LEHRSTUHL FÜR MARKETING

Selected Conceptual and Methodological Contributions on Influencer Marketing and Partial Least Squares Structural Equation Modeling

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Essay 3 has been published in a European journal that publishes in British English and not American English. To ensure comparability with the publication, this part of the dissertation is written in British English, unlike the rest of the dissertation, which is written in American English.

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List of Abbreviations

AMS	Academy of Marketing Science
AtA	Attitude towards Advertising
AtP	Attitude towards Product
Att	Attractiveness
AVE	Average Variance Extracted
BESC	Brand Engagement in Self-Concept
CB-SEM	Covariance-Based Structural Equation Modeling
CCA	Confirmatory Composite Analysis
CFI	Comparative Fit Index
EASA	European Advertising Standards Alliance
eWOM	electronic Word-Of-Mouth
Exp	Expertise
FIMIX-PLS	Finite Mixture Partial Least Squares
FL	Fornell-Larcker
FTC	US American Federal Trade Commission
GoF	Goodness of Fit
GWP	Gesellschaft für angewandte Wirtschaftspsychologie
HTMT	Heterotrait-Monotrait ratio of correlations
IC	Influencer Credibility
IM	Influencer Marketing
MICOM	Measurement Invariance of Composite Models
PI	Purchase Intention
PLS-SEM	Partial Least Squares Structural Equation Modeling
PO	Psychological Ownership
PSI	Para-Social Interaction
RMSEA	Root Mean Square Error of Approximation
SC	Source Credibility
SEM	Structural Equation Modeling
SIC	Self-Influencer Connection
SRMR	Standardized Root Mean square Residual
Tru	Trustworthiness
UWG	Gesetz gegen den unlauteren Wettbewerb
VIF	Variance Inflation Factor
WOM	Word-Of-Mouth
WoS	Web of Science

Preface

This doctoral thesis consists of three essays, each a self-contained unit which presents research in the field of social media-based influencer marketing (hereafter: influencer marketing) and partial least squares structural equation modeling (PLS-SEM) in marketing research. The first essay uses a comprehensive bibliometric analysis to give an overview of and to analyze the published research on influencer marketing and its effects on consumer behavior between the years 2011 and 2020. In addition, it introduces influencer marketing as a counterstrategy to marketing communication commoditization, which has become increasingly challenging for marketers. The second essay focuses particularly on the methodological analysis PLS-SEM. This essay examines publications in the top 30 ranked marketing journals, ranked according to Hult et al. (2009) between 2011 and 2020. Based on the analysis of these publications, the essay considers the use and application of PLS-SEM in detail. Finally, the third essay shows a conjunction of the two previously investigated topics. This research paper examines the impact of psychological ownership on influencer marketing and evaluates the study results with PLS-SEM. Figure 1 illustrates the composition of this dissertation.

Figure 1: Composition of dissertation

In the past two decades, social media have grown in popularity and become an indispensable part of people’s lives. By January 2021, more than half of the world’s population (53.6%) were using social media in their everyday lives, which represents an increase of 13.2%

compared to January 2020 (Hootsuite, 2021). At the same time, social media have changed the way companies do marketing by harnessing these media as an essential advertising channel (Kozinets et al., 2010), especially in the last few decades. Growing into a relevant channel, which "allows the creation and exchange of user-generated content" (Kaplan & Haenlein, 2010, p. 61), marketers can contact a broad audience very easily. Several studies have already shown that social media's user-generated content is increasingly important, as consumers tend to trust this content and follow purchase recommendations more than content generated directly by relevant companies (e.g., Djafarova & Rushworth, 2017; B. K. Johnson et al., 2019; E. K. Johnson & Hong, 2020). Therefore, influencer marketing has turned into a meaningful marketing tool, which companies can use to address their target audience and convince them of their products.

According to Veirman et al. (2017, p. 801), social media-based influencers "are content creators who accumulated a solid base of followers" on at least one social media platform to "provide their followers an insight into their personal, everyday lives, their experiences, and opinions." It becomes influencer marketing if these influencers use their reach to advertise, for example, an endorsed product, brand, service, organization, or idea to their community (Brown & Hayes, 2008; Veirman et al., 2017). Some influencer followers do not even recognize that they are participating in an advertising process and that the influencer wants to sell their company's products directly, in the same way as through direct advertising. Instead, they believe they are just participating in influencers' daily lives by watching the shared content (Abidin, 2016; Brown & Hayes, 2008; Veirman et al., 2017). Therefore, to protect the consumer, influencer marketing has emphasized the necessity of enacting stricter legal requirements to identify advertising in the content they publish (e.g., in Germany §5a(6) Gesetz gegen den unlauteren Wettbewerb (UWG)).

Initially, the majority of marketers and researchers predicted that influencer marketing would not have a long and influential future (e.g., Krüger, 2017) as the frequency of influencer advertising content was becoming too excessive. However, the general opinion has changed considerably. *Forbes*, in an article by Fertik (2020), asked "Why Is Influencer Marketing Such A Big Deal Right Now?" Their answer was straightforward: "Because it works." Business figures and research results give the necessary proof. Regularly studies by the Influencer Marketing Hub Institute forecast that the industry market size of influencer marketing will reach $13.8 billion in 2021, which represents a 42% increase compared to the previous year. According to their results, 90% of the surveyed marketing practitioners believe in influencer marketing's effectiveness, and 62% want to increase their spending on influencer campaigns in

2021 (Influencer Marketing Hub, 2021). Further, it has to be noted that influencer marketing is no longer merely a tool to reach younger people as it initially was. In recent years, older users' interest and share in following influencers has increased significantly. Among US online users, 26% of those between 39 and 54 years old already pay attention to influencer recommendations (ThinkNow, 2019).

Marketing research already offers insight into the effectiveness of this marketing tactic. For example, Djafarova and Rushworth (2017) and Schouten et al. (2019) found that influencers appear to be more credible and trustworthy than many celebrities. They communicate directly via social media, and their background is often the same as those of the followers, which results in greater advertising effectiveness. In addition, Dost et al. (2019) demonstrated the effectiveness of seeding marketing campaigns, such as influencer marketing, as part of the marketing mix. Seeding campaigns can increase the overall sales of fast-moving consumer goods by up to 18% (Dost et al., 2019). A study by Voorveld (2019) even names social media influencers as one of six key directions for future research on brand communication in social media.

The aforementioned highlights how relevant the influencer marketing topic, dealt with in the ***first essay*** (co-authored by Marko Sarstedt), is. The study used a comprehensive bibliometric analysis of social media-based influencer marketing research published between 2011 and 2020. The essay explains how marketers can use influencer marketing as a counterstrategy to the commoditization of marketing communication. Although qualitative literature research on specific aspects of influencer marketing has already been published (e.g., Hudders et al., 2020; Sundermann & Raabe, 2019), this review offers decisive added value using bibliometric analysis. It enables statistical evaluation of a large number of publications and their impact on the research community (Broadus, 1987; Diodato & Gellatly, 2013; Pritchard, 1969). By using keywords, citation networks, or other paper information, we can offer additional and unique insights, enhance the transparency of the research process, and thereby increase the results' reproducibility (Aria & Cuccurullo, 2017).

In addition, the essay provides a possible solution to de-commoditized marketing communication. Commodities are widely understood to be undifferentiated products or services that the majority perceive as homogeneous. Therefore, marketing managers in companies are faced with the problem of appearing irrelevant to customers. They only become visible if they define realizable unique selling propositions and successfully differentiate themselves from the competitors through their marketing instruments (Enke et al., 2014).

Companies' marketing communication has become so omnipresent, that they fail to effectively distinguish their own advertising from their competitors'. We offer a solution to re-establish the distinction by varying the content and perception of the communication through influencer marketing and in such a way de-commoditize it.

The bibliometric analysis results show that four main topics shape influencer marketing, namely (1) influencer marketing principles, (2) advertising disclosure effects, (3) source credibility and endorsement, and (4) para-social interaction. Research already offers a tremendous amount of information that marketers can adapt to improve their strategies and usage behavior. Besides, extant work offers even more research possibilities as it shows research gaps. In addition, marketers can use the recommendations to avoid the commoditization of marketing communications.

This first essay is a preprint version due to be published in 2021 as a chapter (Pick & Sarstedt, 2021) in the international edition of the book *Commodity Marketing - Strategies, Concepts, and Cases* edited by Margit Enke, Anja Geigenmüller, and Alexander Leischnig.

This dissertation's second main focus is PLS-SEM, which became a popular method to estimate complex path models in research, especially in marketing research (Hair et al., 2012). PLS-SEM comprises two parts: *partial least squares* and *structural equation modeling*.

Structural equation modeling enables the analysis of complex research models that examine multiple relationships in a given context. Moreover, there are two types of structural equation modeling of which one relies on the covariance-based and the other on the partial least squares technique (e.g., Hair, Hult, Ringle, & Sarstedt, 2017). In PLS-SEM, the explained variance of the endogenous latent variables is maximized by estimating the partial model's relationships combining principal components analysis with ordinary least squares regressions (Mateos-Aparicio, 2011). In this process, the latent variables' values are estimated as exact linear combinations of their associated manifest variables (Fornell & Bookstein, 1982). In contrast, covariance-based structural equation modeling (CB-SEM) estimates the model's parameters by minimizing the discrepancy between the estimated and the sample covariance matrices (Jöreskog, 1978).

Researchers mainly use PLS-SEM to predict and explain theories (Rigdon, 2012), as PLS-SEM is of a "causal-predictive" and not confirmatory nature (Jöreskog & Wold, 1982, p. 270). Besides, it allows us to evaluate models with several latent variables and paths without making distributional assumptions. It is recommended for small sample sizes in certain contexts (e.g., Hair, Risher, et al., 2019), which describes only an excerpt of PLS-SEM's advantages.

Further, it allows researchers to overcome the apparent dichotomy between explanation and prediction typically described in academic research. Thus, it provides a foundation for marketers' implication development (Hair, Sarstedt, & Ringle, 2019).

For these reasons, it is not surprising that PLS-SEM has become an important analytic tool for marketing researchers (Hair et al., 2012). The number of PLS-SEM publications compared to CB-SEM has increased significantly in the past few years (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017). As we shall explain, the next essay supports the relevance of PLS-SEM in another way.

The ***second essay*** (co-authored by Marko Sarstedt) is a research note. It describes the first results of an extensive analysis of PLS-SEM estimations in marketing research to replicate Hair et al.'s (2012) first extensive study on this topic for the years 1981 to 2010. For this, we collected over 100 variables from 239 papers published between 2011 and 2020 to assess the quality of the provided information on PLS-SEM evaluation and to gain further insight into how this methodological field developed in the last decade. To achieve this, we re-examined the previous paper's criteria to compare the two sets of data with each other. Further, we reviewed the use of new evaluation techniques and upcoming methods and developments to enhance and supplement the existing guidelines as well as highlight areas for improvement. This should make it easier for researchers and practitioners to work with PLS-SEM and improve result-reporting quality.

Since this essay is a replication and actualization of Hair et al.'s (2012) article that was published in the *Journal of the Academy of Marketing Science*, we plan to submit the finalized article to this journal again.

In the single-authored ***third essay***, I combined the two previous topics. This paper examined the impact of psychological ownership on influencer marketing and evaluated the study results with PLS-SEM. Based on Pierce et al.'s (2001, p. 299) seminal paper on psychological ownership, this concept is defined as the "state in which individuals feel as though the target of ownership (material or immaterial in nature) or a piece of it is "theirs" (i.e., "It is MINE!")" even though there is no legal entitlement to the feeling of possession. Although the psychological ownership concept originated in the organizational behavior literature (Dyne & Pierce, 2004; Pierce et al., 2001; Pierce et al., 2004), it has gained considerable value and relevance in marketing research (Jussila et al., 2015) and in other areas such as social media research (e.g., Joo & Marakhimov, 2018; Karahanna et al., 2018; Zhao et al., 2016). To understand how influencer marketing impacts consumer behavior, the essay investigated psychological ownership in the context of influencer marketing. This research specifically examined the impact of (1) consumers' perceived influencer credibility on buying intention, attitude toward the product, and advertising, (2) psychological ownership on attitude toward the product and purchase intention, and (3) the influence of self-influencer connection. The purpose was to understand the relations between influencer and consumer. The research results showed that influencer credibility significantly influences purchase behavior as well as product and advertising evaluation and even increases the perceived connection between influencer and consumer. Moreover, credibility increases the psychological ownership feeling, which positively impacts consumer perception and behavior. Besides, this work demonstrates that previous results regarding celebrity research can be transferred to influencer marketing. Further, the results also show that this area still has a great deal of potential to shed light on consumer behavior regarding influencers.

I presented an early conceptualization of this paper at the annual conference of the *Gesellschaft für angewandte Wirtschaftspsychologie* (GWPs) in Wernigerode, Germany, in 2018. Additionally, I had the opportunity to present this research paper's results at the *Academy of Marketing Science* (AMS) *World Marketing Congress* in Edinburgh, United Kingdom, in 2019. Following this, an extended abstract of the research was published in the conference proceedings (Pick, 2020a), and a full article in the peer-reviewed *European Business Review* in 2020 (Pick, 2020b).

This dissertation's findings contribute to the young research field of influencer marketing, as well as to recommendations regarding PLS-SEM use. The work focuses primarily on advancing marketing research in these areas. The comprehensive bibliometric analysis has structured the field of influencer marketing research quantitatively and thus serves as an orientation for marketers by highlighting the research gaps in this field. Further, it can help other researchers to improve their use of PLS-SEM by following the supplemented guidelines. In addition, we used an empirical study to illustrate PLS-SEM use and provide information on the psychological processes concerning influencer marketing.

Consequently, the three essays expand our understanding of the mechanisms underlying influencer marketing and evaluation using PLS-SEM. However, they only provide a foundation for this, while also providing promising directions for further research.

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Essay 1

Influencer Marketing as a Counterstrategy to the Commoditization of Marketing Communications: A Bibliometric Analysis

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Influencer Marketing as a Counterstrategy to the Commoditization of Marketing Communications: A Bibliometric Analysis

Abstract

Continuous exposure to marketing communication has led to its commoditization. Addressing this concern, marketing practitioners increasingly rely on social media-based influencer marketing as a counterstrategy to effectively position products and brands in the market. Social media-based influencer marketing has also attracted considerable attention in marketing research, with numerous studies shedding light on the contingencies that shape successful influencer marketing and its effect on consumer behavior. In light of its growing prominence, this chapter documents the results of a comprehensive bibliometric analysis of social media-based influencer marketing research published between 2011 and 2020. Our study of 132 research papers discloses the scientific foundations of and emerging trends in the field by analyzing collaboration networks, conducting a citation analysis, and concluding with a keyword trend analysis. We find that four main topics shape the field, namely influencer marketing principles, advertising disclosure effects, source credibility and endorsement, and para-social interaction. Based on our results, we offer guidelines to marketers on how to overcome the commoditization of marketing communications.

1. Introduction

Advertising seems to be everywhere. We wake up in the morning and immediately glance at our smartphones. Pop-up notifications of various apps and newsletters are already waiting on us in our inboxes. As the day progresses, we are exposed to billboards, newspaper advertising, radio and TV commercials, and many other types of advertisements. Consumers are increasingly overwhelmed by the sheer volume of advertising appeals, making it difficult for companies to reach them. This information overflow has drastically reduced advertisements' effectiveness (e.g., Anderson & Palma, 2012), leading to their commoditization.

As marketers became aware of the difficulties of communicating with clients through traditional advertising, they turned to new online marketing formats. A particular promising communication type in this regard is social media-based influencer marketing (IM), which has gained prominence in marketing practice. For example, the Influencer Marketing Hub Institute, which regularly surveys marketing agencies, brands, and other industry professionals, estimates the market size of the IM industry at US$9.7 billion (Influencer Marketing Hub, 2020). According to Relatable (2019), 94% of all marketing practitioners consider IM as a useful marketing tool.

These figures are mirrored in various research studies, which offer empirical support for IM's effectiveness. For example, Dost et al. (2019) underline IM's seeding potential, showing that it can increase the sales of fast-moving consumer goods by up to 18%. Schouten et al. (2019) find that influencer campaigns result in greater advertising effectiveness than traditional celebrity advertising, because consumers trust influencers more. In light of these results, it is unsurprising that Voorveld (2019) considers IM as one of six essential directions for future research on brand communication in social media.

Several researchers have conducted systematic literature reviews of prior research to summarize the state of IM research. For example, Hudders et al.'s (2020) review discloses three research streams that characterize the field: consumers' perception of influencers, the classification of content strategy types, and the perception and efficacy of their content. In previous but related research reviews, Sundermann and Raabe (2019) focused on influencer communication and Veirman et al. (2019) on the impact of IM on children.

While these reviews provide a qualitative summary of the state of research, they do not reveal the collaboration networks that have shaped the field over the years. More specifically, they do not offer any insights into the structure of networks of joint scholarly work, which serve as the basis of the IM domain's state of knowledge (Fritze et al., 2018; Khan et al., 2019).

Addressing this concern, this chapter presents the results of a comprehensive bibliometric analysis of IM research. Bibliometric analyses differ from qualitative literature reviews since they allow the statistical evaluation of a large number of research papers with the aim of measuring their impact on the scientific community (Broadus, 1987; Diodato & Gellatly, 2013; Pritchard, 1969). By relying on citation patterns, keywords, and other paper information, bibliometric analyses offer unique insights that extend beyond qualitative literature reviews and that increase the transparency of the research process, thereby maximizing the reproducibility of results (Aria & Cuccurullo, 2017).

Our bibliometric analysis of 132 papers – published between 2011 and 2020 in 65 peer-reviewed journals with a specific focus on marketing – discloses four prominent research streams in the IM field (principles of IM, advertising disclosure effects, source credibility and endorsement, and para-social interaction) and reveals several research gaps. We also find that the past two years have seen a surge in IM research, involving many authors who have already formed initial collaboration networks on various topics, such as advertising disclosure and its effects on children and adolescents or para-social interaction, and its decisive role in consumer buying behavior. Finally, our keyword analysis also discloses research trends that have emerged over the past four years.

Our findings not only offer insights into the state of IM research but suggest promising areas for future research. They also provide recommendations to marketers, which will allow them to avoid the commoditization of marketing communications by using IM.

2. Theoretical Background

2.1. Marketing Communication Commoditization

When consumers regard services provided by different suppliers as homogeneous and interchangeable, these services turn into a commodity (Rangan & Bowman, 1992). This is the current position of marketing communication. Advertising is omnipresent and companies often fail to adequately differentiate their marketing communication from that of competitors. Companies' response to the Covid-19 pandemic is an excellent example of this commoditization of marketing communications. Practically all Covid-19 pandemic response ads emphasize that we are living in "uncertain times," but that "we're here for you." The companies insist that their main priority is "people" and "families" and by bringing their services to the "comfort and safety of your home", conclude that "we're all in this together!"[1]

This homogenization of advertising appeals has had a detrimental effect on the consumers' experiences, decreasing their involvement and ultimately leading to passive information processing behavior. Similar developments have been observed in other contexts, such as banner advertising (e.g., Braun & Moe, 2013) and mobile in-app advertising (Sun et al., 2017), which drastically reduce the effectiveness of these types of advertising after repeated exposure.

Marketing communication is regarded as a "New Commodity," implying that a service or a good has lost its power of differentiation and has turned into a commodity. In the process, marketing communication has also lost most of its effectiveness.

To de-commoditize new commodities requires re-establishing the differentiation by changing the content or perception of particular service characteristics (Dickson & Ginter, 1987; Matthyssens & Vandenbempt, 2008). As we will argue, IM is a vehicle that caters for this aim.

2.2. Influencer Marketing

Influencers, more specifically social media-based influencers, "are content creators who accumulated a solid base of followers" on one or more social media platforms and "provide their followers an insight into their personal, everyday lives, their experiences and opinions" (Veirman et al., 2017, p. 801). We speak of IM when influencers use their reach to convince their community of a product, brand, or service (Brown & Hayes, 2008; Veirman et al., 2017). Institutions such as the European Advertising Standards Alliance (EASA) and the US American

[1] https://www.youtube.com/watch?v=vM3J9jDoaTA

Federal Trade Commission (FTC) have formulated their own definitions of IM, serving as a standard for regulatory activities (EASA, 2018; FTC, 2017). For example, EASA defines IM as a type of marketing communication “if marketers or brand owners approach users to generate content in exchange for payment or other reciprocal arrangements, and have control of the content” (EASA, 2018, p. 7).

Sundermann and Raabe (2019) differentiate between influencers and regular celebrities in terms of four dimensions: Influencers (1) gain prominence by their social media work; (2) are considered more accessible and connected than celebrities; (3) can create more authentic messages by co-producing and modifying the content of the original advertised message; and (4) have the means to develop unique content since they are usually not employed by a specific company.

Marketing research offers insights into the effectiveness of this marketing type. Followers assume that influencers’ intensions are not to sell – as is the case with direct advertising – but to communicate and inform their community by creating content on social media platforms (Abidin, 2016; Brown & Hayes, 2008; Veirman et al., 2017). They appear more credible than celebrity endorsers because their origins and circumstances are often the same as those of the customers; they communicate directly with their followers (Djafarova & Rushworth, 2017), turning themselves into new role models and opinion leaders.

Initially, IM was used to primarily address younger target groups, as they have become increasingly difficult to reach through traditional advertising media (Audiencenet, 2018; Pick, 2020). However, in recent years, IM has also been successfully used to target older consumer groups. For example, according to ThinkNow (2019), 26% of 39 to 54 year-old US online users pay attention to influencer recommendations.

2.3. Influencer Marketing to De-Commoditize Marketing Communication

Prior research has shown that companies can de-commoditize a product or a service by differentiating their offering through superior customer relationships. To establish superior customer relationships, companies need to communicate directly and individually with their customers. IM offers a suitable means to achieve these goals. The possibility of direct communication and a high level of individualization of the advertised products and services’ messages considerably strengthen the relationship between followers and influencers. The higher perceived proximity results in an increased acceptance of the advertising and a greater willingness to buy the product or service (e.g., Gong & Li, 2019; Munnukka et al., 2019).

Customers' voluntary choice to follow influencers and their content further contributes to IM's effectiveness. This type of self-selection eases the targeting of followers with specific interests.

In addition, IM allows companies to implement better co-marketing strategies that further increase differentiation in marketing communications, thereby contributing to the de-commoditization (Matthyssens & Vandenbempt, 2008; Windahl & Lakemond, 2006). By analyzing the interaction content between influencer and followers and their comments, a company can refine its customer orientation and better meet customer needs, ultimately leading to more profitable customer relationships (Matthyssens & Vandenbempt, 2008).

3. Method

Our bibliometric analysis builds on data from the Web of Science (WoS) and Scopus. To ensure the inclusion of all relevant and most recently published papers, we supplemented the WoS and Scopus data with manual entries. We compiled a comprehensive search term list and defined exclusion or inclusion criteria to identify the relevant papers. After this, we searched the databases with the assistance of the predefined search query and acquired the data. In a final post data-acquisition process, we pre-processed the data and commenced with the data analysis. Figure 1 illustrates our research process.

3.1. Keyword and Paper Search

We conducted a detailed review of previously known literature on IM to extract the most frequently used keywords, in order to generate the search term list. We selected several search terms covering the terms *influencer* (e.g., online celebrity, instafamous) and *influencer marketing* (e.g., sponsored endorsement, selfie promotion), as well as their applications. Based on this analysis, we conducted a first WoS search using the platform's advanced topic search. We reviewed the papers' keywords and WoS keywords (keywords Plus®, Garfield & Sher, 1993) for the most frequently used keywords and added missing but relevant keywords, related to the terms influencer and influencer marketing and their applications, to our initial list.

Using this final list of keywords, we initiated the paper search. We restricted our search to those papers published in journals ranked in the first and second quartile (Q1 and Q2) in the 2019 SCImago journal ranking (SCImago, n.d.). In addition, we set our research's time frame to the period from 2008 to 2020 (data generation date, September 30). We selected 2008 as the starting year, being the year of publication of Brown and Hayes' (2008) seminal work, *"Influencer Marketing: Who really influences your customer."* As our analysis solely focuses on marketing-related topics, we excluded papers that did not fit the categories (e.g., medicine, engineering). Table 1 in the Appendix contains the reduced lists of subject categories considered in our analysis.

In addition, our analysis focused explicitly on IM literature in the context of social media networks like YouTube, Facebook and Instagram. Papers dealing exclusively with weblogs (e.g., Colliander & Dahlén, 2011; Lu et al., 2014) were therefore excluded from the list. These weblogs have lost most of their importance in the context of IM, particularly in recent years, as consumers tend to follow the content of influencers on other platforms (Morning Consult, 2019).

3.2. Bibliometric Analysis

To investigate our data, we ran a series of bibliometric analyses in R (R Development Core Team, 2021), drawing on Aria and Cuccurullo's (2017) Bibliometrix tool and Biblioshiny app. We specifically examined the publications per year, journals, authors, citations, and the topic structure. To determine the first thematic connections, we carried out an author analysis that extracts information on each author's prominence in the network. We searched for research collaborations, thematic foci, and co-authorship developments in collaboration networks and presented them graphically. In order to identify thematic structures, we created a reference co-citation network, which contains the citations between and within the papers' references. Using the network data as input, we applied the Louvain clustering algorithm (Blondel et al., 2008) and used the corresponding Shiny app for the visualization (Aria & Cuccurullo, 2017). Finally, we performed a keyword and related topic analysis to identify additional research themes and topic trends.

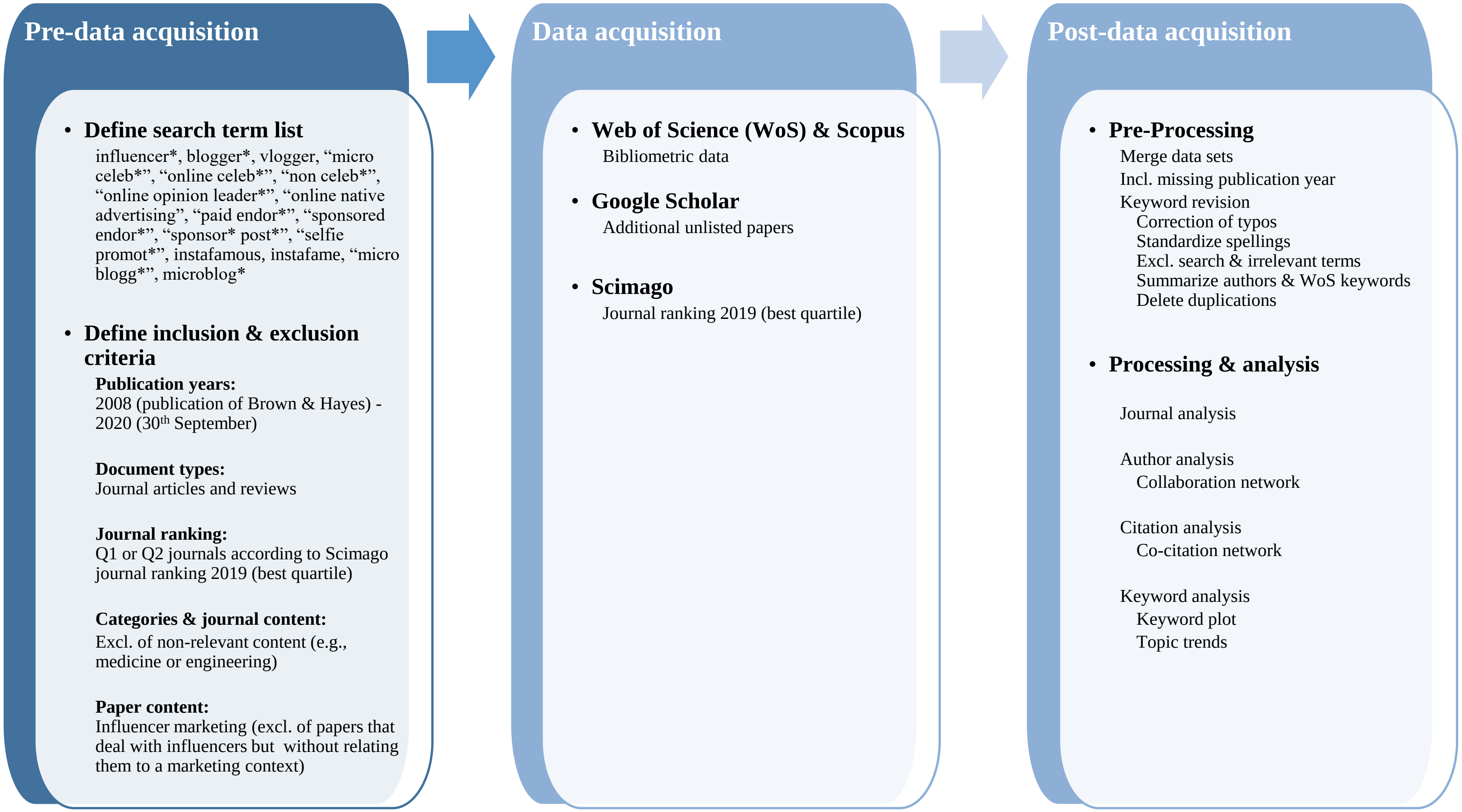

Figure 1: Workflow of data acquisition and the processing of the subsequent bibliometric analysis

4. Results

4.1. Data Pre-Processing

The WoS search yielded 1,663 results. Following a screening of the keywords, titles, abstracts, and journals, we excluded 1,404 publications because of their content. The term "influencer," in particular, resulted in many redundant publications that we excluded from the analysis, yielding a preliminary data set containing 259 papers. In the next step, we screened these papers in order to identify those that deal with IM in a marketing context. This analysis yielded a final data set of 132 papers (129 empirical papers and 3 review papers), 112 (84.85%) of which appear in Q1 journals.

