Online Advertising Channels Used in Study I

Channel	*Description*	*Examples*
Affiliate	▪ Websites about fashion and related topics with links to the advertiser's site. ▪ Publishers are paid when users of their website purchase at the advertiser.	www.shefinds.com www.lesmads.de www.addictedtofashion.net
Link	▪ Websites about fashion and related topics with links to the advertiser's site (often run by newspapers and magazines). ▪ Publishers are paid according to sponsoring agreements.	www.vogue.de www.cosmopolitan.de www.vanityfair.de
Display	▪ Banner ads on third-party websites with links to the advertiser's site. ▪ Publishers are paid for impressions of the advertiser's banner.	www.gmx.net www.spiegel.de www.gala.de
Organic Search (SEO)	▪ Link to the advertiser's site from the organic section of search engine result pages, when users search for advertiser’s name. ▪ Clicks on link are not paid by the advertiser.	Bing Google Yahoo
Paid Search (SEA)	▪ Link to the advertiser's site from the sponsored section of search engine result pages, when users search for advertiser's name. ▪ Clicks on link are paid by the advertiser.	Bing Google Yahoo
Newsletter	▪ E-mails sent regularly from advertiser to users who proactively signed up to receive the newsletter. ▪ Links in e-mail bring users to product pages.	-

Table 2: Online Advertising Channels Used in Study I

4.1.2.1 Number of Channels

In an experimental study, Chang and Thorson (2004) find synergies between offline and online channels: unlike consumers who repeatedly viewed an advertiser message on a single channel, those exposed to messages on different channels reported greater attention, higher message credibility ratings, and more positive thoughts about the advertiser brand. In this context, synergy effects refer to the “effect resulting from exposure to coordinated advertisements" (Chang & Thorson, 2004, p. 75; see also Belch & Belch, 1998; Naik & Raman, 2003). Several studies demonstrate the synergetic effects of offline advertising campaigns through multiple channels; for example, Jagpal (1981) offers empirical evidence that simultaneous newspaper and radio ads for a commercial bank prompt sales synergies. In a series of subsequent studies, Harkins and Petty (1981a, 1981b, 1987) show that multiple message sources can lead to increased information-processing activity. By comparing ad sequences on a single channel with TV–print or print–TV sequences in a controlled laboratory experiment, Edell and Keller (1999) also reveal that mixed channel sequences increase brand and ad evaluative thoughts. Naik and Raman's (2003) model of integrated marketing communications suggests that advertising in one medium has two effects: eliciting direct sales and enhancing the effectiveness of other channels. They empirically validate their model for TV–print synergy.

On the basis of the ELM, which is introduced in Section 3.2.1.2, Chang and Thorson (2004) also offer a cognitive explanation for multichannel synergies. Specifically, messages from multiple sources seem more credible than single-source messages (Petty & Cacioppo, 1986, 1996; Zimbardo & Leippe, 1991). Such message credibility increases processing motivations (Petty & Cacioppo, 1986), which leads to more positive thoughts about the brand and increased purchase intentions (MacInnis & Jaworski, 1989; Petty & Cacioppo, 1986). This path of influence is called the "central route to persuasion". In contrast, repetitive single-source messages induce people to evaluate "peripheral cues, such as source credibility, to form brand attitude" (Chang & Thorson, 2004, p. 77), that is, take a peripheral route to persuasion. Chang and Thorson (2004) show that multisource messages tend to be processed through a central route and lead to a higher advertising response than repetitive single-source messages, which follow a peripheral route. The author hypothesizes that this relationship also holds in an online context, though this link has not been proved previously (Breuer et al., 2011).

> HYPOTHESIS 1 (H_1): Exposure to advertiser messages through multiple channels increases conversion probability.

4.1.2.2 Order of Channels

Section 3.2.2.1 presents research on web search behavior, which shows that users have different goals when using the Internet (for a meta-analysis, see Jansen et al., 2008). Broder (2002) groups web queries according to the primary intent of the user, with three classes: informational, navigational, and transactional (Figure 19). Several subsequent studies have empirically validated this taxonomy (e.g., Jansen et al., 2008; Kellar et al., 2007; Rose & Levinson, 2004). When consumers have different goals, it may indicate different stages of their purchase decision-making process, such that one consumer may be acquiring information about potential product alternatives, while another navigates to an online store to purchase a specific product. The author posits that consumers in different stages have different goals and thus can best be reached, on average, through different digital channels. If this prediction is true, information about the channel on which the user received the advertising message could be used to predict his or her individual conversion rate. If a user switches from one type of channel to another, that shift might indicate the move to another stage in the purchase decision-making process. To examine how the order of exposure to different channels influences purchase probabilities, the author therefore designates online channels according to their primary use by consumers, as information or navigation channels. The latter are also used for transactional user goals, because transactional and navigational goals are closely related in the context of online retailing. The author employs Broder's (2002) logic to classify entire online channels, as Figure 23 depicts.

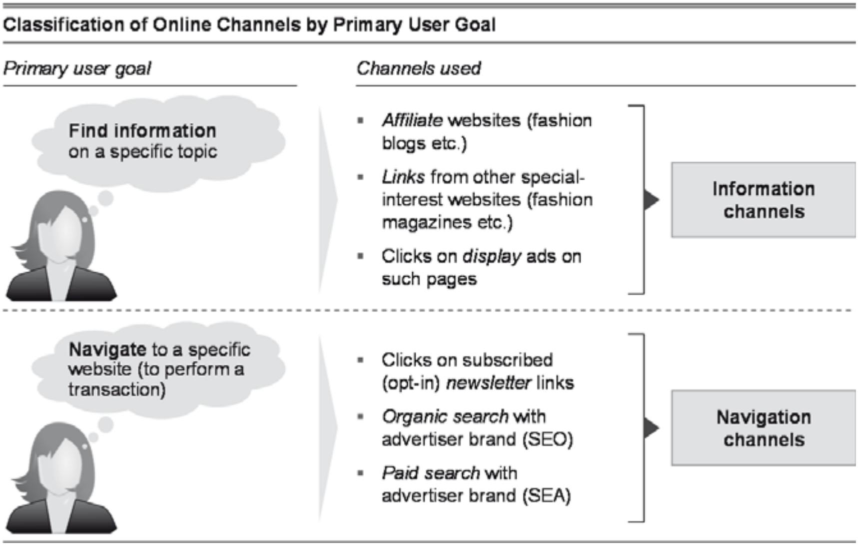


Figure 23: Classification of Online Channels by Primary User Goal
Source: Based on Broder (2002), Rose & Levinson (2004).

According to Rose and Levinson (2004, p. 15), a user's goal is informational if he or she wants "to learn something by reading or viewing web pages". Users generally learn from blogs or websites with professional editorial content (e.g., magazines); accordingly, the author classifies affiliate, display, and link channels as information channels and predicts that when consumers use these channels, they are in an information acquisition mode. In contrast, a navigational user goal implies that the consumer intends to go to a "specific known website that [is] already in mind" (Rose & Levinson, 2004, p. 15), such as by clicking on a link in a subscribed newsletter or on a SERP (organic search, paid search).[5] When consumers use these channels, they are in a navigation mode. It is assumed that users with transactional goals—that is, the user intends to reach a website on which further interaction will occur (Rose & Levinson, 2004)—are also in a navigational mode first. They must browse to the corresponding website before performing the transaction—online shopping in the case of the focal advertiser.

A switch from one mode to another also should affect purchase probabilities, in line with the theory of evoked and consideration sets (Hauser & Wernerfelt, 1990; Howard & Sheth, 1969; Roberts & Lattin, 1991), which is introduced in Section 3.2.2.2. Consumers perceive a limited number of brands as real purchase alternatives, and the brands in these evoked or consideration sets are subsets of the brands of which the consumer actually is aware (Howard & Sheth, 1969). This awareness set is a fraction of the total number of brands available on the market. To build and refine their consideration sets, consumers seek information—in this case, they do so online.

Consider the following scenarios: A user begins browsing in an information acquisition mode by searching magazine websites and blogs, during which he or she also is exposed to advertiser information in the form of a banner ad or a link. The consumer exhibits some initial interest, clicks on the link, and proceeds to the advertiser's website. If this consumer later switches to navigation mode and navigates directly to the advertiser's website, using a search engine or clicking on a link in a received newsletter, it could indicate that he or she plans to include (or already has included) the advertiser's brand into the consideration set and wants more information about this seller. By definition, the purchase likelihood for brands in the consideration set is greater than that for brands outside the set, so conversion probability should increase substantially through advertising exposure after a user switches from information acquisition to navigation mode.

If a user instead starts off in navigation channels and then switches back to information acquisition mode, this can be seen as an indication that his or her evaluation of the advertiser's website provided no clear preferences, so the user still needs to refine the consideration set or could even exclude the advertiser from the evoked set. In this case, advertiser messages in information channels are likely less useful than they were in the prior case, because the consumer already is aware of the advertiser but proactively explores other options. The author therefore anticipates no increase in purchase probability in this case. Considered in relation to

[5] Paid and organic links from search engines are classified as navigational because only traffic from keywords with the advertiser's brand is considered in the analysis. According to Rose and Levinson (2004), users often employ search engines for navigation if they do not know the advertiser's URL or because it is simply more convenient than typing in the URL.

each other, the author predicts that the increase in conversion rates is stronger for information-to-navigation switches than for the opposite direction (in which no effect is expected).

> HYPOTHESIS 2A (H_{2a}): Conversion probability due to advertiser messages increases if a user starts his or her browsing journey in information channels and then switches to navigation channels.

> HYPOTHESIS 2B (H_{2b}): Advertiser messages have no effect on conversion probability if the user starts his or her browsing journey in navigation channels and then switches to information channels.

> HYPOTHESIS 2C (H_{2c}): The increase in conversion probability due to advertiser messages is greater if the user starts his or her browsing journey in information channels and then switches to navigation channels than in the opposite case.

4.1.2.3 Interaction of Channel Characteristics with Previous Purchase

Traditional advertising research suggests that previous purchase affects how advertising works, as discussed in relation to framing and usage dominance effects in the section on the base model (Section 4.1.1.3). The author predicts that these effects influence the relationship between channel-related characteristics and purchase probability, just as they do the exposure–purchasing relationship. That is, framing should increase the effect of channel-related features on conversion rates, but usage dominance diminishes it. The resulting net effect depends on actual product characteristics, so framing dominates when products are complex and ambiguous, whereas usage dominance occurs when products are more simple and consumers can easily evaluate product quality. For the focal advertiser, in the complex, ambiguous fashion and apparel category, the author expects framing effects to outweigh usage dominance, such that the predicted multichannel effects should be stronger among existing than new customers.

> HYPOTHESIS 3A (H_{3a}): Exposure to advertiser messages through multiple channels has a stronger positive effect on conversion probability for existing than for new customers.

> HYPOTHESIS 3B (H_{3b}): The increase in conversion probability due to advertiser messages after a switch from information to navigation channels is greater for existing than for new customers.

> HYPOTHESIS 3C (H_{3c}): The increase in conversion probability due to advertiser messages after a switch from navigation to information channels is greater for existing than for new customers.

4.2 Research Model

Figure 24 indicates how the conceptual model is operationalized. The number of channels in a user journey is represented by the variable CH_i, and its effect on current purchase (CPR_i) is captured by b_1 (similar abbreviations apply to the other variables and coefficients).

Research Model (Study I)

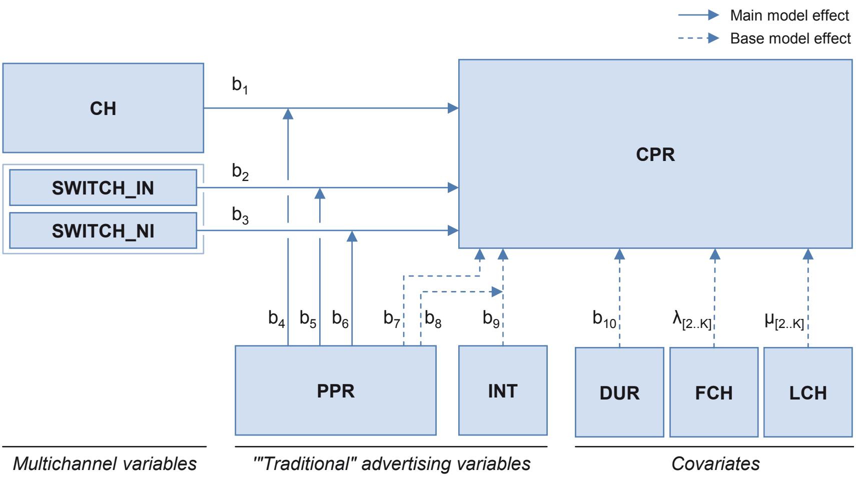


Figure 24: Research Model (Study I)

Source: "Traditional" advertising variables are borrowed from Deighton et al. (1994).

Table 3 provides the definitions for the variables. The dependent variable CPR_i is binary (1 = consumer converts, 0 = not), and the model predicts the probability that an individual consumer ultimately will engage in a transaction. The author therefore uses a logit model, consistent with previous studies that examine the effect of advertising exposure on individual purchasing behavior (e.g., Deighton et al., 1994; Guadagni & Little, 1983; Pedrick & Zufryden, 1991; Tellis, 1988), which is specified as follows:

$$\begin{aligned} Z_i \quad = \; & b_0 + b_1 CH_i + b_2 SWITCH\_IN_i + b_3 SWITCH\_NI_i \\ & + b_4 CH_i \times PPR_i + b_5 SWITCH\_IN_i \times PPR_i \\ & + b_6 SWITCH\_NI_i \times PPR_i + b_7 PPR_i + b_8 INT_i \times PPR_i \\ & + b_9 INT_i + b_{10} DUR_i + S_{k=2..K}(\lambda_k FCH_{k,i}) + S_{k=2..K}(\mu_k LCH_{k,i}) \\ & + e_i. \end{aligned} \tag{1}$$

$$P_i \quad = 1 / [1 + \exp(-Z_i)]. \tag{2}$$

Definition of Variables (Study I)	
I	= 1, …, I individual user journeys.
K	= 1, …, K channels.
Z_i	= log odds ratio for a conversion at the end of user journey i.
P_i	= probability that user journey i will end with a conversion.
CH_i	= number of channels in user journey i.
$SWITCH\_IN_i$	= 1 if the consumer started browsing journey *i* in information channels and then switched to navigation channels, and 0 if otherwise.
$SWITCH\_NI_i$	= 1 if the consumer started browsing journey i in navigation channels and then switched to information channels, and 0 if otherwise.
PPR_i	= 1 if the consumer in user journey i has purchased from the advertiser before, and 0 if otherwise.
INT_i	= square root of the number of clicks from the consumer in user journey i triggered by the advertiser's messages.
DUR_i	= duration of user journey i in seconds.
$FCH_{k,i}$	= 1 if the consumer started user journey i in channel k, and 0 if otherwise.
$LCH_{k,i}$	= 1 if the consumer finished user journey i with channel k, and 0 if otherwise.
λ_k	= coefficient measuring effect of channel k as first channel.
μ_k	= coefficient measuring effect of channel k as last channel.
e_i	= error term for user journey i.

Table 3: Definition of Variables (Study I)

Equation 1 denotes the log odds ratio (logit) for the conversion at the end of user journey i. Equation 2 provides the logistic function, which is used to calculate the probability that user journey i will conclude with a purchase. Furthermore, the term b_1CH_i captures multichannel synergy effects, and b_1 denotes the change in the logit model if the browsing journey of a particular consumer contains another channel. The channel order is operationalized using the dummy variables $SWITCH\_IN_i$ and $SWITCH\_NI_i$: if a switch between navigational and informational channels takes place, the respective variable equals 1 (otherwise 0). Therefore, b_2 measures how an information–navigation switch affects conversion probability, and b_3 measures the same effect for a change from navigation to information channels.

The author operationalizes PPR_i as a binary variable, indicating whether the focal consumer has shopped at the advertiser's online store before (1 = yes, 0 = no). The terms $b_4CH_i \times PPR_i$, $b_5SWITCH\_IN_i \times PPR_i$, and $b_6SWITCH\_NI_i \times PPR_i$ capture interactions between multichannel effects and previous purchase. For new customers, these terms equal 0 (because $PPR_i = 0$), and the multichannel effects are represented solely by b_1, b_2, and b_3. For existing customers, the effect of the number of channels is captured by $b_1 + b_4$, the impact of an information–navigation switch by $b_2 + b_5$, and that from a navigation–information switch by $b_3 + b_6$. This approach to model interactions with previous purchase is consistent with prior work (e.g., Deighton et al., 1994).

The author notes that PPR_i, INT_i, and their interaction also appear in traditional logit models designed to study offline advertising effectiveness (e.g., Deighton et al., 1994). Furthermore, b_7 measures the effect of previous purchases (dynamic brand loyalty), and the direct effect of advertising exposure is measured by b_9. In this study, “exposure” indicates that the user responded to an exposure by following a link or clicking on a banner, to obtain more detailed information on the advertiser’s website. This is in line with the concept of voluntary exposure from Cho’s (1999) adaption of the ELM to display advertising. Intensity is operationalized as the number of clicks by the consumer in user journey i. Consistent with Deighton et al. (1994), the author takes the square root of this number to account for the decreasing marginal effect of advertising, as represented by INT_i.[6] For user journeys from consumers without previous purchases ($PPR_i = 0$), the interaction term $b_8 PPR_i \times INT_i$ is 0, and the effect of advertising exposure is solely represented by b_9. For existing customers, the advertising effect is measured by $b_8 + b_9$.

