MASTER THESIS BUSINESS ADMINISTRATION

Effectiveness of online advertising: a bibliometric analysis

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Abstract

Online advertising has been a rapidly growing research domain in the last decade. However, scholars still lack a comprehensive understanding of the ultimate purchase decisions and the factors that determine short- term and long- term effectiveness. The aim of this paper is to define the current and emerging research patterns in academic literature on the effectiveness of online advertising and to identify the key determinants of the effectiveness of online advertising from an interdisciplinary perspective. In order to explore the complexity of the research domain, synthesize the existing literature and carry out correct interpretations, we conduct bibliometric analysis based on 409 academic publications from Web of Science using co-citation analysis and bibliographic coupling techniques. We find 4 thematic clusters based on co- citation analysis and 7 thematic clusters based on bibliometric analysis. In order to perform a more comprehensive interpretation, we used qualitative content analysis to study the key research patterns in clustered academic publications. Our findings suggest that online advertising effectiveness research domain is highly shaped by technological developments and is becoming more focused on interdisciplinarity. This study contributes to the research on online advertising effectiveness by synthesizing the past, current and emerging research patterns, and therefore setting a basis for further research agenda. The findings of this paper contribute new insights to online marketers concerning the key determinants of online advertising effectiveness, and facilitate further discussion regarding the metrics and estimation models of effectiveness.

1. Introduction

Online advertising is increasingly becoming the core channel for marketing activities (Bergemann & Bonatti, 2011; Choi & Sayedi, 2019; Kireyev, Pauwels, & Gupta, 2016; Liu-Thompkins, 2019; Sayedi, Jerath, & Baghaie, 2018). Online advertising refers to any form of digital content available on the internet, delivered by any channel and presented to inform the audience about a product or service at any degree of depth (Ha, 2008; Harker, 2008; Tanyel et al., 2013; Truong & Simmons, 2010). Online advertising spending worldwide amounts to about 333.25 billion US dollars in 2019, more than a half from a total of 563.02 billion US dollars budget spent on all types of advertising in the same year (Statista, 2019). It is expected to double in the next 10 years and will account for 52% of global advertising expenditure in 2021 (eMarketer, 2019; Statista, 2019). Recent developments in online information technology and information systems enable companies to deliver more targeted and personally customized ads quicker than traditional media (Guixeres et al., 2017; Roy, Datta, & Basu, 2017). Hence, successful execution of online advertising campaigns can potentially improve ad recall, brand recall and stimulate purchasing intention of existing or potential consumers, increasing short- and long-term sales (Breuer & Brettel, 2012; Edelman, Ostrovsky, & Schwarz, 2007; Guixeres et al., 2017).

Furthermore, the rapid dynamics of new technological advancements allow brands to collect and use information not only about the previous consumer online behavior, but also by monitoring consumers in real-time, using the so-called synced advertisement combining data collected from multiple digital platforms simultaneously (Segijn, 2019). This improves the timing and placement of ads adjusted to the stages of purchase decision process of consumers (Bleier & Eisenbeiss, 2015), leading to more precise targeting of ads (Boerman, Kruikemeier, & Zuiderveen Borgesius, 2017). Using the latest artificial intelligence algorithms and consumer monitoring tools, brands can evenly spread their advertising activities among the targeted audience segments and increase the effectiveness of online advertising activities (Kietzmann, Paschen, & Treen, 2018; Lejeune & Turner, 2019).

However, by implementing the synced advertising and omnichannel marketing strategies (Duff & Segijn, 2019; Segijn, 2019), brands use online advertising activities on a combination of platforms simultaneously reaching a cumulative effect that creates externality between the effectiveness of ads (Berman, 2018). As a result, the main credit is given to the 'last click', ignoring the effect of previous advertising activities (Kireyev, Pauwels, & Gupta, 2016). In context where the consumer behavior remains stochastic (Berman, 2018), advertisers are facing a crucial challenge to estimate the actual effectiveness of individual advertisement elements. This, in turn, leads brands to often miscalculating the online advertising activities, resulting in frustration and questioning of the overall effectiveness on digital ad spending (Berman, 2018). Despite current opportunities for real-time monitoring, companies still struggle with interpreting and translating collected data for better customer experience and targeting (Liu & Mattila, 2017). According to statistics, 76% of marketers fail to use behavioral data for online ad targeting (Heine & Heine, 2019). Moreover, by increasingly using consumer data for personalized and individually-targeted ad development, the consequences of the degree of intrusiveness need to be considered in relation to the effectiveness of short- and long-term online advertising activities (Kireyev et al., 2016), as well as, to ethical and legal reasons (Tanyel, Stuart, & Griffin, 2013). According to Brettel et al. (2009) advertisers need to consider the choice of appropriate advertising in different regions and countries.

Consequently, the increasing role of online advertising has attracted notable attention from scholars (see the literature reviews of Liu-Thompkins, 2019 and Petrescu & Korgaonkar, 2011). Figure 1 depicts the evidence of an increasing number of publications in recent years (Source: Web of Science).

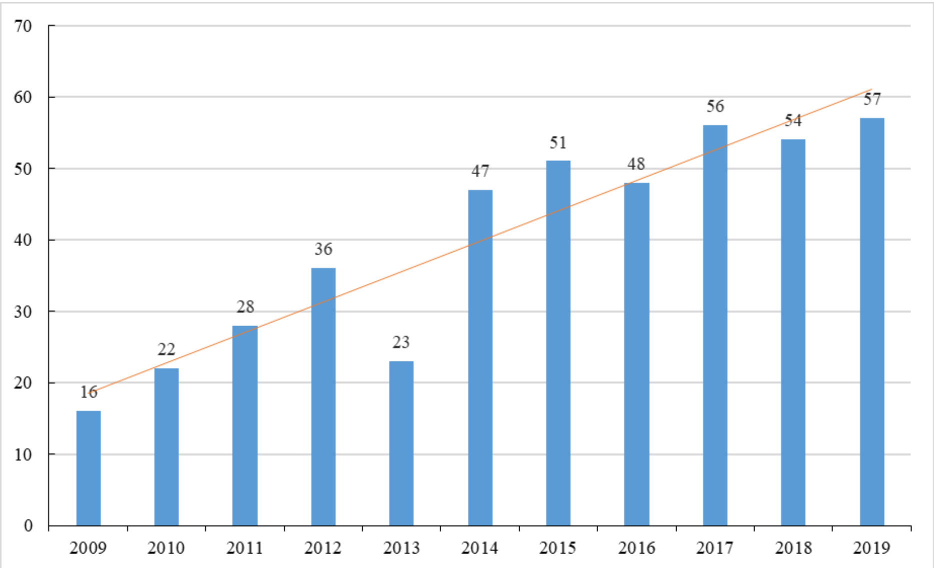

Figure 1. *The number of scientific publications on online, web and internet advertising effectiveness between 2009 and 2019; Source: Web of Science*

While scholars recognize the need for a better understanding of the ultimate purchase decision in different stages of the online purchasing processes (Bleier & Eisenbeiss, 2015), and the effects determining short- and long-term sales (Breuer & Brettel, 2012; Kireyev et al., 2016), the existing literature does not adequately cover the recent interdisciplinary developments. Only a few studies address online advertising as a dynamic research domain that faces major changes associated with the latest technological developments, such as Big Data and Artificial Intelligence (Jordan & Mitchell, 2015; Kietzmann, Paschen, & Treen, 2018), covering the fields of natural language processing, image recognition, speech recognition, and neuroscience (Guixeres et al., 2017). In result, the necessary degree of awareness that online advertisement is making new interconnections into the fields of marketing, business and management, but also computer science, engineering and neuroscience (Boerman, Kruikemeier, & Zuiderveen Borgesius, 2017; Perski, Blandford, West, & Michie, 2017) is mostly neglected. Thus, scholars are facing a lack of understanding of the interdisciplinary and complex nature of online advertising effectiveness, and lack the knowledge necessary to account the effectiveness of individual ads, in comparison to the cumulative digital content presented to various audience segments (Berman, 2018; Bleier & Eisenbeiss, 2015; Breuer & Brettel, 2012).

Therefore, to advance this research field further and minimize the risk of duplicating empirical findings, it is necessary to synthesize the existing literature from different research disciplines and conduct correct interpretations. Since there are various new channels for reaching customers, it is important to find out what are the most efficient ways to do so and what are the implications that are to be solved in the future, considering the recent technological opportunities to personalize and customize the advertising content, based on data and algorithms. We aim to develop an in-depth understanding of variability, rapid evolution and the growing importance of the new media in regards to online advertising.

Thus, this research paper addresses the following research questions:

What are the current and emerging research patterns in academic literature on the effectiveness of online advertising?

What are the main determinants of the effectiveness of online advertising from an interdisciplinary research perspective?

To answer our research questions, we conducted a bibliometric literature review of 409 academic publications retrieved from Web of Science using co-citation analysis and bibliographic coupling techniques. A bibliometric literature analysis was selected due its advantages over other literature review methods, such as: (1) the ability to perform quantitative analysis of a specific research domain from a global perspective, enabling an overarching 'top-down' overview, complementing the local perspective of peer-review; (2) bibliometric analysis enables to summarize the entire research domain, including interconnections to various related or not-related domains, which is crucial for analysis of such an interdisciplinary domain as online advertising; (3) bibliometric analysis enables to assign weighted quantitative measures to analyze publications (e.g. citations and reference-based counts and links) which minimizes the subjective bias of human perception (Web of Science Whitepaper, 2008). By using co-citation analysis and bibliographic coupling techniques, the 'scientific roots' of online advertising were studied and supported with identification of current and emerging research patterns. We also evaluated and discussed statistical patterns to determine characteristics of online advertising research domain. These documents were analyzed and evaluated according to publication distribution and were used to determine the quantitative characteristics of tsunami research. Additionally, a qualitative content analysis was performed to identify the key determinants, and main channels of digital content were studied to outline their role on the effectiveness of online advertising.

This paper has several theoretical and managerial implications. From a theoretical perspective, we develop new insights through a comprehensive overview of the research domain and a systematic categorization of factors that have an impact on online advertising effectiveness, providing basis for a future research agenda. From a managerial perspective, we provide new insights to online marketers and companies for improving online advertising effectiveness by a better understanding of the key determinants, more appropriate advertising budget allocation and optimization of ad delivery to the audience.

2. Foundations of the study

Online advertising remains a relatively new phenomenon, dating back to 1994 when the first banner ads were placed on websites (Ha, 2008; Spilker-Attig & Brettel, 2010). The first academic publication addressing online advertising was published in 1996 by Berthon et al. evaluating the World Wide Web as an advertising platform (Truong & Simmons, 2010). Since the initial developments, a rich spectrum of online advertising models have been introduced, covering any form of digital content available on the internet to inform audience about a product or service, as previously defined. Lately, this includes monitoring consumer online behavior to develop personally-targeted ads (Boerman et al., 2017).

Specifically, after the introduction of a classic banner advertising, additional advertising models were developed unveiling the potential for bridging better communication between consumers and advertisers (Rappaport, 2007; Silverman, 2008). In later years, online advertising evolved into three major types- display (or banner) advertising, affiliate programs, and search engine marketing (SEM) (Jensen, 2008). Display (or banner) advertising refers to advertising messages delivered in graphic formats (e.g. photos or videos) on third-party websites, including pop-ups and interstitials (Breuer & Brettel, 2012; Truong & Simmons, 2010). Affiliate programs allow third- parties to post an individual “affiliate” link on their website or blog that redirects a user to the company’s website, and receive a commission fee when that user makes a purchase using that link (Breuer & Brettel, 2012). Contrary to classic banner advertising which is restricted to a selected third-party website, search engine advertising, including paid and unpaid search engine optimization (SEO) and SEM (such as Google AdWords) offers more targeted approach as it is based on keywords entered by users on the search engine (Dou, Linn & Yang, 2001), and therefore returning a keyword-related advertisement. In more recent years, additional channels of online advertising were introduced, including viral marketing, streaming media, rich media, blogs, digital video ads, dynamic in-game ads placed in video games, podcasts, YouTube, user-generated content, virtual worlds, contests, etc (Lejeune & Turner, 2019; Tanyel et al., 2013).

With the development of technological advancements, an increasing practice to collect, use and share personal data stimulated a development of more personally-targeted advertising. Advertisers use persuasive messages that are aimed at encouraging users to believe and act on the communicator's viewpoint (Matz et al, 2017). These messages are more appealing to the users and more effective in reaching their goals when they are tailored to unique personal characteristics and motivations of those users (Dubois, Rucker & Galinsky, 2016). Targeting evaluates users' digital footprints and constructs a portrait of a user, such as interests, history of online activity, traits and demographics (Lambiotte & Kosinski, 2014). Later, targeted advertising aims to show individually targeted advertising messages to users whose characteristics indicate a preference towards the advertised product (Farahat & Bailey, 2012).

Initially, advertisers primarily segmented users based on characteristics such as location, device type and sociodemographics. (Subasic et al, 2013). With the technological advancement, it became possible to collect data on users' activity online, including their purchases, preferred pages, etc. (Tucker, 2012). Behavioral targeting is a commonly used method that targets users based on their browsing and search history (Yan et al, 2009). Recently, a synced targeting became a new trend in online advertising (Segijn, 2019). The main difference is that synced targeting monitors the current behavior of users instead of the past behavior (e.g. in behavioral targeting), and uses multiple channels and media simultaneously to send individually targeted persuasive messages (Segijn, 2016).