Before initiating a further analysis, we merged the authors' keywords and the WoS keywords (keywords Plus®; Garfield & Sher, 1993). We also corrected typing errors and different spellings (e.g., eWOM and electronic Word of Mouth, singular and plural spelling), and merged terms with the same meaning (e.g., purchase intent and purchase intention). In addition, we excluded the search terms and non-expressive keywords (e.g., social media, model, internet). Finally, we removed duplicates from the data set.

An initial content analysis showed that the papers cover a broad range of products, brands, and services. Not surprisingly, a large proportion of the studies deals with fashion (*n*=25) (e.g., Lenne & Vandenbosch, 2017; McFarlane & Samsioe, 2020), emphasizing IM's importance in this product category (e.g., Esteban-Santos et al., 2018; J. E. Lee & Watkins, 2016). Considering the social media platforms, most studies focus on Instagram (*n*=45) and YouTube (*n*=30), which is understandable since they are the most important global platforms for influencer-brand cooperation (eMarketer, 2018). However, other platforms were considered, including Twitter (*n*=9), Facebook (*n*=4), and Weibo (*n*=2).

4.2. Publication Year

Our search results show that although Brown and Hayes (2008) are regarded as the pioneers of IM, scholarly research on this topic only started some years later with Freberg et al. (2011). While a scant interest was shown in IM during the early years, research picked up in 2015, culminating in a surge of papers in 2019 and 2020. Even though our analysis only covers papers until September 2020, these two years account for 70% of all published papers. Our results nonetheless provide evidence of a substantial increase in research interest during 2020. Figure 2 provides a detailed illustration of these developments.

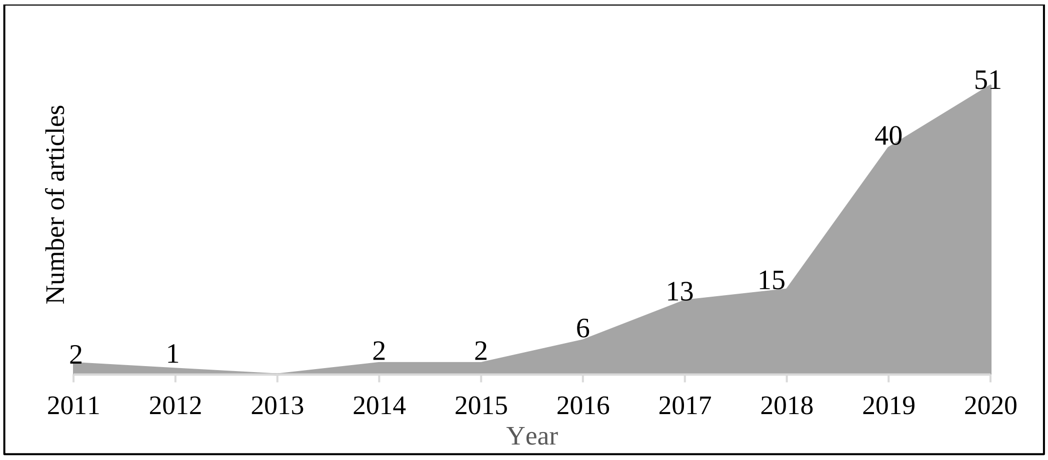

Figure 2: Number of papers per year

4.3. Journal Analysis

The 132 papers were published in 65 journals, confirming that IM research covers a wide range of research outlets.[2] The ten most frequent journals are *Computers in Human Behavior* (*n*=9), *International Journal of Advertising* (*n*=8), *Journal of Retailing and Consumer Services* (*n*=7), *Journal of Fashion Marketing and Management* (*n*=6), *Journal of Business Research*, *Journal of Marketing Management*, *Psychology & Marketing*, *Social Media + Society* (all *n*=5), *Frontiers in Psychology*, and *Journal of Advertising* (both *n*=4).

We also considered the most frequent locally cited journals, that is the number of times a journal was cited in the references of the data set (Aria & Cuccurullo, 2017). The most frequent locally cited journals are the *Journal of Advertising* (*n*=359), *Computers in Human Behavior* (*n*=317), and *Journal of Consumer Research* (*n*=299). The first two journals not only play a key role in the publication of IM research, but they also serve as important references for researchers working in the field. However, according to our search criteria, it is interesting to note that although the *Journal of Consumer Research* features prominently as a reference, it has to date not published a single paper on IM.

4.4. Author Analysis

The 132 papers in our data set have 320 different authors. Only 12 were single-authored papers. The average number of authors was 2.4 per paper. The authors originate from 32

[2] Due to the large number of journals, we were unable to examine journal citation networks, which allow the analysis of citation ties between the various journals. Furthermore, because of the relatively small number of published papers in the early years (2011-2018, *n*=41), we were unable to disclose any temporal developments of papers per journal.

different countries, mainly from the US (*n*=84), the Netherlands (*n*=21), and the UK (*n*=20). Table 2 in the Appendix lists the ten most frequently represented countries.

To further analyze the author data, we created collaboration networks in which the nodes refer to the authors and the node size to their importance for the network, representing the number of interactions with other authors in the network. Authors are connected via edges, the weights of which refer to the number of co-authored papers. To ensure the networks' explanatory value, we only considered networks containing at least two papers. Table 3 in the Appendix lists the most relevant authors in terms of their publication output and their corresponding collaboration network. The analysis disclosed nine collaboration networks (Figure 3) comprising 55 authors.

In the first and most prominent network, Liselot Hudders, Eva A. van Reijmersdal, Esther Rozendaal, Marijke de Veirman, and Veroline Cauberghe are the five authors playing a central role. The studies conducted by these authors and their co-authors mainly concern effects of advertising disclosure, particularly on children and adolescents. For example, research in this network examines the positive impact of advertising disclosure in IM on the brand recall of children in particular (Boerman & Reijmersdal, 2020) and followers in general (Boerman, 2020). Folkvord et al. (2019) show that children's brand recall increases through influencer campaigns, like vlogs, even without considering advertising disclosure.

Two concepts play a decisive role in the authors' considerations, namely *advertising literacy* and *para-social interaction* (PSI). Advertising literacy is the ability of individuals to cope with advertising; that is, when persons are exposed to advertising, they can recognize it as such (Boush et al., 1994). PSI is defined as the relationship that consumers develop with media characters (Horton & Wohl, 1956). This relationship transforms these characters into essential sources of information (Rubin et al., 1985). Research in this field finds no direct effect of advertising disclosure on PSI with the influencer (Boerman, 2020). Instead, PSI serves as a moderator for the effects induced by disclosure (Boerman & Reijmersdal, 2020). The higher the PSI between children and influencers, the lower the disclosure's negative influence (Boerman & Reijmersdal, 2020). Advertising disclosure, however, encourages advertising literacy; disclosure causes an increase in children's (Boerman & Reijmersdal, 2020) and adolescents' advertising literacy (Jans et al., 2019), which in turn decreases the influencer's trustworthiness and PSI and subsequently consumers' purchase intention (Jans et al., 2019).

In addition, advertising disclosure has adverse effects on attitudes toward the brand (Hoek et al., 2020; Reijmersdal et al., 2020), content, and the influencer (Reijmersdal et al., 2020). Veirman and Hudders (2020) confirm the negative effects of advertising disclosure, through increased advertising recognition and skepticism, on brand attitude and perceived influencer credibility. However, these negative effects only become apparent when the influencer campaign is exclusively one-sided; that is, when the product is exclusively viewed in a positive light. According to these authors, influencers should communicate a post if it is a genuine recommendation, even if regulations force them to mark the post as advertising because it positively affects brand perception (Veirman & Hudders, 2020).

Reijmersdal and Dam (2020) find that early adolescents' persuasion knowledge and information processing are less developed than those of middle adolescents, resulting in more information to incite their persuasion knowledge and to process the advertising disclosure. However, in both age groups, the purchase intention remains unaffected by disclosure (Reijmersdal & Dam, 2020).

The timing of the advertising disclosure also plays a decisive role. If the advertising disclosure occurs before the start of the content, children and adolescents internalize the advertising more strongly (Reijmersdal et al., 2020). A further consideration is that adolescents accept the placement as long as a balance is maintained between content and advertising content. If not, the advertising triggers negative brand evaluations (Dam & Reijmersdal, 2019).

Two papers, assigned to this network, cover topics other than advertising disclosure or children and adolescents. First, Veirman et al. (2017) find that the number of followers positively affects the influencer liking and that influencers with many followers do not provide the best option to promote products with unusual and unique product designs. Second, by comparing the posts of the influencer and the posts of the brand, Jans et al.'s (2020) research indicates their respective advantages and disadvantages.

The second network comprises further research on IM's impact on children and their eating habits. Anna E. Coates, Charlotte A. Hardman, Jason C. G. Halford, Paul Christiansen, and Emma J. Boyland's (2019a, 2019b) papers show that children who watch influencer content on unhealthy snacks increase their consumption of these snacks, which is not the case with healthy snacks (Coates et al., 2019b). They also conclude that advertising disclosure compared to untagged content increases children's food consumption (Coates et al., 2019a).

The third network is a collaboration between Jonas Colliander and Carolina Stubb. These authors' research shows that the emphasis on advertising's impartiality positively affects the message's perceived credibility and the influencer in general (Stubb & Colliander, 2019). Even if it is paid advertising, the influencer should justify it, since this leads to better evaluations of the influencer (Stubb et al., 2019). Furthermore, according to these authors, linking an influencer's social media post to a product landing page can have a negative impact on purchase intention and brand attitude. Instead, marketers should provide links to their company's homepage and not to the product landing page (Stubb & Colliander, 2019).

The fourth network, developing around Nathaniel J. Evans, also deals with advertising disclosure. Studies in this network consider how different wording affects the perception of the disclosure. For example, *#Paid Ad* causes a significantly higher advertising recognition compared to *#SP*, *#Sponsorship*, or a non-disclosure (Evans et al., 2017), which has a negative impact on attitude and behavioral intentions (Evans et al., 2017; Hoek et al., 2020; Reijmersdal et al., 2020). Evans et al. (2019) also examined the influence of disclosure on children and the impact of parental response. Their results suggest that marketers should use sponsored pre-roll advertising to make parents aware of the sponsorship (Evans et al., 2019). Other research in this network deals with the impact of advertising agencies (Carpenter Childers et al., 2019) and influencer characteristics (e.g., the number of followers) on consumer perceptions (S.-A. A. Jin & Phua, 2014).

Research in the fifth network, authored by S. Venus Jin, Ehri Ryu, and Aziz Muqaddam, also deals with influencer characteristics and the impact thereof on followers. For example, according to S. V. Jin et al. (2019), consumers regard influencers as more credible than traditional celebrities. Consequently, influencers have a more positive impact on the brand, a higher social presence, and make people more envious; all of which increase the purchase intention, especially of men. For women, the increase in purchase intention is caused by PSI. S. V. Jin and Ryu (2020) examined the effect of the influencer presentation in an image, finding that men prefer selfies and photographs taken by others, whereas women prefer group photos. When influencers present themselves with the product in an image, this has a significant positive effect on corporate credibility and on the attitude toward the post. Researchers attribute this finding to the impact of PSI (S. V. Jin & Muqaddam, 2019). Additionally, S. V. Jin and Ryu (2019) find that luxury brand recognition is higher for influencer posts with product-centric images (i.e., images that show only the product) than for consumer-centric images (i.e., images that show the influencer with the product). Brand posts show no such effect. To summarize the research in this network, it is evident that gender and the form of presentation are crucial factors in attracting an intended target audience.

The sixth network of Juha Munnukka, Hanna Reinikainen, Juha Maity, and Vilma Luoma-aho investigates the causal chain between PSI, source credibility (SC), brand trust, and purchase intention (Reinikainen et al., 2020). These authors show that the number of user comments moderates the effect of PSI on SC. Munnukka et al. (2019) finds that PSI is significantly higher when the audience comment valence regarding the IM campaign is high.

The main characteristic of the three remaining networks is that one particular author is involved in all the papers linked to each of them. The seventh network, involving Colin Campbell, focuses on the classification of influencer types, their functions (Campbell & Farrell, 2020), and challenges (Campbell & Grimm, 2019). Research in the eight network, co-authored by Elmira Djafarova, deals with the characteristics that distinguish influencers from celebrities and their impact on marketing communication effectiveness (Djafarova & Rushworth, 2017; Djafarova & Trofimenko, 2019). Research in the last network, involving Chen Lou, examines the effects of influencers’ trustworthiness, attractiveness, content value, and similarity, showing that these factors positively impact brand awareness and purchase intention (Lou & Kim, 2019; Lou & Yuan, 2019). The research also finds that influencer posts receive fewer negative comments than brand posts (Lou et al., 2019).

Considering the results of the collaboration analysis, it is evident that the research has not settled in stable networks. Instead, it is conducted in isolated silos. Initial collaborations are evident in the following main areas: advertising disclosure, effects on children and adolescents, SC, the influence of PSI, types of influencers, and the post’s presentation. We expect that, over time as research on IM progresses, the collaboration networks will stabilize.

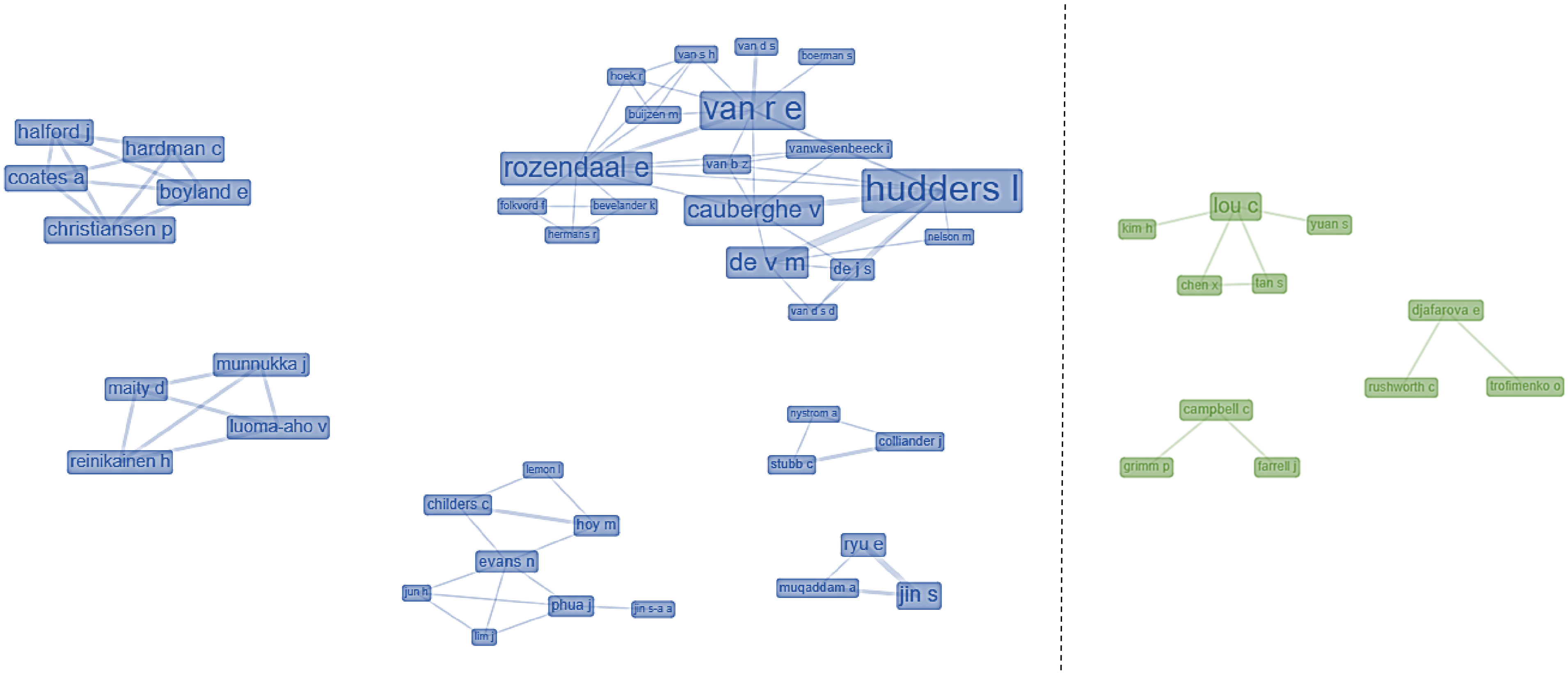

Figure 3: Collaboration networks
left: author networks; right: authors who have published more than once but are not further connected

4.5. Citation Analysis

Table 4 in the Appendix provides an overview of the ten papers with the most local citations (i.e., number of citations in the data set), along with their global citations (i.e., citations in the WoS). Considering the content of these papers, it is evident that they reflect the starting points of different influencer research topics. The most cited paper is that of Veirman et al. (2017). It serves most other papers by providing the basis for the definition of influencers and IM. Moreover, it is among the first papers to conduct an empirical investigation in the Instagram context. The next most cited paper by Djafarova and Rushworth (2017) was the first to show that influencers are more effective than traditional celebrities because they are perceived to be more credible. Other papers in this list define and categorize influencers (Freberg et al., 2011; Marwick, 2015), describe the process of IM (Abidin, 2016), and develop a model to understand the underlying communication (Uzunoğlu & Misci Kip, 2014). The remaining papers serve as the starting point for specific areas of research, among others, PSI (J. E. Lee & Watkins, 2016), self-branding (Khamis et al., 2017), influencer type and related follower numbers (S.-A. A. Jin & Phua, 2014), and the attainment of a celebrity status as a prerequisite for celebrity research (Kapitan & Silvera, 2016).

In the next step, we analyzed 6,633 references included in the papers to disclose citations between and within the papers' reference lists (Figure 4 and Appendix Table 5). In the resulting networks, the nodes refer to references, the size of the nodes to their centrality degree, the edges to co-citations between the references, and the edge weights to the number of citations. Closeness indicates the number of steps required to reach any other node from a given node, and betweenness is an approximation of the number of shortest paths between nodes that pass through a given node (Aria & Cuccurullo, 2017). For the analysis, we used the Louvain clustering algorithm (Blondel et al., 2008), removed isolate nodes, and set the minimum edge to two. This analysis resulted in four clusters.

Cluster one covers the IM principles and includes several IM papers that use the literature as a theoretical background to the research. We explained the largest node containing Veirman et al. (2017) and additional papers (e.g., Freberg et al., 2011) in our previous discussion of frequently cited papers. This cluster's remaining papers provide insights into the motivations to use IM (Petrescu et al., 2018), the importance of contemplating a second person's experience in the decision process (Seeler et al., 2019), the establishment of frameworks to develop brand endorsement during an influencer's career cycle (Nascimento et al., 2020), and influencer communication (Enke & Borchers, 2019).

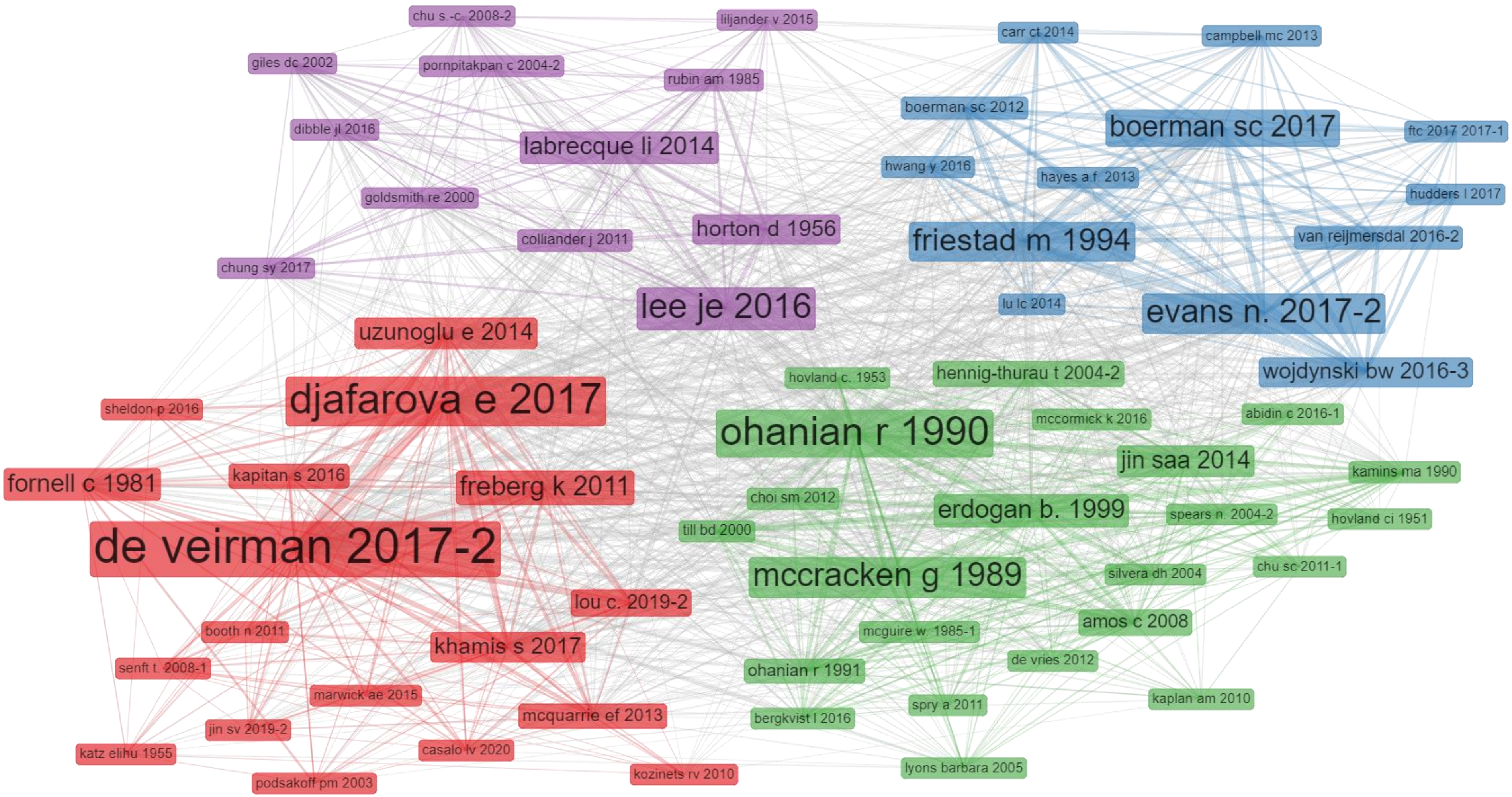

Figure 4: Document co-citation network

Cluster two covers advertising disclosure research and includes pivotal papers by Boerman et al. (2017), Evans et al. (2017), and Friestad and Wright (1994). Evans et al. (2017) dealt with advertising disclosure, Friestad and Wright (1994) introduced the persuasion knowledge model, and Boerman et al. (2017) found that advertising disclosure not only activates persuasion knowledge but results in a higher level of distrust in the advertising. Additional research revealed the positive effect of disclosure on awareness (Dhanesh & Duthler, 2019), and that micro-influencers with disclosure increase purchase intentions (Kay et al., 2020). However, the research also produced contradictory findings, suggesting that disclosure has no effect on advertising outcomes (Hayes et al., 2020) such as purchase intention, electronic word-of-mouth (eWOM), and persuasion knowledge (S. Lee & Kim, 2020). Disclosure may have become the norm, considering that an increasing number of countries are introducing strict labeling rules.

Cluster three focuses on celebrity endorsement and SC-related topics, and several of the representative papers are grounded in McCracken (1989) and Ohanian's (1990) seminal works on the characteristics of celebrity endorsers and the classification of SC dimensions (attractiveness, trustworthiness, and expertise), respectively. These studies document how social media changes the perception of celebrity culture (Jerslev, 2016). Abidin (2016) notes that "influencers are one form of microcelebrity" and are perceived to be more credible and trustworthy than celebrities (e.g., Schouten et al., 2019; Trivedi & Sama, 2020). However, celebrity endorsement is still effective and the processes are comparable (Cheah et al., 2019). However, studies showed as well opposite relations (Agnihotri & Bhattacharya, 2021; O'Neil & Eisenmann, 2017).

S.-A. A. Jin and Phua (2014) were the first to explore the role of SC in an IM context. Berne-Manero and Marzo-Navarro (2020) showed that a higher number of followers positively affects SC, while Hill et al. (2020) found a similar effect for perceived popularity. However, the number of followers is not the only relevant metric in this regard (Ladhari et al., 2020) and marketers should not neglect the like-to-follower ratio, as low values negatively influence followers' account perception (Vries, 2019).

A different research stream evaluated the factors that impact on influencer credibility, showing that it is positively influenced by trustworthiness, expertise, message credibility (Esteban-Santos et al., 2018), PSI (e.g., Reinikainen et al., 2020), influencer-brand-fit (Breves et al., 2019), and influencer-product-fit (e.g., Park & Lin, 2020). By contrast, a strong commercial orientation and a high level of perceived sponsor control (Martínez-López et al., 2020) have a detrimental effect on perceived credibility. In addition, knowing the person personally (Cooley & Parks-Yancy, 2019), positive experiences (Konstantopoulou et al., 2019), perceptual homophily, users' interaction, content quality (Miranda et al., 2021), and avoidance of "muscle display" (Su et al., 2020) increase influencer trustworthiness.

Credibility has positive effects, for example, on purchase intention, attitude toward advertising (e.g., Gong & Li, 2019), attitude toward the brand (Chetioui et al., 2020; B. K. Johnson et al., 2019), and perceived psychological ownership (Pick, 2020). In the long run, SC positively influences brand image (Fink et al., 2020) and loyalty (Cicco et al., 2020). In conclusion, as Balabanis and Chatzopoulou (2019) show, all SC dimensions have a positive influence on consumers. Trustworthiness has the most persuasive power (Martensen et al., 2018) as it positively influences eWOM impact (Konstantopoulou et al., 2019) and information credibility (Xiao et al., 2018).