The author also includes control variables to account for unobserved heterogeneity (Greene, 2002). Lambrecht and Tucker (2011) argue that purchase probability is influenced by the time elapsed since a consumer initially viewed a product in the advertiser’s web store. This potential effect is therefore captured with the term $b_{10} DUR_i$. Systematic differences might exist in the conversion behavior of users with specific first and last channels; for example, users who begin with a newsletter might have an intrinsically higher purchase probability than others, because they already have expressed interest in the advertiser’s offerings by proactively signing up to receive the newsletter. The author therefore adds two sets of K – 1 dummy variables (where K denotes the total number of channels): $FCH_{[2..K],i}$ and $LCH_{[2..K],i}$. Each represents an individual channel and takes a value of 1 if the browsing journey starts (FCH variables) or ends (LCH variables) with that particular channel, and 0 if otherwise. This control is especially important for the SWITCH variables, which would otherwise capture all effects arising from systematic differences between the first and last channels used.

4.3 Data

The model is estimated using cookie-level clickstream data from a European advertiser in the fashion and apparel industry.[7] This pure e-commerce player has no bricks-and-mortar stores. Consumers can only purchase from the advertiser’s online store, so no effects of research shopping should emerge, that is, when “consumers use one channel for search and another for purchase” (Verhoef et al., 2007, p. 129), which otherwise might bias the results (also see Chapter 2.2.2 for a brief discussion of the research shopper phenomenon).

[6] Although the author obtained similar estimation results using a linear term, the square root is preferred for theoretical reasons. Specifically, research shows that the incremental positive effect of multiple exposures quickly diminishes with increasing exposures. In a consumer goods setting, Deighton et al. (1994) and Krugman (1984) show that marginal benefits of advertisements typically disappear after the third exposure.

[7] Because of a confidentiality agreement, the name of the advertiser cannot be disclosed.

The data cover all the digital advertising channels described in Table 2 and show, for each channel, when a consumer clicks on an advertiser message.[8] They also contain conversion information, such that the author can determine whether a consumer has purchased something, the exact time, and the date of the purchase. This information is used to construct user journeys that describe the exposure pattern of an individual consumer to several channels and the reaction in terms of purchasing behavior (see also Section 2.4). Each user journey reflects an individual consumer and ends with either inactivity or a conversion. For consumers with prior purchase, all interactions since that conversion are included in the data. In an initialization procedure, journeys that exhibited only one click or interactions that lasted less than one second were excluded.[9]

The data were collected over a period of six months between 2010 and 2011. The data represent all incoming traffic that generated the site's revenues during this time. In total, journeys from 1,664,673 users were observed, 12,426 of whom converted (.746%). Table 4 contains more descriptive data statistics, and Table 5 lists intercorrelations between the variables.

Beyond the sample size, the data are unique because they combine individual user activity across a wide range of channels with conversion data from a large B2C online store. As laid out in Section 3.1, other empirical studies have either aggregated data for multiple channels (e.g., Breuer et al., 2011; Naik & Peters, 2009) or used consumer-level data for a single channel (e.g., Manchanda et al., 2006).

Descriptive Statistics (Study I)				
Variable	*Mean*	*Std. Deviation*	*Minimum*	*Maximum*
CPR	.007	.086	.000	1.000
CH	1.190	.637	1.000	8.000
SWITCH_IN	.028	.165	.000	1.000
SWITCH_NI	.081	.273	.000	1.000
CH × PPR	.025	.264	.000	8.000
SWITCH_IN × PPR	.001	.031	.000	1.000
SWITCH_NI × PPR	.003	.053	.000	1.000
PPR	.012	.107	.000	1.000
PPR × INT	.035	.360	.000	20.518
INT	1.819	.766	1.414	22.891
DUR	851,679.669	1,270,695.067	1.000	8,388,607.000
FCH	*Nominal variable transformed into 6 dummies (7 channels) in logit model*			
LCH	*Nominal variable transformed into 6 dummies (7 channels) in logit model*			

Table 4: Descriptive Statistics (Study I)

[8] Any advertiser-related information that contains a link to the advertiser's website is considered an "advertising message", including links in organic search results, mentions of an advertiser in a blog, or a display ad posted by the advertiser.

[9] The latter can occur when users double-click on an advertiser message. Double-clicks are counted as single clicks.

Intercorrelations (Study I)

	CPR	*CH*	*SW. IN*	*SW. NI*	*CH × PPR*	*SW. IN × PPR*	*SW. NI × PPR*	*PPR*	*PPR × INT*	*INT*	*DUR*
CPR	1										
CH	.092	1									
	(.000)										
SWITCH_IN	.010	.310	1								
	(.000)	(.000)									
SWITCH_NI	.051	.578	-.050	1							
	(.000)	(.000)	(.000)								
CH × PPR	.328	.222	.048	.102	1						
	(.000)	(.000)	(.000)	(.000)							
SWITCH_IN × PPR	.088	.078	.184	-.009	.339	1					
	(.000)	(.000)	(.000)	(.000)	(.000)						
SWITCH_NI × PPR	.188	.167	-.009	.180	.664	-.002	1				
	(.000)	(.000)	(.000)	(.000)	(.000)	(.031)					
PPR	.400	.145	.036	.065	.879	.287	.492	1			
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)				
PPR × INT	.357	.173	.033	.082	.887	.256	.558	.887	1		
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)			
INT	.129	.427	.112	.247	.194	.048	.138	.163	.245	1	
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)		
DUR	.021	.225	.060	.138	.087	.018	.063	.064	.096	.610	1
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	

Notes. *p*-values (two-sided) are reported in parentheses below correlation coefficients.

Table 5: Intercorrelations (Study I)

4.4 Results

Table 6 provides the results of the maximum likelihood estimation. Both the Nagelkerke and McFadden R-square values are well above 50%, indicating a good overall fit of the model. Furthermore, the estimation produces stable coefficients with low *p*-values and good t-statistics for all six main variables. Except for SWITCH_NI and CH × PPR, all coefficients show the expected signs.

Estimation Results (Study I)

Variable	b	$S.E.$	t-value	$d.f.$	p	VIF	$Exp(b)$	99% CI Exp(b) Lower	99% CI Exp(b) Upper
CH (b_1)	.766	.018	41.937	1	< .001	2.160	2.151	2.052	2.255
SWITCH_IN (b_2)	1.499	.183	8.185	1	< .001	1.258	4.476	2.793	7.172
SWITCH_NI (b_3)	-.347	.048	7.214	1	< .001	1.699	.707	.625	.800
CH × PPR (b_4)	-.280	.029	9.804	1	< .001	9.126	.755	.702	.813
SWITCH_IN × PPR (b_5)	1.040	.114	9.147	1	< .001	1.336	2.829	2.111	3.792
SWITCH_NI × PPR (b_6)	.386	.072	5.334	1	< .001	2.228	1.471	1.221	1.773
PPR (b_7)	3.940	.056	70.096	1	< .001	6.252	51.407	44.478	59.415
PPR × INT (b_8)	-.145	.016	8.861	1	< .001	6.539	.865	.829	.902
INT (b_9)	.407	.010	40.719	1	< .001	1.970	1.502	1.464	1.541
DUR (b_{10})	.000	.000	.000	1	> .999	1.608	1.000	1.000	1.000
$FCH_{[2..K]}$ ($\lambda_{[2..K]}$)			78.659	6	< .001				
$LCH_{[2..K]}$ ($\mu_{[2..K]}$)			66.550	6	< .001				
Constant	-8.392	.425	389.772	1	< .001				
Log-Likelihood					-33,927.203				
R^2 Nagelkerke					.548				
R^2 McFadden					.537				
N					1,664,673				

Table 6: Estimation Results (Study I)

The multicollinearity diagnostics (Table 6) reveal that variance inflation factors (VIF) of the six main variables are lower than the critical level of 10 (Kutner, Nachtsheim, Neter, & Li, 2004). The author therefore does not expect any unstable coefficient estimates due to multicollinearity. The results for each variable are reviewed in detail. To rule out the possibility that the observed effects are mere artifacts of the analysis, an additional robustness test was performed, which is presented after the main results.

4.4.1 Base Model

Except for the interaction between advertising exposure and previous purchase, the traditional advertising variables showed the expected signs. The coefficient of the previous purchase variable was highly significant, with the strongest influence on purchase behavior of all the predictors ($b_7 = 3.940$, $p < .001$). This unsurprising result implies that conversion probability would be more than 50 times greater for consumers who previously shopped with the advertiser than for new customers ($\exp(b_7) = 51.407$). In line with the author's expectation, the direct effect of exposure to online advertising was positive and highly significant ($b_9 = .407$, $p < .001$). Advertising messages on digital channels drove sales. Finally, the coefficient of the interaction between previous purchase and exposure intensity was significant but negative ($b_8 = –.145$, $p < .001$), which was somewhat surprising because a positive relationship caused by diagnostic framing was expected. However, advertising was less effective for existing customers ($b_8 + b_9 = .262$) than for new ones ($b_9 = .407$, $p < .001$). The interaction reduced the effectiveness of advertising, though it was still statistically different from 0 (t = 3.041; critical $t_{d.f. = 1,664,651; \alpha = .01} = 2.326$).

The duration of a browsing journey did not influence purchase probabilities ($b_{10} = .000$, *n.s.*). The model was also estimated without the duration variable, which produced the same results for the other predictors. Finally, the first and last channels employed offered useful controls for heterogeneity, in that they influenced conversion probabilities.

4.4.2 Main Model

As hypothesized, the number of channels had a positive effect on conversion probability ($b_9 = .766$, $p < .001$). It emerged as one of the three strongest explanatory variables in the main model. A good t-value and a low standard error indicated high statistical significance. The exponent of the coefficient b_1 (2.151) quantified the value of the multichannel online communication: every additional channel in a user journey doubled conversion probability, in support of H_1.

Switches between informational and navigational channels also influenced purchase probabilities, and both coefficients were highly significant. The author focuses on the transition from information to navigation channels first (SWITCH_IN). The large and positive coefficient ($b_2 = 1.499$, $p < .001$) suggested a strong increase in conversion probability (by a factor of 4.5) when a consumer began by browsing information channels and then later responded to advertiser messages on navigation channels to reach the online shop again. This finding supported H_{2a}. The coefficient of the SWITCH_NI variable (from navigation to information channels) was also significant but with a negative sign ($b_3 = -.347$, $p < .001$). The exp(b_3) of .707 implied that conversion probability decreased by nearly 30% when consumers responded to advertiser messages on information channels after beginning with the objective to navigate straight to the advertiser. H_{2b} therefore must be rejected. The b_2 and b_3 coefficients implied that the relative strength of the channel switching effects was larger for transitions from information to navigation channels than the opposite direction (H_{2c}). A one-sided t-test for $b_3 > b_2$ validated this observation (t = 9.753; critical $t_{d.f. = 1,664,651; \alpha = .01} = 2.326$), in further support of H_{2c}.

All three interactions of channel characteristics and previous purchase were significant. That is, the effects of multichannel online advertising on conversion probabilities differed for new and existing customers. The author predicted that the interaction between number of channels and previous purchase (CH × PPR) would be positive, but the corresponding coefficient actually was negative ($b_4 = -.280$, $p < .001$), indicating lower synergies from multichannel advertising for existing customers ($b_1 + b_4 = .486$) than for new ones ($b_1 = .766$, $p < .001$). In other words, an additional channel in the user journey of a new customer increased purchase probability by a factor of 2.2, but the increase for existing customers was only approximately 1.6, in contrast with H_{3a}. The results for the interaction between the channel order variables (SWITCH_IN, SWITCH_NI) and previous purchase (PPR) instead were, as expected, positive and significant ($b_5 = 1.040$, $p < .001$; $b_6 = .386$, $p < .001$), indicating stronger effects on purchase probabilities for existing than for new customers. If an existing customer switched from information to navigation channels, the corresponding effect ($b_2 + b_5 = 2.539$) was substantially stronger than that for new customers ($b_2 = 1.499$, $p < .001$), which in turn led to a three-times greater increase in conversion probability among existing ($\exp(b_2 + b_5) = 12.662$) than new ($\exp(b_2) = 4.476$) customers. H_{3b} can be accepted. Similar, the effect of SWITCH_NI was positively influenced by previous purchase. While moving from navigation to information channels decreased conversion likelihood among consumers who had not shopped at the advertiser before ($b_3 = -.347$, $p < .001$), this effect was cancelled out by the interaction for existing customers ($b_3 + b_6 = .039$). Even at a 10% significance level, it did not differ from 0 (t = .643; critical $t_{d.f. = 1,664,651;\ \alpha = .1} = 1.282$). Although there is no increase in conversion rates from a navigation–information switch, its effect on conversion rates for existing customers is more positive than for new customers. H_{3c} therefore is accepted.

4.5 Robustness Test

From a statistical perspective, the results seem stable, due to the low standard errors and a good overall model fit. However, as illustrated previously, consumers who begin in specific channels might intrinsically have different conversion likelihoods. To rule out the potential bias related to this effect, dummy variables for the first and last channels were included in the model (and were significant). Furthermore, the author ran a robustness test in which he removed individual channels from the sample to validate the findings.

Therefore, six subsets were created, each excluding user journeys that contained a specific channel (e.g., affiliate). The model was then estimated for each single group. Any unobserved systematic differences would likely make the coefficient estimates vary across groups and also differ from the coefficients in the “Results” section (4.4.2).

Robustness Test (Study I)							
		User Journeys Without …					
Variable	*All User Journeys*	*AFFILI-ATE*	*DISPLAY*	*LINK*	*ORG. SEARCH*	*PAID SEARCH*	*NEWS-LETTER*
CH	.766 **	.796 **	.790 **	.732 **	.983 **	.950 **	.551 **
SWITCH_IN	1.499 **	.919 **	1.372 **	1.533 **	1.143 **	1.113 **	1.427 **
SWITCH_NI	-.347 **	-.214 **	-.426 **	-.216 **	-.564 **	-.506 **	-.028
CH × PPR	-.280 **	-.171 **	-.175 **	-.204 **	-.463 **	-.486 **	.253 *
SW._IN × PPR	1.040 **	.739 **	2.362 **	.445 **	1.528 **	1.549 **	.334 *
SW._NI × PPR	.386 **	.129	.399 **	.295 **	.663 **	.722 **	.045
PPR	3.940 **	3.739 **	3.778 **	3.801 **	3.903 **	3.775 **	3.248 **
PPR × INT	-.145 **	-.133 **	-.144 **	-.132 **	-.142 **	-.076 **	-.113 **
INT	.407 **	.379 **	.415 **	.388 **	.386 **	.363 **	.412 **
DUR	.000	.000	.000	.000	.000	.000	.000
N	1,664,673	619,749	1,591,448	1,569,923	1,307,006	1,302,370	1,616,888
R^2	.548	.484	.558	.552	.562	.565	.559

Table 7: Robustness Test (Study I)

As the results of the robustness test in Table 7 show, coefficients varied to some extent across individual models, whereas the magnitude and direction of the effects were highly consistent. The only noticeable variations occurred when user journeys containing the channel newsletter were removed from the sample, in which case the SWITCH_NI and SWITCH_NI × PPR coefficients were not significant and the CH × PPR interaction became positive. This faint indication that the newsletter influenced the overall results suggested a minimal effect involving only a few coefficients. In summary, the outcome of the robustness test was promising, in support of the empirical findings, which alleviated concerns that the results might have been caused by unobserved factors rather than the hypothesized effects.

4.6 Discussion and Implications

4.6.1 Research Implications

The author presented and tested a theoretical model to explain how exposure to advertiser messages affects conversion rates in an e-commerce context. He estimated the proposed model using a large, consumer-level data set from an advertiser in the fashion and apparel industry. The data include activities across six online channels, together with conversion data, such that actual purchase behavior can be observed. This study thus makes five major contributions to online marketing and advertising effectiveness research.

First, building on findings from the offline world, the first comprehensive, theoretical model for online advertising effectiveness was presented. The author borrows elements from Deighton et al.'s (1994) model (i.e., previous purchase, direct advertising effect, and their interaction); combines them with the ELM, consideration set theory, and findings from IR research; and incorporates effects of multichannel communication. The model thus fills a significant gap, in that existing models of online advertising effectiveness focus on individual channels or cannot explain behavior on the consumer level because they are based on aggregated variables, such as spending by channel (e.g., Breuer et al., 2011; Hollis, 2005; Ilfeld & Winer, 2002; Sherman & Deighton, 2001).

Second, the analysis shows that basic elements of traditional offline models (e.g., Deighton et al., 1994) also can help explain online conversion. Previous purchase and advertising exposure both have significant, positive influences on conversion probability. Both underlying effects—namely, consumer inertia (dynamic brand loyalty) and the direct effect of advertising—can be observed in an e-commerce context. The author suspects that this influence also holds for other predictors from offline models, such as promotion variables. Bringing them into an online context might help further explain purchasing behavior.

Third, this study provides initial empirical proof of multichannel synergies between purely online communication channels. Thus far, such synergies have been reported only in offline or offline–online contexts (Breuer et al., 2011; Chang & Thorson, 2004; Naik & Raman, 2003). The observed effect is explained with the help of the ELM (Petty & Cacioppo, 1986). Multichannel campaigns can have positive effects on message credibility, which then increases motivation to process the advertising message and thus results in more positive thoughts about the brand, as well as increased purchase intentions. Further studies of the effectiveness of individual online channels should consider an advertiser's activities in other channels. For example, analyzing search engine performance without explicitly controlling for simultaneous campaigns in other digital channels could produce incorrect conclusions and an overestimation of the conversion rates associated with search engine advertising—particularly for studies using data from large advertisers (e.g., Ghose & Yang, 2009; Rutz & Trusov, 2011), which often employ multiple forms of digital advertising at the same time.