To grasp a wide spectrum of online advertising types and ad delivery channels, scholars require a conceptual framework. A prominent example has been recently provided by Lejune and Turner (2019) by classifying ad campaigns as either impression-based, click-based or conversion-based; and guaranteed or nonguaranteed:

> *"Impression-based ads, such as banner, dynamic in game, and digital video ads, incur a cost to the advertiser whenever the publisher places the ad on some viewer's screen. In contrast, click-based and conversion-based ads only charge the advertiser for clicks and conversions (installing an app, or buying a product), respectively.*
>
> *Guaranteed ads are purchased by advertisers from publishers in advance, and involve a promise to deliver a given number of impressions over a particular time window.*
>
> *In contrast, nonguaranteed ads are more opportunistic, and can use complex strategies to decide if, when, where, and to whom they are shown. Many publishers manage both guaranteed and nonguaranteed ads, and researchers have studied how to optimally apportion exposures across these two main channels" (Lejeune & Turner, 2019, p. 1223).*

Understanding the effectiveness of online advertising is increasingly challenging academics and practitioners (Berman, 2018; Bleier & Eisenbeiss, 2015; Guixeres et al., 2017). Prior research has specifically addressed the effectiveness of online advertising (Breuer & Brettel, 2012; Knoll & Schramm, 2015; Spilker-Attig & Brettel, 2010), complementary to the results of bibliometric analysis in a seminal publication by Kim & McMillan (2008). Yet, a clear conceptualization of this concept is lacking in academic literature, especially covering the recent technological and advertising developments (Bleier & Eisenbeiss, 2015; Brettel & Spilker-Attig, 2010; Breuer & Brettel, 2012). In turn, the effectiveness of online advertising is continuously evaluated by a combination of traditional online metrics and increasingly advanced metrics. For example, a notable part of traditional online advertising activities are evaluated in line with the classification proposed by Lejeune and Turner (2019) as either impression-based, click-based or conversion-based metrics. In this case, click-through rate is the number of users who clicked the display ad to the total number of users exposed to the ad (Richardson, 2007), while conversion rate is how many people who were exposed to your message (number of impressions) performed a planned action online (Lee et al, 2012). To develop more insightful estimation of performance of online advertising campaigns, Lejeune and Turner (2019) propose a Gini-based metrics. Additionally, social media platforms refer to other quantitative metrics, such as, number of likes, shares, comments, views, followers in relation to advertising content (Voorveld, van Noort, Muntinga, & Bronner, 2018). With recent developments in neurosciences, the usage of neuro metrics is increasing to measure advertising effectiveness. Guixeres et al. (2017) identify three types of effects pursued by advertising: (1) perception – exposure to the ad as the first step in any evaluation process, (2) the emotional dimension – used in evaluating the effects of advertising, (3) the cognition effect – measured as ad recall. Advertising can also contribute to the purchase behavior through building a brand image and brand awareness on the Internet, increasing recognition and generating referrals (Sasmita & Mohd Suki, 2015). Building a brand image and brand awareness through advertising increases the purchase consideration, and it is important to take into account when a consumer is not in an immediate need for the product (Hollis, 2005; Vakratsas & Ambler, 1996).

Furthermore, an inevitable element of measuring the effectiveness of online advertising is the resulting short- and long-term purchase behavior by consumers, measured in sales and revenues (Breuer & Brettel, 2012). Yet, prior research indicates that the relationship between the online advertising activities and financial outcomes is not straightforward, and requires additional research (Berman, 2018; Bleier & Eisenbeiss, 2015; Duff & Segijn, 2019). There is an ongoing debate about the privacy concerns of targeted advertising (Segijn, 2019) When exposed to an intrusive ad, users are more likely to perceive an ad as manipulative (Kirmani & Zhu, 2007) and develop a prevention focus (Van Noort, Kerkhof & Fennis, 2008). This, in combination with the cumulative nature of current online advertising activities, stochastic consumer behavior online, all seem to influence the effectiveness of online advertising (Berman, 2018; Kireyev et al., 2016; Tanyel et al., 2013).

3. Research design

3.1 Data and search query

To conduct the bibliometric analysis on the effectiveness of online advertising, we collected data using the Clarivate Analytics Web of Science Core Collection database, following the methodological approach of previous bibliometric literature review papers (see e.g. Diez-Vial & Montoro-Sanchez, 2017; Rialti, Marzi, Ciappei, & Busso, 2019; Teixeira & Mota, 2012). We used Web of Science instead of other existing databases (i.e. Scopus, Google Scholar, PsycINFO) because of its ability to retrieve reliable peer-reviewed articles of high-quality from mostly reputable journals (Rialti et al., 2019). Additionally, as indicated by Rialti et al. (2019), the search on Web of Science Core Collection leads to a wide coverage of academic literature with typically smaller number of irrelevant results, which is crucial for correct interpretation of state-of-the-art literature.

We defined the search query in line with the key concepts related to our research question: *(("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*" OR "click*" OR "conversion*"))*. The key term of ‘online advertising’ was extended with the closest synonyms used in titles, abstracts and full texts of the relevant literature (Aslam & Karjaluoto, 2017; Brettel & Spilker- Attig, 2010; Bruce, Murthi & Rao, 2017; Edelman, Ostrovsky & Schwarz, 2007; Shaouf, Lü & Li, 2016). In addition, we excluded terms such as ‘online or digital marketing’ to avoid false positive items that are out of scope of this research paper. Also, we excluded ‘ad’ as a single search key due to high amount of returned publications that are not related to advertisement, for instance, ‘ad hoc’, ‘advanced’ or ‘adaptive’. Furthermore, additional manual check indicated that the main search query grasps the majority of relevant literature, and therefore including ‘ad’ as a single search key is not beneficial due to small number of additional relevant articles and many false positive articles. Similarly, the key term of ‘effectiveness’ was supported with the closest synonym, while avoiding broader terms related to general business outcomes outside the scope of this research paper. The motivation to restrict the search key to ‘effectiveness’ and its closest synonym was three-fold (1) the effectiveness of online advertising is one of the resulting themes of a bibliometric analysis in a seminal article by Kim and McMillan (2008), and therefore we wanted to investigate the development of this topic over the last decade; (2) effectiveness in online advertising is an increasingly used term in relevant publications, and therefore relevant to be studied from a bibliometric perspective (Spilker-Attig & Brettel, 2010); (3) effectiveness includes a variety of online advertising metrics, ranging from traditional click-through rates converting to off/on-lines sales to more advanced consumer neuroscience and emotional metrics (Guixeres et al., 2017). Nevertheless, to reduce the risk of missing relevant articles, we included additional keys based on the classification of online ads provided by Lejune and Turner (2019) and additionally search for variations of ‘impression*’, ‘click*’, and ‘conversion*’. The nature of bibliometric analysis enables us to study the selected literature including the above mentioned reasons simultaneously.

The search process was performed using the ‘topic search’ option selecting journal articles published in English, containing selected keys in titles, abstracts and/or keywords. The ‘topic search’ option generates the most accurate results, while reducing the risk to exclude relevant articles (like in the case of using ‘title search’ option only) (Skute et al., 2019). However, we restricted the search to document type – ‘article’ and exclude publications of other types (i.e. conference proceedings, book chapters, letters, etc.) in order to maintain the peer-reviewed academic literature of high quality and related citation patterns. Additionally, to ensure the inclusion of relevant articles, and therefore correct interpretation of results, we manually examined articles from a list of Web of Science categories, and excluded articles from categories that provide no or minor value for the literature on online advertising (in total, 42 categories, such as obstetrics gynecology, pediatrics, substance abuse, were excluded).

Additionally, the search was restricted to the literature published in the period of 2009 and 2019 to examine the scientific roots of this research domain, while enabling to study the current and especially emerging themes of high relevance for future studies. Specifically, this restriction was based on several reasons: (1) in 2009 there was a major increase in academic publications in comparison to all previous years; (2) in 2009 online advertising overtook TV advertising in the United Kingdom (The Telegraph, 2009) signaling its relevance and future advancements; (3) on the other hand, the search included all recent publications of 2019 to grasp also the increasing research on Artificial Intelligence and its role in online advertising (Kietzmann, Paschen, & Treen, 2018). After additional manual inspection of retrieved articles, seven articles were removed from further analysis due to the scope that is beyond the current research paper (see Appendix 1 for an overview of the step-by-step dataset development process).

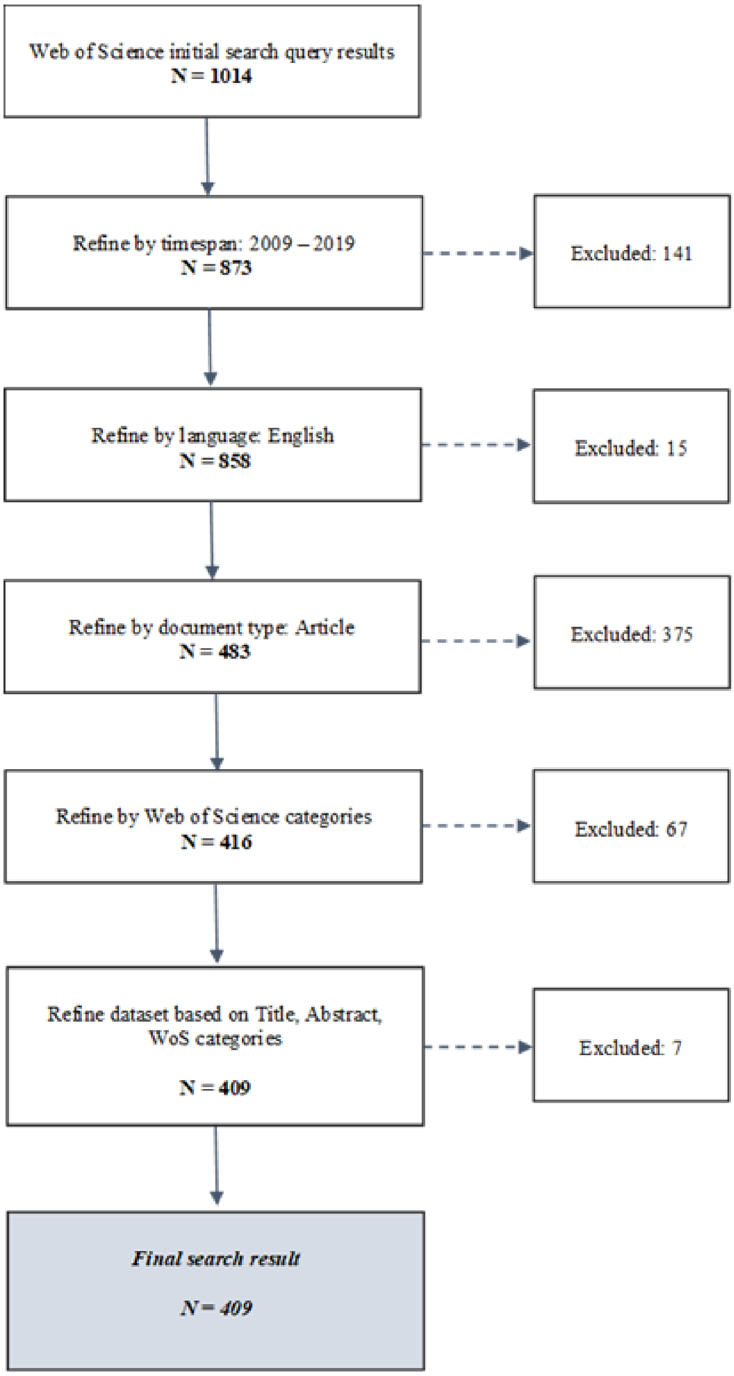

Figure 2. *Flowchart of the dataset development process.*

The generated final sample consisted of 409 journal articles in total, referring to 6,184 total citations and 14,399 total references. All articles included in the final dataset for further analyses were manually examined to ensure the inclusion of relevant search keys in the title, abstract and/or keywords.

3.2. Methods

To map the selected academic literature and construct thematic literature clusters, co-citation analysis and bibliographic coupling were used in line with methodological procedures of prior literature (see e.g. Kim & McMillan, 2008; Meyer, Grant, Morlacchi, & Weckowska, 2014; Rialti et al., 2019; Teixeira & Mota, 2012). Co-citation analysis and bibliographic coupling are widely used bibliometric analysis techniques that could be broadly defined as the application of quantitative analysis and statistics to academic publications and their accompanying citation counts (Web of Science Whitepaper, 2008). Bibliometric analysis enables to perform mapping of the academic literature to highlight the foundations of a specific research domain, as well as to outline the current and promising research areas, therefore enabling a comprehensive evaluation.

The key underlying assumption of co-citation analysis and bibliographic coupling is that the greater the degree of overlap in the referencing patterns of two focal publications, the more relatedness or similarity they share (Boyack & Klavans, 2010; Diez-Vial & Montoro-Sanchez, 2017). However, there is a crucial difference between these two techniques. Co-citation analysis links articles that are cited together (hence, co-cited) by another article. Since this technique focuses on 'cited documents' with consideration that co-cited articles are more similar when cited together more often than with other articles, this enables us to study the foundations of specific research domain. In turn, bibliographic coupling links two articles that cite the same article(s) (hence, coupled) , focusing on shared references. Since this technique focuses on 'citing documents' with consideration that two bibliographically coupled articles are more similar when they have more shared references than with other articles, this enables to study the current and emerging research patterns (Boyack & Klavans, 2010; Diez-Vial & Montoro-Sanchez, 2017; Small et al., 2014). Both techniques were used at the level of individual publications.

Following the methodological approach of previous studies (see e.g. Diez-Vial & Montoro-Sanchez, 2017; Rialti, Marzi, Ciappei, & Busso, 2019; Teixeira & Mota, 2012), in co-citation analysis we included publications with at least ten citations to ensure a high quality of included literature that has been acknowledged by other scholars, reducing the risk of self-citation bias and risk of overly complicating the interpretation of state-of-the-art literature. Since co-citation analysis is based on cited references, as indicated previously in the method section, from the original dataset of 409 publications consisting of 14399 cited references, 65 articles met the threshold of 10 citations. Moreover, the nature of co-citation analysis is focused on studying the historic evolution of a specific research domain, therefore cited references published before 2009 were also included in the analysis as a core element of this technique.

In the case of bibliographic coupling, there is no minimum citation threshold introduced in order to include all recent publications and capture the latest emerging research patterns. Thus, 409 retrieved articles can be used for the analysis. Nevertheless, from a dataset with 409 articles, 388 articles were clustered using bibliographic coupling. The remaining articles were excluded due to lack of shared references with other articles, and therefore could not be connected to the bibliometric network. Also, three smallest clusters consisted of 11, 7, and 3 articles respectively. Due to minor relevance to the core bibliometric network, these clusters were excluded from further analysis. Thus, based on the visualisation of similarities (VOS) approach and the bibliographic coupling, academic literature on the effectiveness of online advertising can be examined with seven thematic clusters consisting of 367 publications.