Cluster four deals with PSI and J. E. Lee and Watkins' (2016) paper, which builds on fundamental PSI literature (e.g., Giles, 2002; Horton & Wohl, 1956; Rubin et al., 1985). Research in this cluster shows that PSI has a positive impact on brand perception (e.g., J. E. Lee & Watkins, 2016), purchase intention, and eWOM intention (e.g., Hwang & Zhang, 2018). In addition, PSI is positively influenced by attractiveness (e.g., M. T. Liu et al., 2019), empathy (Hwang & Zhang, 2018), identity similarity (Hu et al., 2020), self-influencer congruency (Shan et al., 2019), opinion leadership (Quelhas-Brito et al., 2020), and credibility (Sakib et al., 2020).

4.6. Keyword and Trend Analysis

The pre-processing produced 573 terms for the keyword analysis. Figure 5 depicts the keyword frequencies. W*ord-of-mouth* (WOM) (*n*=43) is the most frequent keyword and, unsurprisingly in light of influencers' role in this regard (Brown & Hayes, 2008), is closely related to e*WOM* (*n*=12). For example, Ki and Kim (2019) show that influencers' visual and verbal characteristics positively affect WOM through consumers' desire to mimic influencers. In addition, Casaló et al. (2020) show that Instagram account characteristics (e.g., originality, uniqueness) positively affect perceived opinion leadership. The latter, in turn, positively affects consumer behavior intention, including the intention to interact and recommend the influencer, resulting in increased WOM. The next most common keyword is *consumer* (*n*=26). The decisive role of the consumer was apparent in the earlier discussion of the literature. For example, the literature confirms the influence of age (e.g., Hoek et al., 2020) and the influence of gender (Coco & Eckert, 2020; S. V. Jin & Ryu, 2020). Additional papers consider specific age groups (Johnstone & Lindh, 2018; Mañas-Viniegra et al., 2020; McFarlane & Samsioe, 2020) or character traits (Valsesia et al., 2020).

The keywords *persuasion knowledge* (*n*=24) and *PSI* (*n*=19) are, as previously indicated (see section 4.4), closely related. In addition, the frequency of the keyword *Instagram* (*n*=23) reflects this platform's relevance for IM. The keywords *source credibility* (*n*=21), *credibility* (*n*=20), and *celebrity endorsement* (*n*=18) are also closely related. Other keywords that play a role in IM research, but which have not been considered in the aforesaid analysis, are *brand* (*n*=14), *identification* (*n*=12), and *match-up hypothesis* (*n*=10).

We find that a large body of literature underlines the relevance for brands (e.g., Carter, 2016). Influencers can strengthen the consumer-brand relationship (Sashittal & Jassawalla, 2020) and brand alliances with human-influencer brands can lead to an increase in product sales (Kupfer et al., 2018). Brand engagement in self-concept (BESC), which refers to consumers' "tendency to include important brands as part of their self-concepts" (Sprott et al., 2009, p. 92), plays an important role in this context. People with a greater BESC engage more with posts from other users than with branded posts from influencers and brands (Giakoumaki & Krepapa, 2020). Influencers' perceived influential power can increase BESC, which in turn increases the recommendation behavior of their followers (Jiménez-Castillo & Sánchez-Fernández, 2019). According to Page (2012), self-branding and influencers operate on a continuum, but the brand content diffusion can differ between influencer types (Araujo et al., 2017) and content creator types (Chatterjee, 2011; E. K. Johnson & Hong, 2020). In addition, a sponsored post from a brand generates more likes and a higher purchase intention than a post received from a layperson (E. K. Johnson & Hong, 2020).

The diversity of studies conducted to identify influencers explains the frequency of the keyword *identification*. Research in this stream developed a methodology to quantify and classify influencers (Agostino et al., 2019) and a general strategy to identify them, also across countries (Akdevelioglu & Kara, 2020). Other models detect characteristic subgroups (Litterio et al., 2017), categorize the influencer type (S. Liu et al., 2015), and identify influencers based on popularity and productivity (Lahuerta-Otero & Cordero-Gutiérrez, 2016). In addition, studies have tried to quantify the output generated by influencers as a means to identify relevant influencers (Arora et al., 2019; Gräve, 2019; Li et al., 2017; Schwemmer & Ziewiecki, 2018).

Another notable keyword is *match-up hypothesis* (*n*=10). Introduced by Kamins and Gupta (1994), the match-up hypothesis deals with the importance of fit (congruency, similarity, relevance, and consistency) between the spokesperson and the product or brand. According to this hypothesis, influencers are assumed to be more effective when they appear to fit the product. Xu and Pratt (2018) confirmed this notion in respect of travel destinations. Congruence between the influencer and the advertised product or brand also has general positive effects (e.g., Breves et al., 2019; Cicco et al., 2020; Torres et al., 2019). The congruency of the influencer and the follower shows similar positive effects as confirmed, among others, by Zhang et al. (2017) in a rebroadcasting context.

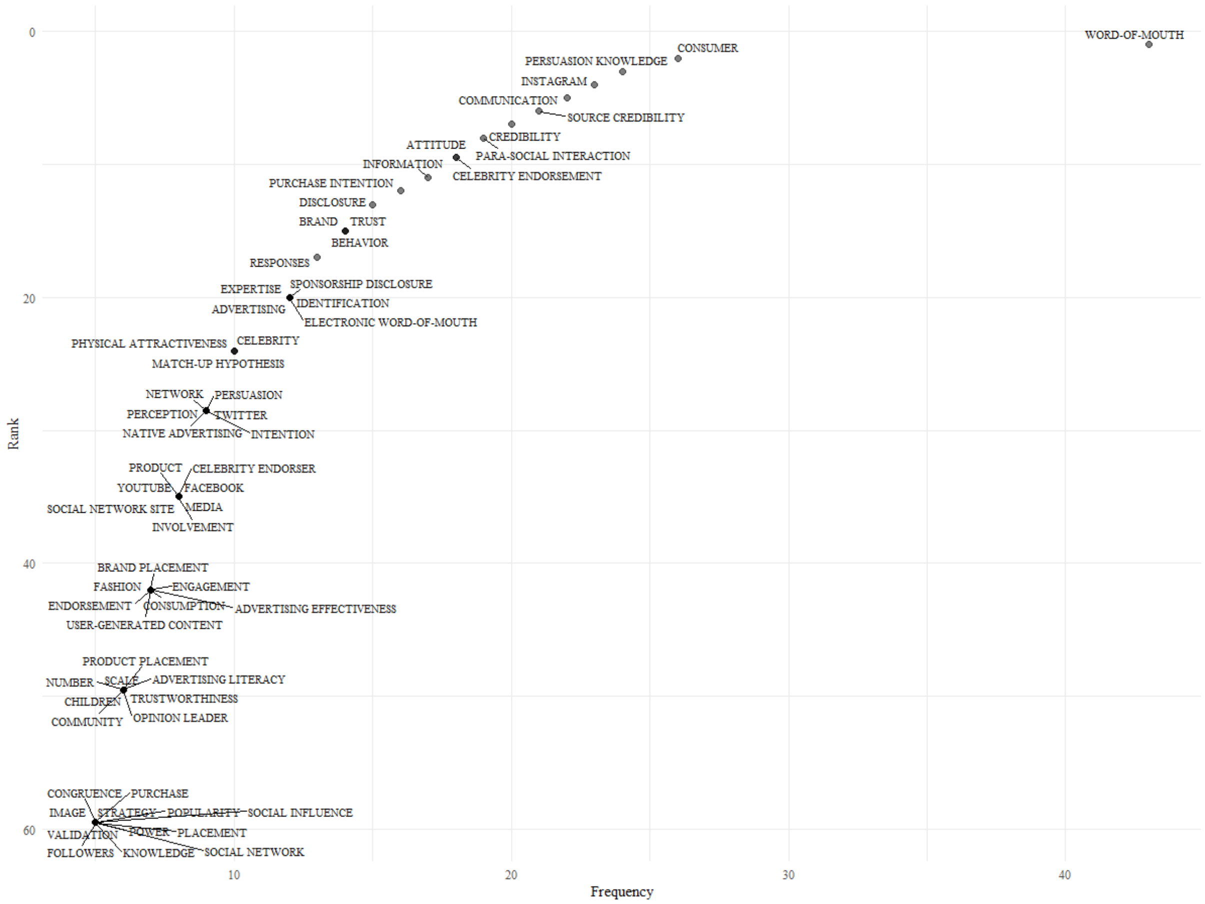

Figure 5: Keyword plot

Concluding the analysis, Figure 6 depicts the results of our trend analysis. Due to the low number of published papers prior to 2017, our analysis only considered papers published between 2017 and 2020. The results show that although Twitter was central to IM research in 2017, Instagram has more recently assumed this role. In addition, a clear thematic development is evident. In 2017 the research focused on social networks and their influence (e.g., Araujo et al., 2017; Litterio et al., 2017), in 2018 on communications and recommendations, and their impact on communities (e.g., Esteban-Santos et al., 2018; Hwang & Zhang, 2018), and in 2019 on celebrity endorsement and the associated SC (e.g., Cheah et al., 2019; Djafarova & Trofimenko, 2019; S. V. Jin & Muqaddam, 2019). The most recent research gives more consideration to the links between PSI and persuasion knowledge (e.g., S. V. Jin & Ryu, 2020; Reinikainen et al., 2020).

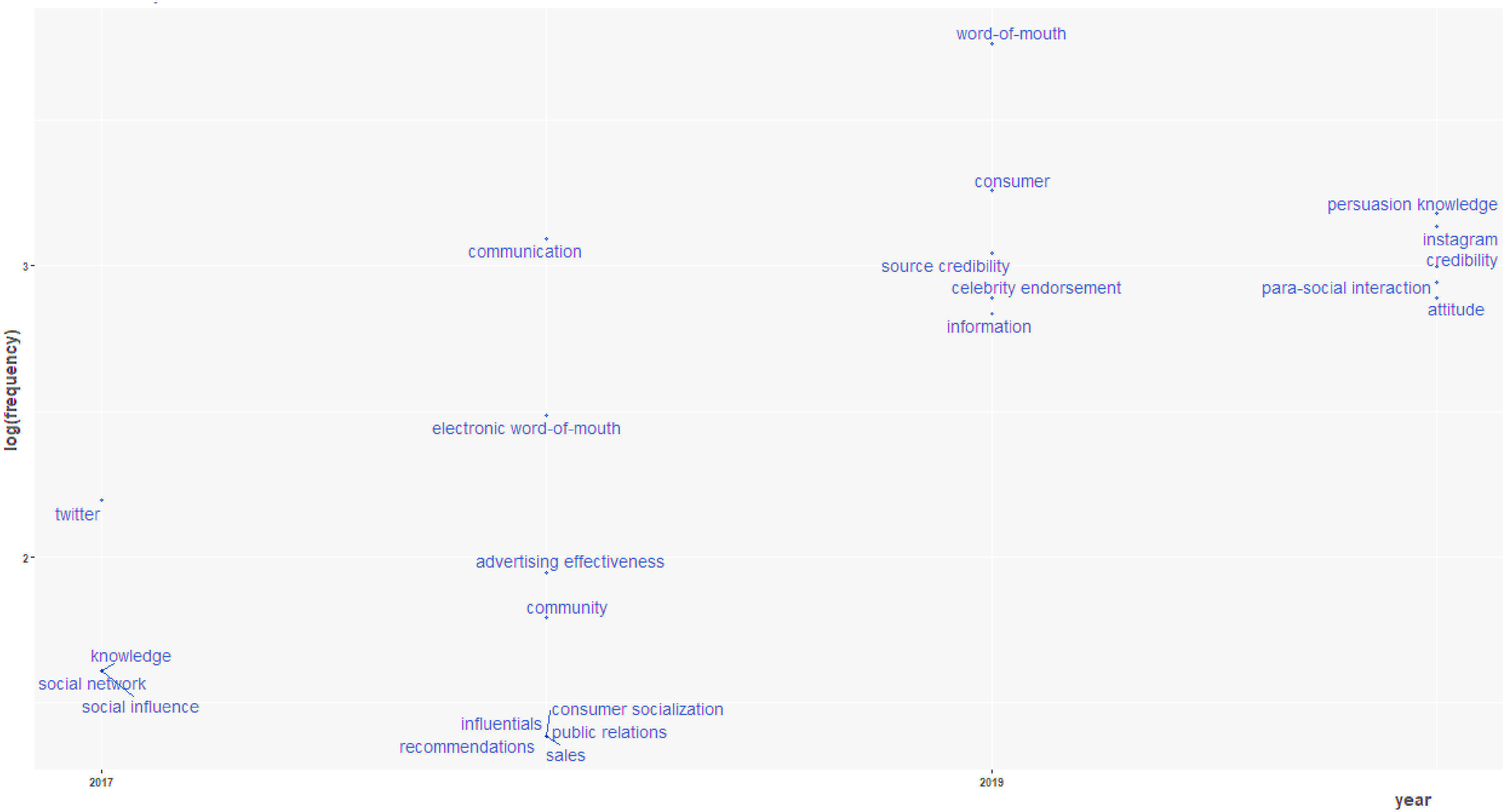

Figure 6: Topic trends

5. Discussion

Our bibliometric analysis extends prior review studies (Hudders et al., 2020; Sundermann & Raabe, 2019; Veirman et al., 2019) and offers a more comprehensive overview of and insights into the IM research field. Table 6 in the Appendix and Figure 7 summarize and depict the paper topics of our data set. Our analysis indicates that 2011 constitutes the starting point of IM research, which peaked in recent years. Typical of emerging research fields, IM research is extremely diverse, covering a range of journals and topics. We also find that IM researchers are gradually developing research networks, along with the emergence of trends.

In terms of content, our analyses present a detailed consideration of disclosure effects, with an added focus on children and adolescents. In addition, our analysis summarize the large number of research papers dealing with the distinction between influencers and celebrities (e.g., Schouten et al., 2019), or influencers and brands (e.g., Lou et al., 2019). Investigations regarding PSI; fit between the influencer, the product, and the follower; and the consideration of influencer types are crucial areas of interest. Our results also underline the role of SC, for example evoked by a close influencer-consumer fit (e.g., Esch et al., 2018), that has a positive effect on consumers' brand perception, probability of purchase (e.g., Fink et al., 2020), and loyalty (Coco & Eckert, 2020).

The author and collaboration network analyses reveal that although this relatively young research field does not yet have a stable core, there are initial collaborations focusing on the indicated research fields. The citation analysis reveals four distinct clusters: principles of IM, advertising disclosure effects, source credibility and endorsement, and para-social interaction. IM's principles contribute to the understanding of this type of marketing. For example, research in this field suggests that advertising disclosure should not in general be seen as unfavorable, as it does not necessarily negatively impact advertising outcomes (Hayes et al., 2020; S. Lee & Kim, 2020). Furthermore, as illustrated by cluster three, there is a large body of literature available on the topic of credibility and celebrity endorsement. Lastly, cluster four demonstrates PSI's relevance for and positive effect on, among others, brand awareness (J. E. Lee & Watkins, 2016; Reinikainen et al., 2020) and eWOM (Hwang & Zhang, 2018). Both determinants are important means to counter commoditization of marketing communications.

The concluding trend analysis provides a rewarding understanding of the development of the papers' contents from 2017 to 2020. The analysis not only indicates changes in the use of social media platforms (from Twitter to Instagram), but also the thematic development of the research fields. Considering these findings, we conclude that IM is an excellent method to de-commoditize marketing communications. Influencers can use the content they create to counteract the homogeneity of present-day marketing communications. Through creativity (Sette & Brito, 2020), the multitude of created content (Kostygina et al., 2020) and direct communication, IM significantly improves consumer experience. This de-commoditization has the potential to increase eWOM (Hwang & Zhang, 2018) and customer loyalty (Coco & Eckert, 2020).

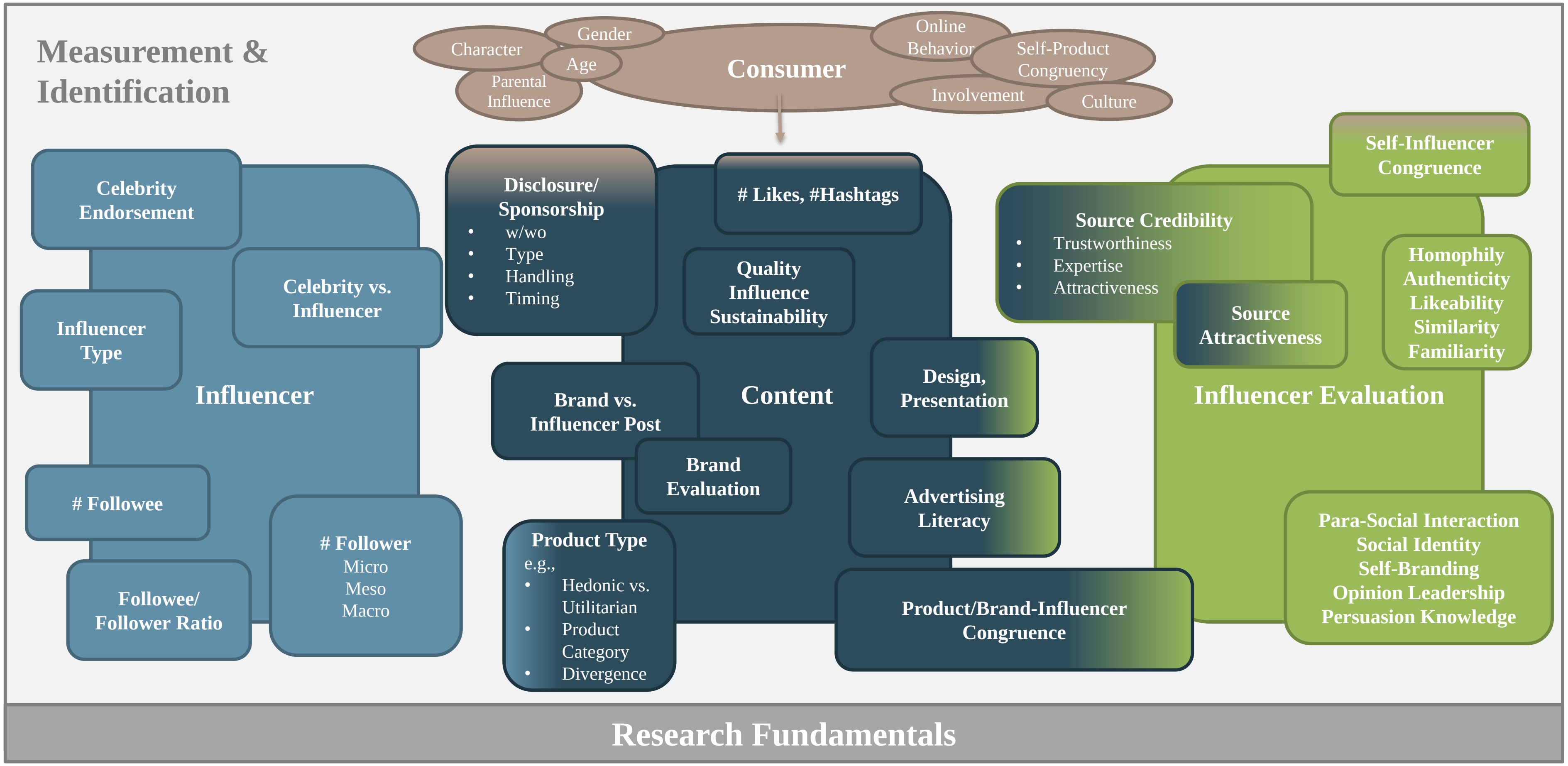

Figure 7: Literature overview

6. Limitations and Further Research

Our analysis not only offers unique insights into the IM research field but also suggests future research areas. Similar to any bibliometric study, our analysis has certain limitations. Among others, it relies on databases which may contain erroneous entries and may not cover most recent research. Furthermore, the identification of papers is inherently limited by the choice of keywords, which is partially subjective.

In addition, we were unable to clearly classify 15 of the 132 identified papers in our bibliometric analysis. One topic not covered in our analysis is the content of IM campaigns, due to its diversity. Studies on this topic have a diverse content as they analyze different content types (García-Rapp, 2017; Hughes et al., 2019), the influence of visual congruency (Argyris et al., 2020), the creativity of influencer content (Sette & Brito, 2020), and even the preference for the left side of the cheek (Messina & Lindell, 2020). We also did not include studies related to the language used (Packard & Berger, 2017), the integration of hashtags (Erz et al., 2018) and emojis (Ge & Gretzel, 2018), as well as the decisive role played by the posts' timing – as shown by some researchers (Topaloglu et al., 2017). We did not cover Driel and Dumitrica (2021) and Audrezet et al.'s (2020) reflections on the topic of authenticity, as well as Wang et al.'s (2020) work on the topic of social power and satisfaction. Finally, other studies not considered in our network analysis include the interaction between agencies, marketers, and influencers (Lin et al., 2018; Stoldt et al., 2019) and the general seeding process using high and low-status users (Lanz et al., 2019).

Our research offers several areas for future research. Only a few papers examined IM's impact and application with reference to cultural differences (e.g., Al-Emadi & Ben Yahia, 2020; Sakib et al., 2020). Furthermore, very little research has been done on the influence of consumer characteristics. A possibility, similar to prior research in social media marketing, is to consider the Big Five personality dimensions (John et al., 2008) in an IM context. For example, future studies should test whether extraversion and openness are also the strongest predictors of influencer-following behavior, as verified by prior research in the context of social networking sites (D. Liu and Campbell (2017).

Moreover, the topic of co-creation in relation to the influencers' content creation is also a promising field for future research, as previous studies have confirmed its positive impact in other areas (e.g., Hair et al., 2016). Further thematic areas of interest are the more detailed consideration of older age groups and the analysis of the effect of new platforms like TikTok. The IM research field is not yet exhausted but certainly has much potential for more detailed investigations.

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Appendix

Table 1: Reduced list of categories

Area Studies	Cultural Studies	Language & Linguistics	Psychology, Multidisciplinary
Asian Studies	Development Studies	Linguistics	Psychology, Social
Behavioral Sciences	Economics	Management	Social Issues
Business	Environmental Sciences	Multidisciplinary Sciences	Social Sciences, Interdisciplinary
Business, Finance	Environmental Studies	Music	Social Work
Communication	Film, Radio, Television	Operations Research & Management Science	Sociology
Computer Science, Artificial Intelligence	Food Science & Technology	Political Science	Sport Sciences
Computer Science, Cybernetics	Green & Sustainable Science & Technology	Psychology	Statistics & Probability
Computer Science, Information Systems	Hospitality, Leisure, Sport & Tourism	Psychology, Applied	Telecommunications
Computer Science, Interdisciplinary Applications	Humanities, Multidisciplinary	Psychology, Developmental	Urban Studies
Computer Science, Theory & Methods	Information Science & Library Science	Psychology, Experimental	Women's Studies

Table 2: Ten most frequently represented countries

Country	Frequency
USA	84
NETHERLANDS	21
UK	20
GERMANY	16
BELGIUM	15
SPAIN	15
CHINA	14
AUSTRALIA	12
PORTUGAL	9
SOUTH KOREA	9

Table 3: Most relevant authors, who published at least two papers, and their corresponding collaboration network

Authors	Authors (short)	Papers	Collaboration Network
Hudders, L.	HUDDERS L	6	1
Reijmersdal, E. van	VAN R E	5	1
Veirman M. de	DE V M	4	1
Jin, S. V.	JIN S	4	5
Cauberghe, V.	CAUBERGHE V	3	1
Rozendaal, E.	ROZENDAAL E	3	1
Ryu, E.	RYU E	3	5
Lou, C.	LOU C	3	9
Boerman, S.	BOERMAN S	2	1
Jans, S. de	DE J S	2	1
Sompel, D. van de	VAN D S	2	1
Boyland, E. J.	BOYLAND E	2	2
Christiansen, P.	CHRISTIANSEN P	2	2
Coates, A. E.	COATES A	2	2
Halford, J. C. G.	HALFORD J	2	2
Hardman, C. A.	HARDMAN C	2	2
Colliander, J.	COLLIANDER J	2	3
Stubb, C.	STUBB C	2	3
Carpender Childers, C.	CHILDERS C	2	4
Evans, N. J.	EVANS N	2	4
Grubbs Hoy, M.	HOY M	2	4
Phua, J.	PHUA J	2	4
Muqaddam, A.	MUQADDAM A	2	5
Luoma-Aho, V.	LUOMA-AHO V	2	6
Maity, D.	MAITY D	2	6
Munnukka, J.	MUNNUKKA J	2	6
Reinikainen, H.	REINIKAINEN H	2	6
Campbell, C.	CAMPBELL C	2	7
Djafarova, E.	DJAFAROVA E	2	8

Table 4: Top ten, most frequent local documents with their global citations

Document	Local Citations	Global Citations
Veirman et al. 2017	45	109
Djafarova and Rushworth 2017	36	100
Lee and Watkins 2016	30	88
Freberg et al. 2011	22	100
Uzunoğlu and Misci Kip 2014	21	69
Jin and Phua 2014	21	172
Khamis et al. 2017	20	111
Kapitan and Silvera 2016	14	32
Marwick 2015	11	196
Abidin 2016	10	68

Table 5: Documents, clusters, and centrality determinants of the document co-citation network

Document	Node	Cluster	Betweenness	Closeness
Veirman et al. 2017	de veirman 2017-2	1	110.701	0.015
Marwick 2015	marwick ae 2015	1	1.440	0.010
Uzunoğlu and Misci Kip 2014	uzunoglu e 2014	1	20.228	0.014
Casaló et al. 2020	casalo lv 2020	1	1.181	0.010
Djafarova and Rushworth 2017	djafarova e 2017	1	73.572	0.015
Fornell and Larcker 1981	fornell c 1981	1	11.839	0.012
Freberg et al. 2011	freberg k 2011	1	25.094	0.013
Kapitan and Silvera 2016	kapitan s 2016	1	6.669	0.011
Khamis et al. 2017	khamis s 2017	1	19.780	0.013
Lou and Yuan 2019	lou c. 2019-2	1	9.268	0.012
McQuarrie et al. 2013	mcquarrie ef 2013	1	10.998	0.012
Podsakoff et al. 2003	podsakoff pm 2003	1	0.427	0.009
Katz and Lazarsfeld 1955	katz elihu 1955	1	1.049	0.009
Sheldon and Bryant 2016	sheldon p 2016	1	0.529	0.009
Booth and Matic 2011	booth n 2011	1	2.513	0.010
Jin and Muqaddam 2019	jin sv 2019-2	1	1.024	0.010
Kozinets et al. 2010	kozinets rv 2010	1	0.840	0.009
Senft 2008	senft t. 2008-1	1	1.119	0.009
Boerman et al. 2017	boerman sc 2017	2	24.299	0.013
Friestad and Wright 1994	friestad m 1994	2	35.422	0.013
Lu et al. 2014	lu lc 2014	2	3.933	0.011
Evans et al. 2017	evans n. 2017-2	2	49.363	0.014
FTC 2017	ftc 2017 2017-1	2	0.779	0.010
Hayes 2013	hayes a.f. 2013	2	1.458	0.010
Hudders et al. 2017	hudders l 2017	2	1.183	0.010
Reijmersdal et al. 2016	van reijmersdal 2016-2	2	6.386	0.011
Wojdynski and Evans 2016	wojdynski bw 2016-3	2	9.378	0.011
Hwang and Jeong 2016	hwang y 2016	2	11.860	0.012
Boerman et al. 2012	boerman sc 2012	2	3.172	0.010
Carr and Hayes 2014	carr ct 2014	2	2.063	0.010
Campbell et al. 2013	campbell mc 2013	2	1.128	0.010
Abidin 2016	abidin c 2016-1	3	2.656	0.011
Jin and Phua 2014	jin saa 2014	3	20.247	0.013
McCracken 1989	mccracken g 1989	3	46.555	0.014
Choi and Rifon 2012	choi sm 2012	3	13.394	0.012
Lyons and Henderson 2005	lyons barbara 2005	3	2.298	0.010
Kaplan and Haenlein 2010	kaplan am 2010	3	0.826	0.009
McCormick 2016	mccormick k 2016	3	0.823	0.009
Spears and Singh 2004	spears n. 2004-2	3	4.107	0.011
Spry et al. 2011	spry a 2011	3	3.948	0.011
Erdogan 1999	erdogan b. 1999	3	34.234	0.014
Hovland et al. 1953	hovland c. 1953	3	7.461	0.012
Ohanian 1990	ohanian r 1990	3	86.762	0.015
Silvera and Austad 2004	silvera dh 2004	3	5.764	0.012
Bergkvist and Zhou 2016	bergkvist l 2016	3	2.760	0.011
Ohanian 1991	ohanian r 1991	3	9.684	0.012
Kamins 1990	kamins ma 1990	3	8.876	0.012
Till and Busler 2000	till bd 2000	3	8.253	0.012
Amos et al. 2008	amos c 2008	3	14.340	0.013
Chu and Kim 2011	chu sc 2011-1	3	1.723	0.010
McGuire 1985	mcguire w. 1985-1	3	2.254	0.010
Vries et al. 2012	de vries 2012	3	3.798	0.011
Hovland and Weiss 1951	hovland ci 1951	3	1.089	0.010
Hennig-Thurau et al. 2004	hennig-thurau t 2004-2	3	8.124	0.011
Dibble et al. 2016	dibble jl 2016	4	1.334	0.011
Horton and Wohl 1956	horton d 1956	4	14.604	0.013
Labrecque 2014	labrecque li 2014	4	14.442	0.012
Lee and Watkins 2016	lee je 2016	4	35.762	0.014
Liljander et al. 2015	liljander v 2015	4	1.791	0.010
Rubin et al. 1985	rubin am 1985	4	3.621	0.011
Chung and Cho 2017	chung sy 2017	4	2.042	0.011
Colliander and Dahlén 2011	colliander j 2011	4	12.410	0.012
Chu and Kamal 2008	chu s.-c. 2008-2	4	1.959	0.010
Goldsmith et al. 2000	goldsmith re 2000	4	4.982	0.011
Pornpitakpan 2004	pornpitakpan c 2004-2	4	1.896	0.010
Giles 2002	giles dc 2002	4	2.483	0.010