Fourth, the author shows for the first time that not only the number but also the order of exposure of channels in multichannel campaigns significantly influences conversion probabilities. In line with an interdisciplinary approach, online channels are categorized in accordance with prior findings about user search and information processing on the Web from IR literature. In particular, the author relies on Broder's (2002) taxonomy of search and its operationalization by Jansen et al. (2008). The new categorization enables grouping of online channels by primary user intent, namely, as informational and navigational channels. With the input of consideration set theory, the author explains how users react to subsequent exposures in informational and navigational channels and also offers promising findings. A transition from information to navigation channels leads to a 4.5 times higher conversion probability, but a switch in the other direction seems to affect conversion rates adversely. This surprising outcome contradicts the previous finding of synergetic effects of multichannel advertising. A robustness check confirmed that the result was not caused by analysis error or unobserved influence from individual channels. Instead, this finding can be interpreted as a real effect. The author hypothesized that advertising is not effective when users switch from navigation back to information mode, because they still have no clear preference for the advertiser or even lost their interest in the firm's products. Given the observed negative effect of advertising, when consumers are contacted after losing interest in the advertiser, the additional information from the ads can reinforce their attitudinal change. Building on previous findings on consumer privacy concerns, this negative effect is expected to be even stronger when users are exposed to targeted advertising after a navigation–information switch. That is, if consumers navigate to the advertiser's site and then find information from that same advertiser (including specific products they have viewed in the online shop) on other websites, such as a banner ad, they are likely to believe that the advertiser has invaded their privacy by failing to obtain their permission to track their moves. Even if they click on the banner, these consumers ultimately are less likely to purchase from the advertiser they consider untrustworthy, leading to an even greater negative effect of advertising after a transition from navigation to information channels. Similarly, Brown and Muchira (2004) find that privacy invasions adversely influence purchase behavior, and Goldfarb and Tucker (2011a) show that obtrusive, targeted ads seem manipulative and raise privacy concerns.

Fifth, the author finds that previous purchase moderates the influence of both multichannel and traditional advertising variables on conversion probability. The interactions between previous purchase and number of channels (b_4) and between previous purchase and exposure to advertising (b_8) were significant and negative, which indicates that the positive effect of multichannel synergies and advertising exposure is smaller for existing customers. This seems counterintuitive since positive relationships were expected, because the focal advertiser is in the fashion and apparel segment, which Hoch and Ha (1986) classify as a high-priced, less mature, and ambiguous category that should be subject to framing effects. To explain the finding that usage dominance outweighs framing, the author acknowledges that in this case, advertising is less effective for existing customers, who appear to prefer information from their own experience over advertising—a tendency that is more common in mature, low-price, less ambiguous categories (Deighton et al., 1994; Hoch & Ha, 1986). Consumers obviously perceived apparel products from the focal firm as more common and less ambiguous than consumers in Hoch and Ha's (1986) study. This might be due either to the specific assortment from the advertiser or to the perception that the apparel category has changed over the past 25 years between these two studies. This study's finding of usage dominance also seems justified and not subject to other effects. First, the VIF scores of both variables are less than 10, so multicollinearity is unlikely to cause this unanticipated outcome. Second, in incremental chi-square tests, each interaction improves the explanatory power of the model significantly, which justifies adding them to the model.[10] Third, consistent results for the interaction coefficients were obtained in the robustness test. Thus, usage dominance influences the relationships between the number of channels and previous purchase (b_4) and between advertising exposure and previous purchase (b_7). In contrast, the situation differs for the channel switching variables (b_5 and b_6), for which both interactions with previous purchase are, as expected, positive and significant (in support of framing effects).

Framing and usage dominance interact differently with the underlying cognitive mechanisms for multichannel synergies (ELM) and channel order effects (evoked sets). With regard to the ELM, the author argues that messages from multiple sources increase message credibility, which may cause consumers to process the message using a central route and develop more positive thoughts about the advertiser. This increase in message credibility should be lower for consumers who have shopped with the advertiser before, because they can rely on their own experiences—that is, usage dominance. For the evoked sets, which are used to explain channel order effects, the relationship reverses. Here, previous purchases facilitate a switch from one stage in the purchase decision-making process to the next, likely because the consumer has developed trust in the advertiser through previous transactions. Further research is needed to clarify these effects; for example, a study might replicate the current analysis with data from different advertisers and categories to verify the findings.

In summary, previous purchase significantly alters the effect of (1) advertising exposure, (2) multichannel synergies, and (3) channel switches on conversion probability. However, the direction of the interaction effects differs. Whereas previous purchase increases the influence of channel switching effects on conversion probability, it reduces the synergetic effect of multichannel communication and advertising exposure. Online marketing research should consider this finding carefully and include corresponding controls in additional studies.

4.6.2 Managerial Implications

These findings provide the first empirical insights into online multichannel advertising, which in practice often relies on trial and error, because the industry lacks a comprehensive body of knowledge. The results of this study thus are relevant for practitioners, with multiple implications.

For advertisers, the findings provide valuable suggestions for improving budget allocations and ad scheduling across multiple online channels. First, the author confirms that offline paradigms work online: advertisers can increase conversion probabilities through advertising

[10] For the interaction between previous purchase and number of channels (b_4), the chi-square of 96.1 exceeds the critical chi-square of 10.8 (.001 level, 1 d.f.). For the interaction between previous purchase and exposure to advertising (b_8), a chi-square of 197.5 is obtained, which also exceeds the critical value (.001 level, 1 d.f.).

exposure. Consumers who have already purchased are much more likely to convert than first-time customers, so customer retention is equally valuable in the online world. Second, for advertising in multiple online channels, 1 + 1 > 2. That is, advertisers benefit from synergies if they send out simultaneous advertising messages on more than one channel. Figure 25 illustrates this finding with concrete empirical numbers from a descriptive analysis of the dataset. It shows that from the 943,806 user journeys that solely comprise the channel affiliate, only four led to a conversion (.0004%). This rate is low compared to user journeys containing multiple channels, e.g., affiliate and search (.5045%), affiliate and display (.0414%), or affiliate and newsletter (3.1457%). This effect continues with an increasing number of different channels in the user journeys.

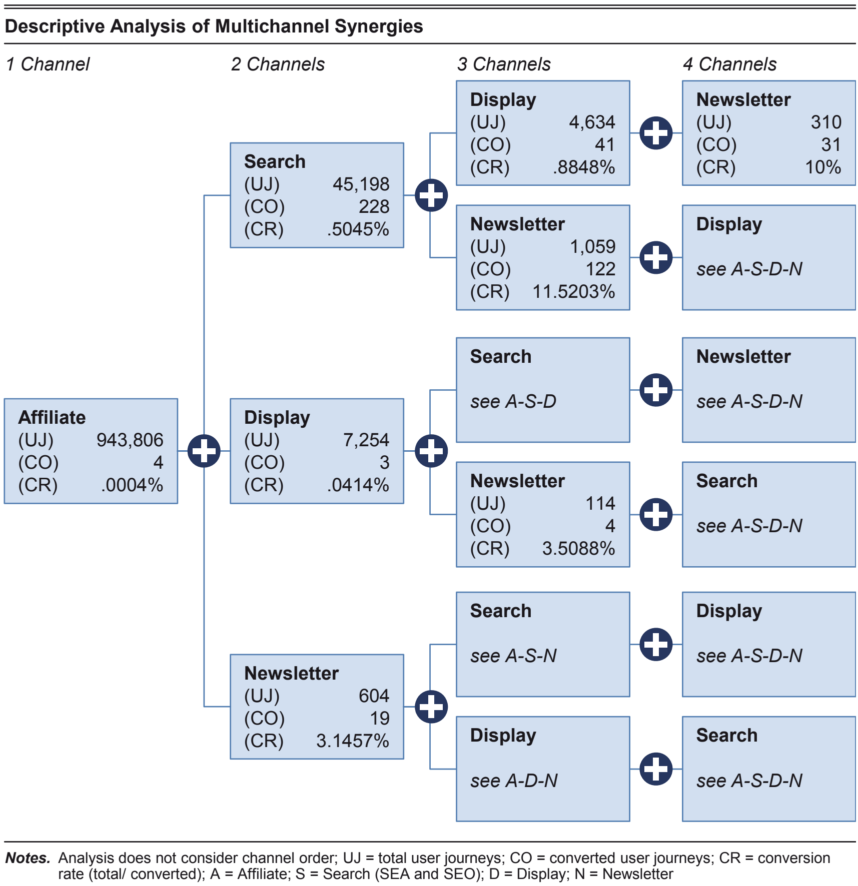


Figure 25: Descriptive Analysis of Multichannel Synergies

Third, advertisers must coordinate their simultaneous advertising messages, in terms of scheduling and targeting and according to the consumer's previous purchase behavior, because specific channel transitions substantially affect conversion probabilities. Consumers whose first contact is through information channels, such as affiliates, blogs, or fashion websites, will exhibit significantly greater purchase probabilities if they subsequently receive an advertiser message through navigation channels. Advertisers therefore should ensure their visibility among these consumers on navigation channels. Although no current search engine advertising provides for real-time bidding for individual users, such a capability could enable advertisers to target individual customers by increasing their bids for users who come from information channels, which would be an effective strategy. If users transition from navigation to information channels, however, advertising can have adverse effects, so advertisers would benefit from less advertising, in terms of cost savings and increased revenues. Executing such a strategy also requires sophisticated targeting mechanisms for the online marketing instruments. In addition to previous channels viewed, the customer's past purchase behavior needs to be considered to schedule the ads, because online advertising works differently for new and existing customers. Finally, these interactions with previous purchase also likely depend on the product category. To operationalize corresponding ad scheduling strategies, real-time targeting mechanisms need to be enhanced to enable considerations of previous purchase behaviors of customers in the specific product category (in the case of multicategory advertisers).

For publishers, search engines, technology providers, and vendors of ad servers or tracking and optimization tools, the study implications are closely related to those for advertisers. That is, providers need to enhance current tracking mechanisms to identify unique consumers throughout their entire user journey. Ideally, this identification would include both advertising exposures (i.e., impressions) and users' reactions (i.e., clicks, conversions). Data used in this study only cover the latter. Targeting mechanisms also should support real-time decisions about whether to present an ad to a certain user. Such mechanisms are emerging, though only for single channels (e.g., retargeting with display ads). In an ideal world, targeting mechanisms would work in an integrated manner across all the channels included in an online campaign. Finally, the decision rules of targeting mechanisms should account for additional criteria, such as previous purchase behavior and product category. Developing a targeting infrastructure to meet these three demands could create significant additional value for advertisers and thus a competitive advantage for technology providers, website publishers, and search engines.

4.6.3 Limitations and Further Research

Although this study marks an important step toward a better understanding of how online multichannel advertising works, it has limitations and thus provides avenues for additional research. They arise mainly from two elements: data limitations and model restrictions.

This study used cookie data, which naturally impose two restraints. First, it is assumed that one cookie represents one consumer, which is not necessarily true, such as when several users share the same computer. However, the author considers this concern relatively minor, because Drèze and Zufryden (1998) indicate that cookies appropriately represent individual users on modern multiuser operating systems. Other published studies similarly use cookie data (e.g., Goldfarb & Tucker, 2011a; Manchanda et al., 2006) because they are the best data available to study individual consumer behavior in online field studies. Second, users can delete cookies at any time (and many modern web browsers provide options to automatically remove them), so they have a limited lifetime. When a cookie is deleted, a user's browsing journey ends, such that any future activities constitute a new journey that cannot be linked to the prior history. In this data set, the author expects an average cookie lifetime of 30 days,[11] which should not pose any problem, because the user journeys in the data indicate a median duration of 2.8 days and an average duration of 9.9 days (SD = 14.7). Thus, journeys that end without conversion are likely not truncated (i.e., deleted cookie) but rather reflect "real" inactivity: the consumer lost interest in the advertiser's offering.

Another data limitation pertains to the exposure variable in the base model. Specifically, clicks by consumers on advertiser messages are captured and treated as advertising exposures. The author believes this approach is valid because, for the current analysis, it is less interesting whether a consumer notices an ad than how he or she reacts to an already perceived ad. This is also in line with Cho's (1999, p. 38) concept of voluntary exposure, defined as clicks "for the purpose of seeing more detailed advertising messages by requesting more information". He shows with an adapted version of the ELM that voluntary exposures work similar to conventional ad exposures. The results obtained for clicks supported this, as they resemble those for exposures that appear in traditional advertising models (i.e., positive coefficient with decreasing marginal effect on conversion probability). However, the elasticities from an additional click are obviously higher than those from an additional exposure, and this point must be kept in mind when comparing these results with exposure-based models.

The data set features only one advertiser and a single product category. In general, data from multiple firms might help control for potential biases from individual, firm-specific effects. Moreover, it would be helpful to analyze the interactions with previous purchase, which are

[11] This value is determined on the basis of both the advertiser's experience and several discussions with industry experts.

believed to depend on the actual product category. Some variance might help reveal the relationship. Replicating the analyses with a multiple-advertiser data set across different product categories could validate the author's findings and produce more differentiated insights into the interaction effects.

Finally, with regard to the presented model, three promising areas for further work emerge. First, as an initial study of multichannel online advertising, this research follows a top-down approach, such that individual online instruments are grouped by user intent into informational and navigational channels. This tactic was helpful for revealing the effects of channel transitions on conversion probabilities. However, the author also believes that the classification is a continuum, rather than a binary decision. For example, if not restricted to advertiser brand keywords (as in the current case), search engines often serve both information and navigation purposes. Subsequent studies should address this by differentiating between traffic from keywords containing the advertiser's name (navigational) and from other keywords, for example, reflecting the product category (informational). Another option that reflects that channels can serve both user goals would be to use a continuous, rather than a binary, variable to address this point. Second, channel-switching effects could be explained on a more granular basis through the use of individual channels in the analysis. This approach might indicate even more differentiated budget allocation and ad scheduling strategies. Third, both online and offline channels influence purchase processes, and consumers can purchase goods and services in both physical and e-commerce shops, so an integrated perspective on the overall advertising activities of a firm seems increasingly important. The current model should be extended even further to include offline channels. Thus, the author recommends two forms of extension: including other explanatory variables from offline channels that might help explain purchase probabilities (e.g., exposure on offline channels) and integrating offline purchase behavior. Although the task certainly is challenging, any results would have extraordinary value for both research and practice. At the end of the thesis, Chapter 6.4 outlines a framework for an integrated approach to online advertising, which reflects the findings from this work.

5 Study II: Effectiveness of Search Engine Advertising

As the first two chapters indicate, paid search advertising is an important, if not the single-most important, form of online advertising. However, the literature review from Chapter 3 shows that little is known about search engine advertising (SEA), particularly about keywords and matching options.[12] This leaves the previously introduced questions unanswered, which are addressed in this section:

1. What criteria can be used to select keywords and evaluate their performance in a systematic way?
2. How do matching options influence the effect of these criteria on keyword performance?

Answering the first question is crucial for successful paid search campaign management because keywords represent the link between user queries and advertiser messages. For example, if an advertiser selects a keyword that is too generic to resolve a user's informational need correctly, the likelihood that the presented ad will be relevant for the user decreases. This eventually results in a lower response to the ad (Gupta et al., 2009). The second question is of equal importance. As Chapter 2.2 emphasizes, generic matching options (*broad* and *phrase*) are an important and commonly used tool for advertisers to increase the reach of their paid search campaigns. However, because matching options drastically alter the matching logic of the underlying ad retrieval system (see also Section 3.2.3.2), they can have a considerable impact on perceived relevance and thus the keyword performance. So far, however, it is not clear when (i.e., for which keywords) *broad* and *phrase* match are advantageous and should be preferred over *exact* match.

The goal of this chapter is to provide answers to these two questions by studying the relationship among keyword characteristics, matching options, and keyword-specific CTRs. Because all the independent variables in the following model relate to the information a keyword carries, they are summarized under the concept of "information content". In doing so, the analysis differentiates between intrinsic information content, defined by characteristics that relate to the keyword text itself, and extrinsic information content, determined through the advertiser's decision on the matching option.

The remainder of this chapter is organized as follows: Section 5.1 presents the underlying conceptual framework of the study. Section 5.2 analyzes the influence of a keyword's intrinsic information content on its performance, and Section 5.3 adds keyword matching options to

---

[12] The matching option (or matchtype) is a parameter that must be specified by the advertiser for each keyword in a campaign. It controls how exactly a user query must match a keyword to trigger the impression of the ad text (see also Chapter 2.2 for an example how matching options work).

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the analysis (extrinsic information content). Section 5.4 presents a discussion of the findings and sheds light on implications before concluding the chapter.

5.1 Framework for Studying Effectiveness of Search Engine Advertising

To explain and model the influence of keyword features on performance in paid search campaigns, insights from prior work on advertising effectiveness theory and concepts from IR research constitute the foundation of the research in this chapter (Figure 26).