To normalize co-occurrence data when constructing and visualizing thematic clusters, an association strength measure was used, in line with the accepted methodological process in previous studies (Perianes-Rodriguez, Waltman & Eck, 2016; van Eck & Waltman, 2009). This approach has proven to perform better than other similarity measures (e.g. Jaccard index) and a comprehensive overview of calculation and comparisons can be seen in Van Eck & Waltman (2009) and Waltman et al. (2010). Clustering and visualization of academic literature is performed using visualization of similarities (VOS) approach using VOSviewer 1.6.5 (van Eck & Waltman, 2007, 2010). VOS is a method for mapping and clustering bibliometric networks that uses optimization and clustering algorithms (Perianez- Rodriguez, Waltman & Eck, 2016). In VOSviewer, the optimization algorithm aims to locate publications in a low- dimensional space so that the distance between them accurately reflects their relatedness (van Eck & Waltman, 2007). The relatedness of the publications is measured relative to the weighted sum of the squared distances between all pairs of publications (van Eck & Waltman, 2014). Therefore, smaller distance between publications indicates a greater association strength (or relatedness). VOSviewer calculates the association strength differently depending on whether we use co-citation or bibliographic coupling methods (van Eck & Waltman, 2011). Further, VOS clustering algorithm groups publications into clusters (Perianez- Rodriguez, Waltman & Eck, 2016).

Next to that, to perform a more comprehensive interpretation, we used qualitative content analysis to study the key research patterns in clustered academic publications. In addition to identification of the previous, current and emerging research patterns, we also manually studied full- text of articles in each thematic cluster. We labelled each thematic cluster as follows: 1) manual check of titles, abstracts and keywords of publications 2) identification of research topics, key variables and research goals 3) finding interlinkages to identify the main (or multiple) field of research within a cluster. The content analysis was conducted in order to reach a more comprehensive thorough understanding of what the identified thematic clusters are about. In each thematic cluster, we discussed the key research papers of that cluster to define qualitative scientific patterns of the research domain, identify the determinants of online advertising effectiveness and address the interdisciplinary nature of the research domain. The key papers were chosen on the basis of the highest number of total link strength and the highest number of citations.

4. Results

4.1 Statistical patterns of the research domain

First, we review the statistical patterns of the online advertising research domain by studying the publications from our sample using Web of Science data. More specifically, we look into the distributions of scientific journals publishing the most literature, Web of Science categories associated with academic articles, Web of Science authors associated with academic articles, author- affiliated research institutions publishing academic articles, author country affiliations publishing academic articles and funding parties contributing to research.

Examination of retrieved Web of Science articles and corresponding bibliometric insights can indicate relevant statistical patterns. As illustrated previously in Figure 1, there is an increasing positive trend of publications related to the effectiveness of online advertising, signaling about the relevance of this research domain among scholars in recent years. Figure 3 shows the distribution of articles on the effectiveness of online advertising per peer-reviewed journals publishing. As indicated in the results of Figure 3, *Marketing Science* is the leading journal in the number of relevant publications (with 18 total publications) in the corresponding time period, followed by *Electronic Commerce Research* with 14 publications (Figure 3). Then, *Management Science; Journal of Marketing Research and Journal of Advertising Research* share an equal number of 12 publications forming the top 5 of peer-reviewed journals. The five leading journals account for 16.6% of total publications on the effectiveness of online advertising, indicating a diverse and well-distributed nature of peer-reviewed journals. This finding is in line with the results presented in Figure 4 that illustrates a distribution of Web of Science categories associated with the retrieved articles. Not surprisingly, *Business; Computer Science Information Systems* and *Management* with 142, 101, and 57 associated articles from the top three categories since the major part of publications on online advertising and the key effectiveness determinants are linked to these categories. It is important to note that one publication can be associated with several Web of Science categories. While these three top categories account for 40.71% of total publications in the dataset, there are 34 additional Web of Science categories that account for 59.29% ranging from *Computer Science Artificial Intelligence; Engineering Electrical Electronic* and *Computer Science Cybernetics* to *Psychology Multidisciplinary* and *Educational Research* reflecting the increasing research and technological advances using Artificial Intelligence and neuroscience in online advertising in addition to more traditional psychology and education-related research.

Figure 3. *Distribution of scientific journals publishing the most literature on the effectiveness of online advertising between 2009 and 2019 (top 25 journals)*

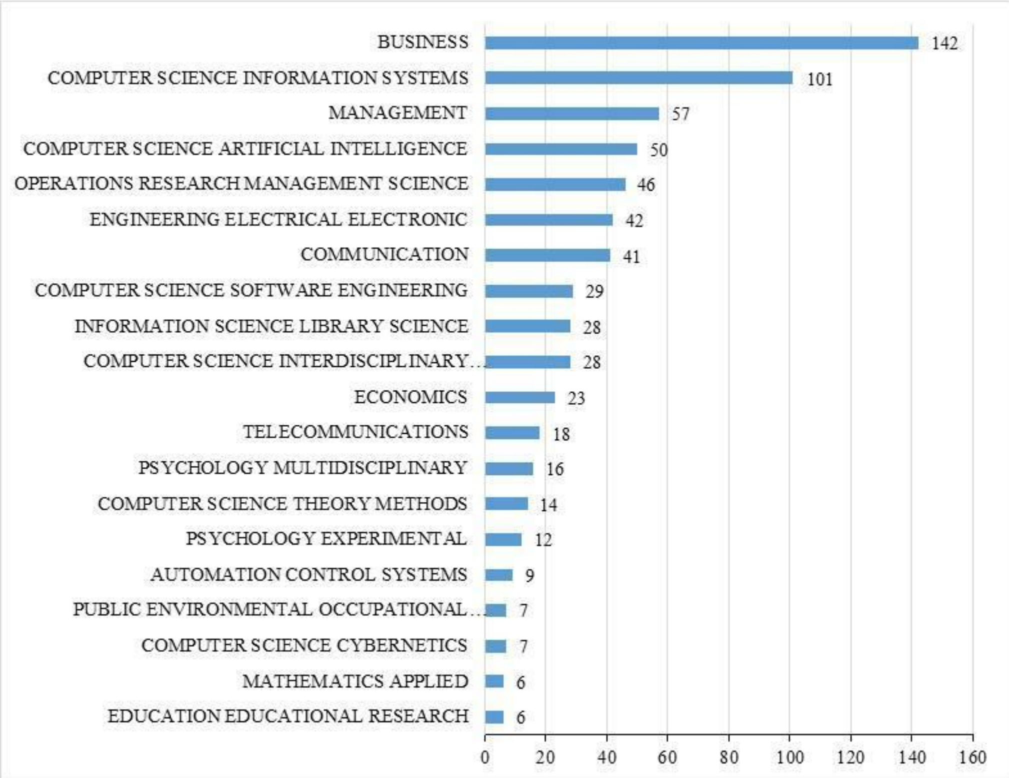

Figure 4. *Distribution of Web of Science categories associated with academic articles on the effectiveness of online advertising between 2009 and 2019 (top 25 categories)*

Similarly, Figure 5 demonstrates distribution of authors and co-authors by the number of related publications in the retrieved dataset. Thus, in the period of 2009 to 2019 three leading (co)authors in the field of online advertising effectiveness are: *Catherine Tucker*, *Cookhwan Kim and Avi Goldfarb* with 6 peer-reviewed academic contributions. In total, 416 retrieved articles were (co)authored by 1056 different researchers. Furthermore, Figure 6 illustrates affiliated academic institutions of (co)authors. Specifically, Figure 6 shows that the highest contributor of peer-reviewed academic literature in the past decade is *University of Texas* with 19 articles (co)authored by affiliated researchers, followed by *Chinese Academy of Sciences* and *Massachusetts Institute of Technology (MIT)* with 12 and 11 publications respectively. However, a distinctive characteristic of this research domain is that among the leading institutions actively contributing to publishing research on the effectiveness of online advertising are two leading tech-giants: *Google* and *Microsoft* with 11 and 10 associated publications respectively.

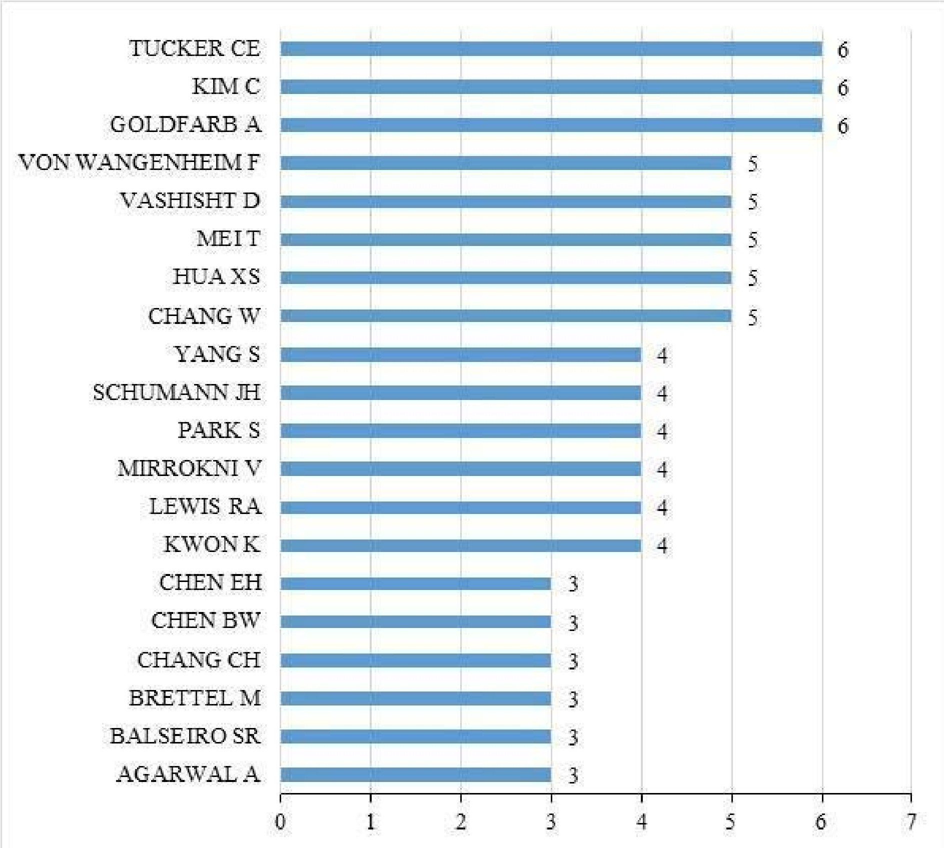

Figure 5. *Distribution of leading Web of Science authors associated with academic articles on the effectiveness of online advertising between 2009 and 2019 (top 25 authors)*

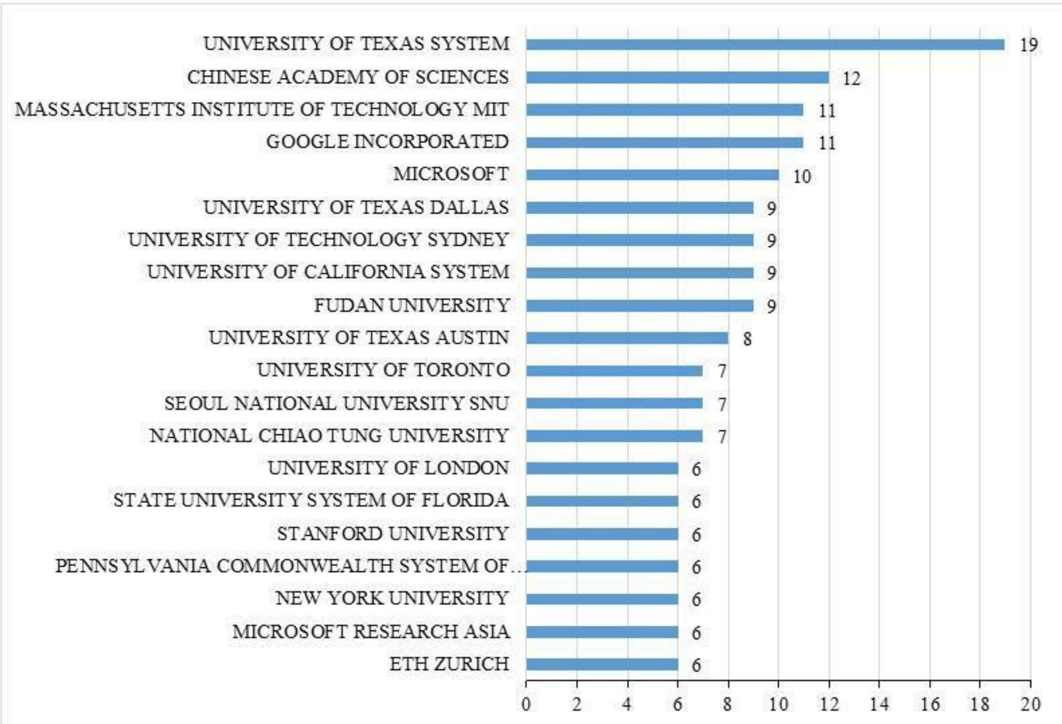

Figure 6. *Distribution of author-affiliated research institutions publishing academic articles on the effectiveness of online advertising between 2009 and 2019 (top 25 authors)*

While previous bibliometric findings demonstrated rather balanced distribution associated with the research published on the effectiveness of online advertising, contrary findings can be seen in Figure 7 and Figure 8 illustrating distribution of (co)author country affiliations and funding agencies, respectively. Figure 7 indicates that authors publishing on online advertising predominantly are affiliated with the *United States* in 179 cases that account for 32% of all (co)author affiliations. In total, 56 different countries around the globe are registered as author country affiliations. In turn, the most active funding agency with 46 contributions to peer-reviewed academic publications on the effectiveness of online advertising is *National Natural Science Foundation of China*, accounting for 15.08% of all registered funding agency' contributions. In total, 195 different funding parties have been reported.