Table 6: Literature overview

General Information			Characteristics									Influencer Evaluation									Content									
			Consumer					Influencer																					
ID	Authors and year	Principles of IM	Age - Children (c), Adolescents (a), Millennials (m), Others (o)	Gender	Character (c), Involvement (i), Online Behavior (o)	Self-Product Congruency	Culture	Number of Followers (fr), Followees (fe), Ratio (r)	Influencer Type	Celebrity vs. Influencer	Celebrity Endorsement	Source Credibility	Source Attractiveness	Credibility (c), Trustworthiness (t), Relibility (r), Expertise (e)	Homophily (h), Authenticity (a)	Likeability(l), Admiration (a), Popularity (p), Familarity (f)	Self-Influencer Congruency (c), Relationship (r), Similarity (s)	PSI (p), Persuasion Knowledge (pk)	Self-Branding	Opinion Leadership	Disclosure - Type (t), With or without (w), Handling (h), Timing (ti)	Content Influence	Brand vs. Influencer	Product Type	Brand Evaluation	Brand-/ Product-Influencer Congruency or Relationship	Advertising Literacy	Design & Presentation	Sustainability	Measurement & Identification
1	Abidin, 2016	x																											
2	Agnihotri & Bhattacharya, 2020						x			x	x							p								x				
3	Agostino et al., 2019								x																				x
4	Akdevelioglu & Kara, 2020						x													x										x
5	Al-Emadi & Ben Yahia, 2020						x					x			h					x		x						x		
6	Araujo et al., 2017								x																x					
7	Argyris et al., 2020																c, s												x		
8	Arora et al., 2019																														x
9	Audrezet et al., 2020														a															
10	Balabanis & Chatzopoulou, 2019				i			fr	x				x	e, t	h, a							x								
11	Berne-Manero & Marzo-Navarro, 2020								x					c															x	
12	Boerman, 2020								x									p			w									
13	Boerman & Reijmersdal, 2020		c															p			w				x		x			
14	Breves et al., 2019											x	x	e, t				p								x				
15	Campbell & Farrell, 2020	x							x	x																					
16	Campbell & Grimm, 2019																				h									
17	Carpenter Childers et al., 2019	x																											
18	Carter, 2016																								x					
19	Casaló et al., 2020				o											c			x		x								
20	Chatterjee, 2011							fr	x												x	x							
21	Cheah et al., 2019									x	x																				
22	Chetioui et al., 2020											x		c, e, t			c													
23	Cicco et al., 2020											x									t					x				
24	Coates et al., 2019a		c																		w			x	x					
25	Coates et al., 2019b		c																						x					
26	Coco & Eckert, 2020			x									r	a							x								
27	Cooley & Parks-Yancy, 2019		m, o						x				x	t														x		
28	Dam & Reijmersdal, 2019		a															pk			t, h						x			
29	Dhanesh & Duthler, 2019																r				w									
30	Djafarova & Rushworth, 2017		m	x						x				c																
31	Djafarova & Trofimenko, 2019											x																		
32	Dost et al., 2019	x																							x					
33	Driel & Dumitrica, 2020													t	a				x				x					x		

Table 6: Literature overview *(continued)*

General Information			Characteristics									Influencer Evaluation									Content									
			Consumer					Influencer																						
ID	Authors and year	Principles of IM	Age - Children (c), Adolescents (a), Millennials (m), Others (o)	Gender	Character (c), Involvement (i), Online Behavior (o)	Self-Product Congruency	Culture	Number of Followers (fr), Followees (fe), Ratio (r)	Influencer Type	Celebrity vs. Influencer	Celebrity Endorsement	Source Credibility	Source Attractiveness	Credibility (c), Trustworthiness (t), Relibility (r), Expertise (e)	Homophily (h), Authenticity (a)	Likeability(l), Admiration (a), Popularity (p), Familarity (f)	Self-Influencer Congruency (c), Relationship (r), Similarity (s)	PSI (p), Persuasion Knowledge (pk)	Self-Branding	Opinion Leadership	Disclosure - Type (t), With or without (w), Handling (h), Timing (ti)	Content Influence	Brand vs. Influencer	Product Type	Brand Evaluation	Brand-/ Product-Influencer Congruency or Relationship	Advertsing Literacy	Design & Presentation	Sustainability	Measurement & Identification
34	Enke & Borchers, 2019	x			c				x	x																				
35	Erz et al., 2018																		x									x		
36	Esch et al., 2018													c, t	a		c, s													
37	Esteban-Santos et al., 2018		m									x		c, e, t				p			w									
38	Evans et al., 2017																				h									
39	Evans et al., 2019		c															pk			t,w,h,ti									
40	Fink et al., 2020										x	x																		
41	Folkvord et al., 2019		c		o																			x	x					
42	Freberg et al., 2011								x																					x
43	García-Rapp, 2017				i																	x								
44	Ge & Gretzel, 2018																					x						x		
45	Giakoumaki & Krepapa, 2020																						x		x					
46	Gong & Li, 2019										x	x	x					p								x				
47	Gräve, 2019																													x
48	Hayes et al., 2020		m																		w	x			x					
49	Hill et al., 2020													c		p								x						
50	Hoek et al., 2020		c																		w				x		x			
51	Hu et al., 2020																c, s	p												
52	Hughes et al., 2019													e								x		x						
53	Hwang & Zhang, 2018				c							x						p, pk			t									
54	Jans et al., 2019		a											t				p			w	x					x			
55	Jans et al., 2020		a									x				a					t		x							
56	Jerslev, 2016	x								x																				
57	Jiménez-Castillo & Sánchez-Fernández, 2019																								x	x				
58	Jin et al., 2019									x				t																
59	Jin & Muqaddam, 2019											x						p					x							
60	Jin & Phua, 2014							fr	x	x		x													x					
61	Jin & Ryu, 2019			x																x			x		x			x		
62	Jin & Ryu, 2020			x					x	x				t				p										x		
63	Johnson et al., 2019											x						p, pk					x		x					
64	Johnson & Hong, 2020																					x	x							
65	Johnstone & Lindh, 2018		m											t															x	
66	Kapitan & Silvera, 2016	x								x	x																			

Table 6: Literature overview *(continued)*

General Information			Characteristics									Influencer Evaluation									Content									
			Consumer					Influencer																						
ID	**Authors and year**	**Principles of IM**	**Age** - Children (c), Adolescents (a), Millennials (m), Others (o)	**Gender**	**Character (c), Involvement (i), Online Behavior (o)**	**Self-Product Congruency**	**Culture**	**Number of Followers (fr), Followees (fe), Ratio (r)**	**Influencer Type**	**Celebrity vs. Influencer**	**Celebrity Endorsement**	**Source Credibility**	**Source Attractiveness**	**Credibility (c), Trustworthiness (t), Relibility (r), Expertise (e)**	**Homophily (h), Authenticity (a)**	**Likeability(l), Admiration (a), Popularity (p), Familarity (f)**	**Self-Influencer Congruency (c), Relationship (r), Similarity (s)**	**PSI (p), Persuasion Knowledge (pk)**	**Self-Branding**	**Opinion Leadership**	**Disclosure** - Type (t), With or without (w), Handling (h), Timing (ti)	**Content Influence**	**Brand vs. Influencer**	**Product Type**	**Brand Evaluation**	**Brand-/ Product-Influencer Congruency or Relationship**	**Advertsing Literacy**	**Design & Presentation**	**Sustainability**	**Measurement & Identification**
67	Kay et al., 2020							fr	x												w									
68	Khamis et al., 2017																		x											
69	Ki & Kim, 2019				c								x	e			c			x		x								
70	Konstantopoulou et al., 2019		m											t	a															
71	Kostygina et al., 2020								x													x	x							
72	Kupfer et al., 2018								x																x					
73	Ladhari et al., 2020													e	h	p														
74	Lahuerta-Otero & Cordero-Gutiérrez, 2016																													x
75	Lanz et al., 2019								x															x						
76	Lee & Kim, 2020											x									t, w				x					
77	Lee & Watkins, 2016					x							x		h			p								x				
78	Lenne & Vandenbosch, 2017		m																										x	
79	Li et al., 2017																													x
80	Lin et al., 2018	x							x					e						x				x						
81	Litterio et al., 2017																			x										
82	Liu et al., 2015													t																x
83	Liu et al., 2019				i								x					p							x					
84	Lou et al., 2019															l					t, w		x		x					
85	Lou & Kim, 2019		a		c				x			x					s	p				x								
86	Lou & Yuan, 2019												x	t			c, s													
87	Mañas-Viniegra et al., 2020		a, o	x																					x			x		x
88	Martensen et al., 2018											x		e, t		l, f	c, s			x										
89	Martínez-López et al., 2020								x	x				t												x				
90	Marwick, 2015							fr	x																			x		
91	McFarlane & Samsioe, 2020		o																									x		
92	Messina & Lindell, 2020			x																								x		
93	Miranda et al., 2019											x		e, t	h							x								
94	Munnukka et al., 2019											x						p												
95	Nascimento et al., 2020	x							x		x														x					
96	O'Neil & Eisenmann, 2017								x			x												x						
97	Packard & Berger, 2017																					x					x			
98	Page, 2012																		x									x		
99	Park & Lin, 2020					x							x	t								x				x				

Table 6: Literature overview *(continued)*

General Information		Principles of IM	Characteristics									Influencer Evaluation									Content									Measurement & Identification
			Consumer					Influencer																						
ID	Authors and year		Age - Children (c), Adolescents (a), Millennials (m), Others (o)	Gender	Character (c), Involvement (i), Online Behavior (o)	Self-Product Congruency	Culture	Number of Followers (fr), Followees (fe), Ratio (r)	Influencer Type	Celebrity vs. Influencer	Celebrity Endorsement	Source Credibility	Source Attractiveness	Credibility (c), Trustworthiness (t), Relibility (r), Expertise (e)	Homophily (h), Authenticity (a)	Likeability(l), Admiration (a), Popularity (p), Familarity (f)	Self-Influencer Congruency (c), Relationship (r), Similarity (s)	PSI (p), Persuasion Knowledge (pk)	Self-Branding	Opinion Leadership	Disclosure - Type (t), With or without (w), Handling (h), Timing (ti)	Content Influence	Brand vs. Influencer	Product Type	Brand Evaluation	Brand-/ Product-Influencer Congruency or Relationship	Advertsing Literacy	Design & Presentation	Sustainability	
100	Petrescu et al., 2018	x																			h									
101	Pick, 2020										x	x					c													
102	Quelhas-Brito et al., 2020				i													p		x		x								
103	Reijmersdal et al., 2020		c, a																		t, ti									x
104	Reijmersdal & Dam, 2020		a															pk			w									
105	Reinikainen et al., 2020											x						p												
106	Sakib et al., 2020						x					x	x		h			p												
107	Sashittal & Jassawalla, 2020																								x	x				
108	Schouten et al., 2019									x		x					s									x				
109	Schwemmer & Ziewiecki, 2018																													x
110	Seeler et al., 2019	x																												
111	Sette & Brito, 2020																					x								
112	Shan et al., 2019																c	p												
113	Sokolova & Kefi, 2020											x	x		h			p												
114	Stoldt et al., 2019	x																												
115	Stubb et al., 2019											x									w, h		x							
116	Stubb & Colliander, 2019											x									t, w, h				x					
117	Su et al., 2020			x										t														x		
118	Sundermann & Raabe, 2019	x																												
119	Topaloglu et al., 2017																							x				x		
120	Torres et al., 2019												x			l, f										x				
121	Trivedi & Sama, 2020		m						x	x				e											x					
122	Uzunoğlu & Misci Kip, 2014																			x										
123	Valsesia et al., 2020				c, o			fr, fe																						
124	Veirman et al., 2017							fr, fe, r								p				x				x		x				
125	Veirman et al., 2019	x	c																		w, h									
126	Veirman & Hudders, 2020											x									w, h	x			x					
127	Voorveld, 2019	x																												
128	Vries, 2019							fr						c								x								
129	Wang et al., 2020																					x								
130	Xiao et al., 2018				i									e, t	h	l						x								
131	Xu & Pratt, 2018		m								x						c									x				
132	Zhang et al., 2017					x																x								

Essay 2

A New Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research: A Research Note

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Research Note/ Working Paper

A New Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research: A Research Note

Abstract

Covering the years 1981 to 2010, Hair et al. (2012) presented a first extensive evaluation on the use of partial least squares structural equation modeling (PLS-SEM) in marketing research. This article aims to provide further insight into this methodological field, as the last ten years have seen further decisive developments. We will highlight the advantages of this analysis method disclosed by its increased use as a research method. To demonstrate this, we replicated Hair et al.'s (2012) extensive search of PLS-SEM estimations in marketing research in the top 30 ranked marketing journals to demonstrate this. This yielded 239 publications in the period from 2011 to 2020. As the previous study had done, we critically examined the content of these publications and considering the key methodological characteristics. Following Hair et al. (2012), we examined reasons for using PLS-SEM, the data and model characteristics, outer and inner model evaluations, as well as reporting again, and compared our findings to those of the previous period. In addition, we reviewed the use of new evaluation techniques and upcoming methods and developments. We summarized the new essential findings and issues, addressing them in an overview intended to reduce still-occurring erroneous considerations. This should make it easier for researchers and practitioners to work with PLS-SEM and improve result-reporting quality.

Keywords

Empirical research methods, Partial least squares, PLS, Path modeling, Structural equation modeling, PLS-SEM

1. Introduction

Structural equation modeling (SEM), which includes the methods covariance-based structural equation modeling (CB-SEM; Jöreskog, 1978, 1993) and partial least squares structural equation modeling (PLS-SEM; Lohmöller, 1989; Wold, 1982, 1985), continues to gain research interest. In recent years, PLS-SEM has become an increasingly common method in marketing research (Hair et al., 2012), as well as in other disciplines (e.g., Ali et al., 2018; Nitzl, 2016; Ringle et al., 2020). A significantly increasing number of published articles have used PLS-SEM in comparison to the similarly popular CB-SEM (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017). Although these two methods have the same roots, their uses often give rise to debate. Regarding PLS-SEM, researchers' opinion evolved from "there is no use for PLS whatsoever" (Antonakis et al., 2010, p. 1103) to "feel the love for PLS" (Petter, 2018, p. 12). This is based on the fact that PLS-SEM is a very appealing method to evaluate complex models containing a large number of latent variables (also called constructs), as well as indicators (also called items), with no need to make distributional assumptions on the data (e.g., Hair, Risher, et al., 2019) and with the ability to provide causal explanations (Sarstedt et al., 2017a; Wold, 1982).

In 2012 Hair et al. critically reviewed PLS-SEM's use that ensured rigorous research and publication practices during the years 1981 to 2010. Our review follows up on this study to critically review the regular practices in using PLS-SEM. Specifically, we consider the subsequent years, 2011 to 2020, since PLS-SEM can still produce incorrect results if the pre-assumptions and interpretation are performed incorrectly. Because using PLS-SEM increased during the last decade, especially in marketing research (e.g., Hair, Hult, Ringle, Sarstedt, & Thiele, 2017), we will critically examine the method's use for this research area again. In doing so, we pursue the following objectives, similar to those in Hair et al.'s (2012) initial article: (1) to examine the published articles, this time during the period 2011 to 2020, with attention to relevant criteria, e.g., the reasons using PLS, the sample size, the number of latent variables, the testing criteria; (2) to extend the reviews and include the current period in terms of researchers' uses, while also reexamining known problems and identifying new ones; and (3) to summarize the new essential findings and the stumbling blocks that still present in using PLS-SEM.

Further, recent years have brought enhancements that have ensured the method continuously develops and expands. These include, for example, the heterotrait-monotrait correlation ratio, which measures the similarity between the reflective latent variables (Henseler et al., 2015), the Rho_A, which is accurately determined to evaluate latent variables' reliability

(Dijkstra & Henseler, 2015), and PLSpredict, which involves assessing the model’s out-of-sample predictive power (Shmueli et al., 2016; Shmueli et al., 2019). We include these instruments in our consideration as well. Finally, since this paper reviews articles published in top-tier journals as the earlier study did, we can again demonstrate possible differences between high and lower-quality journals.

Overall, we aim to show which errors researchers still make, where there is potential for improvement, and where new methods improve on those used in the previous period. Only if researchers use PLS-SEM criteria and methodological properties correctly, can research results provide relevant and valuable information.

2. The Relevance of a Renewed Analysis

The first study conducted by Hair et al. (2012) showed room for improvement regarding correctly evaluating PLS-SEM. This article aims to ascertain whether there has been positive development or whether some weaknesses still remain. In the past decade, a variety of developments and findings in relation to PLS-SEM have been published. We will give a short overview of these to illustrate why we need a renewed analysis.

In the 2012 review, researchers mainly used Cronbach's Alpha (Cronbach, 1951) and the composite reliability Rho_C (Heise & Bohrnstedt, 1970) for evaluating reflective measurements' reliability. Because Cronbach's Alpha underestimates small sample sizes' reliability (Sijtsma, 2009; Yuan & Bentler, 2002) and thus inconsistently estimates reliability for PLS construct scores, scholars suggested using composite reliability Rho_C in the past (Chin, 1998). In their guidelines, Hair et al. (2012) specifically recommend that Cronbach's Alpha should not be used. However, since Rho_C in turn overestimates reliability, Dijkstra and Henseler (2015) have proposed a new reliability coefficient for reflective measurements, namely Rho_A. Compared to Rho_C, it uses the construct's weights and reproduces the off-diagonal elements of a latent variable's indicator correlation matrix for the evaluation (Dijkstra & Henseler, 2015).

A similar situation occurred in connection with determining discriminant validity. Research has already demonstrated that the Fornell-Larcker criterion (Fornell & Larcker, 1981) lacks effectiveness in certain circumstances (Henseler et al., 2014; Rönkkö & Evermann, 2013). Besides, in their simulation study Henseler et al. (2015) showed that both the Fornell-Larcker criterion and cross-loading assessment have a low sensitivity, which means that they are unable to determine the lack of discriminant validity reliably. For this reason, Henseler et al. (2015) developed a new approach in the form of the heterotrait-monotrait ratio of correlations (HTMT), which measures the similarity between the reflective latent variables. Hair, Sarstedt, and Ringle (2019) recommend using the heterotrait-monotrait criterion for discriminant validity testing, and different Monte Carlo simulations have already proven the favorable HTMT classification performance (Franke & Sarstedt, 2019; Voorhees et al., 2016). Our study now investigates whether or not researchers adopted these new measures.

In the past, scholars debated the need to evaluate the PLS path model's goodness-of-fit. According to Hair, Sarstedt, and Ringle (2019), this is unnecessary unless the study uses a purely confirmatory approach. This does not apply to predictive studies, which researchers mostly conduct as they want to formulate managerial implications. The goal of business and social science research generally is to successfully combine explanation and prediction (Hair, Sarstedt, & Ringle, 2019). PLS-SEM captures precisely this since it estimates causal-predictive relations (Jöreskog & Wold, 1982; Wold, 1985). Model-fit measures such as standardized root mean square residual (SRMR), which research suggests for assessing the model-fit of covariance-based models (e.g., Bagozzi & Yi, 2012), determine the divergence between the empirical correlation matrix and the model-implied correlation matrix. This divergence should be minimized as far as possible. However, this contradicts what PLS-SEM does, as it minimizes the combination of bias and error variance. Still, we need more research to determine better-suited model-fit measures for PLS-SEM to use the benefits of the goodness-of-fit measurements (Hair, Sarstedt, & Ringle, 2019).

In the context of this discussion, some have stated that researchers should assess in-sample explanatory power and out-of-sample predictive power for PLS-SEM results (Hair, Sarstedt, & Ringle, 2019). The R^2 statistic, which is often used to evaluate the model's predictive power, is only suitable for assessing the model's in-sample explanatory power. However, it cannot assess the model's out-of-sample predictive power (Dolce et al., 2017; Shmueli, 2010; Shmueli & Koppius, 2011). The Q^2 value (Geisser, 1974; Stone, 1974) has the weakness that it only reflects aspects of the out-of-sample prediction by combining it with the in-sample exploratory power but does not measure the exact out-of-sample predictive power (Sarstedt et al., 2017a; Shmueli et al., 2016). To assess the out-of-sample predictive power, the data set needs to be split into a training and a holdout sample, and out-of-sample prediction metrics should be applied (Hair & Sarstedt, 2021). To facilitate this analysis, Shmueli et al. (2016) developed the PLSpredict procedure that generates holdout sample-based predictions for assessing the model's predictive power. This makes the reporting of the Q^2 redundant. Again, the question is whether these developments and findings have found application.

The controversy on how PLS path models should be evaluated, culminated in developing the confirmatory composite analysis (CCA; Hair, Black, et al., 2019; Henseler et al., 2014; Schuberth et al., 2018). CCA is a set of procedures that can be used to specify and assess composite-based SEM, such as PLS-SEM (Hair et al., 2020; Schuberth et al., 2018). It maximizes the variance extracted from the exogenous variables, allows confirmation and prediction of the endogenous constructs, and can confirm reflective and formative measurement models (Hair et al., 2020). Correspondingly, researchers have conceived CCA differently. Whereas Schuberth et al.'s (2018) approach focuses on evaluating the overall model fit and additional fit indices, Hair et al. (2020) suggest that a CCA should follow a series of evaluation steps, as mentioned in previous guidelines, such as those in Hair, Hult, Ringle, and Sarstedt (2017). As explained earlier in the chapter, the model-fit evaluation plays no role for them.

Recent advances are not limited to standard model evaluation but extend to more complex analysis procedures and modeling practices. For example, Henseler et al. (2016) developed a three-step procedure, which makes detecting misinterpretation based on invariance in multigroup comparisons possible. This procedure measures the invariance of composites when analysts use the variance-based SEM, called MICOM. It can detect no, partial, and full measurement invariance within PLS-SEM.

Heterogeneity, which researchers typically test with the help of specific defined attributes in a multigroup comparison, is not always observable. Uncovered heterogeneity can lead to data misinterpretation. Therefore, the earlier paper (Hair et al., 2012) as well as later publications (e.g., Hair, Sarstedt, & Ringle, 2019) pointed out the necessity to uncover unobserved heterogeneity in order to consider how it influences the results. Procedures that investigate unobserved heterogeneity are usually referred to as latent class techniques (Hair, Sarstedt, & Ringle, 2019). The past decade has shown further development and refinement of methods in this field. Techniques such as the finite mixture PLS (FIMIX-PLS; Hahn et al., 2002; Sarstedt, Becker, et al., 2011), prediction-oriented segmentation (Becker et al., 2013), PLS genetic algorithm (Ringle et al., 2014), iterative reweighted regressions (Schlittgen et al., 2016), or simultaneous non-hierarchical clustering (Fordellone & Vichi, 2018) have been introduced or developed for the PLS-SEM context. Recently, studies showed that FIMIX-PLS is the most common approach (Sarstedt et al., 2017b). With their publication, Sarstedt et al. (2017b) offered a systematic procedure to identify and treat unobserved heterogeneity in PLS-SEM. They also emphasized that researchers should use the most recently developed latent class methods, for their advantage in model evaluation concerning hidden segment detection. The question we now address, is whether researchers have implemented these measures.

In addition to recent new findings and developments, publishing new guidelines on the PLS-SEM already became necessary (Hair, Risher, et al., 2019; Hair, Sarstedt, & Ringle, 2019). This article intends to show why these guidelines were required, to point out weaknesses, and to reflect current knowledge as summarized in the overview at the end of the article. This should enable researchers to improve their reporting and to present their results correctly.

3. Review of PLS-SEM research published between 2011-2020

To ensure comparability, similar to Hair et al.'s (2012) article, we have reviewed PLS-SEM applications in marketing in the top 30 marketing journals according to Hult et al.'s (2009) journal ranking. As Hair et al. (2012) examined the period from 1981 to 2010, this review focuses on the following ten years, 2011 to 2020, to show possible developments and give an overview of PLS-SEM research in the marketing field during this period. We also used the keywords "partial least squares" and "PLS" to conduct a full-text search in *Clarivate Analytics' Web of Science* (previously known as *Thomas Reuters Web of Knowledge*), *EBSCO Information Services*, and *Elsevier's Scopus* databases. In addition, we searched the websites of the journals using the same search terms.[1] We ensured that we found all relevant PLS-SEM marketing articles in the considered journals by searching in different and independent databases and additionally searching on the respective websites.

Next, we controlled the search results and then first checked for incorrect results connected to the keywords. For example, we excluded articles with the theme "Private Labels (PLs)." We also excluded articles that only mentioned PLS-SEM as an analytic method or did not focus their model evaluation on this methodology. Since we intended only to consider articles dealing with PLS-SEM in the further analysis, we excluded articles focusing on path analysis, conventional score-based latent variable regression, and PLS regression, as the previous analysis did. Following these adjustments, we conducted a detailed review of the selected articles' content. Because the list of top 30 marketing journals (Hult et al., 2009) includes studies with interdisciplinary content, we reviewed articles from journals such as *Journal of Business Research*, *Journal of International Business Studies*, *Journal of Product Innovation Management*, and *Management Science* for their marketing relevance. Although highly relevant for the field of PLS-SEM, articles with simulations and empirical PLS-SEM applications to develop the area methodologically (e.g., Henseler et al., 2016; Shmueli et al., 2019) were excluded from the sample because they would influence the results of the subsequent analysis. Further, we excluded Hair et al.'s (2012) earlier methodological article.

The review revealed 20 journals that published relevant articles (Table 1), which brought us to a number of four fewer journals (*Journal of Consumer Psychology*, *Journal of Consumer Research*, *Journal of Marketing Research*, *Management Science*) than in the period up to 2010.

[1] We finished the search on January 12, 2021. Implemented search alerts on the databases did not reveal any further articles after that date.