Theoretical Framework for the Effectiveness of SEA

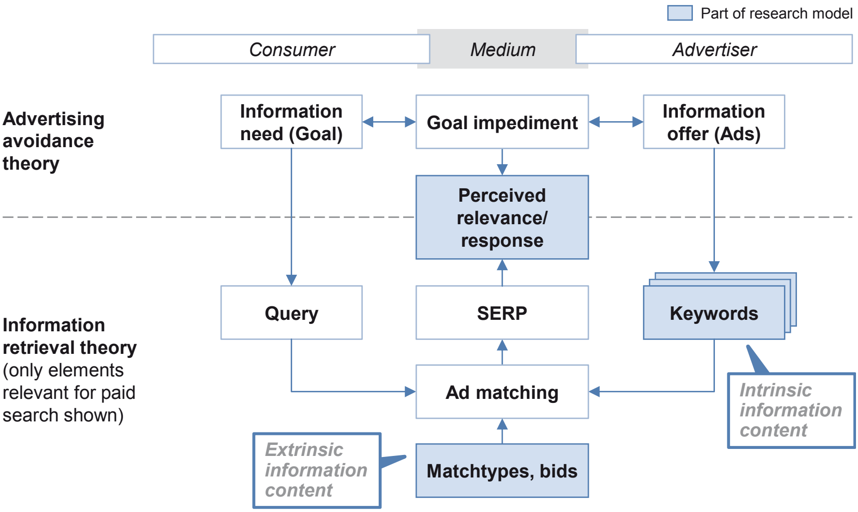


Figure 26: Theoretical Framework for the Effectiveness of SEA

Source: Based on work from Agichtein, Brill, & Dumais (2006), Broder (2002), Buckland & Plaunt (1994), Cho & Cheon (2004), Jansen (2005), Joachims & Radlinski (2007), Kelly & Teevan (2003), Speck & Elliott (1997), Vakratsas & Ambler (1999), van Rijsbergen (1979).

Cho and Cheon (2004) investigate the advertising effectiveness for online marketing campaigns in the context of banner advertising. Building on the work of Vakratsas and Ambler (1999) and Speck and Elliott (1997), they find that the more a user's information need and an advertiser's information offer are aligned, the lower is the perceived goal impediment and the higher is the likelihood that the user will respond positively to the advertising message. In short, an ad can become useful when it matches the user's informational needs.

This principle can be applied to paid search, employing concepts from information retrieval. In the classic IR model, described in more detail in Section 3.2.3, users translate their information need into verbal queries and submit them to a system that selects relevant documents from a collection, the so-called corpus (Buckland & Plaunt, 1994; van Rijsbergen, 1979). This is similar to web search engines, for which Broder (2002) presents an augmented IR model. The author applies Broder's logic to the context of paid search: whereas users verbalize their information need as a search query, advertisers translate their information offer into keywords that form the corpus. When a query is submitted to the retrieval system, it searches the corpus for relevant entries (i.e., keywords) and presents the corresponding ads on the SERP. Implicit feedback theory suggests that the relevance of an ad can be measured through actual user responses, in terms of CTR (Agichtein et al., 2006; Jansen, 2005; Joachims & Radlinski, 2007; Kelly & Teevan, 2003).

Empirical findings from Rutz and Bucklin (2007, 2011) and Ghose and Yang (2009) suggest that keyword-specific criteria (e.g., location- or brand-specific information in the keyword text) have an influence on how well the retrieval system can find more or less relevant ads. Because these criteria relate to the information represented by the text of a given keyword, the author calls them intrinsic features and summarizes them under the concept of a keyword's intrinsic information content. Whereas these intrinsic keyword features are independent of external factors, a keywords' information content can be indirectly changed through the matching options. As mentioned in the introductory part of the chapter, matching options tell the retrieval system how exact a query must match a keyword to be considered relevant. For example, the query "used car" will not be matched to the keyword "car" if the matching option is *exact*, but it will if the advertiser selects the options *phrase* or *broad* (refer to Section 2.2 for a more detailed example). This basically changes the information content of the keyword "car" to "used car". Because this influence comes from an external parameter and has nothing to do with the keyword text itself, the author calls it extrinsic information content of a keyword.

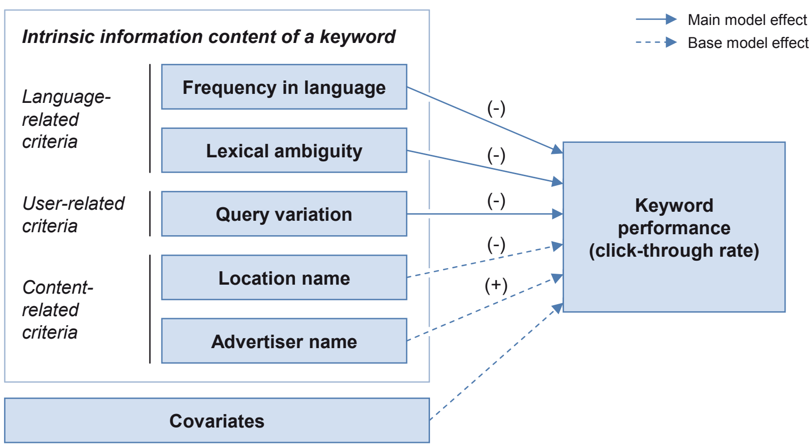
The research model measures the relationship between the intrinsic information content and a keyword's CTR. Extending this model with interaction terms for keyword matching options allows the author to analyze the impact of the extrinsic information content on the main effects. This two-step approach helps maintain a parsimonious research model, because it only introduces matching option interaction terms for the keyword criteria that explain a substantial share of the variance in a keyword's CTR. The CTR refers to the number of clicks received by an ad divided by the number of impressions for that ad—in both cases only, if the ad was triggered by a specific keyword. There are several advantages of using keyword CTR as a proxy for perceived relevance. First, the user's click on the search engine's result page is close to the actual search episode. Other measures, such as conversion rate, are further down the purchasing process and might be influenced by other unobserved factors (e.g., landing page design, product price, online shop usability). Second, other than clicks or conversions, CTR is a ratio that can be used to compare the performance of keywords with different numbers of impressions. Third, CTR is a widely used core metric in practice (Animesh et al.,

2011) and crucial to the success of paid search campaigns: low CTRs lead to low-quality scores, eventually resulting in higher prices for clicks on the same display positions (Google, 2010c). Fourth, previous empirical research has used it as a dependent variable; thus, some experience is available on which to build. Examples include Animesh et al. (2011), Ghose and Yang (2009), Richardson et al. (2007), and Rutz and Bucklin (2011). For a more detailed discussion on digital advertising KPIs, see Section 2.5.

5.2 Model for Keyword Performance in Search Engine Advertising

Figure 27 shows the theoretical model with the proposed criteria to define the intrinsic information content of a keyword. Considering that the content-related criteria have been used in this context previously, no hypotheses are presented. In addition, these criteria are included in a base model to clearly point out the contribution of the new keyword features developed in this study.

Model for Keyword Performance in SEA



Notes. The plus and minus signs denote the direction of the hypothesized effects.

Figure 27: Model for Keyword Performance in SEA

5.2.1 Hypotheses

In total, five keyword-specific characteristics are used to explain a keyword's individual click-through performance. To identify and/or develop these features, relevant literature from IR and marketing research was thoroughly screened. The author also double-checked with industry experts to choose only the features that could be measured and used on a continuous basis in practical campaign management.

5.2.1.1 Language-Related Keyword Criteria

Research in linguistics and information retrieval offers insights into the effect of keyword semantics, syntax, or meta-information on retrieval performance, which are assumed to be relevant factors for better understanding a keyword's CTR. Consequently, the author specifies hypotheses about two such factors: frequency in language and lexical ambiguity.

Frequency in Language. This feature measures how often a keyword term occurs in language, which can be an indicator of its information content. A basic principle of mathematical information theory states that terms appearing frequently in language carry less information (Shannon, 1949), so it is not surprising when they occur in a text, and vice versa. Building on this, Luhn (1958) suggests that common words in a text often do not contribute significantly to its content, which provides the basis for much of the later work in information retrieval (van Rijsbergen, 1979). A common application for this is the practice of stop-word removal in automatic text analysis, in which relatively meaningless, high frequency words, such as "and", are excluded from the index representing a document (van Rijsbergen, 1979). This finding is used and applied to the context of paid search advertising, hypothesizing that less frequent keywords have a higher CTR because they carry greater information content and thus enable more effective matching by the retrieval system.

> HYPOTHESIS 1 (H_1): A decreasing keyword frequency increases a keyword's CTR.

Lexical Ambiguity. The second linguistic feature reflects the semantics of a keyword by specifying its number of senses. Whenever this number is larger than one, the phenomenon of lexical ambiguity can be observed. In this case, words that share the same orthography have several meanings—for example, the word "head".[13] Lexical ambiguity often leads to reduced effectiveness in retrieval tasks, because systems cannot determine the right context for the actual query (Krovetz & Croft, 1992; Stokoe, 2005). Therefore, the information content of a keyword with lexical ambiguity is lower, as additional information on the context would be required to infer its actual meaning. Accordingly, lexical ambiguity should reduce a keyword's CTR. Lexical ambiguity also has not been examined in the context of paid search advertising.

> HYPOTHESIS 2 (H_2): Lexical ambiguity decreases a keyword's CTR.

[13] According to the Oxford Dictionary, this word can be used as noun with 10 different meanings, an adjective, or verb with six meanings (Oxford Dictionaries, 2011).

5.2.1.2 User-Related Keyword Criteria

The main idea behind this class of intrinsic keyword criteria is to infer a keyword's information content from the users' actual search behavior and use this to predict a keyword's performance. The author therefore introduces an indicator that measures the relationship between the users' search queries and the advertisers' keywords in terms of variation. Again, information retrieval—especially search log analysis and user search modeling—constitutes the theoretical foundation for this feature. Because this indicator is entirely new, it is discussed in more detail.

Query Variation. According to Radlinski et al. (2008) and Gupta et al. (2009), the task of matching user queries to keywords is challenging because web search queries tend to be short and encompass no information on the context. For example, multiple studies on online search behavior show that the query length in the context of web search is between two and three terms (Jansen & Spink, 2006; Jansen, Spink, & Saracevic, 2000; Jansen, Spink, Bateman, & Saracevic, 1998; Silverstein, Marais, Henzinger, & Moricz, 1999; Spink, Wolfram, Jansen, & Saracevic, 2000). As a result, there is a high likelihood that a certain share of user queries, which are matched to a keyword, will not be relevant to the actual user's informational need. This applies particularly to the context of paid search advertising, in which the corpus of advertiser keywords is much smaller than the corpus of the organic web search (Jones et al., 2006). The share of irrelevant matches depends on the information content of a keyword: the less specific a given keyword (i.e., the lower its information content), the more different user queries can be matched to this keyword, which increases the likelihood of irrelevant matches.

What are the underlying drivers for keyword specificity? The author argues that the variation in user search queries for a given keyword is influenced by the size of the keyword's informational domain and the position of the keyword within that domain (Figure 28).

Drivers of Query Variation

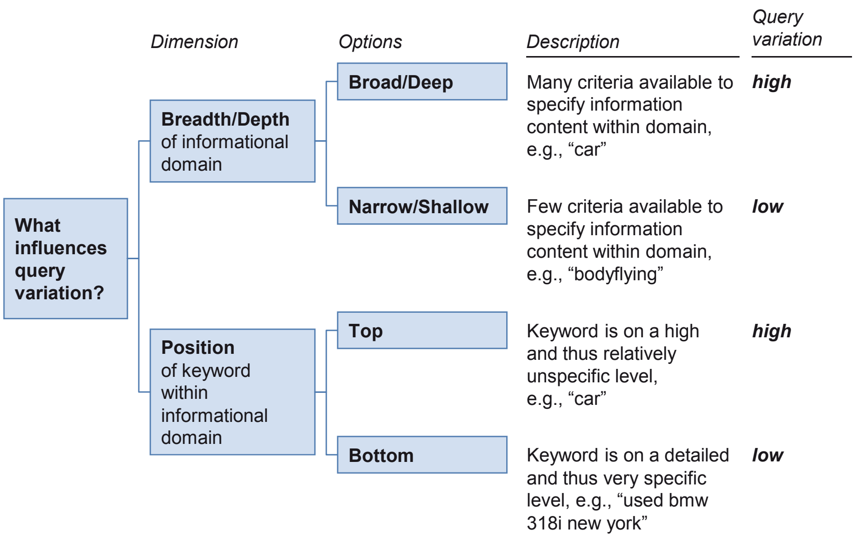


Figure 28: Drivers of Query Variation

If a keyword belongs to a broad and/or deep informational domain, users have significantly more possibilities of adding or changing terms in their queries (i.e., searching for something different that is to some extent related to that keyword) than in a narrow and/or shallow domain. On average, this results in a high variation in user queries. This can be illustrated with an example. The advertiser, a local car dealer trying to sell new cars, bids on the keyword "car", which belongs to a rather large informational domain: in addition to the term itself, top 10 search queries related to "car" for the US in 2010 included "car rental", "used car", "car games", "car insurance", "car wash", and so on (Google, 2011c). If the advertiser opts-in for *phrase* or *broad* matching option, the ad could be displayed for all these search queries—many of them are irrelevant, consequently reducing the keyword's CTR. Another advertiser, which offers bodyflying (an indoor version of parachuting in a vertical wind tunnel) and bids on the corresponding keyword "bodyflying", does not face this problem as much because significantly less query variations occur for this subject (basically all users with related searches try to find a location where they can exercise this sport). In addition to the size of the informational domain, the number of query variations indicates the keyword's position within that domain. If it is on a very high and generic level, there are again many possibilities to add or change terms in the search query (e.g., "car"). Conversely, if the keyword is on a very detailed level (e.g., "used bmw 318i new york area"), there is less leeway for variations, eventually leading to a lower query variation for that keyword. In essence, note that even a short keyword can be specific, if it belongs to a small informational domain or it is at the very bottom of a domain (representing something very detailed within that domain).

The variation in user queries for a given keyword is captured through a new construct, the QVI. The author defines it in Equation 3 for keywords having received at least two clicks over a certain period. Figure 29 presents examples for the calculation of the QVI.

$$\mathrm{QVI}_{k,\Delta t} = (\text{Unique search queries for keyword } k \text{ during } \Delta t) - 1 \,/\, (\text{Total clicks for keyword } k \text{ during } \Delta t) - 1. \tag{3}$$

Calculation of the QVI

	Example with HIGH query variation		*Example with LOW query variation*
Keyword	car		bodyflying
Total clicks	10		9
User Queries (clicks per query)	buy car (2) car insurance (2) rental car (1) bmw 318i (1)	car accident (1) mercedes (1) audi a4 (1) spare parts (1)	bodyflying bavaria (5) where can i do bodyflying (3) gift card bodyflying (1)
QVI (= unique queries–1 / total clicks–1)	(8–1) / (10–1) = 0.78 (high)		(3–1) / (9–1) = 0.25 (low)
Explanation	Users combine keyword with large number of different terms as informational domain very broad and/or keyword on generic level within domain → Keyword alone carries **insufficient information** to identify user's informational need		Users employ significantly less variations as the domain is narrower and/or keyword on more specific level within domain → Keyword alone carries **sufficient information** to identify user's informational need
Resulting CTR	**low**		**high**

Notes. QVI = Query variation index; CTR = Clickthrough rate

Figure 29: Calculation of the QVI

According to the definition in Equation 3, the QVI takes the value of 1 when every click is generated by a different search query and 0 if all clicks are generated by a single query. Because the share of irrelevant matches is higher for keywords with high QVI, it is hypothesized that the CTR decreases with an increasing QVI. If this is the case, the QVI provides a better indication for the specificity of keywords in paid search campaigns than the frequently used criterion *keyword length* (e.g., Ghose & Yang, 2009; Jones et al., 2006).

HYPOTHESIS 3 (H_3): An increasing QVI decreases a keyword's CTR.

5.2.1.3 Content-Related Keyword Criteria

This class of intrinsic keyword criteria reflects the actual content of the keywords. Both of the following two features have been used in recent empirical studies to predict a keyword's CTR, which is why they are included in the base model. No hypotheses are presented for these criteria.

Location Name. Consumers increasingly use search engines to find local products and services (Backstrom, Kleinberg, Kumar, & Novak, 2008). In this case, their search queries often contain location names (e.g., "vegetarian restaurant munich") (Gravano, Hatzivassiloglou, & Lichtenstein, 2003). In an empirical analysis of a hotel chain's paid search campaign, Rutz and Bucklin (2007) find that the presence of geographic location names reduces the CTR of a keyword. Because this relationship is statistically significant, the author includes a variable in the model, which reflects whether a keyword contains a geographic location, and consequently determines a certain aspect of a keyword's intrinsic information content.

Advertiser Name. This characteristic is technically similar to the previous one and reflects the presence of an advertiser's name in a keyword (e.g., "joe's pizza").[14] Empirical studies have shown a clear relationship: keywords with advertiser names have significantly higher CTRs than keywords without advertiser names (Ghose & Yang, 2009; Rutz & Bucklin, 2007). The concept of consideration sets in marketing—introduced in Section 3.2.2.2—provides a potential explanation: consumers searching for advertiser-specific information are at a more advanced stage in the purchasing process and know quite well where or from whom they want to buy their products or services (Ghose & Yang, 2009; Rutz & Bucklin, 2011). This results in a higher likelihood that the consumer will click on an ad carrying advertiser-specific information.