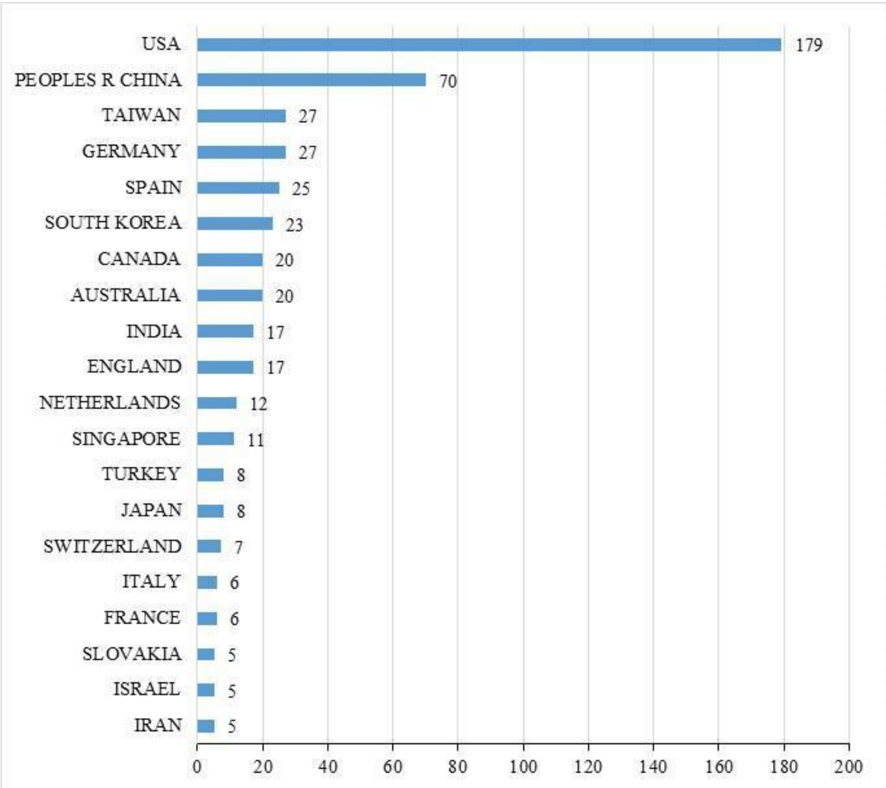

Figure 7. *Distribution of author country affiliations publishing academic articles on the effectiveness of online advertising between 2009 and 2019 (top 25 countries)*

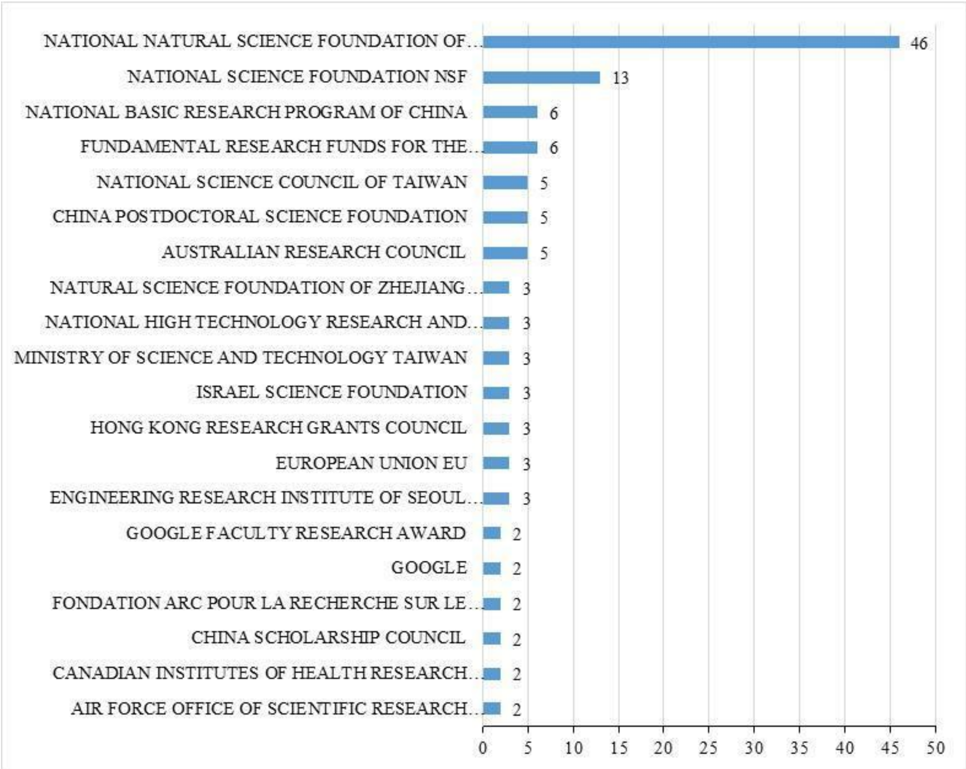

Figure 8. *Distribution of funding parties contributing to research on the effectiveness of online advertising between 2009 and 2019 (top 25 countries)*

4.2 Co-citation analysis results

First, we present the bibliometric findings of seminal literature on online advertising effectiveness using a co-citation analysis technique. Figure 9 illustrates the results of co-citation analysis, based on the constructed dataset with 409 academic articles retrieved from Clarivate Analytics Web of Science Core Collection.

Based on the visualisation of similarities (VOS) approach and the co-citation analysis, considering the minimum ten citation threshold, academic literature on the effectiveness of online advertising is divided into four thematic clusters. Each cited reference in the visualized bibliometric network is clustered based on the likelihood to be cited in combination with other cited references. Cited references that share higher probability to be cited together in a focal publication are assigned to the same cluster, until the bibliometric network is completed. For better interpretation, cited references of the same cluster are in the same colour. Additionally, to represent an individual weight of each clustered reference, a total link strength is assigned based on the links of a given researcher with other researchers (van Eck & Waltman, 2010a, 2010b). Cited references with higher total link strength and higher number of citations are represented in larger sizes. As previously mentioned in the methods section, the nature of co-citation analysis focuses on studying foundation of a specific research domain, therefore cited references published before 2009 were also included in the analysis as a core element of this technique.

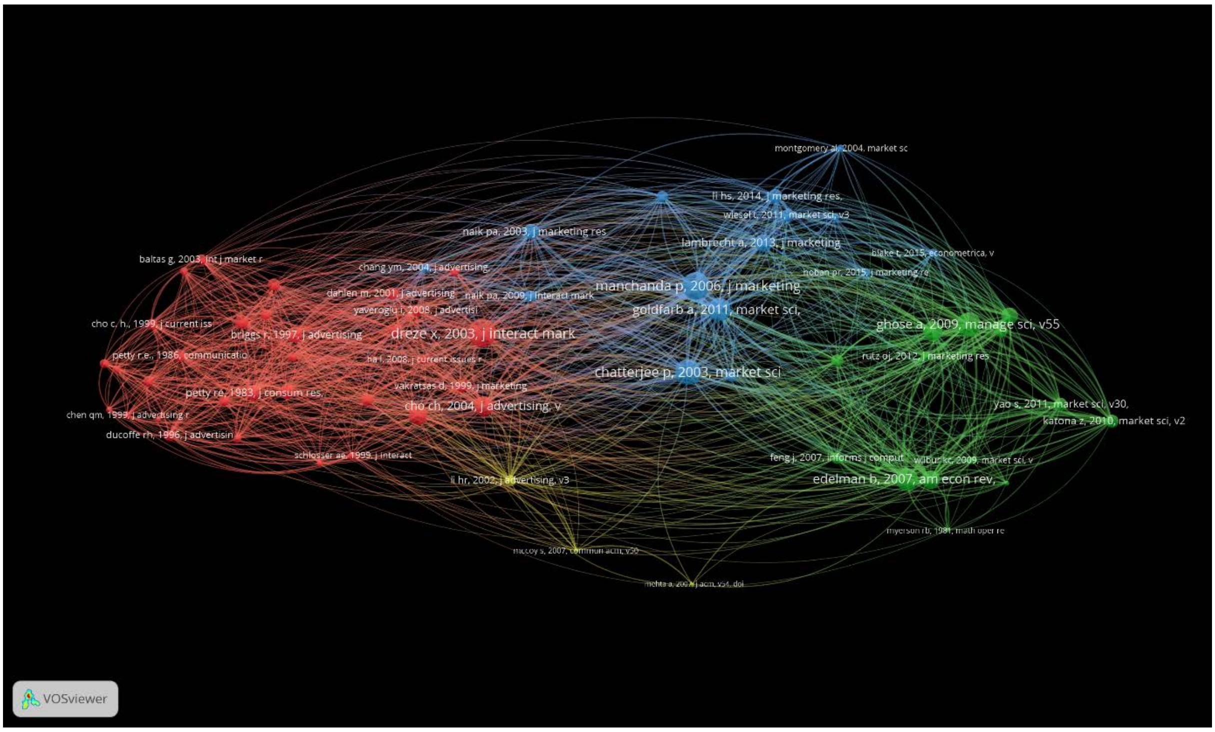

Figure 9. *A resulting visualized bibliometric network of clustered academic articles on the effectiveness of online advertising, using co-citation analysis technique*

Table 1 provides an overview of the main statistical details of the clustered results, based on the co-citation analysis. According to the findings, Cluster 1 is the largest in the associated number of articles, as well as, includes articles with the highest number of citations. The three leading articles of Cluster 1: Fornell & Larcker, 1981; Hoffman & Novak, 1996; Petty & Cacioppo, 1986 respectively, have 78,938 citations in total, indicating a crucial importance for the online advertising scholars. It is crucial to acknowledge that co-citation analysis is based on the cited references of the generated sample, therefore some seminal articles forming the clusters can be broader than the scope of the studied research domain due to high impact of theoretical or methodological implications presented in a specific article. Next, Cluster 2 and Cluster 3, share an equal number of 15 associated articles, followed by the smallest Cluster 4 with just three articles. Nevertheless, Cluster 4 consists of articles that average with 14.67 years of existence, which is the second oldest cluster on average after Cluster 1 with 22.44 years on average. Finally, Cluster 3 can be described as a cluster with the highest number of average links per article, scoring 39.40 links on average. Overall, the results of co-citation analysis present four main thematic areas that provided a foundation for further studies that will be examined in more detail by means of bibliographic coupling results.

Table 1. An overview of co-citation clusters: descriptive statistics and key articles

Clusters	*Number of articles per cluster*	*Number of total links per cluster*	*Number of average links of articles*	*Average existence of publications in years*	*Number of total citations*	*Number of average citations of articles*	*Top 3 most cited articles per cluster*
Cluster 1: Visual characteristics, congruence, and intrusiveness of an ad	32	1229	38.41	22.44	109404.00	3418.88	Fornell & Larcker, 1981 (60.578); Petty & Cacioppo, 1986 (10.401); Hoffman & Novak, 1996 (7.959)
Cluster 2: Paid search advertising	15	486	32.40	13.07	14396.00	959.73	Myerson, 1981 (6.350); Edelman et al., 2007 (1.859); Varian, 2007 (1.274)
Cluster 3: Targeting, retargeting, and multichannel targeting	15	591	39.40	10.27	5301.00	353.40	Naik & Raman, 2003 (604); Chatterjee et al., 2003 (582); Goldfarb & Tucker, 2011 (577)
Cluster 4: Measuring the effects of online advertising	3	68	22.67	14.67	1591.00	530.33	Mehta et al., 2007 (699); Li et al., 2002 (644); McCoy et al., 2007 (248)

4.2.1. Cluster 1: Visual characteristics, congruence, and intrusiveness of an ad

The first cluster focuses on the role of online ad characteristics in ad recall, brand recognition and brand attitudes. This cluster is the largest in both the number of associated articles and the number of citations (see Table 1). More specifically, the research divides the characteristics into three categories: visual appearance, congruence, and intrusiveness. Dreze and Hussherr (2003) conducted research on online user's attention using an eye-tracking device and found that people tend to avoid looking at online banner ads, which contributes to low click-through rates. In order to eliminate this effect, marketers should use effectiveness measures such as ad recall and brand awareness, because those are less affected by ad avoidance.

The visual characteristics of an ad (e.g. size, content, placement, animated versus static) are aimed primarily at attention grabbing and click-through response (Robinson, Wysocka &

Hand, 2015). There are conflicting results on how these characteristics affect the effectiveness of an online ad. For example, some researchers claim that larger ad size is more likely to attract attention and have a higher click-through rate, some found that smaller ads are just as effective, and others found no significant relationships (Baltas, 2003; Cho, 2003; Drezze & Hussherr, 2003).

The congruence of an ad is typically investigated in regards to a website the ad is placed on and the current online activity of a user. When an ad compliments the use 'smotives on the web, it is expected to be more effective, because it matches the user's interests and is currently more relevant than a random targeted ad. Moore, Stammerjohan and Coulter (2005) found that congruity of ad's content and colors with the website it appears on have a positive effect on ad attitude, but negatively affects ad recall and recognition. They suggest that moderate congruity generates the best results in regards to the advertisement's effectiveness.

Edwards, Li and Lee (2002) argued that people are more likely to avoid and get irritated by ads, which are more intrusive. Intrusive ads are less informative, less entertaining, less controllable, and less congruent to the user's task. The same applies to the frequency of an ad-excessive repetition reduces click-through rates (Danaher & Mullarkey, 2003). Overall, while some characteristics of an ad may have a positive effect on its effectiveness, marketers must be aware of the fact that when attention grabbing efforts are overdone, users stop having a positive response after some threshold.

4.2.2. Cluster 2: Paid search advertising

The second cluster is centered around paid search advertising, more specifically it is about the bidding processes, characteristics of a sponsored ad and the subsequent click-through rates and conversion rates. Marketers bid on keywords in order to appear in the paid section of people's search results, because most users do not go beyond the first page of search results (Richardson, Dominowska & Ragno, 2007) . A key aspect is to match users' search query with relevant websites that would otherwise not appear high in organic search results (Rutz, Bucklin & Sonnier).

A substantial part of research in this cluster is dedicated to the process of choosing the right keywords to get the best price-value ratio (or cost per click), and the underlying mechanisms of auction processes. Search engines do not disclose all aspects of the auction and bidding processes, therefore marketers act upon their own beliefs, goals and expectations

(Ghose & Yang, 2009). Generally, the process goes as follows: advertisers place bids on their preferred keywords and the search engine ranks the advertisements basing on multiple criteria (e.g. bidding price, mentions on other websites, relevance to the search query) to choose the winners that appear in the paid search results section (Edelman, Ostrovsky & Schwarz, 2007). Advertisers use different strategies in auctions, but their efficiency is also strongly linked to other criteria that is not auction-related (e.g. target audience and product category), thus there cannot be a uniform strategy that works well in every case (Varian, 2007). (Rutz & Bucklin (2008) found that generic search has a spillover effect on branded search due to the fact that generic search increases awareness about the brand. Therefore, the use of some keywords may affect the performance of other keywords.