Table 1: PLS-SEM studies in the top 30 marketing journals between 2011 and 2020

Advances in Consumer Research[1]
Wauters, Brengman, and Janssens 2011

European Journal of Marketing
Akman, Plewa, and Conduit 2019
Aspara and Tikkanen 2011
Carlson, Gudergan, Gelhard, and Rahman 2019
Chen, Peng, and Hung 2015
Coelho and Henseler 2012
Davari, Iyer, and Guzmán 2017
Dessart, Aldás-Manzano, and Veloutsou 2019
Françoise and Andrews 2015
Gaston-Breton, and Duque 2015
Huang and Tsai 2013
Krishen, Leenders, Muthaly, Ziółkowska, and LaTour 2019
Mo, Yu, and Ruyter 2020
Nath 2020
Olbrich and Schultz 2014
Ormrod and Henneberg 2011
Piehler, King, Burmann, and Xiong 2016
Šerić 2017
Singh and Söderlund 2020
Vidal 2014
Wijayaratne, Reid, Westberg, Worsley, and Mavondo 2018
Willems, Brengman, and Kerrebroeck 2019
Yu, Ruyter, Patterson, and Chen 2018

Industrial Marketing Management
Ali, Ali, Salam, Bhatti, Arain, and Burhan 2020
Berghman, Matthyssens, and Vandenbempt 2012
Camisón and Villar-López 2011
Faroughian, Kalafatis, Ledden, Samouel, and Tsogas 2012
Ferreras-Méndez, Newell, Fernández-Mesa, and Alegre 2015
Genc, Dayan, and Genc 2019
Gupta, Drave, Dwivedi, Baabdullah, and Ismagilova 2020
Harmancioglu, Sääksjärvi, and Hultink 2020
Hazen, Overstreet, Hall, Huscroft, and Hanna 2015
Heirati, O'Cass, Schoefer, and Siahtiri 2016
Hossain, Akter, Kattiyapornpong, and Dwivedi 2020
Inigo, Ritala, and Albareda 2020
Jain, Khalil, Johnston, and Cheng 2014
Joachim, Spieth, and Heidenreich 2018
Lopes de Sousa Jabbour, Vazquez-Brust, Chiappetta Jabbour, and Latan 2017
Mahlamäki, Rintamäki, and Rajah 2019
Mahlamäki, Storbacka, Pylkkönen, and Ojala 2020
Nagati and Rebolledo 2013
Nenonen, Storbacka, and Frethey-Bentham 2019
Ng, Ding, and Yip 2013
Niu, Deng, and Hao 2020
Poucke, Matthyssens, Weele, and Bockhaven 2019
Pulles, Schiele, Veldman, and Hüttinger 2016
Ritter and Geersbro 2011
Rollins, Bellenger, and Johnston 2012
Shahzad, Ali, Takala, Helo, and Zaefarian 2018
Sluyts, Matthyssens, Martens, and Streukens 2011
Stekelorum, Laguir, and Elbaz 2020
Teller, Alexander, and Floh 2016
Vries, Schepers, Weele, and Valk 2014
Yeniaras, Kaya, and Dayan 2020

International Journal of Research in Marketing
Miao and Evans 2012

International Marketing Review
Andéhn and L'Espoir Decosta 2016
Freeman and Styles 2014
Griffith, Lee, Yeo, and Calantone 2014
Jean, Wang, Zhao, and Sinkovics 2016
Kumar, Singh, Pereira, and Leonidou 2020
Moon and Oh 2017
Oliveira Duarte and Silva 2020
Pinho and Thompson 2017
Rahman, Uddin, and Lodorfos 2017
Rippé, Weisfeld-Spolter, Yurova, and Sussan 2015
Singh and Duque 2020
Sinkovics, Sinkovics, and Jean 2013

Journal of Advertising
Coleman, Royne, and Pounders 2020
José-Cabezudo and Camarero-Izquierdo 2012

Journal of Advertising Research
Archer-Brown, Kampani, Marder, Bal, and Kietzmann 2017
Dennis and Gray 2013
Miltgen, Cases, and Russell 2019
Robinson and Kalafatis 2020
Singh, Crisafulli, and La Quamina 2020

Journal of Business Research
Ahrholdt, Gudergan, and Ringle 2019
Albert, Merunka, and Valette-Florence 2013
Ali, Ali, Grigore, Molesworth, and Jin 2020
Ballestar, Grau-Carles, and Sainz 2016
Banik, Gao, and Rabbanee 2019
Barhorst, Wilson, and Brooks 2020
Blocker 2011
Borges-Tiago, Tiago, and Cosme 2019
Caputo, Mazzoleni, Pellicelli, and Muller 2020
Cenamor, Parida, and Wincent 2019
Cervera-Taulet, Pérez-Cabañero, and Schlesinger 2019
Chang, Shen, and Liu 2016
Del Sánchez de Pablo González Campo, Peña García Pardo, and Hernández-Perlines 2014
Ferrell, Harrison, Ferrell, and Hair 2019
Flecha-Ortíz, Santos-Corrada, Dones-González, López-González, and Vega 2019
Galindo-Martín, Castaño-Martínez, and Méndez-Picazo 2019
Gelhard and Delft 2016
Gudergan, Devinney, and Ellis 2016
Hernández-Perlines 2016
Hsieh 2020
Iglesias, Markovic, and Rialp 2019
Japutra and Molinillo 2019
Japutra, Ekinci, and Simkin 2019
Kapferer and Valette-Florence 2019
Kühn, Lichters, and Krey 2020
Leischnig, Henneberg, and Thornton 2016
Leong, Hew, Ooi, and Chong 2020
Martins, Costa, Oliveira, Gonçalves, and Branco 2019
McColl-Kennedy, Hogan, Witell, and Snyder 2017
Méndez-Suárez and Monfort 2020
Merz, Zarantonello, and Grappi 2018
Mourad and Valette-Florence 2016
Navarro-García, Arenas-Gaitán, Javier Rondán-Cataluña, and Rey-Moreno 2016
Navarro-García, Sánchez-Franco, and Rey-Moreno 2016
Ohiomah, Andreev, Benyoucef, and Hood 2019
Oliveira Duarte and Pinho 2019
Padgett, Hopkins, and Williams 2020
Palos-Sanchez, Saura, and Martin-Velicia 2019
Peterson 2020
Picón, Castro, and Roldán 2014
Reguera-Alvarado, Blanco-Oliver, and Martín-Ruiz 2016
Rippé, Smith, and Dubinsky 2018
Roy, Balaji, Soutar, Lassar, and Roy 2018
Saleh Al-Omoush, Orero-Blat, and Ribeiro-Soriano 2020
Schubring, Lorscheid, Meyer, and Ringle 2016
Segarra-Moliner and Moliner-Tena 2016
Sener, Barut, Oztekin, Avcilar, and Yildirim 2019
Sharma and Jha 2017
Skarmeas, Saridakis, and Leonidou 2018
Suhartanto, Dean, Nansuri, and Triyuni 2018
Tajvidi, Richard, Wang, and Hajli 2020
Takata 2016
Thakur and Hale 2013
Tran, Lin, Baalbaki, and Guzmán 2020
Valette-Florence, Guizani, and Merunka 2011
Wu, Raab, Chang, and Krishen 2016
Zhang, He, Zhou, and Gorp 2019
Zollo, Filieri, Rialti, and Yoon 2020

Table 1: PLS-SEM studies in the top 30 marketing journals between 2011 and 2020 (continued)

Journal of Interactive Marketing
Buzeta, Pelsmacker, and Dens 2020
Divakaran, Palmer, Søndergaard, and Matkovskyy 2017

Journal of International Business Studies
Lam, Ahearne, and Schillewaert 2012
Lew, Sinkovics, Yamin, and Khan 2016

Journal of International Marketing
Johnston, Khalil, Jain, and Cheng 2012

Journal of Marketing
Köhler, Rohm, Ruyter, and Wetzels 2011

Journal of Marketing Management
Ashill and Jobber 2014
Balaji and Roy 2017
Barnes and Mattsson 2011
Bennett 2011
Bennett 2018
Bennett and Kottasz 2011
Brettel, Engelen, and Müller 2011
Brill, Munoz, and Miller 2019
Carlson, Rahman, Rosenberger, and Holzmüller 2016
Carlson, Rosenberger, and Rahman 2015
Chiang, Wei, Parker, and Davey 2017
Dall'Olmo Riley, Pina, and Bravo 2015
Falkenreck and Wagner 2011
Fernandes and Castro 2020
Finch, Hillenbrand, O'Reilly, and Varella 2015
Hankinson 2012
Helme-Guizon and Magnoni 2019
Iriana, Buttle, and Ang 2013
Jack and Powers 2013
King, Grace, and Weaven 2013
Ledden, Kalafatis, and Mathioudakis 2011
Mouri, Bindroo, and Ganesh 2015
Ngo and O'Cass 2012
Papagiannidis, Pantano, See-To, and Bourlakis 2013
Richard and Zhang 2012
Ross and Grace 2012
Roy, Balaji, and Nguyen 2020
Roy, Singh, Hope, Nguyen, and Harrigan 2019
Stocchi, Michaelidou, Pourazad, and Micevski 2018
Tabeau, Gemser, Hultink, and Wijnberg 2017
Tafesse and Wien 2018
Taheri, Gori, O'Gorman, Hogg, and Farrington 2016
Teller, Gittenberger, and Schnedlitz 2013
Wu, Jayawardhena, and Hamilton 2014
Wyllie, Carlson, and Rosenberger 2014

Journal of Product Innovation Management
Beuk, Malter, Spanjol, and Cocco 2014
Borgh and Schepers 2014
Brettel, Heinemann, Engelen, and Neubauer 2011
Calantone and Rubera 2012
Carbonell and Rodríguez-Escudero 2016
Carbonell and Rodríguez-Escudero 2019
Dubiel, Durmuşoğlu, and Gloeckner 2016
Ernst, Kahle, Dubiel, Prabhu, and Subramaniam 2015
Feurer, Schuhmacher, and Kuester 2019
Hammedi, Riel, and Sasovova 2011
Heidenreich and Handrich 2015
Heidenreich, Spieth, and Petschnig 2017
Jean, Sinkovics, and Hiebaum 2014
Kock, Gemünden, Salomo, and Schultz 2011
Kuester, Homburg, and Hess 2012
Langley, Bijmolt, Ortt, and Pals 2012
Lee and Tang 2018
Mahr, Lievens, and Blazevic 2014
Matsuno, Zhu, and Rice 2014
Mauerhoefer, Strese, and Brettel 2017
McNally, Akdeniz, and Calantone 2011
McNally, Durmuşoğlu, and Calantone 2013
Ngo and O'Cass 2012
Nijssen, Hillebrand, Jong, and Kemp 2012
Pitkänen, Parvinen, and Töytäri 2014
Schuster and Holtbrügge 2014
Siahtiri 2018
Spanjol, Mühlmeier, and Tomczak 2012
Spanjol, Qualls, and Rosa 2011
Zobel 2017

Journal of Public Policy and Marketing
Hasan, Lowe, and Petrovici 2019

Journal of Retailing
Pelser, Ruyter, Wetzels, Grewal, Cox, and Beuningen 2015

Journal of Service Research
Boisvert 2012
Mullins, Agnihotri, and Hall 2020

Journal of the Academy of Marketing Science
DeLeon and Chatterjee 2017
Ernst, Hoyer, Krafft, and Krieger 2011
Fombelle, Bone, and Lemon 2016
Hansen, McDonald, and Mitchell 2013
Heidenreich, Wittkowski, Handrich, and Falk 2015
Heijden, Schepers, Nijssen, and Ordanini 2013
Hillebrand, Nijholt, and Nijssen 2011
Houston, Kupfer, Hennig-Thurau, and Spann 2018
Hult, Morgeson, Morgan, Mithas, and Fornell 2017
Leroi-Werelds, Streukens, Brady, and Swinnen 2014
Martin, Johnson, and French 2011
Miao and Evans 2013
Nakata, Zhu, and Izberk-Bilgin 2011
Ranjan and Read 2016
Santos-Vijande, López-Sánchez, and Rudd 2016
Steinhoff and Palmatier 2016
Weerawardena, Mort, Salunke, Knight, and Liesch 2015
Wilden and Gudergan 2015
Wolter and Cronin 2016

Marketing Letters
Dugan, Rouziou, and Hochstein 2019

Psychology and Marketing
Barnes and Pressey 2012
Borges-Tiago, Tiago, Silva, Guaita Martínez, and Botella-Carrubi 2020
Devece, Llopis-Albert, and Palacios-Marqués 2017
Evers, Gruner, Sneddon, and Lee 2018
Fatima, Mascio, and Johns 2018
Gong and Yi 2018
Hernández-Perlines, Moreno-García, and Yáñez-Araque 2017
Jain, Malhotra, and Guan 2012
Revilla-Camacho, Vega-Vázquez, and Cossío-Silva 2017
Sheng, Simpson, and Siguaw 2019
Verhagen, Dolen, and Merikivi 2019
Zhang and Zhang 2014

California Management Review, Harvard Business Review, Journal of Consumer Psychology, Journal of Consumer Research, Journal of Marketing Research, Management Science, Marketing Science, Quantitative Marketing and Economics, and *Sloan Management Review* did not produce any relevant articles. *Journal of Business* cease publication of the journal at the end of 2006.

[1] We excluded five studies by Caemmerer and Mogos Descotes (2011), Chen et al. (2011), Kidwell et al. (2012), Luo et al. (2015), and Rippé et al. (2019) published in *Advanced in Consumer Research* as these were only published as extended abstracts.

However, the number of published articles on this topic had increased. While only 204 studies with PLS estimations had been published in the period from 1981 to 2010, the number increased by 17.16% to 239 in the past ten years, and the average number of publications per year increased from 6.80 to 23.90. In total, we considered 486 PLS-SEM models[2], since 38.91% of the articles analyzed two or more alternative models and/or different datasets (collected in, e.g., different years, countries, target groups, or resulting from a segmentation). Considering the frequency of publications per journal, we found a change in the top three journals compared to the previous period. Between 1981 and 2010, the *European Journal of Marketing* (30 articles, 14.71%), *Industrial Marketing Management* (23 articles, 11.27%), and *Journal of Marketing* (17 articles, 8.33%) published the most articles with PLS-SEM estimations; now, only the *Industrial Marketing Management* (31 articles, 12.97%) remains in the top three. The *Journal of Business Research* (58 articles, 24.27%) and *Journal of Marketing Management* (35 articles, 14.64%) are now new in the top three ranking. Table 2 illustrates these results for the journals with more than one publication between 2011 and 2020, and shows the proportions compared to the previous period.

Table 2: Journals with more than one publication between 2011 and 2020 compared to 1981-2010

	Publication number			
Journals	2011-2020 (n=239)	Proportion (%)	1981-2010 (n=204)	Proportion (%)
Journal of Business Research	58	24.27	15	7.35
Journal of Marketing Management	35	14.64	6	2.94
Industrial Marketing Management	31	12.97	23	11.27
Journal of Product Innovation Management	30	12.55	11	5.39
European Journal of Marketing	22	9.21	30	14.71
Journal of the Academy of Marketing Science	19	7.95	13	6.37
International Marketing Review	12	5.02	3	1.47
Psychology and Marketing	12	5.02	9	4.41
Journal of Advertising Research	5	2.09	4	1.96
Journal of Advertising	2	0.84	3	1.47
Journal of Interactive Marketing	2	0.84	2	0.98
Journal of International Business Studies	2	0.84	2	0.98
Journal of Service Research	2	0.84	7	3.43

Examining the number of publications over time shows an upward trend during the years 2011-2020 (Figure 1). This underlines the increasing popularity of PLS-SEM. The years 2019 and 2020 reveal a particularly strong surge in publication output, but taken annually, they still

[2] As in the Hair et al. (2012) article, we will use the term "studies" in referring to the 239 journal articles we considered, and the term "models" to refer to the 486 PLS-SEM estimations examined in these articles.

do not reach the total of the outstanding year 2010, when 51 publications appeared. The future will show whether this trend will continue.

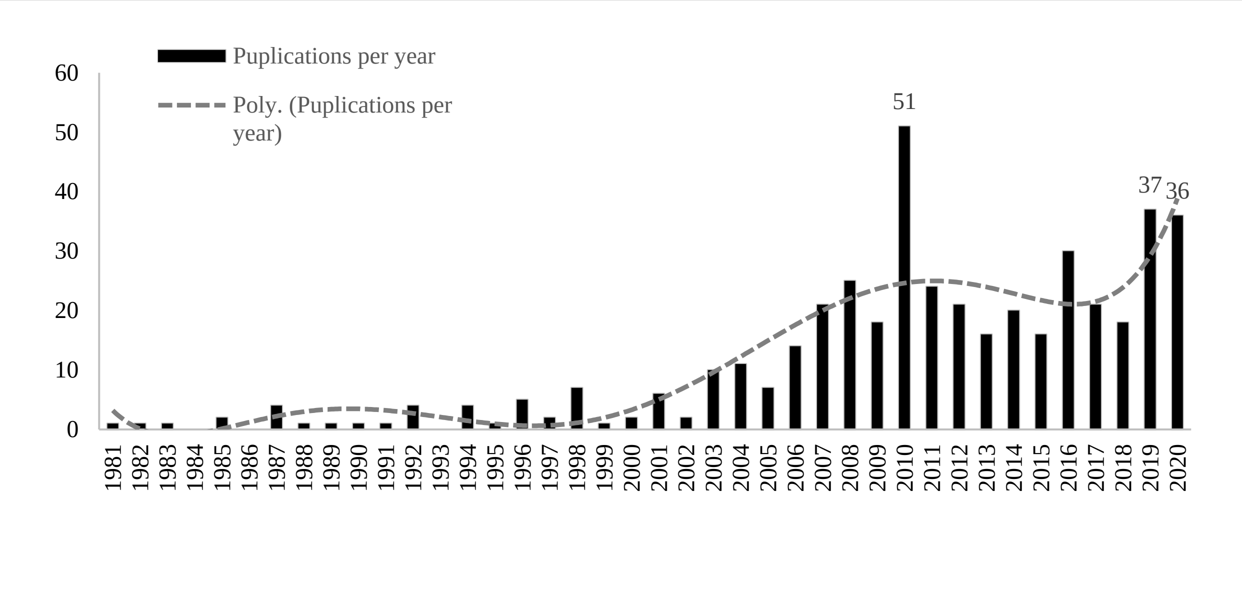

Figure 1: Publications per year

4. Critical Issues in PLS-SEM Applications between 2011-2020

In this section we shall evaluate the articles we found on various criteria almost similar to those of the previous article. The focus, is on (1) the reasons for using PLS-SEM, (2) characteristics of the data, (3) models, (4) outer model evaluation, (5) inner model evaluation, (6) advanced analyses (as a new criteria), and (7) the reporting.

4.1. Reasons for using PLS-SEM

This analysis once again examined the reasons why researchers use PLS-SEM. Overall, quite positively, 193 (80.75%) of the studies gave a reason for their choice to use PLS-SEM. Between the two periods, there was only a moderate change in the given reasons. The analysis shows that the main reasons for using PLS-SEM are a small sample size (114 studies, 47.70%), non-normal data distribution (76 studies, 31.80%), and highly complex models (70 studies, 29.29%). Thus, the top three given reasons had changed slightly from previous years (1981-2010: small sample size 46.08%, non-normal data 50.00%, and formative measurement 32.84%). Formative measurements were still relevant as a reason for using PLS-SEM (56 studies, 23.43%), but no longer as one of the top three. The authors' reference to the predictive background of their studies (61 studies, 25.52%, 1981-2010: 57 studies, 27.94%) was virtually constant, and increasingly aimed to develop theories and to conduct explorative studies (73 studies, 35.78%; 1981-2010: 35 studies, 17.16%).

Several researchers questioned the most commonly used justification, "small sample size" (e.g., Goodhue et al., 2012; Rönkkö & Evermann, 2013; Sosik et al., 2009), as did some reviewers (Lee, 2017). PLS-SEM can be advantageous due to its higher statistical power levels (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017) and its better convergence behavior compared to CB-SEM with small samples (Henseler et al., 2014; Reinartz et al., 2009), but if the population does not justify the sample size, its use is still questionable (Rigdon, 2016). Therefore, considering that PLS-SEM is not necessarily always well suited to small sample sizes, researchers should use this justification cautiously (Hair, Sarstedt, & Ringle, 2019). We were, therefore, pleased to observe that other entirely new reasons for use are also being mentioned.

A few new reasons for PLS-SEM usage included that PLS-SEM was chosen because it had recently been applied in the particular research field, or was a popular and standard tool in various studies (5.86%). Further, the reasoning that PLS-SEM is very well suited for studies with mediations (1.26%) and moderations (5.02%) stood out. Additionally, some mentioned that they preferred to use PLS-SEM for the evaluation because they wanted to evaluate and examine higher-order constructs (3.35%).

4.2. Data Characteristics

Concerning the data characteristics, there were both positive and negative developments. In connection with the criticism of PLS-SEM's suitability to small sample sizes, it is positive that there were favorable developments when considering the average sample size many studies used, and their adherence to the rule of thumb. Researchers increasingly seem to recognize, and reviewers increasingly insist that PLS-SEM *per se* is not a small sample size method.

The 5% trimmed mean increased from 211.29 to 279.19 in the analyzed models. We found a similar trend concerning the medians (1981-2010: 159, 2011-2020: 199). In addition, there were still publications that based their studies on very large sample sizes (Borges-Tiago et al., 2020, n=26,576; Ballestar et al., 2016, n=18,250; Palos-Sanchez et al., 2019, n=14,822; Stekelorum et al., 2020, n=8,876). However, some articles still had less than 100 cases (85 models, 17.86%) but the proportion decreased (1981-2010: 24.44%). Galindo-Martín et al.'s (2019) study had the smallest sample size with 29 cases[3].

On the positive side, the proportion of models that did not fulfill the rule of thumb decreased (17 models, 3.57%, 1981-2010: 9.00%). Besides, we positively observe that, on average, the sample size was only 10.98% below the recommended sample size, which is a considerable improvement compared to the previous period (1981-2010: 45.18%).

In the previous work, the authors pointed out that in PLS-SEM, demonstrating the parameter estimates' robustness by using holdout sampling is of even greater importance than in CB-SEM (Hair et al., 2012). However, it appeared that researchers did not take this seriously. Only 11 of the 239 articles (4.60%) used holdout sampling, i.e., even fewer than in the previous period (1981-2010: 13 articles, 6.37%).

Considering the proportion of non-normal distribution data reported, despite the 2012 study's recommendations, there was also hardly any improvement. Only 24 studies (10.04%, 1981-2010: 9.31%) mentioned a non-normal distribution, and almost none of them included precise statistics on kurtosis and skewness.

Additionally, we checked whether the researchers provided information on the handling of missing values. Only 41 studies (17.15%) gave additional details and almost all of them (95.12%) used casewise deletion as treatment.

Analyzing the critically evaluated use of binary and categorical variables (Hair et al., 2012), we could reveal an improvement. Compared to the previous period, only 15 studies (6.28%, 1981-2010: 21.08%) used binary variables and nine studies (3.77%, 1981-2010:

[3] In this paragraph n=476, as 10 models did not report the sample size between 2011 and 2020.

6.86%) used categorical variables. In contrast, as Hair et al. (2012) had suggested, the latter period's researchers performed a high number of multigroup comparisons (133 models, 27.36%).

4.3. Model Characteristics

We also analyzed the model characteristics' assessment in more detail. This area has not recently seen remarkable research development. However, for most characteristics our analysis indicates a positive development regarding their evaluation. We used the existing tables from the previous article (Hair et al., 2012) and extended them with the current data to give an overview of the model characteristics of all the PLS-SEM studies and to allow a comparison. In our article, Table 3 shows the descriptive statistics of the models. To illustrate, between 2011 and 2020 the average number of latent variables slightly decreased in comparison to the previous period (7.39, 1981-2010: 7.94).

In addition to this observation, we examined the distribution of model types (i.e., focused, unfocused, and balanced). Overall, there were only minor changes in the distribution compared to the previous period. We found 161 focused models (33.13%, 1981-2010: 35.05%), which means that the models contain a smaller number of endogenous latent variables, and we specified that the number of exogenous latent variables had to be at least twice as high as the number of endogenous latent variables. In contrast, we considered the unfocused models as well. These had relatively high numbers of endogenous latent variables and mediative effects, i.e., the number of endogenous latent variables was at least twice as high as the number of exogenous latent variables. There were 149 of these unfocused models (30.66%, 1981-2010: 27.33%). The unclassified ones are balanced models. Of these, there were 176 models (36.21%, 1981-2010: 37.62%). Only the focused and balanced models met the PLS-SEM prediction goal, whereas the CB-SEM would have been more appropriate for the unfocused models (Hair et al., 2012). We analyzed 61 studies that mentioned a prediction purpose, of which 19 (33.33%, 1981-2010: 40.35%) used unfocused models. It seems that, similar to the previous period, there is still a lack of awareness of what model type is appropriate if researchers use PLS-SEM to fulfill prediction goals, albeit with a slight improvement.

Before taking a detailed look at the outer model evaluation, we first examined how researchers measured their latent variables in the models, whether reflective, formative, or a combination of the two. First, we noted that almost half (47.94%) of the studies no longer explicitly reflect on the latent variables' measurement. However, based on the quality criteria they examined, we can deduce the measurement they used. The judgment result showed that almost all models (97.42%) that measured with reflective indicators only, did not give the information. Due to the large amount of missing information, we based the distribution consideration on the judged results as they offer a more realistic picture. The models' distribution shows a deficient number of solely formatively measured latent variables (7 models, 1.44%, 1981-2010: 6.43%), a further decrease compared to the previous period. Something similar happened in combinations of reflectively and formatively measured latent variables (105 models, 21.60%, 1981-2010: 39.55%). These decreases, therefore, increased the number of solely reflectively measured latent variables (347 models, 76.95%, 1981-2010: 42.12%). However, these comparisons should be done cautiously, because in the previous period, when the proportion of missing data was lower (1981-2010: 11.90%), the analysis was based on the explicitly stated classification.

There was almost no change between the two periods in the average number of reflective indicators used per latent variable, which decreased slightly from 3.99 to 3.85. We observed the same for the formative variables (4.28, 1981-2010: 4.62). However, the number is still higher than that of the reflective indicators, which is to be expected since the formative constructs must represent an entire population of possible indicators (Diamantopoulos et al., 2008). The total number of indicators in the models is very similar for the two studies. The average increased slightly from 29.55 to 29.39, in comparison to the previous period. In addition, the average median remained constant at 24.

An occasionally mentioned reason (6 studies) for using PLS-SEM in the current review was the possibility of using a combination of multi- and single-indicators in the model. Researchers used this combination in a large number of models (177 models, 36.42%). However, there is a downward trend in such use. While in 1981-2010, 46.30% of the models used single indicators, in 2011-2020 a reduced 36.42% of the models did so. It is possible that recent research followed the advice given in the previous article, which said that "...single-item measures should be considered with caution when using PLS-SEM" (Hair et al., 2012, p. 423).

As mentioned earlier, another reason (8 studies) given for using PLS-SEM is the advantages it produces in the analysis of higher-order constructs. A first collection of studies of higher-order constructs confirms this, as 74 studies (30.96%) included them. This result offers potential for further research regarding which types of higher-order constructs (reflective-reflective, reflective-formative, formative-reflective, or formative-formative) are used, as well as for evaluating and correctly reporting the constructs as described, for example, in Sarstedt et al. (2019).