5.2.2 Research Model

The author uses a multiple regression model to test the hypotheses and extends it in Section 5.3 with interaction terms to model the influence from matching options. The unit of analysis is the unique combination of a keyword and a matching option. Keyword effectiveness is measured with CTR, the dependent variable. As mentioned previously, CTR is a ratio that makes the performance of keywords with different number of impressions comparable. Animesh et al. (2011) carry out ordinary least squares regressions, with CTRs as the dependent variable. This study follows their approach to weight the observations in the least squares estimation according to their number of impressions. The reason is that the CTR, as an estimate for the true performance of a keyword, becomes more reliable the more often the ad is

[14] This strictly refers to advertiser names and not to third-party product names or brands the advertiser offers.

shown to consumers (Animesh et al., 2011; Richardson et al., 2007). The regression model is displayed subsequently. Table 8 presents the definition of the variables.

$$\begin{aligned} CTR_{k,m} = {} & b_0 + b_1FL_k + b_2LA_k + b_3QVI_k + b_4LOC_k + b_5ADV_k \\ & + b_6LEN_k + b_7LDIFF_k + b_8POS_{k,m} + b_9QS_{k,m} \\ & + S_{i=2..I}(\mu_i IND_{i,k}) + e_{k,m}. \end{aligned} \tag{4}$$

Definition of Variables (Study II)	
K	= 1, …, K individual keywords.
M	= 1, …, M matching options.
I	= 1, …, I advertiser industries.
$CTR_{k,m}$	= click-through rate of keyword k with matching option m.
FL_k	= frequency of keyword k in German language (1 = very frequent, 16 = very rare).
LA_k	= number of meanings of keyword k.
QVI_k	= query variation index of keyword k.
LOC_k	= 1 if the keyword text contains the location of the advertiser, and 0 if otherwise.
ADV_k	= 1 if the keyword text contains the name of the advertiser, and 0 if otherwise.
LEN_k	= length of keyword k (number of terms).
$LDIFF_k$	= percentage of clicks from keyword k with queries longer/shorter than keyword k.
$POS_{k,m}$	= ln of average position of keyword k with matching option m.
$QS_{k,m}$	= average quality score of keyword k with matching option m.
$IND_{i,k}$	= 1 if advertiser belonging to keyword k is from industry i, and 0 if otherwise.
μ_i	= coefficient measuring effect of industry i.
$e_{k,m}$	= error term for keyword k with matching option m.

Table 8: Definition of Variables (Study II)

The keyword data are linked with external data sources, to operationalize some of the intrinsic keyword features. To derive the frequency in language (FL) for a given keyword, the author uses a corpus-based word list (DEREWO) from the Institute for German Language (IDS, 2009a). It provides the relative frequency of the 100.000 most common German word forms (instantiation of a word, specifying its tense or number) on an exponential scale (IDS, 2009b). The DEREWO assigns each word form to one of 18 frequency classes[15], where 0 is the category with the most frequent word forms (e.g., “und” [and]), and 17 is the category with the least frequent forms (e.g., “Fluglotse” [air traffic controller]). The author mapped the DEREWO against the keyword data and stored the frequency class in the independent variable FL. Lexical ambiguity is operationalized by the number of semantic word senses for a keyword stored in variable LA. The data originate from the OpenThesaurus project, an open source thesaurus covering approximately 75.000 German words (OpenThesaurus, 2010). The author ran customized queries on this database to obtain the number of meanings for individual words, which he then matched against the keyword list. The query variation index is stored in the variable QVI and calculated according to the definition in Equation 3. The calcu-

[15] The class numbers determine the relative frequency of word forms. A form belongs to the class N if one of the most frequent forms appears 2^N more often than that form.

lation uses data from the conventional AdWords search query report. Finally, the two content-related keyword criteria—namely, location name and advertiser name—are represented by the binary variables LOC and ADV, respectively. If the advertiser's name or location is included in the keyword text, the respective variable is assigned the value of 1 (otherwise 0).

To address observed heterogeneity and avoid bias from omitted variables (Greene, 2002), the model features a comprehensive set of covariates. The author only uses predictors that have been found to significantly influence a keyword's CTR in previous empirical work. Keyword length (LEN) represents the length of a keyword text measured as the number of terms separated by blanks. For example, it is 1 for the keyword "car" and 2 for "car insurance" (and so on). Ghose and Yang (2009) find a negative relationship between keyword length and CTR, arguing that longer keywords attract more focused, goal-directed consumers who tend to only click on highly relevant ads. In addition to the absolute keyword length, the author considers the average difference between keyword and query length for a given keyword (LDIFF). Extant literature shows that if a query deviates from a keyword in terms of length, there is a high likelihood that the query is a generalization or specification of a keyword (Lau & Horvitz, 1998). This may imply that the users search for something other than what the keyword represents, leading again to a lower CTR for that keyword. The author measures the difference as the percentage of clicks on a keyword that is triggered by queries that contain either more or less terms than the keyword. The relationship between an ad's display position (POS) and the CTR has been well studied and consistently found to be positively related: because of increased visual attention and signaling effects, ads with higher ranks (where 1 indicates the first position in the results list from the top, 2 the second position, and so on) have better CTRs (e.g., Animesh et al., 2011; Brooks, 2004; Ghose & Yang, 2009; Joachims, Granka, Pan, Hembrooke, & Gay, 2005; Rutz & Bucklin, 2007). The rank variable was log transformed, in line with Animesh et al. (2011), who find that the position–CTR relationship is stronger on upper ranks.[16] To improve the user experience and increase expected income from paid search advertising, all major search engines use some kind of keyword-specific metric, often referred to as quality score (QS). This metric is calculated as a function of the landing page's "navigability as well as the relevance and transparency of information on that page" and the past click-through rate of the keyword (Ghose & Yang, 2009, p. 1609). Several studies have found a positive relationship between a keyword's CTR and its quality score or its historical CTR (e.g., Regelson & Fain, 2006; Yang & Ghose, 2011). Finally, 12 dummy variables ($IND_{i,k}$) are included to account for the advertisers' industry, as product-specific characteristics can influence users' click-through and conversion behavior (Animesh et al., 2011; Yang & Ghose, 2011).

[16] Using a linear rank variable leads to consistent results, but less variance is explained.

5.2.3 Data

The analyses are based on real-life data from Google AdWords campaigns in 2010. The author aggregated daily performance data on a keyword level over a six-month period and included advertisers from 13 industries (B2C and B2B) to ensure that the findings are broadly applicable and not limited to a certain business domain. All campaigns were managed by the same online marketing agency, which helps eliminate bias from different AdWords account structures and management practices. The data set is unique because all keywords are consistently booked on all three matching options (exact, phrase, and broad) at the same time. This allows observation of the keyword-specific traffic for each matching option individually and analysis of its effect on keyword performance (see Section 5.3).

Table 9 shows the descriptive statistics, and Table 10 shows the correlations between the variables. The sample contains 3,643 keywords with three observations per keyword—one for each matching option—amounting to 10,929 observations.

Descriptive Statistics (Study II)				
Variable	*Mean*	*Std. Deviation*	*Minimum*	*Maximum*
CTR	0.010	.025	.000	1.000
FL	14.119	2.901	6.000	17.000
LA	1.062	.331	1.000	6.000
QVI	.798	.166	0.123	1.000
LOC	.068	.251	.000	1.000
ADV	.007	.086	.000	1.000
LEN	1.185	.465	1.000	5.000
LDIFF	.757	.227	.000	1.000
POS	1.628	.649	-2.303	4.174
QS	5.049	1.378	.089	10.000
IND	*Nominal variable transformed into 12 dummies (13 industries)*			

Table 9: Descriptive Statistics (Study II)

Intercorrelations (Study II)										
	CTR	*FL*	*LA*	*QVI*	*LOC*	*ADV*	*LEN*	*LDIFF*	*POS*	*QS*
CTR	1									
FL	.129 (.000)	1								
LA	-.043 (.000)	-.168 (.000)	1							
QVI	-.425 (.000)	-.060 (.000)	.072 (.000)	1						
LOC	-.021 (.025)	.120 (.000)	-.050 (.000)	-.047 (.000)	1					
ADV	.387 (.000)	.084 (.000)	-.016 (.091)	-.184 (.000)	-.023 (0,014)	1				
LEN	.099 (.000)	.045 (.000)	-.047 (.000)	-.114 (.000)	.503 (.000)	.113 (.000)	1			
LDIFF	-.010 (.292)	.074 (.000)	.015 (.129)	.119 (.000)	-.272 (.000)	-.089 (.000)	-.366 (.000)	1		
POS	-.266 (.000)	-.217 (.000)	-.027 (.004)	.124 (.000)	-.068 (.000)	-.207 (.000)	-.206 (.000)	-.132 (.000)	1	
QS	.261 (.000)	.020 (.033)	.010 (.277)	-.090 (.000)	.011 (.245)	.087 (.000)	.121 (.000)	-.055 (.000)	.182 (.000)	1

Notes. *p*-values (two-sided) are reported in parentheses below the correlation coefficients.

Table 10: Intercorrelations (Study II)

5.2.4 Results

Table 11 shows the results of the regression analysis. The author followed a stepwise approach beginning with already-known predictors for keyword CTR (Base Models 1 and 2). He then introduced new features in Model 3 to determine their incremental contribution to the predictive power of the model.

Estimation Results (Study II)									
	Base Model 1		*Base Model 2*		*Model 3*				
Variable	*b*	*p*	*b*	*p*	*b*	*S.E.*	*t-value*	*p*	*ΔR² in*
FL (b_1)					.001	< .001	7.962	< .001	.003
LA (b_2)					-.003	.001	-5.122	< .001	.001
QVI (b_3)					-.043	.001	-34.669	< .001	.064
LOC (b_4)			-.001	.163	-.002	.001	-2.106	.035	< .001
ADV (b_5)			.092	< .001	.076	.002	33.283	< .001	.059
LEN (b_6)	.001	.306	.001	.286	-.001	.001	-1.016	.309	< .001
LDIFF (b_7)	-.008	< .001	-.004	< .001	-.001	.001	-.929	.353	< .001
POS (b_8)	-.013	< .001	-.010	< .001	-.007	< .001	-20.629	< .001	.023
QS (b_9)	.005	< .001	.004	< .001	.004	< .001	25.324	< .001	.034
$IND_{[2..I]}$ ($\mu_{[2..I]}$)		< .001		< .001				< .001	.064
Constant (b_0)	.007	< .001	.003	.034	.029	.002	13.312	< .001	
R^2	.288		.380		.453				
N	10,929								

Table 11: Estimation Results (Study II)

Base Model 1 only includes covariates, which in total explain 29% of the variance in CTR. Except for keyword length (LEN), all coefficients are significant and show the expected effects: the lower the CTR, the more often the keyword is matched to longer/shorter user queries (LDIFF), the lower is the display position of the corresponding ad in the result list (POS), and the is lower its quality score (QS). Furthermore, industry dummies explain a significant share of variance in CTR. This is not surprising, because consumer click-through behavior may vary depending on the nature of the good, which is reflected in the keyword. In Base Model 2, the R-square statistic can be significantly increased by 9 percentage points to 38% ($F_{2,10910}$ Change = 754.533, $p < .001$) by introducing two features related to a keyword's intrinsic and extrinsic information content. Whereas the presence of location name (LOC) in the keyword text does not significantly affect the CTR, the influence of an advertiser's name (ADV) is extremely strong ($b_5 = .092$, $p < .001$). If present in the keyword text, it increases the CTR on average by 9.2 percentage points. Including the new keyword characteristics in Model 3 again leads to a significant improvement in terms of explained variance (ΔR-square = .073, $F_{3,10907}$ Change = 456.012, $p < .001$), resulting in an R-square of 45%. Note that the probability of unstable coefficient estimates due to multicollinearity is low. All VIFs range between 1 and 2 and are well below the proposed critical level of 10 (Kutner et al., 2004).

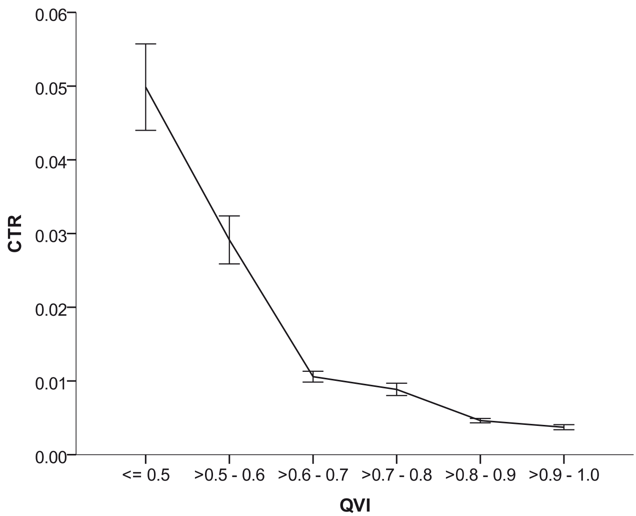
The coefficient of the frequency in language variable (FL) is positive and significant ($b_1 = .001$, $p < .001$): the CTR increases with a decreasing keyword frequency.[17] If included in the fully specified Model 3, the increase in R-square is significant (ΔR-square = .003, $F_{1,10907}$ Change = 63.397, $p < .001$). Therefore, H_1 is supported, which implies that Shannon's law—less frequent words have higher information content—also holds in the context of paid search advertising. For the second language-related keyword criterion, lexical ambiguity (LA), there is also a significant effect on CTR ($b_2 = -.003$, $p < .001$) and again a significant increase in R-square if LA is added to the fully specified model (ΔR-square = .001, $F_{1,10907}$ Change = 26.236, $p < .001$). Thus, H_2 also can be accepted: keywords with more than one semantic meaning have a lower CTR. Finally, the author examines the coefficient of the QVI and finds that it has the strongest influence on the dependent variable of all predictors ($b_3 = -.043$, $p < .001$) and explains the largest share of its variance (ΔR-square = .064, $F_{1,10907}$ Change = 1,201.908, $p < .001$).

Figure 30 shows that CTR decreases monotonically with an increasing query variation. H_3 can be therefore accepted. The more different search queries are matched to a keyword, the lower its specificity and therefore its intrinsic information content. That none of the keyword length–related measures (LEN, LDIFF) are significant in Model 3 implies that the QVI is, as suspected, a better measure for the keyword specificity than its length. In total, all intrinsic

[17] Recall that the frequency classes are coded in such a way that a higher class number indicates a lower frequency.

keyword characteristics explain 16% of the variation in CTR, with the presence of an advertiser's name (ADV) and the query variation (QVI) as main predictors. Before implications from these results are discussed, analysis is further extended to incorporate the effects of the advertiser's decision on the keyword matching options. According to the theoretic model, this external effect may influence the relationship between the intrinsic information criteria and keyword performance.

QVI–CTR Relationship



Notes. Error bars indicate 95% confidence interval.

Figure 30: QVI–CTR Relationship

5.3 Extended Model for Keyword Performance in Search Engine Advertising

Because the advertiser's name (ADV) and query variation (QVI) were found to be the main predictors for CTR, it is relevant to understand if and how these relationships are influenced by the advertiser's decision on matching options. According to the theoretical framework, matching options define a keyword's *extrinsic* information content: they are not directly related to the keyword text. The same keyword can be booked on one or more matching options; in this case, the intrinsic information does not change, but the extrinsic information and consequently the entire information content vary with the matching option. To better understand the impact of this phenomenon on keyword performance, the theoretical model is extended with interaction terms and estimated through a moderated multiple regression (MMR) analysis (Figure 31). The author chooses this sequential approach and tests the interactions only on the most relevant predictors—ADV and QVI—to keep the model as parsimonious as possible.[18]

Extended Model with Matching Options for Keyword Performance in SEA

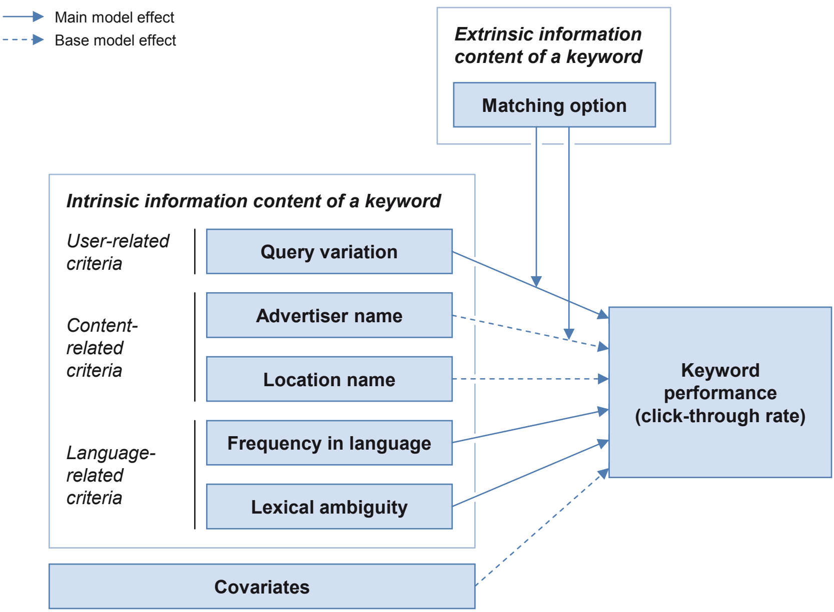


Figure 31: Extended Model with Matching Options for Keyword Performance in SEA

5.3.1 Hypotheses

5.3.1.1 Interaction: Matching Option–Advertiser Name

Along with other empirical work, in the previous section this study showed that keywords containing an advertiser's name have a significantly higher CTR than keywords without an advertiser's name. However, not examined to date is whether this relationship varies with the selected matching option. As mentioned in the beginning of Section 5, generic match types (*broad* and *phrase*), in contrast with *exact* match, permit a less specific match between a user query and an advertiser's keyword. The hypotheses are derived directly from these properties. Dividing consumers into two imaginary groups helps illustrate the phenomenon: Group A

[18] However, to ensure validity of the results, another model was estimated that included interaction terms for all predictors. It produced results consistent to those presented in Table 13.

searching for a specific advertiser with the firm name contained in search queries (e.g., "joe's pizza"), and Group B performing a more general inquiry without any particular advertiser in mind or in search queries (e.g., "italian restaurant"). According to previous research (Ghose & Yang, 2009; Rutz & Bucklin, 2007) and the findings from Section 5.2, compared with Group B, users from Group A will show a higher likelihood to click on an ad from the specific advertiser they searched (e.g., "joe"). Consequently, the larger the share of users from Group A on an advertiser-specific keyword, the higher is its CTR. How do the matching options allocate these two groups to an advertiser keyword ("joe's pizza")? On *exact* match, only consumers from Group A will appear because all search queries must match the keyword precisely and thus contain the advertiser's name. In contrast, *broad* match by definition also matches user queries with less or even completely different terms to a keyword (Gupta et al., 2009). This may also include queries from Group B's users that did not search for any advertiser-specific information. Consequently, there is a high likelihood that at least some consumers from Group B are matched to the keyword "joe's pizza" if booked on *broad* match. The author therefore hypothesizes that the CTR increase through the advertiser name feature (ADV) is smaller for *broad* than for *exact* matches.