Richardson, Dominowska & Ragno (2007) elaborated a model that estimates the click-through rate of a new ad. They developed a number of feature sets (e.g. ad quality, and order specificity) that include multiple ad and search characteristics (e.g. appearance, relevance, landing page quality and number of words), and they are expected to have some impact on the effectiveness of that ad. The model tries to predict the ad ranking and tells what advertisers should change about the ad in order to achieve the best outcomes. Similarly, Google offers a "Traffic Estimator" that gives an estimate of clicks and cost per day based on the set of keywords an advertiser has chosen (Varian, 2007), but unlike the model mentioned before the provided information is very narrow.

4.2.3. Cluster 3: Targeting, retargeting, and multichannel targeting

Targeting and multichannel advertising is the central topic of the third cluster. In comparison to other clusters, this is the largest in the number of average links per article in the corresponding cluster (see Table 1). The research in this cluster suggests that usually targeting improves the click-through rates, however it may also be perceived as a manipulation intent (Goldfarb & Tucker, 2011). Targeted advertising uses personal information of a user such as purchase history, browsing history and demographics to taylor ads specifically for that targeted group, however the impact of targeting is not yet comprehensively studied (Hoban & Bucklin, 2015).

Lambrecht and Tucker (2013) discussed two types of retargeting- generic and dynamic. Retargeting allows companies to target users who have previously visited advertiser's website by exposing them to an ad on external websites or channels. They found that showing users a more generic ad is more effective than using personal information such as viewed products in a tailored (dynamic) ad.

Naik and Raman (2003) discussed the importance of synergy in multimedia communication and claimed that the synchronized use of multiple advertising channels is more effective than their use without a unified message or approach. Li and Kannan (2014) developed an estimation model about the incremental impact of a channel on conversions. As it is based on a multichannel approach, it also takes into consideration carryover and spillover effects to form a basis for estimating the effects of each individual channel.

4.2.4. Cluster 4: Measuring the effects of online advertising

The fourth cluster based on co-citation analysis consists of three articles, and therefore is the smallest out of four resulting clusters. In comparison to previous three clusters that illustrate a major part of the research on the effectiveness of online advertising, this cluster has a specific distinctive nature. While the articles by Li et al. (2002) and McCoy et al. (2007) share a common central theme focusing on the effects of intrusive ads, the article by Mehta et al. (2007) focuses more on search engine ad performance.

However, all three articles can be grouped by a methodological goal to develop and validate a new measurement in their research. For example, Li et al. (2002) addressed the issue of lacking measurement that would estimate perceived intrusiveness of interactive ads, based on the research on aspects causing irritation from ads, as well as, psychological mechanisms causing these feelings. As a result, this article provides a seven-item scale that measures the perceived intrusiveness of ads across media with sufficient levels of reliability and validity (Li et al., 2002).

In turn, the article by McCoy et al. (2007) focuses on a comprehensive measurement of ad intrusiveness as a factor that can cause annoyance and even violation of consumers. To examine their research questions, the authors developed and performed an experiment using artificial web site created for the experiment purposes (McCoy et al., 2007). Experiment participants were asked to perform different actions on the website displaying products including food, health-care, and household products. This controlled study allowed authors to isolate a variety of factors and outcomes, concluding intrusiveness is important for advertisers and web designers and that pop-ups (and pop-unders) are more intrusive than in-line ads, causing interrupted user experience. More importantly, this article provides a new methodological insight that allows other researchers to design future studies using different ad types and different locations on the page (McCoy et al., 2007).

Third article of this cluster addresses a computational problem in the context of AdWords and generalized online matching (Mehta et al., 2007). The paper studies the process of ad effectiveness using paid search engine advertising, aiming to maximize the effectiveness of ads for the bidders. The article presents a simple and time efficient deterministic algorithm, as indicated by authors, achieving a competitive ratio of $1 - 1/e$ for this problem, under the assumption that bids are small compared to budgets (Mehta et al., 2007).

4.3 Bibliographic coupling results

Here, we present the current and emerging research patterns based on the bibliometric findings on the online advertising effectiveness literature, using a bibliographic coupling technique. Figure 9 illustrates the results of bibliographic coupling representing the current and emerging research patterns in the academic literature on the effectiveness of online advertising. To evaluate and interpret the visualized clustering results, a similar methodological approach as regards to co-citation analysis is followed.

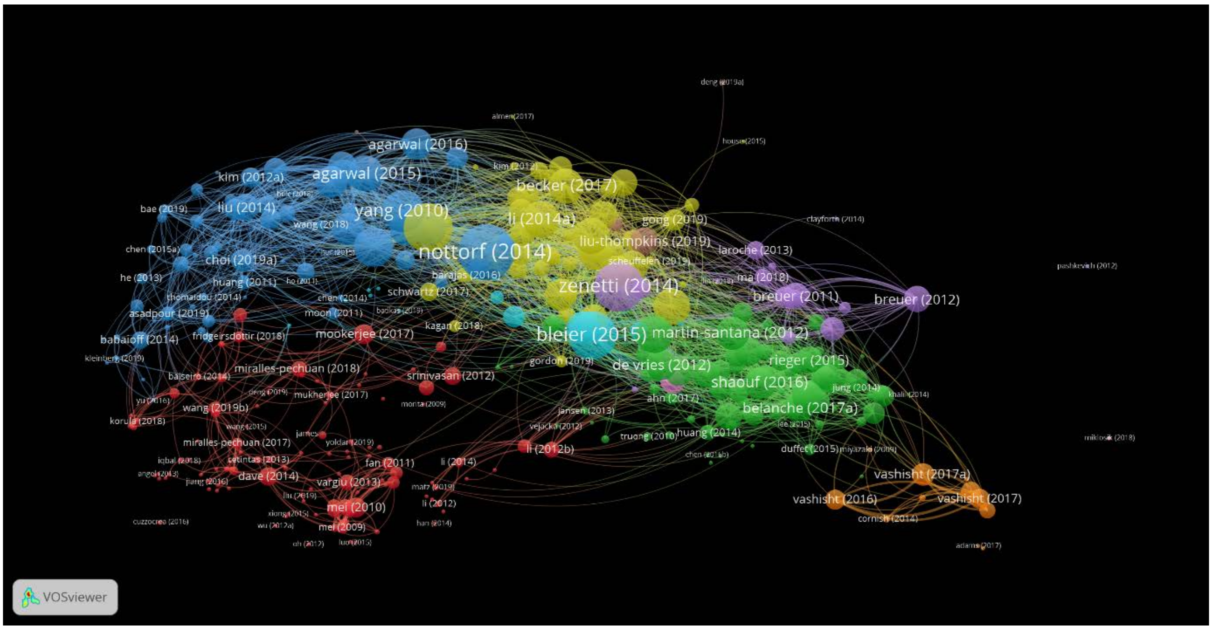

Figure 10. *A resulting visualized bibliometric network of clustered academic articles on the effectiveness of online advertising, using bibliographic coupling technique*

Table 2 provides an overview of the main statistical details of the clustered results, based on the bibliographic coupling analysis. By comparing co-citation analysis (see Table 1) and bibliographic coupling results (see Table 2), we can observe an evolution of the online advertising effectiveness research domain. While the foundations of the research domain can be attributed to 4 main clusters, the findings of bibliographic coupling indicate an evolution of the research domain into seven key thematic clusters with additional statistical patterns. More specifically, Cluster 1 has the highest number of total articles per cluster (n = 114), following the same pattern as co-citation analysis results. However, in comparison to co-citation analysis results, the contrary findings are observed in relation to the number of average citations per article (8.15) which is the lowest from the seven identified clusters based on bibliographic coupling. Cluster 6 shows the highest number of average citations per article (25.80) while simultaneously being the ‘youngest’ cluster consisting of the most recent articles on average (3.87 years). This supports the argument that online ad personalization and privacy issues are receiving increasing attention from scholars. Cluster 2 has the most links per cluster (6443), second-highest number of average citations per article (23.24), as well as, the third highest value related to the average existence of publications in years. Moreover, the three leading articles in Cluster 2: de Vries et. al, 2012; Calder et al, 2009; Lambrecht & Tucker, 2013, have 873 citations in total, the highest number among clusters derived using bibliographic coupling technique. This indicates that Cluster 2 on consumer attitudes, behavioral responses and engagement possesses a major importance for the research domain, and is associated with more seminal articles. Cluster 4 has the highest number of average links per article and second highest number of total links, respectively.

Overall, the results of bibliographic coupling present seven main thematic areas that provide the existing and emerging patterns of online advertising effectiveness research field that will be discussed now more in depth.

Table 2. An overview of bibliographic coupling clusters: descriptive statistics and key articles

Clusters	***Number of articles per cluster***	***Number of total links per cluster***	***Number of average links of articles***	***Average existance of publications in years***	***Number of total citations***	***Number of average citations of articles***	***Top 3 most cited articles per cluster***
Cluster 1: Optimization of contextual advertising	114	3067	26.90	4.67	929.00	8.15	Luo et al., 2015 (81); Li & Shiu, 2012 (57); Haddadi, 2010 (37)
Cluster 2: Consumer attitudes, behavioral responses & engagement	97	6443	66.42	5.34	2254.00	23.24	de Vries et al., 2012 (462); Calder et al., 2009 (281); Lambrecht & Tucker, 2013 (130)
Cluster 3: Automatization, algorithms & ML in SEA	67	4436	66.21	5.52	1038.00	15.49	Ghose & Yang, 2009 (230); Yang & Ghose, 2010 (131); Agarwal et al., 2011 (116)
Cluster 4: Targeting & segmentation	54	4494	83.22	4.35	1005.00	18.61	Goldfarb & Tucker, 2011 (175); Goldfarb & Tucker, 2011c (143); Li & Kannan, 2014a (84)
Cluster 5: Multi-channel advertising	18	1243	69.06	4.94	231.00	12.83	Voorveld, 2011 (52); Pergelova et al., 2010 (30); Breuer et al., 2011 (26)
Cluster 6: Personalization & privacy	15	861	57.40	3.87	387.00	25.80	Tucker, 2014 (143); Aguirre et al., 2015 (79); Liu & Mattila, 2017 (56)
Cluster 7: Advertising in video games & advertising for children	11	343	31.18	5.73	129.00	11.73	Rozendaal et al., 2009 (54); Miyazaki et al., 2009 (19); Cornish, 2014 (14)

4.3.1. Cluster 1: Optimization of contextual advertising

The first cluster is focused on the optimization of contextual advertising and ad effectiveness through the introduction of improved advertising systems.

The traditional advertising systems that use keyword matching as a tool to find relevant ads for a user are not able to do so effectively (Xu, Wu & Li, 2013). Contextual advertising is a form of targeted advertising and it refers to matching the ad context with the content of the target general page or other media (Fan & Chang, 2009). Conventional advertising sees images and videos displayed on a web page as general text and does not consider their characteristics when choosing a contextual ad (Mei, 2012). Nevertheless, visual categorization of image and video through the introduction of im-image advertising can give more precise descriptions and can therefore improve the contextual relevance (Mei & Hua, 2010). In- image advertising is a form of contextual advertising that scans a web page to collect data about images on that page, their tags and surrounding content, and uses that information to display relevant ads that would match with it based on context (Li, Mei & Hua, 2010). In- text advertising, on the other hand, uses only text and keywords of a webpage disregarding the visual content.

Mei & Hua (2010) developed an automated advertising system MediaSense that places the most contextually relevant ads at the most appropriate positions using both textual and visual similarities. The authors identified three main objectives of contextual advertising: contextual relevance (selection of relevant ads), contextual intrusiveness (optimal placement of an ad within an image or video) and insertion optimization (finding the right match between the ad and its placement to maximize effectiveness). Mei et al (2012) presented a contextual advertising system that relies solely on the visual content rather than surrounding text. It automatically decomposes a webpage into several consecutive blocks, selects images from those blocks to categorize them and find the contextual ads, and places those ads on the most optimal non- intrusive positions. Mei, Hua & Li (2008) developed a similar contextual advertising system, but it focused on video categorization.

Vargiu, Giuliani & Armano (2013) proposed a hybrid contextual advertising system that uses collaborative filtering approach to classify the page content and suggest suitable contextual ads. Collaborative filtering makes automatic predictions about the context of a webpage based on similarities with other pages. For example, if a page A is similar to page B in one characteristic, then it is more likely to be similar with page B in another characteristic than with page C. User preferences are also estimated based on the same method.

Miralles-Pechuán, Ponce & Martínez-Villaseñor (2018) tried to solve the issues with configuring a campaign in the most efficient way. The authors used genetic algorithms and machine learning to optimize campaigns to reach certain targets by selecting the best set of ad features. The test results on a real dataset showed that the new methodology is able to satisfy the configuration requirements and give optimal solutions on how to increase effectiveness of an ad.

4.3.2. Cluster 2: Consumer attitudes, behavioral responses and engagement

The second cluster investigates the psychological and behavioral responses of users to advertising. The advertising effectiveness in this cluster is mainly measured in long- term metrics- engagement and attitude towards the brand.

Exposure to an ad does not guarantee either a user's attention or the message to remain in memory after cognitive processing (Lee & Ahn, 2008). Therefore, it is important to reveal the underlying principles of information processing that will contribute to better understanding how ad effectiveness can be increased. Lee & Ahn (2008) used an eye tracking tool to collect data on users' attention to banner ads. The results suggested that animation results in less attention and reduces the positive effect of attention on memory. Moreover, they found that users' attitude towards the brand is influenced even when a user does not consciously notice the ad. Ozcelik & Varnali (2019) focused specifically on the psychology of users to identify what drives the effectiveness of ads that have been customized using behavioural targeting. The results showed that informativeness and entertainment of an ad lead to more positive attitudes, while perceived security risk and irritation have an inverse effect. The findings suggest that the effectiveness of ads is not only dependent on the characteristics of an ad and the medium, but also on the psychological factors. The attitudes and purchase intentions of a user exposed to an ad are also highly dependent on the type of product that is being advertised (Bart, Stephen & Sarvary, 2014). Ads for utilitarian products of higher involvement typically have higher effectiveness, because they serve as better triggers for ad recall and information processing.

The characteristics of a user also play an important role in the effectiveness of an ad. For example, advertising visual cues (e.g. font, colors, size, graphics) are more likely to affect male users than female users (Shaouf, Lü & Li, 2016). Besides that, self- referencing in narrative of an ad has a substantial effect on formation of favorable attitudes towards a product (Ching et al, 2014).