Table 3: Descriptive statistics for model characteristics 1981-2020

	1981-2010		2011-2020		1981-2010		2011-2020	
Criterion	Results (n=311)	Proportion (%)	Results (n=486)	Proportion (%)	Other leading journals (n=250)	Top tier journals (n=61)	Other leading journals (n=446)	Top tier journals (n=40)
Number of latent variables								
Mean	7.94	-	7.39	-	7.76	8.69*	7.43	6.95
Median	7.00		7.00		7.00	8.00	7.00	6.00
Range	(2; 29)		(2; 24)		(2; 29)	(2; 20)	(2; 24)	(2; 12)
Number of inner model path relations								
Mean	10.56	-	11.90	-	10.10	12.41*	11.82	12.78
Median	8.00		10.00		8.00	10.00	10.00	9.00
Range	(1; 38)		(1; 70)		(1; 38)	(1; 35)	(1; 70)	(5; 46)
Model type[1]								
Focused	109	35.05	161	33.13	88	21	158**	3
Unfocused	85	27.33	149	30.66	59	26***	135	14
Balanced	117	37.62	176	36.21	103***	14	153	23**
Mode of outer models[2]								
Only reflective	131	42.12	374	76.95	115***	16	346	28
Only formative	20	6.43	7	1.44	17	3	6	1
Reflective and formative	123	39.55	105	21.60	88	35***	94	11
Not specified[3]	37	11.90	233	47.94	30	7	213	20
Number of indicators per reflective construct								
Mean	3.99	-	3.85	-	4.15**	3.35	3.92***	3.07
Median	3.50		3.00		3.50	3.00	3.00	3.00
Range	(1; 27)		(1; 30)		(1; 27)	(1; 16)	(1; 30)	(1; 12)
Number of indicators per formative construct								
Mean	4.62	-	4.28	-	4.83**	3.99	4.19	5.03
Median	4.00		3.00		4.00	3.50	3.00	4.00
Range	(1; 20)		(1; 38)		(1; 18)	(1; 20)	(1; 38)	(1; 29)
Total number of indicators in models								
Mean	29.55	-	29.39	-	29.47	29.85	29.85	24.38
Median	24.00		24.00		24.00	25.00	24.50	19.00
Range	(4; 131)		(3; 222)		(4; 131)	(7; 101)	(5; 222)	(3; 91)
Number of models with single-item constructs	144	46.30	177	36.42	111	33	148.00	29.00

[1] Focused model: number of exogenous constructs at least twice as high as the number of endogenous constructs in the model; unfocused model: number of endogenous constructs at least twice as high as the number of exogenous constructs in the model; balanced model: all remaining models.

[2] 2011-2020 models were judged by the authors of this paper regarding their use of reflective and formative mode.

[3] Number of models where the authors do not specify the mode.

*** (**, *) indicates a significant difference between “other leading journals”/”top tier journals,” for 1981-2010 and 2011-2020 respectively, at a 1% (5%, 10%) significance level; results based on samples t-test and (one-tailed) Fisher’s exact tests (no tests for median differences)

4.3.1. *Outer Model Evaluation*

In this section, we will discuss the outer model assessment in more detail. There have been some recent developments in this area. What has not changed, is that the outer model assessment includes examining the individual indicator reliability, the internal consistency reliability assessment, which considers the reliability examination of each construct composite, and the convergent and discriminant validity assessment of each construct. Further, the necessity for a differentiated assessment of reflectively and formatively measured latent variables (e.g., Diamantopoulos et al., 2008) also remains unchanged. This is still necessary as an internal consistency perspective remains inappropriate, and convergent and discriminant validities cannot be tested by empirical means for formatively measured constructs (e.g., Hair, Hult, Ringle, & Sarstedt, 2017).

Dijkstra and Henseler (2015) developed the new measure Rho_A to determine the reliability of the latent variables more exactly. This was necessary after it became evident that the reliability measures Cronbach's Alpha (Cronbach, 1951) and Rho_C (Heise & Bohrnstedt, 1970) underestimate or overestimate the reliability.

We see further development concerning discriminant validity evaluation. The Fornell-Larcker criterion (Fornell & Larcker, 1981) or the cross-loadings were commonly and frequently applied to assess discriminant validity. However, research found that they are not appropriate for the evaluation, therefore (Henseler et al., 2015) developed the HTMT criterion, which can be validated using threshold values or bootstrap-based confidence intervals, and statistics should not exceed specific thresholds (conceptually similar (0.90) or not (0.85)) (Henseler et al., 2015). More precisely, the bootstrap-based confidence interval for a certain HTMT value should not include the selected threshold (Franke & Sarstedt, 2019).

In the next subchapters, we examine whether and how various authors correctly assessed the constructs' appropriateness and applied the correct criteria in terms of how the outer latent variables are measured. In addition, we investigate whether, compared to the previous period, the assessment has improved. Further, we consider whether scholars used the new indicators, and thus could improve the quality of the model evaluation.

4.3.1.1. Reflective Outer Models

The indicator reliability (standardized indicator loading), internal consistency reliability (Cronbach's Alpha, Rho_C, and Rho_A), convergent validity (average value extracted (AVE)), and discriminant validity (Cross-loadings, Fornell-Larcker criterion, and HTMT) should be used to assess the reflective outer models (e.g., Dijkstra & Henseler, 2015; Franke & Sarstedt, 2019;

Hair, Hult, Ringle, & Sarstedt, 2017). As part of our investigation, we considered the use of the respective test procedures. We summarized the results in comparison with the previous period in Table 4 (Panel A).

A total of 479 models[4] (98.56%) reported at least one reflectively measured latent variable and thereby gave an evaluation concerning the indicator reliability. In total, 374 models (76.95%) even consist solely of reflective constructs. The number of indicator loadings reported, i.e., 390 of the 479 models (81.42%), made a clear reporting improvement evident, as in the period 1981-2010, there had only been 61.81%.

There were some developments concerning internal consistency reliability. In addition to Cronbach's Alpha and Rho_C, researchers now reported Rho_A as well. A total of 386 models (80.58%) reported at least one indicator to assess internal consistency reliability, which is an improvement compared to the previous period (1981-2010: 69.69%). The majority of the models reported conjunctively using Cronbach's Alpha and Rho_C (190 models, 39.67%), followed by solely Rho_C (27.56%), and solely Cronbach's Alpha (10.23%). Although Hair et al.'s guidelines already discouraged the use of Cronbach's Alpha in 2012, researchers still reported this criterion 249 times (51.98%), thus even more frequently than before (1981-2010: 40.94%). Unfortunately, this point has not been revisited and thought through yet. Moreover, despite Dijkstra and Henseler's (2015) publication regarding Rho_A being slightly dated, only a small proportion of studies reported it (15 models, 3.13%). Therefore, the evaluation of the internal consistency reliability could potentially be improved.

The next aspect we considered regarding the reflective model evaluation is the convergent validity evaluation. In this case, we can positively report that 371 of the 479 models (77.45%) provided information on AVE. This represents an enhancement over the previous period (1981-2010: 57.48%).

The last factor we considered is discriminant validity. This aspect showed development, as the findings also reflect. First, and positively, we noted that 361 of the 479 models (75.37%) used at least one criterion for the investigation. Previously, this accounted for only 60.63%. Most models still use the Fornell-Larcker criterion (36.74%) or a combination of the Fornell-Larcker criterion and cross-loadings (16.91%). Third-most, these assessments relied on a combination of the Fornell-Larcker criterion and HTMT evaluation (7.93%). A total of 16.28% of the models were already using HTMT. Additionally, as the HTMT criterion can be validated using threshold values or bootstrap-based confidence intervals, we conducted a further

[4] This analysis used all models that included at least one reflective construct. We therefore used the models that we judged to be reflective, since the proportion of missing assessments was too large, as described earlier.

examination of this distribution, and found that 47 models (60.26%) used threshold values, two models (2.56%) used confidence intervals, and 23 models (29.49%) reported both.

4.3.1.2. Formative Outer Models

As mentioned above, only seven of the 486 models consist of solely formatively measured latent variables, and another 105 include at least one such measurement. This gave 112 models (23.05%) that we could analyze in detail, which adds up to more than 20% less than in the previous period (1981-2010: 45.98%). Panel B in Table 4 shows an overview of these results.

First, we can positively state that only ten (8.93%) of the models used reflective outer model assessments to evaluate the formatively measured constructs. Such inappropriate evaluative behavior was therefore markedly reduced (1981-2010: 23.08%).

Redundancy analysis assesses the convergent validity of the formatively measured latent variables. It checks whether each formative measured latent variable correlates with an alternative measure of the same concept (Chin, 1998). The researcher can use a global single-item or a reflectively measured multi-item scale as an alternative measurement as a criterion variable (Cheah et al., 2018). In total, only six of these 112 models (5.36%), which used formatively measured latent variables, reported this information.

Another positive point is that the number of reported indicator weights, an essential evaluation criterion, increased. The studies report this for almost two-thirds of the models (74 models, 66.07%), which is a distinct increase compared to the previous period (1981-2020: 17.48%). In addition, the proportion of studies that report such significance by means of resampling by t-values and corresponding p-values, is growing (33.93%, 1981-2010: 17.48%). However, this shows potential for further improvement concerning this important criterion. Moreover, only two of the studies also reported the confidence intervals by using this generated sample’s percentiles.

We find another essential statistical criterion in assessing multicollinearity between the indicators in formative measures to detect indicator weights’ instability (Cenfetelli & Bassellier, 2009). Once again, there is a positive development compared to the previous period, although some potential for improvement remains. Almost half of the studies (53 studies, 47.32%) assessed multicollinearity. They still rely primarily on the variance inflation factor (VIF). The condition index plays almost no role anymore.

Table 4: Evaluation of outer models 1981-2020

Panel A: Reflective outer models		1981-2010		2011-2020		1981-2010		2011-2020	
	Empirical test criterion in PLS-SEM	Number of models reporting (n=254)	Proportion reporting (%)	Number of models reporting (n=479)	Proportion reporting (%)	Other leading journals (n=203)	Top tier journals (n=51)	Other leading journals (n=440)	Top tier journals (n=39)
Indicator reliability	Indicator loadings[1]	157	61.81	390	81.42	126	31	355	35
Internal consistency reliability	Only Rho_c	73	28.74	132	27.56	56	17	125	7
	Only Cronbach's Alpha	35	13.78	49	10.23	31*	4	27	22***
	Only Rho_A	-	-	3	0.63	-	-	3	0
	Rho_c & Cronbach's Alpha	69	27.17	190	39.67	60*	9	184**	6
	Rho_A & Cronbach's Alpha	-	-	1	0.21	-	-	1	0
	Rho_c & Rho_A	-	-	2	0.42	-	-	2	0
	All three	-	-	9	1.88	-	-	9	0
Convergent validity	AVE	146	57.48	371	77.45	119	27	336	35
	Other	7	2.76	16	3.34	6	1	16	0
Discriminant validity	Only Fornell-Larcker (FL) criterion	111	43.70	176	36.74	93	18	151	25**
	Only cross-loadings	12	4.72	8	1.67	9	3	6	2
	Only HTMT	-	-	25	5.22	-	-	25	0
	FL criterion & cross-loadings	31	12.20	81	16.91	20	11*	78	3
	FL criterion & HTMT	-	-	38	7.93	-	-	38	0
	Cross-loadings & HTMT	-	-	3	0.63	-	-	3	0
	All three	-	-	12	2.51	-	-	12	0

Panel B: Formative outer models		1981-2010		2011-2020		1981-2010		2011-2020	
	Empirical test criterion in PLS-SEM	Number of models reporting (n=143)	Proportion reporting (%)	Number of models reporting (n=112)	Proportion reporting (%)	Other leading journals (n=105)	Top tier journals (n=38)	Other leading journals (n=100)	Top tier journals (n=12)
	Reflective criteria used to evaluate formative constructs	33	23.08	10	8.93	29**	4	5	5***
Indicator's absolute contribution to the construct	Indicator weights	33	23.08	74	66.07	14	19***	65	9
Significance of weights	Standard errors, significance levels, t-values/p-values for indicator weights	25	17.48	36	32.14	13	12***	27	9
	Confidence intervals	-	-	0	0.00	-	-	0	0
	Both	-	-	2	1.79	-	-	2	0
Multicollinearity	Only VIF/tolerance	17	11.89	43	38.39	12	5	39	4
	Only condition index	1	0.70	1	0.89	1	0	1	0
	Both	4	2.80	9	8.04	4	0	9	0

[1] Single item constructs were excluded in 1981-2010 and 2011-2020.

*** (**, *) indicates a significant difference between "other leading journals"/"top tier journals," for 1981-2010 and 2011-2020 respectively, at a 1% (5%, 10%) significance level; results based on (one-tailed) Fisher's exact tests.

4.3.2. *Inner Model Evaluation*

Before a detailed discussion of the inner model assessment, we summarize what is necessary for this kind of assessment and what has changed. Table 5 shows how the area of inner model evaluation developed. Researchers should still continually base their evaluation on variance-based, non-parametric evaluation criteria (e.g., Chin, 2010; Hair, Hult, Ringle, & Sarstedt, 2017). Based on Hair, Risher, et al.'s (2019) guidelines, the evaluation coefficient of determination R^2, effect size f^2 (Cohen, 1988), Stone's (1974) and Geisser's (1974) cross-validated redundancy Q^2, relative predicted relevance q^2, and Tenenhaus et al.'s (2004) overall goodness-of-fit (i.e., GoF index) should be reported. However, there have been developments in this area, which make the reporting of the Q^2 redundant, as the Q^2 value (Geisser, 1974; Stone, 1974) has the weakness that it only reflects out-of-sample prediction aspects (Sarstedt et al., 2017a; Shmueli et al., 2016). Besides, as mentioned earlier, the R^2 statistic is only appropriate for assessing explanatory power (Dolce et al., 2017; Shmueli, 2010; Shmueli & Koppius, 2011). Researchers should use a subsample of the original data to estimate the model parameters by first excluding the cases that predictably should assess the out-of-sample predictive power (Hair et al., 2018; Hair, Black, et al., 2019). For this Shmueli et al. (2016) developed the PLSpredict procedure.

Further, researchers discussed the necessity of reporting the model's goodness-of-fit. Hair, Sarstedt, and Ringle (2019, pp. 572–573) concluded that "researchers do not necessarily need to assess a partial least squares path model's goodness-of-fit." Currently, we do not know enough about the applicability and performance of these fit measures in the PLS-SEM context due to their "causal-predictive" and not strictly confirmatory nature (Jöreskog & Wold, 1982, p. 270).

Our study's results show increased adherence to the guidelines, but again there is potential for future improvement. A total of 430 models (88.48%, 1981-2010: 88.42%) reported R^2 as the amount of the endogenous variables' explained variance. A total of 86 models (17.70%) reported the effect size f^2 of the model, which shows an increase compared to the previous period (1981-2010: 5.14%). Similarly, the reported predictive relevance Q^2 of the model has increased (33.33%, 1981-2010: 16.40%). Its redundancy has not yet spread. Even if Hair, Sarstedt, and Ringle (2019) recommend the PLSpredict procedure, only three studies we reviewed used it, which could still be due to the high degree of actuality. In addition, even if the 3.09% of the reported relative predicted relevance q^2 still seems very low, it is nevertheless an improvement since in the previous period researchers did not report this test criterion.

Researchers reported the GoF index in 76 models (15.64%). Apparently, they did not fully disseminate the information that this index does not apply to models with formative and single items, as 27 models (35.53%) still made this error. Although reporting the goodness-of-fit indices is unnecessary, the studies showed an increase compared to the previous period (1981-2010: 5.14%). In addition to the GoF index, a variety of other goodness-of-fit criteria were reported, such as SRMR (13.17%), root mean square error of approximation (RMSEA) (11.93%), Chi-Square (10.49%), and comparative fit index (CFI) (10.49%).

Before researchers begin to test the latent variables for their structural relationship and thus standardized path coefficients, they have to analyze the collinearity between the latent variables to avoid a bias on the regression results (Hair, Risher, et al., 2019). However, only 57 of 239 studies (23.85%) reported the multicollinearity between the latent variables. Considering how studies report the standardized path coefficients, which should give information on the inner model quality, we noted that almost all models (480 models, 98.77%) give these coefficients. This is an improvement compared to the previous period, in which many studies already reported this information (1981-2010: 95.82%). Besides, the researchers should examine their significance using a resampling method. All models that reported the path coefficients also made a statement regarding their significance. Compared to the previous period, first studies reported not only the t-values statistics and/or corresponding p-values, but also confidence intervals or both (11.11%). In the reporting section below, we give additional information on how the researchers arrived at these results.

4.3.3. Advanced Analyses

In connection with considering and evaluating the inner model, further advanced analyses are essential. We summarized the results in Table 5 as well. In this context, as also noted earlier, there have been some developments regarding these analyses.

As mentioned, Henseler et al. (2016) developed the MICOM procedure. Further research (e.g., Hair et al., 2012; Hair, Sarstedt, & Ringle, 2019) pointed out the necessity of uncovering unobserved heterogeneity with latent class techniques, such as FIMIX-PLS (Hahn et al., 2002; Sarstedt, Becker, et al., 2011). We examine the usage of these and other criteria in this section.

The belief that data sets studied in PLS-SEM applications typically come from one population has dissipated somewhat. More and more studies are using PLS-SEM to examine differences within the data. This is more realistic, as this meets best with real-world applications (Hair et al., 2012). Different segments such as gender, age groups, or consumer groups can show different behavior. A total of 115 studies (48.12%) investigated observed heterogeneity by continuous (24.27%) or categorical (23.85%) moderators. Their increased use showed the procedure's growing popularity compared to 1981-2010 (30.39%). In the case of categorical moderators, researchers often compared groups using a multigroup comparison technique (133 models, 27.36%) (Sarstedt, Henseler, & Ringle, 2011). In using continuous moderators to examine interaction effects, the observed research involved 101 models (20.78%). These interaction effects examined the moderator's influence on the examined relationship's strength or direction (e.g., Henseler & Chin, 2010).

In addition, misinterpretation can occur if researchers conduct group comparisons without previously establishing their measurement's invariance. Unfortunately, only 12 studies (5.02%) controlled their data for measurement invariance of composites with the MICOM procedure.

Further, researchers did not investigate unobserved heterogeneity at all in the previous review. The present analysis shows that ten studies (4.18%) used FIMIX-PLS (Hahn et al., 2002 Sarstedt, Becker, et al., 2011) to uncover unobserved heterogeneity. However, the proportion is still far too small. This analysis should be included as a fixed component in the inner model evaluation.

Finally, we focus on the model comparisons. It became apparent that ten studies (4.18%) performed one by comparing different models with the same data set.

Overall, we can say that PLS-SEM evaluation has progressed, but there is still clear potential for further improvement.

Table 5: Evaluation of inner models 1981-2020

		1981-2010		2011-2020		1981-2010		2011-2020	
Criterion	Empirical test criterion in PLS-SEM	Number of models reporting (n=311)	Proportion reporting (%)	Number of models reporting (n=486)	Proportion reporting (%)	Other leading journals (n=250)	Top tier journals (n=61)	Other leading journals (n=446)	Top tier journals (n=40)
Endogenous constructs' explained variance	R^2	275	88.42	430	88.48	221	54	390	40*
Effect size	f^2	16	5.14	86	17.70	14	2	85**	1
Predictive relevance	Cross-validated redundancy Q^2	51	16.40	162	33.33	46**	5	154	8
Relative predicted relevance	q^2	0	0.00	15	3.09	0	0	15	0
Overall goodness-of-fit	GoF	16	5.14	76	15.64	12	4	71	5
Path coefficients	Absolute values	298	95.82	480	98.77	239	59	444***	36
Significance of path coefficients	Standard errors, significance levels, t-values, p-values	287	92.28	419	86.21	230	57	383	36
Confidence intervals	-	0	0.00	11	2.26	0	0	11	0
Both	-	0	0.00	43	8.85	0	0	43	0

		1981-2010		2011-2020		1981-2010		2011-2020	
Criterion	Empirical test criterion in PLS-SEM	Number of studies reporting (n=204)	Proportion reporting (%)	Number of studies reporting (n=239)	Proportion reporting (%)	Other leading journals (n=163)	Top tier journals (n=41)	Other leading journals (n=219)	Top tier journals (n=20)
Observed heterogeneity	Categorical moderator	47	23.04	57	23.85	41	6	53	4
	Continuous moderator	15	7.35	58	24.27	12	3	51	7
Unobserved heterogeneity	Response-based segmentation techniques (e.g., FIMIX-PLS)	0	0.00	10	4.18	0	0	9	1

*** (**, *) indicates a significant difference between "other leading journals"/"top tier journals," for 1981-2010 and 2011-2020 respectively, at a 1% (5%, 10%) significance level; results based on (one-tailed) Fisher's exact tests.

4.4. Reporting

In the guidelines Hair et al. (2012) previously developed, they explicitly indicated that in reporting on a study, information regarding the sample, data distribution, measurements, model evaluation, and results are highly relevant, but not enough. Researchers should also report technically related information, such as which software they used, and what computational and parameter settings.

Concerning many of these points, we can show some positive developments, but this is not true across the board. The crucial factor of knowing which software researchers use for the analysis is a very positive development. Whereas in the previous period, only about every second study mentioned this, recently 80.75% of the studies did so. SmartPLS (Ringle et al., 2015) was the most popular tool named in 69.46% of the studies, followed by PLS-Graph (Chin, 2003) in 7.53% of the cases. Others used software that either played no role in the previous period or did not exist before, which include ADANCO (Henseler & Dijkstra, 2020), WarpPLS (Kock, 2017), and XLSTAT (Addinsoft, 2012). Two studies (Méndez-Suárez & Monfort, 2020: plspm and meboot; Reguera-Alvarado et al., 2016: plspm) used the freely available tool R (R Development Core Team, 2021) in combination with another PLS software for additional analyses. Lohmöller's (1987) LVPLS, however, no longer played a role.

Further, there was a slight improvement over time concerning the resampling procedure, as after 2010 175 studies (73.22%) reported it (1981-2010: 66.18%). All who reported resampling, reported using bootstrapping, and 80.57% gave additional details such as the bootstrap sample used in model evaluation. Jackknifing no longer played a role.

We see no improvement in the number of reported empirical covariance/correlation matrices for the indicator variables as no one reported this between 2011 and 2020 (1981-2010: 4.90%). Researchers should add these matrices as they can lead to a better understanding of the analysis. On the other hand, they rather reported the correlation matrices of the measured constructs (180 studies, 75.31%).

However, looking at the amount of additional information reported regarding computational options and parameter settings, we could reveal further potential for improvement. While researchers did not mention them at all in the previous review, only a very small proportion of studies report them in the later studies. This in spite of Hair et al. (2012) recommending it in their guidelines. Only five studies (2.09%) mentioned parameter or algorithm settings, seven studies (2.93%) computational options (e.g., weighting schemes), and twelve studies (5.02%) the maximum number of iterations.

5. Impact of Journal Quality on PLS-SEM use between 2011-2020

As in the previous review, we looked at the tier journals anew to detect possible differences from the other journals. We, therefore, compared the top five tier journals according to Hult et al. (2009) (i.e., *Journal of Marketing*, *Journal of Marketing Research*, *Journal of Consumer Research*, *Marketing Science*, and *Journal of the Academy of Marketing Science*; 20 studies with 40 models, previously 41 with 61) to the other journals. This disclosed a reduced number of top-tier journals which we analyzed regarding the journal quality, impact on the application, and reporting behavior. In doing so, we noted a few significant differences between the groups. However, changes between the previous comparison of the top-tier journal and others are evident.

While the top-tier journals in the previous period showed significant differences between the compliance to the rule of thumb and a higher number of latent variables, this is no longer evident in the recent study. However, the journals not listed as top tier contained significantly more models (83 models; 19.04%) with less than 100 observations, compared to the top tier journals (2 models; 5.00%) ($p \leq 0.05$). In addition, the top-tier journals used more single-item constructs (29 models, 72.5%, others: 148 models, 33.2%) ($p \leq 0.01$). Besides, the descriptive analysis (Table 3) showed changes regarding the used model type. Top-tier journals used balanced models and other focused models significantly more often ($p \leq 0.05$). Further, the number of indicators per reflective construct was significantly higher for others ($p \leq 0.01$) compared to the previous period.

Considering the outer model evaluation (Table 4), we found changes with respect to the previous period. For the reflective outer models, only Cronbach's Alpha ($p \leq 0.01$) and Fornell-Larcker criterion ($p \leq 0.05$) were reported significantly more often in the top tier journals, and Cronbach's Alpha and Rho_c combined were reported significantly more often in the others. There were no differences in formative reporting, except that top-tier journals used reflective criteria to evaluate formative constructs significantly more often ($p \leq 0.01$), which is inappropriate.

In terms of inner model evaluation (Table 5), we noted more differences than before. Top tier journals consistently reported R^2 and, in doing so, significantly ($p \leq 0.10$) more often than the other journals. The other journals reported f^2 ($p \leq 0.05$) and the path coefficients ($p \leq 0.01$) significantly more often. However, there are still no differences in most of the indicators, suggesting that the journals' reporting is about the same.

6. Conclusion

The increase in the number of published articles compared to the period 1981-2010, shows that PLS-SEM has become an essential part of marketing research. Overall, we can conclude that the applications and reporting have improved, but interpretation errors continue, or important metrics are not reported, even in top-tier journals.

Our results show that there are still comprehensible concrete reasons for using PLS-SEM that are frequently used and to a large extent are the test criteria better applied. However, information is often missing (e.g., the model characteristic (formative or reflective), reporting computational options and parameter settings) or the criteria are not applied correctly (e.g., Cronbach's Alpha for internal consistency, rule of thumb). Researchers often consider PLS-SEM a suitable method for analyzing formative measured latent variables, but unfortunately, they often test these variables incorrectly. Besides, researchers must pay attention to new developments, which can only advance the field if applied in actual cases.

Identified improvements can be based on Hair, Hult, Ringle, and Sarstedt (2017), the textbook already in its second edition, after the first in 2013, and on the previous paper's (Hair et al., 2012) guidelines or on related publications (Hair, Risher, et al., 2019; Hair, Sarstedt, & Ringle, 2019).

Further, researchers should provide all information regarding model evaluation, while journal editors and reviewers should specifically require that in the review process. We collected the results of this article to develop an overview of issues and recommendations. Table 6 summarizes these results. We advise every researcher who uses PLS-SEM to follow these recommendations and already existing guidelines (e.g., Hair et al., 2012; Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Risher, et al., 2019) and encourage reviewers to use them for alignment. This is the only way to ensure comprehensive and correct reporting. We hope that this will contribute to further improvement. If researchers are concerned about the length of their publication and the journal's restrictions, they should consider using a web appendix. This should provide improved transparency and allow replication of the statistical analyses. In this way, other researchers might be able to gain new insight from it and be able to move the research forward.