> HYPOTHESIS 4A (H_{4a}): If booked on *broad* match, the CTR increase from advertiser-specific information in the keyword text (ADV) is weaker than for *exact* matching.

A similar effect may apply to *phrase* matches. According to the grouping logic, only users from Group A are matched to an advertiser-specific keyword booked on this option, because *phrase* requires all keyword terms, including the advertiser's name, to be present in the user's search query. In contrast with *exact*, however, queries may contain additional terms (Google, 2010b). These terms can change the meaning of the user query, resulting in a semantic mismatch (Radlinski et al., 2008). Because the retrieval system does not recognize this, it matches the query to the advertiser-specific keyword and presents an irrelevant (or at least less relevant) ad to the user. This eventually leads to a lower user response. For example, consider again the keyword "joe's pizza", with "joe" as the advertiser's name. If a user searches for "alternatives to joe's pizza", Joe's ad will appear if booked on *phrase*, though the context is entirely different. The likelihood of a click from a user with that search query is presumably low. Additional terms will also leave the original context unchanged (e.g., "joe's pizza restaurant"), but all in all, a certain share of users will be matched to an advertiser-specific keyword booked on *phrase*, even though they searched for something else. Similar to *broad*, it is therefore hypothesized that the effect of the advertiser name characteristic (ADV) is weaker if the keyword is booked on *phrase* than if it is booked on *exact*.

HYPOTHESIS 4B (H_{4b}): If booked on *phrase* match, the CTR increase from advertiser-specific information in the keyword text (ADV) is weaker than for *exact* matching.

5.3.1.2 Interaction: Matching Option–Query Variation

Section 5.2 shows that the specificity of keywords, measured by the variation in search queries on a given keyword (QVI), has a strong impact on its CTR. The author based his theoretical explanation for this effect primarily on keywords booked on *phrase* or *broad* match.[19]

Now, in a more differentiated view, the author argues that this relationship also holds for *exact* match: if an unspecific keyword (with a high QVI) is booked on *exact*, it can only be matched to the same unspecific query; Jones et al. (2006, p. 1) interpreted this as an "imperfect description of [a user's] information need". Consequently, the likelihood that the selected ad will be relevant to the user's information need is rather low, and vice versa. This is a fundamental issue in information retrieval, and it is generally accepted that a plain keyword match, as in the case of *exact* match, can lead to inferior retrieval results (e.g., Mitra, Singhal, & Buckley, 1998; Qiu & Frei, 1993; Xu & Croft, 1996).[20] For example, imagine the keyword "car": the advertiser could be a dealer, an insurance company, or a rental car provider. The same applies to the query: a user searching for "car" could be looking for a new car, insurance, and so on. Because this informational domain is rather large and keyword and query are on a very high level within this domain, the likelihood that the ad will be relevant for the user is low. The situation is similar for unspecific keywords booked on *phrase* match, in which precise queries can be matched to an unspecific and irrelevant keyword. This means that queries such as "rental car new york" or "car insurance comparison" can be matched to the keyword "car" of a car dealer, if it is booked on *phrase*.

Although the author hypothesizes that the direction of the effect is the same for all three matching options, this is not true for the magnitude of the effects. The case of high keyword specificity (and correspondingly low QVI) is considered first: here, according to the findings in Section 5.2, the keyword text carries sufficient information to properly resolve the advertiser's information offer. In this case, an *exact* or *phrase* match with the same precise text as the description of the user's information need will lead to relevant ads. This is not the case for unspecific keywords with high QVI. Again, as shown in Section 5.2.4, these keywords carry too little information to identify their meaning precisely. In the case of *exact* match, an unspecific query is then matched to the same unspecific keyword. In the case of *phrase* match, many different (though more precise) queries can be matched to a single unspecific keyword.

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19 The QVI can only be measured for keywords booked on generic matching options, because there is no query variation on *exact* keywords.

20 Addressing this problem has been a major goal in IR research in the past decades. A common technique to deal with short and unspecific queries is called "query expansion" (Qiu & Frei, 1993).

Both situations, as explained previously, lead to inferior retrieval results. In this situation, *broad* match can outperform *exact* and *phrase* match because it allows the use of query expansion techniques to identify other relevant queries for a given keyword (Google, 2011d). Information retrieval research has shown that such techniques outperform simple keyword matches based on Boolean exact-match models, especially in the case of unspecific terms and lack of information in keywords and queries (Mitra et al., 1998; Turtle, 1992).

HYPOTHESIS 5A (H_{5a}): An increasing QVI decreases a keyword's CTR more if the keyword is booked on *exact* match rather than on *broad* match.

HYPOTHESIS 5B (H_{5b}): An increasing QVI decreases a keyword's CTR more if the keyword is booked on *phrase* match rather than on *broad* match.

5.3.2 Research Model

The author employs an MMR to test the hypotheses regarding the extrinsic information content of keywords. Consistent with the approach in Section 5.2.2, the author maintains the weighting of the observations and includes the covariates also in the extended research model, as follows:

$$\begin{aligned} CTR_{k,m} = {} & b_0 + b_1FL_k + b_2LA_k + b_3QVI_k + b_4LOC_k + b_5ADV_k \\ & + b_6LEN_k + b_7LDIFF_k + b_8POS_{k,m} + b_9QS_{k,m} \\ & + S_{i=2..I}(\mu_i IND_{i,k}) + b_{10}B_{k,m} + b_{11}P_{k,m} + b_{12}ADV_k \times B_{k,m} \\ & + b_{13}ADV_k \times P_{k,m} + b_{14}QVI_k \times B_{k,m} + b_{15}QVI_k \times P_{k,m} + e_{k,m}, \end{aligned} \tag{5}$$

where

B, P = dummy variables for the keyword matching option (exact: B = 0 and P = 0; phrase: B = 0 and P = 1; broad: B = 1 and P = 0).

Matching options are coded with the dummy variables B and P. There are three observations per keyword, one for each matching option. This within-subjects design is advantageous because the same groups are compared. Thus, this approach eliminates any between-subjects variance that might arise when different keywords for each matching option are considered (Greenwald, 1976). Conversely, because the analysis is conducted a posteriori, it also does not suffer from typical drawbacks of within-subject studies, such as sensitization, practice, or carryover effects.

5.3.3 Data

The analyses are performed using the data set described in Section 5.2.3. As mentioned previously, the data set is unique, because each of the 3,643 keywords in the sample was simultaneously booked on all three matching options.[21] Doing so enables examination of the influence of individual traffic components for a given keyword: *exact* reflects traffic from users searching exactly for the keyword terms, *phrase* represents traffic in which users search for the keyword terms plus something else, and *broad* represents traffic from users who do not enter all the keyword terms or search for a related term (e.g., “BMW” instead of “car”). In contrast, if a keyword is booked on only one matching option at a time—a common practice in campaign management—distinguishing between the performance of these individual traffic components is impossible. Whereas that particular booking strategy is required to perform the analyses, the findings and implications are not limited to any specific form of campaign management practice.

To test the hypotheses, the author calculated the interaction terms by multiplying the centered predictor variables ADV and QVI with the matching options dummies. Centering helped account for potential problems that could arise from multicollinearity (Aiken & West, 1991). Table 12 shows the correlation coefficients, including the interactions.

[21] According to Google (2011b), if the same keyword is simultaneously booked on several matching options, the system matches the user query to the most restrictive one, independent of other factors, such as the maximum bid. Therefore, it can be safely assumed that the allocation of traffic is not influenced by other unobserved parameters.

Intercorrelations, Including Interaction Terms (Study II)

	CTR	FL	LA	QVI	LOC	ADV	LEN	LDIFF	POS	QS	B	P	ADV x B	ADV x P	QVI x B	QVI x P
CTR	1															
FL	,129	1														
	(,000)															
LA	-,043	-,168	1													
	(,000)	(,000)														
QVI	-,425	-,060	,072	1												
	(,000)	(,000)	(,000)													
LOC	-,021	,120	-,050	-,047	1											
	(,025)	(,000)	(,000)	(,000)												
ADV	,387	,084	-,016	-,184	-,023	1										
	(,000)	(,000)	(,091)	(,000)	(,014)											
LEN	,099	,045	-,047	-,114	,503	,113	1									
	(,000)	(,000)	(,000)	(,000)	(,000)	(,000)										
LDIFF	-,010	,074	,015	,119	-,272	-,089	-,366	1								
	(,292)	(,000)	(,129)	(,000)	(,000)	(,000)	(,000)									
POS	-,266	-,217	,027	,124	-,068	-,207	-,206	-,132	1							
	(,000)	(,000)	(,004)	(,000)	(,000)	(,000)	(,000)	(,000)								
QS	,261	,020	,010	-,090	,011	,087	,121	-,055	,182	1						
	(,000)	(,033)	(,277)	(,000)	(,245)	(,000)	(,000)	(,000)	(,000)							
B	-,056	-,054	-,018	-,056	,030	-,044	,078	-,105	-,058	-,131	1					
	(,000)	(,000)	(,064)	(,000)	(,001)	(,000)	(,000)	(,000)	(,000)	(,000)						
P	,024	-,096	-,012	,032	-,111	-,030	-,159	,110	,133	,053	-,500	1				
	(,014)	(,000)	(,202)	(,001)	(,000)	(,002)	(,000)	(,000)	(,000)	(,000)	(,000)					
ADV x B	,075	,025	-,005	-,043	-,007	,302	,037	-,009	-,058	,005	,037	-,019	1			
	(,000)	(,009)	(,609)	(,000)	(,460)	(,000)	(,000)	(,360)	(,000)	(,621)	(,000)	(,053)				
ADV x P	,112	,034	-,007	-,053	-,010	,410	,040	-,002	-,079	-,003	-,025	,050	-,001	1		
	(,000)	(,000)	(,488)	(,000)	(,316)	(,000)	(,000)	(,866)	(,000)	(,768)	(,009)	(,000)	(,922)			
QVI x B	-,099	-,037	,009	,602	-,004	-,018	-,052	,120	,067	-,052	-,062	,031	-,071	,002	1	
	(,000)	(,000)	(,333)	(,000)	(,691)	(,059)	(,000)	(,000)	(,000)	(,000)	(,000)	(,001)	(,000)	(,870)		
QVI x P	-,273	-,006	,058	,531	-,032	-,044	-,031	-,039	,065	,028	-,020	,041	-,001	-,102	,001	1
	(,000)	(,509)	(,000)	(,000)	(,001)	(,000)	(,001)	(,000)	(,000)	(,004)	(,033)	(,000)	(,937)	(,000)	(,894)	

Notes. *p*-values (two-sided) are reported in parentheses below the correlation coefficients.

Table 12: Intercorrelations, Including Interaction Terms (Study II)

5.3.4 Results

Table 13 presents the results of the MMR (Model 4). Adding the interaction terms and keyword dummies to the model from Section 5.2.2 leads to a significant increase in R-square of 4% ($F_{6,10901}$ Change = 107.010, p < .001), resulting in a total R-square of 49%. All criteria related to a keyword's information content (intrinsic and extrinsic) explain 20% of the variance in CTR, and the covariates account for another 19%.

Estimation Results, Including Interaction Terms (Study II)

	Model 3		*Model 4 (including interactions)*				
Variable	*b*	*p*	*b*	*S.E.*	*t-value*	*p*	*ΔR² in*
FL (b_1)	.001	< .001	.001	< .001	9.352	< .001	.004
LA (b_2)	-.003	< .001	-.002	.001	-3.850	< .001	.001
QVI (b_3)	-.043	< .001	-.060	.002	-29.890	< .001	.045
LOC (b_4)	-.002	.035	-.003	.001	-3.014	.003	< .001
ADV (b_5)	.076	< .001	.076	.003	28.879	< .001	.042
LEN (b_6)	-.001	.309	.000	.001	-.734	.463	< .001
LDIFF (b_7)	-.001	.353	-.003	.001	-3.369	.001	.001
POS (b_8)	-.007	< .001	-.008	< .001	-22.254	< .001	.025
QS (b_9)	.004	< .001	.004	< .001	25.567	< .001	.033
$IND_{[2..l]}$ ($\mu_{[2..l]}$)		< .001				< .001	.060
B (b_{10})			-.000	< .001	-.139	.889	.003
P (b_{11})			.003	< .001	7.266	< .001	
ADV × B (b_{12})			-.021	.007	-2.882	.004	.001
ADV × P (b_{13})			-.027	.006	-4.868	< .001	
QVI × B (b_{14})			.049	.003	18.600	< .001	.026
QVI × P (b_{15})			-.007	.003	-2.293	.022	
Constant (b_0)	.029	< .001	.042	.003	16.239	< .001	
R²	.453		.485				
N	10,929						

Table 13: Estimation Results, Including Interaction Terms (Study II)

Again, the results are not subject to unstable coefficients from multicollinearity, as all VIF scores in Model 4 range between 1 and 3.5, well below the critical threshold of 10 (Kutner et al., 2004). Adding the interactions does not change the coefficients from Model 3 substantially, but insofar as a change can be observed, the predictor's effect on CTR becomes stronger in almost every case (QVI, LOC, LDIFF, and POS). This indicates that in general, the effect strength is higher on *exact* matches than generic matching options.

The analysis reveals that matching options affect the relationship between the intrinsic keyword characteristic advertiser name (ADV) and a keyword's CTR. Coefficients of the interaction terms for both matching options are statistically significant and negative, in support of H_{4a} and H_{4b}: the positive effect of advertiser-specific information is weaker on generic matching options (b_{12} = –.021, p = .004; b_{13} = –.027, p < .001). On average, the presence of an advertiser's name in the keyword text increases its CTR by 7.6% if the keyword is booked on *exact*, but only by 5.5% if booked on *broad* and 4.9% for *phrase*.

Table 13 also shows that both coefficients for the matching option interaction terms with QVI are statistically significant (b_{14} = .049, p < .001; b_{15} = –.007, p = .022). To examine the moderating effect of matching options at low and high levels of query variation, Figure 32 plots this two-way interaction.

Interaction between QVI and Matching Options

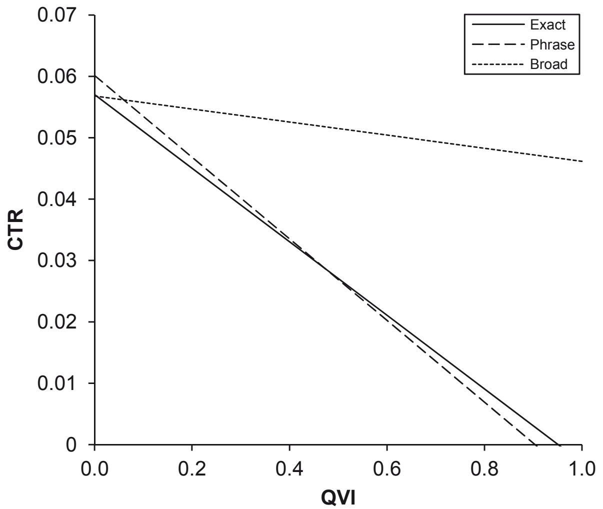

Figure 32: Interaction between QVI and Matching Options

Figure 31 shows the cumulative effect by taking the interaction terms into account. The author finds that matching options influence the magnitude but not the direction of the relationship between QVI and CTR: in all three cases, a higher query variation leads to lower CTRs. However, the performance of keywords booked on *exact* or *phrase* match decreases significantly more with an increasing QVI than the CTR of *broad* match keywords. Therefore, H_{5a} and H_{5b} can be accepted.

In summary, the analysis shows that a keyword's extrinsic information content, defined by its matching options, moderates the effect of ADV and QVI on its individual CTR. Generic matching options reduce the CTR for keywords with advertiser-specific information in the keyword text. This finding is consistent with the hypothesis that the noise from *broad* and *phrase* matching mechanisms (term addition, removal, or replacement) leads to a certain share of irrelevant matches. However, the results also reveal that *broad* matching options can improve the CTR of keywords with high query variation, compared with *exact* and *phrase* match. The results suggest that *phrase* match plays a double role as moderator: in terms of the ADV–CTR relationship, it behaves like a *broad* match, whereas it is highly similar to an *exact* match in the QVI–CTR relationship. This implies that keyword specificity in terms of advertiser-specific information and query variation should be definitely considered, when deciding on the matching options.

5.4 Discussion and Implications

5.4.1 Research Implications

In this study of the thesis, the author presents a model for the effectiveness of paid search campaigns and estimates it using a large data set representing advertisers from multiple industries. The study makes four major contributions to research in online advertising, an emerging stream in both information systems and marketing research.