Calder, Malthouse & Schaedel (2009) introduced the new complementary metrics for online advertising effectiveness that positively affect advertising outcomes- personal and social-interactive engagement. While personal engagement commonly manifests in other types of media, social interactive is more unique to the Web, because the Internet provides more opportunities for participation in discussions and socializing with others (De Vries, Gensler & Leeflang, 2012).

4.3.3. Cluster 3: Automatization, algorithms and machine learning in search engine advertising

The third cluster challenges the current models, as well as the underlying technical algorithms of paid search advertising. More specifically, it discusses the applicability of the existing metrics that drive the processes of online advertising, and suggests what irrelevant metrics can lead to bias in measurements. Hummel & McAfee (2014) suggested that theoretically it is possible to introduce a new model of machine learning system in an auction environment that will maximize the efficiency in terms of the expected payoff of an advertiser. However, in practice the improvement may be exceedingly small due to the simplicity and deficiency of the metrics that are currently used. Ghose & Yang (2009) tested different sponsored search metrics to find out what differences drive those metrics in practice and to provide insights into search engine advertising. They found that the monetary value of a click is not the same across all placement positions- the highest positions typically have higher conversion rates. Agarwal, Hosanagar & Smith (2011) found that despite having the highest click- through rate, the top position does not have the highest conversion rate. In fact the conversion rate first increases and then decreases with position. Overall, this supports the claims that the current set of commonly used metrics does not capture important effects that take place in search engine advertising.

Hu, Shin & Tang (2016) conducted research on the differences between two pricing models- cost per click (CPC) and cost per action (CPA). CPC is the most widely used approach in which advertisers pay only when a user clicks the ad. CPA is the new performance- based approach, in which advertisers pay only when a user completes a specific action specified by the advertiser (e.g. signs up for a newsletter or makes a purchase). CPA is typically more preferred by advertisers, because it leads to risk sharing between the advertiser and the publisher and acts as an incentive for publishers to improve the ad effectiveness. Another benefit of the CPA model is that it minimizes the effect of fraudulent clicks by third parties. Nevertheless, the application of such a model greatly affects the results of auctions and brings new complications for the bidding processes. For example, under CPA approach the winning advertiser has a lower profit margin than when using the CPC approach.

4.4.4. Cluster 4: Targeting and segmentation

The fourth cluster discusses the approaches to targeting and segmentation in online advertising and the effectiveness of such methods. One stream of research in this cluster focuses on segmentation models of online advertising audiences based on different criteria. Reimer, Rutz & Pauwels (2014) introduced a modeling approach that can quantify long- term marketing effectiveness in combination with methods of segmentation. The results suggest that customer segments that differ in size, profile and marketing response can produce a substantially different effectiveness in the short- and long- run. Nissim, Smorodinsky & Tennenholtz (2017) discussed the considerable positive impact of data driven segmentation on online advertising effectiveness. They also indicated the obstacles and drawbacks using data for segmentation purposes. As users have much control over the information that is being collected about them, this can lead to missing or manipulated data and subsequent inferior segmentation (Nissim, Smorodinsky & Tennenholtz, 2017). Scheuffelen, Kemper & Brettel (2019) drew from the value-attitude- behavior model to compare how well different types of segmentation models can predict click- through rates and purchase behavior. They elaborated three separate segmentation models based on human values and different attitudes, and each of them is most effective in some online advertising channels but not the others. Nonetheless, the authors demonstrated that segmentation based on attitudes has more predictive power and is a more explanatory domain than the value- based segmentation.

Another substantial stream in this cluster is centered around the use of segmentation for targeting, and the targeting itself. Targeting can have a great impact on advertising effectiveness (Bruce, Murthi & Rao, 2017). Lewis & Reiley (2013) found that advertising has a larger effect on elderly people aged 65+ with 20 percent increase in purchase behavior and lower cost of advertising. The explanations for that were higher degree of attention to advertisements and more financial opportunities for spending. Song et al (2018) discussed the engagement of firms in contextual advertising, which is about contextually identifying and acquiring prospective customers of your competitors. However, the results showed that this targeting method is only effective for increasing click-through rates, but conversion rates are not affected (Song et al, 2018). Lu, Zhao & Hue (2016) found that behavioral targeting increases click-through rates when behavioral characteristics are loosely related to ad characteristics. Moreover, the positive effect of behavioral targeting on ad effectiveness becomes bigger when it is used in combination with contextual targeting.

4.4.5. Cluster 5: Multi-channel advertising

The research in this cluster is mainly focused on the synergy of various advertising channels. A great concern in advertising is the uncertainty about proper allocation of financial resources across channels (Sridhar et al, 2016). The investments in online advertising generally have a positive effect on the efficiency of marketing expenditures, and increase overall advertising efficiency when used in combination with other advertising channels (Pergelova, Prior & Rialp, 2010). However, as some channels may have a negative effect on the effectiveness of another channel, there is a strong need to strategically integrate them to maximize combined effectiveness (Sridhar et al, 2016).

Lim et al (2015) studied the synergy effect of simultaneous use of different online and offline advertising channels- television, mobile TV and the Internet. The results showed that when users are exposed to repetitive same ads on multiple channels, they perceive the message and the brand as more credible than when ads are repeatedly shown on a single channel only. Moreover, the cross-media synergy effect results in more positive cognitive responses, better attitude towards the brand and higher purchase intention. Voorveld (2011) identified a potential drawback of multi-channel advertising. They investigated the effectiveness of simultaneous exposure to online and radio advertising. The results showed that combining the two results in more positive affective and behavioral responses, but has a negative impact on recall and recognition.

Another stream of research in this cluster is about the complications in planning cross-channel advertising due to differences in channel characteristics. Breuer, Brettel & Engelen (2011) analyzed short-term and long-term effectiveness of different advertising channels. The results showed variations in effect lags, length of the effect and performance. For example, banner advertising had longer effect than price comparison advertising, but the effectiveness in terms of actual sales was lower. Breuer & Brettel (2012) tested the short- and long- term advertising effects of different channels on different customer groups- new and existing customers. They found that the length and intensity of the effect of advertising channels varies depending on a customer group. Zenetti et al (2014) conducted a study on multimedia campaigns and their effect on four effectiveness metrics- advertising awareness, brand awareness, brand image and brand consumption. The differences in channels were estimated in elasticity- the effect of the percentage change in the media variable (intensity of an advertising medium) on effectiveness. They concluded that search engine advertising has the highest effectiveness in a multimedia campaign, but the effects of banner advertising are comparatively small.

4.4.6. Cluster 6: Personalization and privacy

A substantial part of research in this cluster is centered around the impact of personalised advertising on ad effectiveness. Online advertising landscape has a growing segment of behavioural intermediaries and special interest websites that sell valuable audience data to advertisers for targeting and personalisation purposes (Schmeiser, 2018). Marketers use personal information to develop personalised ads that should theoretically enhance click-through rates through being more relevant to users (Liu & Matila, 2016). However, the research shows mixed results in regards to effectiveness of using personalized advertising. The existing research indicates a sharp decrease in click-through rates for personalized ads when users realize that their private information has been used without their consent (Aguirre et al, 2015). Bleier & Eisenbess (2015) revealed the importance of trust for achieving effectiveness of personalized ads. In particular, a more trusted company that uses a certain degree of ad personalization can achieve greater ad effectiveness than a less trusted company. Therefore, companies should assess consumers' trust regarding their business before deciding on ad personalization strategy. When used in retargeting, ad personalization is the most effective just after a user has visited a site, but it starts decreasing as time passes (Bleier & Eisenbeiss, 2015).

There is a growing concern in legal and ethical sense about the collection and potential misuse of personal information (e.g.spamming and data reselling) (Martinez-Martinez Aguado & Boeykens, 2017). Tucker (2014) investigated users' response to having control over the personal information that is being collected and used for advertising. When they had no control, targeted and personalized ads performed worse than other ads. However, when users were given control over their privacy, they were twice as likely to click on personalized ads. The increase for other ads was still significant, yet not as large. Aguirre et al (2015) confirmed that when users are informed about data collection, the increased trust makes users more likely to click the personalised ad.

4.4.7. Cluster 7: Advertising in video games and advertising for children

The seventh cluster focuses on in-game advertising and advertising for minors. Nowadays children are frequently confronted with online advertising that is inappropriate or controversial for their age. That raises ethical concerns and increases the need for promoting moral advertising literacy among adolescents (Adams, Schellens & Valcke, 2017). In addition to that, parents also lack the understanding of the impact of online advertising on their children. Generally, they believe that, because they themselves are able to react appropriately and dismiss unwanted advertising, children respond the same way adults do, but this is not the case (Spiteri Cornish, 2014). However, Rozendaal, Buijzen & Valkenburg (2009) found that advertising literacy of children does not make them less vulnerable to persuasive influence of advertising, and has a reverse effect on younger children. Children aged 10 and older have stronger cognitive defenses, and as a result the advertising effects become weaker (e.g. lower advertised product desire and lower brand awareness) (Rozendaal, Buijzen & Valkenburg, 2009).

Another stream of research in this cluster aims to enhance the knowledge about the effectiveness of placing online advertisements in games. Fogarty (2013) found that when prominent ads are placed in low-involvement games, it results in greater brand recall, but less favorable brand attitude than in case with high-involvement games. Similarly, Vashischt (2015) studied ad effectiveness under varying effects such as game speed, game-product congruence and persuasion knowledge.

As many minors are involved in gaming and the Internet as a whole, advertisers should expect stricter regulations concerning advertising for children and recognize the need for self-regulation (Miyazaki, Stanaland & Lwin, 2009). As of now regulatory bodies focus considerably on disclosure of practices than the practices themselves (Miyazaki, 2008). Miyazaki, Stanaland & Lwin (2009) stated that information collection, particularly from children, had been an ongoing concern that may not only lead to regulatory limitations for advertisers, but can also lead to reevaluation of practices and approaches to advertising on the Internet.

5. Discussion

Our study addresses the topic of online advertising effectiveness on the basis of two research questions: “What are the current and emerging research patterns in academic literature on the effectiveness of online advertising?” and “What are the main determinants of the effectiveness of online advertising from an interdisciplinary research perspective?”. In order to answer those questions we conducted a bibliometric literature review on 409 academic publications. This section includes a comprehensive comparison of the co-citation analysis and bibliographic coupling results. We describe the evolution of online advertising research and discuss additional emerging patterns. For the sake of clarity, in this section we will refer to the seven clusters based on bibliographic coupling results (1,2,3,4,5,6, and 7) as clusters A, B, C, D, E, F and G respectively.

5.1. Past, current and emerging research patterns in academic literature on online advertising effectiveness

The qualitative content analysis of the co- citation clusters sheds light on the foundations of the online advertising domain in regards to effectiveness. The results show that in the early stages of research online advertising strategies primarily relied on knowledge of advertising in general rather than on the extensive research of advertising on the Internet. The clusters reflect the currently outdated belief that the effectiveness of online advertising can be achieved solely by grabbing attention and increasing recall. The research was focused on identifying characteristics of an ad that would attract more attention and generate more clicks (see e.g. Robinson, Wysocka & Hand, 2015). Yet, researchers had doubts about whether these measures always generate a positive response from users (see e.g. Edwards, Li & Lee, 2002). For example, Danaher and Mullarkey (2003) argued that excessive repetition reduces click through rates. Furthermore, the research did not yet extensively focus on the technical opportunities due to limited technological capabilities of online advertising that could potentially improve its effectiveness. Lambrecht and Tucker (2013) discussed targeting and retargeting techniques, however their effects were not yet comprehensively studied (Hoban & Bucklin, 2015). The technological aspect of online advertising was mainly discussed in terms of paid search advertising and auctions with a purpose of estimation models and auction characteristics (see Ghose & Yang, 2009; Varian, 2007; Richardson, Dominowska & Ragno, 2007).

The qualitative content analysis of the bibliographic coupling clusters demonstrates the current and emerging patterns of online advertising domain in regards to effectiveness. Based on the content analysis, we developed a diagram that demonstrates the evolution of online advertising effectiveness research domain from the foundation to the current and emerging patterns (see Diagram 1). The research domain has broadened to a large extent. In the co-citation analysis results, we can see 4 clusters that had a great impact on the further development of the research domain towards more complex topics that construct 7 clusters.

Cluster A (Optimization of contextual advertising) originated from the co- citation cluster 1 (Visual characteristics, congruence, and intrusiveness of an ad) and cluster 4 (Measuring the effects of online advertising). This cluster focuses on contextual advertising systems that use algorithms to place ads in a way that they appear in the most effective and least intrusive positions (see Li, Mei & Hua, 2010; Mei & Mua, 2010; Vargiu, Giuliani & Armano, 2013). They operate on the basis of analyzing page's content, estimating what effects an ad would generate from each position, and finding an optimal placement (Miralles-Pechuán, Ponce & Martínez-Villaseñor, 2018).

Cluster B (Consumer attitudes, behavioral responses and engagement) also originates from co-citation cluster 1 (Visual characteristics, congruence, and intrusiveness of an ad). This cluster goes beyond the simple metrics such as click-through rate and pleasantness of an ad, and develops theories based on neuroscience. The research argues that personal characteristics of a user define the psychological response to visual and other stimuli (Shaouf, Lü & Li, 2016). Moreover, more complex concepts were introduced, e.g. user attention, attitudes, involvement, engagement and consciousness (see Bart, Stephen & Sarvary, 2014; Calder, Malthouse & Schaedel, 2009; Lee & Ahm, 2008; Ozcelik & Varnali, 2019).

Cluster C (Automatization, algorithms and machine learning in search engine advertising) originates from co-citation cluster 2 (Paid search advertising). This cluster discusses the groundlessness of the existing processes that worsen the predictions of ad effectiveness, e.g. deficient metrics for estimating ad effectiveness (see Ghose & Yang, 2009). It also became an issue for search engines, because when ad effectiveness measures are not representative, a less effective ad that will generate less clicks can win and bring in less revenue. The researchers aim to integrate machine learning systems into the auction environment and develop new pricing approaches (see Hu, Shin & Tang, 2016; Hummel & McAfee, 2014).