Table 6: Issues/ developments and recommendations in the application of PLS-SEM

Issue/ development	Recommendation / rules of thumb	Suggested references
General		
Missing or questionable reason	Give a reason for using PLS-SEM; use the justification "small sample size" cautiously, as it is not always well suited.	Hair et al. 2019, Rigdon 2016
Data characteristics		
Distribution of the sample	PLS-SEM delivers robust results when applied to highly skewed data; but report skewness and kurtosis and their statistics, especially if non-normal distribution is given as a reason.	Cassel et al. 1999, Hair et al. 2012, Reinartz et al. 2009
Missing values	Report information regarding missing values and the used treatment.	Hair et al. 2012
Model characteristics		
Model type	Keep in mind that only focused and balanced models meet the PLS-SEM prediction goal; CB-SEM is preferred for unfocused models.	Hair et al. 2012
Description of the outer models	Report a detailed list of indicators in the appendix; distinguish between reflective and formative measurements and report the used measurement.	Hair et al. 2012
Single items	Consider using single-item measures cautiously; PLS-SEM can handle a combination of multi- and single-items, but single items do have weaknesses.	Cheah et al. 2018, Hair et al. 2012
Higher-order constructs	If a higher-order construct is used, the appropriate guidelines for the evaluation should also be followed	Sarstedt et al. 2019
Outer model evaluation: reflective		
Internal consistency reliability Cronbach's Alpha, Rho_c or Rho_A	Cronbach's Alpha underestimates reliability for small sample sizes and thus inconsistently estimates reliability for PLS construct scores; Rho_c overestimates the reliability in return; since Rho_A usually lies between these bounds, it is a very good alternative. Recommended 0.70-0.90 (or 0.60 in exploratory research, max. 0.95 to avoid indicator redundancy) In addition, test whether the internal consistency reliability is significantly higher (lower) than the minimum (maximum) thresholds that are recommended; to construct the bootstrap-based confidence interval, use the percentile method; use the bias-corrected and accelerated (BCa) method in the case of a skewed bootstrap distribution.	Dijkstra & Henseler 2015, Hair et al. 2019, Sijtsma 2009, Yuan & Bentler 2002
Discriminant validity Fornell-Larcker criterion, cross-loadings or HTMT	Fornell-Larcker criterion and cross-loading assessment have a low sensitivity. Preferred criterion should be HTMT. HTMT < 0.90, for conceptually similar constructs HTMT < 0.85, for conceptually different constructs In addition, test whether the HTMT is significantly lower than the threshold value.	Hair et al. 2019, Henseler et al. 2015
Outer model evaluation: formative		
Convergent validity (redundancy analysis)	Use the redundancy analysis to assess the convergent validity; a global single-item or a reflectively measured multi-item scale can be used as an alternative measurement. Correlations $\geq$ 0.70	Cheah et al. 2018, Chin 1998, Hair et al. 2019
Significance of weights	Report not only the weights, test whether the weights are significant, report t-values, p-values or standard errors; p-value < 0.05 or the 95% confidence interval does not include zero; to construct the bootstrap-based confidence interval, use the percentile method; in the case of a skewed bootstrap distribution use the BCa method.	Hair et al. 2019
Multicollinearity	Assess multicollinearity between the indicators in formative measures to detect indicator weights' instability. VIF $\geq$ 5 critical collinearity issues VIF 3-5 possible collinearity issues	Cenfetelli & Bassellier 2009, Hair et al. 2011, Hair et al. 2019
Inner model evaluation		
Predictive relevance Q^2	Keep in mind that Q^2 is not a measurement for the out-of-sample prediction; it only combines aspects of out-of-sample prediction and in-sample exploratory power.	Sarstedt et al. 2017, Shmueli et al. 2016, Hair et al. 2019, Hair & Sarstedt 2021
Model's predictive power PLSpredict	Use PLSpredict or another method to assess the model's predictive power (data set needs to be split into a training and a holdout sample, and apply out-of-sample prediction metrics); this makes the reporting of the Q^2 redundant; check whether the PLS-SEM analysis yields higher prediction errors compared to the linear model.	Hair et al. 2019; Hair & Sarstedt 2021; Shmueli et al. 2016 & 2019
Multicollinearity	Analyze the collinearity between the constructs, to avoid a bias on the regression results. VIF $\geq$ 5 critical collinearity issues VIF 3-5 possible collinearity issues	Hair et al. 2019

Table 6: Issues/ developments and recommendations in the application of PLS-SEM (continued)

Issue/ development	Recommendation / rules of thumb	Suggested references
Advanced analyses		
Measurement Invariance Assessment (MICOM)	Use the MICOM procedure to assess the measurement invariance of composite models, to detect misinterpretations based on invariance in multigroup comparisons.	Henseler et al., 2016
Latent class techniques / Uncovered heterogeneity	Uncovered heterogeneity can lead to misinterpreting the data, to uncover unobserved heterogeneity use latent class techniques; Techniques are, for example, the FIMIX-PLS, iterative reweighted regressions, prediction-oriented segmentation, PLS genetic algorithm, or simultaneous non-hierarchical clustering; FIMIX-PLS showed as the most common approach.	Hair et al. 2019, Sarstedt et al. 2011, Sarstedt et al. 2017
Model comparisons	If necessary use model comparison methods to compare different models for a dataset.	Hair et al. 2019
Reporting		
Correlation/covariance matrix (or appendix with raw data)	Provide the correlation/covariance matrix of the indicators, which leads to a better understanding of the analysis.	Hair et al. 2012
Technical related information	Do not forget to report technically related information such as used software, computational and parameter settings.	Hair et al. 2012

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Essay 3

Psychological Ownership in Social Media Influencer Marketing

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Psychological Ownership in Social Media Influencer Marketing

Abstract

Purpose - Social media, especially social media-based influencer marketing, has become an important factor in consumer decision-making. Studies have recently begun investigating how influencers affect consumer behaviour. Despite the increasing interest, the purpose of this study is to examine influencers' evaluation impact on consumer behaviour are scarce.

Design/methodology/approach - An online study undertook research to gain further understanding. Specifically, the study examines the following: firstly, the impact of consumers' perceived influencer credibility (IC), using the source credibility model in respect of purchase intention, attitude towards advertising and product; secondly, the impact of the organizational behaviour concept psychological ownership (PO) on consumer behaviour by showing that the concept has significant positive effects on attitude towards the product and purchase intention like in prior research; thirdly, the perceived connection and relationship between the influencer and consumer to understand the relations.

Findings - Results show that perceived IC serves as a significant criterion, determining purchase intention, attitude towards advertising and product, while contributing an instrument for transferring convincing messages, which increase the perceived connection to the influencer and the PO feeling for a product and, thus, influence consumer behaviour positively.

Originality/value - Theories on source credibility and a connection to the PO concept allowed to develop a framework to assess the importance of IC and its influence on consumers' perception of the products that influencers advertise to better understand the interactions in the influencer marketing context.

Keywords

Consumer behaviour, Psychological ownership, Influencer marketing, Source credibility

1. Introduction

Social media has gained considerable importance in the past years – especially in the past decade from a marketing perspective. With the help "of internet-based applications that build on the ideological and technological foundations of Web 2.0" that "allow the creation and exchange of user generated content" (Kaplan & Haenlein, 2010, p. 61) social media has become an indispensable part of people's lives. Instagram, YouTube and others are no longer mere private sharing platforms. Over the past decade, they have grown into important advertising channels.

Different social media offers lead to a democratization of communication because it is now possible to access a large audience without the communicator needing an institutional position (McQuarrie et al., 2013). One way of contacting this audience is the relatively new form of advertising through social media-based influencers, which has become an important factor in consumer decision-making. A survey conducted in 2018 shows that 94% of surveyed marketing professionals from 30 different countries consider influencer marketing an effective form of marketing and 79% of the respondents have an influencer marketing budget for 2019 (Relatable, 2019). Influencers are substitutes for the pre-digital age's role models and opinion leaders and appear to communicate personally with their followers. Owing to these influencers' origins, they often appear more credible than celebrity testimonials (Djafarova & Rushworth, 2017). Consequently, they are deemed to have a greater influence than conventional advertising activities. Their social media content is a preferred advertising medium for companies, as this younger target group is increasingly difficult to reach with traditional media. In 2018, only 1% of US citizens year of age 16-24 years mentioned watching terrestrial television as their preferred media activity. Instead, their preferred media activities are, for example, watching the content of video streaming platforms (13% 16-19 years, 18% 20-24 years) or viewing social media content (19% 16-19 years, 21% 20-24 years) (Audiencenet, 2018). Furthermore, Dost et al. (2019) have recently illustrated the effectiveness of seeding marketing campaigns like influencer marketing as a part of the marketing mix. Their results indicate that seeding campaigns can increase the total sales of fast-moving consumer goods by between three and 18%.

Despite the increasing interest, studies examining influencers' evaluation impact on consumer behaviour are scarce. Researchers have only recently started investigating the influencers' effects empirically. These studies have shown that celebrities are less credible than influencers although both celebrities and influencers impact consumers' purchase behaviour (Djafarova & Rushworth, 2017; Schouten et al., 2019). Furthermore, studies have shown that highly followed Instagram personalities are more likeable, partly because they are regarded as more popular although the authors could not decisively conclude that their number of followers has a positive influence on product or brand evaluation (Veirman et al., 2017). Lim et al. (2017) found that influencers' source attractiveness has a positive effect on consumer attitudes, which mediates the relationship between source attractiveness and consumers' purchase intention. Furthermore, they obtained a positive relation between the product/source fit and purchase intention.

While these studies shed a first light on influencer evaluation's importance for consumers' purchase intention, scholars know little about concrete mechanisms whereby influencers impact consumer behaviour. This paper undertook research to gain further understanding. Specifically, the study examines the following:

- Firstly, the impact of consumers' perceived influencer credibility (IC), using the source credibility model by Ohanian (1990) in respect of attitude towards product, advertising and purchase intention.
- Secondly, the impact of the organizational behaviour concept psychological ownership (PO) on consumer behaviour by showing that the concept had significant positive effects on the attitudes towards product, advertising and consumers' purchase intention like in prior research
- Thirdly, the self-influencer connection between the influencer and the consumer to understand the before-mentioned relations.

These gaps are addressed by using the social media channels Instagram and YouTube to identify the overall effects of and possible differences between them.

2. Theoretical Background/Hypotheses

2.1. Influencer Marketing

The term social media-based influencers refers to people who have built a large social community of followers on one or more social media platforms (Veirman et al., 2017). Influencer marketing refers to influencers using their reach to convey messages about a company's product or brand to their community (Brown & Hayes, 2008). People tend to refuse to believe direct advertising messages about brands, but are inclined to believe influencers, because they think that direct advertising's goal is merely to sell products, while influencers do not have such an objective (Brown & Hayes, 2008).

A few studies started investigating influencers' effects on consumer behaviour. Influencer marketing – as a part of seeding marketing strategies − was established as an important factor in the new marketing mix of fast-moving consumer goods companies. Dost et al. (2019) found that firm-created seeded word of mouth via, for example, influencers interacted negatively with other advertising forms such as TV or digital banner advertising, but positively with promotions such as direct mailing and increasing total sales by 3-18%. A qualitative study by Uzunoğlu and Misci Kip (2014) collected relevant criteria from brand and digital agency representatives for the selection of bloggers also defined as influencers or opinion leaders. Their results show that the match between blogger and brand, blogger's writing style, content, credibility and popularity are important criteria. Instagram influencers with a high number of followers are rated as more likeable, but if influencers themselves follow very few other accounts, this can have the opposite effect. Companies should choose influencers who are not extremely popular in promoting divergent products, because popular influencers may negatively influence consumers' perceptions of a brand´s uniqueness and, consequently, negatively affect consumers' attitude towards the brand (Veirman et al., 2017). A first research study on the effects of source evaluation found that influencers' source attractiveness had positive effects on consumer attitudes and on the relationship between source attractiveness and consumers' purchase intention (Lim et al., 2017). Xu and Pratt (2018) studied influencers' impact on travel promotion and concluded that influencer–consumer congruence contributes positively to consumers' intention to visit the influencer-promoted destination. Djafarova and Rushworth (2017) showed qualitatively that young women perceive celebrities on Instagram as less credible than influencers on Instagram, but that both celebrities and influencers affect consumers' purchase behaviour. Moreover, the research by Cheah et al. (2019) demonstrates that celebrities and influencers' advertising via social media posts has a comparable effect on customers' decision-making processes.

As previous research regarded credibility and attractiveness as decisive criterions (Djafarova & Rushworth, 2017; Lim et al., 2017; Schouten et al., 2019), this study uses prior research on source credibility to investigate the existing relationships in the context of influencer marketing.

2.2. Transfer of Prior Research

Celebrities are famous and well-known persons who achieved public recognition, which they use to promote products by appearing with them in advertisements (McCracken, 1989). Based on Bandura's (1977) social learning theory, people acquire new behaviour by observing and imitating other individuals in their environment (i.e., parents, TV characters). Nowadays the latter persons can also be individuals who appear on social media, such as influencers, as these media have become a part of everyday life. The attribution-based framework by Kapitan and Silvera (2016) proposes that the consumers' dispositional attributions, which result from the way in which an endorser likes, uses and appreciates an advertised product, can help understand the endorser's influence independent of the endorser type and platform on which they interact with consumers. In summarizing these definitions and attributions of endorsers and celebrities, influencers can be regarded as endorsers or non-traditional celebrities, thus enabling the transfer of source credibility research. Various possibilities and advantages result from the use of celebrities or endorsers, for example, image improvement, positive influence on consumer attitudes towards advertisement and product and, consequently, on consumers' consumption behaviour (Erdogan, 1999; Friedman & Friedman, 1979; Kaikati, 1987).

To disentangle influencers' impact on consumer behaviour, the study draws on Ohanian's (1990) source credibility model, which captures the three source effects that have the highest influence on purchase intentions and attitudes towards advertising (Amos et al., 2008). The model measures endorsers' perceived credibility by means of three dimensions, namely, trustworthiness, expertise and attractiveness. The perceived credibility shows that endorsers have different positive and significant effects on customers' consumption and evaluation behaviour and this research is used to explain influencers' marketing effects.

Highly opinionated messages from a highly trustworthy messenger lead to effective changes in consumer attitudes (Miller & Baseheart, 1969). Based on the elaboration likelihood model by Petty and Cacioppo (1981; 1986), Priester and Petty (2003) showed that such messages cause a higher persuasive power regarding product attitudes. Researchers found proven evidence for this persuasiveness in the online context, as Reichelt et al. (2014) showed that trustworthiness serves as a decisive influencing factor on the attitude towards eWOM and

Erkan and Evans (2016) confirmed that credibility in social media eWOM has a positive effect on purchase intention. Consumers' purchase intention for celebrity-endorsed products increases if they consider the endorsers as more experienced (Ohanian, 1991). The endorsers' attractiveness has a positive effect on consumers' brand attitude (Till & Busler, 2000), product attitude (Kim & Na, 2007; Silvera & Austad, 2004) and purchase intention (Kahle & Homer, 1985; Till & Busler, 2000). Pornpitakpan (2004) confirmed endorsers' positive influence on consumers' purchase intention regarding all the source credibility model's dimensions. Furthermore, negative information about celebrities that could destroy their credibility might also damage the product brand evaluation (Till & Shimp, 1998). Various research have already proven the positive influence of trustworthiness and competence on brand and product perception (Eisend & Langner, 2010; Erdogan, 1999; Kim & Na, 2007). First concrete studies on influencer posts showed that more trustworthy posts have a positive effect on brand evaluation (Jin et al., 2019) and a better endorser's evaluation (celebrity or influencer) in terms of expertize and trustworthiness has a positive influence on the attitude towards product and purchase intention (Schouten et al., 2019).

Based on these findings, the following hypotheses are used to investigate the celebrity credibility research's transferability to the influencer marketing context:

H1a. The perceived IC has a positive effect on consumers' attitude towards the advertised product.

H1b. The perceived IC has a positive effect on consumers' purchase intention regarding the advertised product.

One can conclude from the aforementioned results that the purchase will satisfy customers if the latter perceive the endorsers as credible, leading to an increase in the acceptance of the advertising message and thereby better evaluating the advertised brand and product. First findings for video bloggings confirm this connection (Chapple & Cownie, 2017) and derive the following mediation:

H1c. Consumers' attitude towards the advertised product mediates the relationship between the perceived IC and consumers' purchase intention.

Furthermore, according to Goldsmith et al. (2000) celebrity credibility also has an indirect positive impact on consumers' buying behaviour via the credibility's effect on consumers' attitude towards advertising. Lafferty and Goldsmith (1999) proved the positive effect of perceived endorsers' credibility on attitude towards advertising and Schouten et al. (2019)

confirmed this for expertize and trustworthiness in the influencer context. Moreover, Lu et al. (2014) stated that the attitude towards sponsored blog recommendation has positive effects on the consumers' purchase intention. Summarizing these findings, the following hypothesis is used to control the mediated relation in the influencer marketing context:

H2. Consumers' attitude towards advertising mediates the relationship between the perceived IC and consumers' purchase intention.

The PO concept is examined in the following section, as it could lead to better product evaluations and also increase consumers' purchase intentions (Fuchs et al., 2010; Kamleitner & Feuchtl, 2015).

2.3. Psychological Ownership

PO refers to consumers saying "It feels as if it is mine" or, in the words of Pierce et al. (2001, p. 299), the "state in which individuals feel as though the target of ownership (material or non-material in nature) or a piece of it is 'theirs'", even though there is no legal justification for this feeling or actual possession. Originating from the organizational behaviour literature (Dyne & Pierce, 2004; Pierce et al., 2001; 2004), the concept has recently gained prominence in marketing (Jussila et al., 2015) and social media research (Joo & Marakhimov, 2018; Karahanna et al., 2015; Karahanna et al., 2018).

In their research, Jussila et al. (2015) found that a variety of PO-based individual concepts, evidence and implications can be transferred to marketing research, providing a basis for deriving the relationships between the PO concept and consumer behaviour. These scholars took a comprehensive view of the phenomenon when discussing the construct's possibilities and importance for further research. The conclusions they mentioned in their paper and follow-up studies based on their results, form the basis of this paper's research. These studies include those of Fuchs et al. (2010) and Kamleitner and Feuchtl (2015) who related the PO concept to better product evaluations and higher consumer purchase intentions. Their results showed that consumers whose product selection process was empowered exhibited a higher level of PO in terms of a product, experienced a higher purchase intention and exhibited an increased willingness to pay (Fuchs et al., 2010). According to Kamleitner and Feuchtl's (2015) findings, mental imagery has a significant direct effect on PO, while PO has a direct effect on consumers' product attitude and on their intention to consider the product in the future. Hair et al. (2016) found similar results, concluding that a product's PO arises through customer co-creation processes and that consumer empowerment positively increases consumers' engagements, specifically their product evaluation and willingness to pay. By transferring these results, a positive relationship was assumed between the PO feeling for a presented product, the attitude towards the product and the purchase intention:

H3. The perceived PO feeling for an advertised product positively influences consumers' attitude towards the advertised product.

H4. The perceived PO feeling for an advertised product positively influences consumers' purchase intention.

As this research investigates the influencer marketing's underlying mechanism, it refers to research on the connection between social media and PO. Based on Pierce et al.'s (2001; 2004) fundamental research, individuals develop PO of a company if they have control over the company, are closely acquainted with the company and invest time and effort in a company. Karahanna et al. (2015) transferred these results to social media usage. They concluded that an individual's PO roots drive the usage as social media provides affordances that satisfy PO's fundamental needs. Social media offers its users the possibilities to generate their own content, control their interactions and express their opinions on the existing platforms. Social media users feel that they have power over other people by shaping them with their opinions on their social media profiles. Moreover, social media provides the tools for users to create a personal online space, thus fulfiling the need for having a place. Furthermore, it helps define social media users' self-identity by means of social interactions; it provides them with tools that allow them to express themselves through different types of generated content and to recapitulate and evaluate their past with the help of their generated timeline (Karahanna et al., 2015; Pierce et al., 2001). In Karahanna et al.'s (2018) continuing research, this was proven in respect of Facebook. These results can be transferred to Instagram and YouTube, the social media platforms that are used in this research, as these platforms fulfil the PO underlying needs, too. A private profile page offers users a personal space that they can call their own. They can express themselves as individuals by designing their profile pages by, for example, uploading content pictures or videos and by learning how others perceive them via likes or feedback comments. Furthermore, by shaping their profiles over a period of time, users develop a self-identity and begin to understand themselves better. Furthermore, users can fulfil their needs by following influencers and their content. Influencers' profiles can be permanently added to users' profiles, making the influencers part of the users' feed page. It offers individuals the possibility to control the content that they watch. Users invest their time in becoming better acquainted with influencers by following their content. These criteria result in developing PO regarding the influencer and the shown content because they fulfil the users' underlying needs.

To empirically test this transferability, this research examines the PO's influence in the influencer marketing context and on influencers' evaluation by using the source credibility model by Ohanian (1990). As far as known, there is as present no research on how source credibility affects PO. However, consumers' PO feelings for products can be increased if the target fulfils certain attributes such as attractiveness or if a feeling emerges that the target can satisfy the PO needs. If people believe that they are capable and worthy of an organization, this organizational-based self-esteem increases PO (Pierce & Jussila, 2011). Owing to attractiveness, trustworthiness and expertize being dimensions of source credibility, the positive relationship between PO feeling for a product and the evaluation of an influencer is investigated:

H5a. The perceived IC positively influences the perceived PO feeling for an advertised product.

Taking into account the connection between perceived credibility, the attitude towards a product and purchase intention, PO serves as an appropriate process variable to explain this relationship. An individual's positive evaluation of an influencer is, therefore, transferred to a product and should increase the PO feeling for an advertised product, which, in turn, mediates how the positive influencer evaluation affects the attitude towards a product and the consumers' purchase intention:

H5b. The positive relationship between the perceived IC and consumers' attitude towards the advertised product is mediated by the perceived PO feeling for an advertised product.

H5c. The positive relationship between the perceived IC and consumers' purchase intention is mediated by the perceived PO feeling for an advertised product.

Subsequently, the self-influencer connection is examined closely to explain the relationship between the perceived credibility, the PO feeling for a product and the consumers' purchase intention. Can the connection between an influencer and a consumer strengthen the feeling of ownership? In 1986, McCracken established that meanings could pass from celebrities to products and from consumer goods to consumers. Kelman's (2006) model of social influence analysed the relationship between individuals and social systems, distinguishing between three processes of social influence, namely, compliance, identification and internalization. The identification process, which is relevant for this research, occurs when a person wants to receive influence from others to build a relationship or sustain a fulfiled relationship with each other that the individual can self-define (Kelman, 2006). One can conclude that if people identify with an endorser and accept the latter's influence, they might purchase to claim the transferred meanings for themselves. Transferring these results could lead to the following conclusions, namely, influencers whose perceived credibility is high evoke a stronger feeling of a personal connection to them, which, in turn, increases the likelihood that consumers will regard an advertised product as belonging, which subsequently exhibits a higher purchase intention:

H6. The positive relationship between the perceived influencer's credibility and consumers' purchase intention is serially mediated by the self-influencer connection and by the perceived PO feeling for an advertised product.

Figure 1 summarizes all the hypotheses.

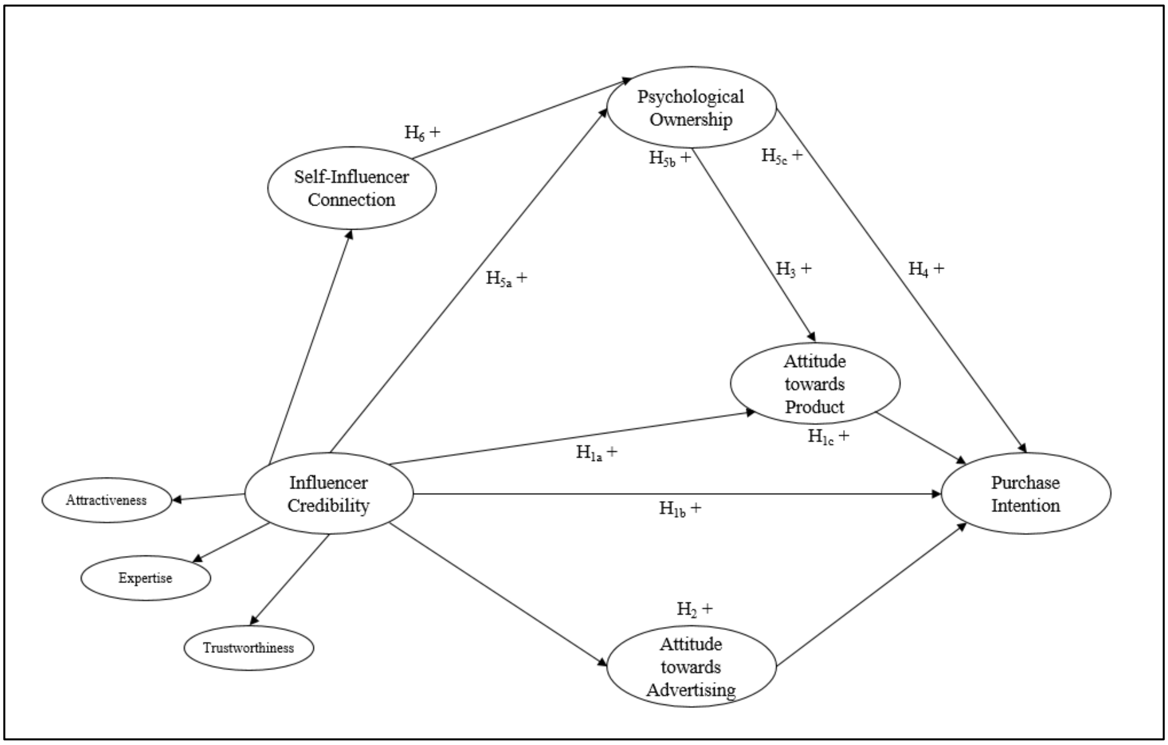

Figure 1: Hypothesized model

3. Research Design/Methods

3.1. Research Design

The study, using a between-subjects design, collected data between 14 January and 4 April 2019 by means of an online questionnaire about two influencer advertisements.

The first influencer was a fictitious female shown in either an Instagram picture or a YouTube video. Worldwide, these were the most important channel formats that influencers used for brand cooperation (eMarketer, 2018). In the video and in the picture, the influencer recommended a recipe and a hand blender while she gave her followers the opportunity to become better acquainted with her everyday life. Fictitious Instagram and YouTube profiles and advertisements were created that resembled, – as far as possible, – actual influencer profiles to maximize the internal validity and minimize the external influences' impact and to compare these with an actual profile and campaign.

The second influencer was an actual male fitness-focussed influencer who recommended a fitness drink powder. His profile and additional content informed the participants about his fitness background and showed his everyday life.

The used stimuli are shown in Figure 2.

After presenting the questionnaire's topic, the stimuli types (video or picture) introduced either the fictitious female or the actual fitness influencer by means of a screenshot of the relevant influencer's profile followed by a short description of the influencer. Subsequently, the participants viewed the advertisement in which the influencer presents either hand blender or fitness drink powder. In both cases, the influencers recommend the products. After viewing the advertisement, the participants answered questions about influencer, product, advertisement and about their perceived and actual connection to the influencer. In this context, all followers of the actual influencer were screened out, because no special relationship could be observed with the fictitious influencer. The survey was concluded by collecting information on the participants' demography, social media usage, general influencer interaction and on the influencers' effect on previous buying behaviour.

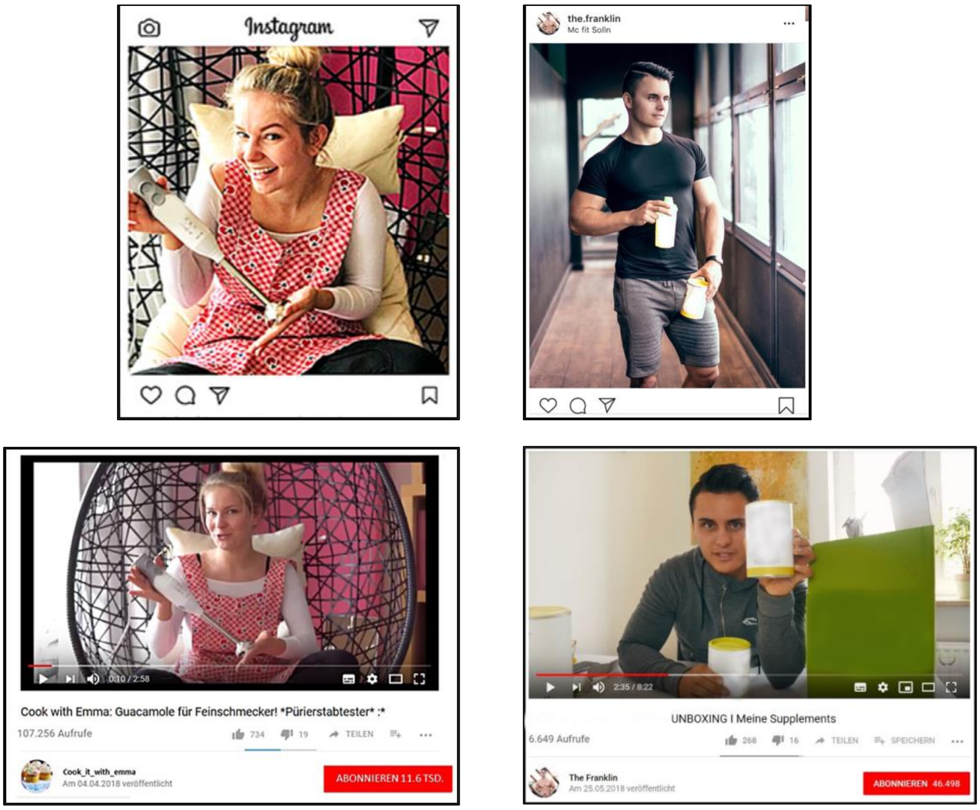

Figure 2: Stimuli Instagram and YouTube

3.2. Measures/Method

The credibility measurement based on the source credibility conceptualization by Ohanian (1990), who evaluated an endorser's consumer-perceived credibility by means of the perception of attractiveness, which refers to consumer perceptions of an endorser's physical appeal, expertize regarding the endorsed product and trustworthiness. This study followed Ohanian's conceptualization and operationalized the IC construct as a higher-order construct, which is reflected by the lower-order components' attractiveness, trustworthiness and expertize, as a meta-analysis by Amos et al. (2008) showed that the purchase intention is most influenced by these three source effects. However, there are more techniques for measuring source credibility, i.e. via source's likability or familiarity. Furthermore, previous studies (Ohanian, 1990), – like this study, – showed that the components are highly correlated, which means that they are reflective by nature (Dwivedi et al., 2015). In the extended evaluation the construct was regarded as a reflective-reflective higher-order construct, considering that the items only reflect parts of the lower-order components and are highly correlated too.