First, this study is the first to formulate a theoretical model that explains the click-through performance of individual keywords in paid search campaigns. It fills a significant gap, as related work lacks theoretically grounded explanations for the observed phenomena: marketing literature has tended to focus on methodological issues, such as development and empirical application of Bayesian estimation techniques (e.g., Ghose & Yang, 2009, 2010; Rutz & Bucklin, 2007, 2011), and studies in information retrieval have primarily dealt with technical problems, such as improving ad selection algorithms for search engines (e.g., Hillard et al., 2010; Regelson & Fain, 2006; Richardson et al., 2007). By integrating theory and previous research from linguistics, information retrieval, and marketing, the author develops a comprehensive model and shows that a keyword's click-through performance is heavily influenced by its information content. This interdisciplinary approach has a clear value. Adding these features to a base model with known covariates increases the share of explained variance in CTR by 20%, to a total of nearly 50%. This gain originates equally from criteria related to marketing (*advertiser name*) and linguistics and information retrieval (*frequency in language, lexical ambiguity, QVI*). To the best of the author's knowledge, this is the highest R-square for a CTR model on a keyword level based on transactional log data.

Second, this study complements extant literature on matching options with an advertiser perspective and integrates them as extrinsic information content in the model. So far, IR research has exclusively covered this topic from the perspective of search engines (e.g., Gupta et al., 2009; Jones et al., 2006; Radlinski et al., 2008). Taking the advertiser perspective is equally important because choosing the "right" matching option constitutes a core task in campaign management, and existing knowledge is sparse. Holding all other keyword-related factors constant, the analysis reveals that matching options can significantly influence click-through performance and that *phrase* keywords can behave like *broad* or *exact* keywords, depending on the moderated relationship.

Third, the findings of this study provide support for prior research and offer new insights derived from the joint analysis with matching options. In line with Rutz and Bucklin (2007) and Ghose and Yang (2009), the analysis shows that keywords containing the advertiser's name have significantly higher CTRs on average. Yet, when comparing the results from the joint analysis from this study with their prior individual analyses, the author finds that this effect is strongly moderated by matching options: for *exact* keywords, the increase in CTR due to the presence of an advertiser name in the keyword text is approximately 50% higher than that for *phrase* or *broad* keywords. This can be explained by the larger share of irrelevant matches, as generic matching options can alter the context (*phrase*) or remove the advertiser name from the keyword text (*broad*). The author also applied well-known principles from linguistic and information theory for the first time to paid search advertising and showed that they are valid in this context: more frequent words carry less information (Luhn, 1958; Shannon, 1949; van Rijsbergen, 1979), and ambiguous words can lead to retrieval problems (Krovetz & Croft, 1992; Stokoe, 2005). Both conditions result in a less effective matching of information need and offer and consequently lead to lower keyword CTRs and user response.

Fourth, the author develops a new index that provides a powerful tool for both academics and practitioners to predict keyword performance. In contrast with related literature (Belkin et al., 2003; Finkelstein et al., 2002; Ghose & Yang, 2009; Jones et al., 2006; Xu & Croft, 1996), he finds that the commonly used length of a keyword is not a good indicator of its information content. Keyword length does not account for the context of the keyword ("informational domain"). Even short keywords can be specific and carry sufficient information if they are in a small informational domain, and vice versa. The new measure *QVI* addresses this problem and provides a significantly better read on keyword specificity. Information retrieval, especially search log analysis and user search modeling, constituted the theoretical foundation for this indicator. QVI turns out to be the strongest individual predictor of keyword performance, explaining more than 6% of the variance in CTR (Model 3). In the same model, the coefficient for the covariate keyword length is not significant (even at $\alpha = 10\%$). The results also show that the relationship between QVI and CTR is heavily influenced by keyword matching options. Keywords on *broad* match seem to be less sensitive to a reduction in specificity than *phrase* or *exact* keywords. This suggests that the query expansion techniques used by search engines are helpful in selecting more relevant ads.

Because of its high predictive power with regard to CTR, query variation should replace corresponding measures in related studies. Furthermore, it could be used in other IR settings to evaluate the quality of document indices (e.g., organic web search or conventional database queries). High QVIs would then indicate that the index is too generic to represent knowledge items within the corresponding informational domain, and a more specific index could lead to better retrieval results.

5.4.2 Managerial Implications

The empirical results offer actionable managerial implications for improving day-to-day campaign management. First, they reaffirm that the covariates *display position*, *quality score*, and *industry dummies* are helpful in predicting CTRs. However, the fully specified Model 4 shows that their share of explained variance is rather low (e.g., 2% for *display position*). This suggests that many practitioners overestimate the influence of *display position* on CTR, which can lead to wrong assumptions for campaign strategies. Second, and in line with previous studies, keywords incorporating advertiser names show significantly higher CTRs. This effect is very strong, which underscores the importance of bidding on advertiser-specific keywords, if the CTR of a paid search campaign is maximized. What has not been shown so far is that this relationship heavily depends on matching options: the CTR increase is roughly 50% higher on *exact* match than on generic matching options. Thus, advertisers should understand that setting the appropriate matching options is especially important for advertiser-specific keywords. Third, linguistic features affect keyword performance. The more frequently a keyword appears in the German language and the more different meanings it has, the lower is its CTR. Incorporating this finding in information systems for campaign management (e.g., through automated notifications for high-frequency words) can make ads more relevant for search engine users. Fourth, the variation in user queries matched to a specific keyword heavily influences the CTR. This finding has several key implications. Most important, advertisers should be aware of its influence and constantly measure query variation for their keywords. This information can be used as diagnostic in the case of inferior keyword performance: if the QVI of a slow-performing keyword is high, too many different queries are matched to it (i.e., the keyword is not specific enough). As a remedy, advertisers can bid on several additional keywords that reflect the query variations more precisely. This is relevant in practice and promises significant improvements in campaign performance, as more than 50% of the clicks in the sample, though managed by a professional agency, are generated through keywords with a QVI of 0.8 and above. Because the QVI can be calculated with information available through the search engine’s application programming interface, it can be easily incorporated into algorithms of automated bid management systems. Finally, matching options also significantly influence the relationship between QVI and keyword performance. Whereas there is little difference for specific keywords with a low query variation, *broad* matches perform tremendously better on unspecific keywords. Understanding this relationship can lead to further improvements by employing more differentiated campaign management techniques.

5.4.3 Limitations and Further Research

The study's limitations mainly arise from the data set. First, no information is available on the advertising texts displayed to the users. As Animesh et al. (2011) and Ghose and Yang (2009) argue, ad texts may influence click-through behavior. Although considering texts in the analysis could further increase the share of explained variance in CTR, the author believes that the estimates are not biased from omitting this information. The reason for this assumption is that noise from different texts is diminished because advertisers use the same set of ads across several keywords, regardless of the matching option. Second, although advertisers from several industries were chosen to ensure broad applicability of the findings, all campaigns are managed by a single agency. On the one hand, this helps eliminate potential noise from different management practices; on the other hand, it requires empirical proof that the findings can be generalized to other settings. The author believes this is the case because the study controls for statistics (e.g., display position, quality score) that are influenced by campaign management. The third limitation pertains to the dependent variable, which measures CTRs instead of real conversions. Although sales data would be the ultimate measure for relevance, conversions are influenced by many other factors that are difficult to control (e.g., landing page design). In line with other studies in a paid search context (e.g., Animesh et al., 2011; Ghose & Yang, 2009; Richardson et al., 2007; Rutz & Bucklin, 2011), the focus is on CTR, which is closely related to the actual search process and a commonly used core metric in paid search advertising. Fourth, the author bases the analyses solely on transactional click-through data and does not ask individual users for their preferences that could reveal underlying cognitive drivers of perceived relevance. This is also the case in previous studies. Finally, the data set features only paid search campaigns on Google. The generalizability to other search engines needs empirical proof, though paid search programs have converged over time and now virtually follow the same rules and mechanisms. In contrast, there is little need for generalization in countries such as Germany, where Google's market share is greater than 93% (Webtrekk, 2011).

Several promising areas for further work also arise from this study. The first pertains to the query variation concept, in which three potential topics emerge: further exploring and validating the conceptual model behind the QVI (e.g., finding evidence that the QVI is influenced by the size of the informational domain and its position within it), integrating the QVI into technical algorithms for improving paid search campaigns, and analyzing whether the QVI also influences consumer decisions at a more advanced stage in the buying process (e.g., purchases, sign-ups). Second, researchers could conduct confirmatory studies to validate the findings for other search engines or different campaign management practices.

Similar to the first study, findings from this chapter provide a major input to an integrated framework for online advertising, which is drafted in Section 6.4.

6 Conclusion, Implications, and Outlook

The relevance of online advertising has substantially increased in the past several years (Section 2.2). However, both research and practice have not been able to keep pace and develop a structured body of knowledge in this area. Existing work in this field is phenomenologically driven and selective, which leaves crucial questions unanswered (Sections 1.1 and 3.1). This thesis aims to provide answers to some of those questions. It provides a theoretical foundation to better understand what influences the effectiveness of multichannel online advertising (Chapter 4) and search engine advertising (Chapter 5). Both frameworks were empirically validated using large sets of previously unavailable data. In the following section, conclusions from both studies are presented (Sections 6.1.1 and 6.1.2) before overall conclusions are drawn from both projects (Section 6.1.3). Theoretical (Section 6.2) and managerial (Section 6.3) implications of this work are discussed. Finally, Chapter 6.4 outlines an integrated framework for online advertising. It builds on key findings from this thesis, as well as previous work, and describes a holistic approach to online advertising based on three guiding principles: *transparency*, *integration*, and *execution based on sophisticated channel knowledge*. Figure 33 shows the structure of this chapter.

Structure of Chapter 6

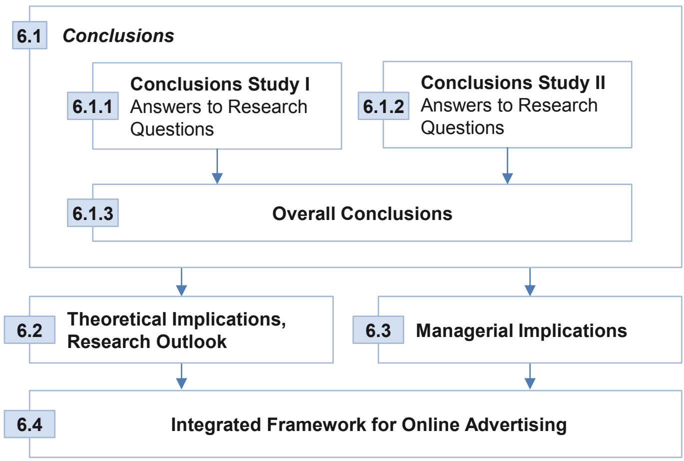

Figure 33: Structure of Chapter 6

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6.1 Conclusion

A multitude of conclusions can be drawn from this work. Key findings from each project of this thesis are summarized before conclusions are drawn from a joint consideration of both studies.

6.1.1 Conclusions from Study I

The first study in this thesis attempted to shed light on multichannel online advertising by answering the following three research questions:

1. Can simultaneous advertising on multiple online channels increase purchase propensities when targeting individual users?
2. If so, is there a difference in the effects, depending on the sequence of the channels in the user journey of individual consumers?
3. Do these effects differ for existing versus new customers?

The answer to Question 1 is a clear yes. The study produced the first empirical evidence for multichannel synergies in online advertising. On average, every additional channel in a user journey more than doubles the likelihood of purchase. This is a significantly higher uplift than that from an additional exposure on the same channel (which lifts the conversion likelihood approximately 50%). Building on research from the offline context, Study I relies on the ELM to explain this effect: consumers are more likely to elaborate multisource messages through the central route of persuasion. This means that they cognitively process message arguments (rather than inferring message content from peripheral clues), resulting in a more favorable attitude change toward the advertiser.

Answering Question 2 shows that consumers use different online channels, depending on their stage in the purchase decision-making process. When they browse from information to navigation channels, this can be an indication that they made progress in their purchase decision and included the advertiser in their consideration set. The analyses produced evidence that, in this case, advertising on navigation channels (i.e., search engines and newsletters) can be highly favorable: conversion likelihoods more than quadrupled. However, when consumers browse channels in the other direction (navigation to information), they have not yet developed a clear preference for the advertiser or even excluded the firm from their consideration set. Advertising on information channels can be disadvantageous in this case. A decrease in conversion likelihood of 30% occurred.

Question 3 can be approved, because advertising works differently for new and existing customers. For existing customers, channel switching effects were stronger, whereas multichannel synergies decreased. With framing and usage dominance effects as an explanation, these effects are expected to vary by product category.

6.1.2 Conclusions from Study II

The second study in this thesis comprised an in-depth investigation into search engine advertising and explored the following two questions.

1. What criteria can be used to select keywords and evaluate their performance in a systematic way?
2. How do matching options influence the effect of these criteria on keyword performance?

With regard to Question 1, the study identified three different types of criteria that significantly affect a keyword's CTR. From the content-related characteristics (properties referring to the actual meaning of the keyword text), the analysis reconfirmed the positive effect of advertiser names in keywords. The CTR of such keywords was, on average, nearly eight percentage points higher than those without the advertiser's brand name. The reason is that consumers searching for the advertiser's brand name are in a navigation mode, with the clear objective to browse the advertiser's website. Language-related criteria also influenced CTRs. The more often a keyword appears in language, the more generic it is and the lower is its CTR. This is in line with Shannon's law, which postulates that more frequent words carry less information. Another finding from this category was that keywords with more than a single meaning also generate lower response. The information content of such words is lower, because additional information (e.g., the context) is required to resolve their meaning properly. However, one of the most influential keyword characteristics belongs to the class of user-related keyword criteria—namely, QVI, which implicitly measures keyword specificity by evaluating the number of different user queries that are matched on a single keyword; a large number indicates that the keyword is too generic. On average, keywords with high QVI exhibited substantially lower CTRs. Except for the first criterion (advertiser name), all characteristics have not been used previously in the context of search engine advertising and therefore provide significant potential for improved keyword selection and evaluation in practice.

To shed light on Question 2, the study analyzed whether matching options affect the relationship between CTR and its strongest predictors: advertiser name and query variation. The results show that the CTR uplift from the advertiser's name in keywords was substantially larger for exact than phrase or broad keywords. This implies that setting the correct match type is particularly important on such keywords: a strategy to maximize campaign CTR would use these advertiser brand keywords on exact match only. Matching options also affect the QVI–CTR relationship in such a way that broad keywords are less sensitive to an increasing query variation than phrase or exact keywords. As a result, the adverse impact of high query variation is less distinct for broad keywords. Again, if the campaign goal is to maximize CTR, keywords with high query variation should be booked on broad rather than exact or phrase match.

6.1.3 Overall Conclusions

From these findings, three overall conclusions can be drawn. First, a vast amount of **untapped potential** in online advertising remains. This applies to both research (i.e., need for models that better fit data and explain effects theoretically) and practice (i.e., need for more differentiated campaign management practices). The potential resides in two areas. On the one hand, a more sophisticated use of single channels can lead to significant improvements in ad effectiveness. Study II has shown this for search engine advertising. However, similar enhancements might be possible on other channels. On the other hand, improvements can be achieved through a more coordinated use of multiple online advertising channels. Empirical results from Study I underpin this argument.

Second, to unleash this potential, an **interdisciplinary approach**—in both practice and research—is important. Variables and concepts from this thesis that generated the most surprising insights and worked best to explain variance in the dependent variables were developed by combining different research areas. The studies mainly borrowed theories from marketing, linguistics, and information retrieval (which in itself is interdisciplinary and based on computer science, library science, information science, cognitive psychology, and statistics).

Third, from a holistic consideration of the results, **three guiding principles** for online advertising can be derived: transparency, integration, and execution based on sophisticated channel knowledge. With regard to *transparency*, analyses in both studies have shown that different situations require different advertising measures. For example, it is significantly better to reach consumers who have switched from information to navigation channels than vice versa. To implement such campaigns in practice, or formulate more sophisticated advertising effectiveness models in theory, transparency on the consumer's browsing history—that is, the user journey—is mandatory. A similar example could be provided for keyword characteristics in paid search advertising. However, creating transparency requires that highly granular data are available and used in theoretical and managerial models. With regard to *integration*, the user journey analysis has shown that individual online ad channels must be considered jointly to obtain a differentiated view of the consumer. This is a prerequisite to send advertising messages through the most appropriate vehicle. In addition, an isolated view can result in biased findings, as synergetic effects lead to interrelations between single channels. Evaluating, for example, the performance of a paid search campaign without considering simultaneous display ads can lead to an overestimation of the search campaign's performance. Finally, whereas an integrated view helps advertisers decide which channel to use at what point in time, the subsequent *execution* has to be *based on sophisticated channel knowledge* to run advertising on the respective channel more effectively. Also research can profit from deeper channel knowledge, as it would allow formulating more comprehensive theoretical models to explain the effectiveness of that channel. Because of the different nature of online channels, each requires other skills from advertisers and researchers. For example, keyword selection in paid search campaigns and affiliate partner management are two fundamentally distinct tasks that demand highly specialized skill sets.

From these conclusions, implications for research and practice are discussed in Sections 6.2 and 6.3 before an integrated model for online advertising is outlined in Chapter 6.4.

6.2 Theoretical Implications and Research Outlook

This chapter discusses implications of the three overall conclusions for research in marketing and other related areas. Then, it summarizes common limitations of the two studies and explains how these could be addressed in further research.

6.2.1 Theoretical Implications

6.2.1.1 Untapped Potential

Many phenomena in online advertising are still not understood, and research lacks a systematic and holistic theoretical basis for explaining the effectiveness of online advertising, which leaves the potential for improvement unaddressed (Ha, 2008; Yao & Mela, 2008). This thesis aimed to fill this gap. Unlike previous work, which focuses on selective phenomena (e.g., Chittenden & Rettie, 2003; Lambrecht & Tucker, 2011; Manchanda et al., 2006) or methodological issues (e.g., Ghose & Yang, 2009; Rutz & Trusov, 2011), this thesis intended to provide a holistic view on multichannel online advertising (Study I) and search engine advertising (Study II). Though far from complete, the models in this thesis explained observed behavior significantly better than existing work (e.g., Animesh et al., 2011; Breuer et al., 2011; Rutz & Bucklin, 2007). Therefore, they provide fertile ground for exploiting further potential to increase predictive power of online ad effectiveness models.