Clusters D, E and F (Targeting and segmentation; Multi- channel advertising; Personalization and privacy) all originated from co-citation cluster 3 (Targeting, retargeting, and multichannel targeting). Cluster D (*based on bibliographic coupling*) moves forward from targeting based on data collected about users towards contextual and behavioral targeting (Lu, Zhao & Hue, 2016). More specifically, they incorporate machine learning to develop data-driven modelling approaches and segmentation models that target users without human intervention using algorithms (Nissim, Smorodinsky & Tennenholtz, 2017; Reimer, Rutz & Pauwels, 2014).

While co-citation cluster 3 claimed that ad effectiveness can be achieved through simplification and consistency of a message across platforms (see Naik & Raman, 2003), cluster E discusses the differences in channel characteristics that have a strong impact when used simultaneously (see Breuer, Brettel & Engelen, 2011; Zenetti, 2014). For example, some channels may have either positive or negative impact on effectiveness of another channel due to spillover effects (Lim et al, 2015).

Cluster F identifies an important emerging branch of research, which is ethical and legal concerns about the use of online advertising. Due to the great technological progress that enabled improved user monitoring and personalization, users started questioning what data about them is being collected and whether it can potentially be misused by spamming and data reselling (Martinez- Martinez Aguado & Boeykens, 2017). Most importantly, users do not respond well to highly personalized messages due to those concerns (Aguirre et al, 2015).

Cluster G (Advertising in video games and advertising for children) originates from co-citation cluster 1 (Visual characteristics, congruence, and intrusiveness of an ad) and co-citation cluster 3 (Targeting, retargeting, and multichannel targeting), and discusses the effects different ad characteristics for in-game advertising, most frequently in terms of intrusiveness (see Fogarty, 2013). Moreover, the cluster touches on the ethical and legal aspects of in-game advertising. Because minors inevitably get confronted with online advertisement, the research calls for advertising literacy among children and parents (Adams, Schellens & Valcke, 2017; Rozendaal, Buijzen & Valkenburg, 2009). In order to confront unregulated collection and misuse of personal information, regulatory bodies get involved in the development of regulations and disclosure of online advertising practices (Miyazaki, 2008; Miyazaki, Stanaland & Lwin, 2009).

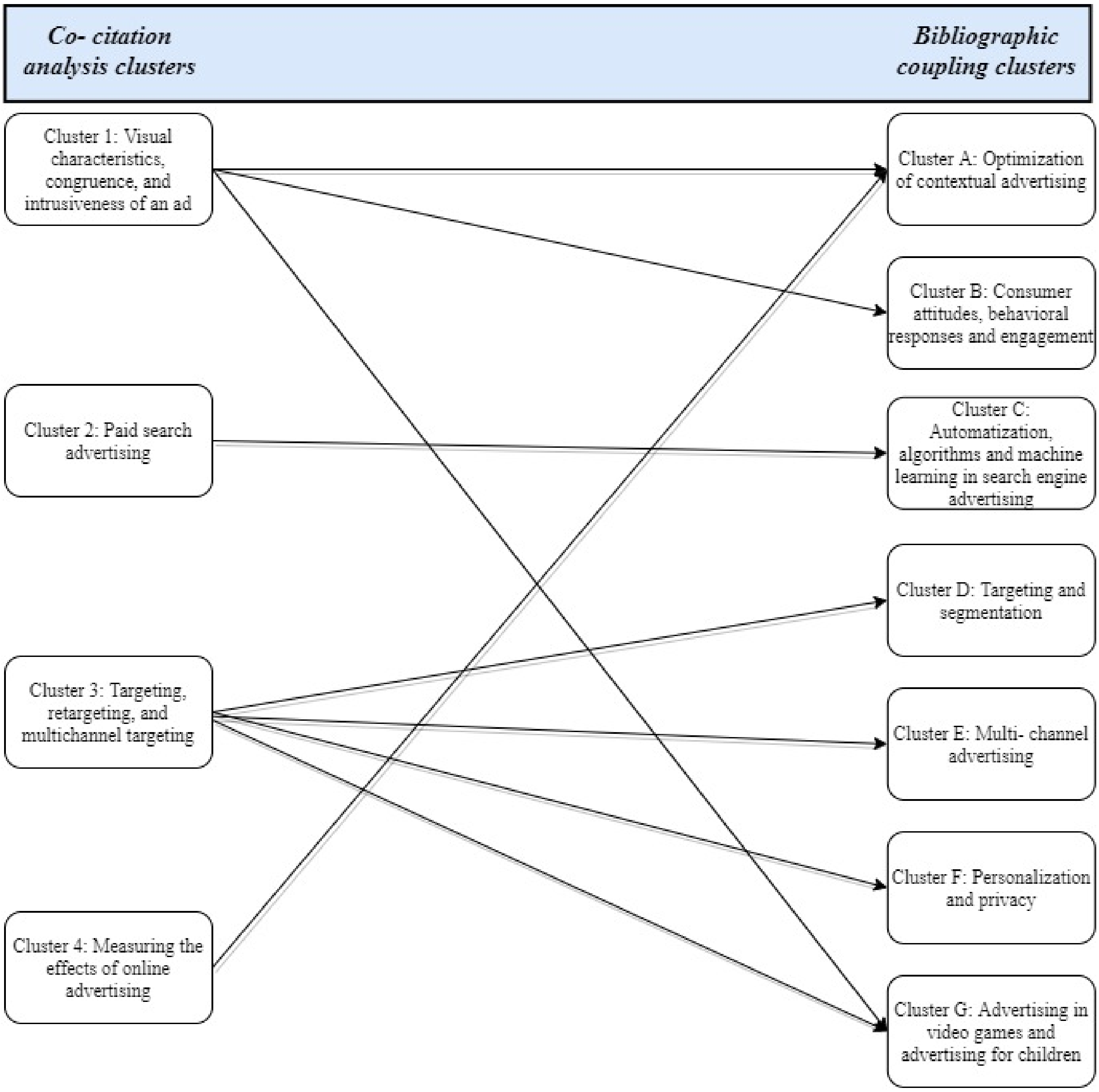

Diagram 1: The evolution of online advertising effectiveness research domain: from the foundations (based on co-citation analysis results) to the current and emerging patterns (based on bibliographic coupling results).

5.2. Towards an interdisciplinary research domain on online advertising effectiveness

Based on a comprehensive content analysis, research papers belonging to the co-citation clusters do not yet touch on an interdisciplinary approach to online advertising effectiveness. Cluster 1 (Visual characteristics, congruence and intrusiveness of an ad) involves a psychological perspective when explaining the role of ad characteristics, investigating what users might perceive as intrusive, and predicting user response. For example, Moore, Stammerjohan & Coulter (2005) argued that despite having no connection to the advertised product, congruity of ad's content and colors with the website it appears on triggers psychological responses such as an increased ad attitude. Nevertheless, other disciplines are not yet involved in the early stages of the research domain.

On the contrary, the content analysis of bibliographic coupling clusters clearly shows the development of the research domain towards interdisciplinarity. More specifically, the emerging patterns indicate a growing importance of machine learning, natural language processing, automatization, neuroscience and ethics. For example, targeting and personalization are becoming mostly automated with the use of contextual advertising approaches (Fang & Chang, 2009). Moreover, the scientific literature elaborates on new methods of collecting information about users, estimating the profiles of users based on collected data and neuroscience, and using improved algorithms (see e.g. Hummel & McAfee, 2014; Vargiu, Giuliani & Armano, 2013; Zhao & Hue, 2016).

5.3. Main determinants of online advertising effectiveness

The bibliometric analysis using co-citation and bibliographic coupling methods revealed four and seven thematic clusters respectively, which showed the main academic themes that contain the key determinants for online advertising effectiveness. As we also conducted a qualitative content analysis, we have more in-depth information concerning what are the exact subjects of these key determinants. In order to provide nuanced insights, we summarized key variables of the articles used in the content analysis in each cluster and gave examples in Diagram 2. As it is evident from Diagram 2, ad effectiveness is influenced by and not limited to this large list of variables. We identified 5 types of key determinants of online advertising effectiveness: (1) appearance and characteristics of an ad, (2) ad delivery, (3) the user, (4) use of estimation models, and (5) ad ethics/ degree of privacy violation. First, the appearance and characteristics of an ad play a role in determining ad effectiveness. That includes variables like visual characteristics, ad placement, ad intrusiveness, ad informativeness, ad entertainment and congruence (see e.g. Edwards, Li & Lee, 2002; Robinson, Wysocka & Hand, 2015). Second, ad effectiveness is also influenced by the way a user is reached (ad delivery), for example the type of segmentation and targeting, channel mix, degree of personalization, use of contextual advertising and ad repetition (see e.g. Lambrecht & Tucker, 2013; Nissim, Smorodinsky & Tennenholtz, 2017). Third, a user has an impact on ad effectiveness, e.g. targeted group, user characteristics and degree of attention (see e.g. Shaouf, Lü & Li, 2016). Fourth, the ability of an advertiser to correctly estimate future ad effectiveness and change ad characteristics respectively positively affects the ad effectiveness, e.g. through the right keyword choice (see e.g. Richardson, Dominowska & Ragno, 2007). Fifth, ad ethics and the degree of privacy violation also determine ad effectiveness (see e.g. Bleier & Eisenbess, 2015; Tucker, 2014). The findings of bibliometric analysis indicate that there is no one distinctive set of determinants resulting in increased or decreased effectiveness. Instead, the results signal that scholars and practitioners need to adjust their online ads by altering different variables to reach individual online advertising goals. These goals can be broad or specific, short- term or long- term, and include different aspects of effectiveness, e.g. purchase, brand recall or engagement. This requires a combination of online advertising techniques and models, a use of a unique channel mix and a targeting strategy.

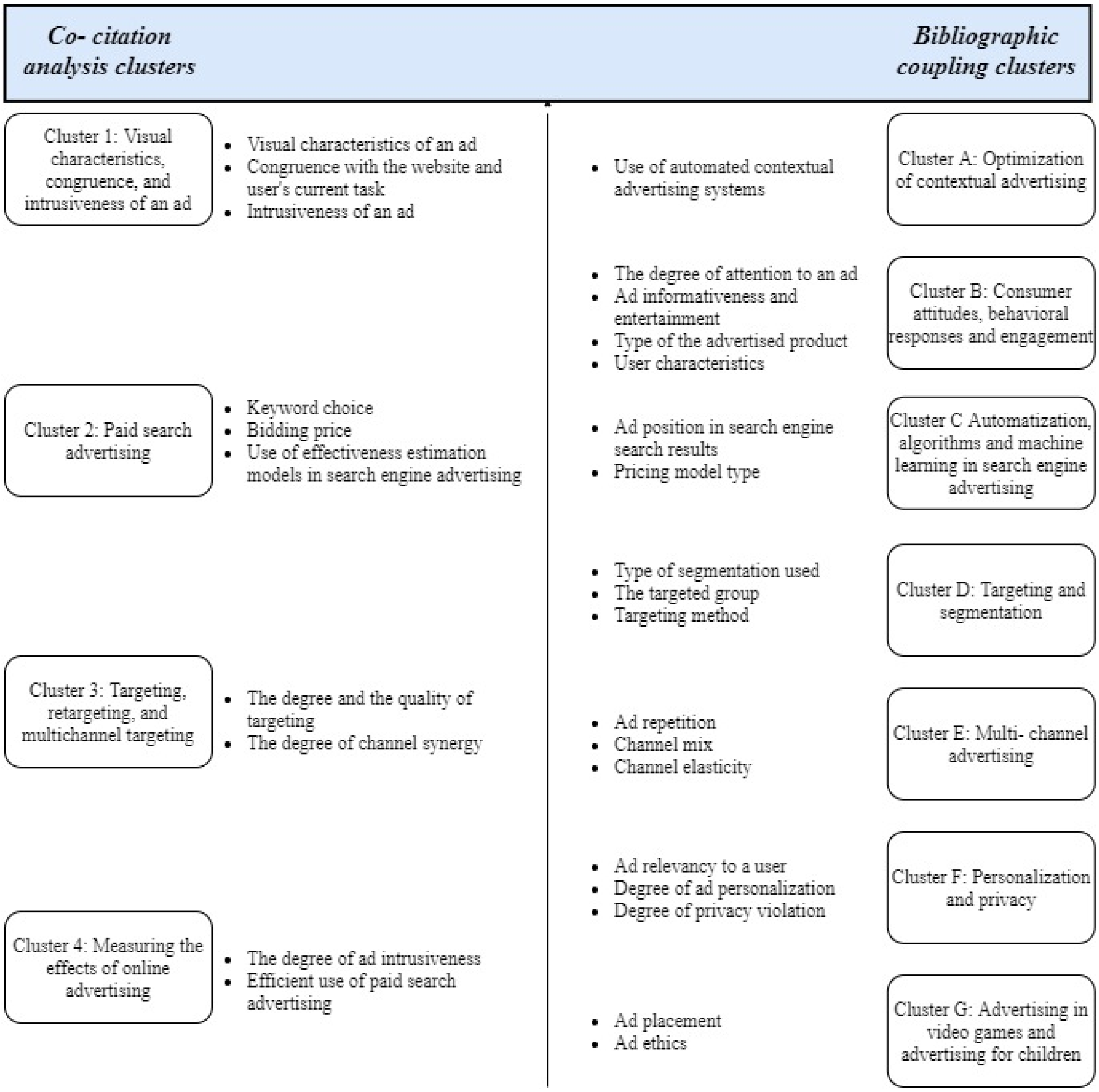

Diagram 2: The key determinants of online advertising effectiveness based on qualitative content analysis results

6. Theoretical and managerial implications

This research paper presents several important theoretical and managerial implications. From a theoretical perspective, this research paper follows the call of recent studies by Kireyev et al. (2016), Liu-Thompkins (2019) and West et al. (2019) to develop stronger theoretical basis of the online advertising research domain. While the research domain has grown considerably, it lacks comprehensive insights on online advertising effectiveness as a whole. By conducting a bibliometric analysis using co-citation and bibliographic coupling, we synthesize the past, current and emerging research patterns in this particular research domain. Furthermore, we contribute to an ongoing discussion on the key determinants of online advertising effectiveness. Bibliometric analysis helps to generate theoretical implications by summarizing the entire research domain from a global perspective through quantitative analysis.