Moreover, adapted scales were used to measure purchase intention (Coyle & Thorson, 2001) attitude towards product, and advertising (Lee & Mason, 1999; Wang et al., 2009). The PO scale by Dyne and Pierce (2004) and Shu and Peck (2011) was adapted and used to measure this construct. To ensure there were no significant differences between the test groups regarding their general opinion of the product category, an adapted scale by Zaichkowsky (1985) was used to measure their category involvement. The self-brand connection scale by Edson Escalas and Bettman (2003) was adapted to measure the self-influencer connection to evaluate the perceived connection with the influencer. All constructs were measured by means of seven-point Likert scales.

To analyse the research model's relationships, partial least squares structural equation modelling (PLS-SEM) was used, as it has become increasingly important in research over the last years. In their paper, Hair et al. (2019) highlight the reasons for using PLS-SEM, namely that it was developed to allow the estimation of causal-predictive relations (Jöreskog & Wold, 1982; Wold, 2006). PLS-SEM fulfils the requirements to provide explanations and predictions, thus ensuring causal explanations' practical relevance. These scholars verify the practicability of using PLS-SEM with particularly small sample sizes and confirm that it is superior to regression analysis at assessing mediations (Hair et al., 2019). Research has shown that PLS-SEM performs very well with such data and model constellations (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017; Henseler et al., 2014; Rigdon et al., 2017; Sarstedt et al., 2016). Given the developed model's complexity, the above reasons are decisive regarding PLS-SEM's usage. The model was, therefore, estimated with the software SmartPLS3 (Ringle et al., 2015) and, based on the recommendations by Hair, Hult, Ringle, and Sarstedt (2017), with a path weighting with a maximum of 500 iterations and a stop criterion of 10^7 in the algorithm setting.

3.3. Sample/Procedures

Overall, 274 people participated. A control question in the second half of the questionnaire helped exclude lower quality answers. As a number of the participants viewed the fictitious influencer marketing campaign for the hand blender and there was a slight possibility that they might know this actress in their personal environment, a control question was inserted to ensure that they would be omitted afterwards. In sum, the sample was reduced to 222 participants. The sample size had a statistical power of 91.3% based on a 5% significant level (α) and an effect size (f^2) of 0.05, which can be considered satisfactory.

The participants were either assigned to the fictitious campaign's YouTube video (n=59) or Instagram picture (n=63) or to the actual campaign's YouTube video (n=57) or Instagram picture (n=43). In total, 67.1% of the survey respondents were female. The average age was 25.5 years, ranging in age from 13 to 66 years, with almost 90% (13-30 year olds) of the sample belonging to Generations Y and Z. In total, 98.6% of the participants use social media channels with 58.1% actually following influencers, – on average 25.3 persons. The sample comparing tests showed that there were no significant differences between the samples regarding their demographics and social media usage behaviour. However, the participants' assessments of the hand blender's and fitness drink powder's product quality and their product involvement showed differences between the groups, which is logical based on the different evaluated products. If the influencer groups are considered separately (fictitious image/video and actual image/video), there are no significant differences. This is decisive in respect of the later pooling of the groups.

The online survey was primarily shared on different social media channels. The data collection was therefore random, but focussed in terms of the social media context, which was thematically best suited.

4. Results

4.1. Measurement Model Evaluation

The analysis focuses first on the measurement model's quality. In keeping with Hair, Hult, Ringle, and Sarstedt (2017), the assessment included controls for internal consistency reliability, indicator reliability, reflective constructs' discriminant validity and convergent validity to evaluate the results' stability. To start with, the constructs attitude towards the product, purchase intention, PO, attitude towards advertising, and self-influencer connection were evaluated; the higher-order construct was considered in due course. The constructs' Cronbach alphas and Rho_a were determined to control their reliability. As all values are above 0.7, the results in Table 1 in the Appendix indicate that the variables' measures are reliable and no items need to be excluded. The constructs' items have outer loadings of above 0.7, concluding the items' reliability. As all the constructs' extracted average variances are above 0.5, convergent validity is given. The HTMT ratio (Henseler et al., 2015) was used to examine and confirm the reflective constructs' discriminant validity because the HTMT values are below the conservative threshold of 0.85 with respect to all the combinations (IC evaluated separately) of construct relations (see Appendix Table 2). The higher-order construct IC was analysed to find support for the reflective relation between it and the lower-order components, namely, attractiveness, trustworthiness and expertize. Based on the paper by Sarstedt et al. (2019), the lower-order components should first be evaluated based on the standard reliability and validity criteria to assess the reflective-reflective higher-order construct. The results yield satisfactory levels of convergent validity and internal consistency reliability (see Appendix Table 3). The higher-order construct's reliability and validity assessment does not reflect concerns in terms of the convergent validity (average variance extracted (AVE) above 0.5 threshold), internal consistency reliability (Cronbach's Alpha slightly below, Rho_c above 0.7) and the assessment of the higher-order construct's discriminant validity (heterotrait-monotrait (HTMT) criteria - all values lower than 0.85 threshold) (see Appendix Table 4). Consequently, the results indicate the higher-order construct IC's reliability and validity. In total, the model does not offer concerns regarding its reliability and validity.

4.2. Structural Model Evaluation

The evaluation and comparison of the model's predictive power, using the PLS-SEM analysis and a naïve linear model, support the usage of PLS-SEM. Table 5 in the Appendix shows the results of PLS predict with 10 folds, based on the guidelines by Shmueli et al. (2019) and focussing on the model's key endogenous construct purchase intention. The results show that the constructs' indicators outperform the naïve linear model benchmark, as all the indicators show $Q^2_{predict}$ values above zero. Furthermore, comparing the RMSE values yields lower prediction errors for all the PLS-SEM usage construct indicators, which reflect the model's high predictive power.

The hypotheses tests were set as two-tailed tests to investigate the hypothesized effects. The examination of the first derived relationship regarding the transferability of the existing source credibility research to influencer marketing shows significant total effects between influencers' perceived credibility, attitude towards the product (0.420, $p < 0.001$) and purchase intention (0.363, $p < 0.001$). Moreover, the attitude towards the product's partial mediation of the relationship between perceived credibility and purchase intention (0.196, $p < 0.001$) was verified. The attitude towards advertising's full mediation of the relationship between perceived credibility and purchase intention (0.095, $p = 0.042$) was confirmed. These findings prove the perceived credibility's positive effect on the product; H1a to H2 are, therefore, supported. Furthermore, a significant relationship is shown between attitude towards the product and purchase intention (0.623, $p < 0.001$), which is not considered any further due to its missing contextual relevance. With regard to PO's effects, the outcomes showed that PO has significant effects on attitude towards the product (0.315, $p < 0.001$) and purchase intention (0.459, $p < 0.001$), and the perceived credibility has a positive effect on PO (0.335, $p < 0.001$). The results confirm a partial mediation of PO on the relationship between perceived credibility and attitude towards the product (0.105, $p = 0.002$), and on purchase intention (0.088, $p = 0.009$). Consequently, H3 to H5c are supported. Despite the influencer advertising a product and legally owning it, influencers seem to be able to increase the PO feeling through consumers' belief in their sense of connection to such influencers. The positive relationship between perceived credibility and the participants and influencers' perceived self-influencer connection (0.564, $p < 0.001$) confirms the hypothesis resulting in the perceived self-influencer connection's full mediation of the relationship between credibility and PO (0.218, $p < 0.001$). These interrelationships result in the explanation being extended through the indirect effects via the self-influencer connection and PO's direct effect on the perceived credibility and purchase intention (0.057, $p = 0.002$), which confirms H6. The results of the bootstrapping process are summarized in Table 6 in the Appendix.

To control the overall model's robustness and test whether the different groups can be pooled, a multi-group analysis was conducted. The invariance's assessment based on Henseler et al.'s (2016) measurement invariance of composite models procedure. The results presented in Table 7 in the Appendix show that partial measurement invariance is indicated with the exception of one control variable in one comparison. Given the great number of parameters to be estimated across all the comparisons, deviations are expectable (Schlägel & Sarstedt, 2016). Next, a multi-group analysis was conducted to check for potential group-related differences. The results indicate no significant effect differences (see Appendix Table 8). Consequently, pooled data can be used for the analysis. Concluding this result, it can be assumed that the effects are generally valid for different products, influencers and formats, as the groups do not show significant differences.

5. Conclusion

Influencer marketing has become an emerging topic in research and marketing practice over the past years. This study is the first to consider influencers' positive impact on consumer behaviour using the source credibility model and PO concept. Scholars have already considered them in numerous research and demonstrated that they enable positive customer influences (Kamleitner & Feuchtl, 2015; Till & Busler, 2000).

The results conclude that established findings on the source credibility model can be confirmed in the influencer context when considering endorsers' positive evaluation on buying behaviour, product evaluation (Till & Busler, 2000) and attitude towards advertising (Goldsmith et al., 2000). It also demonstrates that PO can serve as an additional explanation by mediating these effects. As PO has already been proven to have positive effects on product evaluation and purchase intention (Fuchs et al., 2010; Kamleitner & Feuchtl, 2015), this study's results replicate and contribute to the relationship between influencer's evaluation and PO. The concept was applied to a specific case of social media use and, thus, proved and extended the results of Karahanna et al. (2015), as influencer marketing can meet PO needs and, in doing so, develop PO feeling for a product. Furthermore, it confirms, firstly, the positive impact that perceived credibility has on the felt influencer connection and, secondly, the influence on the purchase intention. Consequently, when credible influencers transfer their message, it increases customers' PO feelings and positively influences consumers' consumption behaviour. Theories on celebrity endorsement, their credibility and the connection to the PO concept enabled the development of a framework to assess the importance of influencer's credibility and its influence on consumers' perception of the products that the influencers advertise to better understand the interactions. The possibility to transfer PO feeling to a product with the help of a positively evaluated influencer recommendation opens new fields for investigation. Considering PO, this can improve purchase intention if consumers believe in and feel connected to the testimonial. The multi-group analysis's results allow the assumptions that these relationships are generally valid for different products, influencers and formats.

In addition to gaining knowledge for research, the findings are relevant for marketing practice as well, as Jussila et al. (2015) already stated for PO. The inclusion of the PO's effect and possible activation together with the marketers' targeted actions can bring the communication activities to success and help understand the relationship between customer and product. One of the challenges for influencer marketing marketers is to identify the right influencer for a campaign. The developed model, thus, helps understand which influencers need to be selected to achieve a higher purchase intention. It is critically important to invest effectively in influencers to create the most valuable content with them. The results suggest that it is essential for companies to consider the kind of people who regarded as attractive, competent and trustworthy. Strategies should be implemented that aim to increase customer participation so that customers develop a PO feeling. This could be achieved, for example, through co-creation processes within the campaign (Hair et al., 2016) or the ability to respond via comments to posts from influencers and, thus, become part of the process (Karahanna et al., 2015).

6. Limitation and Further Research

The study reviewed influencer marketing, which is a new and dynamic research field offering many opportunities for further research. However, as this is one of the first studies in this field, there are also limitations, which might even be extended in additional research. The participants' demographics could represent a limitation, as they were mainly from Generations Y and Z. This research focussed on YouTube and Instagram, but there are many more types of social media, which should be taken into account. The differences between followers and non-followers should receive special attention. Including consumers in creating products within the framework of co-creation via social media and its effects would be another promising research area. Future research could also investigate cross-cultural differences; this study is limited because it focussed on Germans. Previous studies showed that there are differences in social media's patterns between countries (Tsai & Men, 2017). This research is the first study to examine the relationship between perceived credibility and PO for a product. In this regard, studies could concentrate on different advertising contexts and examine the connection's stability. Another research option could be to examine influencers' other characteristics beyond their credibility (i.e., product evaluation number). An additional field of research could be to explore the differences in the effect of influencer marketing, which depends on specific consumers' personality traits, for example, social physique anxiety (Hart et al., 1989) or conformity (Mehrabian & Stefl, 1995), as people react differently to messages.

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Appendix

Table 1: Constructs and dimensions/items - Univariate statistics, internal consistency, convergent validity estimates

Construct	Loading	N	Mean	SD	AVE_a	Rho_a	Cronbach's $alpha_a$
-AtA-							
AtA_01	0.843	222	2.923	1.641	0.665	0.932	0.928
AtA_02	0.833		2.563	1.600			
AtA_03	0.777		3.108	1.788			
AtA_04	0.734		3.523	1.805			
AtA_05	0.862		2.865	1.647			
AtA_06	0.874		2.613	1.615			
AtA_07	0.779		3.441	1.854			
AtA_08	0.813		3.239	1.730			
-AtP-							
AtP_01	0.918	222	3.775	1.779	0.822	0.929	0.928
AtP_02	0.895		3.932	1.758			
AtP_03	0.939		3.149	1.761			
AtP_04	0.874		3.333	1.869			
-PI-							
PI_01	0.869	222	2.189	1.605	0.81	0.942	0.941
PI_02	0.890		2.685	1.833			
PI_03	0.912		3.279	2.028			
PI_04	0.876		2.446	1.675			
PI_05	0.950		2.477	1.845			
-PO-							
PO_01	0.967	222	1.604	1.232	0.938	0.969	0.967
PO_02	0.975		1.441	1.033			
PO_03	0.963		1.450	1.141			
-SIC-							
SIC_01	0.853	222	2.563	1.206	0.687	0.925	0.923
SIC_02	0.849		1.820	1.160			
SIC_03	0.875		2.122	1.365			
SIC_04	0.784		1.770	1.195			
SIC_05	0.728		1.532	0.952			
SIC_06	0.811		1.892	1.283			
SIC_07	0.889		1.383	0.829			

Table 2: Discriminant validity estimates - HTMT

Construct	AtA	AtP	Att	Exp	IC*	PI	PO	SIC	Tru
AtA									
AtP	0.505								
Att	0.477	0.202							
Exp	0.556	0.271	0.235						
IC*	0.757	0.436	0.753	0.838					
PI	0.489	0.815	0.163	0.214	0.370				
PO	0.347	0.443	0.205	0.228	0.350	0.568			
SIC	0.569	0.441	0.430	0.385	0.612	0.390	0.479		
Tru	0.657	0.486	0.371	0.531	0.894	0.435	0.344	0.553	

*Notes: AtA: attitude towards advertising, AtP: attitude towards product, Att: attractiveness, IC: influencer credibility, Exp: expertize, PI: purchase intention, PO: psychological ownership, SIC: self-influencer connection, Tru: trustworthiness; *higher-order construct*

Table 3: Higher-order construct and dimensions/items - Univariate statistics, internal consistency and convergent validity estimates

					AVE_c	Rho_c	Cronbach's $Alpha_c$
					0.570	**0.795**	**0.621**
Higher-order construct	**Loading**	**N**	**Mean**	**SD**	**AVE_a**	**Rho_a**	**Cronbach's $Alpha_a$**
					0.434	**0.918**	**0.902**
-Att-							
Att_01	0.847		4.257	1.459			
Att_02	0.872		3.914	1.527			
Att_03	0.794	222	2.932	1.504	0.663	0.881	0.872
Att_04	0.809		3.441	1.546			
Att_05	0.742		2.833	1.532			
-Tru-							
Tru_01	0.886		3.892	1.553			
Tru_02	0.917		3.842	1.521			
Tru_03	0.887	222	3.838	1.418	0.823	0.947	0.946
Tru_04	0.939		3.734	1.509			
Tru_05	0.906		3.743	1.546			
-Exp-							
Exp_01	0.873		4.131	1.707			
Exp_02	0.900		3.869	1.538			
Exp_03	0.823	222	3.09	1.516	0.742	0.918	0.913
Exp_04	0.902		4.257	1.549			
Exp_05	0.804		4.288	1.509			

Table 4: Discriminant validity estimates - HTMT higher-order construct

Construct	HTMT(IC, …)
AtA	0.827
AtP	0.472
Att	0.450
Exp	0.570
PI	0.399
PO	0.379
SIC	0.670
Tru	0.663

Table 5: PLSpredict assessment

	PLS-SEM		LM	PLS-SEM - LM
Key endogenous construct	**RMSE**	**$Q^2_{predict}$**	**RMSE**	**RMSE**
PI_01	1.743	0.115	1.756	-0.013
PI_02	1.945	0.088	1.988	-0.043
PI_03	1.585	0.114	1.597	-0.012
PI_04	1.753	0.094	1.832	-0.079
PI_05	1.548	0.078	1.591	-0.043

Table 6: SEM

		Pooled (n = 222)	
		Path coefficient	**95% BCa CI**
H_{1a}	IC→AtP	0.420***	[0.313; 0.517]
H_{1b}	IC→PI	0.363***	[0.228; 0.490]
H_{1c}	IC→AtP→PI	0.196***	[0.121; 0.276]
H_2	IC→AtA→PI	0.095**	[0.012; 0.199]
H_3	PO→AtP	0.315***	[0.179; 0.421]
H_4	PO→PI	0.459***	[0.327; 0.582]
H_{5a}	IC→PO	0.335***	[0.183; 0.454]
H_{5b}	IC→PO→AtP	0.105***	[0.058; 0.168]
H_{5c}	IC→PO→PI	0.088***	[0.044; 0.149]
H_6	IC→SIC→PO→PI	0.057***	[0.027; 0.095]
	R^2		
	AtA	0.494	
	AtP	0.265	
	Att	0.351	
	Exp	0.584	
	PI	0.651	
	PO	0.214	
	SIC	0.318	
	Tru	0.777	

Note: ***p ≤ 0.01; **p ≤ 0.05; *p ≤ 0.1

Table 7: Measurement invariance assessment

Construct relation	**Original correlation c**	**5% quantile of c_u**	**Composite mean values**		**Composite variance ratios**	
			Difference	**95% BCa CI**	**Difference**	**95% BCa CI**
Actual/Fictitious						
AtA	1.000	0.998	0.172	[-0.260; 0.265]	-0.037	[-0.269;0.289]
AtP	*0.999*	*1.000*	*0.680*	[-0.261; 0.249]	-0.219	[-0.269;0.274]
Att	0.997	0.991	*0.302*	[-0.281; 0.276]	0.256	[-0.351;0.327]
Exp	1.000	0.999	0.090	[-0.244; 0.280]	-0.028	[-0.314;0.314]
IC	0.995	0.991	*0.468*	[-0.266; 0.269]	0.001	[-0.347;0.375]
PI	1.000	1.000	*0.596*	[-0.253; 0.259]	0.271	[-0.341;0.393]
PO	1.000	1.000	0.214	[-0.252; 0.246]	0.547	[-0.908;0.906]
SIC	1.000	0.998	*0.417*	[-0.256; 0.262]	*0.618*	[-0.590;0.623]
Tru	1.000	1.000	*0.596*	[-0.276; 0.256]	-0.078	[-0.323;0.329]
Pictures/Videos						
AtA	0.999	0.998	**0.385**	[-0.273; 0.266]	0.145	[-0.299; 0.277]
AtP	1.000	1.000	0.205	[-0.263; 0.265]	-0.229	[-0.284; 0.291]
Att	0.996	0.990	-0.111	[-0.270; 0.265]	-0.170	[-0.337; 0.326]
Exp	1.000	0.999	*0.641*	[-0.245; 0.234]	-0.071	[-0.343; 0.341]
IC	0.997	0.991	0.242	[-0.246; 0.245]	-0.130	[-0.369; 0.381]
PI	1.000	1.000	0.106	[-0.263; 0.274]	-0.207	[-0.389; 0.365]
PO	1.000	1.000	-0.096	[-0.255; 0.264]	-0.175	[-0.927; 0.904]
SIC	0.999	0.998	0.254	[-0.260; 0.250]	0.334	[-0.650; 0.591]
Tru	1.000	1.000	0.017	[-0.262; 0.259]	-0.066	[-0.332; 0.352]
Picture/Video Fictitious						
AtA	0.996	0.996	*0.382*	[-0.361; 0.353]	0.108	[-0.391; 0.393]
AtP	0.999	0.998	-0.132	[-0.324; 0.353]	-0.301	[-0.439; 0.482]
Att	0.998	0.991	*-0.364*	[-0.347; 0.357]	-0.020	[-0.425; 0.450]
Exp	0.999	0.997	*0.806*	[-0.363; 0.339]	-0.217	[-0.414; 0.440]
IC	0.996	0.983	0.204	[-0.368; 0.319]	-0.185	[-0.519; 0.517]
PI	1.000	0.999	-0.047	[-0.349; 0.344]	-0.364	[-0.395; 0.421]
PO	1.000	1.000	-0.164	[-0.379; 0.360]	-0.428	[-1.130; 1.146]
SIC	0.999	0.996	0.249	[-0.362; 0.327]	0.160	[-0.791; 0.706]
Tru	1.000	0.999	0.013	[-0.384; 0.323]	-0.139	[-0.437; 0.466]
Picture/Video Actual						
AtA	1.000	0.998	0.358	[-0.420; 0.391]	0.188	[-0.490; 0.442]
AtP	1.000	0.999	*0.474*	[-0.413; 0.378]	0.259	[-0.502; 0.482]
Att	0.994	0.914	0.178	[-0.412; 0.390]	-0.258	[-0.601; 0.543]
Exp	0.999	0.998	*0.436*	[-0.396; 0.402]	0.088	[-0.492; 0.481]
IC	0.996	0.981	0.189	[-0.432; 0.413]	-0.097	[-0.562; 0.549]
PI	0.999	0.999	0.204	[-0.396; 0.394]	0.135	[-1.070; 0.923]
PO	1.000	0.998	-0.049	[-0.378; 0.408]	0.257	[-1.711; 1.594]
SIC	0.997	0.992	0.191	[-0.399; 0.423]	0.562	[-1.273; 1.164]
Tru	1.000	0.999	-0.098	[-0.422; 0.430]	-0.055	[-0.513; 0.473]
Picture Fictitious/Actual						
AtA	1.000	0.995	0.148	[-0.402; 0.398]	-0.091	[-0.401; 0.415]
AtP	0.999	0.999	0.375	[-0.390; 0.402]	*-0.466*	[-0.456; 0.523]
Att	0.997	0.949	0.058	[-0.403; 0.395]	0.321	[-0.494; 0.532]
Exp	1.000	0.997	0.245	[-0.392; 0.404]	-0.318	[-0.487; 0.533]
IC	0.998	0.980	*0.513*	[-0.382; 0.396]	-0.074	[-0.539; 0.559]
PI	0.999	0.998	*0.498*	[-0.394; 0.382]	0.015	[-0.470; 0.566]
PO	1.000	0.999	0.159	[-0.383; 0.388]	0.168	[-1.300; 1.708]
SIC	0.999	0.993	*0.422*	[-0.392; 0.377]	0.390	[-0.866; 0.916]
Tru	1.000	1.000	*0.668*	[-0.369; 0.426]	-0.114	[-0.480; 0.544]
Video Fictitious/Actual						
AtA	0.997	0.997	0.151	[-0.389; 0.365]	-0.002	[-0.483;0.522]
AtP	0.999	0.999	*0.901*	[-0.374; 0.335]	0.100	[-0.372;0.388]
Att	0.997	0.990	*0.536*	[-0.369; 0.347]	0.170	[-0.441;0.472]
Exp	0.999	0.998	-0.140	[-0.359; 0.384]	-0.006	[-0.467;0.446]
IC	0.990	0.988	0.411	[-0.348; 0.364]	0.072	[-0.547;0.560]
PI	1.000	1.000	*0.668*	[-0.381; 0.357]	0.510	[-0.544;0.527]
PO	1.000	1.000	0.281	[-0.356; 0.371]	0.865	[-1.266;1.315]
SIC	0.999	0.995	0.385	[-0.344; 0.361]	0.831	[-0.866;0.885]
Tru	1.000	0.999	*0.538*	[-0.365; 0.357]	-0.026	[-0.417;0.414]

Notes: 95% BCa CI = 95% bias-corrected and accelerated confidence interval (Hair et al., 2017); violations partial/full measurement invariance in Italic

Table 8: Multi-group analysis

	Actual/fictitious		Pictures/videos		Picture/video fictitious		Picture/video actual		Picture fictitious/cctual		Video fictitious/actual	
	Total effects-differences	p-value	Total effects-differences	p-value	Total effects-differences	p-value	Total effects-differences	p-value	Total effects-differences	p-value	Total effects-differences	p-value
AtA->PI	0.252	0.035	0.184	0.905	0.323	0.958	0.029	0.555	0.033	0.432	0.033	0.432
AtP->PI	0.153	0.930	0.102	0.866	0.082	0.771	0.052	0.381	0.191	0.904	0.191	0.904
PO->PI	0.015	0.480	0.148	0.869	0.072	0.679	0.235	0.218	0.054	0.423	0.054	0.423
PO->AtP	0.036	0.401	0.206	0.954	0.263	0.960	0.192	0.200	0.044	0.594	0.044	0.594
IC->AtA	0.009	0.559	0.003	0.480	0.133	0.071	0.129	0.117	0.120	0.124	0.120	0.124
IC->ATT	0.150	0.110	0.077	0.773	0.081	0.740	0.030	0.554	0.110	0.238	0.110	0.238
IC->EXP	0.106	0.941	0.043	0.709	0.003	0.502	0.175	0.033	0.042	0.390	0.042	0.390
IC->PI	0.013	0.465	0.089	0.253	0.241	0.074	0.118	0.275	0.231	0.100	0.231	0.100
IC->AtP	0.135	0.890	0.067	0.711	0.075	0.327	0.207	0.114	0.046	0.411	0.046	0.411
IC->PO	0.011	0.484	0.095	0.772	0.137	0.812	0.052	0.432	0.024	0.568	0.024	0.568
IC->SIC	0.030	0.676	0.040	0.284	0.050	0.293	0.008	0.541	0.024	0.616	0.024	0.616
IC->TRU	0.003	0.497	0.046	0.053	0.006	0.461	0.076	0.946	0.060	0.957	0.060	0.957
SIC->PI	0.050	0.650	0.068	0.753	0.019	0.572	0.152	0.221	0.003	0.466	0.003	0.466
SIC->AtP	0.025	0.606	0.089	0.855	0.089	0.797	0.121	0.207	0.032	0.582	0.032	0.582
SIC->PO	0.120	0.737	0.020	0.539	0.016	0.464	0.086	0.429	0.066	0.584	0.066	0.584

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