6.2.1.2 Interdisciplinary Approach

Both models were developed in an interdisciplinary approach, which proved helpful in explaining the observed effects. As indicated in the conclusion, the most powerful concepts and surprising insights of this work are based on theories from different research areas (e.g., the QVI or channel switching effects in multichannel advertising). Further work on online advertising should therefore consider borrowing concepts from related disciplines, such as information retrieval or linguistics. However, although research seems to be headed in this direction—for example, Rutz et al.'s (2011) study, in which the authors create keyword clusters based on previous findings from IR research (e.g., Carrasco et al., 2003; Regelson & Fain, 2006; Wen et al., 2002)—interdisciplinary work should not be considered a one-way route in which marketing research relies solely on theories from other disciplines. Rather, a mutual exchange should take place, because adapted concepts can also be "given back" to their originating field to create value there. The QVI provides an example of this; that is, it might also be used to evaluate the performance of document indices in classic IR contexts.

6.2.1.3 Three Guiding Principles

With regard to the first principle, **transparency**, a research implication is to base analyses on more granular data. This is the key prerequisite to better differentiate between consumers, keywords, or other entities. However, much of the existing work in online advertising uses more aggregated (e.g., Animesh et al., 2011; Breuer et al., 2011; Ghose & Yang, 2009) or purely attitudinal (e.g., Chang & Thorson, 2004; Cho & Cheon, 2004; Goldfarb & Tucker, 2011a; also see Table 1) data. Today, highly granular data are increasingly easy to obtain. In addition, several studies have—besides this work—shown that well-established statistical standard procedures (e.g., OLS and logit regression models) can be used with these data (e.g., Animesh et al., 2011; Goldfarb & Tucker, 2011b; Richardson et al., 2007). This indicates that there is no need "per se" to employ complex and bulky methods, such as Bayesian networks or Markov chain Monte Carlo sampling, whose usage several studies heavily promote (Ghose & Yang, 2009, 2010; Rutz & Bucklin, 2007, 2011). The main implication of the second principle, **integration**, is that research should consider all the channels an advertiser uses. As indicated in the conclusion, the reasons are twofold: first, significantly more can be learned about individual consumers when observing them on multiple channels, and second, analyses focusing on individual channels can be biased if advertisers also use other ones at the same time. Study I has shown, for example, that the effectiveness of advertising channels is also determined by the number of channels on which the consumer has been previously exposed as well as the order of these channels. If this information is not included in research models, a certain share of variance in the dependent variable will not be explained. Several studies that build on data from large advertisers and focus on a single channel (e.g., Ghose & Yang, 2009; Rutz & Trusov, 2011) might be challenged by this issue, as large companies tend to use multiple digital channels at the same time (Absatzwirtschaft, 2011; Efficient Frontier, 2010). The third principle, **execution based on sophisticated channel knowledge**, implies that models on the effectiveness of individual channels need to become more sophisticated and incorporate additional factors. Study II has shown that matching options significantly influence the effect of various predictors, such as display position or advertiser keywords, on CTR. These options should therefore be considered in analyses on paid search performance. However, this is not the case in previous research (e.g., Agarwal et al., 2011; Animesh et al., 2011; Jerath et al., 2011). The same applies to research on multichannel advertising (e.g., Abraham, 2008; Breuer et al., 2011), which does not factor in the effects of exposure sequences on different online channels (Study I).

6.2.2 Common Limitations and How Further Research Can Address Them

This chapter focuses on three general limitations common to both studies (specific limitations of the projects are addressed in Sections 4.6.3 and 5.4.3). Potential routes for research to address these issues are discussed.

First, the thesis is purely built on **behavioral data**. This has several advantages over attitudinal studies. Perhaps the most obvious is that the explained effects are based on real consumer actions and not on stated intents. This is important, because correlations between attitudes and behavior are usually low (e.g., Fazio et al., 1978; Palda, 1966; Ray, 1973; Wicker, 1969). The analysis does not interfere with the process itself, because it was performed afterward. However, a disadvantage of behavioral studies is that they cannot reveal the cognitive processes that explain *why* people do something (see Section 3.2.1). Although this thesis builds on previous theoretical work to explain the observed effects, it cannot prove that they are caused by the hypothesized effects. Further research could address this and validate the findings of this work by building models that combine behavioral and attitudinal data (e.g., through the use of electronic surveys for consumers whose behavior has been observed).

A second limitation to both studies is the potential for **unobserved heterogeneity**, which would imply that the observed effects are caused by variables other than the ones featured in the models (Greene, 2002). To account for this, both studies include controls—namely, different starting and ending channels of user journeys (Study I) and different advertiser industries (Study II). The author assumes that unobserved heterogeneity does not adversely affect the results, because both models indicate good fit statistics, which are greater than those from prior work (e.g., Animesh et al. 2011). The R-square is 55% for Study I (Table 6) and 49% for Study II (Table 13).[22] However, as these statistics are not equal to 100%, a systematic influence from other unobserved effects cannot be precluded. This issue could be addressed by research that features a different research setting: replicating the studies in an experimental design would help increase the internal validity of the results by controlling for heterogeneity from the participants and the environment (Bortz & Döring, 2006).

Third, both studies could be subject to potential **biases from individual, firm-specific effects**, which is a form of unobserved heterogeneity. The data set from Study I is based solely on one advertiser, and campaigns from all advertisers in Study II are managed by a single

[22] The R-square of Study I denotes Nagelkerke's pseudo-R-square.

agency. However some variance in these variables would be helpful to validate that the findings are broadly applicable across advertisers and online marketing agencies. Therefore, further research might run the analyses with a multitude of advertisers from different industries as well as different campaign management techniques.

6.3 Managerial Implications

Specific implications for practitioners from the two projects were presented in the corresponding sections (4.6.2 and 5.4.2). Thus, this chapter discusses what the overall conclusions mean for the practice of online advertising.

6.3.1 Untapped Potential

Both studies have shown that a great amount of untapped potential remains in contemporary campaign management. For example, though managed by a professional agency, 50% of the paid search clicks in Study II were generated by keywords with high query variation (QVI > 0.8). These keywords are unspecific, which results in an inferior CTR. Replacing these terms with ones that match the context more precisely could lead to vast improvements in the effectiveness of paid search campaigns. A similar conclusion can be drawn from the study on multichannel online advertising. Analyses show that users switching from information to navigation channels react far more positively to advertising than consumers with an opposite channel sequence. Consequently, when advertisers use this information for a more differentiated targeting of ad messages, huge gains in conversion rates might be achieved. All in all, the results indicate that the potential to increase effectiveness in online advertising has not yet been maxed out. Through more sophisticated ad scheduling and campaign management techniques based on the findings of the two studies, CTR and conversion rates might be substantially raised. To the best of the author's knowledge, the concepts developed and evaluated in this work are new and have not been used in practice before. Rather, current approaches to the management of individual online advertising channels as well as multichannel campaigns have simply scratched the surface of what is actually possible.

6.3.2 Interdisciplinary Approach

To expedite further gains in effectiveness, it is necessary to develop campaign and channel management techniques in an interdisciplinary approach. Algorithms, tools, and processes should be built on existing knowledge from information retrieval, linguistics, economics, and other related disciplines. As both projects revealed, such concepts can "bring something new to the party" and significantly drive innovation. Another prominent example for such an approach is Google, which revolutionized web search through application of a ranking algorithm originally used in academic citation analysis (Page et al., 1998). With regard to online advertising, interdisciplinary development might particularly pay off for third party service providers, offering tools for campaign management. These firms are in a neutral position—they are independent of media channels that promote advertising on their own channels—and serve multiple advertisers. This allows them to invest more into interdisciplinary development of algorithms and tools as the resulting system is scalable and cost can be allocated to a multitude of advertisers. However, also advertisers and agencies themselves can profit from interdisciplinary approaches to campaign management by adapting their management processes and campaign strategies to these findings (e.g., through consideration of the IR-related channel order effects for strategic campaign planning and message scheduling, which would imply that advertisers should first build ad pressure on information and subsequently on navigation channels).

6.3.3 Three Guiding Principles

Achieving greater **transparency** is a prerequisite for a more differentiated management of online advertising campaigns. Advertisers therefore need to perform sophisticated analyses based on highly granular data. In some cases, these data might be readily available (e.g., the QVI can be calculated on the basis of regular paid search campaign reports). In other cases, advertisers might be required to collect additional data (e.g., individual user journeys in multichannel tracking). However, more standard tools have become available in the past months that assist in performing these tasks (e.g., Efficient Frontier, IntelliAd, Omniture). Vendors of these tools continuously need to enhance them with additional criteria for a more sophisticated ad scheduling (e.g., purchase history, impression data).

This conclusion directly leads to the next principle, **integration**, and implies that optimizing a single channel only works as long as advertisers do not also use any other digital advertising channel. If they do, an isolated consideration of a channel could be biased through synergies or sequence effects of other channels. Thus, there is need to develop campaign management algorithms, which integrate information from all active online channels and determine in real time whether an individual consumer should be targeted on a specific channel at a specific point in time. This again can be illustrated with the example from the first study: after consumers switch from navigation to information channels, it can be favorable for advertisers not to expose them further with ads on information channels. Additional information might reinforce the consumer's decision against the advertiser. In addition, privacy concerns might adversely affect conversion. To implement this strategy, the advertiser needs to be aware of the previous exposure pattern for this specific user on all digital channels from the campaign.

When the decision has been made to expose an individual user on a given channel, it should be **executed on the basis of sophisticated channel knowledge**. Doing so has two major implications for practice. First, some channels need to be enhanced in such a way that individual users can be identified and targeted through precise ad delivery. However, this is currently not possible on search engines. Second, individual channels need to be used more intelligently than what occurs in practice. A simple but effective example again relates to the QVI, which can be automatically calculated using standard metrics from campaign reports. However, it provides valuable insights that can help increase the effectiveness of paid search campaigns. Sophisticated channel knowledge also implies that advertisers regularly need to probe existing paradigms of campaign management. The results from Study II show that the influence of existing channel-specific factors, such as display position in paid search advertising, might be heavily overestimated by practical campaign management (compare Section 5.4.2). Building on these implications, the next chapter drafts an integrated framework for online advertising.

6.4 Proposing an Integrated Framework for Online Advertising

The goal of this section is to outline a future approach to online advertising. This framework addresses weaknesses and limitations of current approaches in practice and research. It is based on the three guiding principles: transparency, integration, and execution based on sophisticated channel knowledge. By adhering to these paradigms, large gains in the effectiveness of online advertising can be achieved, and a new S curve in online advertising can be entered. In line with the entire thesis, the framework is formulated from an advertiser's perspective. Furthermore, it provides a systemic view that can be easily translated into the architecture of an information system that performs the described tasks autonomously. Figure 34 depicts the components of the framework and their relationship.

The framework comprises a continuously repeating feedback loop, which consists of data collection/analysis, decision making, and execution; each step reflects one of the guiding principles. Furthermore, a core feature of the approach is that each step works on the level of individual users. The single elements are described along this flow. Also discussed is whether every element can be realized through current technologies or whether new approaches must be developed.

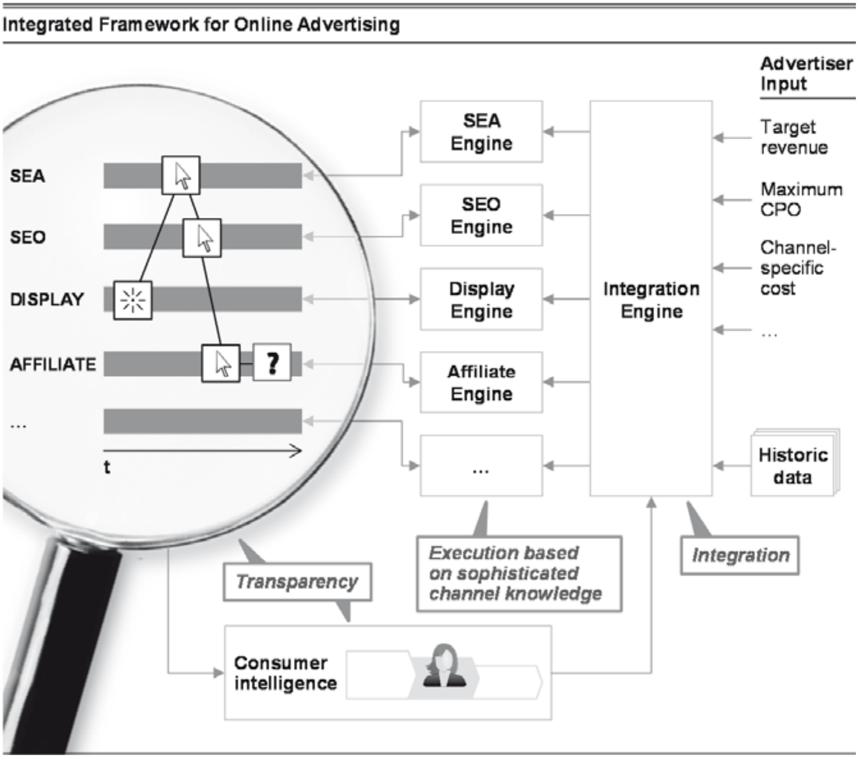

Figure 34: Integrated Framework for Online Advertising

Transparency represents the first stage of the approach and consists of two major elements: user tracking and data analysis (also denoted as “consumer intelligence”). These elements provide the basis for fact-based decision and execution at later stages. The main objective of user tracking is to monitor and record all user interactions on active advertising channels. In this case, an interaction depicts both advertising stimuli (i.e., ad impressions) and user responses (i.e., clicks, conversions). Current tracking solutions and practices solely focus on the latter, because impression tracking generates very large amounts of data. However, because of the continuously decreasing processing and storage costs, vendors have already announced the introduction of impression tracking (intelliAd, 2011b). As discussed previously, user interactions on all active advertising channels must be tracked. In an ideal world, this would also include offline channels, because studies have shown that offline advertising also interacts with ads on digital channels (e.g., Chang & Thorson, 2004; Naik & Peters, 2009). In the case of multichannel retailers, consumers can also perform the actual purchasing transaction on the offline channel (Verhoef et al., 2007). Being equipped with this knowledge can be helpful for online advertising. For example, a consumer, who was exposed to online ads from a PC retailer and consequently bought a laptop in one of the retailer's offline stores, could be exposed to more targeted online ads in the future (e.g., promoting accessories for the purchased device). However, an important prerequisite for tracking is that individual users can be identified on the channels. This frequently poses difficulties to many offline channels (e.g., How can advertisers know whether a specific consumer saw their TV ad?), but certain digital instruments also are subject to this limitation: as mentioned previously, search engines do not support identification of individual users, which needs to be addressed in the future. The second element of the transparency stage is data analysis. Here, analytical methods need to condense the vast amount of information from tracking and additional sources to relevant information that can be used for decision making at later stages. The sum of this information is referred to as consumer intelligence. In addition to the determinants of purchase likelihood, which have been identified in this thesis (e.g., stage in purchasing process, previous exposure patterns/number of previous exposure channels, previous purchase behavior), consumer intelligence needs to be augmented with additional variables unveiled by future research.

Together with further information, consumer intelligence serves as input to the integration engine—the core element of the **integration** phase. The main objective of the integration engine is to decide whether a specific consumer should be exposed to an advertiser message on a specific channel at a specific point in time. This decision needs to be made under consideration of all available information. The decision can be triggered by a consumer browsing on a channel with an available advertising slot—in this case, the integration engine must react and decide whether to deliver the ad. Here, it is in a *reactive mode*. However, the integration engine could also use adequate channels to proactively push ad messages (e.g., through e-mail marketing). Here, it is in a *proactive mode*. The reactive mode in particular sets relatively high requirements for the implementation of an underlying information system. It must be powerful and feature low response times, because analysis, decision, and execution all must be performed in almost real time. Real time bidding systems become more and more available, however they only feature single channels, mostly display advertising. Regardless of the actual system mode, the integration engine bases its decisions on three major types of information: the previously described consumer intelligence, constraints imposed by the advertiser (e.g., target revenues, maximum cost per orders), and historical data. Historical data are of particular importance because previous experience can be used to predict expected uplifts in response rates from additional advertising exposures. One way to extract such insights from historic user journeys could be the use of data-mining methods. The entire framework therefore is designed as a learning system.

When the integration engine decides to expose a consumer, it passes this information to a channel-specific engine, which performs the **execution based on sophisticated channel knowledge**. These execution engines incorporate all channel-specific features to deliver the advertising message on that channel in the most effective and efficient way. They communicate with the individual channels and control them in real time through dedicated application programming interfaces. They also pull channel-specific data, which are required for a more differentiated execution, directly over this interface. This could include, for example, data on user queries in the case of search engine advertising to evaluate the QVI for individual keywords. There is still a need to better understand how individual channels work. Study II has shown that exemplarily for paid search advertising. This new knowledge should assist in designing more powerful channel-specific engines for ad execution. Finally, after the ad is delivered, the consumer may react to it, and the loop starts from the beginning.

This integrated framework offers the potential to shape online advertising into a more effective (and certainly efficient) ecosystem. Advertisers are likely to profit most from this in the short run. However, this provides an incentive for firms to invest more dollars into online advertising, which is favorable for all stakeholders within the online advertising eco system, including search engine vendors, website publishers, affiliate marketers, and providers of technical infrastructure solutions.

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