In particular, the findings of this research paper indicate that online advertising effectiveness is a complex phenomenon that entails a range of interdisciplinary elements. Specifically, this research paper outlines that online advertising effectiveness is not determined by a specific set of variables, but instead by a different mix of variables depending on a strategic goal and effectiveness metric. In the content analysis, we identified 5 different types of key determinants of online advertising effectiveness: (1) appearance and characteristics of an ad, (2) ad delivery, (3) the user, (4) use of estimation models, and (5) ad ethics/ degree of privacy violation.

Furthermore, this paper provides additional bibliometric and methodological insights in general, and to online advertising research domain in particular. More specifically, Roy et al. (2017) identified overlapping theoretical concepts in previous studies, which could be minimized by addressing and categorizing a few more subject areas. In addition, Roy et al. (2017) identified that future studies should include publications from various academic journals, which is covered in this research paper. In turn, Aslam and Karjaluoto (2017) call for additional research that would not exclude studies based on device-type used in digital advertising, as well as, studies not limited to paid advertising spaces (IAPS).

This bibliometric research paper aimed to address these issues, as described in the methods section and elaborated in the results section (see section 4.1). We covered articles published in 210 peer reviewed academic journals, which focus on a wide scope of topics such as marketing, computer science, artificial intelligence, education research and psychology (e.g.

Marketing Science; Computer Science Artificial Intelligence; Engineering Electrical Electronic and Computer Science Cybernetics; Psychology Multidisciplinary and Educational Research). Each journal has a specific research field, which makes them distinctive from one another. Furthermore, our sample refers to 1056 unique (co)authors of 409 analyzed articles, 546 unique academic institutions from 56 different countries, and 195 funding parties, indicating a global interest in this research domain with specific cultural and institutional environments.

Moreover, we study articles from 37 different Web of Science categories, ranging from business and management, computer science and telecommunications, to neurosciences and psychiatry, supporting the claim calling to investigate this research domain from an interdisciplinary nature. It is important to acknowledge that several statistical indicators related to bibliometric findings can have multiple subjects related to one article. For example, one article can be related to several Web of Science categories. In the same way one Web of Science article can have multiple authors with affiliations to different universities and countries, respectively.

Similarly, this research paper provides new methodological insights to online advertising research domain by combining bibliometric analysis techniques with a subsequent content analysis, contributing to the previous seminal bibliometric analysis by Kim & McMillan (2008) covering a decade of new academic publications, and responding to additional calls for new interdisciplinary systematic and bibliometric research findings (see e.g. Aslam & Karjaluoto, 2017; Kireyev, Pauwels, & Gupta, 2016; Liu-Thompkins, 2019; Roy, Datta, & Basu, 2017; West, Koslow, & Kilgour, 2019).

To our knowledge, there has been no bibliometric study that would cover such interdisciplinary scope of the online advertising effectiveness research domain in such a comprehensive manner.

From a managerial perspective, this paper contributes new insights to online marketers inviting professionals to devote a special attention to the recent technological advancements and increasing connections of different business spheres, ranging from marketing and finance to data analytics and policing, as regards to online advertising activities. The increasing interdisciplinarity of online advertising suggests that managers should formulate and execute more extensive strategies through recruiting professionals from diverse disciplines and implementing strategic alignment of various organizational entities.

The findings of our bibliometric analysis support the notion suggesting online marketers to focus on development of additional control and personalization options for customers, instead of purely collecting personal information (Liu & Mattila, 2017). Online marketers should learn to target customer psychological motivations and tune their advertising algorithms to facilitate a customer to continue engagement with the ad (Liu & Mattila, 2017). This requires a symmetric digital content delivery to various audiences, using more individually-targeted and timely approach (Berman, 2018; Lejeune & Turner, 2019). Similarly, online marketers are required to carefully segment their customers, e.g. by demographics and gender with existing research indicating that male users respond more effectively to visual and summary-content, while female users tend to respond better to verbal and text-rich ads (Shaouf, Lü, & Li, 2016). Moreover, online marketers should learn to efficiently employ the existing automated advertising systems that estimate the characteristics of a user and provide solutions for further personalization (Vargiu, Giuliani & Armano, 2013).

Furthermore, we invite online marketers to devote a notable attention to implementation of new online advertising effectiveness metrics, especially in the context of multi-channel advertising. For example, Guixeres et al. (2017) suggest new metrics like facial gesture coding (McDuff et al., 2014) and fNIRS (Kopton and Kenning, 2014) that can be complemented with additional techniques for ad classification and performance prediction using e.g. Linear Discriminant Analysis, Marquardt Backpropagation Algorithm or other supervised and unsupervised machine learning algorithms.

Additionally, online marketers should experiment with various models of budget allocation on online advertising to increase its effectiveness of both offline and online sales (de Haan, Wiesel, & Pauwels, 2016). For example, Kireyev et al. (2016) find that dynamic version of classic metrics of CPA and ROI notably outperform static metrics, improving the correct budget allocation. Online marketers are suggested to experiment with structural vector autoregressive model (de Haan et al., 2016) or different multivariate time series models (Kireyev, Pauwels, & Gupta, 2016) for more accurate estimations of budget allocations. Finally, we suggest online marketers to further consider identified key determinants in the process of delivering ads to potential and existing customers in order to boost the short- and long-term sales by carefully coordinating their cross-media advertising efforts.

While this research paper does not directly focus on developing new policy implications, we certainly acknowledge the importance to address this topic in more details for at least two reasons: (1) the resulting cluster 6 and cluster 7 based on bibliographic coupling analysis address personalization and privacy concerns of online advertising, including advertising for children; (2) with recent technological advancements, advertisers are able to collect and use personal and online behavior data to develop more personally-targeted digital content oftentimes resulting in skeptical business practices (Boerman et al., 2017). Online marketers should acknowledge that the misuse of personal information and the use of highly personalized messages can lead to legal issues and negative effects on effectiveness.

In previous years, this discussion has received attention from U.S. Federal Trade Commission and European Data Protection Authorities (‘European Commission’, 2019). Recent studies have identified that the degree of intrusiveness have an impact on the perception of advertising activities by users, calling also for consideration of cultural differences (see e.g. Brettel & Spilker-Attig, 2010). On the other hand, Wicken and Karlsson (2017) indicated ad blocking was estimated to have cost publishers nearly $22 billion during 2015. Gardette and Bart (2018) support the notion that interest of consumers online do not need to align with the interests of advertisers, proposing a solution that would enable a user to fully disclose his details when desired, potentially reducing price discrimination and increasing ad effectiveness. Advertisers would also prefer to receive more heterogeneous user profiles at the early phases of marketing funnel to increase effectiveness of subsequent actions (Gardette & Bart, 2018). As suggested by Robinson (2017), customers online are frequently faced with ‘opt-out’ choice that require users to request that information is not being collected, while the ‘opt-in’ option would be more preferred. Thus, advertisers supporting the latter option potentially can increase consumers' perception of the advertiser as pro-consumer and trustworthy. Thus, policy-makers can potentially benefit from the insights in this paper analyzing the research on this debate, especially, in regards to the development of new data protection acts and regulations.

7. Research limitations and future research directions

While this paper presents important contributions to scholars and practitioners, it certainly is not excluded from several limitations that indicate new directions for future research agenda. First, the search query was limited to five search terms to define the 'effectiveness' of online advertising. Although we aimed to grasp the most relevant literature, a broader search query could lead to additional findings on online advertising effectiveness that were out of scope for this particular study. Expanding a list of keywords will however result in a larger dataset that will require more innovative bibliometric analysis tools to overcome the existing difficulties of working with large bibliometric datasets. For example, there is an increasing recognition of unsupervised text analysis methods, such as, topic modeling as a technique to detect additional thematic patterns and to reduce the potential subjective bias related to topic labelling process (see e.g. Antons et al., 2016).

Second, the article selection for co-citation analysis was limited to a threshold of 10 citations to focus on the most relevant high quality literature, reduce the risk of self- citation bias and avoid overly complicated interpretations. Nevertheless, lowering the minimum citation threshold to a smaller number would increase the number of articles included in the co-citation analysis leading to additional interlinkages in the bibliometric network. This could reveal additional bibliometric patterns and findings.

Third, this paper presents online advertising from an interdisciplinary perspective with frequent technological advancements, indicating that effectiveness metrics identified in this paper can potentially be outdated in the near future. Therefore, we expect new effectiveness metrics to emerge that will require new monitoring systems. These future developments are expected to generate a new stream of academic literature that is currently not existing, such as, live tracking of advertisement effectiveness across different media channels, or, development of accurate prediction rates of ad effectiveness based on machine learning algorithms.

Fourth, this study is limited to use of the Clarivate Analytics Web of Science Core Collection database. Web of Science has proven to be a preferred database of choice for multiple bibliometric studies, however it has its indexing algorithms that can slightly affect the search results over time and influence the citation patterns. The changes will not have much influence on the results of the co-citation analysis, but the bibliographic coupling may be slightly more affected.

Finally, the findings of this bibliometric analysis determine crucial factors affecting the effectiveness of online advertising. However, the nature of this research method does not directly enable to establish causal relationships between the factors, therefore we suggest to test the identified relationships in this study by additional quantitative and qualitative research methods across different research domains and time periods.

8. Conclusion

This paper investigated the effectiveness of online advertising. We conducted a bibliometric literature review to objectively access variability, rapid evolution and the growing importance of the online advertising domain. First, we constructed a database that included 438 Web of Science academic publications. Next, we performed co-citation and bibliographic coupling techniques to identify current and emerging topics and patterns in the research domain. Co- citation analysis that reflects the foundations of the online advertising field identified four clusters. Bibliographic coupling analysis that identified seven clusters revealed the rapid dynamics of scientific development. Further, we conducted a content analysis to make an in-depth investigation of the identified topics. Our findings show that online advertising research domain focuses on interdisciplinary developments and gets heavily shaped by technological advancements. There is an exponentially growing interest and variety of scientific literature, which is reflected in the publication patterns. The findings of this paper present several valuable future research avenues for scholars interested in online advertising developments, as well as, addresses key areas for improvement for online advertisers.

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Appendix

Appendix 1: Search query and dataset development process

Results: 1,404

(from Web of Science Core Collection)

You searched for: TOPIC: ("online adverti*")

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 267

(from Web of Science Core Collection)

You searched for: TOPIC: ("web adverti*")

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 488

(from Web of Science Core Collection)

You searched for: TOPIC: ("internet adverti*")

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 180

(from Web of Science Core Collection)

You searched for: TOPIC: ("digital adverti*")

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 77

(from Web of Science Core Collection)

You searched for: TOPIC: ("e-adverti*")

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 2,250

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*"))

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 627

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*"))

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 788

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*"))

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 854

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*"))

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 1,003

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*" OR "click*"))

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 1,014

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*" OR "click*" OR "conversion*"))

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 873

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*" OR "click*" OR "conversion*"))

Timespan: 2009-2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 858

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*" OR "click*" OR "conversion*"))

Refined by: LANGUAGES: (ENGLISH)

Timespan: 2009-2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 483

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*" OR "click*" OR "conversion*"))

Refined by: LANGUAGES: (ENGLISH) AND DOCUMENT TYPES: (ARTICLE)

Timespan: 2009-2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Results: 416

(from Web of Science Core Collection)

You searched for: TOPIC: (("online adverti*" OR "web adverti*" OR "internet adverti*" OR "digital adverti*" OR "e-adverti*") AND ("effective*" OR "efficien*" OR "impression*" OR "click*" OR "conversion*"))

Refined by: DOCUMENT TYPES: (ARTICLE) AND LANGUAGES: (ENGLISH) AND [excluding] WEB OF SCIENCE CATEGORIES: (ONCOLOGY OR CHEMISTRY ANALYTICAL OR CLINICAL NEUROLOGY OR ENGINEERING ENVIRONMENTAL OR MEDICINE GENERAL INTERNAL OR ENVIRONMENTAL STUDIES OR ERGONOMICS OR OBSTETRICS GYNECOLOGY OR FOOD SCIENCE TECHNOLOGY OR GENETICS HEREDITY OR GERIATRICS GERONTOLOGY OR INFECTIOUS DISEASES OR GERONTOLOGY OR GREEN SUSTAINABLE SCIENCE TECHNOLOGY OR MATERIALS SCIENCE MULTIDISCIPLINARY OR HEALTH CARE SCIENCES SERVICES OR MATHEMATICAL COMPUTATIONAL BIOLOGY OR METALLURGY METALLURGICAL ENGINEERING OR PEDIATRICS OR MEDICAL INFORMATICS OR PHARMACOLOGY PHARMACY OR PHYSICS APPLIED OR HEALTH POLICY SERVICES OR PHYSICS CONDENSED MATTER OR IMMUNOLOGY OR PHYSICS MATHEMATICAL OR INSTRUMENTS INSTRUMENTATION OR REGIONAL URBAN PLANNING OR SOCIAL SCIENCES BIOMEDICAL OR MEDICINE RESEARCH EXPERIMENTAL OR NUTRITION DIETETICS OR SOCIAL WORK OR SPORT SCIENCES OR SURGERY OR SUBSTANCE ABUSE OR BIOLOGY OR TRANSPLANTATION OR BIOPHYSICS OR VIROLOGY OR BIOTECHNOLOGY APPLIED MICROBIOLOGY OR WOMEN S STUDIES)

Timespan: 2009-2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

Additionally, after a comprehensive manual check of all included articles, seven articles that were out of scope of this bibliometric literature review were excluded.

1. Candeub, A 2019 Nakedness and Publicity.

2. Mao, AM; Bottorff, JL 2017 A Qualitative Study on Unassisted Smoking Cessation Among Chinese Canadian Immigrants.

3. Jonas, B; Leuschner, F; Tossmann, P 2017 Efficacy of an internet-based intervention for burnout: a randomized controlled trial in the German working population.

4. Golrezaei, N; Nazerzadeh, H 2017 Auctions with Dynamic Costly Information Acquisition.

5. Jorgensen, C; Carnes, CA; Downs, A 2016 Know More Hepatitis: CDC's National Education Campaign to Increase Hepatitis C Testing Among People Born Between 1945 and 1965.

6. Webster, GM; Teschke, K; Janssen, PA 2012 Recruitment of Healthy First-Trimester Pregnant Women: Lessons From the Chemicals, Health & Pregnancy Study (CHirP).

7. van Osch, L; Lechner, L; Reubsaet, A; Steenstra, M; Wigger, S; de Vries, H 2009 Optimizing the efficacy of smoking cessation contests: an exploration of determinants of successful quitting.

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